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Herder-Related Violence, Agricultural Work, and the Informal Sector as a Safety Net

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Abstract

Violent conflict between nomadic herders and settled—mostly agricultural—communities in Nigeria occurs as both groups clash over the use of land and resources, in part, due to a changing climate. This paper uses panel data from 2010 through 2019 to study the labor responses of individuals to exposure to herder-related violence during the post-planting and post-harvest seasons. Specifically, it considers a "shadow of violence" channel, where recent exposure to a violent event alters labor-related responses to a subsequent event. Results find that in the post-planting season, exposure to a herder-related violent event leads to an increase in informal work for both men and women, a decrease in agricultural work for men, and an increase in total hours worked for women among households that have previously been exposed to herder-related violence in the preceding six months. The paper also considers two other specific forms for a "shadow of violence" channel—namely, raised tensions over open-grazing bans enacted in 2016 and 2017 within three states and a drastic peak in violence in the first half of 2018—and find similar results. Lastly, findings show how household exposure to violence can have so-called knock-on effects. Households exposed to herder-related violence in the previous post-planting season shift consumption and crop selling patterns in the post-harvest season. These findings highlight the gender-specific labor response to violence and document the role of the informal sector as a partial safety net for individuals in the presence of adverse shocks.

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1 Introduction

Throughout the developing world, informal work prevails. In many countries, the informal sector is large, persistent, and seems to react counter-cyclically to macroeconomic trends and immediate external shocks (Fiess *et al.*, 2010; Loayza and Rigolini, 2011). Although existing research includes analyses of the informal sector's response to economic contractions, financial crises, trade opening, and environmental shocks (Gunther and Launov, 2012; Epstein and Shapiro, 2017; Adhvaryu *et al.*, 2019; Colombo *et al.*, 2019), the degree to which the informal sector acts as a safety net in response to conflict and violent unrest remains an open question. In particular, individuals may supply labor—that is make different decisions about where and how they work—based on the perceived threat of violence. The option of self-employment or an informal business run by a household member—as opposed to work for someone else, even if that work is informal—may present an available option for work if other types of work become limited or risky (Gunther and Launov, 2012).[1] Yet, despite being increasingly salient in many areas around the world, little is known about how households, and in particular agricultural households, turn to informal activity in the form of self-employment or in a household-run enterprise as a way to cope with increased risk of conflict and violence.

Within Nigeria, the last decade has seen a sharp rise in violence propagated by Boko Haram in the northeast region and escalating inter-group conflict between farmers and Fulani pastoralists in the north-central region. Severe violence led to states of emergency in both 2011 and 2013,[2] and despite Boko Haram dominating the news, conflicts between Fulani pastoralists and settled agricultural communities have proven to be more deadly.[3] Moreover, emerging evidence suggests that increased temperatures driven by climate change will likely lead to increased conflict between farmers and pastoralists across Sub-Saharan Africa and within Nigeria specifically (McGuirk and Nunn, 2020; Eberle *et al.*, 2020).

We study a specific series of shocks—namely, violence between Fulani nomadic herders and sedentary (largely agricultural) communities in Nigeria—and their effect on economic, primarily labor-related, activities. These violent incidents in the so-called 'herder-farmer conflict' led to over 3,600 deaths in a period of heightened violence between 2016 and 2018.[4] In addition to the loss of life, these conflicts also led to widespread destruction of property, displacement, and civil unrest. These conflicts are, in part, related to increasing competition for scarce land and water resources used by both farming and herding communities (George *et al.*, 2021a). Over time, nomadic herders have moved farther away from traditional routes and have remained in areas for longer periods of time, due to prolonged dry seasons

[1] The definition of informality is often broad and subject to some specific (and localized) criteria (Ohnsorge and Yu, 2022; Aga *et al.*, 2023). Generally, the informal sector is regarded as both informal work—employment not covered by publicly funded, social safety nets—and unregistered, often un-taxed, economic activity. While throughout we may refer to informality more broadly, in this paper we are particularly concerned with self-employment and/or work in a non-farm, household enterprise, as both present often readily available employment options in the face of adverse shocks.

[2] BBC News. December 31, 2011. "Nigeria's president declares state a emergency." available here. Last accessed: November 12, 2020.

[3] The Washington Post. July 26, 2018. "This little-known conflict in Nigeria is now deadlier than Boko Haram." available here. Last accessed: November 12: 2020.

[4] Amnesty International. December 17, 2018. "Harvest of Death: Three Years of Blood Clashes Between Farmers and Herders in Nigeria." available here. Last accessed: February 3, 2021.

driven by climate change and displacement from the country's ongoing conflict with Boko Haram in the northeast. Simultaneously, settled communities have expanded, and dry farming techniques have lengthened their land and water use throughout the year. In response to these tensions, three Nigerian states (Benue, Ekiti, and Taraba) passed outright bans on open grazing in 2016 and 2017. These bans exacerbated previous tensions and directly contributed to a peak of violence in the first half of 2018.

We combine detailed panel data of households and individuals from Nigeria's General Household Survey (GHS) with data on violent events from the Armed Conflict Location and Event Data (ACLED) project (Raleigh *et al.*, 2010). The GHS data contain four survey rounds, each including two seasonal visits—post-planting and post-harvest. This means that individuals can be observed in (up to) eight separate periods between 2010 and 2019. Herder-related violence typically follows a seasonal pattern, with events worsening as herders remain to graze their cattle in areas past May, when they historically moved north.[5] With these data, we leverage variation across time and space using the presence of herder-related violent incidents within a given radius around households (i.e., 10 km) and within a given time frame (i.e., within the last month) as an indicator of exposure to herder-related violence.[6] The granularity of these data allows us to include fixed effects at the level of a comparatively small geographic area, which combined with time and individual-level fixed effects, allows us to estimate changes in economic activities associated with herder-related violence while ruling out confounding variation between narrowly defined locations over time. Therefore, our identification strategy relies upon the fact that exposure to these violent events varies meaningfully, even within narrowly defined geographic areas. This empirical approach helps ensure that we are comparing households with similar agro-ecological and economic conditions. In particular, we include fixed effects by river sub-basins, which are a primary locus of shared space between farmers and herder-grazers. We also differentiate our analysis by the agricultural season, by restricting comparisons within either the post-planting or post-harvest seasons.

This research design presents a challenge in our study context. Recent work demonstrates that two-way fixed effect regressions with staggered treatment timing can be biased in the context of heterogeneous treatment effects (De Chaisemartin and D'Haultfœuille, 2020a; Goodman-Bacon, 2021). In particular, bias can intensify when units treated at the end of the panel use units at the beginning of the panel as a counterfactual (Goodman-Bacon, 2021) and the presence of persistent treatment effects can contaminate estimates from two-way fixed effect regressions (Baker *et al.*, 2022). In our study context, heterogeneity may be driven by prior exposure to violent events. Estimating effects while differentiating by "cohorts" defined based on previous exposure to conflict allows us to implement an estimator akin to those developed by Sun and Abraham (2021) and Wooldridge (2021). To this end, we include an additional series of

[5] This pattern contrasts with more general patterns of conflict following agricultural harvest seasons (Guardado and Pennings, 2020; Ubilava and Atalay, 2021).

[6] Our preferred specification defines our indicator of exposure to herder-farmer conflict in a highly localized way with a radius around households of 10 km. and a time frame of the previous one month. At times, the narrower time window of 1 month (combined with the smaller distance window of 10 km.) leads to having a lower-n sample of treated individuals. To address this, we also include estimates using a larger distance window of 20 km. The results using this distance window are virtually unchanged. We do not have a good prior for the appropriate selected distance window; nor do we have full access to unmasked data to vary the distance window freely (as proposed by, e.g., Butts (2021)). In light of these limitations, we present both the 10 km. and 20 km. window, with a preference for the former, as it is the more localized measure.

specifications that include an interaction term of whether an individual was also recently exposed to a prior violent event. These specifications, in turn, allow us to estimate the marginal effect of exposure to a violent event conditional on other, recent exposure.

We find that labor allocation decisions of individuals respond to exposure to violence, and these effects seem to operate through a "shadow of violence" mechanism. Our main results show that both men and women exposed to herder-related violence (i.e., an event occurring within 10 km. within the previous month), and that have also been previously exposed to this violence (i.e., a previous event occurring within the previous six months), shift toward informal work in the post-planting season at both the extensive and intensive margins and shift away from informal work in the post-harvest season at the extensive margin. This shift toward informal work in the post-planting season seems to act as a substitute activity for agricultural work for men in households exposed to herder-related violence and that have also been previously exposed to this violence. Agricultural work does not decline for women; instead, the total number of hours worked increases if women live within households exposed to herder-related violence and that have also been previously exposed. For these women, the increase in total hours worked is predominantly allocated to self-employment or household-enterprise work.

To further explore the "shadow of violence" mechanism, we investigate heterogeneity across both time and space by exploiting the spike in violence just before the 2018-2019 GHS survey rounds and within Nigerian states implementing open-grazing bans, which have been attributed as a contributor to increased violence in the conflict. We find that the shift toward informal work and away from agricultural work is larger within ban states and during the 2018-2019 survey round, especially during the post-harvest season. Finally, to investigate possible welfare implications of the measured labor responses after exposure to herder-related violence, we also estimate additional "knock-on" or lagged effects that materialize during the post-harvest period of the 2018-2019 GHS survey and are associated with exposure to herder-related violence in the previous planting season. We find that households exposed to herder-related violence and who have also been previously exposed to this violence (i) shift their consumption toward food and away from other expenditures, (ii) are more likely to sell raw crops to relatives/friends or via the farmgate, and (iii) are more likely to operate a non-farm enterprise.

Our paper is closely related to two sets of existing literature. The first set studies the role of the informal sector as a safety net in response to adverse shocks (Gunther and Launov, 2012; Epstein and Shapiro, 2017; Adhvaryu *et al.*, 2019; Colombo *et al.*, 2019). For example, Adhvaryu *et al.* (2019) study the effect of price shocks in the global coffee market on informal work in Tanzania. The authors document that households cope with declines in the global price for coffee by increasing informal household enterprise ownership. Our paper documents the labor-related effects of a different type of shock, specifically exposure to heightened violence, exposure to which may reasonably be expected to alter individual labor allocation.

The investigation of the specific effects of Nigeria's farmer-herder conflict links our paper to a second set of literature, which examines exposure to conflict in Nigeria specifically. This violence has been shown to influence agricultural output (Adelaja and George, 2019), food security, (George *et al.*, 2020), and farm

labor supply (Odozi and Oyelere, 2021). Our paper differs from these existing studies in that, although we use a similar research design with similar data, we take advantage of the highly-granular nature of the geo-location data to define exposure to conflict within a very narrow window (as close as 10 km.), where earlier studies using a similar estimation approach have relied on exposure to violence at the level of the local governance area (LGA). Our approach allows us to narrowly define a set of comparison individuals and to test for sensitivity to the definition of treatment. Additionally, we provide more specific results that take into account the seasonality of herder-related violence and characterize how individuals respond to exposure throughout the agricultural season. Lastly, our results complement these studies by focusing on an additional dimension, the informal sector, which has previously received little attention.

This study makes three core contributions. First, we add to the literature on coping mechanisms in low- and middle-income countries. In the absence of adequately functioning markets for savings, credit, and insurance (Burgess and Pande, 2005; Cole *et al.*, 2013; Dupas and Robinson, 2013; Karlan *et al.*, 2014), informal coping mechanisms in the form of, for example, intra-household transfers (Townsend, 1994), temporary migration (Bryan *et al.*, 2014; Morten, 2019), and selling assets such as livestock (Lange and Reimers, 2020) persist. Specifically, we add to a subset of this literature on coping mechanisms for households exposed violence and conflict (Verpoorten, 2009), and show that work in the informal sector can act as a safety net for individuals exposed to herder-related violence, specifically for those under a so-called "shadow of violence" that may heighten reactions to violence exposure.

Second, we add to the literature on the role of the informal sector in the process of economic development. This literature finds that the informal sector plays an important counter-cyclical role amid macroeconomic dynamics (Fiess *et al.*, 2010; Loayza and Rigolini, 2011). While recent research documents the informal sector acting as a 'safety net' in response to price shocks (Gunther and Launov, 2012; Epstein and Shapiro, 2017; Adhvaryu *et al.*, 2019; Colombo *et al.*, 2019), our study highlights that the informal sector can act as a 'safety net' for those exposed to violence and conflict. Notably, both price shocks and exposure to violence and conflict can reduce the expected earning potential of agricultural production. Since we are able to look at the effects of such violence in both planting and harvest periods, we are also able to show that, even temporary shifts to informal work can also be accompanied by lagged effects in the economic activity of households several months after exposure to violence has occurred. Such results are important since climate change will likely continue to exacerbate tensions between farmers and pastoralists both across Sub-Saharan African and specifically in Nigeria (McGuirk and Nunn, 2020; Eberle *et al.*, 2020).

Finally, we add to the literature on the consequences of exposure to violence and conflict. This literature documents adverse health effects (Camacho, 2008; Akresh *et al.*, 2012a,b; Grimard and Laszlo, 2014; Minoiu and Shemyakina, 2014; Weldeegzie, 2017), lower levels of educational attainment (Chamarbagwala and Moran, 2011; Singh and Shemyakina, 2016; Brown and Velasquez, 2017; Weldeegzie, 2017), a diminished preference for risk (Bundervoet, 2010; Voors *et al.*, 2012; Moya, 2018; Jakiela and Ozier, 2019), shifts toward less risky agricultural portfolios (Rockmore, 2020), and reduced psychological well-being

(Alloush and Bloem, 2022). Specifically, we add to a subset of this literature studying the consequences of exposure to conflict and violence on agricultural outcomes (Singh, 2013; Adelaja and George, 2019; Kaila and Azad, 2019; George *et al.*, 2020; Avuwadah, 2020; George *et al.*, 2021b). We find that individuals reduce agricultural work but increase informal work when exposed to violence. Although the informal sector can act as a 'safety net' by partially shielding households from the consequences of increased production costs and decreased farm profits, this diversification in economic activities can come at a cost and, in turn, amplify the economic consequences of violence and conflict (Colombo *et al.*, 2019). In particular, our results offer additional context to existing research on the relationship between conflict and agriculture in Nigeria specifically, which finds that exposure to conflict reduces agricultural output (Adelaja and George, 2019) and food security (George *et al.*, 2020).

The remainder of this paper is organized as follows: In the next section we discuss background details about herder-related violence and informal work in Nigeria. In Section 3, we present our empirical framework by discussing the data we use in our analysis, reporting descriptive statistics, and summarizing our identification strategy. In Section 4, we present our main results on the labor response to exposure to herder-related violence in the planting and the harvest seasons. We also report results on the use of agricultural harvest, agricultural marketing, and non-farm enterprise sales. Section 5 concludes.

2 Background

Amnesty International estimates that between 2016 and 2018, there were more than 3,600 deaths recorded due to clashes and escalating violence between nomadic herders and agricultural-centered communities—with the largest surge in these attacks occurring in the early part of 2018.[7] Figure 1 shows the number of violent incidents associated with either Boko Haram or herder-related violence from 2004 through 2019.[8] While the absolute number of incidents involving Boko Haram is higher over the period, the vast majority of these attacks occurred in the epicenter of that conflict, Borno state. By contrast, the herder-farmer conflict grew in both intensity and its geographic reach over this period: in fact, the herder-farmer conflict became increasingly more deadly than violence involving Boko Haram, in part as the latter conflict was the focus of the Nigerian government's enforcement efforts and as the spread of herder-farmer violence grew beyond areas where such clashes had been located previously, mainly in the country's Middle Belt.[9]

While some accounts have attributed this herder-farmer violence to ethno-religious tensions (e.g., based on the observation that nomadic herding communities, including those such as the Fulani, are predominantly Muslim, and farmers located in the southern regions of the countries are Christian), the tensions are largely driven by conflicts over scarce land and water resources (McGuirk and Nunn, 2020; George *et al.*, 2021a). Specifically, competition for these resources has been regarded as a violation of a long-standing understanding in and near the Middle Belt zone, which is comprised of the country's

[7] Amnesty International. December 17, 2018. "Harvest of Death: Three Years of Blood Clashes Between Farmers and Herders in Nigeria." available here. Last accessed: February 3, 2021.

[8] Additional details on definitions are included in the Data section and Data Appendix.

[9] The Middle Belt refers to North-central Nigeria and includes Abuja, Benue, Plateau, Kogi, Nasarawa, Niger and Kwara.

central states and has been a historical locus of herding activity, mostly in the first half of the year. This unwritten rule traditionally permitted nomadic herders the open use of lands during the dry season, as this is a low period of agricultural activity. Farmers often welcomed this use as the wandering cattle naturally fertilized the region's agricultural plots. At the end of the dry season, herders historically vacated areas in and around the Middle Belt around May to return the following January. Extended dry seasons, however, and the Boko Haram conflict in the north have increasingly pushed herders south for longer periods of time. Simultaneously, farming communities have expanded their land use and extended their agricultural season through the adoption of dry farming techniques. As a result, the annual period preceding the planting season, which typically commences as rains arrive at the end of the dry season, became a time of spikes in violent events in the conflict, though these sharp increases have grown dramatically over recent years (Figure 2).

The outbreak of violence is often referred to as the herder-farmer conflict, however, these incidents are not exclusively between herding and farming communities. Herding communities have also engaged in agriculture in these areas. Likewise, reprisal attacks have been perpetuated against parties who were neither herders nor farmers: violent events include attacks on civilians, kidnappings, and the destruction of crops and property.[10] Armed militias (many identified with either herding tribes or agricultural communities) clashed occasionally, many times as reprisal for earlier violence. Whole communities protested and rioted following the movement of herders into an area—this unrest often simmered over into more violence, including attacks targeted at herding tribes themselves.

The raised profile of the conflict has also been entangled with political action, which may have increased tensions. In response to tensions and outbreaks of violence between herders and farming communities, in 2016 and 2017, three Nigerian states (Benue, Ekiti, and Taraba) passed bans on open grazing.[11] Each of these states, particularly Benue and Taraba, was a traditional location of herding and farming activity, particularly prior to the violent incidents. In 2016, Ekiti passed the first open-grazing prohibition, which banned grazing activities in some areas of the state following the killing of two residents. The law also forbade the carrying of firearms by herders; any herder found carrying a firearm could be declared a 'terrorist' under the statute.[12] Two other states, Benue and Taraba, followed suit in 2017, both passing stricter open grazing prohibitions.[13] The Open Grazing Prohibition & Ranches Establishment Law in Benue state banned open grazing outright—requiring the establishment of permitted ranches—and allowed for the confiscation of cattle by authorities and imposed a daily 2,000 naira fine for each cow held by authorities.[14] The Open Grazing Prohibition and Ranches Establishment Bill in Taraba instituted

[10] This observation is based on the authors' reading of events recorded in ACLED.

[11] These laws were, Benue: Open Grazing Prohibition & Ranches Establishment Law in Benue state (enacted in November 2017). Taraba: Open Grazing Prohibition and Ranches Establishment Bill (enacted in January 2018). Ekiti: "Prohibition of Cattle and Other Ruminants Grazing" (enacted in September 2017). A fourth state, Edo, also passed a limited 90-day ban on night grazing, but not an outright ban and is not considered.

[12] The Punch. September 8, 2016. "Force and limits of Ekiti State's anti-grazing law," available here. Last accessed: March 31, 2020.

[13] Though passed in 2017, Taraba's bill was enacted in January-February of 2018.

