MYANMAR

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Agricultural mechanization services, rice productivity, and farm/plot size: Insights from Myanmar

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ABSTRACT

The relationship between productivity and farm size has been at the center of considerable debate. Agricultural mechanization – that is rapidly taking off in a large number of low- and middle-income countries – has been identified as one of the emerging technologies in these settings with a critical, yet complex, influence on this productivity-size relation. However, knowledge gaps remain as how agricultural transformation due to the adoption of new technologies and the change in factor costs, such as mechanization fees, are associated with this productivity - size relation. In the case of Myanmar, where mechanization use has dramatically increased over the last decade, we find a significant inverse productivity - plot size relationship, with small rice plots having productivity levels approximately 30 percent higher than large plots. However, rising mechanization fees – more so in conflict-affected townships – attenuated this inverse relation between rice productivity (yield and profit per land) and plot size substantially. These results primarily hold on the largest rice plot cultivated by each farmer, but also generally hold when comparing total rice area and major non-rice area. Our results are likely explained by the fact that, in Myanmar, smallholders have become more dependent on mechanization services than larger farms (who can rely on their own machines) do, that alternatives to mechanization services have become scarce (as mechanization use changed little, despite these price increases), and that mechanization service costs account for a significant share of the total production costs among smallholders.

Keywords: productivity-farm size relation, mechanization service fees, inverse probability weighted generalized method of moments, conflict, Myanmar

1. BACKGROUND

The relationship between productivity and farm size has been at the center of considerable debate in the agricultural development literature (Chayanov 1965; Schultz 1965; Johnson & Ruttan 1994; Barrett et al., 2010; Rada & Fuglie 2019). A stylized fact in that literature has been the inverse relationship between farm size and productivity (e.g., Sen 1962; Schultz 1965; Barrett et al. 2010). However, new research is increasingly putting caveats on that finding, illustrating issues with measurement (Abay et al. 2021; Kosmowski et al. 2021; Desiere and Jolliffe 2018) or showing inverse relationships only over specific domains (Muyanga & Jayne 2019; Aragon et al. 2021; Omotilewa et al. 2021; Foster & Rozenzweig 2022). Understanding this relationship matters as the productivity-size relations have significant implications for directing overall agricultural policies toward either supporting smallholders or promoting the growth of larger farms to exploit economies of scale.

Agricultural mechanization has been identified as one of the technologies with critical, yet complex, linkages with productivity-size relations. This has been particularly so in developing countries in Asia and parts of Africa, where the smallholder-dominated agricultural sector has seen significant and rapid growth in mechanization (Diao et al. 2020). Under certain conditions, agricultural mechanization has been associated with a relative increase in returns-to-scale features (Otsuka et al. 2016; Takeshima 2017; Takeshima et al. 2018), which raise the comparative advantage of larger farms relative to smaller farms (Foster & Rosenzweig 2022). On the other hand, the growth of mechanization hiring services in developing countries has contributed to transforming mechanization as scale-neutral technologies accessible for smallholders (e.g., Lu et al. 2016; Zhang et al. 2017; Belton et al. 2020; Takeshima & Liu 2020) including through greater use of ICT (Daum et al. 2021). To the extent that smallholders become more dependent on hired mechanization services than larger farmers who can instead use their own machines, changes in mechanization service costs may have greater effects on productivity of smallholders. Overall, knowledge gaps remain on how mechanization technologies relate to productivity-size relations.

Narrowing this knowledge gap is vital because agrifood market risks (including risks in markets for agriculture-related services like mechanization services and inputs such as fertilizers) remain significant in low- and middle-income countries due to factors ranging from weather shocks, changes in oil prices, supply chain problems, and policy changes (e.g., World Bank 2008; Jaffee et al. 2010; Ola & Menapace 2020). Conflicts, in particular, are an important source of increased risk on the performance of agricultural markets (World Bank 2021). Conflicts have steadily increased due to climate change (Burke et al., 2009; Maystadt & Ecker 2014; Breckner & Sunde 2019) and increased global pandemic risks like COVID-19 (Ide 2021), among others. Increased conflicts often negatively affect regional trade (Qureshi 2013), input markets (e.g., Adelaja & George 2019), and economic activities in general (Dupas & Robinson 2012). Assessing mechanization service fee changes as a pathway linking conflicts and productivity-size relations also offers insights into conflicts' potential distributional effects.

We attempt to narrow this knowledge gap using the case of Myanmar. Specifically, we focus on the significant increase in mechanization service fees over the period 2020-2021 and assess how it has been associated with changes in the productivity-size relationship in rice production. We do so by using nationally-representative panel rice production data on the largest rice plots of farmers, and information on mechanization service fees, and their changes between 2020 and 2021 (MAPSA 2022), supplemented by spatial data on violent incidents, satellite-based rice and agricultural areas, and panel data on mechanization service providers. While we primarily focus on the largest rice plot of respondents, we also show that results are generally robust when considering all plots combined for rice, as well as main non-rice crops.

Myanmar is a suitable case to assess this issue. Agricultural mechanization – often obtained for a fee from mechanization service providers – has rapidly taken off in the last decade in Myanmar and is now widespread for all types of farmers in different agro-ecological zones (Belton et al. 2021). Moreover, the country experienced a significant increase in conflicts since February 2021 after the military coup (MAPSA 2023). While the effects of increased violence have been devastating, they have also led to price increases for agricultural inputs. Those changes offer valuable lessons for many low- and middle-income countries that experience constant recurrence of conflicts, and other risks, in agrifood markets, including markets for mechanization hiring services.

