MYANMAR

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Conflict and agricultural productivity: Evidence from Myanmar

Livelihoods and Food Security Fund

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ABSTRACT

Evidence is scarce on how conflict affects technology adoption and consequent agricultural productivity in fragile states, an important topic given the high share of the extreme poor living in fragile environments globally. Our study contributes to filling this knowledge gap by using unique large-scale data on rice producers in Myanmar before and after a military coup in 2021, leading to a surge of conflicts in the country. We find that the increase in violent events significantly changed rice productivity. Specifically, increases in fatal violent events between 2020 and 2021 reduced rice Total Factor Productivity (TFP) – a measure of how efficiently agricultural inputs are used to produce rice – by about 4 percent on average in the short-run. Moreover, poorer farmers are more affected by conflict, as seen through an increased output elasticity to agricultural equipment owned, indicating reduced output resilience for less-capital owning, and therefore poorer, farmers. This seems partly due to reduced access to agricultural extension services, which would otherwise help farmers maintain productivity, even with limited capital ownership, through substitution with human capital and skills. Lower mechanization service fees partly mitigate these effects. Our results consistently hold for both short- and long-run production functions, across various specifications, and in Upper and Lower Myanmar. These findings suggest that containing and reducing violent events is critical in restoring rice productivity. Improved access to extension services, as well as to cheap mechanization service provision to mitigate lack of equipment ownership, could compensate for these losses and boost the productivity of farmers, especially for those with less production capital, in such fragile settings.

Keywords: conflict, production function, total factor productivity, inverse-probability weighted GMM, rice, Myanmar

1. BACKGROUND

The increasing and widespread adoption of improved technologies has been shown to be one of the key long-run drivers of agricultural output growth globally, including in the developing world (Hayami & Ruttan 1985; Evenson & Westphal 1995; Gollin et al. 2021). Many studies have examined how agricultural technologies change in response to various production factors (e.g., Mundlak 1988). An important strand of the literature has focused on technologies expressed in the form of production functions. It shows empirically how agricultural productivity is explicitly affected by, among others, changes in market prices (Fulginiti & Perrin 1993), type of inputs used (e.g., improved varieties (Rozelle et al. 2003), agricultural mechanization (Takeshima 2017; Takeshima et al. 2018)), ICTs (Lio & Liu 2006), human capital and health (Allen et al. 2014; Wouterse 2016, 2019), or agricultural policies (e.g., Gong 2018; Feng et al. 2021).

However, an important knowledge gap exists on how fragile environments – characterized by conflicts and violence - affect agricultural technology adoption and productivity. This is an important topic as most of the extreme poor globally reside in fragile environments (OECD 2020). As markets are often dysfunctional, these areas often rely on their own agricultural production to ensure survival and food security. However, given data on agriculture in fragile areas are scarce, there is a lack of understanding the role of agricultural technology adoption and consequent productivity in these settings. Filling this knowledge gap is vital because fragility, leading to disruptions in agri-food systems, is on the rise, particularly in countries with low income and weak governance (e.g., OECD 2020; Binswanger & Deininger 1997; Blattman & Miguel 2010; Leon 2014; OECD 2020).

This study aims to (partly) fill this gap by examining the case of rice in Myanmar during the period 2020 and 2021. Myanmar over this period is a suitable case because a military coup in February 2021 led to dramatic nationwide increases (by 10-fold on average in 2021, compared to 2020) in violent events such as battles, explosions, and violence against civilians, each with different levels of fatality. The intensity of these incidents has been heterogeneous across space, with relatively little inter-spatial correlations, providing significant temporal and spatial exogenous variations in the extent of violent events and shocks to agricultural production technologies. We capture production practices across farmers with varying exposures to violent events before and after the military coup, which we exploit to identify their effects on rice production, the country's most important staple.[1]

We do so by estimating farm household-level rice production functions, and their variations in response to the changes in the intensity of violent events, using nationally representative phone surveys panel data on farm households' rice production practices combined with monthly township-level data on violent events. We also apply recently developed methodologies in the impact-evaluation literature, i.e. the inverse-probability weighted generalized method of moments (IPW-GMM, that can mitigate potential endogeneity in both input variables in the production function and exposures to possible consequences of conflict. Our results indicate that increases in violent events lowered total factor productivity (TFP) in rice production and made the prevailing rice production technologies more dependent on their own agricultural capital. Rice production technologies have therefore changed in favor of farmers owning more agricultural capital but against farmers with less agricultural capital, often the poorest. We also find that lower mechanization service fees partly mitigate these effects.

The paper contributes to various strands of the international literature. Thematically, the study contributes to the endogenous productivity analysis (Mundlak 1988; Fulginiti & Perrin 1993; Lio &

[1] Phone surveys have been increasingly used with reasonable reliability for collecting nationally representative farm household data in developing countries, particularly since the onset of COVID-19 (e.g., Gourlay et al., 2021). Despite some shortcomings of phone surveys, specific evidence associated with social insecurity combined with the COVID-19 type pandemic in developing countries may often be available only through phone surveys because of considerable challenges in gathering data through in-person interviews under these conditions. Our study can offer the second-best critical evidence, otherwise unavailable.

Liu 2006; Allen et al. 2014; Wouterse 2016, 2019; Gong 2018; Feng et al. 2021) by providing additional evidence of how agricultural production technologies may be directly affected by conflict. The study also relates to the literature on the relationship between capital ownership and productivity (e.g., Takeshima et al. 2018; Qian et al. 2022) by showing how the changes in output elasticity of capital in production functions result from increased conflicts. Methodologically, the study contributes to the impact evaluation literature that combines IPW-GMM with the estimation of endogenous production functions (Takeshima 2017; Takeshima et al. 2018). While international conflict assessments have often focused on causes and consequences of violence (e.g., Collier 2003; Blattman & Miguel 2010), the studies that looked at the agro-food system have all almost exclusively looked at agricultural price effects (e.g., Bellemare 2015; Maystadt & Ecker 2014) and few have assessed agricultural productivity relations. Finally, the study adds to the literature on Myanmar by focusing on the effects of recent crises (e.g., Boughton et al. 2021; Goeb et al. 2022a, b; Headey et al. 2022; Takeshima et al. 2022) by offering additional evidence on their effects on agricultural production technologies.

This study is structured as follows. Section 2 presents background contexts linking rice production, agricultural extension services, and conflict. Section 3 describes the data. Section 4 discusses empirical methodologies. Section 5 discusses the results. Finally, section 6 concludes.

2. RICE PRODUCTION, AGRICULTURAL EXTENSION SERVICES, AND CONFLICT IN MYANMAR

Rice is one of Myanmar's most important staple crops, accounting for 51 and 62 percent of urban and rural calories consumed respectively (MAPSA 2022), and for approximately 1/3 and 1/2 of total agricultural and crop production in gross values respectively (FAO 2022). Rice production in Myanmar involves many smallholders, with average rice farm areas at 5.3 acres (about 2.1 hectares) (MAPSA 2022 Table 2). While the production is predominantly in the lowland, rice production is scattered across different ecologies, including Lower Myanmar (which corresponds to the Delta (Yangon, Bago, Ayeyarwady, Mon) and the Coastal zones (Rakhine, Tanintharyi)) and Upper Myanmar (which corresponds to the Central Dry zone (Mandalay, Magwe, Nay Pyi Taw, Sagaing) and the Hills and Mountains areas (Chin, Kachin, Kayah, Kayin, Shan)).

In both Upper and Lower Myanmar, major monsoon rice production typically occurs from June/July through October. A significant number of people are involved in rice production in Myanmar, as the agricultural sector employed 49 percent of the labor force in 2019, higher than in South Asia (42 percent) and East Asia & Pacific (27 percent) (World Bank 2022). A growing share of rice farmers own agricultural equipment, including about 1/3 for small tractors and ½ for water pumps (as described more in detail later) used for mechanization of land preparation, transportation, and water lifting (MAPSA 2022). Using their machines, especially tractors, supplements the custom-hiring services other tractor owners provide.

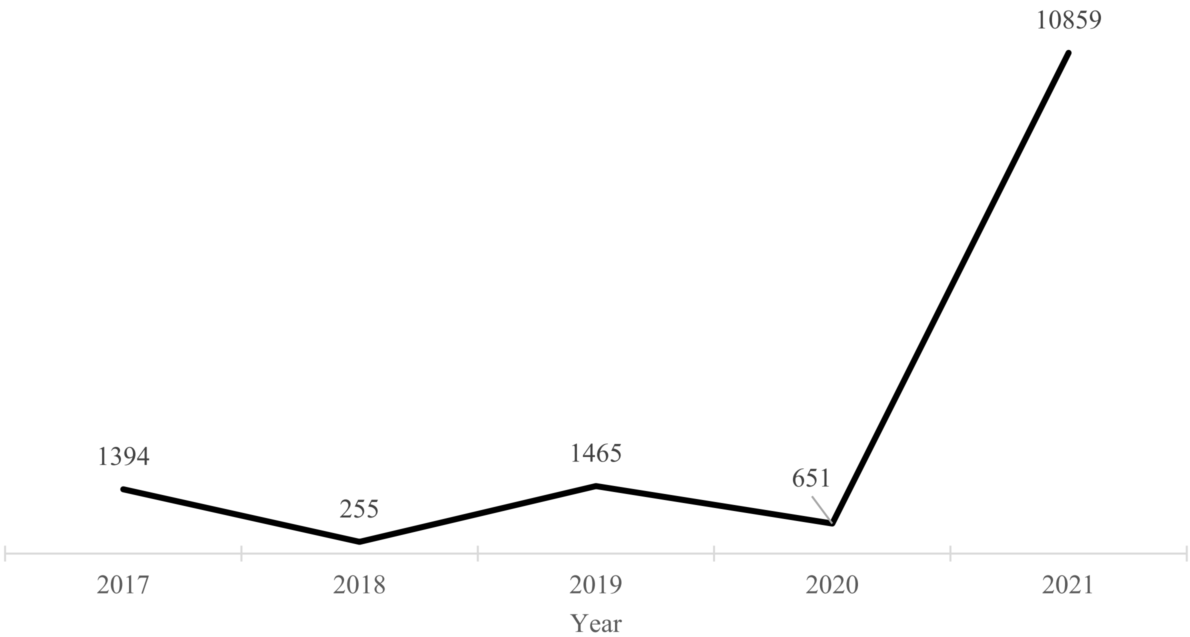
Rice production in Asia, including Myanmar, has remained knowledge-intensive, with productivity dependent on good husbandry practices by manual workers, irrigation application methods, planting techniques (transplanting or direct seeding), weeding and herbicide applications, pest management (Barker et al. 1985), and grain quality (Unnevehr 1986), among others. Consequently, knowledge transfer roles have remained significant in Asia's rice intensification process in recent decades especially (e.g., Fafchamps et al. 2021; Barrett et al. 2022). Given rapid transformation of the rice sector (Reardon et al. 2014) and the susceptibility of rice production to yearly biotic and abiotic shocks, which grow increasingly intensive due to climate change[2], frequent access to extension