[14] Reuters. June 26, 2019. "Deadly clashes over cattle continue in Nigeria despite grazing ban," available here. Last accessed: March 31, 2020.

similar bans on open grazing.

Following the enactment of the Benue and Taraba anti-grazing laws, particularly, violence between herders and farming communities intensified. These bans required herders to establish formal ranches, but plots and permits were scarce, adding to a sentiment that the laws targeted and hindered herders' livelihood.[15] The laws were enforced sporadically, or not at all, in remote areas, where authorities' reach was limited.[16] In these areas there were reports that unofficial civilian groups seized herders' cattle under the guise of enforcing the grazing prohibition.[17] Violence quickly escalated. During the first week of January 2018, six villages in Benue were raided by alleged herder groups; the attacks killed more than 80 people.[18] These incidents were followed by several dozen more, killing between 200 and 300 people in the following months. In January alone, nearly 170 people were killed as Amnesty International warned that events were spiraling out of control.[19] Following the escalation, the Nigerian government deployed Army forces in Benue, Taraba, and Nasarawa; civilian militia groups were mobilized, notably in Benue.[20] Several local government areas (LGAs) instituted nighttime curfews, severely limiting mobility.[21]

In response to rising violence levels and anti-grazing statutes, several herders fled into bordering states, including Nasarawa and Cross River states. Two evident consequences of these movements emerged: first, the migrating herders were met with resistance in these bordering states, resulting in attacks by civilian militias and herder-related groups, including protests, riots, and reprisals. Second, violent events occurred near state border areas. Several accounts alleged that herder-related groups would cross into grazing-prohibition states—where they would destroy property, burn fields, or attack individuals under nightfall—only to return across those borders by daylight.[22]

2.1 Informal Work in Nigeria

As in many other low- or middle-income countries, informal work represents a large share of Nigeria's economy (La Porta and Shleifer, 2014). In 2019, the International Monetary Fund (IMF) estimated that over 60 percent of Nigeria's GDP belonged to the informal sector. Despite the relative share of the informal sector in terms of GDP, agriculture remains an important sector for employment. Figure 3 shows the sample mean of those working in farming and own-account/household enterprise work (which we define as informal work) over the four GHS rounds with two observations per round: post-planting and

[15] Washington Post. July 26, 2018. "This little-known conflict in Nigeria is now deadlier than Boko Haram". Last accessed via Factiva: March 31, 2020.
[16] New York Times. September 22, 2018. "Nigerian Herders Face Threat from Farmers Competing for Land". Last accessed via Factiva: March 31, 2020.
[17] International Crisis Group. July 26, 2018. "Stopping Nigeria's Spiralling Farmer-Herder Violence," available here. Last accessed: March 31, 2020.
[18] International Crisis Group. July 26, 2018. "Stopping Nigeria's Spiralling Farmer-Herder Violence," available here. Last accessed: March 31, 2020.
[19] Agence France Presse. January 31, 2018. "Herder-farmer violence kills 14 in Nigeria". Last accessed via Factiva: March 31, 2020.
[20] Agence France Presse. January 11, 2018. "Nigeria: mass burial for farmers killed in herder clashes". Last accessed via Factiva: March 31, 2020.
[21] Agence France Presse. February 7, 2018. "Nigeria grapples with mob justice in farmer-herder clashes". Last accessed via Factiva: March 31, 2020.
[22] International Crisis Group. July 26, 2018. "Stopping Nigeria's Spiralling Farmer-Herder Violence," available here. Last accessed: March 31, 2020.

post-harvest. The trends for the post-planting (rainy season) and post-harvest (dry season) rounds are separated for agricultural, (e.g., farming) activity. While there is no notable trend for the post-harvest/dry season, there is a distinctly upward trend for the post-planting/rainy season. This is consistent with either a larger proportion of workers engaged in agricultural activity or, also, a greater number of engagements later and into the dry season, as cited in several accounts of the herder-farmer conflict. We also observe a notable peak in self-employment between 2016 and 2018, which corresponds to the intensification of herder-involved conflict events documented in Figure 1.

The role of informal work, in relation to economic development in general, and more specifically as a means to a 'safety net' in response to adverse shocks remains an open debate among researchers and policymakers. Specifically, while some argue that the informal sector is the result of competitive market forces, others contend that informal work is the result of market segmentation, and more recently, some argue that the informal sector offers either attractive employment opportunities or a coping strategy of last resort (Gunther and Launov, 2012). Although the extent to which informal work acts as a 'safety net' is an empirical question, existing work demonstrates the potential of informal work to buffer individuals from the consequences of adverse shocks (Loayza and Rigolini, 2011), such as exposure to conflict.

3 Empirical Framework

This section includes four sub-sections. First, we introduce the two primary sets of data we use to construct an individual-level panel data set of exposure to violent conflict events and labor allocation. Second, we discuss some descriptive statistics which characterize our study sample. Third, we specify our core identification strategy and discuss the interpretation of our preferred estimates. Finally, we discuss the potential consequences of sample attrition and discuss how we address these concerns.

3.1 Data

We combine two detailed panel datasets. The first set of data is from the Nigeria General Household Survey (GHS), which is a product of the Nigeria Bureau of Statistics and the World Bank's Living Standard Measurement Study (LSMS).[23] The GHS was conducted over four rounds in 2010–2011, 2012–2013, 2015–2016, and 2018–2019, and each survey round includes two data points for each household: one in the post-planting (rainy season) period and one in the post-harvest (dry season) period, regardless of whether the household engages in agricultural activities. Data collection in the post-planting period generally occurs in the later fall months, while fieldwork in the post-harvest season occurs within the first few months of the next year. Figure 2 illustrates the timing of GHS survey rounds and shows how these data collection periods correspond with the trend in herder-related violence in Nigeria.

The GHS is designed to include a nationally (and zonally) representative set of enumeration areas,

[23]These data (and all documentation) were accessed via the World Bank's microdata catalog. Data were downloaded on November 8, 2019.

which act as the primary sampling units from which households are selected.[24] Individuals within households are enumerated in a full roster; individuals are tracked if they leave a household, though this does result in some individual-level attrition. Starting in 2010, 5,000 households in 500 enumeration areas were selected for the panel dataset; however, due to attrition, by the fourth round (2018–2019), a refresh sample of 360 enumeration areas was required.

Due to this sampling design, two points merit some attention. First, non-random attrition poses a challenge to identification. If, for example, attriting individuals are more or less likely to be those that engage in a particular type of economic activity, estimates will be accordingly biased. A related but distinct concern is that attrition itself is related to violent events, which would make treatment endogenous to violence in the sample. Second, the sampling procedure for the fourth round of the GHS included new enumeration areas. Since the main treatment (e.g., exposure to violent events around the farmer-herder conflict) is determined by location, a panel including those new enumeration areas would be inappropriate and therefore, the refreshment enumeration areas are excluded from all analysis of panel data, where individuals (households) appear over multiple rounds of the GHS. We discuss the relative risk to bias from attrition and our approach to account for non-random attrition below.

The second data source is a panel of violent events taken from the Armed Conflict Location and Event Data (ACLED) project (Raleigh *et al.*, 2010). The ACLED project provides several pieces of detailed information, including the approximate date and geo-coded location of an incident, as well as reported information on primary and associated actors in each event. The recorded events are based on accounts from media, NGOs, international organizations, partner reports, and new media (e.g., social media such as Twitter or Facebook). A single account can include several events (as would be the case of one news article describing a series of violent attacks), however, the ACLED database includes one observation per event-location.

We use the detailed information provided by the ACLED project to code individual events. Since the ACLED project also provides information on events such as treaties and peaceful protests, events are classified as i) violent and/or ii) herder-related. Violent events are defined as those with an ACLED coding with a clearly defined violent event type or sub-type. These events include attacks, murders, and kidnappings, but also civil unrest (e.g., mob violence), which may emanate from reprisal or public reaction. The violent destruction of property (such as arson or burning of fields) is also included, given that such events were frequent around the farmer-herder conflict. All fatal events are considered violent.

We code all incidents as herder-related if they include the terms "pastoralist," "herder," or "herdsmen" as either an actor or associated actor.[25] As noted above, the incident data largely rely on public accounts, and so one risk is that the narrative framing of events could affect the terms used to record each event in the ACLED database. This would occur if terms like "herder" are used when these groups were considered perpetrators, but if another term is used when such groups were the victims of, say, reprisal violence. To

[24] Nigeria includes 6 geopolitical zones, which are one administrative level up from states.
[25] Or variants of these terms, including e.g. "Herder."

mitigate this, we also code incidents involving the term "Fulani" (e.g., the tribe most identified with the nomadic herding) as herder-related. Thus, these data include violent events that occur between herders and civilians, clashing militias, and/or reprisals or actions taken against herdsmen or Fulani tribes. Due to this, we prefer to use the general term herder-related violence. In total, we code 1,564 incidents between 2009 and 2019 as both violent and herder-related.

We combine the GHS and ACLED datasets using GPS coordinates, which are available in both datasets. To construct our main treatment variable of exposure to a herder-related violent event, we create a series of binary variables that take a value of one if a household was within a given distance from any herder-related violence in the month prior to the start of the GHS interview. The exposure measures are calculated for distance windows of 10, 20, and 30 kilometers (km.). We are able to calculate exposure measures that are as precise as 10 km. because we were able to use the restricted-use unmasked GPS coordinates from the GHS data.[26] Our preferred specifications use the 10 km. exposure radius as it is the most precise available in our measures, while allowing for potential mis-measurement of the exact location of violent events in the ACLED data.

3.2 Descriptive Statistics

Table 1 shows basic descriptive statistics for our set of key, labor-related outcomes at the individual level. We focus on seven labor outcomes. The first three are binary values that take a value of one if an individual reports to have worked in own-account or household-enterprise work, agricultural work, or work outside the home, respectively, in the last week. These variables are available in all four rounds of the GHS and provide information on the extensive margin of changes in labor supply. Starting in the 2015-2016 round, the GHS began recording the number of hours individuals worked in each of these activities as well as total hours worked.

Descriptive statistics on these seven outcomes are found in Table 1 in six panels (for the pooled sample, men, and women, separately, each for both the post-planting and post-harvest period). One important thing made clear by the table is that, while the mean values of hours worked appear in a reasonable range (the mean total hours worked is 18 hours in the post-planting season and 12 in the post-harvest period), there is substantial variation in all measures of the hours worked (the standard deviation for total hours, e.g., is 22 and 20 hours in both periods, respectively). As shown in Appendix Figures A2–A4, these moments of the data are the result of bunching at zero values, with a large rightward skew, though for work outside the home, there is visual evidence of bunching at 40 hours, which makes intuitive sense under many ideas of a "full" work week. Due to the rightward skew and the incidence of zero-value responses, we also consider results using the inverse hyperbolic sine (IHS). However, the use of IHS-transformed measures as outcome variables can be problematic at the point of interpretation, especially

[26] We are indebted to the World Bank's LSMS team for producing these measures using the unmasked GPS coordinates. Note that this process involved, first, calculating exposure variables using publicly available GPS data; this process was replicated by the LSMS team using the unmasked data. To assure household anonymity, we never gained access to linked data between individual households and specific violent events.

given the mass of values at zero (Bellemare and Wichman, 2019; Chen and Roth, 2022; Mullahy and Norton, 2022). For these reasons, we report the (non-transformed) levels of hours worked in each activity in the main text but also provide the IHS-transformed results in the Appendix.

The descriptive statistics appear in six panels. All panels are limited to individuals that appear in the data in the 2018-2019 round and in at least one prior GHS round, meaning the sample roughly corresponds to panel specifications with the inclusion of an individual-level fixed effect. The GHS documentation notes that there was a change in the covered enumeration areas with the addition of a refresher set of enumeration areas in the 2018-2019 round. By limiting this sample to individuals who appear in the 2018-2019 round and at least one prior GHS round, any sample attrition originates from individuals who dropped from the sample for reasons other than changes in the areas enumerated.[27] The sample is also restricted to individuals who are at least 5 years old as of their first appearance in the data, as this is the age threshold for applying the labor module in the GHS. Panel A shows the descriptive statistics for the full sample in the post-planting round; Panel B the same, but in the post-harvest GHS data. Likewise, Panel C and D show the same figures for men, in both post-planting and post-harvest periods, respectively. Panels E and F show the same for women.

Some patterns are immediately evident.[28] A larger proportion of men, compared to women, work in agricultural work, in both seasons. Both men and women are more likely to work in agricultural work in the post-planting season, compared to the post-harvest season. At the same time, a larger proportion of women work in self-employment or household-enterprise work; and such work is comparatively lower in the post-harvest period (though this is driven by the reductions in such work among women). Both men and women also show a pattern of working fewer total hours in the post-harvest season, when compared to the post-planting season. This reduction in total hours seems to come—for both men and women—in the form of reduced hours worked in both agriculture and informal work (hours for work outside the home for someone else increase).

In Table A1, for completeness, we also include the descriptive statistics of some potential control variables, which we discuss in 3.3. Since there were many accounts that herder-related violent incidents tended to occur in more isolated, highly agricultural areas, specifically, we consider three measures of a household's location: each a binary measure taking a value of 1 if a household was located within 10 km. of an administrative center, a market, or a population center with at least 20,000 people, respectively. The table is divided into three panels. The first is the full sample[29]; the second is the sample of individuals who were exposed (at any time) to a herder-related violent event in the post-planting season; the third is restricted to individuals who were exposed (at any time) in the post-harvest period.[30] Indeed, across the three co-variates, those individuals exposed to a herder-related violent event tended to be more isolated

[27] Individuals who moved and were tracked are included.

[28] Each of the relative comparisons in this paragraph is also tested in a simple, difference of means test through an OLS specification.

[29] Excluding Borno state, and restricted to individuals appearing in the 2018-19 round and at least one previous GHS round.

[30] The table is at the individual level, however, the patterns are nearly indistinguishable when analyzed at the household level.

from administrative centers, markets, and population centers.[31]

3.3 Estimation Strategy

As noted above, our data comes from four separate GHS rounds, run approximately every two years, with an observation for both the post-planting and post-harvest periods (Figure 2). While these data allow us to observe many of the same individuals at different time periods, the irregularity of the timing of the GHS rounds presents a few challenges for analysis. First, we expect individual and household labor decisions to be different in post-planting and post-harvest seasons (the patterns in Table 1 suggest this expectation has merit). Secondly, since exposure to violent events (as measured by the ACLED data) can happen at any time relative to GHS data collection, we must decide on a reasonable time window for that exposure. However, any choice of a time window for such exposure will require an assumption about the expected duration and form of any effect on labor-related outcomes. To clarify this point: if the effects of violence exposure are relatively long-lasting—that is, if exposure to violence has effects on individual work several months afterward—then a time window that is too short will be contaminated by prior exposure. For instance, if we were to choose a time window for exposure equal to one month, when the true effect of exposure to violence had effects that lasted over six months, then an individual coded as *not* being exposed within the last month (but who *was* exposed in the last six months) would be coded as not treated, even though such an individual would be experiencing the effects of prior violence exposure. Just the same, if we were to choose a time window that was too long (e.g., a time window of six months when the true effect lasted one month), any employment effects would be attenuated.

To more formally discuss our approach, we first use the baseline specification given by:

$$y_{iet} = \beta_0 + \delta V_{iet'} + \alpha_i + \gamma_t + \boldsymbol{J'} + (\boldsymbol{X'\beta}) \times r + \epsilon_{iet} \tag{1}$$

Where y_{iet} is one of the seven labor-related outcome variables shown in Table 1: three dummy variables if there was informal, agricultural, or out-of-the-home work reported for individual i in the last seven days, and three variables for the total hours worked, as well as in each respective type of work, over the same period.[32] Enumeration areas are indexed by e and the month-year period of the interview is indicated by t; α_i is an individual-level fixed effect and γ_t is a month-year fixed effect. The main treatment variable, $V_{iet'}$, is a dummy variable that takes a value of one if a herder-related violent event occurred within an indicated distance window and a given time window, $t' \in 1, 3, 6$ months.

We include two vectors of additional controls, $\boldsymbol{J'}$ and $\boldsymbol{X'}$. The vector $\boldsymbol{J'}$ is a series of additional fixed effects that are likely to be pertinent. Unsurprisingly, many accounts of the herder-farmer conflict noted that incidents tended to occur in heavily agricultural areas and disproportionately involve households working in agriculture. And, so, we include a fixed effect if anyone in person i's household had engaged in any agricultural cultivation over the period covered by a given GHS round. A concern may be that

[31] Although the magnitudes of these differences are small, they are significant at a level of $p<0.05$.
[32] The outcomes for hours worked are only available in the 2015-2016 and 2018-2019 data.

unobserved variables could simultaneously affect both the likelihood of exposure to a violent event and individuals' employment choices. As noted above, we are able to use a fine level of geographic detail, given that we can isolate exposure using exact GPS-coordinates, and so we include enumeration area fixed effects. However, there may be common agricultural and/or weather conditions at a courser level, and so we also include state-level fixed effects and river sub-basin fixed effects to account for common local shocks, which could be important especially given the attributed role of water scarcity in the conflict (as noted by, e.g., McGuirk and Nunn (2020)).

Turning to $\boldsymbol{X'}$, some household-level, location characteristics may also be important to consider. Specifically, many reports, particularly around the 2018 spike in violence, noted the prevalence of night-time raids, frequently in remote areas, as well as roadside skirmishes or attacks, as farmers or herders were in transit. In turn, we anticipate that it will be important to consider the specific remoteness of individuals' households. Thus, in $\boldsymbol{X'}$, we include dummy variables for three location co-variates: if a household was located within 10 km. of a population center with at least 20,000 inhabitants, the state-level administrative center, and a market, respectively (re-visit, as well, Table A1). As the vast majority of individuals in our sample are within one household for the entire time they are observed in the data, these controls will be perfectly collinear with individual fixed effects. As a result, we fix the values of the elements of $\boldsymbol{X'}$ as of their first observation in the data and interact each element with a non-linear time trend in the form of time dummies for each round-season in the data (r).

As previously discussed, we need to be cautious in the presence of issues that may arise due to the timing of the survey rounds. All specifications include a month-year fixed effect, which adjusts for common temporal shocks. In addition, we also treat the planting and harvest data separately: we estimate equation (1) separately for the post-planting and post-harvest periods, more directly comparing patterns in like seasons (planting to planting and harvest to harvest). These separate specifications can also reveal some additional patterns in the effects of exposure to herder-related violence in different seasons, just as the demands of individuals' work may change from season to season. Note, however, that—even if we specify the time and distance windows correctly—the specification given in equation (1) can only estimate an effect of violence exposure within those chosen windows, which are often arbitrary (Butts, 2021).

To broaden our baseline specification, in turn, we consider the possibility that the effect of exposure to violence could be mediated by other, recent exposure to the conflict. There is some validating evidence available that escalating violence can affect education and the accumulation of human capital more broadly. For instance, Brown and Velásquez (2017) find that in Mexico, escalations in cartel-related violence reduced the educational attainment of young adults; they propose a financial mechanism, where the children of self-employed parents were most affected, as those households were the most financially at risk. Also using evidence from cartel-related violence in Mexico, Velásquez (2020), finds adverse labor outcomes for self-employed workers exposed to increases in violence. The implied mechanism in such studies is that escalated violence reduces economic opportunities, which shifts the opportunity costs of certain types of work.