This study contributes to various strands of literature. It provides additional insights into the productivity-size relationships in developing countries (Chayanov 1965; Schultz 1965; Johnson & Ruttan 1994; Barrett et al., 2010; Rada & Fuglie 2019) and contributes to the literature that focuses on potential factors that are associated with a relative shift in less-inverse relations (Feder 1985; Kevane 1996; Eastwood et al. 2008; Deininger & Byerlee 2012; Collier & Dercon 2014; Zhang et al. 2019). The study also contributes insights linking mechanization technologies and productivity-size relationships (Foster & Rosenzweig 2022) or production characteristics that have implications on such relationships (Zhang et al. 2017; Takeshima 2017; Takeshima et al. 2018) by offering evidence on the linkage between productivity-size relationship and mechanization hiring services. Furthermore, this study adds to the knowledge on the relations between conflicts and agricultural productivity (e.g., González & Lopez 2007; MAPSA 2023) by linking conflicts with changes in mechanization service fees and productivity-size relations. Finally, the study contributes methodologically to the impact evaluation literature that combines IPW-GMM with the estimation of endogenous productivity-size relationships (Takeshima 2017; Takeshima et al. 2018; MAPSA 2023).

The remainder of this study is structured as follows. Section 2 describes the mechanization use for rice production in Myanmar. Section 3 describes the data. Section 4 discusses the empirical methodologies. Section 5 presents descriptive statistics. Section 6 discusses the empirical results. Finally, section 7 concludes.

2. RICE PRODUCTION AND MECHANIZATION IN MYANMAR

Smallholders are still dominant in the agricultural sector in Myanmar, including in rice production (MAPSA 2022). The average rice area per farm in the 2021 monsoon season was 5.3 acres (about 2.1 ha) at the national level. This is similar to many Asian countries but considerably smaller than rice farms in other regions. Nonetheless, as described in later sections, some rice plots are relatively larger (e.g., exceeding 1 ha), either rainfed or irrigated. The average rice farm size (and size distribution) is larger than in some other Asian countries like Vietnam, where the productivity-size relation has been studied recently (e.g., Liu et al. 2020), suggesting that assessing similar issues in Myanmar is meaningful.

The use of mechanization in farming, including rice production, has grown rapidly during the 2010s in Myanmar (Belton et al. 2020; Win et al. 2020). Two-wheel tractors are more commonly used on irrigated plots (although they are also sometimes used on rainfed rice plots as seen in Thailand (Diao et al. 2020)) for land preparation in wetland areas and rotovation to soften soils, which allows manual transplanting. Using two-wheel tractors through custom-hiring, rather than own machines, is common, though not as much as for four-wheel tractors (as is common in countries like Bangladesh (Diao et al. 2020)). Four-wheel tractors are commonly used on rainfed dryland for plowing / harrowing and leveling.

The use of four-wheel tractors might also be associated with an increased switch from transplanting to direct seeding, enabled by the increased use of herbicides as alternative ways to control weeds instead of flooding plots (Naylor 1994). Four-wheel tractors may also be used where the speed of land preparation has economic benefits. For example, four-wheel tractors can prepare 1 ha of land in 3 hours, while it takes 10 hours for two-wheel tractors and 50 hours for draft animals (Belton et al. 2021). Combine-harvesters have also substantially replaced manual harvesting or intermediate mechanization, like reapers and threshers (Belton et al. 2021). Much of these mechanization services have been provided by custom-hiring services, offering mechanization services as significantly divisible and scale-neutral technologies for smallholders.

Using tractors has significantly replaced animal traction in Myanmar during the 2010s (Belton et al. 2021). Even in the Dry Zone, where animal traction is still used for harrowing and inter-cultivation, primary tillage to break up hardened soils has been largely replaced by tractors (Belton et al. 2021). Figure 1 illustrates the relatively recent take-off of mechanization in Myanmar, based on a nationally representative survey fielded in the beginning of 2023. Farmers in the survey were asked to indicate if they were owners of a tractor and if so, when they acquired this tractor. For two-wheel tractors, half of those only became an owner of such a tractor in the 7 years before the survey. In the case of farmers that relied on rented-in services of 4-wheel tractors or of combine-harvesters, half of the users only started doing this in the last 5 years.

The substantial spread of tractor use in the last decade in Myanmar might be irreversible. Although Asian countries had a long history of using animal traction, this has been found to be a knowledge and skill-intensive process (e.g., Hoffman et al. 1989; Lawrence & Pearson 2002), which may not be easily recovered once tractors have replaced animal traction for some time (as in Myanmar in the 2010s). Significant mechanization of harvesting processes during the last decades in Myanmar might have also been associated with a substantial increase in agricultural wages, as predicted by Binswanger (1986). In fact, a significant wage increase occurred in Myanmar during the 2010s (Belton et al. 2021). By 2020, it seemed to have reached a level where manual harvesting is no longer a viable substitute to combine-harvester services unless the cost of the latter would increase considerably. These conditions are also likely to have made mechanization a highly irreversible process. Consequently, many smallholders nowadays might have limited adaptation capacity to rising mechanization service fees in Myanmar. These trends also motivate our study to assess the effects of increasing mechanization fees on productivity-size relationships in Myanmar in recent years.

3. DATA

Myanmar Agricultural Performance Survey (MAPS)

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 the 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.[1] 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. 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 latter based on recall), which is necessary for the analyses of production functions. We, therefore, focus on these 2,348 rice-producing farm households.

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

Mechanization Service Provider (MSP) phone surveys

We also rely on data come from the Mechanization Service Provider (MSP) survey, which we use to assess the supply-side factors associated with the changes in mechanization service fees between 2020 and 2021. The data consist of 8 rounds of an unbalanced panel data of MSP interviewed during land preparation and harvesting seasons in 2020 and 2021. Rounds 1 – 3 and 6 – 7 were conducted during the land preparation and monsoon planting season in 2020 and 2021, while rounds 4 – 5 and 8 were implemented during the monsoon harvesting seasons. MSPs were purposively sampled, using the contact information obtained from previous studies (Belton et al. 2017, 2018, and 2019), as well as snow-balling methods. In total, we ended up with 1,850 observations, among which 1,592 also reported mechanization fees. Among these observations, approximately 55 percent are tractor service providers and 45 percent are combine-harvester service providers.

