Policy Research Working Paper 10053

Inequality and Security in the Aftermath of Internal Population Displacement Shocks

Evidence from Nigeria

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WORLD BANK GROUP
Social Sustainability and Inclusion Global Practice
May 2022

Abstract

This paper studies the security implications of internal displacement shocks for host communities. It focuses on changes in wealth within host communities induced by the inflow of internally displaced persons (IDPs) as a potential mechanism that triggers local conflicts. The sudden insurgency of the jihadist terrorist organization Boko Haram, which led to the internal displacement of over 2.5 million persons in northeastern Nigeria, is used as a quasi-natural experiment. Applying both a two-way fixed effects analysis and an instrumental variable strategy based on historical ethnic ties between the areas of displacement and receiving areas, the results show that the presence of IDPs is associated with a decrease in aggregate wealth and an increase in inequality within host communities, between 2010 and 2019. These effects are accompanied by an increased risk of conflict onset in the short and long run. The inequality–conflict link is likely to be caused by grievances among low-wealth segments of the host community towards new arrivals rather than by changes in social cohesion within host communities, which increased in response to the inflow of IDPs. The analysis further indicates that an improvement in IDPs' living conditions is accompanied by a decrease in violence and improved relations between hosts and IDPs. Taken together, findings from this study call for a two-pronged immediate relief and recovery approach that alleviates adverse economic effects on vulnerable segments of host communities and increases IDPs' welfare in displacement settings.

This paper is a product of the Social Sustainability and Inclusion Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at sedova@pik-potsdam.de.

Inequality and security in the aftermath of internal population displacement shocks: evidence from Nigeria*

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JEL codes: D63, D74, O15, O55

Keywords: displacement, inequality, conflict, Africa

*This paper was commissioned by the World Bank Social Sustainability and Inclusion Global Practice as part of the activity "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts." The activity is task managed by Audrey Sacks and Susan Wong with assistance from Stephen Winkler. This work is part of the program "Building the Evidence on Protracted Forced Displacement: A Multi-Stakeholder Partnership". The program is funded by UK aid from the United Kingdom's Foreign, Commonwealth and Development Office (FCDO), it is managed by the World Bank Group (WBG) and was established in partnership with the United Nations High Commissioner for Refugees (UNHCR). The scope of the program is to expand the global knowledge on forced displacement by funding quality research and disseminating results for the use of practitioners and policy makers. This work does not necessarily reflect the views of FCDO, the WBG or UNHCR. BŠ also acknowledges funding from the German Federal Foreign Office.

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1 Introduction

At the end of 2020 there were an estimated 82 million forcibly displaced persons (FDPs)[1] around the world, approximately 48 million of whom are *internally* displaced persons (IDPs)[2] (UNHCR, 2021). Forced displacement mostly occurs in low- and middle-income countries (Schneiderheinze et al., 2020; Verme and Schuettler, 2021). The sudden inflow of a large number of displaced persons (DPs) creates demand and supply shocks in labor and consumer markets and is typically accompanied by a substantial demand for increased public expenditures. It is associated with profound wage and employment effects within host communities, as well as short-run food and housing price increases and an increased demand for public goods such as health care services and education (Verme and Schuettler, 2021). The aggregate welfare effects of DP inflows depend on the context, and have distributional consequences that create winners and losers (Becker and Ferrara, 2019; Maystadt et al., 2019; Verme and Schuettler, 2021). At the same time, previous studies demonstrate that increases in inequality – and the individual (Dyrstad and Hillesund, 2020; Miodownik and Nir, 2016; Rustad, 2016) and/or between-group (Alesina et al., 2016; Cederman et al., 2013; Østby, 2008; Stewart, 2016) grievances it creates – are associated with a higher risk of conflict.

We therefore consider inequality, in addition to an aggregate decrease in welfare, as a potential mechanism explaining conflict onset (i.e., violence against civilians and riots) in hosting areas. We address the following three research questions: RQ 1.) How does forced displacement affect wealth and inequality in host communities? RQ 2.) Do these changes causally impact social cohesion and conflict onset? and RQ 3.) Is persistent inequality between IDPs and the host community associated with between-group social cohesion and conflict onset? We hypothesize that if displacement shocks have adverse welfare effects on the host community and these effects are disproportionately borne by segments of the population that are already disadvantaged, the decrease in wealth and the increase in inequality raise the risk of conflict onset and violence more generally. We expect a similar effect if large inter-group inequalities between displaced and host communities persist.

To explore these research questions, we use large-scale population flows caused by the Boko Haram insurgency in Nigeria as a quasi-natural experiment. For roughly two decades, parts of northeastern Nigeria have been subject to the insurgency of the Islamist terrorist group Boko Haram (Kamta et al., 2020b). Since 2009, over 3.4 million Nigerians have been displaced as a result, over 2.5 million of them to northeastern parts of the country; IDP numbers peaked in 2014 (UNHCR, 2019b). We construct a unique data set by merging displacement-related data from the Displacement Tracking Matrix collected by the International Organization for Migration (IOM), the World Bank's Nigerian General Household Survey (NGHS), the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018, and the Armed Conflict Location and Event Data Project (ACLED) database at the geographically granular local government area (LGA) level. To

[1]Following Verme and Schuettler (2021), we use the term FDPs to refer to refugees, returnees, expellees, escapees and internally displaced persons. These persons have been subjected to forced displacement due to some form of either conflict, violence, persecution, human rights violations, natural disasters or high levels of insecurity or uncertainty resulting in a sudden and large-scale movement of people. We sometimes refer to forced displacement as forced migration. These terms are used interchangeably in this paper.

[2]IDPs are persons who have been forced to flee their home but never crossed an international border.

study the effect of IDPs inflows on host communities' wealth and conflict, we then apply two causal inference techniques. We first study the implications in a two-way fixed effects design, exploiting the combination of the sudden shock and the spatially heterogeneous nature of IDP inflows across LGAs. In a second step, we instrument IDPs' movements using predicted migration flows based on historical ethnic ties between LGAs of displacement and receiving LGAs to account for potentially endogenous IDPs' destination choices. Finally, we correlate IDP-related estimated changes in local inequality and welfare measures with local violence and cohesion to shed new light on their role in conflict onset.

We show that IDPs' presence is associated with a decrease in aggregate wealth and adverse distributional consequences within host communities. Households in the bottom three quartiles of the Nigerian expenditure distribution experienced a significant reduction in wealth after the IDPs' arrival; those in the lowest quartile were the most negatively affected. These adverse economic consequences are accompanied by an increased risk of conflict onset in hosting areas in both the short and long run. In line with our theoretical considerations, this evidence suggests that aggregate welfare and inequality caused by a population displacement shock are plausible mechanisms for explaining conflict onset in IDP hosting areas. We further show that, despite the rise in wealth inequality between households following such a shock, conflicts are unlikely to emerge between members of host communities. Rather, our findings indicate that the presence of IDPs *increases* intra-community trust among members of host communities. Finally, we find indications that reducing negative inequality between IDPs and hosts, and improving IDPs' living conditions, can decrease local tensions. A possible explanation is that hosts benefit from IDPs' higher wealth levels as their higher demand for goods and services boosts local economies. Table 1 reports the main results.

Table 1: Overview of the main results

Outcome	Effect of IDPs inflow	
	Direction	Magnitude
Hosts' consumption		
Overall (Table 5, Model 2)	-	-0.14 std.dev.
Poor (Table 5, Model 4)	—	-0.27 std.dev.
Medium wealth (Table 5, Model 6)	–	-0.20 std.dev.
Rich (Table 5, Model 8)	+	0.05 std.dev. (insignif.)
Conflict onset		
Short run (Table 13, Model 3)	+	3.7 p.p.
Long run (Table 13, Model 5)	++	40 p.p.

This table presents evidence of the effect of IDP inflows on various outcomes at the destination. The direction of the effects is either negative (-) or positive (+) and the number of symbols (i.e., - and +) indicates the relative effect size. The magnitudes of the effects capture changes in outcomes in response to a 1 percentage (p.p.) increase in IDPs at the destination. All effects are significant at least at the 10% level unless stated otherwise.

Our findings have at least three immediate implications for policies and programs designed to prevent the emergence and escalation of tensions in displacement contexts. First, since host-community households at the lower end of the wealth distribution are the most likely to suffer economic losses in the aftermath of a population displacement shock, measures to shield these segments of the population from adverse economic consequences should be integrated into DP protection and support programs. In northeastern Nigeria, where the security situation is rarely conducive to the structured implementation of labor market programs, social protection programs should be improved. Such measures would not only serve as a poverty reduction tool; they are also likely to help prevent conflict. Second, facilitating DPs' access to basic public services and improving their standard of living more generally is likely to reduce tensions between DPs and the host community. It remains crucial to ensure that there is broad public support for social assistance and that it targets the most vulnerable DPs and host community members and reaches the intended beneficiaries, for example by employing third-party monitoring (e.g., by local civil society organizations). Finally, forward looking policies should aim to increase resilience among the host communities, for instance, by developing and advancing early warning systems. To this end, novel data and approaches should be explored on an ongoing basis.

Our paper contributes to two streams of literature with novel evidence from IDP shocks caused by Boko Haram insurgencies in Nigeria. First, we add to the literature analyzing the economic implications of FDP inflows by explicitly focusing on the distributional consequences in addition to the aggregate welfare effects they might have on host communities.[3] Our study therefore complements the Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts project.[4] Our paper is most closely related to that of Foltz and Shibuya (2021), who examine the implications of IDP inflows on income and income inequality in host communities in Mali. However, on aggregate they do not find any significant evidence. Further, Murard (2021); Coniglio et al. (2021) and Zhou et al. (2021) show that overall, host communities benefit from FD, as it is accompanied by an inflow of public goods and services. For instance, Groeger et al. (2021) find that an inflow of relatively more skilled Venezuelan refugees to Peru has had positive labor market outcomes on locals. This evidence contrasts with our results, likely due to the particularities of the displacement crises in northeastern Nigeria, which have been severely underfunded (UN OCHA, 2019, 2020), thus generating high levels of direct competition between IDPs and hosts in the consumer and labor markets.

Second, we advance the literature on the implications of FD for peace and security in hosting areas. While recent studies have intensively analyzed this link, the evidence is mixed and the mechanisms underexplored (Maystadt et al., 2019). Our study addresses this gap in the research by considering inequality in addition to aggregate welfare effects as mechanisms that may explain conflict onset in displacement settings. To the best of our knowledge, Fisk (2019) is the only published study that uses economic marginalization to assess the link between the presence of DPs and conflict, but it fails to show any significant association. Further analyses in this area have emerged as a part of the Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts project. Albarosa and Elsner (2021); Groeger et al. (2021); Murard (2021); Coniglio et al. (2021); Zhou et al. (2021) and Pham et al. (2021) study the implications of FD on conflicts in host communities, and treat economic conditions as potential drivers. Overall, these

[3] Verme and Schuettler (2021)'s recent meta-analysis of the well-being implications of FD proposes that the aggregate distributional aspects in particular should become a priority for future research, as they are poorly understood.

[4] The project is part of the Building the Evidence on Protracted Forced Displacement: A Multi-Stakeholder Partnership by the UK government's Department for International Development, the World Bank, and the UNHCR.

studies conclude that if FD reduces the economic welfare of host community members, conflicts in the area become more likely, and vice versa. They also find evidence of a correlation between hosting refugees and greater social cohesion within host communities. Both results are in line with evidence from our study. Our findings and evidence reported in Hoseini and Dideh (2021) suggest that persistent inequalities between DPs and hosts can also be a source of tension. Such inequalities have also been identified by Blanko et al. (2021) in Chile and by Kovac et al. (2021) in Bosnia and Herzegovina, who show that DPs have systematically worse educational outcomes.

The remainder of the paper proceeds as follows. The next section provides background information on the displacement crisis caused by the Boko Haram insurgency in northeastern Nigeria. Section 3 reviews the relevant literature, presents our hypotheses, and outlines the paper's conceptual contributions. Section 4 details our empirical strategy. Section 5 reports the findings, and Section 6 discusses the resulting policy and program implications.

2 Context

2.1 The rise of Boko Haram

In 2002, Ustaz Mohammed Yusuf founded Boko Haram in Maiduguri, the capital of the northeastern Nigerian state of Borno (Kamta et al., 2020b). He preached against the corruption and inequality of the state, rejected Western influences, and called for the establishment of an Islamic state to enforce his fundamentalist version of Sharia law (IRD and AFD, 2018; Vivekananda et al., 2019). The group believes that everyone who is opposed to its ideology should be killed (Ogbogu, 2015). Yusuf's followers called themselves *Jama'atu Ahlis Sunna Lidda'awati wal-Jihad (JAS)* (People Committed to the Propagation of the Prophet's Teachings and Jihad) (Ekhator-Mobayode and Abebe Asfaw, 2019; Genocide Watch, 2016). The media (mis)labelled JAS "Boko Haram" (Western education is forbidden) – referring to a slogan members would chant at their rallies (Vivekananda et al., 2019).

While Boko Haram began as a non-violent group, the insurgency started in 2009 when Yusuf clashed with the authorities (Comolli, 2015). The violence was concentrated mainly in the northeastern states of Borno, Yobe and Adamawa (Adelaja and George, 2019; Kamta et al., 2020b). The violence gradually escalated after Yusuf's execution while in custody in July 2009 (Bertoni et al., 2019). Under the new leadership of self-proclaimed Imam Abubakar Shekau (IRD and AFD, 2018), Boko Haram has become a brutal insurgent group (Ekhator-Mobayode and Abebe Asfaw, 2019). Over the next five years, it gained control over much of Nigeria's Borno state and some territory of neighboring states, and started to operate in the border areas of neighboring countries Niger, Chad, and Cameroon. Boko Haram plundered villages and bombed markets, churches and mosques, which it considered *infidel* (ICG, 2018; Vivekananda et al., 2019). In response, numerous communities have formed militias, thus triggering a civil war (Vivekananda et al., 2019). The mass abduction of 276 schoolgirls in Chibok, Borno state in April 2014 — one of the group's many attacks (ICG, 2018) — attracted international attention and led to the internationalization of the military response.

The Multi-National Joint Taskforce (MNJTF), from Benin, Cameroon, Chad, Niger and Nigeria, was activated in 2014; together with local militias, it recovered significant territory from Boko Haram in 2014 and 2015 (Vivekananda et al., 2019). They have been partially successful in fighting violence. However, their measures to undermine Boko Haram's activities and protect civilians (e.g., restrictions on the movement of people and items such as fertilizers, trade, and fishing, as well as closing local markets) coupled with human rights abuses (e.g., sexual violence) have had the opposite effect, severely undermining livelihoods and reducing people's ability to adapt to the changing climate (IRD and AFD, 2018; ICG, 2018; Vivekananda et al., 2019).

Without a charismatic leader such as Ustaz Mohammed Yusuf, the group fragmented. Some segments criticized Abubakar Shekau's brutality and persecution of primarily Muslims, further implying that the conflict is not truly of an ethno-religious nature. In 2012, a splinter group called Ansaru emerged; its full name, *Jama'at Ansar Al Muslimin Fi Bilad al-Sudan*, means the Community of the Defenders of the Muslims in the Land of the Blacks. In 2015, as an international anti-terrorist coalition was being formed, a faction of Boko Haram fighters led by Shekau pledged allegiance to the Islamic State in Iraq and Syria (ISIS), calling itself Islamic State West Africa Province (ISWAP) (*Wilayat Gharb Ifriqiyah*) (IRD and AFD, 2018). ISWAP split into two groups the following year. Led by Mamman Nur and Abu Musab al-Barnawi, a son of Ustaz Mohammed Yusuf, many senior leaders left and retained the name ISWAP; this faction gained recognition from ISIS and attracted an increasing number of militants. Shekau remained in charge of the remaining members and reassumed the group's original name, JAS (ICG, 2018).

In contrast to JAS, ISWAP has attacked military targets and government installations in an effort to increase its territorial control. Both groups' influence remains limited to the marshland around and the islands of Lake Chad, parts of the Mandara hills on the Nigeria–Cameroon border, and the forests of Borno and Yobe states. While both groups remain very potent military forces, ISWAP has an estimated 3,500–5,000 fighters, and JAS only 1,500–2,000; ISWAP's dominance was further demonstrated by the May 2021 death of Abubakar Shekau during a clash with ISWAP (BBC, 2021). ISWAP has been growing in power, expanding its reach, overrunning dozens of army bases and killing hundreds of soldiers since August 2018.[5] The group has experienced an ongoing leadership shuffle since the execution of its leader Mamman Nur in 2018; hardline militants continue to dominate. Its current leader is Sani Shuwaram (Nigerian News, 2021). ISWAP has built a good relationship with the Lake Chad area's inhabitants, making it difficult to displace. It treats Muslims better than JAS – and better than the Nigerian state in many ways – by providing access to health care, education, and water (ICG, 2018; Vivekananda et al., 2019).