Until now, we have mainly considered the issue of the choice of the time window by simply varying the window to exposure, using $t' \in 1, 3, 6$. However, this treatment may not be sufficient and, in fact, obfuscate cumulative effects. Since a 3-month window is inclusive, the 1-month window, and the 6-month window is inclusive of both, the widening of time windows can increase the likelihood that a longer time window is, in fact, inclusive of exposure to more events. Since we have GPS-linked ACLED data over the full period before each GHS round, this conjecture can be tested. Specifically, in the full sample (excluding Borno) the likelihood that any individual was exposed to a herder-related violent event is a minuscule 0.8 percent. However, conditional on having been exposed to a violent event in the six months prior (that is, violence exposure in $t-2, ..., 6$, outside of $t-1$), the likelihood of exposure to violence in the last month increases to 8.2 percent, indicating a factor increase of 13.6x.[33] That is, very recent violence exposure is much higher in areas with other, *recent* exposure.

If individuals change their labor supply decisions based upon their expectation of violence, then a reasonable assumption would be that continued exposure to such violence would elicit different reactions than among those for individuals who were not recently exposed to some herder-related violent event. To consider these possibilities, we amend equation (1) by adding an interaction term for exposure to another, recent event. Specifically, we fix the time window of our treatment to one month ($t' = 1$), interacted with a dummy variable taking the value of one if there was other, recent exposure in the five months prior to that last month ($-t' = 6$), giving:

$$\begin{aligned} y_{iet} = \beta_0 + \delta V_{iet'} + \delta_{pv} V_{iet'} PV_{ie-t'} + \beta_{pv} PV_{ie-t'} \\ + \alpha_i + \gamma_t + \boldsymbol{X'} + (\boldsymbol{X'\beta}) \times r + \epsilon_{iet} \end{aligned} \tag{2}$$

To make the key coefficients of interest more tractable, the terms in equation (2) can be simplified in terms of the marginal effects of interest (dropping the subscripts for simplicity). Specifically:

$$E[y|V=1, PV=0] - E[y|V=0, PV=0] = \delta \tag{3}$$

$$E[y|V=1, PV=1] - E[y|V=0, PV=1] = \delta_{pv} - \beta_{pv} \tag{4}$$

Where equation (3) is the marginal effect of herder-related violence exposure, *given no other recent violence exposure*. Equation (4) gives the marginal effect of exposure to violence *given some exposure to recent violence*, specifically at ($-t' = 6$). As a result, the term $\delta_{pv} - \beta_{pv}$ would capture a heightened or muted response based on individuals reacting to violence exposure under the shadow of other, repeated violent events related to the conflict. Given the above discussion, a non-zero effect in equation (4) would be of particular interest, as it would indicate a stronger (or weaker) labor response under the shadow of

[33] The average among individuals not previously exposed is .006, compared to that of .082 for recently exposed households, giving $.082/.006 \approx 13.6$.

recent violence.[34]

Lastly, as an implied mechanism in this specification is that violence exposure raises or lowers the relative opportunity cost certain types of work, we also divide our results into the full, pooled sample ("All") as well as by "Men" and "Women". In particular, reports of the conflict noted that women were at particular risk of attack, including sexual assault.[35] Such a division also comports with other work, which has found differential labor responses for women versus men in the face of escalated violence (Velásquez, 2020; Tsaneva *et al.*, 2019).

3.4 Sample Attrition

Endogenous sample attrition represents a further threat to credible identification. This could well be the case if prior violent events or unobserved shocks affect the likelihood that an individual remains in the panel sample. Indeed, in our study context this is a sizeable threat. There are 12,918 individuals in the GHS data who were first interviewed in the 2010 and who are also located in enumeration areas that were part of the coverage of all four rounds. Of these, 3,732 (or 29 percent) are observed all the way through wave 4 of the GHS, including those who moved and were tracked. This gives a back-of-the-envelope, cumulative attrition rate of approximately 16 percent for each period. While this is not worrisome for each individual period, it does present problems cumulatively. Although a relatively long household-level panel dataset provides the ability to track individuals and households over time and account for time-invariant individual or household characteristics, they also inherently lead to a greater risk of attrition bias. To address non-ignorable attrition, we use the following probit estimation to estimate attrition-corrected sampling weights:

$$pr(attrit = 0) = \Phi[\theta V_{et'} + \gamma_{et} + (\boldsymbol{X'\beta})t + \epsilon_{it}] \tag{5}$$

Equation (5) includes the enumeration area herder-related violent events, a state-time fixed effect and the full list of time-interacted co-variates as described above. From equation (5) we calculate a predicted probability of survival (attrit=0) for each individual and time period. We then average these probabilities and invert them to produce inverse probability weights (IPWs). We use these weights throughout our analysis of panel-level data, which provide a correction for potential attrition bias by up-weighting those individuals with a higher probability of attriting but who remain in the sample. The mean value for our IPW is 3.2, with a standard deviation of 1.8, a minimum value of 1.3, and a maximum value 12.8. This adjustment relies on the assumption that attrition is random, conditional on the factors included in equation (5). We include individual-level fixed effects in all specifications to adjust for any unobserved time-invariant factors that could affect selection into exposure to herder-related violence.

[34] Note then, as well, that the interaction terms give a cleaner cohort for comparison to determine the marginal effect of recent violence (and as such in the spirit of recent papers, such as Wooldridge (2021), to isolate relevant treatment cohorts to address the problem of contaminated effects in two-way fixed effects regressions (Baker *et al.*, 2022; Goodman-Bacon, 2021; De Chaisemartin and D'Haultfœuille, 2020b)).

[35] As noted by the International Crisis Group in a 2018 report.

4 Results

We provide three sets of results. In the first set of results, we analyze the labor response driven by exposure to herder-related violence. We show these results by season (i.e., in the post-planting and post-harvest seasons), estimate differential effects based on previous exposure to herder-related violence, and report results both for the full sample and for sub-samples of men and women. In the second set of results, we further explore the "shadow of violence" mechanism by estimating effects specifically in the survey waves collected after the 2018 spike in violence and within Nigerian states that implemented open grazing bans. Finally, in the third set of results, we examine household consumption patterns, agricultural marketing choices, and non-farm enterprise sales using a cross-sectional subset of our panel data to understand the possible welfare implications of the measured labor responses after exposure to herder-related violence.

4.1 Labor Response to Herder-Related Violence

We first estimate how exposure to herder-related violence influences labor allocation decisions of individuals. As previously mentioned, we analyze three main types of work documented by in the GHS: self-employed, informal work (that is, own-account work or work for a non-farm enterprise run by someone in the household), agricultural work, and work for someone outside the household, including paid, wage work. We consider both outcomes on the extensive (whether they worked in each category at all in the last week) and intensive margin (how many hours they worked) for each type of work. One specific caveat applies: due to the fact that the majority of HRV incidents immediately precede and occur in the planting period, and because the measures of hours worked were only reported from 2015 onward, we do not observe a satisfactorily high number of observations for specification (2) for the intensive margin in the post-harvest period. As a result, we only report intensive-margin estimates for the post-planting period. The total number of hours worked is also presented as a key outcome variable.

We initially consider our baseline specification, as given in equation (1), that is one that does not differentiate by other, recent violence exposure. The time window is varied between one, three, and six months; these results are given in the Appendix (Figures A8–A14) and do not give any salient reason to favor a longer time window. Rather, we adopt a preferred specification with the narrowest time window of $t' = 1$ month, as it presents the most acute measurement of violence exposure. But, also, such a narrow time window also lends itself to the inclusion of the interaction term as in in equation (2), where acute violence exposure ($V_{iet'=1}$) is interacted with other, recent exposure ($PV_{ie-t'=6}$), where the latter term takes a value of one if an individual was within 10 km. of an herder-related violence event in the six months prior (exclusive of the last month).[36] Given that our choice of the narrow time window of 1 month is combined with a narrow distance window, we also extend the distance window to 20 and 30

[36] Though the description of the term $PV_{ie-t'=6}$ may be contorted at times, an example makes the logic plain. That is, consider an individual interviewed on October 1st of a given year. The term $V_{iet'=1}$ is an indicator term $(0, 1)$ of violence exposure from September 1 to 30. The reference time window for $PV_{ie-t'=6}$ for this person is the period April 1 to August 31, i.e., the five months preceding September, in this case.

km., providing those results in the Appendix.

Figure 4 shows estimates of shifts in informal work associated with exposure to herder-related violence for both men and women. Panel (a) reports results on the extensive margin where we use a binary indicator of whether an individual has worked on their own account or household enterprise within the last week. In the post-planting season, we find that exposure to herder-related violence leads to an increase in informal work specifically for those who have previously experienced exposure to herder-related violence. In the full sample, including both men and women, we find that exposure to herder-related violence among those who have previously experienced herder-related violence leads to over a 20 percentage point increase in the probability that an individual has worked on their own account or household enterprise in the last week. Relative to a sample mean of 0.19, this effect represents more than a 100 percent increase in the probability of informal work in the previous week. This effect qualitatively holds among sub-samples of either men or women. Interestingly, we find the opposite result for individuals living in households that did not recently experience exposure to herder-related violence, implying that labor responses may differ *outside* of the shadow of violence (though we note that such patterns would be consistent if individuals resumed previous work more intensively, doing so because they considered the threat of violence as transitory). Moreover, as shown in panel (b), these results qualitatively persist at the intensive margin in the post-planting season where we use a continuous indicator of the number of hours worked on their own account or household enterprise within the last week. Our data do not allow us to estimate intensive margin results in the post-harvest season due to an insufficient variation in recent exposure. Taken together, these results indicate that this labor response is, in part, driven by the combination of an impending threat of herder-related violence along with recent exposure to this violence; a mechanism we dub the "shadow of violence."

Next, we estimate shifts in agricultural work. Figure 5 reports estimates on changes in agricultural work, at both the extensive and (post-planting) intensive margins, associated with exposure to herder-related violence. Panel (a) reports results on the extensive margin where we use a binary indicator of whether an individual has engaged in on-farm agricultural work within the last week. In the post-planting season, we find that exposure to herder-related violence leads to a decrease in agricultural work specifically for men living in households that have previously experienced exposure to herder-related violence. We find that exposure to herder-related violence among men who have previously experienced herder-related violence leads to over a 30 percentage point decrease in the probability that an individual has worked in on-farm agricultural work in the last week. Relative to a sample mean of 0.28, this effect represents more than a 100 percent decrease in the probability of agricultural work in the previous week. However, we find that on the intensive margin, in the post-planting period, there is a more widespread reduction in the hours worked in agriculture among men, regardless of their recent exposure to a violent incident (as shown in panel (b)). These results indicate that the shift toward informal work, documented in Figure 4, at least partially accounts for a shift away from agricultural work for men exposed to herder-related

violence who live in households that have previously experienced this type of violence.[37]

Finally, we investigate changes in total hours worked, among both men and women, associated with exposure to herder-related violence. Figure 6 shows results where we use a continuous measure of total hours worked within the last week. In the post-planting season, we find that exposure to herder-related violence leads to an increase in total hours worked specifically for women living in households that have previously experienced exposure to herder-related violence. We find that exposure to herder-related violence among women who have previously experienced herder-related violence leads to roughly a 170 percent increase in total hours worked within the last week. Additionally, we find the opposite result for women living in households that did not recently experience exposure to herder-related violence. Among men, we find null results across all subsets of our sample in the post-planting season. These results highlight that the shift toward informal work, documented in Figure 4, leads to an overall increase in hours worked for women exposed to herder-related violence who live in households that have previously experienced this type of violence.

4.2 "Shadow of Violence" Mechanism

The results in 4.1 imply that the labor responses to exposure to violence around the herder-farmer conflict operate through a mechanism that is often magnified by other, recent exposure to such violence. One could call such an implied mechanism as a labor response under a "shadow of violence," that is an environment where the anticipation, and often the fear, of continued violence alters individuals' labor-supply decisions.

As we show in the previous sub-section, labor responses to exposure to herder-related violence are more meaningful among households who have previously been exposed to herder-related violence. This suggests that labor responses operate through a mechanism of repeated exposure to violence and the threat of increasing exposure to violence in the future, rather than one-off idiosyncratic exposure. To further study this mechanism we leverage two contextual details about herder-related violence in Nigeria. First, herder-related violence spiked in 2018 and 2019—with the number of events increasing from less than 50 per quarter of the year to over 150, as shown in Figure 2. Second, between 2016 and 2018 three Nigerian states (i.e., Benue, Ekiti, and Taraba) enacted bans on open grazing, which raised tensions between farmers and herders and led to more frequent and more severe herder-related violence in these states.

To explore these channels, therefore, in this subsection, we present results where we differentiate effects across time (i.e., household surveyed in 2018-2019 vs. previous rounds) and space (i.e., household located in ban state vs. other states). Figure 7 reports shifts in both informal and agricultural work associated with exposure to herder-related violence differentiated across time and space. Panel (a) shows results on informal work where we use a binary indicator of whether an individual has worked on their own account or household enterprise within the last week. In the post-planting season, we find that

[37] For completeness, Figure A15 also presents effects on individual work for someone else outside of the home however, the results do not merit much attention and are left for reference to the Appendix.

exposure to herder-related violence is not meaningfully different between the 2018-2019 survey rounds and previous rounds. In the post-harvest season, however, we do find meaningful differences. Specifically, informal work increases more with exposure to herder-related violence in the 2018-2019 survey round when compared with other rounds. Rather, during the post-planting season, exposure to herder-related violence amid the spike in events in 2018 and 2019 led to an increase in informal work in ban states and a decrease in informal work in non-ban states. Panel (b) shows results on agricultural work where we use a binary indicator of whether an individual has worked in on-farm agriculture within the last week. The results in panel (b) essentially mirror those in panel (a). In the post-planting season, we again find that exposure to herder-related violence is not meaningfully different between the 2018-2019 survey rounds and previous rounds. In the post-harvest season, however, we do find agricultural work decreases more with exposure to herder-related violence in the 2018-2019 survey round when compared with other rounds. Moreover, during the post-planting season, exposure to herder-related violence amid the spike in events in 2018 and 2019 led to a decrease in agricultural work in ban states and a statistically insignificant average increase in agricultural work in non-ban states.

Taken together, the results shown in Figure 7 suggest that our main results shown in Figures 4, 5, and 6 operate through a "shadow of violence" mechanism. That is, shifts in labor activities are driven, at least in part, by repeated exposure to violence and the threat of increasing violence.

4.3 Lagged Effects

We now investigate the lagged (i.e., harvest time) consequences of exposure to herder-related violence in the planting season on household consumption patterns, agricultural marketing choices, and non-farm enterprise sales. These outcomes explore possible mechanisms that might explain why previous research finds that exposure to conflict can lead to diminished food security (George *et al.*, 2020). Our analysis in this section requires that we restrict our data to the 2018-2019 round of data, where the variables measuring harvest use, agricultural marketing, and enterprise sales are consistently and accurately recorded and available. The use of these cross-sectional data requires a similar but slightly more restrictive identifying assumption compared to the use of our panel data in previous sections. In particular, our analysis in this section requires we assume that exposure to herder-related violence is exogenous to our outcome variables of interest within the 2018-2019 cross-section of our data, and does not allow us to account for time-invariant household-level characteristics.

Table 2 reports estimates of changes in household consumption patterns in the 2019 post-harvest season associated with exposure to herder-related violence in the previous planting season. The first two columns use a continuous measure of total household consumption, in terms of (log) naira. We find no statistically significant relationship between exposure to herder-related violence in the post-planting season and overall consumption. The exception is that when we differentiate the effect by previous violence exposure, those households that both were exposed to an HRV event in the post-planting season and with

repeated exposure consumed significantly more than those households that were exposed *without* prior exposure (the magnitude represented by $\delta_{lag,pv} - \delta lag$). The remainder of Table 2 reports estimates of changes in the share of household consumption in three broad categories: (i) food, (ii) non-food, and (iii) education and health. We find a shift toward food consumption and away from non-food consumption in the 2019 post-harvest season associated with exposure to herder-related violence in the previous planting season. We find no change in education and health spending in the last two columns of Table 2. Taken together these results highlight that households increase consumption, possibly drawing on savings or liquidating assets/investments, for the purpose of consuming more food and less non-food items.

Next, we investigate changes in agricultural marketing patterns in Table 3. Since all outcomes in the table refer to those of agricultural households, we restrict the sample to only those households that planted crops in the 2018 planting season. The shown outcomes are potentially important outcomes because violence, especially herder-related violence, can disrupt agricultural value chains and output markets. Therefore, agricultural households might shift their marketing behavior when exposed to herder-related violence. Although we do not find any change in the probability of selling raw crops or the total amount of crops sold, we do find that households were more likely to sell their crops at the farmgate or to relatives/friends, and no more likely to sell in the main market, in the 2019 post-harvest season when exposed to herder-related violence in the previous planting season. We interpret this finding as plausible support that exposure to violence may limit the overall scope of marketing activity by virtue of those households narrowing the range of their selling market—that is, they sell to a closer range of likely known buyers.

Finally, we examine changes in non-farm enterprise sales in Table 4. This is an important outcome to study because the informal sector seems to play the role of a partial safety net for households exposed to herder-related violence, at least in the domain of labor allocation choices. This raises the question, do households exposed to herder-related violence earn any additional sales revenue when they spend more time working on their own account or household enterprise? Although the estimates are relatively imprecise, the results in Table 4 suggest that in the 2019 post-harvest season households are more likely to operate a non-farm enterprise but do not earn any additional non-farm enterprise sales revenue when exposed to herder-related violence in the previous planting season.

5 Conclusion

We study how households cope with the consequences associated with exposure to conflict. In the absence of conflict, the benefit of agricultural work is worth the risk. When exposed to conflict, however, the risk associated with agricultural work may outweigh the benefit and, therefore, agricultural households must seek strategies to cope with this risk. To do this we investigate how agricultural households in Nigeria respond to a specific type of conflict. Herder-related violent conflict events describe clashes between nomadic herders and sedentary agricultural communities in Nigeria, which are partly motivated

by increasing competition for scarce land and water resources (McGuirk and Nunn, 2020; George *et al.*, 2021a). As agricultural seasons have shifted associated with climate change, nomadic herders have changed the timing of their migratory patterns and agricultural households have lengthened their growing seasons. Rising tensions motivated several Nigerian states to implement open-grazing bans in 2016 and 2017. These bans are associated with a sharp escalation of violence in the first half of 2018, which represents the core source of variation in herder-related violence in our study.

We construct panel data by combining information from Nigeria's General Household Survey and the ACLED Project from 2010 through 2019 and pay particular attention to both the seasonality in herder-related conflict and how agricultural households respond to exposure throughout the agricultural season.

We find that both men and women exposed to herder-related violence and that have also been previously exposed to this violence shift toward informal work in the post-planting season and shift away from informal work, on the extensive margin, in the post-harvest season. This shift toward informal work in the post-planting season seems to act as a substitute activity for agricultural work for men in households exposed to herder-related violence and that have also been previously exposed to this violence. Agricultural work, however, does not decline for women. Rather, the total number of hours worked increases if women live within households exposed to herder-related violence and that have also been previously exposed. For these women, the increase in total hours worked is predominantly allocated to informal work. These results are consistent with the view that work in the informal sector can act as a partial 'safety net' for agricultural households exposed to herder-related violence in Nigeria.