[2] Myanmar is ranked 2nd among climate hazardous countries globally, according to the Global Climate Risk Index (Eckstein et al. 2021).

services (e.g., at least yearly) is also becoming increasingly important. In Myanmar, these extension services are provided by public sector extension agents, private sector ones like commercial trade companies and various associations related to rice production and export, NGOs (GFAS 2022), and mobile-phone-based apps (Thar et al. 2021). As described in the later section, about half of rice producers had access to extension services before the coup in 2020.

The rice sector, as well as the overall society in Myanmar, has been significantly affected by political instability since early 2021, including through increased incidences of violent events. According to the definitions by the ACLED, the number of reported incidences of violent events increased almost 10-fold in 2021 compared to the previous years (Figure 1). These violent events have been observed across the country in a spatially heterogeneous way (Figure 2).[3] MAPSA (2022) shows that, partly due to the increased political crisis, rice production at the national level dropped by 3.4 percent between 2020 and 2021. In addition to the overall production reduction, there is concern about the degradation of rice production technologies in Myanmar. As is indicated in subsequent sections, the share of rice producers receiving extension services in at least some forms declined by about 10 percentage points from 50 percent to 40 percent (an almost 20 percent decline) between 2020 and 2021, with a more significant reduction in areas with more violent events. The aforementioned rice production characteristics and trends in violence and extension access motivate our analyses of the potential changes in rice production functions in Myanmar.

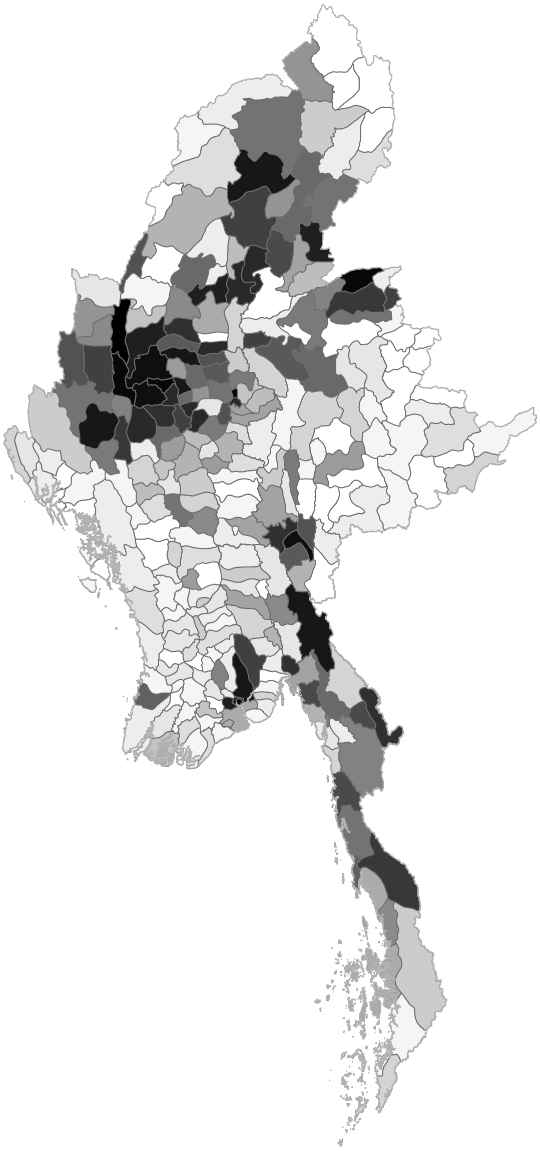
Figure 1. Number of fatal violent events in Myanmar, 2017 ~ 2021 (nationwide annual total)



Source: Authors based on ACLED (2022).
Note: Violent events include battles, explosions/remote violence, and violence against civilians (Raleigh et al. 2010).

[3] Spatial correlation coefficient (Moran's I) at township levels based on Figure 2 is around 0.3, indicating somewhat limited spatial correlations and rather significant spatial heterogeneity across townships.

Figure 2. Spatial distributions of incidences of violent events (annual total in 2021, by township)



Source: Authors based on ACLED (2022).

3. DATA

Our primary household data come from the Myanmar Agricultural Performance Survey (MAPS), a sub-sample of 12,100 households interviewed by phone during the first round of the Myanmar Household Welfare Survey (MHWS) fielded at the beginning of 2022. The MAPS focused on agricultural activities of 5,465 households identified as crop farmers in the MHWS. This survey was implemented by phone by Myanmar Survey Research (MSR) from February 11th until March 25th, 2022. Approximately 71 percent of the farmers (3,891) interviewed in the first round of the MHWS could be reached for a second follow-up interview.[4] Of the 3,891 crop farmers in the MHWS, 2,672 farmers (69 percent) cultivated rice in the 2021 monsoon. The analysis presented in this paper focuses on these rice farmers in particular. Among 2,672 rice-producing farm households, 2,348 reported all the information on production factors for both the 2021 and 2020 monsoon seasons (the

[4] Further details of the datasets are provided in MAPSA (2022).

latter based on recall), which is necessary for the analyses of production functions. We, therefore, focus on the data from these 2,348 rice-producing farm households in our analyses.

We supplement the aforementioned primary data with various spatial data on weather, agroclimatic conditions, COVID-19 incidence, and data on the incidence of conflict. Historical rainfall data are obtained from The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) (Funk et al. 2015). Historical monthly temperature data are obtained from NOAA (2022), soil data from FAO et al. (2012), and nighttime light data from Elvidge et al. (2021). COVID-19 cases by township are extracted from COVID Myanmar Dashboard 2022.[5] Lastly, the data on the total monthly figures of fatal violent events at township levels in 2020 and 2021 are extracted from The Armed Conflict Location & Event Data Project (ACLED) (Raleigh et al. 2010). Violent events include battles, explosions/remote violence, and violence against civilians.[6]

4. EMPIRICAL APPROACH

One of the common approaches in the literature on endogenous technology analysis is to express technologies in the form of production functions and examine the endogeneity of technologies by assessing how the shape of production functions changes in response to external shocks. The effects on the shape of the production function can be examined under both “short-run” and “long-run” conditions. Some argue that production functions sometimes might exhibit long-run technology relations (e.g., Basu 2008), in which case different estimation methods are employed, as described below.

4.1 Short-run production function

In the short-run, farmer fixed-effects are assumed to be unchanged. In such case, a standard fixed-effects panel data model can be estimated. Specifically, we estimate

$$\ln y_{it} = \alpha_0 + \alpha_s \cdot s_{it} + \beta_X \cdot \ln x_{it} + \beta_{XS} \cdot (\ln x_{it} \cdot s_{it}) + \gamma \cdot z_{it} + c_i + \varepsilon_{it} \quad (1)$$

where the rice production by a farmer i in year t (y_{it}) is expressed in a Cobb-Douglas function form, with a vector of the quantity of production factors x_{it} (capital (agricultural equipment), land, family labor (adult male, adult female, child), chemical fertilizer, irrigation, and other cash expenses) and coefficients β_X, controlling for the effects of other covariates z_{it} and farmer fixed effects c_i. The parameter β_X corresponds to the output elasticity with respect to each production factor. Changes in the intercept term in the log form of the Cobb-Douglas production function are often interpreted as changes in Hicks-Neutral productivity levels (Lio & Liu 2006; Lee et al. 2019) or changes in TFP (e.g., Gong 2018). In (1), the term ($\alpha_0 + \alpha_s \cdot s_{it} + c_i$) corresponds to the intercept, and changes in this term can be roughly interpreted as the change in TFP under reasonable assumptions. Coefficient α_s proxies the effects of s_{it} on TFP change. Notation ε_{it} represents idiosyncratic errors. Production function coefficients are allowed to vary as a linear function of the effects of external shocks s_{it} (number of violent incidents in the township), measured by β_{XS}. We use the statistical significance

[5] Available at https://datastudio.google.com/u/0/reporting/445c1281-c6ea-45e4-9bc0-5d561c511354/page/DoBKB. Accessed December 7, 2022.