2.2 Displacement and other consequences

The fighting between the insurgents, Nigerian security forces, and MNJTF has been particularly intense since 2013, leading to the loss of at least 20,000 lives (The World Bank, 2016) and the large-

[5] In December 2018, for instance, it overran a major military base in Baga, located on the shores of Lake Chad. On 23 February 2019 ISWAP launched its first ever attack on the capital of the state of Borno, Maiduguri, firing rockets at military targets on election day (ICG, 2018). The group has also demonstrated its growing capabilities by attacking further afield, including in Diffa, Niger and the Far North of Cameroon (Vivekananda et al., 2019).

scale internal displacement of over 2.5 million people; many Nigerians have also fled to neighboring countries (Gwadabe et al., 2018). New waves of displacement occurred in 2018, adding to the already high numbers of IDPs in the Northeast of the country (UN OCHA, 2019). Nigeria now has one of the largest IDP populations in the world (IDMC, 2021).

The IDPs[6] have spread across the six northeastern states and beyond, with strong concentrations in Borno, Yobe and Adamawa, as well as in neighboring Taraba, Gombe and Bauchi. The ongoing unrest, escalations and insecurity in the country, particularly in Borno state, have generated further (often repeated) waves of FD and returns (IRD and AFD, 2018).[7] Most IDPs have headed to nearby cities from territories controlled by terrorist groups, which has emptied the rural Northeast of residents. Maiduguri, which was attacked but never taken by Boko Haram, has become the country's main city of refuge with an estimated 800,000 IDPs (IRD and AFD, 2018). The most affected groups have been women, children, and young people, who together account for nearly 80% of the displaced population (Gwadabe et al., 2018).

Some of the IDPs have been dispersed across multiple host communities, which makes it difficult for humanitarian organizations to reach them (UN OCHA, 2019). A large part of IDPs and civilians live in overcrowded and under-serviced camps within *garrison towns* established by the Nigerian military; their livelihood activities (e.g., farming, fishing, and petty trading) are often limited in the camps by movement restrictions and insufficient access to agricultural land and safe transport. Camp residents are dependent on humanitarian assistance provided by international organizations, while an estimated 1.2 million IDPs living outside the garrison towns lack access to aid and protection as of late 2019 (UN OCHA, 2019). Starting in August 2019 the Nigerian military consolidated the 40 garrison towns into 22 *super camps*, which has exacerbated these dynamics (UN OCHA, 2019, 2020; Stoddard et al., 2020). The situation has been further challenged by violence between herders and farmers that has caused the deaths of more than 1,300 people between January and July 2018 (ICG, 2018). The conflict in Benue, Plateau, Adamawa, Nasarawa and Taraba states has led to the displacement of 300,000 persons, additionally burdening Nigeria's security services and diverting resources from counter-insurgency efforts (Eberle et al., 2020; ICG, 2021; ISS, 2021).

Empirical research to date has focused on the effects of the Boko Haram insurgency on agricultural production (Adelaja and George, 2019), economic welfare (Odozi and Oyelere, 2019), food security (George et al., 2020), child health (Ekhator-Mobayode and Abebe Asfaw, 2019; Nwokolo, 2015), school attendance (Bertoni et al., 2019), migration (Kamta et al., 2020b), and intimate partner violence (Ekhator-Mobayode et al., 2020). Our paper most closely relates to Kamta et al. (2021), who analyze the tensions between IDPs displaced by the Boko Haram insurgency and host communities. Their evidence suggests that IDPs' presence has the potential to trigger tensions, as 85% of the members of the host communities interviewed for the study do not agree with the IDPs' presence.

[6] Boko Haram attacks across Nigeria's borders have also led to internal displacement in Niger, Cameroon, and Chad (IRD and AFD, 2018).

[7] More than 70% of IDPs have experienced secondary displacement since they first left home (UN OCHA, 2019).

3 Theoretical motivation

3.1 Economic migration vs. FD

While economic migration is voluntary, thoroughly planned, and likely the result of economic cost–benefit considerations, FD is usually the result of a decision made quickly following a shock (due to, e.g., a conflict, persecution, or natural disaster) and can involve large numbers of people. FDPs typically bring only a small amount of assets and savings, compared to economic migrants who tend to bring more savings and assets or transfer them ahead of their move. Economic migrants are also more likely to enjoy support from extended networks at their origin and destination locations. FDPs do so to a lesser extent. FDPs typically choose destinations based on their proximity and security. Given these differences, FD requires different theoretical and empirical assessment methods from those used to evaluate economic migration (Becker and Ferrara, 2019; Verme and Schuettler, 2021).

3.2 Economic implications of FD

The sudden inflow of a large number of DPs creates two types of quasi-simultaneous, short-term shocks. The first is a sudden population supply shock in a particular geographical area. The second is a public expenditure shock caused by increased financial flows such as aid from international donors and/or increased government spending. Combined, they have three main effects: (1) alter the demand and supply shifts in local labor and (2) consumer markets, and (3) have a lasting impact on the host community's welfare and levels of inequality (Schneiderheinze et al., 2020; Verme and Schuettler, 2021). This section discusses each impact in turn.

Labor market effects: According to economic theory, the presence of a large number of DPs constitutes an expansive supply-side shock to local labor markets. At the same time, an influx of international aid, an increase in private and public spending (and on public services) raises the demand for skilled and unskilled labor. The overall impact on employment levels in host communities depends on a number of factors such as the scale of the displacement and public spending, the socio-economic characteristics of the DPs and the host community, as well as the rules that govern their integration into the local economy (e.g., freedom to work, access to income-generating activities) (Becker and Ferrara, 2019; Maystadt et al., 2019; Schneiderheinze et al., 2020; Verme and Schuettler, 2021). For example, the situation of IDPs and refugees might differ in many aspects, refugees are more likely to face language barriers and lack freedom to work compared to IDPs (Schuettler and Caron, 2020).

Prior research has found mixed empirical evidence regarding how FD affects host communities' labor market outcomes. For instance, Ruiz and Vargas-Silva (2015) show that increased refugee inflows to Tanzania made host community residents more likely to work for the government or in professional occupations. Tumen (2016) further finds that in areas along the Syrian—Turkish border with a higher inflow of Syrian refugees, original residents of the host community were more likely to shift from informal to formal employment. Since the Syrian refugees were not permitted to work, they seem to have substituted for locals in the informal sector. Groeger et al. (2021) find that an inflow of relatively more skilled Venezuelan refugees to Peru has had positive labor market outcomes on locals. However, numerous studies document adverse labor market outcomes for host communities in the aftermath of an FD shock. For example, Calderón-Mejía and Ibáñez (2016) find negative wage effects from an increase in competition between IDPs and host community natives in Colombian cities; among the host population, low-skilled and informally employed individuals suffered disproportionately adverse impacts. Morales (2018) also documents negative wage effects caused by IDP inflows in Colombia. Similarly, Ruiz and Vargas-Silva (2016) demonstrate that greater exposure to the refugee shock in Tanzania reduced hosts' likelihood of working outside the household as employees. This effect was especially strong among casual workers, who were in more direct competition with refugees for employment opportunities.

Consumer market effects: A sudden inflow of DPs also has profound implications for consumer markets as it creates substantial demand-side shocks induced by savings, aid, and public spending. DPs typically bring some savings which are spent at the destination on primary goods and services such as food, health services, and shelter. International aid and government spending also augment their spending capacity. Consumer demand usually increases as a result, followed by a rise in prices and consumption. Local producers are expected to expand production in response, motivated by higher prices and cheaper labor, which in turn increases the supply (and decreases the price) of goods and services (Verme and Schuettler, 2021).

While it is challenging to estimate the net effect of these forces, evidence from prior studies confirms that FD is likely to cause sudden short-term price changes in host communities. For instance, Alix-Garcia and Bartlett (2015) document increased prices for goods due to a spike in demand from DPs in Sudan. Similarly, Alix-Garcia et al. (2018) find that the presence of refugees in Kenya, where they were not allowed to work, increased the demand for locally produced agricultural and livestock products. By stimulating local economic activity, the host population was able to increase consumption. In markets where the supply is much slower to adjust, such as housing and farmland, competition for consumption is likely to increase. For instance, Alix-Garcia et al. (2012) illustrate that international aid prevented food prices from rising in Sudan after the Darfur conflict, but housing prices increased. Similarly, Alhawarin et al. (2021) find that the inflow of Syrian refugees to Jordan increased rents and reduced the quality of housing in receiving communities. Rozo and Sviatschi (2021) report that the arrival of 1.3 million Syrian refugees to Jordan resulted in greater housing expenditures as well as increased rental and property income for highly educated native-born residents. Depetris-Chauvin and Santos (2018) also find a substantial increase in housing prices in Colombian cities after the inflow of IDPs, which was unevenly distributed across the population. While the increased demand for low-income accommodation raised prices for this type of housing, the prices of high-income accommodation fell, likely because of excess supply and an increase in homicide rates.

Aggregate welfare and inequality effects: Recent literature reviews (see, e.g., Becker and Ferrara (2019); Maystadt et al. (2019); Verme and Schuettler (2021)) have summarized the evidence on how FD affects overall welfare. The findings suggest that forced migration is mostly positively associated with the overall well-being of residents in receiving communities (Verme and Schuettler, 2021). FD is also likely to generate profound distributional consequences, and produces winners and losers within the host community. Households with access to (physical, human or social) capital are typically better positioned to make use of the emerging economic opportunities associated with the inflows of DPs. Yet while poorer households may profit from the improved access to public goods (e.g., infrastructure, health care), they typically lose out due to increased competition with DPs and are likely to become trapped in poverty (Maystadt et al., 2019). High-skilled, formal employees tend to gain an advantage in the labor market, and low-skilled, informal workers tend to lose out. In the consumer markets, food and rental prices are expected to increase in the short run in the aftermath of an FD shock. The prices of other items and services are also likely to shift, but the direction of the change is difficult to predict. These processes also have distributional effects. While winners are likely to be concentrated among net producers in rural areas and asset owners in urban areas, losers are typically manual laborers in rural areas and consumers in urban areas (Becker and Ferrara, 2019; Maystadt et al., 2019; Verme and Schuettler, 2021).[8]

3.3 Security implications of FD

FD can change the level of violence in host communities by affecting inequality and wealth among hosts.[9] This is the primary focus of this paper. On the one hand, the predation (or rapacity) and deprivation theories suggest that FD can *increase* the violence within host communities. According to the former, higher prices raise the value of the appropriable surplus, leading to more conflicts (Besley and Persson, 2008; Dube and Vargas, 2013). The latter indicates that among households that are likely to face disproportionate welfare losses from FD, an increase in prices or a decrease in employment can induce perceptions of relative deprivation that lead to public unrest (Hendrix and Haggard, 2015). Similarly, tensions can also emerge, where DPs receive aid and services and could be perceived by the hosts as privileged giving rise to resentments (Duncan, 2005; Fisk, 2019). The assumed mechanism is that inequality motivates individuals to challenge the status quo (Dyrstad and Hillesund, 2020).[10] On the other hand, the opportunity costs theory posits that higher prices, lower labor costs, or access to better jobs *decrease* violence by raising the opportunity costs of insurrection, for example for farmers, highly skilled workers, or asset owners (Bazzi and Blattman, 2014; Dube and Vargas, 2013).

[8] Inflows of DPs can further affect productivity and structural change (Braun and Kvasnicka, 2014; Paserman, 2013; Peters, 2017), the creation of new enterprises (Akgündüz et al., 2018; Altındağ et al., 2020), raise foreign direct investment (Mayda et al., 2019), offer new trade opportunities to local communities (Bahar and Rapoport, 2018; Mayda et al., 2019; Parsons and Vézina, 2018), and improve local infrastructure as a result of investments by international organizations (Maystadt and Duranton, 2019).

[9] Risks to peace and security in displacement contexts could further emerge through multiple other channels. For instance, DPs can change the ethnic composition in the host areas, and camps hosting DPs may encourage the expansion of rebel social networks across geographies and/or be used for mobilization and logistical coordination to perpetuate violence (Bohnet et al., 2018; Maystadt et al., 2019; Salehyan and Gleditsch, 2006).

[10] Prior research typically emphasizes that security risks emerge if the distributional changes occur along group identities (e.g., within the host community or between IDPs and the host community) and thus affect inter-group inequality. Grievances linked to strong group identities are theorized to facilitate leadership and collective action (Alesina et al., 2016; Detges, 2017; Cederman et al., 2013; Østby, 2008; Stewart, 2016). However, recent micro-level studies have demonstrated that violence may emerge from both individual- and group-based grievances (Dyrstad and Hillesund, 2020; Miodownik and Nir, 2016; Rustad, 2016).

While the presence of DPs is often associated with more violence in policy debates, the existing empirical evidence remains mixed (Maystadt et al., 2019). Numerous studies have found that hosting DPs is associated with more conflicts and violence (see, e.g., Böhmelt et al. (2019); Bove and Böhmelt (2016); Salehyan and Gleditsch (2006)). Yet, some papers suggest a negative association between FD and conflict (see, e.g., Masterson and Lehmann (2020); Zhou and Shaver (2019)). In their literature review, Maystadt et al. (2019) conclude that more evidence and a better understanding of the mechanisms behind the security outcomes of FD are needed.

3.4 Hypotheses and contribution

Based on the theoretical considerations in Sections 3.2 and 3.3, we derive the following hypotheses:

- **H1:** By having profound impacts on the labor and consumer markets, FD affects aggregate welfare and inequality within host communities.
- **H2:** The aggregate observed effect of FD on wealth and inequality in the host communities is *a priori* ambiguous, and depends on the distribution of persons within the host community, who stand to either lose or gain from an inflow of FDPs.
- **H3:** The aggregate observed effect of FD on conflict in the destination community is an interplay of the area's overall i) welfare and ii) distributional consequences of FD. Communities hosting DPs experience higher rates of violence if the aggregate adverse consequences (i.e., increase in inequality, decrease in welfare via, e.g., higher competition in farm and non-farm enterprises or higher housing and food prices) outweigh the economic gains (e.g., lower labor costs, access to jobs).

We complement the two literature streams discussed above. First, we add to studies on the economic implications of FD by focusing on the distributional and aggregate welfare consequences. Verme and Schuettler (2021)'s meta-analysis of the welfare effects of FD proposes that aggregate distributional aspects should be a priority for future research, as they are not well understood. Along these lines, our paper most closely relates to that of Foltz and Shibuya (2021), who examine the effects of IDP inflows on income and inequality in host communities in Mali, but find no significant evidence. It is also linked to Murard (2021); Coniglio et al. (2021); Zhou et al. (2021), who show that overall, host communities benefit from FD, as it is accompanied by an inflow of public goods and services, and to Groeger et al. (2021), who find that an inflow of more skilled Venezuelan refugees to Peru has had positive labor market effects on locals.

Second, we advance understanding of the mechanisms driving the peace and security effects of FD by considering inequality in addition to a decline in aggregate welfare as mechanisms that may help explain conflict onset in displacement settings. Few studies have analyzed how wealth and economic marginalization can explain the association between the presence of DPs and conflict. Fisk (2019) fails to demonstrate any significant association between economic marginalization and conflict in displacement contexts, emphasizing the need for more evidence. Albarosa and Elsner (2021), Groeger et al. (2021), Murard (2021), Coniglio et al. (2021), Zhou et al. (2021), and Pham et al. (2021) study the implications of FD on conflicts in host communities, and conclude that economic welfare is an important driver.[11] This evidence suggests that if FD reduces host communities' economic welfare, it is associated with more conflicts at the destination (and vice versa), and with greater social cohesion within host communities. Hoseini and Dideh (2021) illustrate that persistent inequalities between DPs and hosts can also trigger tensions. Blanko et al. (2021) identified such inequalities in Chile and Kovac et al. (2021) did so in Bosnia and Herzegovina as they showed that DPs have systematically worse educational outcomes.

We contribute to both literature streams by testing the relationships between IDP inflows, and welfare, inequality and conflict i) across several novel data sets and ii) using various state-of-the-art causal inference techniques. This study is also the first to provide evidence on the economic and conflict implications of FD from Nigeria, which has tremendous policy relevance since the country has among the most IDPs in Sub-Saharan Africa.