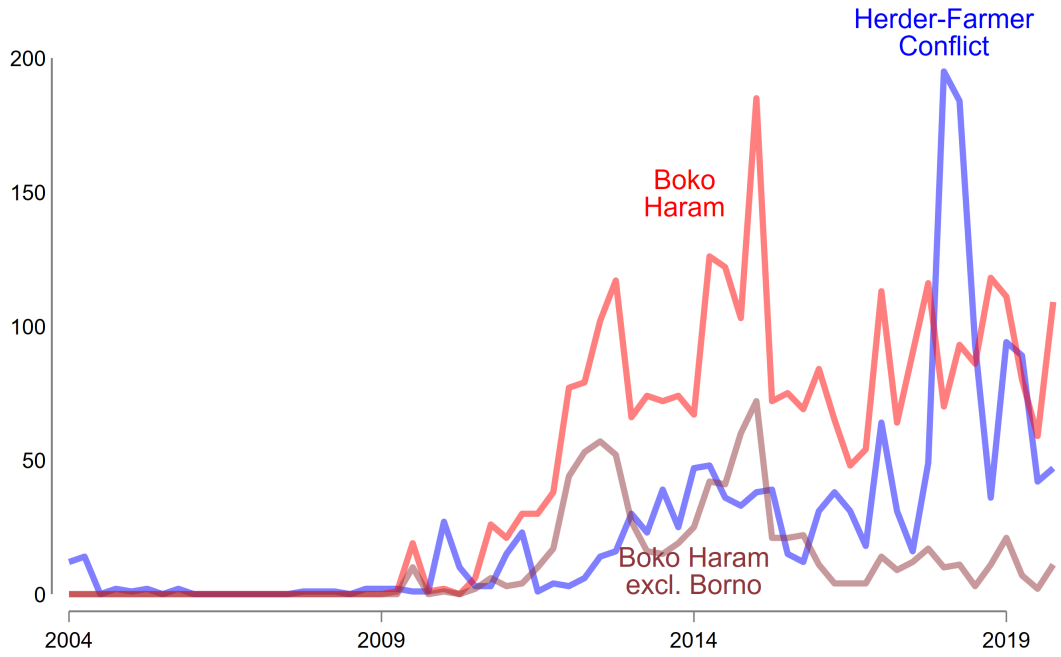
Furthermore, we investigate heterogeneity across both time and space by exploiting the spike in violence just before the 2018-2019 GHS survey rounds and within Nigerian states implementing open-grazing bans, which have been attributed as a contributor to increased violence in the conflict. We find that the shift toward informal work and away from agricultural work is larger within states implementing an open-grazing ban and during the 2018-2019 survey round, especially during the post-harvest season.

Finally, we investigate the consequences of this labor response to exposure to herder-related violence. We specifically estimate "knock-on" or lagged effects that materialize during the post-harvest period of the 2018-2019 GHS survey and are associated with exposure to herder-related violence in the previous planting season. We find that households exposed to herder-related violence and who have also been previously exposed to this violence (i) shift their consumption toward food and away from other expenditures, (ii) are more likely to sell raw crops to relatives/friends or via the farmgate, and (iii) are more likely to operate a non-farm enterprise.

Despite our finding that agricultural households exposed to herder-related violence in Nigeria might use the informal sector as a way to cope with the increased risk associated with agricultural production, this 'safety net' does not seem to effectively guard against these households experiencing adverse economic consequences. Therefore, herder-related violence can have wide-reaching indirect costs beyond the direct costs associated with the loss of human life and the destruction of property. In the absence of the elimi-

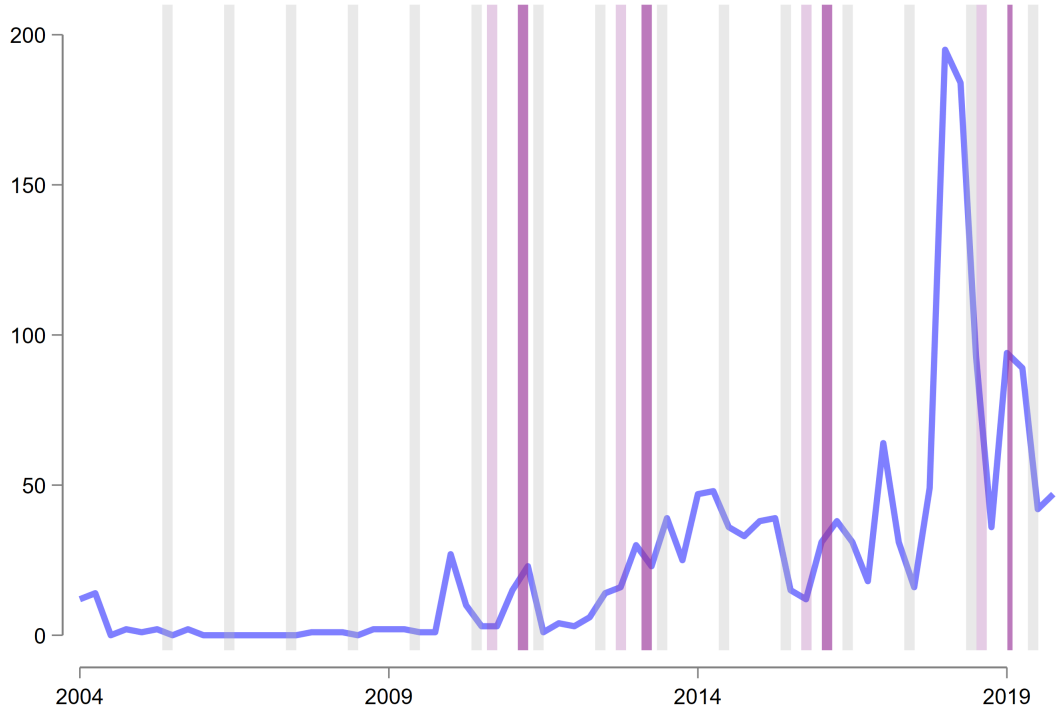
nation of violence and conflict in the future, future policy-relevant research could focus on understanding how to most effectively provide formal economic support for households exposed to violence and conflict to supplement informal coping mechanisms.

Figure 1: **Violent Events in Nigeria, 2004–2019**



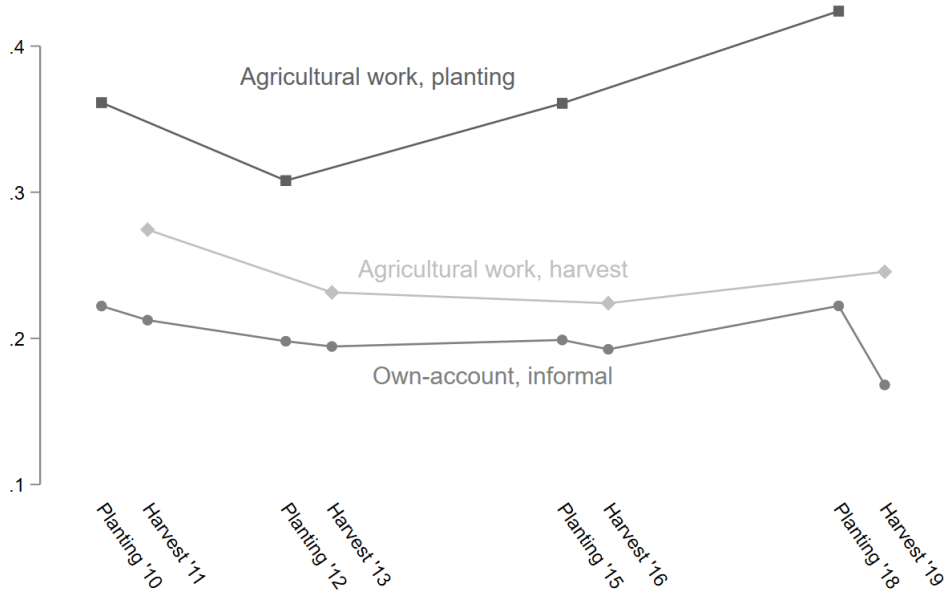
Notes: Authors' calculations based on ACLED data. Violent events are summed over each quarter of the year.

Figure 2: **Herder-Related Violence and GHS Data Collection**



Notes: Authors' calculations based on ACLED data. The light grey shaded areas correspond to the period of May–July each year, a standard time for seasonal planting (though, this period may vary year to year, based on conditions). The lighter purple areas mark the post-planting GHS (General Household Survey) data collection periods; post-harvest data collection is marked in the darker purple areas. Violent events are summed over each quarter of the year.

Figure 3: **GHS Sample Means: Farming and Self-Employment**



Source: Authors' calculations based on GHS data.

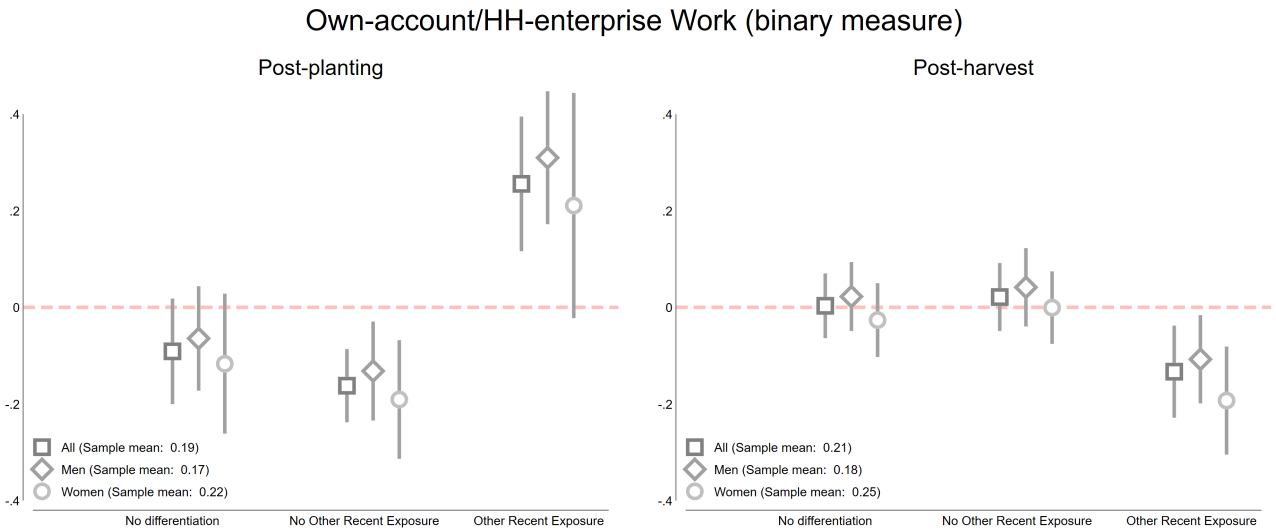
Table 1: Descriptive Statistics

(A) Full sample, post-planting	Mean	SD	Min.	Max	n
Own-account HH-enterprise work (Y=1)	0.22	0.42	0	1	21,988
Agricultural work (Y=1)	0.38	0.49	0	1	21,997
Work outside the home (Y=1)	0.07	0.26	0	1	21,989
Hrs. total worked	18.29	22.18	0	114	13,543
Hrs. own-account HH-enterprise work	6.57	15.70	0	100	13,543
Hrs. agricultural work	9.52	15.93	0	84	13,543
Hrs. work outside the home	2.21	9.64	0	92	13,543
(B) Full sample, post-harvest	Mean	SD	Min.	Max	n
Own-account HH-enterprise work (Y=1)	0.20	0.40	0	1	21,756
Agricultural work (Y=1)	0.26	0.44	0	1	21,757
Work outside the home (Y=1)	0.07	0.26	0	1	21,758
Hrs. total worked	12.45	20.33	0	124	14,212
Hrs. own-account HH-enterprise work	5.50	14.87	0	105	14,212
Hrs. agricultural work	4.58	11.59	0	84	14,212
Hrs. work outside the home	2.37	9.99	0	96	14,212
(C) Men, post-planting	Mean	SD	Min.	Max	n
Own-account HH-enterprise work (Y=1)	0.19	0.39	0	1	10,913
Agricultural work (Y=1)	0.44	0.50	0	1	10,924
Work outside the home (Y=1)	0.09	0.29	0	1	10,920
Hrs. total worked	21.31	23.40	0	114	6,351
Hrs. own-account HH-enterprise work	5.70	14.98	0	98	6,351
Hrs. agricultural work	12.64	17.62	0	84	6,351
Hrs. work outside the home	2.97	11.17	0	92	6,351
(D) Men, post-harvest	Mean	SD	Min.	Max	n
Own-account HH-enterprise work (Y=1)	0.18	0.38	0	1	10,907
Agricultural work (Y=1)	0.30	0.46	0	1	10,908
Work outside the home (Y=1)	0.09	0.29	0	1	10,909
Hrs. total worked	14.11	21.61	0	118	6,780
Hrs. own-account HH-enterprise work	5.08	14.50	0	98	6,780
Hrs. agricultural work	5.86	13.17	0	84	6,780
Hrs. work outside the home	3.16	11.58	0	96	6,780
(E) Women, post-planting	Mean	SD	Min.	Max	n
Own-account HH-enterprise work (Y=1)	0.26	0.44	0	1	10,384
Agricultural work (Y=1)	0.31	0.46	0	1	10,382
Work outside the home (Y=1)	0.05	0.22	0	1	10,378
Hrs. total worked	16.61	20.98	0	104	6,147
Hrs. own-account HH-enterprise work	7.99	16.87	0	100	6,147
Hrs. agricultural work	7.02	13.98	0	72	6,147
Hrs. work outside the home	1.60	8.12	0	84	6,147
(F) Women, post-harvest	Mean	SD	Min.	Max	n
Own-account HH-enterprise work (Y=1)	0.24	0.42	0	1	10,432
Agricultural work (Y=1)	0.22	0.41	0	1	10,432
Work outside the home (Y=1)	0.05	0.22	0	1	10,432
Hrs. total worked	11.57	19.34	0	105	6,611
Hrs. own-account HH-enterprise work	6.31	15.63	0	105	6,611
Hrs. agricultural work	3.53	9.93	0	70	6,611
Hrs. work outside the home	1.74	8.40	0	96	6,611

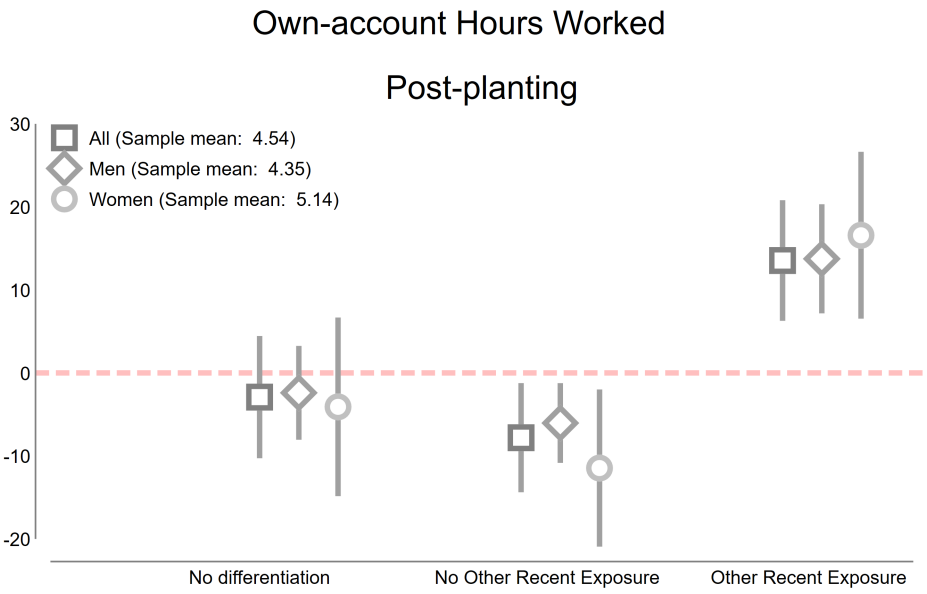
Source: Authors' tabulations of individual-level GHS data. All panels include observations that are observed in the 2018-2019 GHS round and also at least one previous round; the sample is restricted to those that were at least 5 years old as of their first appearance in the data (when the labor module is first applicable). Borno state is excluded.

Figure 4: Exposure to Violence Shifts Informal Work for Men and Women

(a) Extensive Margin



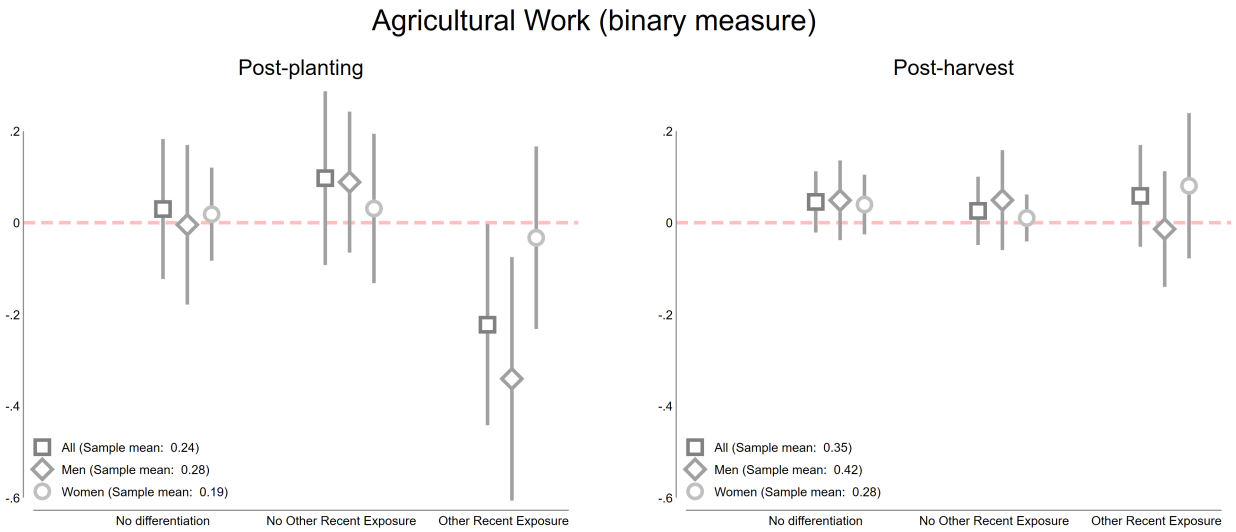
(b) Intensive Margin



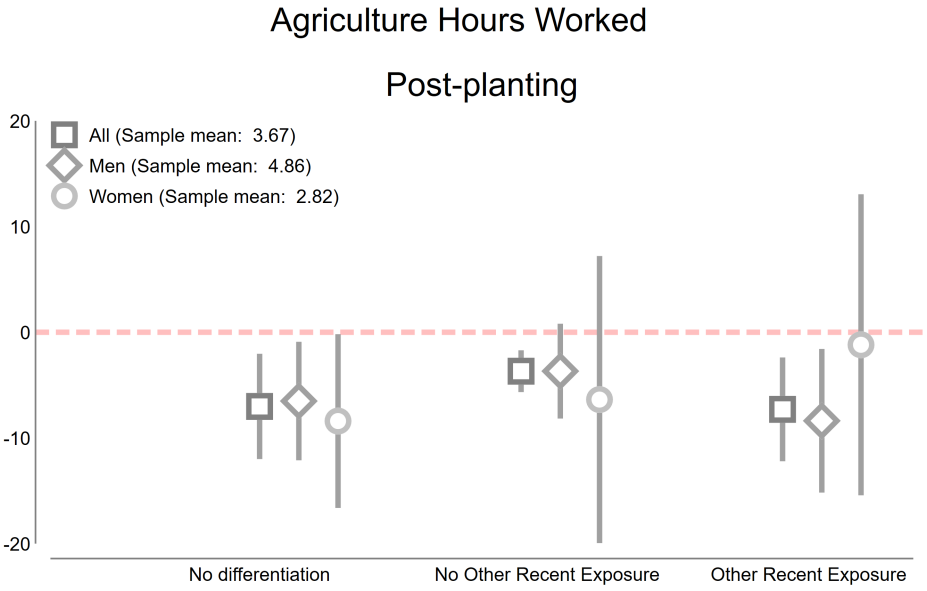
Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure 5: Exposure to Violence Shifts Agricultural Work for Men, but not Women