[6] More detailed definitions of violent events are provided in https://acleddata.com/acleddatanew/wp-content/uploads/2021/11/ACLED_Codebook_v1_January-2021.pdf. Battles can include armed clashes, the government’s regaining territories, and non-state actors’ overtaking territories. Explosions/remote violence include chemical weapons, air/drone strikes, suicide bombs, shelling/artillery/missile attacks, remote explosives/landmines/IED (improvised explosive devices), and grenades. Violence against civilians includes sexual violence, attacks, and abduction/forced disappearances.

of β_{XS} as measures for variations in the level of shocks s_{it} in Myanmar between 2020 and 2021 significantly affecting rice production and underlying production technologies.[7]

Among inputs x_{it}, the agricultural capital variable is measured by the number of different types of agricultural equipment owned by the respondent household. Specifically, these consist of small tractors (two-wheel tractors or power tillers), four-wheel tractors, *trawlarjees* (a rudimentary motorized vehicle consisting of a tractor engine mounted onto a cart or trolley), and motorized water pumps for agriculture. Past studies (e.g., Mottaleb et al. 2016) use similar indicators in Bangladesh to characterize agricultural equipment ownership.[8] In the short-run model (1), production factors x_{it} can be assumed as exogenous once we control for time-invariant household fixed effects c_i. The long-run production function analyses described in the subsequent sections handle potential endogeneity more explicitly.

4.2 Long-run production function

In contrast to a short-run fixed-effects model (1), a long-run production function is better assessed through a cross-sectional specification because in the long-run, farm household fixed effects also change (Basu 2008; Gollin et al. 2016). In this framework, however, endogeneity from two sources, i.e., that of exposures to shocks S, as well as that of input variables X in the production function, poses bigger challenges for estimation than in (1).

The inverse probability weighting model (IPW) (Horvitz & Thompson 1952; Imbens & Wooldridge 2009) addresses the first type of endogeneity. Instrumental variable (IV) regressions, including Generalized method of moments (GMM) can be used to address the second type of endogeneity issues. IPW-methods have been used in the literature to estimate the effects on production function parameters or similar frameworks (Cavatassi et al., 2011), with extensions to IPW-GMM (Takeshima 2017). Under the assumption of conditional independence (ignorability), GMM estimation using self-selected samples is consistent when weighted by the inverse of the probability (Abowd et al., 2001; Nicoletti, 2006; Chen et al., 2008).

We therefore use IPW-GMM to estimate the long-run production function. Our IPW-GMM model proceeds as follows (modified from Takeshima 2017). We first estimate a Probit model,

$$\text{Probability}\left(R^* = 1 | \mathcal{Z}_{i,t=0}\right) = \hat{p} = \Phi(\mathcal{Z}\theta) = \int_{-\infty}^{\mathcal{Z}\theta} \phi(v)dv. \tag{2}$$

where $\mathcal{Z}_{it}$ is the set of exogenous variables, including time-variant variables z_{it} that appear in (1), and other time-invariant variables that are omitted in (1). $\hat{p}$ is the predicted propensity of farm households' exposures to shocks above certain thresholds, R^* is a binary variable indicating such exposure, and θ is a set of parameters to be estimated. Φ is the standard normal distribution function, while ϕ and v are the standard normal density function and its element.

We then estimate production functions separately for farmers with $R^* = 1$ and $R^* = 0$, using cross-section data at t = 1,

[7] The use of recall data to construct panel specifications has been increasingly common in the literature. For example, Takeshima & Yamauchi (2012) uses recall data of a one-year lag to assess the impact heterogeneity of development intervention in Nigeria. Recall data for periods shorter than 5 years may be reasonably reliable (Deaton 1995 p.1805). Even for agricultural data, recall data bias from relatively short lag may be minimal (Beegle et al. 2012). Some studies show that recall errors may be more significant on marginal plots (Gaddis et al. 2021). This is unlikely the case in our study as we focus on the largest rice plot, one of the farmer's primary plots. Furthermore, the quality of recall data may be enhanced for memorable events or periods (Deaton 1995). This may be the case for Myanmar during 2020 and 2021, both of which were characterized by unusual shocks of COVID-19 restrictions and enhanced social insecurity due to a political crisis.

[8] We also tried an alternative approach of using the first principal component of the number of each type of machine, as is sometimes done to characterize agricultural equipment ownership (e.g., Calderón et al., 2015; Hassan et al., 2017). We find that our main results still hold using this indicator.

$$\ln y_i = \alpha + \beta_X \cdot \ln x_i + \gamma \cdot \mathcal{Z}_i + \varepsilon_i. \tag{3}$$

In IPW-GMM, equation (3) for farmers with $R^* = 1$ is estimated by

$$\hat{\beta} = \arg\min_{\beta} \left[E\left(m/\sqrt{\hat{p}}\right)\right]' \widehat{W} \left[E\left(m/\sqrt{\hat{p}}\right)\right]' \tag{4}$$

and those for $R^* = 0$ is estimated by

$$\hat{\beta} = \arg\min_{\beta} \left[E\left(m/(\sqrt{1-\hat{p}})\right)\right]' \widehat{W} \left[E\left(m/(\sqrt{1-\hat{p}})\right)\right]' \tag{5}$$

where E is the expectation over samples and $\widehat{W}$ is the suitable weighting matrix estimated in GMM. Weights are the inverse of "square root" of $\hat{p}$. $m(\cdot)$ is the moment condition,

$$m = \mathbf{Z}'[\ln y_i - (\alpha + \beta_X \cdot \ln x_i + \gamma \cdot \mathcal{Z}_i)]. \tag{6}$$

where $\mathbf{Z}$ contain both $\mathcal{Z}_i$, as well as a set of excluded IVs, $\mathcal{Z}_i^*$, to instrument endogenous variables x_i.

Specifically, our excluded IVs ($\mathcal{Z}_i^*$) are lagged values of inputs ($X_{i,t-1}$) (where *t* = 2021). The broad strands of development literature have commonly used lagged endogenous variables as IVs for contemporaneous values of these variables in static models (Angrist & Krueger 2001; Bloom & Van Reenen 2006; Sharma et al. 2016; Jetter & Parmeter 2018). The approach is valid if they are strongly correlated with the contemporaneous values of these variables while being independent of the contemporary error terms (Sharma et al. 2016). IPW-GMM is "doubly-robust" (Robins & Rotnitzky 1995), meaning that the overall model is consistent as long as either the model of the propensity score $\hat{p}$ in (2), or the model of the production function (3) is consistent, even when the other model is misspecified (Takeshima 2017).

We then compare production function parameters, α and β_X's, between two types of farmers ($R^* = 1$ and $R^* = 0$). The statistically significant differences in α and β_X, respectively, between these groups are then interpreted as evidence that the shape of the production function changes in response to R^*. This is because weights applied to each sample based on IPW lead to matching samples, so that any differences in parameters from two samples can be attributed to the difference in R^*.

Since the estimation approaches (3) through (6) involve IPW based on estimated probability $\hat{p}$, standard errors are estimated through 100 bias-corrected paired bootstraps, as done in the previous studies (Efron & Tibshirani 1993; Barrett et al. 2008; Takeshima et al. 2018).

Production function form

Our analyses primarily use Cobb-Douglas production function forms for (1) and (3). The Cobb-Douglas specification provides reasonable estimates of production function parameters when samples are small, and the endogeneity of multiple x_i must be addressed, but it forces the elasticity of substitution between all factors to be one. The translog specification drops these restrictions but often complicates controlling for the endogeneity of multiple x_i, and the method leads to inefficient estimates if multicollinearity is severe. We, however, estimate translog production function forms as part of the robustness checks while treating all x_i as exogenous and show that our results based on Cobb-Douglas production functions are robust.

4.3 Control variables

Time-variant variables z_{it} in (1) include general biotic and abiotic shocks that affect rice production. Specifically, they include annual rainfall and average temperature, measured as z-value with respect to historical averages, and whether the respondent experienced major incidences of pest outbreak or destruction by wild animals. Variable z_{it} also includes the total annual COVID-19 case count in the township of respondent households.

The set of variables $\mathcal{Z}$ in (2) through (6) include the aforementioned time-variant variables z_{it}, as well as household demographics (age, gender, and education of primary farm decision maker of the household, the number of household members who are adult male, adult female, and children), the size of farm owned, household assets (the first principal component of asset items owned, similar to Filmer & Pritchett (2001)), and whether having a nonfarm income source. The variable $\mathcal{Z}$ also includes a night-time light luminosity index that captures the urbanization level in the respondent's township. The variable $\mathcal{Z}$ also includes agroecological variables of respondents' townships, including soil types (soil alkalinity, organic contents, textures, salinity, sodicity, drainage characteristics) and historical averages of annual rainfall and average temperature.

4.4 Robustness of the effects on TFP

As mentioned above, coefficient α_s in the short-run function (1) can measure the effects of violent events on TFP under the parametric specification of production technologies. We also estimate the same effects on TFP in a nonparametric specification to obtain robust insights. Specifically, we estimate the Malmquist index, which was initially developed by Malmquist (1953) and has been used as one of the popular TFP indicators in nonparametric settings in the literature (e.g., Alene 2010; Pastor et al. 2011), and assess how this indicator is associated with changes in violent events. Specifically, we estimate a Sequential, Biennial Malmquist index (Pastor et al. 2011), which can accurately measure TFP changes even when underlying technologies exhibit variable, non-constant returns-to-scale, and under the assumptions that technologies available in 2020 were also available in 2021 in Myanmar (see Alene 2010; Pastor et al. 2011 for more detailed discussions).[9]

Once the Malmquist TFP index is obtained, we revert back to parametric settings and estimate

$$\Delta\pi_{it} = \delta_0 + \delta_s \cdot \Delta s_{it} + \delta_z \cdot \Delta z_{it} + \varepsilon_i \quad (7)$$

where $\Delta\pi_{it}$ is the growth rate of the Malmquist TFP indicator for farmer i between 2020 and 2021, Δs_{it} and Δz_{it} are changes between 2020 and 2021 in the number of violent events and other time-variant exogenous factors for farmer i. Parameters δ's are estimated coefficients, while ε_i is an idiosyncratic error term that further affects $\Delta\pi_{it}$. The coefficient δ_s is then used to assess the effect of violent events on the Malmquist TFP indicator. Past studies use similar two-step approaches, whereby TFP indicators are estimated first and then regressed on potential factors of interest (e.g., Evenson & Pray 1991; Alene 2010).