Other spatial data on weather and events

We further use various spatial data on weather, agroclimatic conditions, COVID-19 incidence, and data on the incidence of social instability. 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 come 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.[2] 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.[3] Lastly, for robustness checks to deal with potential measurement errors in reported plot size, we use satellite-image based estimates of agricultural areas between 2016-2018 (Zhang et al. 2021) and rice planted areas in 2020 (Han et al. 2022), extracted at township levels.

4. EMPIRICAL APPROACH

We estimate the effects of mechanization service fee changes on the productivity-size relationships in both "short-run" and "long-run" frameworks. As is described below, the "long-run" specification accommodates a greater degree of endogeneity in plot size, and correlations between mechanization service fees and farmer characteristics.

4.1 Effects of mechanization service costs on productivity-size relationship

4.1.1 Short-run specification

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

$$Y_{it} = \alpha + \beta_A \cdot A_{it} + \beta_M \cdot M_{it} + \beta_{AM} \cdot A_{it} \cdot M_{it} + \beta_X \cdot X_{it} + \beta_Z \cdot Z_{it} + c_i + \varepsilon_{it} \tag{1}$$

and,

$$Y_{it} = \alpha + \beta_A \cdot A_{it} + \beta_M \cdot M_{it} + \beta_{AM} \cdot A_{it} \cdot M_{it} + \beta_Z \cdot Z_{it} + c_i + \varepsilon_{it} \tag{2}$$

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

[3] 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.

in which Y_{it} is an indicator of productivity (yield, profit per area) on the largest rice plot cultivated by farmer i in year t, and regressed on mechanization service fees (M_{it}), plot size (A_{it}), and other time-variant exogenous factors (Z_{it}). Model (1) also includes other inputs use per area (X_{it}) and thus is conditional on X_{it}, while (2) is unconditional on X_{it}.[4] Notations α, β's are estimated parameters, c_i is a time-invariant respondent fixed effect, and ε_{it} is an idiosyncratic error term. The parameter of interest β_{AM} measures how the productivity-size relationship changes due to the change in mechanization service fees. It is important to note that X_{it} includes the use of mechanization services. We focus on mechanization service fees, M_{it}, rather than actual mechanization use. This is because, as is shown in later section, the former exhibited greater variations between 2020 and 2021, while the latter remained fairly stable during this period.

In the short-run model (1), A_{it} as well as X_{it} and M_{it} can be assumed 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.[5]

4.1.2 Long-run specification (IPW-GMM)

In contrast to a short-run fixed-effects model (1), a long-run specification 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 changes in mechanization service fee M_{it}, as well as that of plot size A_{it} and inputs use per area X_{it} poses bigger challenges for estimation than in (1).

The inverse probability weighting (IPW) model (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 issue. IPW-methods have been used in the literature to estimate the effects on 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 specification. Our IPW-GMM model proceeds as follows (modified from Takeshima 2017). We first estimate a Probit model,

$$\text{Probability}\left(R^* = 1 | \mathcal{Z}_{i,t=0}\right) = \hat{p} = \Phi(\mathcal{Z}\theta) = \int_{-\infty}^{\mathcal{Z}\theta} \phi(v) dv. \quad (3)$$

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 mechanization service fee changes between 2020 and 2021 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.

[4] While unconditional models are somewhat more common in the literature, some studies also estimate conditional models (e.g., Ali & Deininger 2015; Sheng et al. 2019; Wineman & Jayne 2021; Omotilewa et al. 2021).

[5] Recall data have been increasingly used to construct panel specifications in the literature. For example, Deaton 1995 (p.1805) argues that Recall data for periods shorter than 5 years may be reasonably reliable. Takeshima & Yamauchi (2012) uses recall data of a one-year lag to assess the impact heterogeneity of development intervention in Nigeria. Recall data bias from relatively short lag may be minimal for agricultural data (Beegle et al. 2012). Our focus on the largest plots also assures that recall errors may be smaller compared to more marginal plots (Gaddis et al. 2021). 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.

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

$$Y_i = \alpha + \beta_A \cdot A_i + \beta_X \cdot X_i + \beta_Z \cdot \mathcal{Z}_i + \varepsilon_i. \tag{4}$$

In IPW-GMM, equation (4) for farmers with $R^* = 1$ is estimated by

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

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

$$\hat{\beta} = \arg\min_{\beta}\left[E\left(m/(\sqrt{1-\hat{p}})\right)\right]'\widehat{W}\left[E\left(m/(\sqrt{1-\hat{p}})\right)\right]' \tag{6}$$

where E is the expectation over samples and $\widehat{W}$ is the suitable weighting matrix estimated in GMM. $m(\cdot)$ is the moment condition,

$$m = \mathbf{Z}'[A_i - (\alpha + \beta_A \cdot A_i + \beta_X \cdot X_i + \beta_Z \cdot \mathcal{Z}_i)]. \tag{7}$$

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

Our excluded IVs ($\mathcal{Z}_i^*$) are lagged values of A_i ($A_{i,t-1}$) and X_i ($X_{i,t-1}$) (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 (e.g., Angrist & Krueger 2001; Bloom & Van Reenen 2006; Sharma et al. 2016; Jetter & Parmeter 2018). 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 (3), or the model of productivity-size relationship (4) is consistent, even when the other model is mis-specified (Takeshima 2017).

We then compare parameters β_A between two types of farmers ($R^* = 1$ and $R^* = 0$). A statistically significant difference in β_A between these groups is then interpreted as evidence that the productivity-size relationship 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 (4) through (7) involve IPW based on estimated probability $\hat{p}$, standard errors are estimated through 100 bias-corrected paired bootstraps, as in previous studies (Efron & Tibshirani 1993; Barrett et al. 2008; Takeshima et al. 2018).

4.1.3 Other 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. Z_{it} also includes the total annual COVID-19 case count in the township of respondent households.

The set of variables $\mathcal{Z}$ in (3) through (7) include the aforementioned time-variant variables Z_{it}, as well as factors influencing market imperfections as suggested in previous studies (e.g., Cohen 2019; Omotilewa et al. 2021; Gourlay et al. 2021), such 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.