4 Research design

4.1 Data and variables

We draw on several data sets, which are described in more detail below. We restrict our sample to the six states in northeastern Nigeria – Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe. The central and southern states are plagued by different conflict dynamics between farmers and herders (ICG, 2017) and thus would not serve as plausible control groups. Our sample further includes the northwestern states of Jigawa and Katsina (Figure 4a).[12] We further restrict our sample to LGAs that are different from IDPs' LGAs of origin (Figure 4b, Appendix B) to avoid wrongly attributing the outcomes of interest to IDPs' presence, which could be a consequence of the ongoing Boko Haram activity. The only exception is the analyses using data from the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 (Section 4.1.4), which only covers LGAs that are simultaneously origins and destinations of IDPs. However, this database explicitly collects information related to displacement, so the information we draw on should not capture outcomes directly caused by the insurgency.

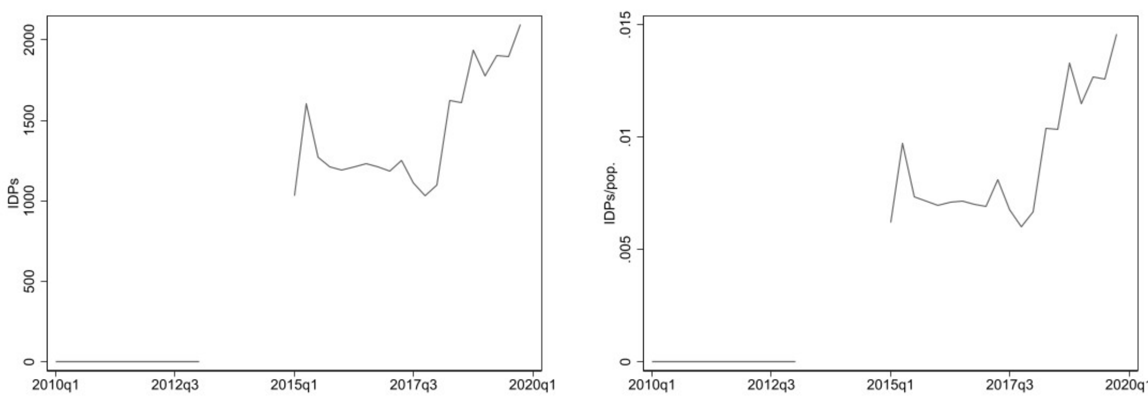
[11] For more details on these papers, see Appendix A.

[12] We note that so-called bandits were active in some of the LGAs in Katsina over our observation period. Bandits are criminal gangs involved in different forms of violent activities, including cattle rustling, kidnapping for ransom, pillage and robbery (ICG, 2020). To address the potentially confounding effect of these activities, we conduct a robustness test of the main conflict analysis in which LGAs located in Katsina are excluded from the sample. The robustness test shows that results are not sensitive to the exclusion of Katsina. We therefore keep Katsina in the working sample to ensure a sufficiently large sample of LGAs. All results pertaining to this robustness test are available upon request.

4.1.1 Displacement-related data

We use data from the IOM's Displacement Tracking Matrix (DTM) (IOM, 2021). IOM has implemented the DTM program in the region to monitor the escalation of violence in northeastern Nigeria and the resulting mass displacement in the six northeastern states that began in 2014. Since 2015, the DTM has tracked population displacement and records information on IDPs' origin and destination, and living conditions at the destination (e.g., access to water and sanitation, health, and protection) 4–6 times per year.

We use the information on quarterly IDPs stocks to generate the primary treatment variable, i.e., the fraction of IDPs over the host community population at the LGA-quarter/year level. To calculate this variable, we divide the number of IDPs in each LGA by the LGA-specific population averaged for the pre-treatment years 2000, 2005, and 2010, derived from the Gridded Population of the World collection (CIESIN Columbia University, 2018). The DTM data only goes back to 2015, yet most LGAs in our sample experienced their first IDP inflows in 2014; some were even earlier (Figure 5, Appendix B). We therefore treat IDP numbers between IDPs' first arrival and before DTM data collection began as missing. Figure 1 displays the sample's average IDP stocks (a) and fraction (b) over time.



(a) IDPs (b) IDPs/pop.

Figure 1: IDP inflows over time

To further probe our results, we construct two additional treatment variables. First, for the difference-in-differences (DiD) analysis (Equation 3), we split our sample into LGA-specific pre- and post-treatment periods. For the treated LGAs, the first quarter/year of IDPs' arrival determines this split. For the untreated LGAs, we consider periods before the first quarter of 2014, when most of the IDPs arrived (Figure 5, Appendix B) as pre-treatment. Then, we calculate the LGA-specific mean of the IDP shock for the pre- and post-treatment periods. Second, for the long-differences approach (Equation 4), we calculate the LGA-specific difference between the average treatment intensity in the last (i.e., 2019) and first (i.e., 2010) years of our sample period. Since displacement had not yet started in 2010, the number of IDPs in this year is set to zero.

4.1.2 Conflict data

Conflict data are taken from the ACLED database (Raleigh et al., 2010). ACLED provides temporally and geographically disaggregated information on dates, actors, locations, fatalities, and types of all reported political violence and protest events, collected from a range of media and agency sources. It uniquely records all conflicts, without specifying a minimum battle-related deaths threshold, which enables us to capture a wide range of violence forms. Given that IDPs typically flee to relatively secure destinations (Section 3.1), our primary variable of interest captures the emergence of new conflicts (i.e., conflict onset).[13] Understanding these dynamics is essential to preventing potential escalations and intensification of violence in displacement contexts.

We collect information on violence against civilians and riots from ACLED. In the main analysis (Equation 2) we exploit the fine temporal resolution of the displacement and conflict data and merge them at the LGA-quarter/year level. Following the common practice (e.g., Bazzi and Blattman (2014); Theisen et al. (2012) and von Uexkull et al. (2016)), we code conflict onset as a binary variable that takes a value of 1 in the first quarter/year of reported violence, and in the first quarter/year of violence after at least 2 years with no reported conflict events. Subsequent years of ongoing conflict are coded as missing. We also run model specifications collapsing conflicts to the LGA-year resolution.

We construct two additional variables to further probe our results. First, for the DiD analysis (Equation 3), we aggregate our sample into LGA-specific pre- and post-treatment periods.[14] The dependent variable captures whether an LGA experienced at least one conflict onset in each period. Second, we conduct a long-differences analysis to explore the long-term implications of IDPs' presence for conflict (Equation 4). The generated dependent variable captures the difference between two binary indicators, recording whether an LGA experienced at least one conflict onset in the last (i.e., 2019) and first (i.e., 2010) years of our sample. Table 10 in Appendix E.1 presents the summary statistics.

4.1.3 Household- and community-level data

We gather household- and community-level socio-economic data on host communities from the World Bank's NGHS carried out in 2010/11, 2012/13, 2015/16 and 2018/19. The survey's sample is representative both nationally and at the level of the six geopolitical areas. Yet since it does not cover all LGAs, it is more restricted than the comprehensive sample we use for the conflict analysis. The fourth wave of the NGHS is resampled; only a small share of communities and households from previous waves were kept. A simple attrition analysis does not suggest that households with particular characteristics would systematically drop out of the survey (results available upon request).

[13]To understand the conflict dynamics within our sample, we also used data from the Uppsala Conflict Data Program Georeferenced Event Dataset version 20.1 (Pettersson and Öberg, 2020; Sundberg and Melander, 2013). This global data set on organized violence from 1989 to 2019 records all dyads with 25 or more battle deaths per year. The incidence of these relatively large-scale conflicts in our sample is very close to zero, which further validates the assumption that IDPs likely move to relatively peaceful areas.

[14]We define the pre-treatment period of untreated LGAs as before 2014, the first year of IDPs' arrival in the majority of treated LGAs.

Our final sample covers 7 treated and 24 untreated LGAs, which have a total of 358 households that are observed in at least two waves of the sample. We use this data to conduct an unbalanced panel analysis.

To address RQ1, we construct a comprehensive household-level wealth index to employ as a dependent variable in Equation 1. Following Dustmann and Okatenko (2014), we conduct a principal component analysis using variables that capture whether a household has access to electricity, experienced food insecurity, owns valuable assets (i.e., electric stove, fridge, car or other vehicle, air conditioner, fan, tv, computer), whether its floor is made of materials other than mud or dirt, and the number of meals consumed per adult household member per day (see summary statistics in Table 2, Appendix D.1). We use the factor loadings of the first principle component as weights to construct an aggregate wealth index. The corresponding Kaiser-Meyer-Olkin measure of sampling adequacy indicates a value of 0.85, which supports the suitability of the approach (Dziuban and Shirkey, 1974). The wealth index is standardized and expressed as the "number of standard deviations".

To assess RQ2, we draw on NGHS community-level data on perceptions of changes within communities compared to 3 years ago. We construct an index of trust within host communities using principal component analysis of three categorical variables – change in local trust, change in help within the host community, and change in the cash contributions of the host community members.[15] The Kaiser-Meyer-Olkin measure of sampling adequacy indicates a value of 0.68, which again demonstrates the suitability of the approach. The resulting trust index is then standardized. It enters Equation 2 on the left-hand side and the model is estimated at the community-NGHS wave level. Table 11, Appendix E.1 presents the corresponding summary statistics.

4.1.4 Profile of IDPs in North-East Nigeria 2018

We also use the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 data set to conduct the main analysis of RQ3, based on Equation 5. The data set provides cross-sectional information from displacement contexts in the six northeastern states from 2018, covering households in 77 communities hosting IDPs and 48 camp-like settings. We employ a categorical variable *Good relations* as a dependent variable. It captures IDPs' perceptions of their relationships with hosts, addressing the question: *Tell me if you agree with this statement: IDPs and locals of the area have good relations with each other*; the variable takes on 5 different values, where higher values signal better relationships. As explanatory variables, we draw on household-specific information on total consumption per capita (p.c.) per day in Nigerian Naira to construct household-level measures of negative and positive inequality between IDPs and hosts, inspired by Buhaug et al. (2014). We first calculate the hosts' LGA-specific daily average consumption p.c. We then identify displaced households with higher and lower consumption levels compared to their hosts in a given LGA. We use this information to construct two internally displaced household-level indicators to capture the relative gap in consumption between the hosts and i) poorer and ii) richer internally displaced households in a given LGA, as follows (see summary statistics in Table 17, Appendix F.1):

[15] All components of the trust index are scored to indicate whether the situation got: much worse (1), worse (2), remained about the same (3), better (4) or much better (5).

- **Negative inequality=**average consumption p.c. of hosts (LGA level)/consumption p.c. of poorer IDPs (household level)

- **Positive inequality=** consumption p.c. of richer IDPs (household level)/average consumption p.c. of hosts (LGA level).

4.2 Empirical strategy

4.2.1 Two-way fixed effects approach

To investigate the research question (RQ1) of the wealth and inequality implications of FD within host communities more formally, we estimate the following two-way fixed effects panel model:

$$Y_{hwt} = \alpha_h + \phi_t + \beta_1 D_{wt} + \epsilon_{hwt} \tag{1}$$

Here, the left-hand-side variable captures the wealth Y of household h residing in an LGA w in year t. Years correspond to the waves of the NGHS (2010, 2012, 2015, 2018). We use a constructed wealth index to proxy for Y_{hwt} (Section 4.1.3). The coefficient of interest is β_1, which captures the treatment effect, i.e., the effect of the displacement shock, D_{wt}, measured by the fraction of IDPs over the host community population. We further control for year-specific fixed effects to account for common shocks (ϕ_t) and household-specific fixed effects (α_w) to account for time-invariant and slow-moving differences across LGAs. Standard errors are clustered at the treatment level (LGA). In our instrumental variable (IV) regressions, we replace the observed values of displacement shocks with the predicted values $\hat{D}_{wt}$ (Section 4.2.2).

To study the distributional effects of displacement shocks, we estimate Equation 1 for three different sub-samples of households: poor, medium wealth, and rich. To determine the sub-samples, we draw on the distribution of per capita expenditures at the household level in the first wave of the NGHS (i.e., 2010, before displacement started, to avoid reverse causality) and calculate wealth quartiles representative of the whole of Nigeria using the sample weights.[16] Households with expenditure levels below the bottom quartile threshold are classified as poor; those in the second and third quartiles are categorized as being of medium wealth, and those with expenditures above the third quartile as rich. Given that northeastern Nigeria is poorer than the rest of the country, the resulting sample has substantially more poor and medium wealth than rich households.

To address RQ2, we analyze the implications of displacement shocks for conflict emergence in a similar two-way fixed effects panel design:

$$C_{wqt} = \theta_w + \gamma_{qt} + \beta_1 D_{wqt} + \epsilon_{wqt} \tag{2}$$

where we explain conflict onset (C_{wqt}) at the LGA-quarter/year (qt) level. In our IV regressions,

[16] An alternative approach would be to categorize households by wealth only for our working sample of Nigerian LGAs. However, the survey sample weights provided allow us to calculate the wealth distribution more accurately for the entire country.

we replace the observed values of displacement shocks with the predicted values $\hat{D}_{wqt}$ in a two-stage estimation procedure. We further control for quarter/year-specific fixed effects (γ_{qt}) and LGA-specific fixed effects (θ_w). Standard errors are again clustered at the LGA level.[17] We also run this analysis at the community-NGHS wave level, using community perceptions of local trust – and, as a sensitivity test, conflict onset and perceptions of robbery levels on the left-hand side.

We repeat the main conflict analysis using two alternative analytical designs. First, we run a more traditional DiD analysis with two time periods. We collapse the data set into LGA-specific pre- and post-treatment periods, as explained in Sections 4.1.1 and 4.1.2. We then estimate the following equation:

$$C_{wi} = \beta_1 D_{wi} + \delta_i + \alpha_w + \epsilon_{wi} \tag{3}$$

Here, the subscript i distinguishes the pre- and post-treatment periods ($i \in \{pre, post\}$). We cluster standard errors at the LGA level. In the second alternative design, we apply a long-differences approach to understand the long-run effects of displacement on conflict. We first calculate the difference between conflict onset (ΔC_w) and displacement (ΔD_w) in the last (i.e., 2019) and first (i.e., 2010) years of our sample period. Then we estimate the following model:

$$\Delta C_w = \eta + \beta_1 \Delta D_w + \epsilon_w \tag{4}$$

Here, η controls for an unobserved general trend. We again cluster standard errors at the LGA level.

To explore RQ3 (how inequality between IDPs and the host community affects the risk of conflict), we estimate the following model:

$$R_h = \beta_1 E_h + \theta_w + \epsilon_h \tag{5}$$

where we explain IDPs' perceptions of their relations with host community members (R_h) using a measure of (positive or negative) inequality between IDPs and the host community (E) at the internally displaced household level and LGA-specific fixed effects (θ_w). We further apply robust standard errors, given the limited number of clusters we have when using this data. Given the model's potential endogeneity concerns, we consider the estimated coefficients to have a descriptive rather than causal meaning.

4.2.2 IV approach

While we can reasonably assume that the shocks causing displacement at the origin are exogenous to circumstances at the destination, IDPs might be choosing their destinations because they are safer and less prone to violence, or for other characteristics that may be correlated with these variables, such as differences in wealth. If this is the case, it may lead to a spurious correlation between the

[17] Given that we only observe displacement during the treatment period (Section 4.1.1), this setup (also adopted to estimate equation 1) corresponds to a DiD estimation with multiple time periods, varying treatment intensities and differences in timing of the treatment (Angrist and Pischke, 2008; Callaway and Sant'Anna, 2020).

presence of IDPs and the onset of conflict, or the level of wealth and inequality. To deal with the endogenous choice of destinations, we instrument contemporaneous displacement patterns by the historical distribution of ethnic groups in the region. The core idea of this instrumental variable, pioneered by Card (2001), is based on the premise that immigrant networks are an important determinant of locational choices. This approach combines aggregate shifts – in our case, the total number of displaced people – and local shares – given by the historical ethnic composition of the origin and destination areas. A range of recent migration impact assessment studies have used versions of this "shift-share" instrument for migration patterns (see, e.g., Dehos (2021),Tabellini (2020) and Giuntella et al. (2018)).