[9] The index is estimated using the STATA command `malmq2`.

5. RESULTS

5.1 Descriptive statistics

Table 1 summarizes the descriptive statistics of rice production practices during the monsoon season, on the respondent's largest rice plots, in 2020 and 2021. Rice production is typically done on small plots of 1 acre, with outputs of about 1.3 tons at the median. Approximately 50 kg of fertilizer is used on the plot. On these largest plots, a median 156,750 Kyat of other expenses were made for seeds, agrochemicals and hired labor in 2020 (about USD 80), while the figure was higher at 200,000 Kyat in 2021 (about USD 100). Typically, about 2 family members worked in rice production. The household also typically owned 1 type of agricultural equipment, commonly water pumps, small tractors, and in some cases *trawlarjee* or four-wheel tractors. About 31-32 percent of these plots were irrigated.

Table 1: Rice production practices during the monsoon season on the respondent's largest rice plots in 2020 and 2021

Variables	Mean		Median	
Year	2020	2021	2020	2021
Rice outputs (tons)	1.588	1.573	1.254	1.254
Size of plots (acre)	1.288	1.289	1.000	1.000
Fertilizer used (kg)	85.300	72.728	51.000	50.000
Monetary expenditures on largest plot (1,000 Kyat)	238.043	260.155	156.750	200.000
Number of family labor regularly working on the farm	2.259	2.000	2.269	2.000
Agricultural capital ownership (yes = 1)				
Own small tractors (1 or 2 wheels, power tiller)	0.267	0.267	0.000	0.000
Own 4-wheel tractors	0.046	0.047	0.000	0.000
Trawlarjee	0.148	0.149	0.000	0.000
Motorized water pump for agriculture	0.428	0.435	0.000	0.000
Number of the type of machines owned (among 4)	1.177	1.197	1.000	1.000
Use irrigation (yes = 1)	0.320	0.313	0.000	0.000

Source: Authors.

Table 2 shows the typical extent of fatal violent events experienced and receiving agricultural extension services. Typically, the number of fatal violent events increased from 0.4 to 2.9 between 2020 and 2021 at sample medians (from about 1.5 to 16.7 at the means). During the monsoon season, the figures also increased from 0 to 1 at the median (from about 1.3 to 4.5 at the means). While almost 50 percent of the sample had access to agricultural extension services from any sources, the share dropped to 41.5 percent in 2021.

Table 2. Fatal violent events in the township and access to agricultural extension services

Variables	Mean		Median	
Year	2020	2021	2020	2021
Number of violent events in the township (12 months total)	1.516	16.701	0.368	2.943
Number of violent events in the township (monsoon season)	1.309	4.469	0.000	1.000
Had access to agricultural extension services (yes = 1)	0.499	0.415	0.000	0.000

Source: Authors.

Table 3 summarizes the descriptive statistics of baseline variables in 2020 used in the assessment of the long-run production function, differentiated by the level of exposure to violent events and extension service access in 2021. Most farm management decision-makers are male, with about half having completed education above standard 4. Most are smallholders, about half of them also have nonfarm incomes, and located about 0.7 hours from the nearest input market. About 15 percent of them experienced pests/disease challenges in 2021. Typically, they are in areas with average rainfall of 2,000 mm per year, and 26.7 degrees centigrade. They are also scattered across various states and regions. Importantly, those who experienced greater violent events or less extension services have statistically significant different characteristics than other types of farmers.

Table 3. Descriptive statistics in 2020

Variables	Farmers in townships below median level of violent events in 2021	Farmers in townships above median level of violent events in 2021	Farmers with access to extension in 2021	Farmers with no access to extension in 2021
Age	42.025	42.491	43.329	41.160***
Gender of primary farm decision maker (female = 1)	0.316	0.356	0.260	0.409***
Education (above standard 4 = 1)	0.589	0.588	0.659	0.514***
Household member – adult male	1.854	1.997	1.979	1.863**
Household member – adult female	1.949	2.114	2.011	2.040
Household member – children	1.003	1.051	0.950	1.100***
Farm size owned in ha (natural log)	0.718	0.665	0.841	0.546***
Asset (principal component)	–0.074	0.208	0.376	–0.258***
Nonfarm income (yes = 1)	0.559	0.555	0.578	0.537**
Nighttime light (index)	0.118	0.239	0.177	0.173
Distance to input market (hours)	0.742	0.694	0.660	0.779***
COVID case (annual total, per 1,000 population in the township)	0.928	0.865*	0.904	0.893
Mechanization service fees (four-wheel tractors, 1,000 MMK / acre)	28.113	26.644***	26.644	28.205***
Soil properties				
Soil alkalinity (pH)	5.863	5.754	5.835	5.788*
Organic contents (g / kg of soil)	2.135	1.541***	1.797	1.917**
Soil texture (% fine)	0.292	0.292	0.290	0.294
Salinity (deciSiemens per meter)	0.410	0.521***	0.504	0.420*
Sodicity (% of soil)	4.131	2.352***	3.005	3.591***
Poor drainage (%)	0.537	0.395***	0.463	0.478
Pests or disease (yes = 1)	0.149	0.145	0.156	0.137***
Animal damage (yes = 1)	0.031	0.026	0.025	0.032
Historical average rainfall (mm)	2233.569	1874.585***	1996.366	2133.808**
Historical average temperature (℃)	26.657	26.618*	26.769	26.508*
Rainfall anomaly (absolute value of z-statistics with respect to historical distribution)	0.952	1.282***	1.153	1.060***
Temperature anomaly	0.498	0.827***	0.662	0.642
State (Kachin)	0.009	0.058***	0.027	0.036**
State (Kayah)	0.001	0.020***	0.011	0.009
State (Kayin)	0.012	0.055***	0.031	0.033
State (Chin)	0.000	0.006**	0.004	0.002
State (Sagaing)	0.041	0.330***	0.182	0.171
State (Tanintharyi)	0.000	0.037**	0.017	0.018
State (Bago)	0.202	0.089***	0.172	0.126***
State (Magway)	0.101	0.062*	0.115	0.051***
State (Mandalay)	0.078	0.096	0.079	0.094
State (Mon)	0.020	0.035*	0.029	0.025
State (Rakhine)	0.095	0.000*	0.044	0.057
State (Yangon)	0.036	0.062**	0.045	0.051
State (Shan)	0.141	0.101*	0.103	0.142**
State (Ayeyawady)	0.241	0.023***	0.111	0.168***
State (Nay Pyi Taw)	0.024	0.025	0.033	0.017

Source: Authors. Asterisks indicate the statistically significant differences from farmers with access to extension (*** 1% ** 5% * 10%).

5.2 Associations of violent events and access to extension services with rice productivity

Short-run production function

Table 4 summarizes the estimated short-run production function parameters from (1), where the output elasticity with respect to each factor is allowed to vary depending on the levels of violent events or access to extension services. Importantly, for all of Myanmar (columns (a) and (b)), a greater intensity of violent events, or the lack of access to extension services, is associated with lower estimated values of intercepts, which are proxies of overall productivity, as indicated by significantly negative coefficients of –0.029 and –0.030 in columns (a) and (b), respectively. These coefficients suggest that one standard deviation increase in fatal violent events, or the lack of access to extension services, is associated with 2.9 percent and 3.0 percent lower overall productivity. At sample averages, the results translate into a 3.5 percent reduction in TFP between 2020 and 2021 due to the increased violence. The degree of TFP reduction of 3.5 percent is sizable in Myanmar where agricultural-sector TFP growth has been fairly modest in recent years. Available estimates of recent annual TFP growth rates range from 0.5 percent / year between 2001-15 (IFPRI 2019), 0.13 percent / year between 2002-2016) (Liu et al. 2020), and almost 0 percent / year between 2008 – 2020 (USDA 2022).