4.1.4 Further specifications for robustness checks

4.1.4.1 Effects on TFP-size relations

Some studies argue that the relationship between farm size and Total Factor Productivity (TFP) is more appropriate for most policy questions than looking at partial land productivity, such as yield, because comprehensive measures such as TFP take into account the productivity with which all resources are utilized (e.g., Rada & Fuglie 2019; Helfand & Taylor 2021; Aragón et al. 2022). Assessing the relationship between farm size and TFP allows checking the robustness of the effects in farm size and productivity relations across broader productivity indicators.

We assess this in a nonparametric specification by estimating 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 we evaluate how this indicator is associated with plot size and mechanization fees.[6] 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 features, 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). The index is estimated using the STATA command `malmq2`.

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

$$\Delta\pi_{it} = \gamma_0 + \gamma_A \cdot A_{i,t-1} + \gamma_M \cdot \Delta M_{it} + \gamma_{AM} \cdot A_{i,t-1} \cdot \Delta M_{it} + \gamma_z \cdot \Delta Z_{it} + \varepsilon_i \qquad (8)$$

where $\Delta\pi_{it}$ is the growth rate of the Malmquist TFP indicator for farmer i between 2020 and 2021, ΔM_{it} and ΔZ_{it} are changes between 2020 and 2021 in mechanization service fees and other time-variant exogenous factors for farmer i, and $A_{i,t-1}$ is the plot size in 2020. Parameters γ's are estimated coefficients, while ε_i is an idiosyncratic error term that further affects $\Delta\pi_{it}$. The coefficient γ_{AM} is then used to assess the effect of mechanization service fees on the relationship between the Malmquist TFP indicator and plot size. 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).

4.1.4.2 Measurement errors in plot size

Our approach of using panel data has advantages in mitigating measurement errors if the same individual tends to make similar errors over time (Deaton 1997). Available evidence also generally suggests that directions of measurement errors tend to be consistent, with the size of smaller plots often overreported while larger plots often underreported (De Groote & Traoré 2005; Carletto et al. 2013). Nonetheless, plot size measurement errors have been shown to potentially cause biases in estimated productivity-size relationships (e.g., Gourlay et al. 2019; Cohen 2020; Abay et al. 2022).

[6] We focus on an approach where TFP index is estimated nonparametrically. This is because assessing TFP-size relationship remains challenging where TFP is estimated parametrically. For example, in specification (1), coefficients on plot size A_{it} cannot distinguish the effects on TFP from the effects on returns-to-scale (Helfand & Taylor 2021).

We therefore also check the robustness of our results by addressing the potential measurement errors in reported plot size.

One approach to mitigate biases due to measurement errors is an IV approach, whereby plot size is instrumented by IVs whose measurement errors are orthogonal to measurement errors in plot size (Wooldridge 2002). For such IVs, we use township-level agricultural areas and rice planted areas per agricultural worker, which can be associated with plot sizes of farmers in each township. Specifically, we extract township-level areas from satellite-image based estimates of agricultural areas between 2016-2018 (Zhang et al. 2021) and rice planted areas in 2020 (Han et al. 2022), and agricultural workers based on the working-age (15-64) population who were primarily engaged in agriculture in each township, reported in Myanmar's last census in 2014 (Government of Myanmar 2014). We then re-estimate the IPW-GMM model (4) through (7) by using as additional excluded IVs the aforementioned township-level estimates of agricultural and rice areas per agricultural population.

4.1.4.3 Household level size-productivity relationship for rice and main non-rice crops

As was described above, we focus our primary analyses on the largest rice plot because of the presumed accuracy of production and input-use information. Nevertheless, we also provide supplementary evidence, albeit to a limited extent, from rice production as well as 3 main non-rice crops aggregated across all plots cultivated by the respondents. Specifically, we estimate (1) through (7) by replacing Y_{it}, A_{it} with rice or 3 other main non-rice crops, total area cultivated for rice or 3 other main non-rice crops, and X_{it} with family labor used, number of the types of agricultural equipment, use of irrigation, and the number of other types of input used (such as herbicides, chemical fertilizers, organic fertilizers, pesticides, other purchased inputs, and hired labor).

4.2 Supply-side determinants of mechanization fees

We further gain insights into whether the increase in mechanization service fees between 2020 and 2021 has been partly driven by supply-side factors experienced by MSPs (Mechanization Service Providers). Using the MSP survey data described in the earlier section, we estimate

$$M_{js} = \delta_0 + \delta_V \cdot V_{js} + \delta_Z \cdot Z_{js} + c_j + \varepsilon_{js}. \quad (9)$$

M_{js} is a vector of various indicators, including the mechanization service fees for tractor or combine harvester services charged by MSP j at MSP survey round s. Other indicators include perceived changes in prices of machines, attachments / spare parts, mechanics / service repairs, operators and fuels.

V_{js} is the number of violent events reported in the township of j, during the month that corresponds with survey round s. Z_{js} is a vector of additional shocks experienced by MSP j. Following Takeshima et al. (2023) which assessed similar relations between COVID-19 related restrictions and MSP activities in 2020 before the political crisis, Z_{js} includes indicators of movement restrictions within state/region, an equipment market constraints index, and a financial constraints index. Z_{js} also includes survey round dummies interacted with region dummies to separate out any other region- and survey-round specific factors.

5. DESCRIPTIVE STATISTICS

5.1 Descriptive statistics from farm survey

Table 1 present the descriptive statistics of respondents' production practices on their largest rice plots, as well as on all plots combined. Most respondents are smallholder rice producers; their largest rice plot is commonly 1 acre or so, from which about 1.2 tons of rice are harvested. A typical farm will use 50kg of fertilizer on these plots, and about 1/3 of the plots are irrigated. Two family members work regularly on these plots, and most farmers own at least one type of machine. About a quarter of farmers own small tractors and 5 percent own 4-wheel tractors.