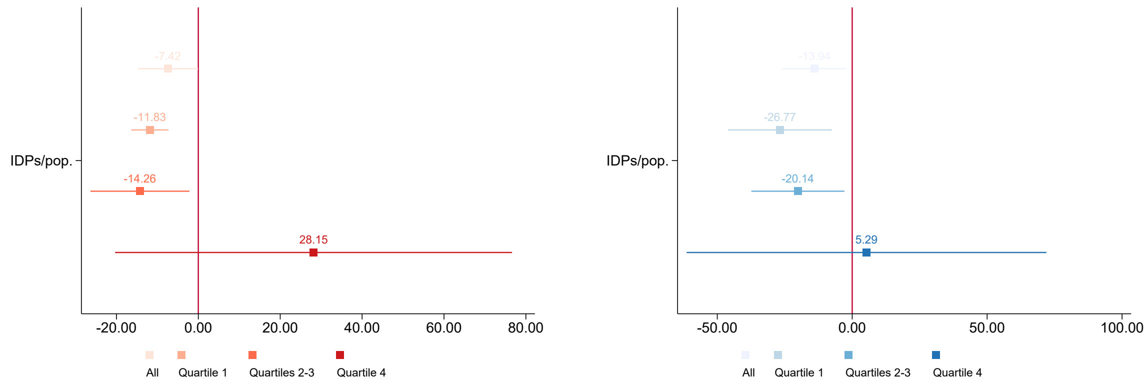
We combine the IV approach with the panel structure of the data. The identifying assumption for a causal interpretation of the model is that the historical distribution of ethnic groups in the area is correlated with changes in conflict onset, wealth, and inequality in the period 2015–2019 (or 2010–2019 in the long-difference model) only through their effect on IDP inflows. For a detailed explanation of the instrument's construction, see Appendix C.

5 Results

5.1 Effect of IDPs' presence on inequality within host community

Table 5, Appendix D.2 reports the main results of the inequality implications of a population displacement shock. We estimate every model using two techniques: i) a panel data analysis with two-way fixed effects and ii) an IV approach that substitutes the observed values of the displacement shock with the predicted values (Section 4.2.2). In Models 1–2, we study the wealth implications of a displacement shock for the full sample of households. We then split the sampled households by wealth quartiles (Section 4.2.1) to study distributional consequences, i.e., how a displacement shock affects poor (Q1, Models 3–4), medium wealth (Q2–Q3, Models 5–6) and rich (Q4, Models 7–8) households. The F-statistics for the full sample suggest that our instrument is sufficiently strong. The evidence from models (Models 1, 3, 5 and 7) using observed values is shown in Figure 2 (a), and from models using predicted values (Models 2, 4, 6 and 8) — our preferred specification — in Figure 2 (b).

Our models suggest that on aggregate, IDPs' presence is significantly and negatively associated with household wealth. The local average treatment effect (LATE) identified by the IV approach in Model 2 indicates that wealth decreases by 0.14 standard deviations if IDPs' fraction within the host community increases by 1 p.p. in a given year. This effect is approximately halved when using the two-way fixed effects analysis, suggesting that IDPs might to some extent select to wealthier LGAs. Hence, failing to correct for endogeneity leads to an attenuation bias. Focusing on the IV regressions (Models 4, 6, and 8), we find clear evidence that displacement shocks generate distributional consequences. A 1 p.p. increase in the IDPs' fraction within the host community induces a 0.27-standard-deviation decrease in wealth for the poorest and a 0.2 s.d. decrease for medium-wealth households, and becomes positive (though insignificant) for the richest segment of the population.



(a) Two-way fixed effects estimates (b) Instrumental variable estimates

Figure 2: IDPs' effect on overall wealth and inequality (models in Table 5, Appendix D.2)

This figure presents evidence from Table 5, Appendix D.2 addressing RQ1 on the wealth effects of displacement on poor (quartile 1), medium-wealth (quartiles 2–3), and rich (quartile 4) households in host communities. The dependent variable is a wealth index expressed in standard deviations. Figure 2 (a) illustrates the results from two-way fixed effects models. Figure 2 (b) displays our preferred specifications, using an IV approach.

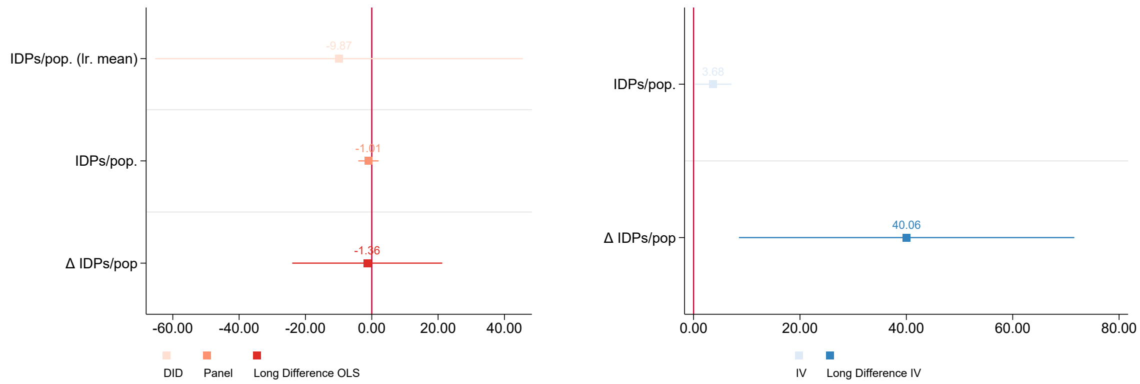
In Appendix D.3, we present a series of sensitivity tests. In Table 6, we compare the main findings with an analysis of community-level perceptions of wealth and inequality in the aftermath of IDP inflows. In Table 7 we run an analysis similar to the main analysis presented in Table 5, using an alternative outcome variable – a wealth index that also includes households' total expenditures. In Table 8, we use the cross-sectional data from Section 4.1.4, interacting the displacement shocks with expenditure quintiles in an IV setting. Overall, the sensitivity tests validate evidence from the main analysis that IDPs' presence decreases wealth and increases inequality in host communities. Using the cross-sectional data, in Table 9 we further analyze whether the distributional consequences align with ethnic identities, and find no evidence that this is the case.

Our findings provide support for H1 (Section 3.4) – that FD affects host communities' aggregate welfare and inequality. We show that the welfare and inequality implications of an IDP shock are negative at the net level. As implied by H2, these adverse net effects can be attributed to the lower levels of development and higher levels of poverty in the North of Nigeria (The World Bank, 2016), which corresponds to a higher concentration of individuals who lose out from the presence of IDPs (e.g., by directly competing with IDPs in the farm and non-farm enterprises and/or micro and small enterprise sector, as suggested in Section 3.2). Our findings from Nigeria — a lower-middle-income country (The World Bank, 2021b) — are in line with the evidence from Verme and Schuettler (2021)'s meta-analysis that countries at these stages of economic development are likely to suffer disproportionate economic losses from displacement shocks. Our findings also bolster the conclusion of Maystadt et al. (2019)'s literature review, that displacement shocks have profound adverse distributional consequences. Yet our results differ from those of Foltz and Shibuya (2021), who on aggregate find no significant evidence of adverse income and distributional consequences of IDPs' presence in Mali. One possible explanation is that Mali has a long-standing strong cultural history of hospitality to outsiders, called *Diatiguiya*. Moreover, Foltz and Shibuya's study observes IDPs' presence only in large humanitarian operations, so it is possible that the evidence might differ for smaller crises. Our findings are also at odds with those of Murard (2021); Coniglio et al. (2021) and Zhou et al. (2021), who show that overall, host communities benefit from FD, as it is accompanied by an inflow of public goods and services. This is likely because the displacement crises in northeastern Nigeria has been severely underfunded (UN OCHA, 2019, 2020), which reduces the positive spill-over effects on hosts and increases the competition among hosts and IDPs.

5.2 Effect of IDPs' presence on conflict onset and social cohesion

Appendix E.3 reports the main results. Table 13 presents the outcomes from the analysis of FD's impact on violence, based on analyzing conflict onset, while Table 14 focuses on the implications for social cohesion in host communities. In Table 13, Model 1 uses a two-period DiD design, and Model 2 applies panel analysis with two-way fixed effects. In our preferred specification — Model 3 — we replace the observed with the predicted values of the displacement shock. In Models 4 and 5 we assess the long-term implications via the long-differences approach, using the observed and predicted (in an IV setting) values of the shock, respectively. The F-statistics on the excluded instruments in the first stage in Models 3 and 5 are significantly larger than 10, suggesting that our instrument has sufficient strength. Put differently, the geography of historical ethnic group settlements is a strong predictor of contemporaneous displacement inflows from the same ethnic groups. The evidence from models using observed values is shown in Figure 3 (a), and from models using predicted values — our preferred specification — in Figure 3 (b).

When using the observed values of the displacement shocks (Models 1, 2 and 4) we find that IDPs' presence is negatively, though insignificantly, associated with conflict onset at the destination. When using the predicted shock values (Models 3 and 5) the coefficients become positive and significant. In line with the theoretical considerations presented in Section 3.1, this implies that IDPs have some choice in where they locate and typically move to more peaceful areas. When conducting the standard pre-trend analysis (Appendix E.2, Figure 7) to justify the DiD design, we found no evidence of parallel trends. If anything, the figure suggests that IDPs do not select into regions with an increasing risk of conflict onset. After accounting for IDPs' selection, our preferred specification (Model 3) indicates that conflict onset increases by almost 4 p.p. if IDPs' fraction within the host community increases by 1 p.p. in a given quarter. In the long run, this effect becomes ten times as large (Model 5), suggesting that the protracted presence of IDPs might increase risk of conflict even more than a shorter temporary shock.



(a) Two-way fixed effects estimates (b) Instrumental variable estimates

Figure 3: IDPs' effect on conflict onset

This figure presents evidence from Table 13, Appendix E.3. The dependent variable in DiD Model is binary and captures whether an LGA experienced at least one conflict onset during the pre- and post-treatment periods. The dependent variable in Models Panel and IV is binary and captures LGA-specific conflict onset at the quarter/year level. The dependent variable in Long Difference Models is categorical and captures the difference between two binary indicators, recording whether an LGA experienced at least one conflict onset in the last (i.e., year 2019) and first (i.e., year 2010) years of our study period. The treatment variables capture either the observed fraction of IDPs over the host community population (Figure 3 (a)) or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV (Figure 3 (b)), as explained in Section 4.2.2.

In Table 14, we analyze the effect of a displacement shock on trust within host communities using information from the World Bank's NGHS community-level data set. Model 1 corresponds to a panel data analysis using two-way fixed effects, while Model 2 relies on the IV approach. Both models produce a positive estimate of almost the same magnitude, though in Model 2 the estimate loses significance. Model 1 suggests that trust within the host community increases by approximately 1 standard deviation if the fraction of IDPs fraction within the host community increases by 1 p.p. in a given year. We interpret the similarity between the two estimates as evidence that IDPs do not select into destinations based on the level of trust among hosts.

Appendix E.4 presents a series of sensitivity analyses. According to the results reported in Table 15, IDPs' presence is positively associated with community-level perceptions of a higher prevalence of robbery in host communities. In Table 16 we show analyses conducted on households within communities hosting IDPs in a cross-sectional IV design. Models 1–4 assess whether hosts are more likely to feel unsafe (walking alone at night) and Models 5–6 evaluate whether the likelihood of killing changes with a stronger intensity of the treatment. Across these models, we find evidence that the feeling of being unsafe and the likelihood of killing decrease among hosts in LGAs that are more intensively treated. This indicates that the increase in violence in the aftermath of IDP shocks, as revealed in the main analysis, is unlikely to be directed at members of the host community. Rather, it signals that members of the host community are likely to be antagonistic towards IDPs. Models 7 and 8 further reveal that larger displacement crises are likely to attract stronger support from government authorities and aid organizations. This implies that violence is less likely to increase if the displacement crises receive better support, which often benefits members of the host community as well.

Overall, the evidence from Section 5.1 suggests that in northeastern Nigeria, the adverse economic consequences of displacement shocks outweigh the economic gains, as we observe an aggregate decrease in welfare – especially among the poorer segments of the population – and an increase in inequality. Following our theoretical considerations (Section 3.3), these mechanisms create a risk of conflict onset in areas that host IDPs. The findings from this section confirm that IDPs' presence is associated with more conflicts, which is in line with, e.g., Böhmelt et al. (2019); Bove and Böhmelt (2016), and Salehyan and Gleditsch (2006) (Section 3.3). Combining the evidence from these two sections reveals support for H3: *... Communities hosting DPs experience higher rates of violence if the aggregate adverse consequences ... outweigh the economic gains ...* Both aggregate welfare and inequality in the aftermath of a displacement shock constitute plausible mechanisms for explaining conflict onset. Our findings advance emerging efforts to assess the aggregate distributional implications of FD, as identified by Verme and Schuettler (2021), and is in line with those of Albarosa and Elsner (2021); Groeger et al. (2021); Murard (2021); Coniglio et al. (2021); Zhou et al. (2021) and Pham et al. (2021), who demonstrate that if FD reduces hosts' economic welfare, it is associated with more conflicts at the destination as well as greater social cohesion within host communities. Yet they contrast with the null evidence cited by Fisk (2019), who fails to show that economic marginalization plays a significant role in explaining conflict in displacement settings.

We provide evidence that FD increases social cohesion and trust among hosts, which suggests that conflicts are unlikely to emerge between members of the host community, but rather between the host community and IDPs. This is in line with Dadush and Niebuhr (2016)'s argument that IDPs' presence reinforces the "us vs. them" narrative by increasing trust among the hosts. The group identities (hosts vs. IDPs) seem to serve the purpose of mobilization as implied by Alesina et al. (2016); Cederman et al. (2013); Østby (2008); Stewart (2016). Lastly, while we show that IDPs' presence increases violence, the hosts are less likely to feel unsafe, indicating that the violence is more likely to be directed at IDPs rather than hosts.

5.3 Inequality between IDPs and hosts – social cohesion and conflict onset

Table 19, Appendix F.2 presents the main evidence related to RQ3. The table correlates measures of positive (Models 1–3) and negative (Models 4–6) inequality with IDPs' perceptions of their relationship with members of the host community, according to Equation 5. Models 1 and 4 are Ordinary Least Squares (OLS) regressions with state-specific and Models 2 and 5 with LGA-specific fixed effects. Models 3 and 6 are estimated with an ordered logit. All of the analyses are purely descriptive rather than causal; we therefore focus on the direction of the associations only. Models 1–3 robustly indicate that the lower consumption levels of poorer IDPs (with lower consumption levels than the hosts) are, the worse their relations with hosts, while Models 4–6 suggest that the higher consumption levels richer IDPs (with higher consumption levels than the hosts) have the better are their relations with hosts. Table 20 in Appendix F.2 presents further evidence from the sensitivity analysis which implies that IDPs' welfare and living conditions are negatively correlated with the probability of conflict onset.

Our findings contrast with the general notion that tensions between DPs and hosts may be more prevalent, perhaps because hosts resent DPs, who they perceive as privileged since they receive aid and services (Duncan, 2005; Fisk, 2019). One possible explanation is that hosts indirectly benefit from DPs' higher wealth levels, as their higher demand for goods and services boosts local economies (Section 3.2), in line with Lehmann and Masterson (2020). Similarly, our results are in line with those of Hoseini and Dideh (2021), who show that after a bad economic shock that had disproportionately adverse effects on the welfare of Afghan refugees compared to local Iranians, social cohesion between the two communities decreased.

In general, Nigerian IDP camps remain severely underfunded and provide poor living conditions (Arhin-Sam, 2019). As shown in Table 19, we have many more observations when studying negative than positive inequality, which implies that most IDPs are poorer than their hosts. Persistent inequalities between DPs and natives have been also found by Blanko et al. (2021) in Chile and by Kovac et al. (2021) in Bosnia and Herzegovina, who demonstrate that DPs have worse educational outcomes. In line with our findings and evidence by Hoseini and Dideh (2021), such inequalities could be a source of tension between hosts and DPs, especially since education has been shown to be a reliable predictor of income (Duflo, 2001). Müller et al. (2021) show that initially better labor market conditions and hostile attitudes to refugees in Switzerland improve refugees' labor market performance.

6 Policy and program implications

This paper joins previous scientific efforts to examine the implications of FD on violence and welfare in host communities (see Maystadt et al. (2019) or Verme and Schuettler (2021) for reviews of this literature). We exploit the large-scale internal displacement caused by the Boko Haram insurgency in northeastern Nigeria and examine conflict onset, while considering wealth and inequality within host communities as potential mechanisms. We apply two-way fixed effects and IV analyses using a version of the shift-share instrument (Card, 2001) and check the robustness of our findings using several novel data sets.

We show that conflict onset within host communities following the inflow of IDPs is likely to have economic roots: displacement shocks reduce aggregate wealth and increase inequality within host communities. These effects increase the risk of conflict onset in both the short and long run. Our evidence indicates that the inequality–conflict link is likely to be a result of grievances among low-wealth segments of the host community towards new arrivals rather than a lack of within-community social cohesion, which increased in response to the inflow of IDPs. We also find that an improvement in IDPs' living conditions is accompanied by a decrease in violence and improved relations between hosts and IDPs.