Table 4. Short-run production function estimations

Variables	(a)	(b)	(c)	(d)	(e)	(f)
Regions	All Myanmar	All Myanmar	Lower Myanmar	Lower Myanmar	Upper Myanmar	Upper Myanmar
Type of shocks	Violent events	No Extension	Violent events	No Extension	Violent events	No Extension
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.014 (0.027)	–0.010 (0.029)	0.009 (0.024)	0.004 (0.036)	0.026 (0.021)	0.035 (0.051)
Capital × Shocks	0.008* (0.004)	0.038* (0.020)	0.011*** (0.003)	0.053*** (0.016)	0.006* (0.003)	0.022 (0.034)
Land	0.488*** (0.036)	0.479*** (0.042)	0.592*** (0.085)	0.578*** (0.124)	0.473*** (0.065)	0.432*** (0.042)
Land × Shocks	–0.002 (0.007)	0.006 (0.030)	–0.009 (0.009)	–0.023 (0.033)	–0.003 (0.007)	0.002 (0.051)
Labor	–0.033 (0.027)	–0.058 (0.042)	0.003 (0.028)	–0.001 (0.039)	–0.059 (0.045)	–0.024 (0.054)
Labor × Shocks	–0.001 (0.005)	0.035 (0.022)	–0.005 (0.005)	0.024 (0.018)	0.000 (0.003)	0.001 (0.040)
Fertilizer	0.039*** (0.012)	0.057*** (0.017)	0.057*** (0.013)	0.059*** (0.017)	0.041*** (0.014)	0.065** (0.032)
Fertilizer × Shocks	–0.007 (0.006)	–0.032* (0.018)	–0.005 (0.007)	–0.011 (0.014)	–0.009 (0.008)	–0.005 (0.031)
Irrigation	0.005 (0.017)	0.013 (0.021)	–0.004 (0.010)	–0.006 (0.018)	0.011 (0.017)	–0.044 (0.041)
Irrigation × Shocks	–0.002 (0.005)	–0.008 (0.018)	0.005 (0.007)	–0.009 (0.012)	–0.002 (0.006)	0.049 (0.034)
Other expenses	0.037* (0.020)	0.022 (0.021)	0.017 (0.027)	0.026 (0.039)	0.034* (0.021)	0.036 (0.049)
Other expenses × Shocks	0.003 (0.007)	0.020 (0.026)	0.011 (0.008)	0.016 (0.024)	0.002 (0.008)	0.039 (0.046)
Intercept	7.040*** (0.013)	7.046*** (0.018)	7.169*** (0.012)	7.167*** (0.020)	6.948*** (0.010)	6.937*** (0.027)
Intercept × Shocks	–0.029** (0.015)	–0.030* (0.017)	–0.011 (0.010)	–0.029** (0.014)	–0.010* (0.006)	–0.027 (0.028)
Farmer fixed effects	Included	Included	Included	Included	Included	Included
Other controls	Included	Included	Included	Included	Included	Included
Sample	4,696	4,696	2,118	2,118	2.578	2.578
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

Furthermore, a one standard deviation increase in violent events, or the lack of access to extension services, is associated with 0.008 and 0.038 greater output elasticity, respectively, with respect to agricultural capital. To the extent that production technologies affect the welfare of producers, such increase in output elasticity with respect to agricultural capital owned can lead to significant reallocation of wealth from farmers with less capital to farmers with more capital. These technical changes may also occur during standard agricultural transformation processes in which declining capital price relative to labor price induces capital-biased technological changes (e.g., Binswanger & Ruttan 1978). However, the difference in our case is that a significant reduction in overall TFP is also involved, which is less likely under standard agricultural transformation processes.

Appendix Table 15 further provides insights into which sources of extension services may drive the aforementioned effects, obtained by re-running (1) by specifying access to different types of extension services (public sector, private sector, NGOs, cellphone apps). Results indicate that not accessing extension services from the public sector has the most significant effects compared to other sources. These may be because public sector extension services are often provided at subsidized costs, and not receiving it can be a significant net loss, while extension services from the private sector, NGOs, or mobile apps may be often received with greater costs and not receiving extension services from them can be somewhat offset by saving in payments to extension services.

The patterns of reduced overall productivity, and higher output elasticity of agricultural capital, are also relatively robust in each of Lower Myanmar and Upper Myanmar, as shown in columns (c) through (f). These results suggest that the observed patterns of changes in short-run production functions hold in diverse rice ecologies in Myanmar. However, they are most robust and significant in Lower Myanmar, the site of most of Myanmar's rice production.

Other estimated coefficients are relatively reasonable. Production elasticity is approximately 0.5 for land, 0.05 for fertilizer, and somewhat minor and insignificant for other factors. While the output elasticity of labor is slightly low and close to zero, similar results are observed with surplus labor in rural areas including, for example, in China in the earlier days of agricultural transformation (e.g., Wan & Cheng 2001; Fleisher & Liu 1992 p119).

Long-run production function

Table 5 through Table 7 summarize the estimated long-run production function (2) through (6), as well as the statistical significance of their differences between farmers with $R^* = 1$ and farmers with $R^* = 0$, based on the primary specification for various shock factors for which R^* is constructed. The correlates of R^* from the first stage probit regression (2) are of secondary importance and thus presented in the Appendix.

Table 5 suggests that primary results are consistent with the short-run production functions in Table 4; farmers in townships with greater intensity of violent incidents in 2021 experienced significantly lower overall productivity of rice production (as reflected in estimated values of intercepts which proxy TFP in Cobb-Douglas production function). Similarly, farmers in these townships experienced higher production elasticity of agricultural capital compared to those in townships with a lower incidence of violence. As was described in the methodology section above, these differences are solely attributable to the violent events, given that these production functions are estimated using IPW-samples.

It is important to note that our focus in long-run production function results is the signs rather than the magnitudes of statistically significant coefficients. For example, results in Table 5 show that the estimated difference in intercept is -1.909. This can be interpreted as the reduction of TFP by a ratio of 2.9 (= 1.909 + 1), roughly equivalent to the differences in TFP in China between 1960 and 2020 (USDA 2022). In other words, if the current violence continues at this rate for a very long time, it will eventually amount to a reduction in TFP in a similar magnitude than the counterfactual of fewer violent events.

Table 5. Long-run estimates of Cobb-Douglas production functions (differentiated by the median of violent events)

Variables	(a)	(b)	(c) = (b) – (a)
Samples	Less violent events (below median)	More violent events (above median)	Statistical significance of differences
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.047 (0.079)	0.349*** (0.046)	0.302*** (0.078)
Land	0.687*** (0.070)	0.647*** (0.065)	–0.040 (0.089)
Labor	0.058 (0.049)	0.123*** (0.026)	0.066 (0.053)
Fertilizer	–0.011 (0.029)	0.101*** (0.019)	0.113*** (0.037)
Irrigation	0.192** (0.079)	0.124** (0.061)	–0.068 (0.107)
Other expenses	0.086 (0.062)	0.167*** (0.062)	0.080 (0.088)
Intercept	4.698*** (0.915)	2.789*** (0.831)	-1.909* (1.119)
Other controls	Included	Included	Included
Sample size	1110	1238	
P-value			
H_0: no endogeneity	.123	.007	
H_0: underidentified	.000	.000	
H_0: jointly insignificant	.000	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

Similar to the short-run production results in Table 4, we further assess if the reduced access to extension services serves as a potential pathway for the observed effects in Table 5. Table 6 shows the determinants of the extension service access, including the intensity of violent events in the township. Table 6 shows that a one standard deviation increase in violent events in the township led to a 2.6 percent lower likelihood of having visits by agricultural extension staff.

Table 6. Effect of violence on the likelihood of having access to some forms of extension services (marginal effects of one-standard deviation change evaluated at sample means)

Variables	Coef.	(Std.err)
Violent events	–0.026**	(0.013)
Age	0.029***	(0.011)
Gender (female = 1)	–0.053***	(0.011)
Education (above standard 4 = 1)	0.118***	(0.022)
Household member – adult male	0.004	(0.010)
Household member – adult female	–0.010	(0.010)
Household member – children	–0.012	(0.009)
Farm size owned in ha (natural log)	0.010	(0.007)
Asset (principal component)	0.042***	(0.007)
Nonfarm income (yes = 1)	0.013	(0.021)
Nighttime light (index)	–0.025	(0.021)
Distance to input market (hours)	–0.034**	(0.013)
Mechanization service fees	–0.003	(0.013)
Soil alkalinity (pH)	–0.010	(0.031)
Organic contents (g / kg of soil)	–0.029***	(0.010)
Soil texture (% fine)	–0.186	(0.126)
Salinity (deciSiemens per metre)	0.081***	(0.030)
Sodicity (% of soil)	–0.008***	(0.003)
Poor drainage (%)	0.053	(0.045)
Pests or disease (yes = 1)	0.095***	(0.028)
Animal damage (yes = 1)	0.033	(0.062)
Rainfall	0.010	(0.021)
Temperature	0.006	(0.027)
Incidence of COVID	0.344	(0.708)
State dummy	Included	
Sample size	2,348	
P-value (H_o: variables jointly insignificant)	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

Table 7 shows similar results as Table 5, but with samples differentiated by whether or not having access to extension services instead. The results suggest that losing access to agricultural extension services was associated with significantly lower overall productivity and significantly higher elasticity of agricultural capital. While results for other production factors, such as fertilizer or labor, are also statistically significant, they are not consistent with the results in Table 5.

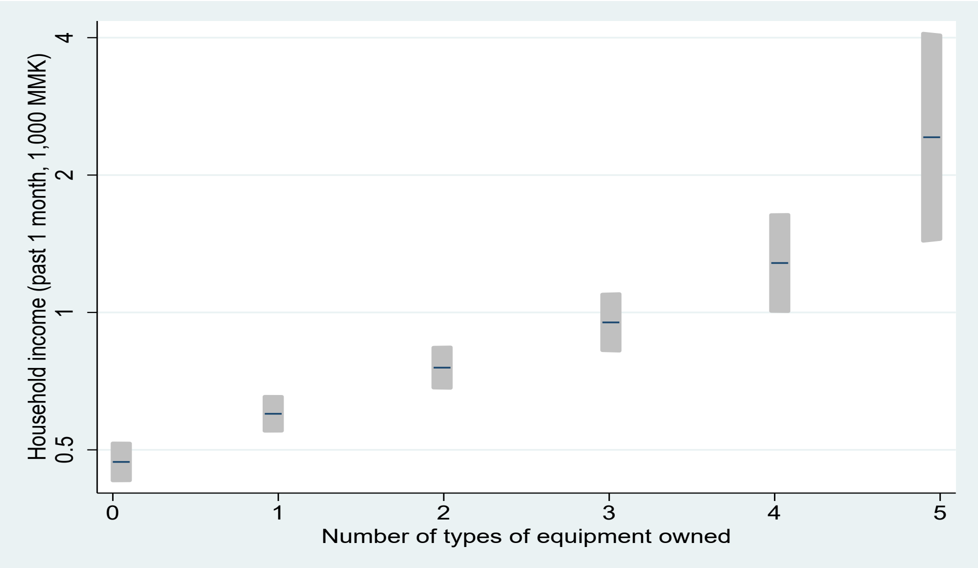
Table 7. Long-run estimates of Cobb-Douglas production functions (differentiated by extension access)

Variables	(a)	(b)	(c) = (b) – (a)
Samples	Having extension access	No extension access	Statistical significance of differences
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	–0.024 (0.059)	0.145*** (0.046)	0.169** (0.074)
Land	0.823*** (0.102)	0.722*** (0.056)	–0.102 (0.124)
Labor	0.037 (0.037)	0.011 (0.031)	–0.026 (0.050)
Fertilizer	0.076*** (0.022)	0.032* (0.018)	–0.045* (0.025)
Irrigation	0.107 (0.081)	0.101** (0.045)	–0.005 (0.097)
Other expenses	–0.005 (0.087)	0.199*** (0.055)	0.204** (0.101)
Intercept	4.989*** (1.116)	2.742*** (0.887)	-2.247* (1.364)
Other controls	Included	Included	Included
Sample size	990	1358	
P-value			
H_0: underidentified	.000	.000	
H_0: jointly insignificant	.000	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%.