(a) Extensive Margin

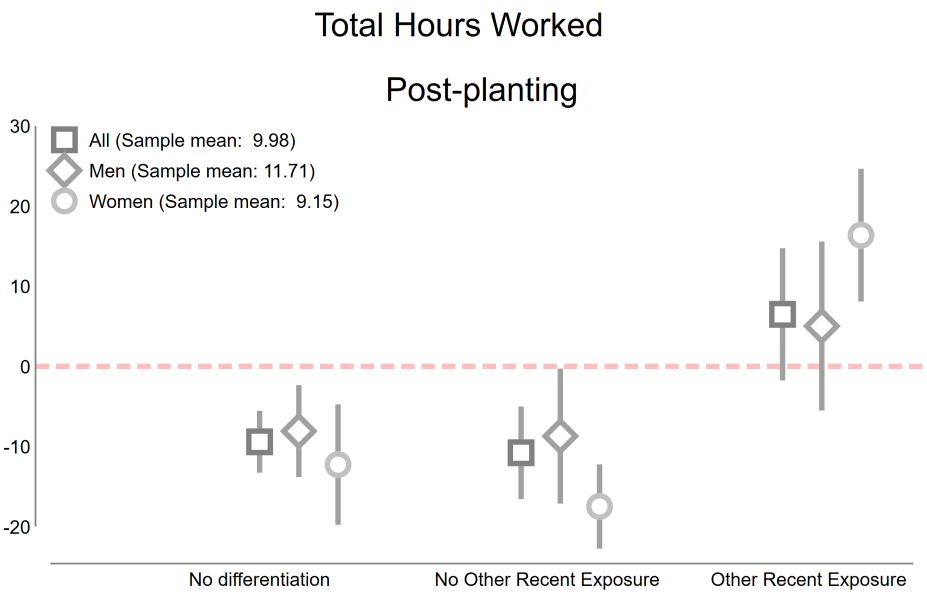


(b) Intensive Margin



Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

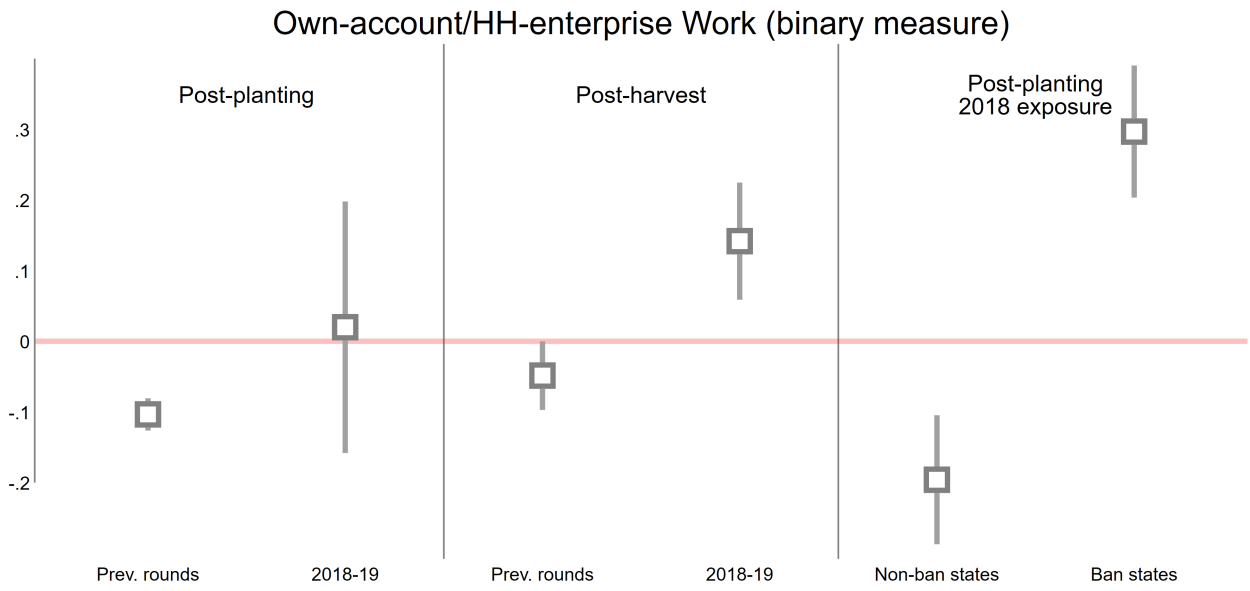
Figure 6: Exposure to Violence Shifts Total Hours Worked for Women, but not Men



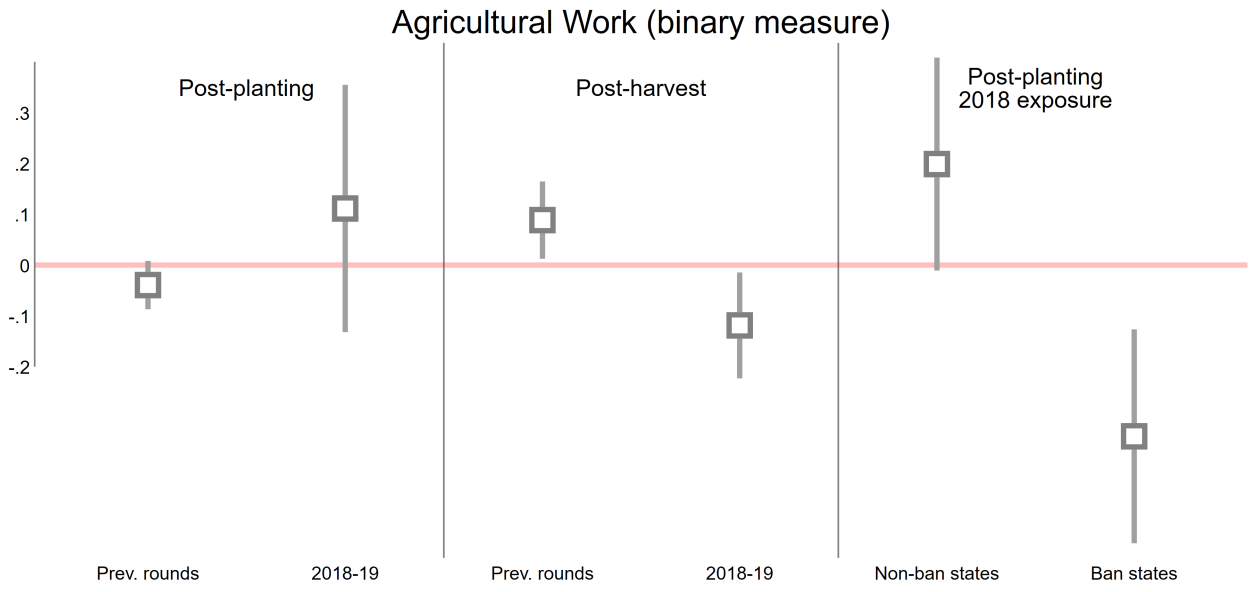
Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. The left panel shows results in the post-planting season. The right panel shows results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure 7: Effects Under "Shadow of Violence"

(a) Informal Work Increases



(b) Agricultural Work Decreases



Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on informal work. Panel B reports results on agricultural work. The left panels show results in the post-planting season before and after the 2018 spike in violence. The middle panels show results in the post-harvest season before and after the 2018 spike in violence. The right panels show results in the post-planting season between states that implemented an open grazing ban or not.

Table 2: Lagged Shift in Household Consumption Patterns

	HH Consumption		Share of HH Consumption on...					
	Naira (log)		Food		Non-food		Edu. & Health	
δ_{lag}	-0.0272	-0.124	0.0865**	0.0342	-0.0401	0.000115	-0.0464*	-0.0343
	(0.106)	(0.112)	(0.0409)	(0.0474)	(0.0253)	(0.0308)	(0.0275)	(0.0329)
$\beta_{lag,pv}$		0.106		-0.0497**		0.0573***		-0.00761
		(0.0745)		(0.0233)		(0.0221)		(0.0151)
$\delta_{lag,pv}$		0.603**		0.168***		-0.101*		-0.0673
		(0.307)		(0.0608)		(0.0534)		(0.0574)
Constant	12.56***	12.55***	0.651***	0.655***	0.269***	0.265***	0.0794***	0.0799***
	(0.0235)	(0.0235)	(0.00533)	(0.00571)	(0.00523)	(0.00544)	(0.00449)	(0.00460)
Obs.	5,020	5,020	5,020	5,020	5,020	5,020	5,020	5,020
R^2	0.597	0.598	0.370	0.372	0.387	0.389	0.169	0.169
$\delta_{pv} - \beta_{pv}$		0.497		0.218***		-0.158***		-0.0597
S.E.		0.324		0.0655		0.0592		0.0628

Notes: * p<.1, ** p<.05, *** p <.01. Household-level data. S.E.s allow for clustering at the level of enumeration area (EA). All columns include a co-variate adjustment for the number of household members, as well as fixed effects for if a household was located within 10 km. of a population center with at least 20,000 inhabitants, the state-level administrative center, and a market. Additionally EA-level, state-level, month, and river sub-basin fixed effects are included, as is a dummy for whether the household was engaged in agriculture. Borno state is excluded.

Table 3: Lagged Shift in Agricultural Marketing Patterns

	Sold raw crops (0/1)		Total Kgs. Sold (log)		Raw crops were sold ...(0/1) Farmgate/Relatives/Friends		Main Market	
δ_{lag}	0.210	0.191	1.382**	1.523**	0.0174	-0.224**	-0.171	-0.210
	(0.179)	(0.212)	(0.608)	(0.756)	(0.184)	(0.112)	(0.196)	(0.238)
$\beta_{lag,pv}$		-0.0898		-0.148		-0.150		0.0311
		(0.111)		(0.296)		(0.0995)		(0.101)
$\delta_{lag,pv}$		0.00883		-0.764		1.152***		0.214
		(0.551)		(0.913)		(0.191)		(0.270)
Constant	0.533***	0.539***	5.853***	5.860***	0.0910***	0.101***	0.214***	0.213***
	(0.00207)	(0.00787)	(0.00804)	(0.0173)	(0.00242)	(0.00556)	(0.00258)	(0.00680)
Obs.	3,882	3,882	2,116	2,116	2,050	2,050	2,050	2,050
R^2	0.304	0.304	0.521	0.521	0.297	0.302	0.289	0.289
$\delta_{pv} - \beta_{pv}$		0.0986		-0.616		1.302***		0.183
S.E.		0.583		0.909		0.223		0.321

Notes: * p<.1, ** p<.05, *** p <.01. Household-level data, restricted to households engaged in agriculture. S.E.s allow for clustering at the level of enumeration area (EA). All columns include fixed effects for if a household was located within 10 km. of a population center with at least 20,000 inhabitants, the state-level administrative center, and a market. Additionally EA-level, state-level, month, and river sub-basin fixed effects are included. Borno state is excluded.

Table 4: Lagged Shift in Non-Farm Enterprise Sales

	Non-farm Enterprise (NFE)		NFE Sales			
	(0/1)		Naira (IHS)		Naira (log)	
δ_{lag}	0.149*	0.0952	-1.174	-1.899*	-0.585	-0.617
	(0.0854)	(0.113)	(0.748)	(1.004)	(0.387)	(0.527)
$\beta_{lag,pv}$		-0.0405		-0.159		0.205
		(0.0418)		(0.392)		(0.303)
$\delta_{lag,pv}$		0.259		1.979*		0.226
		(0.192)		(1.156)		(0.737)
Constant	0.148***	0.151***	11.65***	11.66***	11.12***	11.10***
	(0.000990)	(0.00300)	(0.00822)	(0.0275)	(0.00430)	(0.0198)
Obs.	3,882	3,882	2,002	2,002	1,978	1,978
R^2	0.243	0.244	0.264	0.264	0.321	0.321
$\delta_{pv} - \beta_{pv}$		0.299		2.138		0.0213
S.E.		0.201		1.327		0.887

Notes: * p<.1, ** p<.05, *** p <.01. Household-level data. All columns include fixed effects for if a household was located within 10 km. of a population center with at least 20,000 inhabitants, the state-level administrative center, and a market. S.E.s allow for clustering at the level of enumeration area (EA). Borno state is excluded.

References

Adelaja, A. and George, J. (2019). Effects of conflict on agriculture: Evidence from the boko haram insurgency. *World Development*, **117**, 184—195.

Adhvaryu, A., Kala, N. and Nyshadham, A. (2019). Booms, busts, and the household enterprise: Evidence from coffee farmers in tanzania. *The World Bank Economic Review*, **Available online: December 2019**.

Aga, G., Francis, D. C., Jolevski, F., Rodriguez Meza, J. and Wimpey, J. S. (2023). An application of adaptive cluster sampling to surveying informal businesses. *Journal of Survey Statistics and Methodology*, p. smac037.

Akresh, R., Bhalotra, S., Leone, M. and Osili, U. (2012a). War and stature: Growing up during the nigerian civil war. *American Economic Review*, **102** (3), 273–277.

—, Lucchetti, L. and Thirumurthy, H. (2012b). Wars and child health: Evidence from the eritrean-ethiopian conflict. *Journal of Development Economics*, **99** (2), 330—340.

Alloush, M. and Bloem, J. (2022). Neighborhood violence, poverty, and psychological well-being. *Journal of Development Economics*, **154**.

Avuwadah, B. (2020). Heterogeneous effects of conflict on household participation in income generating activities: Evidence from nigeria. *Working Paper*.

Baker, A. C., Larcker, D. F. and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, **144** (2), 370–395.

Bellemare, M. and Wichman, C. (2019). Elasticities and the inverse hyperbolic sine transformation†. *Oxford Bulletin of Economics and Statistics*, **82**, 50–61.

Brown, R. and Velasquez, A. (2017). The effect of violent crime on the human capital accumulation of young adults. *Journal of Development Economics*, **127**, 1—12.

— and Velásquez, A. (2017). The effect of violent crime on the human capital accumulation of young adults. *Journal of Development Economics*, **127**, 1–12.

Bryan, G., Chowdhury, S. and Mobarak, A. (2014). Underinvestment in a profitable technology: The case of seasonal migration in bangladesh. *Econometrica*, **82** (5), 1671–1748.

Bundervoet, T. (2010). Assets, activity choices, and civil war: Evidence from burundi. *World Development*, **38** (7), 955—965.

Burgess, R. and Pande, R. (2005). Do rural banks matter? evidence from the indian social banking experiment. *American Economic Review*, **95** (3), 780–795.

Butts, K. (2021). Difference-in-differences with geocoded microdata. *arXiv preprint arXiv:2110.10192*.

Camacho, A. (2008). Stress and birth weight: Evidence from terrorist attacks. *American Economic Review*, **98** (2), 511—515.

Chamarbagwala, R. and Moran, H. (2011). The human capital consequences of civil war: Evidence from guatemala. *Journal of Development Economics*, **94** (1), 41—61.

Chen, J. and Roth, J. (2022). Log-like? identified ates defined with zero-valued outcomes are (arbitrarily) scale-dependent.

Cole, S., Gine, X., Tobacman, J., Topalova, P., Townsend, R. and Vickery, J. (2013). Barriers to household risk management: Evidence from india. *American Economic Journal: Applied Economics*, **5** (1), 104–135.

Colombo, E., Menna, L. and Tirelli, P. (2019). Informality and the labor market effects of financial crises. *World Development*, **119**, 1–22.

De Chaisemartin, C. and D'Haultfœuille, X. (2020a). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, **110** (9), 2964–96.

— and D'Haultfœuille, X. (2020b). Difference-in-differences estimators of intertemporal treatment effects. *Available at SSRN 3731856*.

Dupas, P. and Robinson, J. (2013). Savings constraints and microenterprise development: Evidence from a field experiment in kenya. *American Economic Journal: Applied Economics*, **5** (1), 163–192.

Eberle, U., Rohner, D. and Theonig (2020). Heat and hate, climate security and farmer-herder conflicts in africa. *ESOC Working Paper, No. 22*.

Epstein, B. and Shapiro, A. (2017). Employment and firm heterogeneity, capital allocation, and the countercyclical labor market policies. *Journal of Development Economics*, **127**, 25–41.

Fiess, N., Fugazza, M. and Maloney, W. (2010). Informal self-employment and macroeconomic fluctuations. *Journal of Development Economics*, **91** (2), 211–226.

George, J., Adelaja, A., Awokuse, T. and Vaughan, O. (2021a). Terrorist attacks, land resource competition and violent farmer-herder conflicts. *Land Use Policy*, **102**.

—, — and Awokuse, T. O. (2021b). The agricultural impacts of armed conflicts: the case of fulani militia. *European Review of Agricultural Economics*, **48** (3), 538–572.

—, — and Weatherspoon, D. (2020). Armed conflicts and food insecurity: Evidence from boko haram's attacks. *American Journal of Agricultural Economics*, **102**, 114–131.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Grimard, F. and Laszlo, S. (2014). Long-term effects of civil conflict on women's health outcomes in peru. *World Development*, **54**, 139—155.

Guardado, J. and Pennings, S. (2020). The seasonality of conflict. *Policy Research Working Paper No. 9373*.

Gunther, I. and Launov, A. (2012). Informal employment in developing countries: Opportunity or last resort? *Journal of Development Economics*, **97**, 88–98.

Jakiela, P. and Ozier, O. (2019). The impact of violence on individual risk preferences: Evidence from a natural experiment. *The Review of Economics and Statistics*, **101**, 547—559.

Kaila, H. and Azad, A. (2019). Conflict, household victimization, and welfare: Does the perpetrator matter? *HiCN Working Papers, No. 315*.

Karlan, D., Osei, R., Osei-Akoto, I. and Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics*, **129** (2), 579–652.

La Porta, R. and Shleifer, A. (2014). Informality and development. *Journal of Economics Perspectives*, **28** (3), 109–126.

Lange, S. and Reimers, M. (2020). Livestock as a buffer in poorly integrated markets. *Economic Development and Cultural change*, **forthcoming**.

Loayza, N. and Rigolini, J. (2011). Informal employment: Safety net or growth engine? *World Development*, **39** (9), 1503–1515.

McGuirk, E. and Nunn, N. (2020). Nomadic pastoralism, climate change, and conflict in africa. *NBER Working Paper, No. 28243*.

Minoiu, C. and Shemyakina, O. (2014). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Development Economics*, **108**, 237—255.

Morten, M. (2019). Temporary migration and endogenous risk sharing in village india. *Journal of Political Economy*, **127** (1), 1–46.

Moya, A. (2018). Violence, psychological trauma, and risk attitudes: Evidence from victims of violence in columbia. *Journal of Development Economics*, **131**, 15—27.

Mullahy, J. and Norton, E. C. (2022). *Why Transform Y? A Critical Assessment of Dependent-Variable Transformations in Regression Models for Skewed and Sometimes-Zero Outcomes*. Tech. rep., National Bureau of Economic Research.