Interpreted in conjunction with previous research, our findings have important implications for immediate relief and recovery policies, as well as for long-term programs that aim to prevent the emergence and escalation of tensions between host communities and DPs.

In the short run, it is crucial to minimize the economic losses from displacement shocks within host communities and promote the economic integration of vulnerable DPs and host community members. Our results demonstrate that these losses appear to be disproportionately borne by households at the lower end of the wealth distribution, which could create resentments against DPs and increase the risk of violence. For instance, poorer households are most likely to suffer from a rise in food and housing prices or increased competition for business among farm and nonfarm enterprises in the formal and informal sectors in the aftermath of a displacement shock. These dynamics are exacerbated by the COVID-19 pandemic, which has contributed to the inflation especially for food items in Nigeria (The World Bank, 2021a).

Policy measures to shield disadvantaged groups among DPs and host communities from economic shocks are important to minimize negative externalities and conflict risks. These policy measures could include the provision of social assistance which can assume many forms including cash assistance, vouchers, grants to communities, workfare programs, and in-kind transfers in the form of food, school scholarships, livelihoods tools and equipment (e.g., seeds, fertilizer, computers, wireless internet, greenhouses), as well as skills training programs (World Bank, 2017). Such interventions have also been found to improve social cohesion between displaced and host communities through multiplier effects that stimulate local economies (UNHCR, 2019a). With any intervention that transfers cash or assets to vulnerable households, it remains crucial to ensure that the intervention receives broad public support and targets and reaches the most vulnerable DPs and host community members via efforts such as third-party monitoring (e.g., by local civil society organizations).[18] The design of any development intervention would need to take into account the security situation that could affect the delivery of cash, assets and training programs and also the security of the beneficiaries themselves.

Investments in infrastructure and services are also critical to meet the increased demand due to the population shocks and to enhance social cohesion between IDPs and host communities. Improving the accessibility and quality of basic public services such as drinking water, hygiene facilities, energy, health, and education are likely to mitigate conflict, particularly in states such as Borno where the camp conditions are currently precarious. To minimize the spread of COVID-19 and other diseases, sanitation and hygiene facilities should be prioritized.[19] In the context of northeastern Nigeria, there is also a need for interventions that address housing needs and improve the connectivity in host communities. As an example, a cash for shelter program in Kalobeyi Settlement in Kenya addressed the housing needs of refugees, as well as contributed to the local economy by sourcing construction materials from local vendors and relying on local masons, mitigated tensions by enabling host community members to access services provided within the refugees settlements, and promoted positive economic interactions between refugees and host communities (UNHCR, 2018, 2019a). Moreover, in northeastern Nigeria, the perimeters of the government-secured 'garrison towns' could be expanded to increase freedom of movement and give DP communities better

[18]Geographic-based targeting may help social transfers reach the poorest and most vulnerable Nigerians given that most inequality is inter-community rather than intra-community in Nigeria (Blumenstock et al., 2021). In designing social assistance interventions, as in many countries, careful attention will need to be paid to ensuring the coverage of vulnerable IDPs and host community members, which is often challenging.

[19]Borno and Yobe states experienced a cholera outbreak in September 2018. Cases of cholera and acute watery diarrhea also rose in Adamawa state around the same time (UN OCHA, 2019).

access to land, local markets, and basic services. Such measures would particularly benefit women and girls, who increasingly face gender-based violence and security risks when engaging in simple activities such as collecting firewood (UN OCHA, 2019).

While it is important to address the immediate consequences of FD as soon as DPs arrive at their destination, forward-looking programs to increase resilience among potential hosting communities could also help reduce welfare losses. The development of early warning systems could help predict future inflows of DPs and allow local governments and service providers to prepare potential host communities to receive population inflows before DPs arrive (World Bank, 2017). Leveraging historical ties between ethnic groups – as we do in this study – in combination with novel data sources such as Google search data will make such predictions possible in the future as internet usage in developing countries increases.[20]

While not the focus of this paper, a forward-looking policy approach would further seek to address the root causes of FD. For instance, the Boko Haram insurgency has been linked to extreme levels of poverty and economic fragility, which are continuously exacerbated by worsening climatic and environmental conditions in the North-East of Nigeria. The resulting lack of opportunities have made young people vulnerable to joining rebel groups (Kamta et al., 2020a; Nett and Rüttinger, 2016; Vivekananda et al., 2019). Future research could explore how climate change adaptation, education and development opportunities can improve resilience of communities and thus support conflict prevention efforts.

References

Adelaja, A. and George, J. (2019). "Effects of conflict on agriculture: Evidence from the Boko Haram insurgency". *World Development*, 117:184–195.

Akgündüz, Y. E., van den Berg, M., and Hassink, W. (2018). "The Impact of the Syrian Refugee Crisis on Firm Entry and Performance in Turkey". *The World Bank Economic Review*, 32(1):19–40.

Albarosa, E. and Elsner, B. (2021). "Forced Migration, Social Cohesion and Conflict: The 2015 Refugee Inflow in Germany". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Alesina, A., Michalopoulos, S., and Papaioannou, E. (2016). "Ethnic Inequality". *Journal of Political Economy*, 124(2):428–488.

Alhawarin, I., Assaad, R., and Elsayed, A. (2021). "Migration Shocks and Housing: Short-run Impact of the Syrian Refugee Crisis in Jordan". *Journal of Housing Economics*, page 101761.

Alix-Garcia, J. and Bartlett, A. (2015). "Occupations under Fire: the Labour Market in a Complex Emergency". *Oxford Economic Papers*, 67(3):687–714.

[20]See Böhme et al. (2020) for an application to predict international migration flows using Google search data.

Alix-Garcia, J., Bartlett, A., and Saah, D. (2012). "Displaced Populations, Humanitarian Assistance and Hosts: A Framework for Analyzing Impacts on Semi-urban Households". *World Development*, 40(2):373–386.

Alix-Garcia, J., Walker, S., Bartlett, A., Onder, H., and Sanghi, A. (2018). "Do Refugee Camps Help or Hurt Hosts? The Case of Kakuma, Kenya". *Journal of Development Economics*, 130:66–83.

Altındağ, O., Bakış, O., and Rozo, S. V. (2020). "Blessing or Burden? Impacts of Refugees on Businesses and the Informal Economy". *Journal of Development Economics*, 146:102490.

Angrist, J. D. and Pischke, J.-S. (2008). *"Mostly Harmless Econometrics: An Empiricist's Companion"*. Princeton University Press.

Arhin-Sam, K. (2019). "The Political Economy of Migration Governance in Nigeria". *Arnold Bergstraesser Institute, Freiburg.*

Baetschmann, G., Ballantyne, A., Staub, K. E., and Winkelmann, R. (2020). "feologit: A new command for fitting fixed-effects ordered logit models". *The Stata Journal*, 20(2):253–275.

Bahar, D. and Rapoport, H. (2018). "Migration, Knowledge Diffusion and the Comparative Advantage of Nations". *The Economic Journal*, 128(612):F273–F305.

Bazzi, S. and Blattman, C. (2014). "Economic Shocks and Conflict: Evidence from Commodity Prices". *American Economic Journal: Macroeconomics*, 6(4):1–38.

BBC (2021). "Abubakar Shekau: Nigeria's Boko Haram Leader is Dead, Say Rival Militants". Online. https://www.bbc.com/news/world-africa-57378493.

Becker, S. O. and Ferrara, A. (2019). "Consequences of Forced Migration: A Survey of Recent Findings". *Labour Economics*, 59:1–16.

Bertoni, E., Di Maio, M., Molini, V., and Nistico, R. (2019). "Education is Forbidden: The Effect of the Boko Haram Conflict on Education in North-East Nigeria". *Journal of Development Economics*, 141:102249.

Besley, T. J. and Persson, T. (2008). "The Incidence of Civil War: Theory and Evidence". Technical report, National Bureau of Economic Research.

Blanko, F., Meneses, F., and Villamizar-Chaparro, M. (2021). "Why Student Aid Matters? Roadblocks to the Transition into Higher Education for Forced Migrants in Chile". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Blumenstock, J., Lain, J., Smythe, I., and Vishwanath, T. (2021). "Using Big Data and machine learning to locate the poor in Nigeria". Online. https://blogs.worldbank.org/opendata/using-big-data-and-machine-learning-locate-poor-nigeria.

Böhme, M. H., Gröger, A., and Stöhr, T. (2020). "Searching for a Better Life: Predicting International Migration with Online Search Keywords". *Journal of Development Economics*, 142:102347.

Böhmelt, T., Bove, V., and Gleditsch, K. S. (2019). "Blame the Victims? Refugees, State Capacity, and Non-state Actor Violence". *Journal of Peace Research*, 56(1):73–87.

Bohnet, H., Cottier, F., and Hug, S. (2018). "Conflict-induced IDPs and the Spread of Conflict". *Journal of Conflict Resolution*, 62(4):691–716.

Bove, V. and Böhmelt, T. (2016). "Does Immigration Induce Terrorism?". *The Journal of Politics*, 78(2):572–588.

Braun, S. and Kvasnicka, M. (2014). "Immigration and Structural Change: Evidence from Post-war Germany". *Journal of International Economics*, 93(2):253–269.

Buhaug, H., Cederman, L.-E., and Gleditsch, K. S. (2014). "Square Pegs in Round Holes: Inequalities, Grievances, and Civil War". *International Studies Quarterly*, 58(2):418–431.

Calderón-Mejía, V. and Ibáñez, A. M. (2016). "Labour Market Effects of Migration-related Supply Shocks: Evidence from Internal Refugees in Colombia". *Journal of Economic Geography*, 16(3):695–713.

Callaway, B. and Sant'Anna, P. H. (2020). "Difference-in-differences with Multiple Time Periods". *Journal of Econometrics*, 225(2):200–230.

Card, D. (2001). "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration". *Journal of Labor Economics*, 19(1):22–64.

Cederman, L.-E., Gleditsch, K. S., and Buhaug, H. (2013). *"Inequality, Grievances, and Civil War"*. Cambridge University Press.

CIESIN Columbia University (2018). "Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11 [Data set]". Technical report, NASA Socioeconomic Data and Applications Center (SEDAC), Palisades, NY.

Comolli, V. (2015). *"Boko Haram: Nigeria's Islamist Insurgency"*. Oxford University Press.

Coniglio, N. D., Peragine, V., and Vurchio, D. (2021). "The Geography of Displacement, Refugees' Camps and Social Conflicts". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Dadush, U. and Niebuhr, M. (2016). "The Economic Impact of Forced Migration". Technical report, Policy Center for the New South.

Dehos, F. T. (2021). "The Refugee Wave to Germany and its Impact on Crime". *Regional Science and Urban Economics*, 88:103640.

Depetris-Chauvin, E. and Santos, R. J. (2018). "Unexpected Guests: The Impact of Internal Displacement Inflows on Rental Prices in Colombian Host Cities". *Journal of Development Economics*, 134:289–309.

Detges, A. (2017). "Droughts, State-citizen Relations and Support for Political Violence in Sub-Saharan Africa: A Micro-level Analysis". *Political Geography*, 61:88–98.

Dube, O. and Vargas, J. F. (2013). "Commodity Price Shocks and Civil Conflict: Evidence from Colombia". *The Review of Economic Studies*, 80(4):1384–1421.

Duflo, E. (2001). "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment". *American Economic Review*, 91(4):795–813.

Duncan, C. R. (2005). "Unwelcome Guests: Relations Between Internally Displaced Persons and their Hosts in North Sulawesi, Indonesia". *Journal of Refugee Studies*, 18(1):25–46.

Dustmann, C. and Okatenko, A. (2014). "Out-migration, Wealth Constraints, and the Quality of Local Amenities". *Journal of Development Economics*, 110:52–63.

Dyrstad, K. and Hillesund, S. (2020). "Explaining Support for Political Violence: Grievance and Perceived Opportunity". *Journal of Conflict Resolution*, 64(9):1724–1753.

Dziuban, C. D. and Shirkey, E. C. (1974). "When is a Correlation Matrix Sppropriate for Factor Analysis? Some Decision Rules". *Psychological Bulletin*, 81(6):358.

Eberle, U., Rohner, D., and Thoenig, M. (2020). "Heat and Hate: Climate Security and Farmer-Herder Conflicts in Africa". ESOC Working Paper 22.

Ekhator-Mobayode, U. E. and Abebe Asfaw, A. (2019). "The Child Health Effects of Terrorism: Wvidence from the Boko Haram Insurgency in Nigeria". *Applied Economics*, 51(6):624–638.

Ekhator-Mobayode, U. E., Hanmer, L. C., Rubiano Matulevich, E. C., and Arango, D. J. (2020). *"Effect of Armed Conflict on Intimate Partner Violence: Evidence from the Boko Haram Insurgency in Nigeria"*. The World Bank.

Fisk, K. (2019). "Camp Settlement and Communal Conflict in Sub-Saharan Africa". *Journal of Peace Research*, 56(1):58–72.

Foltz, J. and Shibuya, S. (2021). "The Effects of Internally Displaced Peoples on Income and Inequality in Mali". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Genocide Watch (2016). "The Historical Background of Boko Haram". Online. http://genocidewatch.net/2015/02/24/the-historical-background-of-boko-haram/.

George, J., Adelaja, A., and Weatherspoon, D. (2020). "Armed Conflicts and Food Insecurity: Evidence from Boko Haram's Attacks". *American Journal of Agricultural Economics*, 102(1):114–131.

Giuntella, O., Nicodemo, C., and Vargas-Silva, C. (2018). "The Effects of Immigration on NHS Waiting Times". *Journal of Health Economics*, 58:123–143.

Groeger, A., León-Ciliotta, G., and Stillman, S. (2021). "Immigration, Labor Markets and Discrimination: Evidence from the Venezuelan Exodus in Perú". *Unpublished Working Paper*. Commissioned as part of the “Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts” Series. Washington, DC: World Bank Group.

Gwadabe, N. M., Salleh, M. A., Ahmad, A. A., and Jamil, S. (2018). "Forced Displacement and the Plight of Internally Displaced Persons in Northeast Nigeria". *Humanities and Social Science Research*, 1(1):p46–p46.

Hendrix, C. S. and Haggard, S. (2015). "Global Food Prices, Regime Type, and Urban Unrest in the Developing World". *Journal of Peace Research*, 52(2):143–157.

Hoseini, M. and Dideh, M. J. (2021). "How Do Shared Experiences of Economic Shocks Impact Refugees and Host Communities? Evidence from Afghan Refugees in Iran". *Unpublished Working Paper*. Commissioned as part of the “Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts” Series. Washington, DC: World Bank Group.

ICG (2017). "Herders against Farmers: Nigeria's Expanding Deadly Conflict". Technical Report 252, International Crisis Group (ICG).

ICG (2018). "Stopping Nigeria's Spiralling Farmer-Herder Violence". Technical Report 262, International Crisis Group (ICG).

ICG (2020). "Violence in Nigeria's North West: Rolling Back the Mayhem". Technical Report 288, International Crisis Group (ICG).

ICG (2021). "Ending Nigeria's Herder-Farmer Crisis: The Livestock Reform Plan". Technical Report 302, International Crisis Group (ICG).

IDMC (2021). "Global Internal Displacement Database". Online. https://www.internal-displacement.org/database/displacement-data.

IOM (2021). "Displacement Tracking Matrix: Nigeria". Online. https://dtm.iom.int/nigeria.

IRD and AFD (2018). "Crisis and Development. The Lake Chad Region and Boko Haram". Technical report, Research Institute for Development (IRD) and French Agency for Development (AFD).

ISS (2021). "Nigeria's Growing Insecurity Offers Expansion Opportunities for Boko Haram". Online. https://issafrica.org/iss-today/nigerias-growing-insecurity-offers-expansion-opportunities-for-boko-haram.

Kamta, F. N., Azadi, H., and Scheffran, J. (2020a). "The Root Causes of the Crisis in Northeast Nigeria: Historical, Socioeconomic and Environmental Dimensions". *Mediterranean Journal of Social Sciences*, 11(3):95–95.

Kamta, F. N., Schilling, J., and Scheffran, J. (2020b). "Insecurity, Resource Scarcity, and Migration to Camps of Internally Displaced Persons in Northeast Nigeria". *Sustainability*, 12(17):6830.

Kamta, F. N., Schilling, J., and Scheffran, J. (2021). "Water Resources, Forced Migration and Tensions with Host Communities in the Nigerian Part of the Lake Chad Basin. *Resources*, 10(4):27.

Kovac, D., Efendic, A., and Shapiro, J. (2021). "Forced Displacement, War Exposure and Long-run Education and Income Inequality: Evidence from Croatia and Bosnia and Herzegovina". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Kwaja, C. (2011). *"Nigeria's Pernicious Drivers of Ethno-religious Conflict"*. Africa Center for Strategic Studies Washington, DC.