Results Table 4 through Table 7 collectively suggest that increases in violent events led to significant changes in the rice production function, reduced TFP, and increased elasticity of agricultural capital. These changes were likely catalyzed through reduced access to agricultural extension, among others. This might have been causes by reduced access to agricultural extension affecting farmers' overall knowledge and thus reduced overall productivity while making the production more dependent on own agricultural capital, like equipment in which significant knowledge is already embedded (e.g., Douthwaite et al. 2001) and its use may be less knowledge-intensive. These patterns also imply that farmers with limited ownership of agricultural equipment particularly suffer through the deterioration of production technologies resulting from increased violence and lost access to extension services. These findings suggest potentially regressive effects of an increase in violent events because owning fewer types of agricultural equipment is associated with lower household incomes (Figure 3).

Figure 3. Relation between agricultural equipment ownership and average household income



Source: Authors.
Note: Shaded bars are confidence intervals based on log-scale of average incomes (1,000,000 MMK ≈ USD 500). Household incomes include incomes from household members' economic activities, as well as remittances received and other unearned incomes like rental incomes and pensions.

Partial mitigation by access to mechanization services

The observed effects on output elasticity of owned equipment raise a question as to how access to mechanization hiring services can partly substitute for the lack of own agricultural equipment, given the significant growth of such hiring services in Myanmar and other developing countries (Diao et al. 2020; Belton et al. 2021). One possible way to gain insights into this question is to assess how the effects on output elasticity of owned equipment vary depending on the changes in mechanization fees between 2020 and 2021. This can be done by re-estimating production functions by adding another interaction term $\ln x_{it} \cdot s_{it} \cdot \theta_{it}$ in the short-run production function (1) and $\ln x_i \cdot \theta_{it}$ in the long-run production function (3), with θ_{it} indicating the per-acre hiring fees of four-wheel tractors, computed as sample median at township levels.[10]

Table 16 through Table 18 show the short-run and long-run production function results. In Table 16, the coefficient for capital interacted with violent events and mechanization fees is statistically significantly positive in Lower Myanmar (0.089), and that for capital interacted with extension and mechanization fees is statistically significantly positive for the whole of Myanmar (0.016). In the short-run, higher mechanization service fees are associated with further (albeit insignificant) reduction in TFP. These effects are more pronounced in Lower Myanmar, where mechanization is more prevalent. These results imply that increases in output elasticity of equipment owned are mitigated (magnified) by lower (higher) mechanization fees for hiring four-wheel tractors. These results are consistent with the hypothesis that having access to more affordable mechanization services can mitigate the increased dependence on equipment ownership for rice production under increases in violent events.

Similarly, in Table 17 and Table 18, rows for "Capital × Mechanization fee" suggest that the effects of mechanization fees are significantly more positive where there are more violent events and/or farmers do not access extension services, as indicated by the right-most column. These

[10] In theory, terms $\ln x_{it} \cdot \theta_{it}$ should also enter short-run production function (1). We, however, dropped these terms in (1) to avoid excessive multicollinearity problems. When included, no coefficient for these terms is significant, so excluding them does not bias the results.

results are again consistent with the hypothesis that lower mechanization fees partly mitigate the effects of violent events or lack of extension access on increased dependency on owned equipment.

5.3 Robustness checks

We check the robustness of our main findings. First, Table 8 shows the estimates based on the translog production function form instead of a Cobb-Douglas function form. As mentioned in section 2, estimates of the output elasticity of each production factor are computed at sample medians. The results are generally consistent with our main results; the greater intensity of violent events is associated with a statistically significant decrease in the estimated intercept (an indication of reduced overall productivity) and a greater elasticity of agricultural capital. Similarly, the lack of access to extension services is associated with a greater elasticity of agricultural capital and reduced intercept (albeit with lower statistical significance). These results suggest that our main results hold under flexible production function forms and are unlikely the artifact of Cobb-Douglas production function forms.

Table 8. Robustness check for Table 5 based on IPW-translog production function form (elasticity evaluated at sample medians)

Variables	(a)	(b)	(c)	(d)	(e)	(f)
Shocks	Violent events			No extension access		
Samples	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (b) – (a))	Having extension access	No extension access	Statistical significance of differences (= (e) – (d))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.096*** (0.033)	0.203*** (0.049)	0.107* (0.065)	0.009 (0.055)	0.125*** (0.043)	0.115* (0.069)
Land	0.651*** (0.069)	0.789*** (0.101)	0.138 (0.135)	0.708*** (0.111)	0.720*** (0.091)	0.012 (0.140)
Labor	–0.087 (0.083)	–0.129 (0.109)	–0.041 (0.139)	–0.049 (0.122)	–0.052 (0.092)	–0.003 (0.150)
Fertilizer	0.326*** (0.101)	0.493*** (0.188)	0.167 (0.228)	0.286* (0.150)	0.209* (0.108)	–0.078 (0.181)
Irrigation	0.197** (0.080)	0.011 (0.139)	–0.186 (0.162)	0.074 (0.115)	0.224*** (0.090)	0.150 (0.140)
Other expenses	0.122*** (0.028)	0.119** (0.048)	–0.003 (0.051)	0.093 (0.067)	0.130*** (0.044)	0.037 (0.076)
Intercept	4.830*** (0.506)	2.704** (1.005)	-2.126* (1.125)	4.892*** (0.928)	3.486*** (0.761)	-1.407 (1.200)
Other controls	Included	Included	Included	Included	Included	Included
Sample size	1110	1238		990	1358	
P-value						
H_0: underidentified	.000	.000		.000	.000	
H_0: jointly insignificant	.000	.000		.000	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%.

Second, our main results are also robust against different thresholds and timing of violent events measured. Table 9 replicates the IPW-GMM result in Table 5, but using 33 and 67 percentiles of the intensity of violent events to split the samples, instead of a 50 percentile done in Table 5. The main results still hold; regardless of the thresholds used, coefficients for capital are statistically significantly greater among samples facing more violent events. At the same time, intercepts are not statistically significantly different, suggesting that differences in factor coefficients are more dominant components of technology changes, as in Table 5.

Table 9. Robustness checks for Table 5 using different thresholds

Variables	(a)	(b)	(c)	(d)	(e)	(f)
Thresholds	Sample split by 33 percentiles of the number of violent events			Sample split by 67 percentiles of the number of violent events		
Samples	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (b) – (a))	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (e) – (d))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	–0.005 (0.057)	0.130*** (0.042)	0.135** (0.068)	0.067 (0.046)	0.164*** (0.057)	0.097* (0.051)
Land	0.743*** (0.070)	0.772*** (0.050)	0.030 (0.087)	0.740*** (0.043)	0.745*** (0.080)	0.005 (0.089)
Labor	–0.018 (0.046)	0.037 (0.025)	0.055 (0.050)	0.016 (0.027)	0.013 (0.033)	–0.003 (0.044)
Fertilizer	0.005 (0.028)	0.046*** (0.015)	0.042 (0.033)	0.035** (0.016)	0.080*** (0.027)	0.044 (0.032)
Irrigation	0.033 (0.062)	0.116* (0.060)	0.083 (0.093)	0.118*** (0.045)	0.177** (0.075)	0.059 (0.089)
Other expenses	0.193** (0.076)	0.110** (0.051)	–0.084 (0.088)	0.113*** (0.041)	0.187*** (0.060)	0.074 (0.070)
Intercept	3.237*** (1.313)	4.183*** (0.865)	0.946 (1.511)	4.572** (0.723)	1.689 (1.267)	-2.883** (1.465)
Other controls	Included	Included	Included	Included	Included	Included
Sample size	989	1359		1602	746	
P-value						
H_0: underidentified	.000	.000		.000	.000	
H_0: jointly insignificant	.000	.000		.000	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%.

We also checked whether the results differ if we focus on the violent events during the monsoon production season (i.e., July through October for Upper Myanmar and June through October for the rest of the country) instead of all year round (Table 10). The results are again consistent with Table 5 that coefficients for capital are statistically significantly greater among the sample facing more violent events.