Odozi, J. and Oyelere, R. (2021). Does violence conflict affect the labor supply of farm households? the nigerian experience. *Agricultural and Resource Economics Review*, **50**, 401–435.

Ohnsorge, F. and Yu, S. (2022). *The long shadow of informality: Challenges and policies*. World Bank Publications.

Raleigh, C., Linke, A., Hegre, H. and Karlsen, J. (2010). Introducing acled: An armed conflict location and event dataset. *Journal of Peace Research*, **47** (5), 651–660.

Rockmore, M. (2020). Conflict-risk and agricultural portfolios: evidence from northern uganda. *The Journal of Development Studies*, **56** (10), 1856–1876.

Singh, P. (2013). Impact of terrorism on investment decisions of farmers: Evidence from the punjab insurgency. *Journal of Conflict Resolution*, **57** (1), 143—168.

— and Shemyakina, O. (2016). Gender-differential effects of terrorism on education: The case of the 1981-1993 punjab insurgency. *Economics of Education Review*, **54**, 185—210.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, **225** (2), 175–199.

Townsend, R. (1994). Risk and insurance in village india. *Econometrica*, **62** (3), 539–591.

Tsaneva, M., Rockmore, M. and Albohmood, Z. (2019). The effect of violent crime on female decision-making within the household: evidence from the mexican war on drugs. *Review of Economics of the Household*, **17**, 615–646.

Ubilava, D. and Atalay, K. (2021). Commodity price shocks and the seasonality of conflict. *Working Paper*.

Velásquez, A. (2020). The economic burden of crime evidence from mexico. *Journal of Human Resources*, **55** (4), 1287–1318.

Verpoorten, M. (2009). Household coping in war and peacetime: Cattle sales in rwanda, 1991-2001. *Journal of Development Economics*, **88** (1).

Voors, M., Nillesen, E., Verwimp, P., Bulte, E., Lenink, R. and van Soest, D. (2012). Violent conflict and behavior: A field experiment in burundi. *American Economic Review*, **102** (2), 941—964.

Weldeegzie, S. (2017). Growing-up unfortunate: War and human capital in ethiopia. *World Development*, **96**, 474—489.

Wooldridge, J. M. (2021). Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.

A1 Data Appendix

A1.1 General Household Survey (GHS), Nigeria Bureau of Statistics

The following discusses the main outcome variables we use from the GHS data.

Own-account work or in a household-enterprise—A binary measure taking the value of 1 if the answer is "yes" to the following:

> During the past 7 days, has [NAME] worked on their own account or in a business enterprise belonging to [NAME] or another household member, for example, as a trader, shop-keeper, barber, dressmaker, carpenter or taxi driver?

In the 2015–16 and 2018–19 GHS rounds, information on the number of hours in this type of work was also recorded:

> During the past 7 days, how many hours has [NAME] worked in the household nonfarm enterprise?

Agricultural work—A binary measure taking the value of 1 if the answer is "yes" to the following:

> During the past 7 days, has [NAME] worked on a farm owned or rented by [NAME] or another member of your household, either in cultivating crops or in other farming tasks, or has [NAME] cared for livestock belonging to [NAME] or another member of your household?

In the 2015–16 and 2018–19 GHS rounds, information on the number of hours in this type of work was also recorded:

> During the past 7 days, how many hours has [NAME] done this agricultural work for the household?

Work outside the household—A binary measure taking the value of 1 if the answer is "yes" to the following:

> During the past 7 days, has [NAME] worked for someone who is not a member of your household, for example, an enterprise, company, the government or any other individual for payment in cash or in-kind?

In the 2015–16 and 2018–19 GHS rounds, information on the number of hours in this type of work was also recorded:

> During the past 7 days, for how many hours in total has [NAME] worked for payment?

A1.2 Conflict Event Data, ACLED Project

The following discusses how we use the data from the ACLED project.

Definition of a Violent Event—The ACLED Project includes coded definitions of event types and sub-types. Values for violent `event type` include:

- Violence against civilians
- Explosions/remote violence
- Battles

Violent `sub event types` values include:

- Abduction/forced disappearance
- Attack
- Looting/property destruction
- Sexual violence
- Armed clash
- Excessive force against protesters
- Mob violence
- Remote explosive/landmine/IED
- Violent demonstration

Definition of Herder-Involved Conflict—All events including the terms "herder," "herdsmen," or "pastoralist" (or variants of those words, e.g., "herder") as a direct or associated actor were coded as herder-involved; as were occurrence of those terms in the detailed event descriptions. Similarly, if the term "Fulani" was included, the event was coded as herder-involved. Specific areas with the term "Fulani," such as the village "Birim Fulani" were excluded if they did not include a term such as "pastoralist." Positively coded events were reviewed for wording such as "likely not Fulani." Such cases were re-coded as not herder involved.

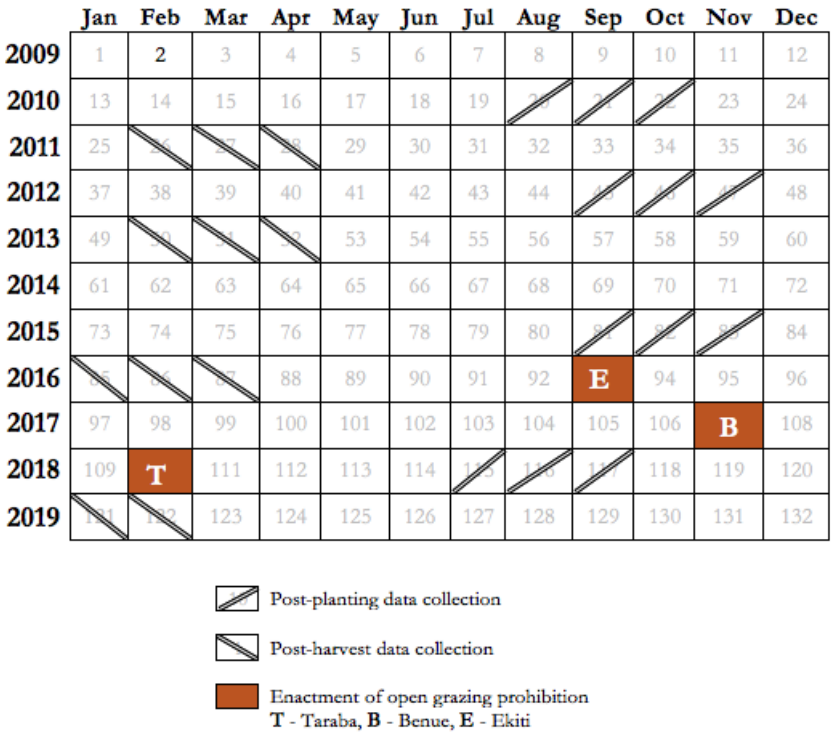
A1.3 Data Combination

Often, the exact location of an event is unknown or imprecise. ACLED's database notes these cases and includes a variable `geo precision`. Events take a value of 1 for *geo precision* if a specific town or locale is noted. In these cases, the corresponding latitude and longitude coordinates for the town/locale are used. In less precise cases, where a part of a region or sub-region is indicated, a representative town/locale is used, and these cases take a value of two for `geo precision`. Cases with a value of three for `geo precision` are those that are reported in a larger area; the GPS coordinates for those cases are those of the closest identified landmark, such as a town, border crossing, or geographic point of interest, such as a lake or road.

Of the herder-involved incidents coded in the ACLED data, 899 (50.4 percent) take a value of one for `geo precision`; 845 (47.3 percent) are coded two; and 41 (2.3 percent) are coded as three.

The Figure A1 below shows the timing of the GHS collection periods and their alignment to the ACLED data and key dates. Each square represents a month in a given year. Squares are numbered sequentially for illustration and begin in January 2009 (1) and end in December 2019 (134). The GHS panel was conducted in four rounds: 2010–11, 2012–13, 2015–16, and 2018–19. Each round consisted of two visits, one in the post-planting period, a second in the post-harvest period. The legend below the figure indicates which data collection periods aligned to the post-planting (dry season) and post-harvest (rainy season) periods.

Figure A1: **GHS Data Collection Timing**



Working with the World Bank's LSMS team, we were able to receive matched GHS data, using unmasked (and precise) GPS coordinates. For confidentiality reasons, we were not granted unrestricted access to the unmasked data and received, at our request, matched data for distance windows of 10, 20, 30, and 50 km. Time windows were available for 1 and 3 months, with 3 months.

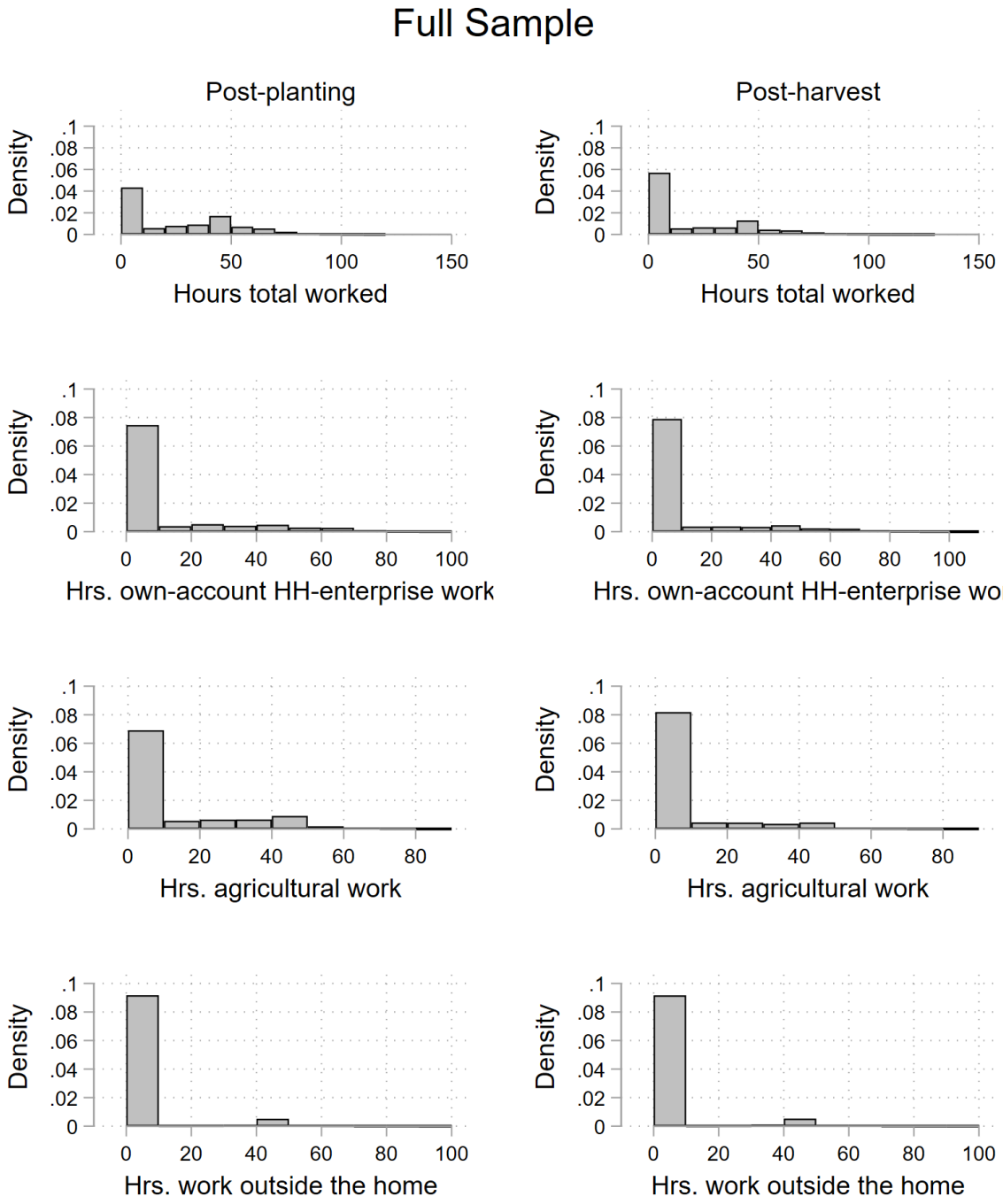
Our team is indebted to the LSMS team for this support.

A2 Additional Tables and Figures

The following tables and figures provide additional results to supplement the discussion in the main manuscript.

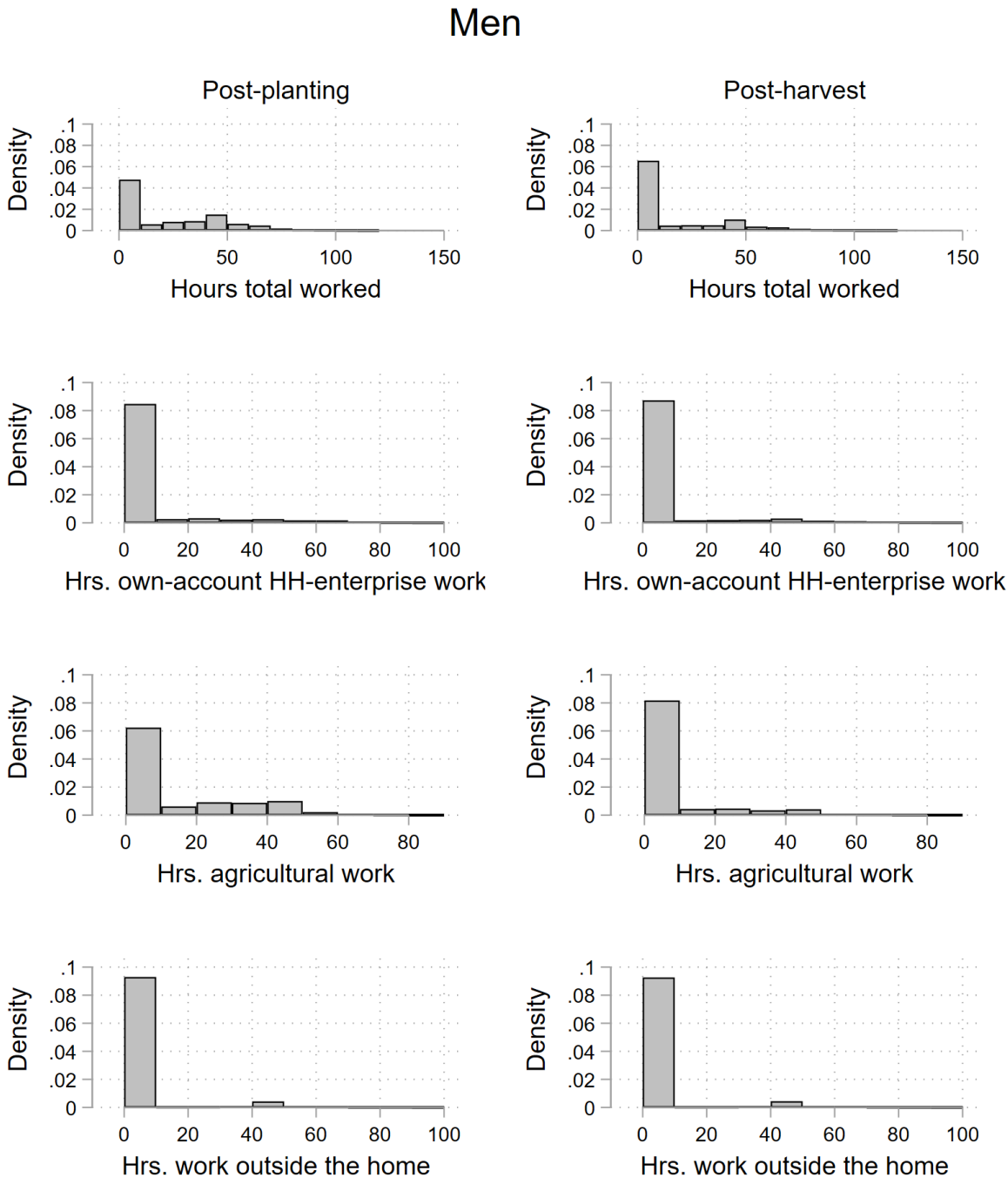
- Figures A2 through A4 show the distribution of hours worked last week, in the post-planting and post-harvest seasons, for total hours worked, informal work, agricultural work, and work outside the home for the full sample and the men and women sub-samples, respectively.
- Table A1 reports additional descriptive statistics, supplementing Table 1 in the main manuscript.
- Figures A5 through A7 report results on the effect of exposure to herder-related violence on hours worked, transformed using the inverse hyperbolic sine transformation.
- Figures A8 through A14 report results for various alternative time windows used to define exposure to herder-related violence.
- Figure A15 reports results representing estimates of the effect of exposure to violence on work outside the home.
- Figure A16 through A18 report results supplementing our core labor response results from the main manuscript using an alternative 20 km distance window defining exposure to herder-related violence.
- Figure A19 through A19 report results supplementing our core labor response results from the main manuscript using an alternative 30 km distance window defining exposure to herder-related violence.

Figure A2: **Distribution of Hours Worked in the Last Week (2015/16–2018/19 rounds)**



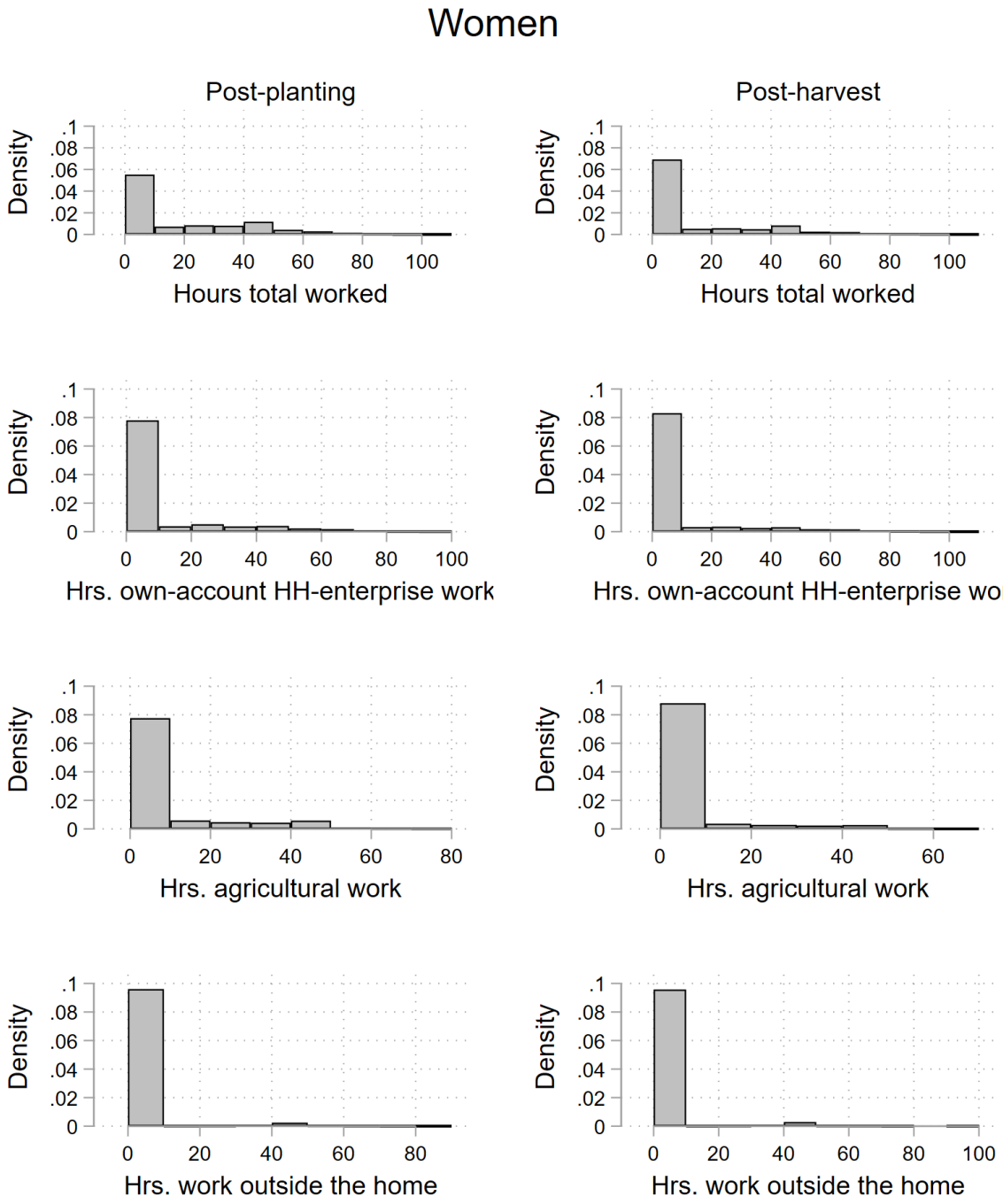
Excluding Borno state. Sample is restricted to those who appeared in the 2018/19 round and at least one previous GHS round and among those individuals who were at least 5 years old (when the survey's labor module is applicable) as of their first appearance in the data. Each bin is equal to an increment of 10 hrs.