Lehmann, M. C. and Masterson, D. T. (2020). "Does Aid Reduce Anti-refugee Violence? Evidence from Syrian Refugees in Lebanon". *American Political Science Review*, 114(4):1335–1342.

Masterson, D. and Lehmann, M. C. (2020). "Refugees, Mobilization, and Humanitarian Aid: Evidence from the Syrian Refugee Crisis in Lebanon". *Journal of Conflict Resolution*, 64(5):817–843.

Mayda, A. M., Parsons, C. R., Pham, H., and Vézina, P.-L. (2019). "Refugees and Foreign Direct Investment: Quasi-experimental Evidence from US Resettlements".

Maystadt, J.-F. and Duranton, G. (2019). "The Development Push of Refugees: Evidence from Tanzania". *Journal of Economic Geography*, 19(2):299–334.

Maystadt, J.-F., Hirvonen, K., Mabiso, A., and Vandercasteelen, J. (2019). "Impacts of Hosting Forced Migrants in Poor Countries".

Miodownik, D. and Nir, L. (2016). "Receptivity to Violence in Ethnically Divided Societies: A Micro-level Mechanism of Perceived Horizontal Inequalities". *Studies in Conflict & Terrorism*, 39(1):22–45.

Müller, T., Pannatier, P., and Viarengo, M. (2021). "Labor Market Integration, Local Conditions and Inequalities: Refugees in Switzerland". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Morales, J. S. (2018). "The Impact of Internal Displacement on Destination Communities: Evidence from the Colombian Conflict". *Journal of Development Economics*, 131:132–150.

Murard, E. (2021). "Mass Refugee Inflow and Social Cohesion in the Long-run: Evidence from the Greek Population Resettlement". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Nett, K. and Rüttinger, L. (2016). "Insurgency, Terrorism and Organised Crime in a Warming Climate: Analysing the Links Between Climate Change and Non-state Armed Groups". Technical report, adelphi, Berlin, Germany.

Nigerian News (2021). "Report: ISWAP Appoints Sani Shuwaram as New Leader". Online. https://pmnewsnigeria.com/2021/11/06/report-iswap-appoints-sani-shuwaram-as-new-leader/.

Nwokolo, A. (2015). "Terror and Birth Weight: Evidence from Boko Haram Attacks Department of Economics". Working Paper.

Odozi, J. C. and Oyelere, R. U. (2019). "Conflict Exposure and Economic Welfare in Nigeria". Technical report, GLO Discussion Paper.

Ogbogu, J. (2015). "Analysing the Threat of Boko Haram and the ISIS Alliance in Nigeria". *Counter Terrorist Trends and Analyses*, 7(8):16–21.

Østby, G. (2008). "Polarization, Horizontal Inequalities and Violent Civil Conflict". *Journal of Peace Research*, 45(2):143–162.

Parsons, C. and Vézina, P.-L. (2018). "Migrant Networks and Trade: The Vietnamese Boat People as a Natural Experiment". *The Economic Journal*, 128(612):F210–F234.

Paserman, M. D. (2013). "Do High-skill Immigrants Raise Productivity? Evidence from Israeli Manufacturing Firms, 1990-1999". *IZA Journal of Migration*, 2(1):1–31.

Peters, M. (2017). "Refugees and Local Agglomeration: Evidence from Germany's Post-war Population Expulsions". *Unpublished manuscript*.

Pettersson, T. and Öberg, M. (2020). "Organized Violence, 1989–2019". *Journal of Peace Research*, 57(4):597–613.

Pham, P., O'Mealia, T., Wei, C., Bindu, K. K., Makoond, A., and Vinck, P. (2021). "Hosting New Neighbors: Perspective of Host Communities on Displacement and Social Cohesion". *Unpublished Working Paper*. Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Raleigh, C., Linke, A., Hegre, H., and Karlsen, J. (2010). "Introducing ACLED: an Armed Conflict Location and Event Dataset: Special Data Feature". *Journal of Peace Research*, 47(5):651–660.

Rozo, S. V. and Sviatschi, M. (2021). "Is a Refugee Crisis a Housing Crisis? Only if Housing Supply is Unresponsive". *Journal of Development Economics*, 148:102563.

Ruiz, I. and Vargas-Silva, C. (2015). "The Labor Market Impacts of Forced Migration". *American Economic Review*, 105(5):581–86.

Ruiz, I. and Vargas-Silva, C. (2016). "The Labour Market Consequences of Hosting Refugees". *Journal of Economic Geography*, 16(3):667–694.

Rustad, S. A. (2016). "Socioeconomic Inequalities and Attitudes toward Violence: a Test with New Survey Data in the Niger Delta". *International Interactions*, 42(1):106–139.

Salehyan, I. and Gleditsch, K. S. (2006). "Refugees and the Spread of Civil War". *International Organization*, pages 335–366.

Schneiderheinze, C., Lücke, M., et al. (2020). "Socio-economic Impacts of Refugees on Host Communities in Developing Countries". *PEGNet Policy Studies*, (3). Kiel Institute for the World Economy (IfW), Poverty Reduction, Equity and Growth Network (PEGNet), Kiel.

Schuettler, K. and Caron, L. (2020). "jobs interventions for refugees and internally displaced persons". World Bank, Washington, DC. https://openknowledge.worldbank.org/bitstream/handle/10986/33953/Jobs-Interventions-for-Refugees-and-Internally-Displaced-Persons.pdf?sequence=5.

Stewart, F. (2016). *"Horizontal Inequalities and Conflict: Understanding Group Violence in Multiethnic Societies"*. Springer.

Stoddard, A., Harvey, P., Czwarno, M., and Breckenridge, M.-J. (2020). "Humanitarian Access SCORE Report: Northeast Nigeria". Technical report, US Aid.

Sundberg, R. and Melander, E. (2013). "Introducing the UCDP Georeferenced Event Dataset". *Journal of Peace Research*, 50(4):523–532.

Tabellini, M. (2020). "Gifts of the Immigrants, Woes of the Natives: Lessons from the Age of Mass Migration". *The Review of Economic Studies*, 87(1):454–486.

The World Bank (2016). "Poverty Reduction in Nigeria in the Last Decade". Technical Report 273, The World Bank, Washington, DC.

The World Bank (2021a). "The COVID-19 Crisis in Nigeria: What's Happening to Welfare? New Data Call for Expanded Social Protection in Africa's Most Populous Country". Online. https://blogs.worldbank.org/africacan/covid-19-crisis-nigeria-whats-happening-welfare-new-data-call-expanded-social-protection.

The World Bank (2021b). "World Bank Country and Lending Groups". https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

Theisen, O. M., Holtermann, H., and Buhaug, H. (2012). "Climate Wars? Assessing the Claim that Drought Breeds Conflict". *International Security*, 36(3):79–106.

Tumen, S. (2016). "The Economic Impact of Syrian Refugees on Host Countries: Quasi-experimental Evidence from Turkey". *American Economic Review*, 106(5):456–60.

UN OCHA (2019). "Humanitarian Needs Overview 2019 - Nigeria". Technical report, UN OCHA.

UN OCHA (2020). "Humanitarian Needs Overview 2020 - Nigeria". Technical report, UN OCHA.

UNHCR (2018). "Cash for Shelter in Kenya - a Field Experiment". Technical report, UNHCR.

UNHCR (2019a). "Effects of Cash on Social Cohesion in Kalobeyei Settlement, Kenya - Executive Summary". Technical report, UNHCR.

UNHCR (2019b). "Nigeria Emergency". https://www.unhcr.org/nigeria-emergency.html.

UNHCR (2021). "Global Trends: Forced Displacement in 2020". Technical report, UNHCR.

Verme, P. and Schuettler, K. (2021). "The Impact of Forced Displacement on Host Communities a Review of the Empirical Literature in Economics". *Journal of Development Economics*, 150:102606.

Vivekananda, J., Wall, M., Sylvestre, F., Nagarajan, C., and Brown, O. (2019). "Shoring Up Stability: Addressing Climate and Fragility Risks in the Lake Chad Region". Technical report, Adelphi, Berlin, Germany.

von Uexkull, N., Croicu, M., Fjelde, H., and Buhaug, H. (2016). "Civil Conflict Sensitivity to Growing-season Drought". *Proceedings of the National Academy of Sciences*, 113(44):12391–12396.

World Bank (2017). "Forcibly Displaced: Toward a Development Approach Supporting Refugees, the Internally Displaced, and Their Hosts".

Zhou, Y.-Y., Grossman, G., and Ge, S. (2021). "When Refugee Exposure Improves Local Development and Public Goods Provision: Evidence from Uganda". *Unpublished Working Paper.* Commissioned as part of the "Preventing Social Conflict and Promoting Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group.

Zhou, Y.-Y. and Shaver, A. (2019). "Reexamining the Effect of Refugees on Civil Conflict: a Global Subnational Analysis". *Available at SSRN 3107830.*

Appendices

A Review of relevant project papers

Here, we review papers from the project "Preventing social conflict and promoting social cohesion in forced displacement contexts" that are of relevance for our study.

Albarosa and Elsner (2021) find that the inflow of refugees to Germany led to an increased risk of anti-immigrant violence, especially in areas with higher unemployment levels and support for right-wing parties.

Groeger et al. (2021) evaluate the presence of Venezuelan refugees, who tend to be more educated and more skilled than their Peruvians hosts, and find decreased crime rates and improved labor outcomes among locals in hosting areas, as well as lower levels of social cohesion and hostility towards refugees.

Murard (2021) focuses on the longer-run social cohesion and integration of forcibly displaced Greek Orthodox groups from Turkey, 80 years after their resettlement in Greece. Although clashes occurred in the host communities at the time of the shock, he finds no present-day impact on political fragmentation and crime, and high levels of socio-economic integration and social cohesion of second-generation refugees.

Coniglio et al. (2021) show that the presence of refugee camps across the African continent drives protests only in the initial period, as they have a positive effect on long-run economic growth.

Zhou et al. (2021) find that Uganda's progressive hosting approach increases host communities' access to public goods and services, and thus does not worsen tensions or encourage locals to have negative attitudes towards refugees.

Pham et al. (2021) apply a mixed-method participatory approach to develop a locally led measure of social cohesion in the Democratic Republic of Congo. They find some evidence of greater perceived social cohesion within communities hosting in IDPs, which is similar to our results.

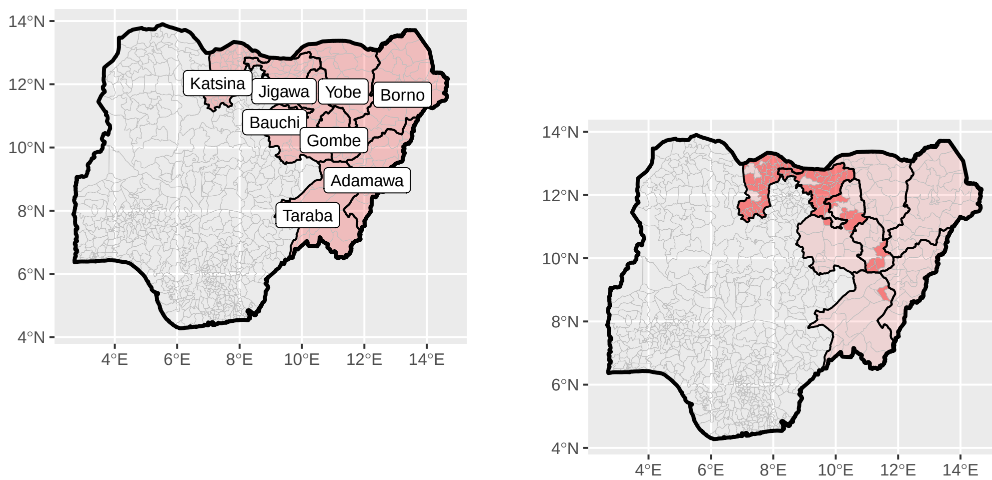
Hoseini and Dideh (2021) show that after a bad economic shock, the welfare of Afghan refugees was disproportionately more adversely affected compared to the wealth of local Iranians, leading to a decrease in social cohesion between these two communities. However, in contrast to our results they find no evidence that positive economic shocks, which have a stronger impact on the refugees, affect social cohesion.

Comparing refugees' labor market performance to that of natives and other migrants in Switzerland, Müller et al. (2021) find that initial labor market conditions and attitudes explain the largest share of the variation. Higher unemployment rates impede the refugees' integration, while more hostile environments accelerate it.

Blanko et al. (2021) find that migrants to Chile have educational outcomes comparable to natives at every school level; the gap broadens at higher levels of education and is stronger for forced migrants.

Kovac et al. (2021) find that the long-term educational attainments of forcibly displaced persons in Croatia are slow to catch up to those of the host population, especially for younger siblings. The results suggest that forcibly displaced persons' disadvantages stem from a combination of short-term trauma and long-term changes.

B Descriptive analyses



(a) Focus states in red (b) Focus LGAs in dark red

Figure 4: Sample area of this study

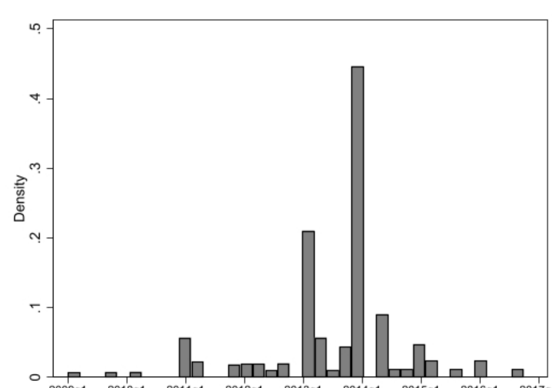


Figure 5: First arrival of IDPs at their destination LGA (Source: IOM's DTM data)

C Instrumental variable approach

The instrument is constructed using information on IDPs' LGA of origin from the IOM's DTM baseline assessment (BA). Data on the distribution of ethnic and cultural groups in Nigeria comes from the Murdock's map of ethnographic and cultural regions for Africa, which was digitized and complemented with attribute data from the Human Area Relations Files (HRAF) by Nathan Nunn, Suzanne Blier and Julia Finkelstien (Murdock HRAF 1959), as shown in Figure 6.[21] The DTM BA data contains the variable "LGA of origin of the majority of IDPs" for each destination site in each assessment round. The "projected" IDP stock to be used as an instrument is then obtained as follows:

$$projIDP_{jt} = v_{je}(\sum_{e} w_{ek} IDP_{kt})$$

and

$$w_{ek} = \frac{Area\,of\,the\,intersection\,between\,LGA\,k\,and\,ethnic\,territory\,e}{Area\,of\,LGA\,k}$$

$$v_{je} = \frac{Area\,of\,the\,intersection\,between\,LGA\,j\,and\,ethnic\,territory\,e}{Area\,of\,ethnic\,territory\,e}$$

where IDP is the observed number of IDPs at time t; j is the destination LGA; k is the LGA of origin; and e is the ethnic group. In the regression analysis, we use the projected number of IDPs $projIDP_{jt}$ to instrument for the observed number of IDPs in a two-stage procedure. F-statistics from the first stage are reported in the results tables.

The instrument was constructed such that for each round of the DTM, we:

1. Sum across sites within the LGA of origin to calculate the number of people that originated from each LGA. To do this, we use the variable "LGA of origin of the majority" at the site level. We assume that all IDPs in a site come from that LGA, as we have no further information on what share actually comes from the reported LGA and where the rest of the IDPs come from.

2. Assign IDPs to ethnic groups according to the share of land of their LGA of origin that intersects the territory of the ethnic group (if the surface area of LGA X is 40% within the territory of group A and 60% in the territory of group B, we assign 40% of the IDPs to group A and 60% to group B).

3. Calculate the total number of IDPs from each ethnic group.

4. Assign the IDPs to destination LGAs according to the share of land that intersects with the ethnic group's territory (if the surface area of group A is 80% within the territory of LGA X and 20% in LGA Y, we say that 80% of the IDPs have LGA X as their destination and 20% have destination LGA Y).

[21] Africa Murdock 1959 by George Murdock, Suzanne Blier, Nathan Nunn.

5. Sum within LGAs to calculate the projected number of IDPs, $projIDP$, that is expected to settle in each destination LGA based on its historical ethnic composition.