Importantly, about 60 percent of respondents hired tractors and combine-harvesters (user shares are about 88 percent and 64 percent respectively if own machines are included), and about 80 percent of respondents hired at least one tractor or combine-harvester on their largest rice plots. These shares remained mostly unchanged between 2020 and 2021 despite the increase in mechanization fees shown in the subsequent section. Use of mechanization services has been, therefore, widespread among rice producers in both years, while the increase in mechanization service fees in 2021 had significant effects on production costs.

Production values from all rice plots, and for 3 major non-rice crops were typically about 0.9 million and 0.1 ~ 0.2 million Kyat at median, respectively, although figures were much higher at means. A majority of respondents used various types of purchased inputs.

Figure 1 illustrates the cumulative distributions of the years when respondents who either own two-wheel tractors or use 4-wheel tractors or combine harvesters acquired / started using mechanization for the first time. It shows that half of them had owned two-wheel tractors since 2015, and used 4-wheel tractors or combine harvesters since 2018. In other words, by 2021, these respondents had commonly used two-wheel tractors for 6 years, and 4-wheel tractors or combine-harvesters for 3 years, deepening their reliance on mechanization.

Table 2 presents how mechanization service fees changed for two-wheel and four-wheel tractors between 2020 and 2021, and how it compared to the changes in paddy prices during the same period. At the sample mean and median, mechanization service fees increased by about 12 percent for two-wheel tractors, and about 20 percent for four-wheel tractors. These rates were significantly higher than paddy price increase of about 8-9 percent, confirming that most respondents experienced significant increase in mechanization service fees in real terms.

Table 3 shows the relative significance of mechanization hiring costs relative to total production costs. On average, tractor hiring costs and combine-harvester hiring costs accounted for about 10 ~ 20 percent respectively, and 25 ~ 37 percent combined. The shares also increased significantly between 2020 and 2021, from 25 to 29 percent at the median, and 33 to 37 percent on average. These patterns indicate that increased mechanization service fees might have had significant effects of squeezing spending for other inputs.

Mechanization service fees also increased in spatially dispersed ways, as is illustrated in Figure 2. Spatial autocorrelation is measured by Moran's I = 0.058, which is much lower than 0.3 that is often considered as meaningful spatial correlation (O'Sullivan & Unwin 2010). These patterns suggest that the changes in mechanization service fees were affected by various localized factors including increases in violent events in 2021, which too occurred in spatially dispersed ways (MAPSA 2023). Such spatial dispersion of mechanization service fee increases also allows us to separate out its effects from other factors that are more spatially correlated (such as weather).

5.2 Yield and mechanization by plot size

The relationship between plot size and yield, mechanization use, and costs per unit of land associated with it, changed considerably between 2020 and 2021. Figure 3 illustrates local polynomial estimates of relationships between plot size and yield and profit per acre for 2020 and 2021. In the upper panel, while the inverse relationship between yield and plot size generally holds, this relationship somewhat weakened in 2021 compared to 2020. The differences between 2020 and 2021 can be arguably substantial; for example, yield increased on average by about 0.05 tons / are in 5-acre plots, while it decreased by about 0.05 tons / are in 0.25-acre plots. The net difference of 0.1 ton/ha (= 0.05 + 0.05) accounts for about 1/3 of the difference in yields within this range of plot size (= 0.1 / 0.3) in 2020. Similar patterns also hold for profit per acre (lower panel of Figure 3), implying a significant attenuation of inverse-relationship within a year between the monsoon seasons of 2020 and 2021.

Figure 4 illustrates the shares of rice producers using mechanization for either land preparation by tractors or harvesting by combine-harvesters (either by own machines or hired services) by plot size. Figure 4 implies that mechanization is fairly common regardless of plot size, with more than 80 percent of farmers using mechanization even on plots less than 0.25 acres.

Figure 5 illustrates how the mechanization costs through hiring are associated with plot size in 2020 and 2021. Notably, the mechanization service hiring costs and their increase between 2020 and 2021 is larger on medium-sized plots (around 2 acres) than those on larger plots. These patterns further motivate our analyses that small-to-medium farmers suffered disproportionately from rising mechanization service fees than larger farmers.

5.2.1 Other general characteristics

Table 4 summarizes the descriptive statistics of baseline variables in 2020 used in assessing the long-run specification, differentiated by the extent of changes in mechanization service fee experienced in 2021. Most farm management decision-makers are male, with about half having completed education above standard 4. Most are smallholders, and about half have nonfarm incomes, 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 an average rainfall of 2,000 mm per year and a temperature of 26.7 degrees centigrade. They are also scattered across various states and regions. Importantly, those who would experience higher mechanization service fees in 2021 have statistically significantly different characteristics than other farmers.

Table 4 also shows the similar statistics after samples are weighted by IPW estimated through (3). In IPW samples, only 2 out of 26 variables exhibit statistical significance at 10 percent, which would hold under the null hypothesis that farmer characteristics are now comparable across different levels of mechanization service fees. Therefore, IPW-GMM can successfully attribute any remaining differences in outcomes to the difference in mechanization service fees.

5.3 Descriptive statistics from MSP surveys

Table 5 summarizes the basic characteristics of the MSP survey respondents from 8 rounds combined. MSPs generally charged 20,000 and 47,000 Kyat per acre on average throughout the periods for tractors and combine-harvester hiring services, respectively. In each survey round, most respondents indicated facing higher prices than in previous years, particularly for machines, attachments, spare parts (imported and locally manufactured), and fuels/diesel. A fraction of respondents also indicated price increases for repair services/mechanics and operators.

About 20 percent of respondents indicated that their movement was restricted within village tracts, and nearly all (96 percent) were restricted within their respective states/regions. A significant share of MSPs faced various financial constraints, including indebtedness, inability to receive loan payment extensions, delayed payments from customers, and imminent risk of financial asset exhaustion. On average, MSPs faced 2 of these financial constraints. Typically, MSPs' townships experienced 1 violent event during the survey month. About 57 percent of responses are for the planting season, where tractors are used, while the remaining are for the harvesting season and combine-harvesters. MSPs are spread in both the Delta and the Dry Zone, with the majority located in Ayeyarwady and Magway regions.