Table 10. Robustness checks for Table 5 focusing on violent events in monsoon rice production months

Variables	(a)	(b)	(c)
Samples	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (b) – (a))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	–0.024 (0.061)	0.124*** (0.047)	0.148* (0.083)
Land	0.741*** (0.070)	0.646*** (0.061)	–0.095 (0.098)
Labor	0.005 (0.031)	0.010 (0.029)	0.005 (0.044)
Fertilizer	0.003 (0.020)	0.040* (0.023)	0.036 (0.031)
Irrigation	0.120 (0.087)	–0.006 (0.068)	–0.126 (0.123)
Other expenses	0.160** (0.072)	0.236*** (0.055)	0.076 (0.098)
Intercept	2.801** (1.298)	1.984* (1.035)	–0.817 (1.623)
Other controls	Included	Included	Included
Sample size	1138	1210	
P-value			
H_0: underidentified	.000	.000	
H_0: jointly insignificant	.000	.000	

Source: Authors. *** 1% ** 5% * 10%

Our main results are also generally robust in both Lower and Upper Myanmar. Table 11 shows the IPW-GMM results in Table 5 separately for the Lower Myanmar the Upper Myanmar region. In both regions, the coefficients for capital are statistically significantly greater in regions that experienced more violent events in 2021.

Table 11. Robustness checks for Table 6 differentiated by Lower and Upper Myanmar

Variables	(a)	(b)	(c)	(d)	(e)	(f)
Regions	Lower Myanmar			Upper Myanmar		
Samples	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (b) – (a))	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (e) – (d))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.037 (0.056)	0.532*** (0.077)	0.495*** (0.098)	0.024 (0.052)	0.263*** (0.095)	0.238** (0.103)
Land	0.763*** (0.079)	0.438*** (0.168)	–0.325 (0.179)	0.600*** (0.078)	0.873*** (0.115)	0.273** (0.135)
Labor	0.021 (0.037)	0.364*** (0.055)	0.343*** (0.065)	0.052 (0.043)	–0.031 (0.052)	–0.083 (0.061)
Fertilizer	0.065** (0.029)	0.058 (0.039)	–0.008 (0.052)	0.031 (0.019)	0.063** (0.039)	0.031 (0.045)
Irrigation	0.001 (0.078)	0.280** (0.123)	0.246 (0.155)	0.117 (0.075)	–0.046 (0.110)	–0.162 (0.137)
Other expenses	0.065 (0.081)	0.288* (0.152)	0.223 (0.177)	0.214*** (0.062)	0.062 (0.096)	–0.153 (0.121)
Intercept	7.690*** (1.501)	4.595 (4.050)	-3.095 (4.506)	3.131*** (1.077)	0.437 (2.369)	-2.694 (2.525)
Other controls	Included	Included	Included	Included	Included	Included
Sample size	545	514		656	633	
P-value						
H_0: underidentified	.000	.000		.000	.000	
H_0: jointly insignificant	.000	.000		.000	.000	

Source: Authors. *** 1% ** 5% * 10%

Similarly, Table 12 shows the IPW-GMM results in Table 7 separately for the Lower Myanmar and the Upper Myanmar cropping systems. Here, the statistical significance of the difference is somewhat weak, possibly due to the smaller sample size. However, a qualitatively similar difference is still observed. Coefficients for capital are statistically significant for the sample with no extension access (0.107 in Lower Myanmar) and (0.167 in Upper Myanmar). In contrast, these coefficients for the sample with extension access are statistically insignificant (0.047 and 0.031, respectively). These findings are consistent with the hypothesis that the observed effects of extension access (Table 7) generally hold in both Lower Myanmar and Upper Myanmar cropping systems.

Table 12. Robustness checks of Table 7 differentiated by Lower and Upper Myanmar

Variables	(a)	(b)	(c)	(d)	(e)	(f)
Regions	Lower Myanmar			Upper Myanmar		
Samples	Having extension access	No extension access	Statistical significance of differences (= (b) – (a))	Having extension access	No extension access	Statistical significance of differences (= (e) – (d))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.022 (0.051)	0.100* (0.053)	0.078 (0.076)	–0.002 (0.080)	0.185* (0.102)	0.186* (0.110)
Land	0.715*** (0.053)	0.750*** (0.074)	0.035 (0.086)	0.752*** (0.122)	0.723*** (0.112)	–0.029 (0.185)
Labor	–0.004 (0.041)	0.041 (0.035)	0.045 (0.053)	0.031 (0.049)	–0.005 (0.057)	–0.036 (0.083)
Fertilizer	0.032 (0.033)	0.055** (0.026)	0.023 (0.041)	0.034 (0.038)	–0.007 (0.034)	–0.041 (0.053)
Irrigation	0.048 (0.082)	0.058 (0.064)	0.015 (0.108)	0.090 (0.091)	0.137 (0.102)	0.047 (0.148)
Other expenses	0.113 (0.076)	0.110 (0.086)	–0.003 (0.111)	0.206** (0.097)	0.220*** (0.085)	0.014 (0.137)
Intercept	6.939*** (1.592)	6.430*** (1.747)	–0.509 (2.185)	3.026* (1.737)	2.042 (1.550)	–0.984 (2.403)
Other controls	Included	Included	Included	Included	Included	Included
Sample size	526	533		669	627	
P-value						
H_0: underidentified	.000	.000		.000	.000	
H_0: jointly insignificant	.000	.000		.000	.000	

Source: Authors. *** 1% ** 5% * 10%

Table 13 shows the magnitude of various factors associated with the change in Malmquist TFP indicators, estimated through regression (7). One standard deviation increase in the number of violent events is associated with a 1.5 percentage point lower growth rate of the Malmquist TFP indicator. Based on the average changes in the number of violent events in the sample between 2020 and 2021, the results translate into approximately a 3.6 percent lower TFP due to the increases in violent events in Myanmar between 2020 and 2021. The estimated magnitude is quite similar to the estimate of 3.5 percent based on the short-run production function mentioned above (Table 4).

Coefficients for other variables suggest that the Malmquist TFP indicator is negatively affected by more extraordinary temperature anomalies, pests or disease incidence, as expected. The estimated constant term indicates that, in the absence of all these shocks (including violent events), Malmquist TFP would have increased by 1.9 percent on average between 2020 and 2021 in Myanmar.

Table 13. Correlates of Malmquist TFP growth rates (effects of one-standard deviation changes)

Variables	Coef. (std.err)
Violent events	–0.015* (0.008)
COVID case	0.009 (0.008)
Rainfall anomalies	0.010 (0.008)
Temperature anomalies	–0.020** (0.008)
Pests or disease (yes = 1)	–0.031*** (0.007)
Animal damage (yes = 1)	–0.001 (0.007)
Intercept	0.019*** (0.007)
Sample size	2,348
p-value (H_0: jointly insignificant)	.000

Source: Authors' estimations. *** 1% ** 5% * 10%

6. CONCLUSIONS

The relationship between conflict and agricultural production technologies has important implications for agricultural productivity in fragile settings, where food availability and food security problems are often severe. Understanding such a relationship is particularly important in Myanmar, which has experienced a significant rise in conflict following a military coup in 2021. This study assesses whether the increase in violent events associated with the political crisis in Myanmar in 2021 affected the underlying rice production function that represents rice production technologies, using nationally representative panel data of rice farmers in 2020 and 2021, from before and after the coup.

We find that increases in violent events led to changes in the shape of the rice production functions. Specifically, increases in violent events are associated with reduced total factor productivity (TFP) and an increased output elasticity of agricultural capital proxied by the number of different types of agricultural equipment owned, indicating more negative effects of the conflict for poorer farmers. Reduced access to extension services has been a potential explanation for such changes. Increases in violent incidents in the township are significantly associated with reduced access to extension services, contributing to reduced TFP and increased output elasticity of agricultural capital. These results consistently hold for Cobb-Douglas and translog production function forms, between Lower Myanmar and Upper Myanmar, and for alternative definitions of the intensity of violent events. The results also hold for short-run and long-run production functions that address a more extensive set of endogeneity issues.

Our results imply that increases in violent events in Myanmar since 2021 have lowered the TFP in rice production and transformed the prevailing rice production technologies into being more dependent on agricultural capital owned by the farms. In other words, rice production technologies are likely to have changed in favor of farmers owning more agricultural capital but against farmers with less agricultural capital. We also find that lower mechanization service fees partly mitigate these effects. Reduced access to extension services might have driven such changes, which would otherwise compensate resource-poor farmers with human capital and skills that can potentially substitute agricultural capital. The absence of agricultural capital may remain a binding constraint for these farmers to the extent that the credit market is imperfect (so that greater output elasticity does not induce sufficient investments in agricultural capital), and a high incidence of violent events disrupts access to agricultural equipment and cheap mechanization service provision.

Our results have several policy implications. Containing and reducing violent events is critical in restoring the TFP of rice production. Assuring access to extension services could compensate for this loss and boost farmers' productivity with less production capital. Direct support to restore agricultural extension services, including in pluralistic ways (by mobilizing both the public and private-sector extension services), can also have similar benefits. Supports to improve access to credit and agricultural equipment can help more farmers adjust more efficiently to the changes in rice production function associated with increased violent events. Finally, assuring access to affordable mechanized service providers might mitigate the lack of ownership of machinery.

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APPENDIX

Table 14. Probit regression results on factors associated with violent events and receiving no access to extension services (expressed as marginal effects on probability evaluated at sample means)

Variables	Dependent variables	
	Likelihood of being in township with violent events exceeding median	Likelihood of receiving no extension visits
Intensity of violent events in the township		0.026**
Age	0.001*	–0.002***
Gender (female = 1)	0.020	0.108***
Education (above standard 4 = 1)	0.019	–0.118***
Household member – adult male	–0.004	–0.004
Household member – adult female	0.007	0.010
Household member – children	–0.006	0.012
Farm size owned in ha (natural log)	–0.004	–0.010
Asset (principal component)	–0.010**	–0.042***
Nonfarm income (yes = 1)	0.025*	–0.013
Nighttime light (index)	0.018	0.025
COVID case (natural log)	3.698***	-3.444
Distance to input market (hours)	0.021**	0.034***
Mechanization fees	0.000	–0.003
Soil alkalinity (pH)	0.027	0.009
Organic contents (g / kg of soil)	0.045***	0.029***
Soil texture (% fine)	0.810***	0.186
Salinity (deciSiemens per metre)	0.210***	–0.081***
Sodicity (% of soil)	–0.175***	0.008***
Poor drainage (%)	–0.055*	–0.053
Pests or disease (yes = 1)	0.044**	–0.095***
Animal damage (yes = 1)	–0.026	–0.033
Historical average rainfall	0.001***	–0.010
Historical average temperature	0.004	–0.006
State dummies	Included	Included
Sample size	2,348	2,348
p-value (H_0: jointly insignificant)	.000	.000

Source: Authors. *** 1% ** 5% * 10%.