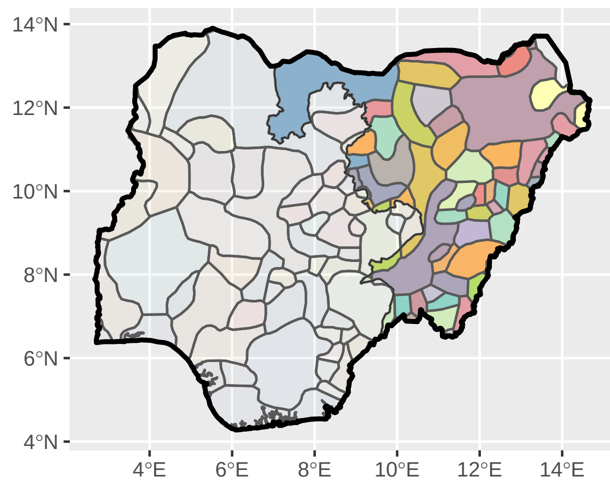


Figure 6: Ethnic and cultural groups in Nigeria according to the Murdock HRAF (1959) map. Darker colors signify the focus regions.

D Inequality-related analyses

D.1 Descriptive statistics

Table 2: Summary statistics: wealth index of host households

Variable	Obs	Mean	Std. Dev.	Min	Max
Wealth index standardized (main analysis)	1124	-.452	.8569	-1.1178	4.0747
Access to electricity	1,139	.3775	.485	0	1
Food secure	1,136	.8125	.3905	0	1
Floor wood/tile/concrete	1,138	.4903	.5001	0	1
Quantity of computers owned	1,141	.0412	.2389	0	2
Has TV set	1,141	.177	.3819	0	1
Has fan	1,141	.17	.3758	0	1
Has fridge	1,141	.071	.2569	0	1
Has car and other vehicles	1,141	.0605	.2385	0	1
Has airconditioner	1,141	.0079	.0885	0	1
Nr. of meals per adult, daily	1,140	2.9342	.5201	0	7
Has electric stove	1,141	.0175	.1313	0	1
Wealth index standardized (alternative)	1042	-.5038	.8553	-1.4718	3.6451
Log(Total expen. p.c.)	1,056	11.6942	.7316	9.8247	15.0277

The data is from the World Bank's NGHS. It records the living conditions of households within the host community, which are used to construct wealth indices via a principal component analysis. These indices are then standardized to be expressed as the "number of standard deviations." The first wealth index is employed as a dependent variable in the main analysis of the distributional consequences of a displacement shock within host communities (RQ1), presented in Table 5. The alternative wealth index is employed in the sensitivity analysis of RQ1 in Table 7 and additionally considers total expenditures. For more information on the variables, see Section 4.1.3.

Table 3: Summary statistics: host communities' wealth and inequality perceptions

Variable	Mean	Std. Dev.	Min.	Max.	N	Description
Wealth index	0.49	0.191	0.024	0.9	93	Continuous
Poverty reduction	3	1.02	1	5	99	Categorical
Employment	2.615	0.966	1	4	96	Categorical
Portable water avail.	3.517	1.034	1	5	116	Categorical
Firewood avail.	3.283	0.807	1	5	113	Categorical
Equality	3.337	0.941	1	6	98	Categorical

The data is from the World Bank's NGHS. It records perceptions of changes of various issues within the host communities compared to 3 years ago (preceding survey wave) at the community level. It is used to construct a wealth index via a principal component analysis applied on four variables: *Poverty reduction*, *Employment*, *Portable water availability*, and *Firewood availability*. The resulting wealth index is then standardized to be expressed as the "number of standard deviations." It is employed as a dependent variable together with the equality perceptions in the sensitivity analyses addressing RQ1, presented in Table 6.

Table 4: Summary statistics: wealth-related variables of households in host communities

Variable	Mean	Std. Dev.	Min.	Max.
Log(Consumption)	4.4573	0.9797	0.6186	10.7893
Poorest	0.3082	0.4619	0	1
Quintiles	3.0187	1.407	1	5
N		1444		

The data is from the World Bank's cross-sectional data set Profile of Internally Displaced Persons in North-East Nigeria 2018 that captures households in host communities. *Log(Consumption)* is continuous and captures household-level logarithms of consumption per capita, per day in Nigerian Naira in 2018. *Poorest* is a binary variable indicating whether a household belongs to the poorest ethnic group in a given LGA. *Quintiles* divides households into consumption quintiles. *Log(Consumption)* is employed as a dependent variable in the sensitivity analyses addressing RQ1, presented in Tables 8 and 9. *Quintiles* and *Poorest* are interacted with the displacement shock variable in Tables 8 and 9, respectively, to help analyze the distributional consequences (along ethnic lines).

D.2 Main analyses

Table 5: Effect of IDPs' inflow on wealth and inequality, household-level analysis

	Wealth index							
	ALL		Q1		Q2-Q3		Q4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	wlt	wlt	wlt	wlt	wlt	wlt	wlt	wlt
IDPs/pop.	-7.425**	-13.940**	-11.825***	-26.768***	-14.258**	-20.143**	28.154	5.289
	(3.611)	(5.993)	(2.200)	(9.810)	(5.906)	(8.799)	(22.245)	(34.008)
Observations	1,095	1,095	591	591	422	422	82	82
Model	Panel	IV	Panel	IV	Panel	IV	Panel	IV
Fstat		14.035		5.507		13.419		3.766

The dependent variable is a continuous household-level wealth index. It is constructed using principal component analysis as presented in Section 4.1.3 and is expressed as the "number of standard deviations." The treatment variables capture either the observed fraction of IDPs over the host community population or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Models 1, 3, 5 and 7 are estimated in a panel setting using two-way fixed effects. Models 2, 4, 6 and 8 are estimated using an IV approach. Models 1–2, we run the analyses on the full sample. In Models 3–4, we run the analysis on the poorest quartile of households, in Models 5–6 on households in the 2nd and 3rd quartiles, and in Models 7–8 on the richest quartile of households. The information on the dependent variable is derived from the World Bank's NGHS. The treatment-level variable is constructed using information from the IOM's DTM. Clustered standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

D.3 Sensitivity tests

Here, we present several sensitivity analyses addressing RQ1. First, we construct a community-level wealth index using NGHS data (Section 4.1.3) on perceptions of changes within host communities compared to 3 years ago. We conduct a principal component analysis on four categorical variables, capturing changes related to poverty reduction, employment, and the availability of potable water and fire wood. The Kaiser-Meyer-Olkin measure of sampling adequacy indicates a value of 0.6, indicating the suitability of the approach. The resulting wealth index is then standardized. We separately draw on perceptions of local changes in equality.[22] The corresponding summary statistics are in Table 3 in Appendix D.1. The wealth index and equality measure are used on the left-hand-side of Equation 1, estimated at the community level. The corresponding results are presented in Table 6. Models 1, 3, and 4 apply panel analysis with two-way fixed effects and Models 2 and 5 apply an IV approach. Since the equality measure is a categorical variable, in addition to simple OLS analysis we also estimate the model as an ordered logit with fixed effects.

Table 6: Effect of IDPs' inflow on community wealth and equality perceptions

	Wealth index		Equality		
	(1)	(2)	(3)	(4)	(5)
IDPs/pop.	-22.584	-63.123*	35.676	297.810	-21.281
	(41.423)	(35.847)	(39.141)	(225.526)	(57.948)
Observations	91	91	96	116	96
Time trend	Common	Common	Common	Common	Common
Model	Panel	IV	Panel	Panel - Ologit	IV
Fstat		20.033			17.611

The community-specific dependent variable *Wealth index* is continuous. It is constructed using principal component analysis as presented in Section 4.1.3 and is expressed as the "number of standard deviations." The second dependent variable, *Equality*, is measured at the community level and is categorical, capturing how the situation has changed since the last survey wave; higher values signal greater equality. The treatment variables capture either the observed fraction of IDPs over the host community population or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Models 1, 3, and 4 are estimated in a panel setting using two-way fixed effects. Models 2, and 5 are estimated using an IV approach. With the exception of Model 4, which is estimated using ordered logit, all remaining models are estimated via OLS. The information on the dependent variables is derived from the World Bank's NGHS. The treatment-level variable is constructed using information from the IOM's DTM. The analyses are conducted at the community-wave level. Clustered standard errors are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Second, in Table 7, we apply the same estimation strategy and data sources as in the main analysis (Table 5), however with an alternative outcome variable – a wealth index that also accounts for total household expenditures. Since this information is missing from the 4th wave of the NGHS, the analysis is run using only the first three waves of NGHS data. We then study the distributional consequences of displacement shocks by estimating Equation 1 separately for poor (Q1), medium-wealth (Q2–3), and rich (Q4) households. Models 1, 3, 5 and 7 are estimated in a panel setting using two-way fixed effects. Models 2, 4, 6 and 8 are estimated using an IV approach.

Third, we draw on household-specific information on daily total consumption per capita in Nigerian Naira from the 2018 cross-sectional data introduced in Section 4.1.4. We then i) split

[22] All components of the wealth index as well as the equality perceptions are categorical variables scored based on whether the situation got: much worse (1), worse (2), remained about the same (3), better (4) or much better (5).

Table 7: Effect of IDPs' inflow on wealth and inequality using an alternative wealth index, household-level analysis

	Wealth index							
	ALL		Q1		Q2–Q3		Q4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IDPs/pop.	-5.582*	-10.780	-8.339**	9.158	-12.240***	-23.267*	56.351	85.352
	(3.202)	(8.343)	(3.898)	(8.697)	(4.341)	(12.947)	(33.063)	(105.080)
Observations	1,013	1,013	554	554	388	388	71	71
Model	Panel	IV	Panel	IV	Panel	IV	Panel	IV
Fstat		4.867		2.297		5.043		0.917

The dependent variable is a continuous *alternative* wealth index at the household level. It is constructed using principal component analysis as presented in Section 4.1.3 and is expressed as the "number of standard deviations." The treatment variables capture either the observed fraction of IDPs over the host community population or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Models 1, 3, 5 and 7 are estimated in a panel setting using two-way fixed effects. Models 2, 4, 6 and 8 are estimated using an IV approach. In Models 1–2, we run the analyses on the full sample. In Models 3–4, we run the analyses on the poorest quartile of households, in Models 5–6 on households in the 2nd and 3rd quartiles, and in Models 7–8 on the richest quartile of households. The information on the dependent variable is derived from the World Bank's NGHS. The treatment-level variable is constructed using information from the IOM's DTM. Clustered standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

households into consumption quintiles and ii) capture the poorest ethnic group in a given LGA. For summary statistics, see Table 4 in Appendix D.1. In Table 8, we interact the displacement treatment with consumption expenditure quintiles in an IV setting to analyze vertical inequality. Column 2 includes household-level controls (religion, ethnicity, ownership of sanitation facility). In Table 9, we further analyze whether the distributional consequences align with ethnic identities. To this end, we similarly interact the treatment variable in an IV setting with a binary variable distinguishing whether a household belongs to the poorest ethnic group in a given LGA, in a model without (Model 1) and with (Model 2) household-specific controls. Then, in both tables we study the implications for consumption.

Table 8: Effect of IDPs' inflow on households' consumption by consumption quintile, household-level analysis

	log(Consumption)	
	(1)	(2)
IDPs/pop.	-0.026*	-0.026*
	(0.015)	(0.014)
IDPs/pop. × Quintiles=2	0.039**	0.039**
	(0.018)	(0.018)
IDPs/pop. × Quintiles=3	0.053*	0.053*
	(0.030)	(0.028)
IDPs/pop. × Quintiles=4	0.022	0.024
	(0.021)	(0.022)
IDPs/pop. × Quintiles=5	-0.060	-0.058
	(0.090)	(0.093)
Observations	1,444	1,444
Fixed effects	State	State
Model	IV - Cross-sec.	IV - Cross-sec.
Sample	Hosts	Hosts
Fstat (IDPs/pop.)	38.55	41.46
Fstat (Quintile=2)	31.98	25.49
Fstat (Quintile=3)	7.20	8.45
Fstat (Quintile=4)	7.77	7.21
Fstat (Quintile=5)	8.26	8.65
KP Fstat	4.773	7.89
Controls	No	Yes

The sample includes households in communities hosting IDPs in northeastern Nigeria. The dependent variable is continuous and captures household-level logarithms of consumption per capita, per day in Nigerian Naira in 2018. The treatment variable (IDPs/pop.) captures the fraction of IDPs over the host community population and is instrumented by our version of the shift-share IV, as explained in Section 4.2.2. The treatment variable is interacted with a variable dividing households into consumption quintiles to study the distributional implications of a displacement shock. Column 2 includes additional household-level controls (i.e., religion, livelihood, ethnicity, households' sanitation facilities). Both models control for state-specific fixed effects. The information on the dependent variable and controls is derived from the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 dataset. The treatment-level variable is constructed using information from the IOM's DTM. Robust standard errors in parentheses. F-stat is the Kleibergen–Paap F-stat for joint significance of instruments. F-stat (IDPs/pop.) and F-stat (Quintile=x) refer to the partial F-stats for joint significance of the instruments in the separate first stages.* p<0.10, ** p<0.05, *** p<0.01.

Table 9: Effect of IDPs' inflow on households' consumption by LGA-specific wealth of ethnic groups, household-level analysis

	log(Consumption)	
	(1)	(2)
	Log(Consumption)	Log(Consumption)
IDPs/pop.	0.0167	-0.0357
	(0.0360)	(0.237)
Poorest × IDPs/pop.	0.157	1.361
	(0.109)	(7.272)
Poorest	-0.682*	-3.726
	(0.379)	(19.77)
Observations	1,444	1,444
Fixed effects	State	State
Model	IV - Cross-section	IV - Cross-section
Sample	Hosts	Hosts
Fstat (IDPs/pop.)	121.14	89.45
Fstat (Poorest)	13.54	0.41
KP Fstat	12.60	0.0187
Controls	No	Yes

The sample includes households in communities hosting IDPs in northeastern Nigeria. The dependent variable is continuous and captures household-level logarithm of consumption per capita, per day in Nigerian Naira in 2018. The treatment variable (IDPs/pop.) captures the fraction of IDPs over the host community population and is instrumented by our version of the shift-share IV, as explained in Section 4.2.2. The treatment variable is interacted with a binary variable indicating whether a household belongs to the poorest ethnic group in a given LGA to study the distributional implications of a displacement shock along ethnic lines. Column 2 includes additional household-level controls (i.e., religion, livelihood, ethnicity, households' sanitation facilities). Both models control for state-specific fixed effects. The information on the dependent variable and controls is derived from the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 data set. The treatment-level variable is constructed using information from the IOM's DTM. Robust standard errors in parentheses. F-stat is the Kleibergen–Paap F-stat for joint significance of instruments. F-stat (IDPs/pop.) and F-stat (Poorest) refer to the partial F-stats for joint significance of the instruments in the separate first stages.* p<0.10, ** p<0.05, *** p<0.01

E Conflict-related analyses

E.1 Descriptive statistics

Table 10: Summary statistics: conflict onset, 2000–2019

Variable	Obs	Mean	Std. Dev.	Min	Max	Description
Conflict onset	2,619	.016	.126	0	1	Binary
Violence against civilians onset	2,628	.013	.115	0	1	Binary
Riot onset	2,636	.006	.078	0	1	Binary
Δ Conflict onset	66	.242	.498	-1	1	Categorical
Conflict onset (lr. mean)	132	.242	.43	0	1	Binary: pre-/post treat.

The conflict data is from the ACLED database (Raleigh et al., 2010). We use information on violence against civilians and riots to generate our main variable of interest, *Conflict onset*. We code conflict onset at the LGA-quarter/year level as a binary variable that takes a value of 1 in the first quarter/year of reported violence, as well as in the first quarter/year of violence after at least 2 years without conflict. Subsequent years of ongoing conflict are coded as missing. *Conflict onset (lr. mean)* captures whether an LGA experienced at least one conflict onset during the i) pre- and ii) post-treatment periods. Δ *Conflict onset* captures the difference between two binary indicators, recording whether an LGA experienced at least one conflict onset in the last (i.e., year 2019) and first (i.e., year 2010) years of our study period. For more information on the construction of the variables, see Section 4.1.2. The variables are employed as dependent variables in the main analysis addressing RQ2, presented in Table 13.

Table 11: Summary statistics: robbery and trust change perceptions over time

Variable	Obs	Mean	Std. Dev.	Min.	Max.	Description
Robbery	89	2.618	0.923	1	5	Categorical
Trust index	0.711	0.157	0.173	1	99	Continuous
Trust change	3.88	0.700	2	5	100	Categorical
Help change	3.96	0.768	1	5	99	Categorical
Cash contribution change	3.667	0.937	1	5	99	Categorical

The data is from the World Bank's NGHS data. It records perceptions of changes of various issues within communities compared to 3 years ago (preceding survey wave) at the community level. It is used to construct a trust index via a principal component analysis applied on three variables: *Trust change*, *Help change* and *Cash contribution change*. The resulting trust index is then standardized, to be expressed as the "number of standard deviations." It is employed as a dependent variable in the main analysis addressing RQ2, presented in Table 14. Perceptions of robbery levels are used in the sensitivity analysis addressing RQ2 presented in Table 15.