6. RESULTS

6.1 Effects of rising mechanization fees on inverse productivity-size relations

Table 6 shows the results of the short-run specification (1) for relations between land productivity (yield, profit per acre) and plot size area, and the effect of mechanization service fees on these relationships. Results are shown for both conditional models (conditional on other inputs) and unconditional models. The coefficient of our primary interest is that of the mechanization fee and the natural log of plot size area (first row). In all specifications, the estimated coefficients are statistically significantly positive; an increase in mechanization service fees in 2021 shifts the relationship between land productivity and plot size in a more positive (less inverse) direction. The coefficients are scaled to show the effects of the average increase in mechanization service fees between 2020 and 2021 on the inverse relations. For example, an increase in mechanization service fees equivalent to its average changes between 2020 and 2021 is associated with a net 0.012 increase in the elasticity of yield with respect to plot size, about 4 percent of the average elasticity of -0.332 (rows for "ln (Area)"). When the yield is regressed without natural log transformation, a 0.47 standard deviation decline in yield is associated with a doubling of plot size, and a mechanization service fee increase weakens this relation by 0.03 standard deviation in yield (or about 6 percent of the yield-size relations (= 0.03/0.47)). With similar interpretations, we find that effects on profit per acre are relatively larger, with an increase in mechanization service fee reversing the inverse relation by about 17 percent (= 0.041/0.244). These effects are in addition to the effects on average yield and profit per acre of about -0.023 and -0.057 standard deviations, respectively. Statistical significance and magnitudes of these effects are relatively in similar order even when we omit other input variables from the models.

Table 7 presents similar relations in the long-run framework. The estimated differences in coefficients (columns (c) and (f)) measure how the relations between yield or profit-per-acre are associated with inputs including plot size, when mechanization service fees exceed thresholds equivalent to 66.7 percentiles among the sample.

Statistically significantly positive differences for coefficients on "ln (Area)" indicate that in the long-run a mechanization service fee increase is associated with a shift of yield or profit-size relation to less-inverse directions. Importantly, as we also show in Table 7, overall average yield and profit-per-acre decline by 10.6 percent and 0.311 standard deviations, respectively, in the long-run.

Results in both short-run (Table 6) and long-run (Table 7) are consistent with our hypothesis. Mechanization has become a divisible and scale-neutral technology (much as other land-saving inputs like seeds and fertilizer) through significant growth of custom-hiring services in Myanmar. In such a context, a significant increase in mechanization service fees in real terms - which occurred between 2020 and 2021 in Myanmar - has been associated with attenuation of inverse-relations between rice land productivity and plot size.

Irrigated vs. rainfed plots

Table 8 provides further insights into how these patterns vary across rainfed and irrigated plots. Specifically, we find that results indicated in Tables 6 and 7 are more pronounced on rainfed rather than irrigated plots, at least in the short run.[7] Most rice plots are still rainfed in Myanmar (Table 1) due to insufficient public irrigation infrastructures and/or insufficient development of modern varieties more responsive to irrigation that would encourage the adoption of private irrigation, as has been observed during the Green Revolution in modern Asia (e.g., Kikuchi et al. 2003). Such dominance of rainfed rice farming may also explain our findings because rainfed plots receive greater use of 4-wheel tractors, which rely more on custom-hiring services, than 2-wheel tractors and are more susceptible to changes in mechanization service fees.

Robustness check

Table 9 presents tests whether similar results as described above hold if we focus on TFP proxied by a Malmquist index instead of land productivity. Results indicate that the Malmquist index of TFP has a significantly inverse relation with plot size (doubling of plot size is associated with a 0.538 standard deviations decline in the Malmquist index). Results also indicate that an increase in mechanization service fee equivalent to its average change between 2021 and 2020 attenuated this inverse relation by about 8 percent (=0.042/0.538). These results are consistent with the hypothesis that an increase in mechanization service fees attenuates the inverse relations between productivity and plot size. Furthermore, as the Malmquist index is nonparametrically estimated, results indicate the robustness of our hypothesis, and that our results in Table 6 through Table 8 are not artifacts of parametric restrictions of the relations.

Table 10 and Table 11 present how the results remain robust, when we use additional IVs (satellite and census-based agricultural and rice planted areas per agricultural worker) to alleviate the biases due to potential measurement errors of the plot size. Although the models now have extra IVs, tests of overidentification and under-identification suggest that these additional IVs satisfy the suitability as an IV. Results, as indicated by statistically significant positive effects (columns (c) and (f)), are generally consistent with those of Table 7; an increase in mechanization service fee leads to less inverse relations between productivity and plot sizes. These results indicate that our results are robust against potential measurement errors in plot size.

Table 12 and Table 13 show that our results largely hold if they are based on production from all rice plots, as well as 3 main non-rice crops, in both a short-run and a long-run context. Statistically significantly positive coefficients for the mechanization fee variable interacted with the area variable confirm that rising mechanization fees shifted production values per acre in favor of larger farms. These results suggest that our primary findings based on the largest rice plot may have broader implications.

Correlates of mechanization service fee increases

Table 15 provides insights into how supply-side factors have driven mechanization service fee increases. While it is not possible to explicitly separate the supply-side effects from demand-side effects, results indicate that changes in relevant factors are more likely to have been affected by the supply side than by the demand side. For example, increases in violent incidents at the township during the survey months have been associated with increases in mechanization service fees, as well as perceptions of increased prices of machines, attachments (both imported and locally manufactured), fuels/diesel, repair service/ mechanics, and operators, which directly affect the costs of supplying mechanization services. Furthermore, movement restrictions imposed originally as COVID-19 containment measures in 2020, which often persisted or got worse after the military coup

[7] Significant effects are not detected in the long-run framework due to smaller sample sizes and thus inconclusive.

in 2021, as well as financial constraints, have been significantly associated with increased prices of attachments/spare parts or fuels/diesel. These results provide better insights into the factors related to mechanization service fee increases.