Figure A3: **Distribution of Hours Worked in the Last Week (2015/16–2018/19 rounds)**



Excluding Borno state. Sample is restricted to those who appeared in the 2018/19 round and at least one previous GHS round and among those individuals who were at least 5 years old (when the survey's labor module is applicable) as of their first appearance in the data. Each bin is equal to an increment of 10 hrs.

Figure A4: **Distribution of Hours Worked in the Last Week (2015/16–2018/19 rounds)**



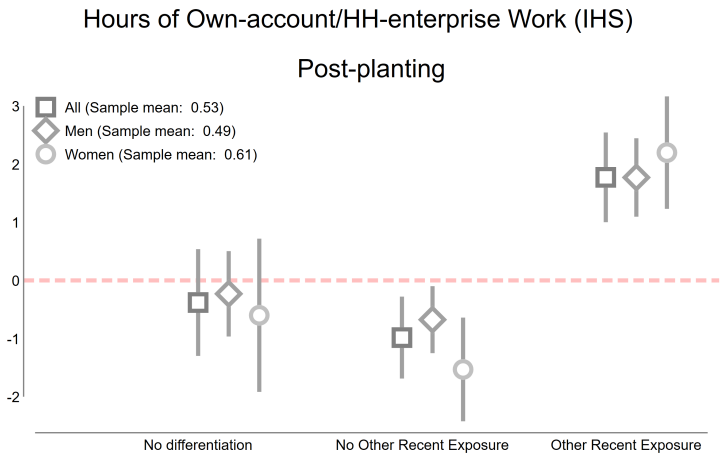
Excluding Borno state. Sample is restricted to those who appeared in the 2018/19 round and at least one previous GHS round and among those individuals who were at least 5 years old (when the survey's labor module is applicable) as of their first appearance in the data. Each bin is equal to an increment of 10 hrs.

Table A1: Descriptive Statistics

(A) Full sample, post-planting	Mean	SD	Min.	Max	n
Within 10 km. of state admin. center	0.14	0.34	0	1	69,254
Within 10 km. of a market	0.10	0.29	0	1	69,254
Within 10 km. of a 20k population center	0.24	0.43	0	1	69,254
(B) Full sample, post-harvest	Mean	SD	Min.	Max	n
Within 10 km. of state admin. center	0.12	0.33	0	1	2,503
Within 10 km. of a market	0.12	0.33	0	1	2,503
Within 10 km. of a 20k population center	0.12	0.33	0	1	2,503
(C) Men, post-planting	Mean	SD	Min.	Max	n
Within 10 km. of state admin. center	0.23	0.42	0	1	2,080
Within 10 km. of a market	0.18	0.38	0	1	2,080
Within 10 km. of a 20k population center	0.59	0.49	0	1	2,080

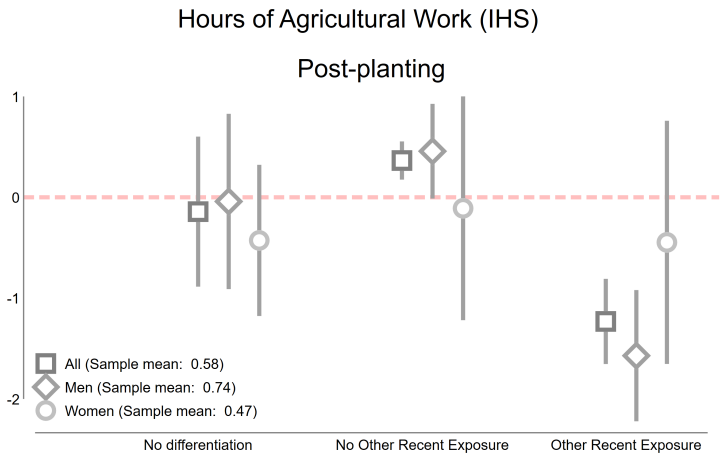
Source: Authors' tabulations of individual-level GHS data. All panels include observations that are observed in the 2018-19 GHS round and also at least one previous round. Borno state is excluded.

Figure A5: Effect of HRV on IHS Hours Worked on Own-account Work



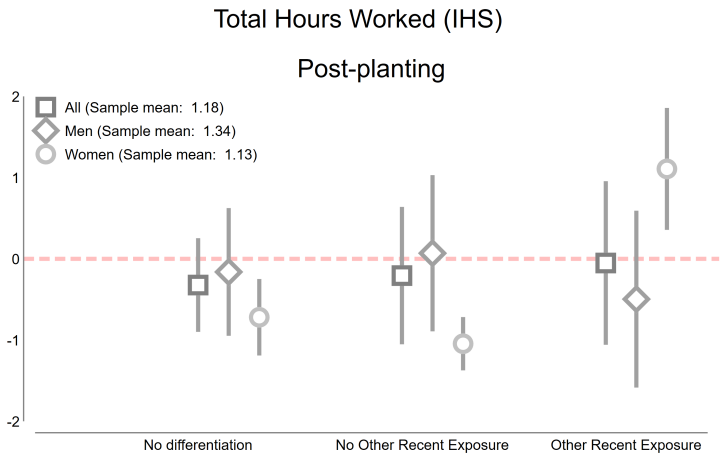
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equations (1) and (2). The figure reports hours worked transformed by the IHS function.

Figure A6: Effect of HRV on IHS Hours Worked on Agricultural Work



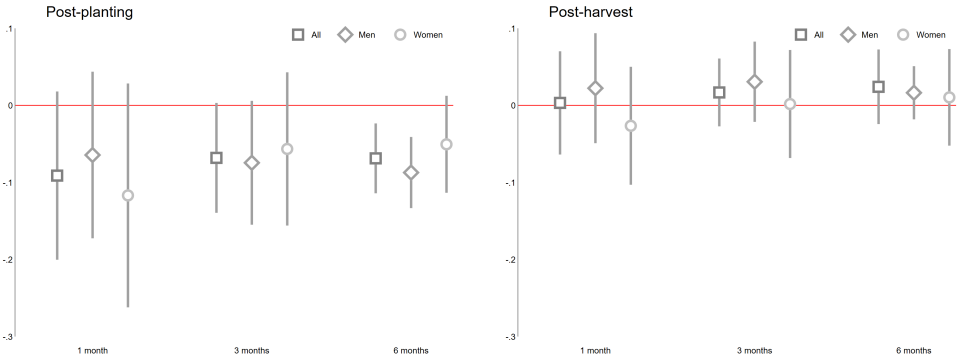
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equations (1) and (2). The figure reports hours worked transformed by the IHS function.

Figure A7: Effect of HRV on IHS Hours Worked on Total Hours Work



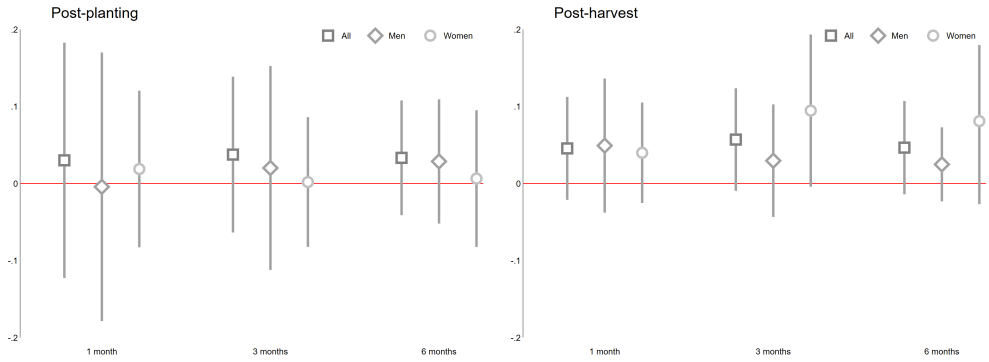
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equations (1) and (2). The figure reports hours worked transformed by the IHS function.

Figure A8: **Effect of HRV on Own-account Work (Y=1), varying time window**



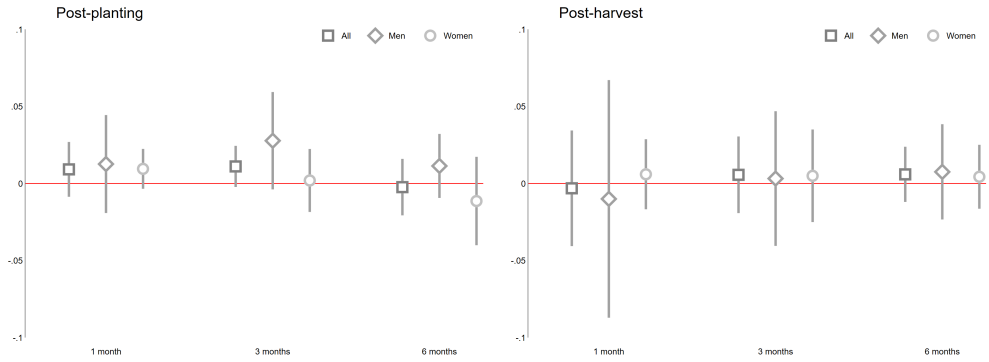
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

Figure A9: **Effect of HRV on Agricultural Work (Y=1), varying time window**



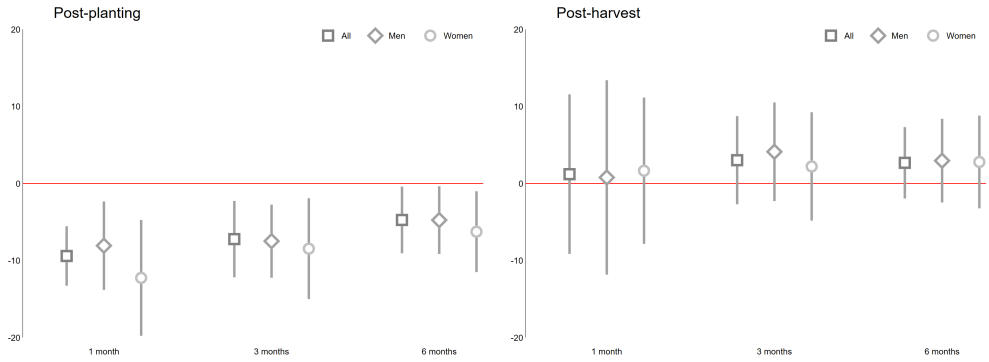
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

Figure A10: **Effect of HRV on Work Outside the Home (Y=1), varying time window**



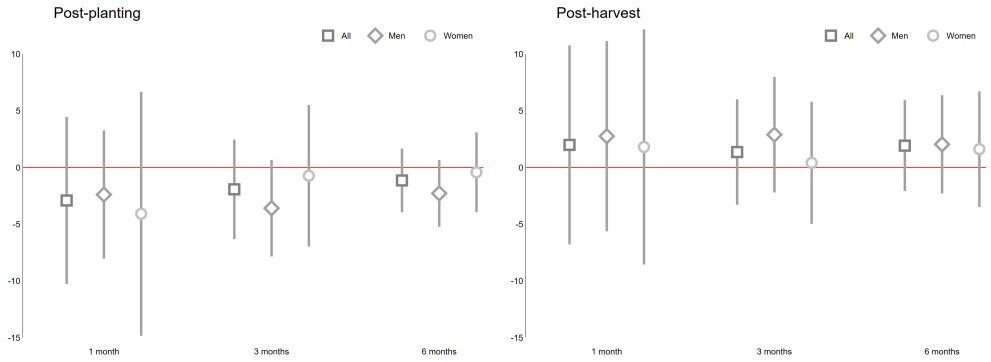
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

Figure A11: **Effect of HRV on Total Work Hours, varying time window**



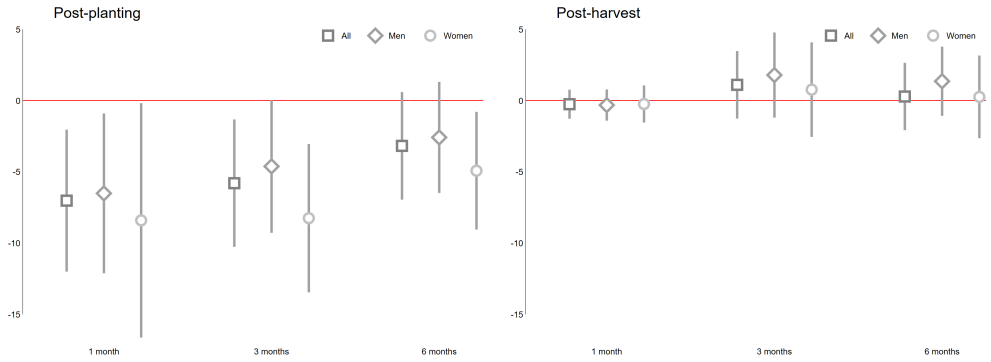
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

Figure A12: **Effect of HRV on Own-account Work Hours, varying time window**



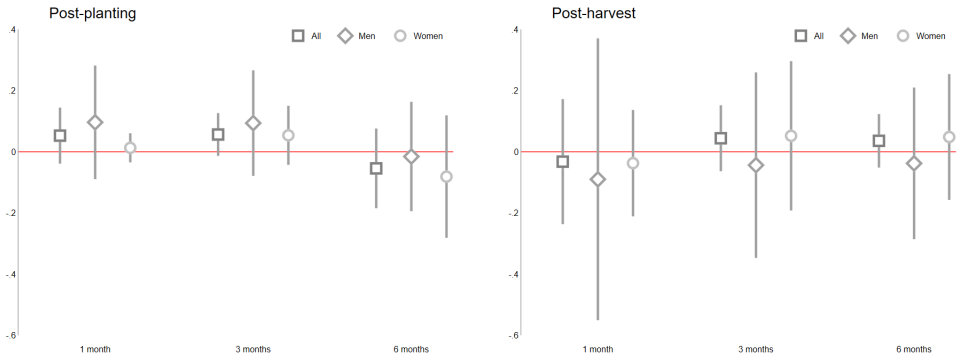
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

Figure A13: **Effect of HRV on Agricultural Work Hours, varying time window**



Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

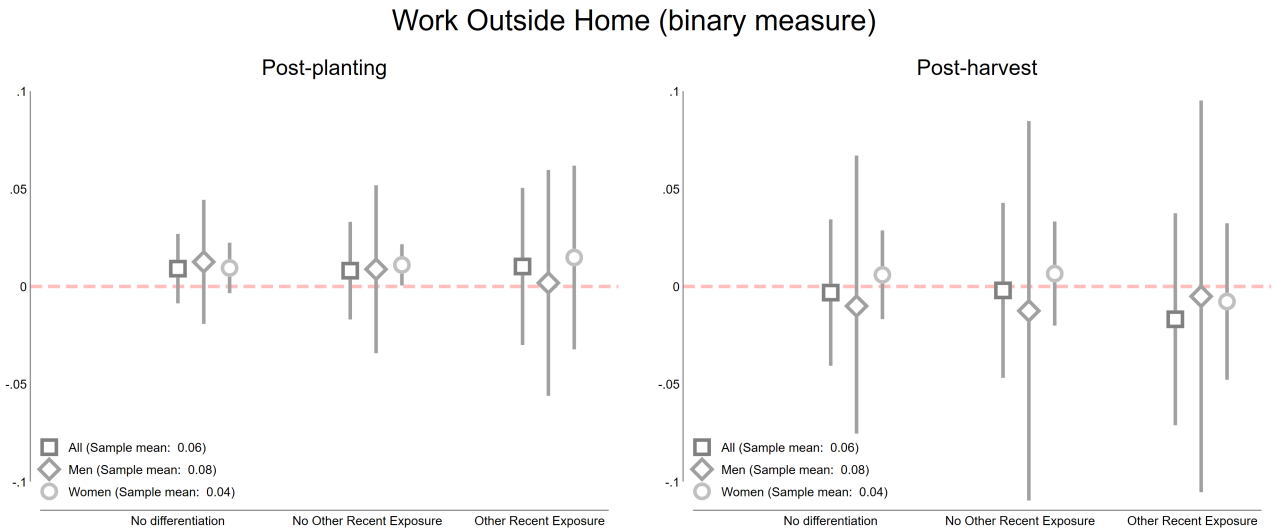
Figure A14: **Effect of HRV on Work Hours Outside the Home, varying time window**



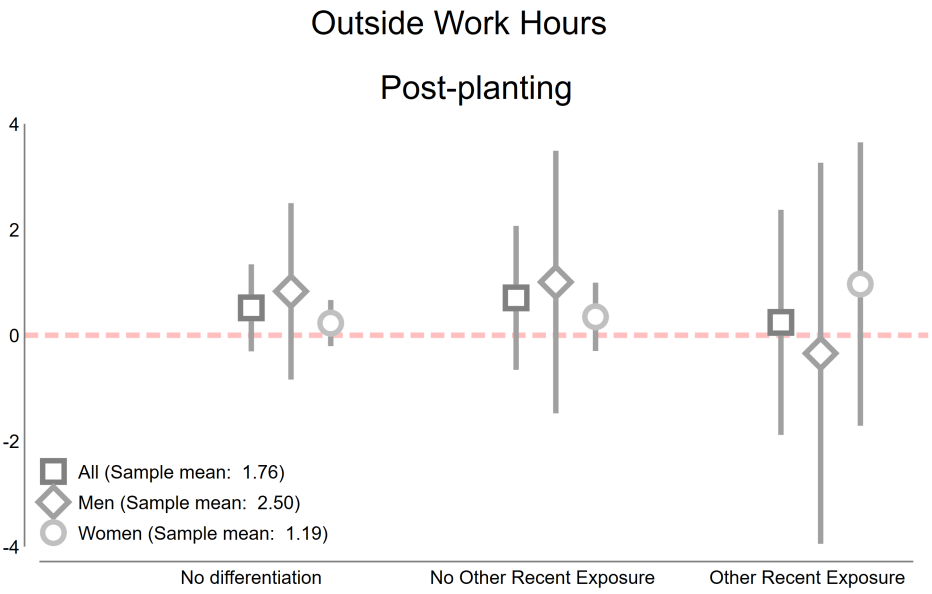
Notes: HRV - herder-related violent event. Coefficient point estimates shown with 95% confidence intervals, based on the baseline specification, equation (1). The figure varies the time window for the main coefficient of interest into 1 month, 3 months, and 6 months.