Table 12: Summary statistics: violence-related perceptions of households in host communities

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Unsafe	1.6925	0.6822	1	5
Unsafe at night	2.0602	0.9410	1	5
Killing	0.0409	0.198	0	1
Support	3.3151	1.1742	1	5
N		1444		

The data is from the World Bank's cross-sectional data set "Profile of Internally Displaced Persons in North-East Nigeria 2018" that captures households in host communities. *Unsafe* and *Unsafe at night* are categorical and take five different values. *Killing* is binary. Higher values signal that hosts perceive/experience a decrease in safety levels. These three variables approximate the security-related situation as perceived by households in the host community. *Support* is also categorical and takes five different values; higher values indicate that host households perceive that IDPs receive strong support from the government and aid organizations. All variables are employed as dependent variables in the sensitivity analysis addressing RQ2, presented in Table 16.

E.2 Parallel-trends analysis

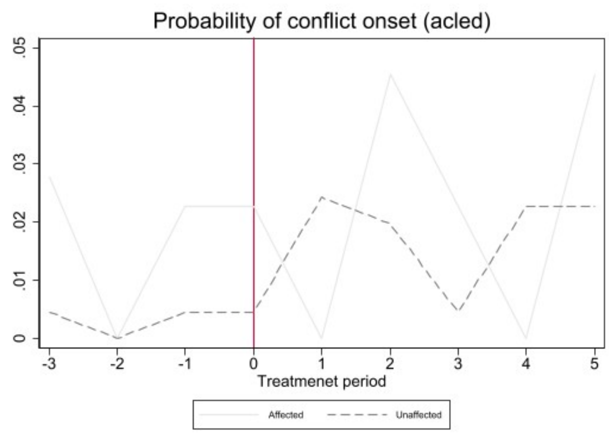


Figure 7: Probability of conflict onset during pre-/post-treatment periods, for LGAs treated and untreated by IDPs inflows

E.3 Main analyses

Table 13: Effect of IDPs inflows on conflict onset

	Conflict onset			Δ Conflict onset	
	(1)	(2)	(3)	(4)	(5)
	ACLED (lr. mean)	ACLED	ACLED	ACLED	ACLED
IDPs/pop. (lr. mean)	-9.872				
	(27.758)				
IDPs/pop.		-1.010	3.675**		
		(1.532)	(1.762)		
Δ IDPs/pop.				-1.361	40.058**
				(11.322)	(16.088)
Observations	132	2,538	2,538	64	64
Time trend	Pre/post	Common	Common	Common	Common
Model	DiD	Panel	IV	LD-OLS	LD-IV
Fstat			35.168		192.888
Sample	No origin	No origin	No origin	No origin	No origin

The dependent variable in Model 1 is binary and captures whether an LGA experienced at least one conflict onset during the pre- and post-treatment periods. The dependent variable in Models 2—3 is binary and captures LGA-specific conflict onset at the quarter/year level. The dependent variable in Models 4—5 is categorical and captures the difference between two binary indicators, recording whether an LGA experienced at least one conflict onset in the last (i.e., year 2019) and first (i.e., year 2010) years of our study period. The treatment variables capture either the observed fraction of IDPs over the host community population or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Models 1, 2 and 4 are estimated in a panel setting using two-way fixed effect. Models 3 and 5 are estimated using an IV approach. Models 4 and 5 are estimated as long differences, Model 1 in a DiD setting and Models 2–3 at the quarter/year level, as explained in Section 4.2.1. The information on the dependent variable is derived from the ACLED database. The treatment-level variable is constructed using information from the IOM's DTM. Clustered standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 14: Effect of IDPs inflows on cohesion within the host community: perceptions

	Trust index	
	(1)	(2)
IDPs/pop.	121.617**	109.219
	(55.411)	(72.814)
Observations	97	97
Time trend	Common	Common
Model	Panel	IV
Fstat		20.627

The dependent variable is continuous, at the community-wave level. It captures perceptions of how local trust within the host community has changed since the last survey wave; higher values signal more trust. It has been constructed using a principal component analysis, as explained in Section 4.1.3 and is expressed in standard deviations. The treatment variables capture either the observed fraction of IDPs over the host community population or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Model 1 is estimated in a panel setting using two-way fixed effects. Model 2 is estimated using an IV approach. The information on the dependent variable is derived from the World Bank's NGHS. The treatment-level variable is constructed using information from the IOM's DTM. Clustered standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

E.4 Sensitivity tests

Here, we present several sensitivity analyses addressing RQ2. First, we draw on community-level data from the NGHS (Section 4.1.3) on perceptions of local changes in the prevalence of robbery compared to 3 years ago. We employ this categorical variable as a dependent variable in Equation 2 and estimate it at the community-wave level. The results are presented in Table 15, in Models 1–3. Given the coverage of the NGHS, we run this analysis on a much more restricted sample of LGAs than the main analysis (Table 13). To make the results more comparable, as a sensitivity test, Models 4 and 5 verify our conclusions from the comprehensive main analysis in this geographically more restricted setting at the LGA-year level. Models 1, 2 and 4 correspond to the panel data analysis with two-way fixed effects. Given that the dependent variable is categorical, in Model 2 we apply an ordered logit with fixed effects (Baetschmann et al., 2020). Models 3 and 5 use the instrumented displacement shocks in an IV setting. For both models, the F-statistics suggest that our instrument has sufficient strength.

Table 15: Effect of IDPs inflows on community violence perceptions and LGA conflict onset

	Robbery			Conflict onset	
	(1)	(2)	(3)	(4)	(5)
IDPs/pop.	126.203***	407.145**	218.646**	13.294	20.811*
	(40.258)	(174.170)	(93.288)	(13.619)	(11.878)
Observations	87	94	87	260	260
Time trend	Common	Common	Common	Common	Common
Model	Panel	Panel - Ologit	IV	Panel	IV
Fstat			18.212		46.420
Sample	No origin	No origin	No origin	No origin	No origin

The first dependent variable, *Robbery*, is categorical at the community-wave level. It captures how the situation has changed since the last survey wave; higher values indicate perceptions of more robberies. The second dependent variable *Conflict onset* is binary and captures LGA-specific conflict onset at the NGHS wave level. The treatment variables capture either the observed fraction of IDPs over the host community population or the predicted fraction of IDPs over the host community population instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Models 1, 2 and 4 are estimated in a panel setting using two-way fixed effects. Models 3 and 5 are estimated using an IV approach. Models 1–3 are run at the community-wave level. Models 4–5 are run at the LGA -quarter/year level. All models are estimated via OLS except Model 2, which is run via ordered logit. The information on the first dependent variable (*Robbery*) is derived from the World Bank's NGHS data. The information on the second dependent variable (*Conflict onset*) is from the ACLED database. The treatment-level variable is constructed using information from the IOM's DTM. Clustered standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Second, we draw on four variables from the cross-sectional data introduced in Section 4.1.4 on the security situation as perceived by 1,444 households in the host community: i) a categorical variable *Unsafe* (*In general, how safe from crime and violence do you feel when you are alone where you are staying?*), ii) a categorical variable *Unsafe at night* (*How safe do you feel when walking around alone after dark?*), and iii) a binary variable *Killing* (*Was any family member killed in the last 12 months?*). Higher values signal that hosts perceive a decrease in safety. Lastly, we draw on iv) a categorical variable, where higher values indicate that hosts perceive that IDPs receive strong support from the government and aid organizations (see summary statistics in Table 12, Appendix E.1). We analyze the security effects of displacement in a cross section using an IV analysis, in a setting without (Models 1, 3, 5 and 7) and with (Models 2, 4, 6 and 8) household-specific controls.

Table 16: Effect of IDP inflows on violence-related indicators at the household level

	Unsafe		Unsafe at night		Killing		IDPs' Support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IDPs/pop.	-0.125***	-0.114***	-0.131***	-0.112**	-0.022*	-0.025*	0.157***	0.131***
	(0.037)	(0.040)	(0.044)	(0.047)	(0.012)	(0.014)	(0.046)	(0.050)
Ethnicity (ref.: Hausa)								
Yoruba		0.019		0.098		-0.007		0.207
		(0.271)		(0.369)		(0.023)		(0.356)
Igbo		0.106		0.232		0.102**		0.249
		(0.148)		(0.239)		(0.051)		(0.213)
Kanuri		-0.014		-0.018		0.023		-0.051
		(0.051)		(0.068)		(0.014)		(0.083)
Fulani		-0.213**		-0.223**		-0.020		0.079
		(0.092)		(0.103)		(0.022)		(0.126)
Other		-0.115		-0.097		-0.013		-0.116
		(0.077)		(0.097)		(0.022)		(0.115)
Religion (ref.: Christian)								
Islam		-0.325***		-0.329**		0.010		0.146
		(0.108)		(0.133)		(0.023)		(0.138)
Observations	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444
Fixed effects	State	State	State	State	State	State	State	State
Model	IV - Cross sec.	IV - Cross sec.	IV - Cross sec.	IV - Cross sec.	IV - Cross sec.	IV - Cross sec.	IV - Cross sec.	IV - Cross sec.
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Sample	Hosts	Hosts	Hosts	Hosts	Hosts	Hosts	Hosts	Hosts
Fstat	237.043	196.535	237.043	196.535	237.043	196.535	237.043	196.535

The sample includes households in communities hosting displaced persons in northeastern Nigeria. The dependent variables capture households' security perceptions in 2018. The dependent variables in Models 5—6 are binary and the remaining variables are categorical and take on five different values; higher levels signal that hosts perceive a decrease in safety levels (Models 1–6) and that IDPs receive strong support (Models 7–8). The treatment variable (IDPs/pop.) captures the fraction of IDPs over the host community population and is instrumented by our version of the shift-share IV, as explained in Section 4.2.2. Columns 2, 4, 6 and 8 include additional household-level controls (i.e., religion, livelihood, sanitation facilities, ethnicity). All models control for state-specific fixed effects. The information on the dependent variable and controls is derived from the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 data set. The treatment-level variable is constructed using information from the IOM's DTM. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

F Inequality between IDPs and hosts – related analyses

F.1 Descriptive statistics

Table 17: Summary statistics: relative wealth of displaced households vs. hosts

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Negative inequality	3.9655	3.4202	1.0045	39.4833	1,069
Positive inequality	2.3435	5.3255	1.0026	53.9661	194

The data is from the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 data set collected in a cross section, providing information on displaced households. The variable *Negative inequality* captures hosts' LGA-specific average consumption as a fraction of IDP households' consumption, which are on average poorer than the hosts. The variable *Positive inequality* captures IDP households' consumption (which is higher than the average LGA-specific average consumption of hosts) as a fraction of the LGA-specific average consumption of hosts. In both cases, higher values indicate higher levels of inequality. All variables are employed as explanatory variables in the main analysis addressing RQ3, presented in Table 19. For more information on the variables, see Section 4.1.4.

Table 18: Summary statistics: IDPs' living conditions

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Wealth (index) IDPs	0.8547	0.1077	0.2193	1	90
Access to electricity IDPs	2.0111	0.9539	0	4	90
Access to income gener. IDPs	1.9556	0.2072	1	2	90
Access to potable water IDPs	1.9333	0.2508	1	2	90
Shelter	3.9778	0.2108	2	4	90

The data is from the IOM's DTM (IOM, 2021). It records IDPs' living conditions on a quarterly basis. Higher values signal better living conditions but are not straightforward to interpret. To construct a quarterly wealth index, we run a principal component analysis on these variables. The index is normalized between 0 and 1. These variables are employed in the sensitivity analysis addressing RQ3 presented in Table 20.

F.2 Main analysis

Table 19: Cross-sectional correlation between IDPs' consumption relative to hosts' and relationships in the community

	Good relations					
	(1)	(2)	(3)	(4)	(5)	(6)
Negative inequality	-0.0142**	-0.0211***	-0.0506***			
	(0.0066)	(0.0063)	(0.0188)			
Positive inequality				0.0195***	0.0195***	0.5833***
				(0.0034)	(0.0028)	(0.1891)
Observations	1,069	1,069	1,069	194	194	194
Fixed effects	State	LGA	State	State	LGA	State
Model	OLS	OLS	Ologit	OLS	OLS	Ologit
Controls	No	No	No	No	No	No
Sample	IDPs	IDPs	IDPs	IDPs	IDPs	IDPs

The sample includes IDPs in northeastern Nigeria. The dependent variables are categorical and capture IDPs' perceptions of their relations with hosts in 2018. Higher values signal better relations. The treatment variable *Negative inequality* captures the LGA-specific average consumption of hosts as a fraction of IDP households' consumption, which are on average poorer than the hosts. The treatment variable *Positive inequality* captures IDP households' (who are richer than the average LGA-specific average consumption of hosts) consumption, as a fraction of hosts' LGA-specific average consumption. In both cases, higher values signal greater inequality. Except Models 3 and 6, which are estimated with an ordered logit, all the models are estimated with OLS. The information is derived from the World Bank's Profile of Internally Displaced Persons in North-East Nigeria 2018 data set. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

F.3 Sensitivity test

Here, we present sensitivity analyses addressing RQ3. We draw on IOM's DTM data (Section 4.1.1), which records IDPs' living conditions to proxy for their wealth. We use site assessment information on the percentage of IDPs with access to electricity and living in shelters, as well as information on whether the water on site is potable and whether IDPs generally have access to income-generating activities. We aggregate this information at the LGA-quarter/year level to approximate IDPs' average living conditions; site-specific IDP numbers are used to calculate weighted averages. Higher values signal better living conditions.[23] Following Dustmann and Okatenko (2014), we use these variables to construct a quarterly wealth index at the LGA level. We conduct a principal component analysis on these variables and use the factor loadings of the first principle component as weights to construct an aggregate wealth index. The corresponding Kaiser-Meyer-Olkin measure of sampling adequacy indicates a value of 0.55, which supports the suitability of the approach (Dziuban and Shirkey, 1974). The resulting wealth index is then normalized to lie between 0 and 1. The corresponding summary statistics are presented in Appendix F.1, Table 18.

To address RQ3 on how inequality between IDPs and the host community affects the risk of conflict, we estimate the following model:

$$C_{wqt} = \theta_w + \beta_1 Y_{wqt} + \gamma_{qt} + \epsilon_{wqt} \tag{6}$$

[23] The variables that capture the percentage of IDPs with access to electricity and living in shelters are categorical. Each splits IDPs into one of five categories, i.e. 0%, 1–24%, 25–50%, 50–75% and 76–100%. The variables that capture access to potable water and income-generating activities are binary.

where we measure conflict onset (C_{wqt}) at the LGA-quarter/year level using a measure of IDPs' wealth (Y), as well as observable characteristics that vary over time (Z_{wqt}), quarter/year-specific fixed effects (γ_{qt}) and LGA-specific fixed effects (θ_w). Due to endogeneity concerns, we consider the estimated coefficients to have a descriptive rather than causal meaning. Standard errors are clustered at the LGA level.

Table 20 presents the outcomes of the analysis; components of the wealth index also enter the model independently (Models 2–5). The correlations have been conducted on a very limited sample size focusing on a few treated LGAs during the treatment periods with a quarter/year temporal variation. This evidence should serve as an impulse for future analyses, with potentially important policy implications.

Table 20: Correlation between IDPs' wealth and conflict onset

	Conflict onset				
	(1)	(2)	(3)	(4)	(5)
Measures of IDPs wealth					
Wealth (index)	-0.008				
	(0.046)				
Access to electricity		0.020			
		(0.017)			
Access to income generat.			-0.031+		
			(0.021)		
Access to potable water				-0.033+	
				(0.023)	
IDPs with shelter					-0.014+
					(0.010)
Observations	90	90	90	90	90
Time trend	Common	Common	Common	Common	Common
Model	Panel	Panel	Panel	Panel	Panel
Controls	No	No	No	No	No
Sample	IDPs	IDPs	IDPs	IDPs	IDPs

The sample includes IDPs in northeastern Nigeria. The dependent variable is binary and captures LGA-specific conflict onset at the quarter/year level. The independent variables approximate IDPs' wealth at the LGA level. The variable *Wealth* uses the independent variables from Models 2–5 to construct a quarterly wealth index at the LGA level applying a principal component analysis. The wealth index is then normalized to lie between 0 and 1. All models are estimated using two-way fixed effects. The information on the dependent variable is derived from the ACLED database and on the independent variables from the IOM's DTM. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01