Table 16 in Appendix summarizes the correlates of mechanization service fees, estimated from probit regression (3), where the dependent variable takes the value of 1 if the mechanization service fee is above the sample median. Similar to Table 15, the likelihood of facing higher mechanization service fees was positively associated with a greater incidence of violent events in the township. The likelihood of facing higher mechanization service fees was also associated with a greater distance to input markets, and a higher number of COVID cases. It is also significantly correlated with agroecological conditions, including soil characteristics, historical rainfall, temperature, and their anomalies in 2021. While equation (3) is not a structural equation, results in Table 16 suggest that our IPW methods (3) through (7) mitigate the biases and improve the internal validity of the effects of mechanization service fees on productivity-size relationships.

6.2 Discussions on possible pathways

While it is beyond the scope of this paper to investigate the potential pathways of how increased mechanization service fees attenuate inverse-relations between productivity and plot size, we provide further supplementary results and discuss how past literature offers insights into potential pathways.

Specifically, we estimate an unconditional short-run model (2) by replacing Y_{it} with potential intermediate outcomes, namely, whether the respondent used tractor through hiring services, tractor hiring spending per acre, amount of fertilizer used per acre, and total spending for all inputs and services per acre. Table 14 summarizes the results. Table 14 suggests that the increases in mechanization fee in 2021 had insignificant effects on the use of tractor hiring services, which confirms that farmers continued using tractor-hiring services in 2021 despite increased hiring costs. As a result, increased mechanization service fees in 2021 led to increased tractor hiring spending per acre (column (b)). Statistically significantly positive coefficients for the mechanization fee variable interacted with the area variable confirm - column (c) - that fertilizer use per acre declined more on smaller plots due to rising mechanization service fees. The result in column (d) shows that rising mechanization fees did not affect the total spending per acre. These results are consistent with the hypothesis that increased mechanization service fees in 2021 forced farmers to incur greater costs for mechanization services, reducing financial capacity for purchasing other inputs like chemical fertilizer, and that these effects were relatively more pronounced for smaller plots.

One possible explanation may be that increased mechanization service fees can magnify the effects of certain market failures that shift relative productivity advantages from smaller farms to larger farms, although inverse-relations still largely hold in the short-run, even under increased mechanization service fees at the level in 2021. For example, credit and insurance market imperfections, which are still prevalent in developing countries, including Myanmar, and generally affect smallholders disproportionately, is one factor that retains scale economies in agriculture (e.g., Kevane 1996; Zaibet & Dunn 1998; Eastwood et al. 2008). In Brazil and China, larger farms have seen more considerable yield growth partly due to credit market imperfections (WB 2008, p.91). Increased mechanization service fees may intensify the effects of such credit market imperfections, particularly among smallholders in Myanmar who, by the early 2020s, have come to rely pervasively on mechanization hiring services. In addition, larger farms have been generally associated with greater allocative efficiency in China (Zhang et al. 2019). Furthermore, economies of scale have also been suggested in knowledge diffusions, whereby learning is faster in large farms than individual smallholders learning separately (e.g., Collier & Dercon 2011). While other types of factor-market imperfections (such as labor-market imperfections) can also cause more inverse-relations (e.g., Ali & Deininger 2015; Wineman & Jayne 2021), it might have been that in Myanmar in 2021, effects of credit and insurance market imperfections have had greater effects than the effects of imperfections in other markets like labor markets.

7. CONCLUSIONS

The relationship between productivity and farm size has been at the center of considerable debate. Agricultural mechanization has been identified as one of the technologies with critical, yet complex, linkages with productivity-size relations. However, a knowledge gap remains as to how the change in mechanization services fees is associated with productivity-size relations. This is important given the rapid rise of mechanization use in a large number of low- and mid-income countries (Diao et al. 2020). Narrowing this knowledge gap is vital because agrifood market risks (including risks in markets for agriculture-related services like mechanization services) remain significant in low- and mid-income countries due to factors ranging from weather shocks and policy changes to conflicts. We attempt to narrow this knowledge gap by assessing the associations between increases in mechanization service fees and changes in productivity-size relationship in rice production in Myanmar before and after the military coup in 2021.

We find that mechanization service fees increased substantially in real terms during 2020 and 2021 in Myanmar, and that it was significantly associated with increases in violent events at township levels during this period. We then find that increased mechanization fees attenuated inverse-relations between rice productivity (both yield and profit per land) and plot size. These patterns are more pronounced on rainfed plots where four-wheel tractors are more likely to be used than two-wheel tractors. Results are robust when using the Malmquist index as a proxy for TFP, and satellite-based data of agricultural and rice areas per agricultural workers to mitigate potential measurement errors in plot size.

Our results are likely to be driven by a particular pattern of evolution of mechanization technologies and their economic characteristics in Myanmar. In Myanmar, mechanization offered through hiring service is likely to have become a divisible and scale-neutral technology (much as other land-saving inputs such as seeds and fertilizer) among smallholders. Over time, mechanization service is also likely to have become significantly cheaper than substitutes like animal traction or manual labor, and farmers may continue relying on the mechanization services even in the face of a sudden change in fees. The share of mechanization service hiring costs to overall production costs is significant, and its increase may squeeze the use of other inputs among smallholders. Meanwhile, scale economies may still exist for own machines - producers operating on larger plots can use their own machines as viable alternatives - so that they have become less dependent on mechanization services offered by others. In such a context, a significant increase in mechanization service fees in real terms which occurred between 2020 and 2021 in Myanmar has been associated with attenuation of inverse-relations between rice land productivity and plot size. In addition to negative effects on average rice yields and profits, mechanization fee increases in 2021 disproportionately affected smaller rice plots than larger plots.