Figure A15: Exposure to Violence and Work Outside the Home

(a) Extensive Margin



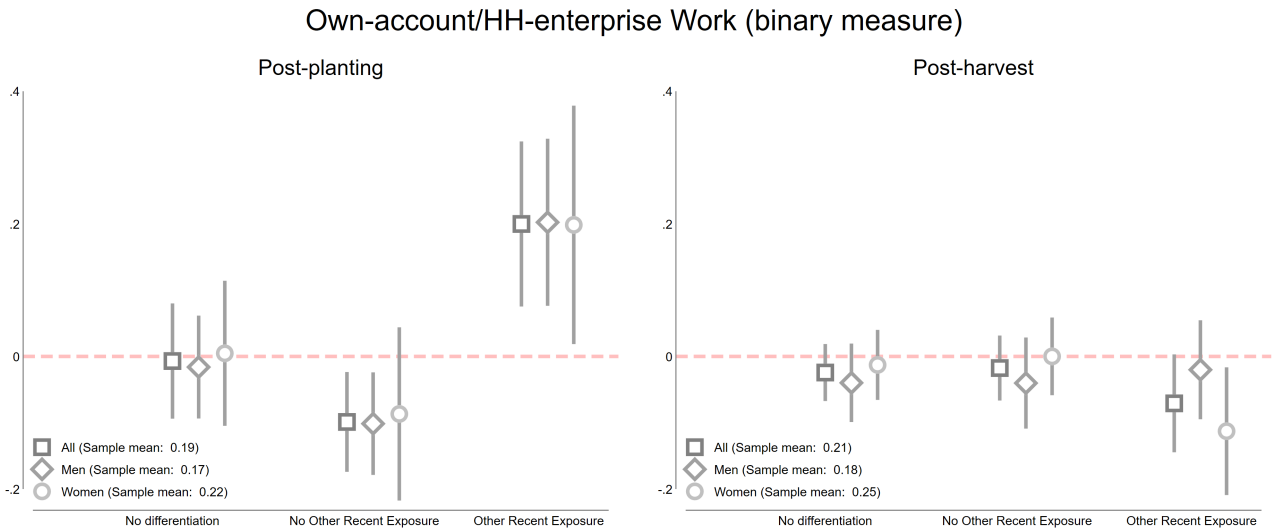
(b) Intensive Margin



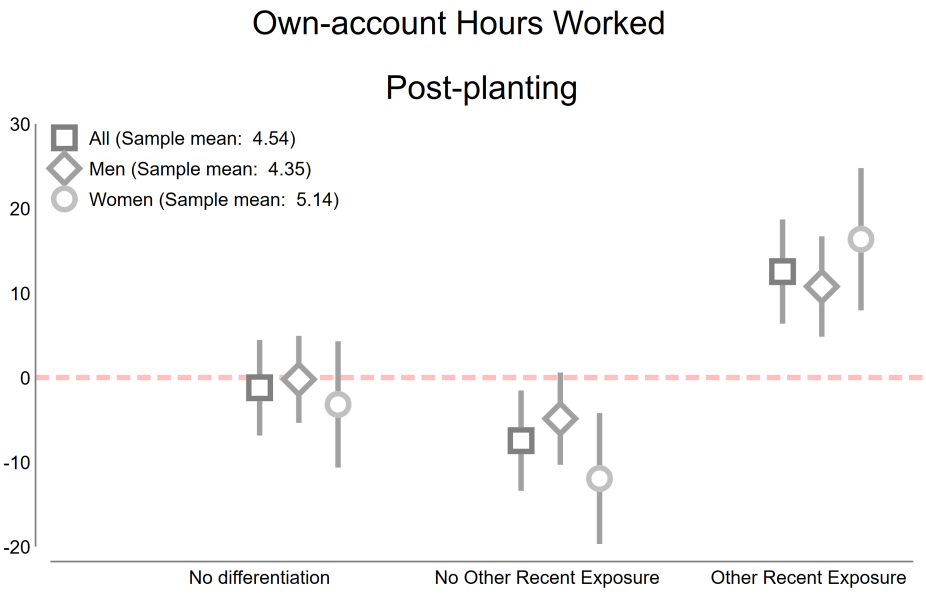
Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure A16: Exposure to Violence and Own-Account/HH-Enterprise Work (20 km. window)

(a) Extensive Margin



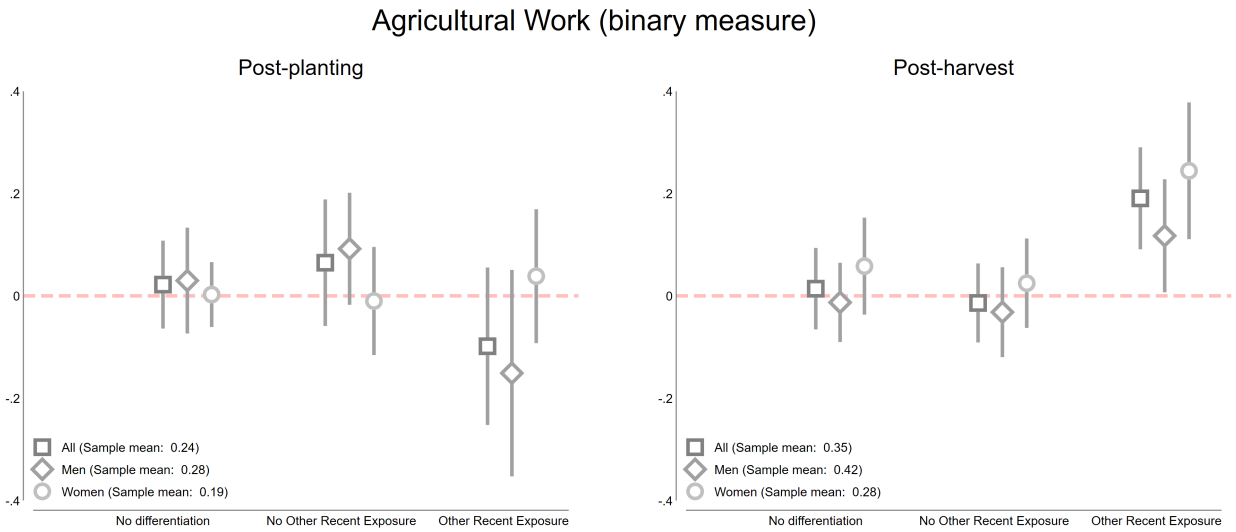
(b) Intensive Margin



Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure A17: Exposure to Violence and Agricultural Work (20 km. window)

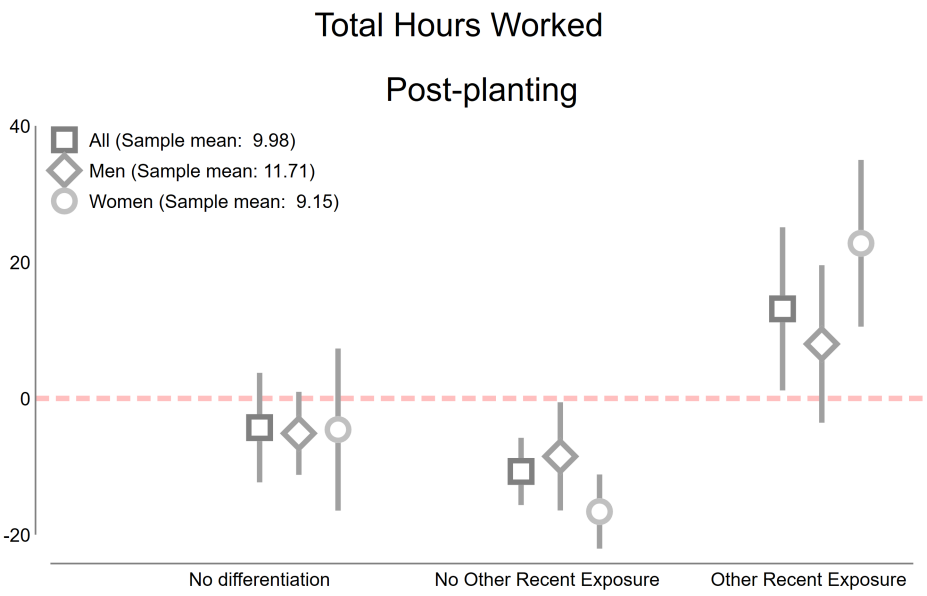
(a) Extensive Margin



(b) Intensive Margin

Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

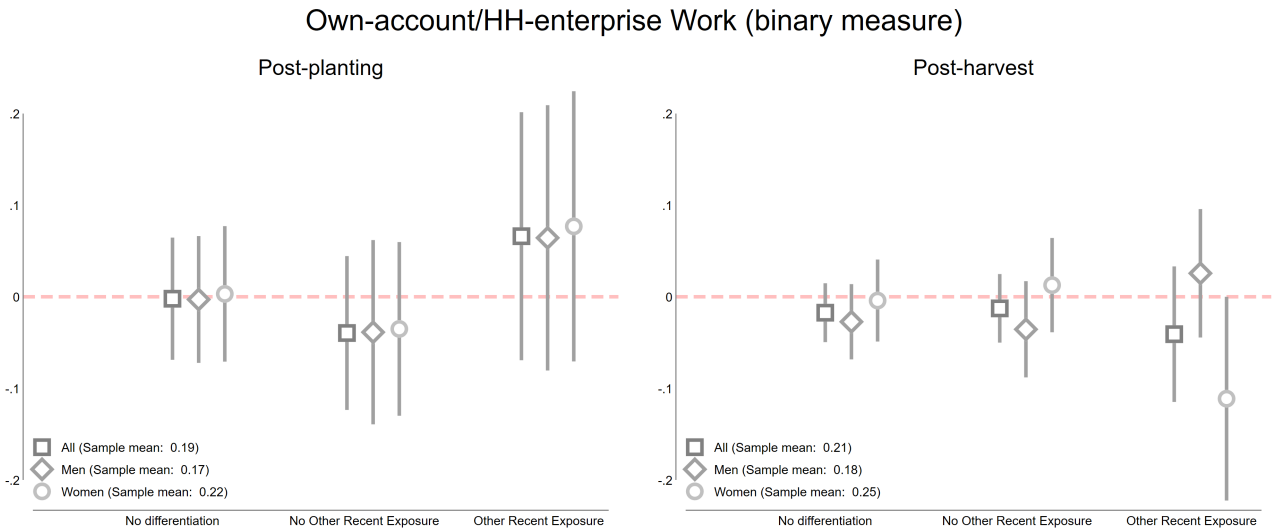
Figure A18: Exposure to Violence and Total Hours Worked (20 km. window)



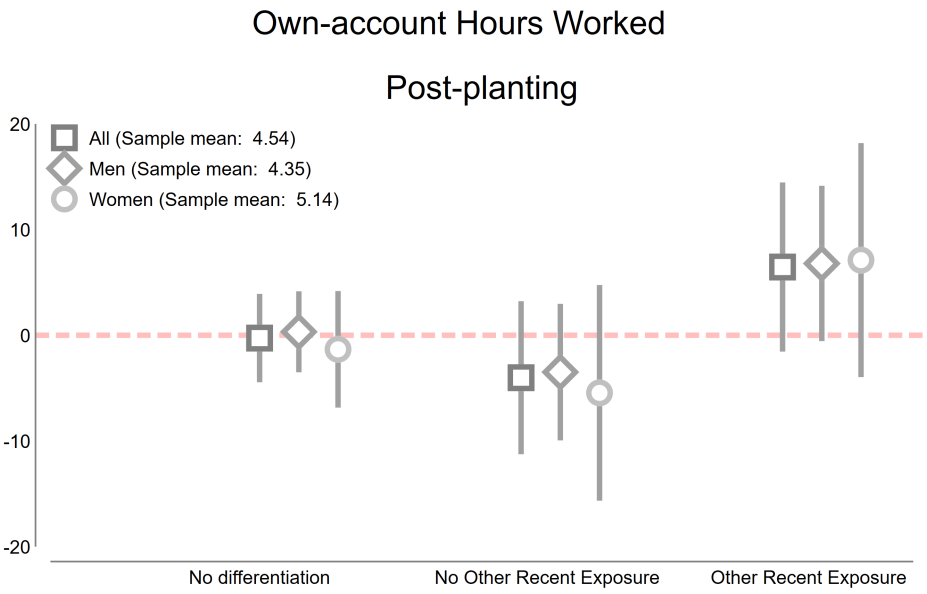
Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. The left panel shows results in the post-planting season. The right panel shows results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure A19: Exposure to Violence and Own-Account/HH-Enterprise Work (30 km. window)

(a) Extensive Margin



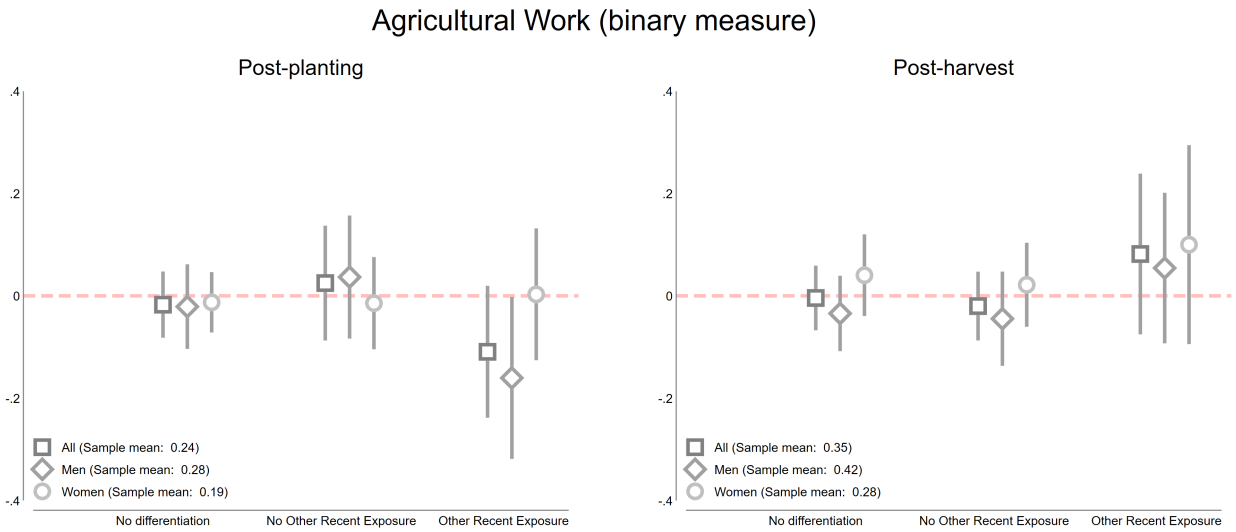
(b) Intensive Margin



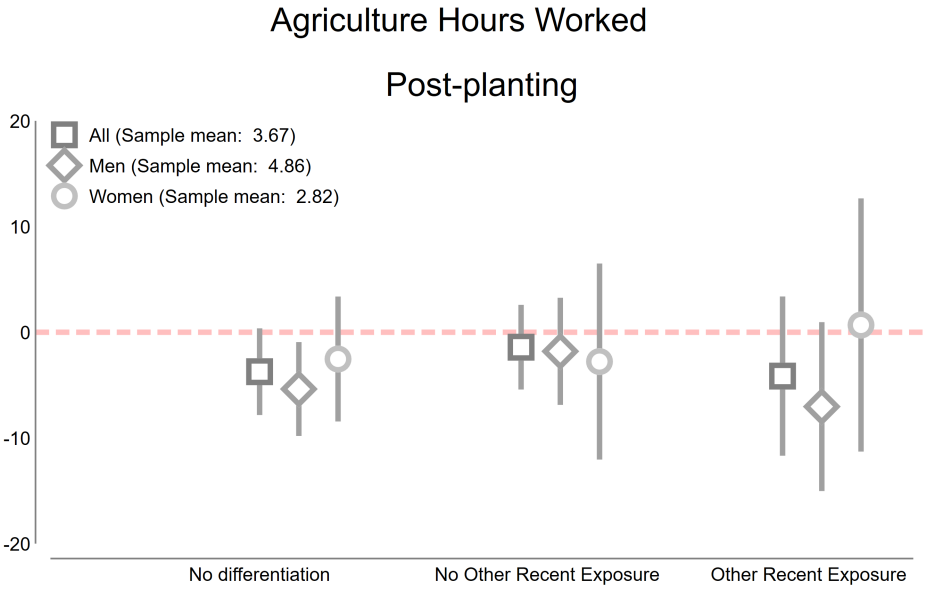
Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure A20: Exposure to Violence and Agricultural Work (30 km. window)

(a) Extensive Margin

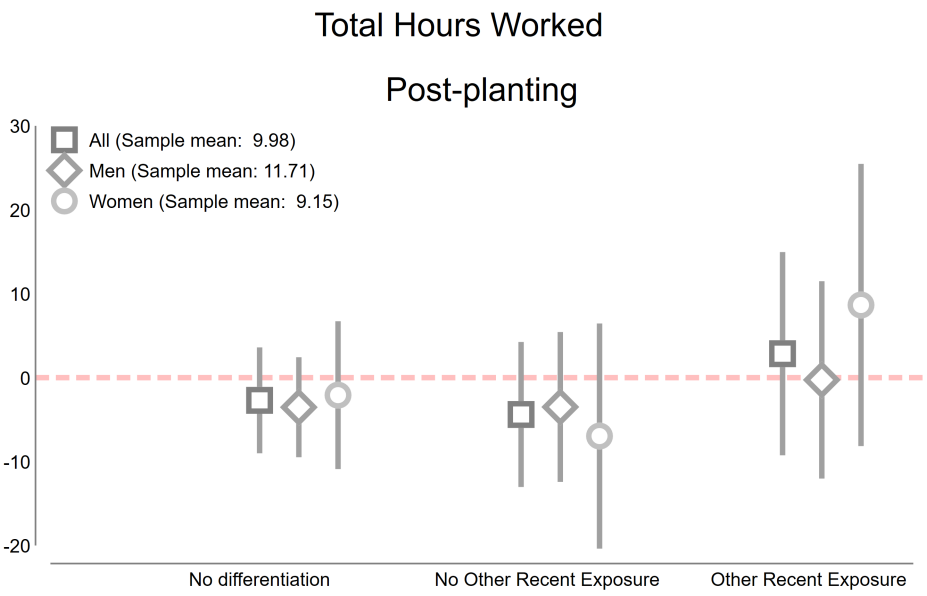


(b) Intensive Margin



Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. Panel A reports results on the extensive margin using a binary outcome variable. Panel B reports results on the intensive margin using a continuous outcome variable. The left panels show results in the post-planting season. The right panels show results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.

Figure A21: Exposure to Violence and Total Hours Worked (30 km. window)



Notes: This figure plots coefficient point estimates and associated 95% confidence intervals. The left panel shows results in the post-planting season. The right panel shows results in the post-harvest season. Three groupings are shown. "No differentiation" corresponds to the coefficient of the effect of exposure to herder-related violence without differentiating by previous exposure. "No other recent exposure" and "Other recent exposure" differentiate the effect of exposure to herder-related violence by whether the household had previously been exposed to violence. In all cases, we report results for the full sample, the sub-sample of men, and the sub-sample of women.