Table 15. Short-run production function estimations with different sources of extension services

Variables	(a)	(b)	(c)	(d)
Sources of extension services	Public sector	Private sector	NGOs	Cellphone app
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	–0.006 (0.022)	0.013 (0.020)	0.004 (0.024)	–0.015 (0.026)
Capital × No extension	0.025* (0.015)	0.002 (0.013)	0.010 (0.015)	0.032 (0.028)
Land	0.469*** (0.056)	0.500*** (0.056)	0.500*** (0.053)	0.516*** (0.058)
Land × No extension	0.019 (0.026)	–0.020 (0.022)	–0.015 (0.027)	–0.039 (0.038)
Labor	–0.061 (0.035)	–0.054 (0.035)	–0.066 (0.046)	–0.080 (0.046)
Labor × No extension	0.035** (0.017)	0.026* (0.016)	0.035* (0.020)	0.056** (0.027)
Fertilizer	0.067*** (0.014)	0.074*** (0.015)	0.089*** (0.019)	0.032 (0.020)
Fertilizer × No extension	–0.040** (0.015)	–0.051*** (0.017)	–0.058*** (0.019)	0.003 (0.022)
Irrigation	0.003 (0.017)	0.018 (0.017)	–0.030 (0.021)	0.017 (0.019)
Irrigation × No extension	0.005 (0.013)	–0.015 (0.013)	0.037** (0.017)	–0.013 (0.018)
Other expenses	0.024 (0.025)	0.012 (0.025)	–0.014 (0.032)	–0.015 (0.026)
Other expenses × No extension	0.017 (0.023)	0.033* (0.020)	0.055** (0.026)	0.019 (0.036)
Intercept	7.060*** (0.016)	7.046*** (0.015)	7.083*** (0.017)	7.015*** (0.022)
Intercept × No extension	–0.013 (0.015)	0.006 (0.015)	–0.041** (0.017)	0.043 (0.027)
Farmer fixed effects	Included	Included	Included	Included
Other controls	Included	Included	Included	Included
Sample	4,696	4,696	4,696	4,696
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

Table 16. Short-run production function estimations with mechanization fees

Variables	(a)	(b)	(c)	(d)
Types of shocks	Violent events			Extension
Regions	Myanmar	Lower	Upper	Myanmar
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.010 (0.025)	0.001 (0.028)	0.028 (0.048)	–0.008 (0.028)
Capital × Shocks	0.027 (0.018)	0.063** (0.026)	0.013 (0.025)	0.033 (0.025)
Capital × Shocks × Mechanization Fees	0.018 (0.040)	0.089** (0.044)	–0.027 (0.064)	0.016* (0.009)
Land	0.509*** (0.034)	0.571*** (0.053)	0.528*** (0.049)	0.503*** (0.073)
Land × Shocks	–0.003 (0.020)	–0.045 (0.031)	0.025 (0.034)	0.005 (0.033)
Land × Shocks × Mechanization Fees	0.013 (0.045)	–0.100** (0.046)	0.153* (0.082)	0.024 (0.021)
Labor	–0.030 (0.028)	0.007 (0.035)	–0.079 (0.043)	–0.062 (0.047)
Labor × Shocks	–0.003 (0.020)	0.007 (0.025)	–0.010 (0.029)	0.036 (0.025)
Labor × Shocks × Mechanization Fees	0.013 (0.045)	0.065 (0.046)	–0.091 (0.080)	0.001 (0.012)
Fertilizer	0.044*** (0.014)	0.054*** (0.015)	0.032 (0.026)	0.058*** (0.019)
Fertilizer × Shocks	–0.027 (0.021)	0.014 (0.032)	–0.013 (0.031)	–0.029 (0.023)
Fertilizer × Shocks × Mechanization Fees	0.024 (0.037)	0.112*** (0.042)	–0.041 (0.066)	–0.007 (0.013)
Irrigation	0.005 (0.017)	–0.020 (0.022)	0.030 (0.026)	0.015 (0.023)
Irrigation × Shocks	–0.008 (0.018)	–0.005 (0.023)	–0.017 (0.025)	–0.014 (0.020)
Irrigation × Shocks × Mechanization Fees	–0.039 (0.041)	–0.011 (0.046)	–0.024 (0.064)	0.011 (0.008)
Other expenses	0.004 (0.010)	–0.020 (0.012)	0.034* (0.019)	–0.003 (0.025)
Other expenses × Shocks	0.013 (0.020)	0.029 (0.026)	–0.019 (0.027)	0.035 (0.027)
Other expenses × Shocks × Mechanization Fees	–0.047 (0.033)	–0.084** (0.037)	0.001 (0.053)	–0.024*** (0.009)
Intercept	7.017*** (0.025)	7.164*** (0.028)	6.901*** (0.052)	7.050*** (0.022)
Intercept × Mechanization Fees	–0.036* (0.021)	–0.013 (0.026)	–0.005 (0.050)	0.000 (0.020)
Intercept × Shocks	0.037 (0.031)	–0.002 (0.038)	0.017 (0.052)	–0.007 (0.024)
Intercept × Shocks × Mechanization Fees	0.068 (0.051)	0.026 (0.057)	0.026 (0.099)	–0.018 (0.017)
Farmer fixed effects	Included	Included	Included	Included
Other controls	Included	Included	Included	Included
Sample	4,696	2,528	2,168	4,696
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

Table 17. Long-run estimates of Cobb-Douglas production functions (differentiated by the median of violent events)

Variables	(a)	(b)	(c)
Samples	Less violent events (below median)	More violent events (above median)	Statistical significance of differences (= (b) – (a))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.139 (0.091)	0.025 (0.107)	0.114 (0.119)
Capital × Mechanization fee	–0.143 (0.141)	0.118 (0.074)	0.261* (0.147)
Land	0.725*** (0.054)	0.875*** (0.044)	0.150** (0.069)
Land × Mechanization fee	0.130** (0.065)	–0.021 (0.041)	–0.151** (0.073)
Labor	0.056 (0.035)	0.016 (0.032)	–0.039 (0.050)
Labor × Mechanization fee	–0.062* (0.036)	0.011 (0.029)	0.073 (0.046)
Fertilizer	0.073*** (0.021)	0.050*** (0.017)	–0.023 (0.018)
Fertilizer × Mechanization fee	–0.017 (0.029)	–0.002 (0.016)	0.015 (0.027)
Irrigation	0.134** (0.055)	0.130* (0.071)	0.004 (0.097)
Irrigation × Mechanization fee	0.042 (0.091)	–0.034 (0.067)	–0.076 (0.104)
Other expenses	0.022* (0.012)	0.032* (0.019)	–0.010 (0.023)
Other expenses × Mechanization fee	–0.023 (0.025)	0.014 (0.015)	0.037 (0.027)
Intercept	4.698*** (0.915)	2.789*** (0.831)	-1.909* (1.119)
Mechanization fee	-5.996*** (0.244)	-5.466*** (0.159)	0.530** (0.269)
Other controls	Included	Included	Included
Sample size	1110	1238	
P-value			
H_0: underidentified	.000	.000	
H_0: model insignificant	.000	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

Table 18. Long-run estimates of Cobb-Douglas production functions (differentiated by the access to extension services)

Variables	(a)	(b)	(c)
Samples	Having extension access	No extension access	Statistical significance of differences (= (b) – (a))
Labels	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Capital	0.073 (0.084)	0.179** (0.073)	0.107 (0.096)
Capital × Mechanization fee	–0.153 (0.115)	0.121* (0.074)	0.274** (0.124)
Land	0.683*** (0.062)	0.746*** (0.062)	0.063 (0.081)
Land × Mechanization fee	0.115 (0.090)	–0.057 (0.061)	–0.172* (0.103)
Labor	0.055* (0.031)	0.011 (0.029)	–0.044 (0.044)
Labor × Mechanization fee	–0.049 (0.031)	0.015 (0.030)	0.063 (0.044)
Fertilizer	0.070*** (0.022)	0.036*** (0.018)	–0.033 (0.021)
Fertilizer × Mechanization fee	–0.026 (0.027)	–0.006 (0.016)	0.020 (0.027)
Irrigation	0.107* (0.063)	0.126** (0.050)	0.019 (0.088)
Irrigation × Mechanization fee	0.042 (0.074)	–0.037 (0.063)	–0.079 (0.090)
Other expenses	0.090 (0.061)	0.169*** (0.054)	0.079 (0.080)
Other expenses × Mechanization fee	–0.015 (0.102)	0.044 (0.057)	0.059 (0.110)
Intercept	4.927*** (0.914)	3.302*** (0.794)	-1.626 (1.263)
Intercept × Mechanization fee	0.194 (1.180)	–0.586 (0.680)	–0.780 (1.293)
Other controls	Included	Included	Included
Sample size	990	1358	
P-value			
H_0: underidentified	.000	.000	
H_0: model insignificant	.000	.000	

Source: Authors' estimations based on IFPRI (2022). *** 1% ** 5% * 10%

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