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APPENDIX

Table 1. Production practices during the monsoon season in 2020 and 2021

Variables	Mean		Median	
Year	2020	2021	2020	2021
Largest rice plot				
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
Expenditures due to machine hiring	52.931	63.941	36.000	44.000
Number of family labor regularly working on the farm	2.259	2.000	2.269	2.000
Use irrigation (yes = 1)	0.320	0.313	0.000	0.000
Use tractors (Yes = 1)	0.877	0.879	1.000	1.000
Use tractors through hiring (Yes = 1)	0.600	0.602	1.000	1.000
Use combine-harvesters (Yes = 1)	0.639	0.639	1.000	1.000
Use combine-harvesters through hiring (Yes = 1)	0.607	0.605	1.000	1.000
Use either tractors or combine-harvesters through hiring (Yes = 1)	0.807	0.804	1.000	1.000
All plots combined (including non-producers)				
Rice outputs (production values; 1,000 Kyat)	2076.024	2197.238	900.000	900.000
Size of rice plots (acre)	4.623	4.649	2.500	2.000
Production values of 3 main non-rice crops (1,000 Kyat)	3096.877	2834.550	200.000	135.000
Size of plots for 3 main non-rice crops (acre)	3.155	3.125	1.000	0.800
Use chemical fertilizer (yes = 1)	0.860	0.843	1.000	1.000
Use organic fertilizer (yes = 1)	0.357	0.346	0.000	0.000
Use irrigation (yes = 1)	0.320	0.313	0.000	0.000
Use machines (yes = 1)	0.817	0.815	1.000	1.000
Use herbicides (yes = 1)	0.568	0.550	1.000	1.000
Use pesticides (yes = 1)	0.595	0.576	1.000	1.000
Use hired labor (yes = 1)	0.774	0.765	1.000	1.000
Use purchased seeds (yes = 1)	0.573	0.529	1.000	1.000
Agricultural capital ownership (yes = 1)				
Small tractors (1 or 2 wheels, power tiller)	0.267	0.267	0.000	0.000
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

Source: Authors.

Table 2. Rates of changes (%) in mechanization service fees and paddy prices between the monsoon of 2020 and 2021

Variables	Mean	Median	Std.dev
Two-wheel tractors	12.5	12.5	15.3
Four-wheel tractors	21.7	19.9	16.7
Paddy price	8.0	9.0	12.1

Source: Authors.

Table 3. Approximate proportion of mechanization costs to total paddy production costs (tractors and combine-harvesters)

Variables	Median		Mean	
	2020	2021	2020	2021
Tractors	10.6	12.0	13.7	15.6
Combine-harvesters	15.0	17.2	18.9	21.7
Tractors + Combine-harvesters	25.0	29.1	32.6	37.3

Source: Authors.
Note: Tractor hiring fees are averages of hiring fees for four-wheel tractors and two-wheel tractors. Combine-harvester hiring fees are assessed at 45,000 and 55,000 (MMK/acre) in 2020 and 2021, respectively, based on MAPSA (2022b).

Table 4. Descriptive statistics

Samples Variables	Raw sample Farmers in townships below threshold[a] of mechanization fees in 2021	Farmers in townships above threshold of mechanization fees in 2021	IPW sample Farmers in townships below threshold of mechanization fees in 2021	Farmers in townships above threshold of mechanization fees in 2021
Violent events in 2021 (in township)	3.158	2.982**	3.335	3.184
Age	42.523	41.099**	43.619	42.870
Gender of primary farm decision maker (female = 1)	0.330	0.350	0.456	0.353
Education (above standard 4 = 1)	0.602	0.540**	0.483	0.582
Household member – adult male	1.913	1.953	1.760	1.901
Household member – adult female	2.030	1.999	2.188	2.092
Household member – children	0.967	1.207***	0.870	1.096
Farm size owned in ha (natural log)	0.737	0.591**	0.532	0.523
Asset (principal component)	0.147	-0.235***	0.217	0.096
Nonfarm income (yes = 1)	0.547	0.563	0.641	0.607
Nighttime light (index)	0.155	0.136	0.162	0.254
Distance to input market (hours)	0.690	0.807**	0.644	0.722
COVID case in 2021 (annual total, per 1,000 population in the township)	1.001	1.001	1.001	1.001
Soil properties				
Soil alkalinity (pH)	5.902	5.631***	5.856	5.977
Organic contents (g / kg of soil)	1.812	1.997**	1.867	1.928
Soil texture (share of fine texture; 100% = 1)	0.299	0.276***	0.240	0.289
Salinity (deciSiemens per metre)	0.548	0.280***	0.404	0.742*
Sodicity (% of soil)	3.192	3.705	2.969	3.309
Poor drainage (proportion)	0.491	0.448*	0.394	0.447
Pests or disease in 2021 (yes = 1)	0.152	0.143	0.121	0.143
Animal damage in 2021 (yes = 1)	0.033	0.020	0.026	0.045
Historical average rainfall (mm)	1810.301	2699.199***	1979.079	1855.513
Historical average temperature (℃)	27.167	25.312***	24.917	27.219
Rainfall anomaly in 2021 (absolute value of z-statistics with respect to historical distribution)	1.165	0.959***	1.140	1.350
Temperature anomaly in 2021	0.648	0.691	0.669	0.809**
Upper Myanmar	0.588	0.487***	0.638	0.641
Lower Myanmar	0.412	0.513***	0.362	0.359

Source: Authors. Asterisks indicate the statistically significant differences from farmers with access to extension (*** 1% ** 5% * 10%).
Note: Figures are those in 2020, unless otherwise stated.
[a]Threshold = 66.7 percentile.

Table 5. Descriptive statistics of MSP surveys

Variables	Unit	Means
Outcome variables		
mechanization fees (tractors)	Kyat per acre	21,460
mechanization fees (combine-harvesters)	Kyat per acre	47,495
face higher prices than previous year for:		
- machines	Yes = 1	0.681
- attachments and spare parts (imported)	Yes = 1	0.705
- attachments and spare parts (locally manufactured)	Yes = 1	0.532
- fuel / diesel	Yes = 1	0.598
- repair services / mechanics	Yes = 1	0.343
- operators	Yes = 1	0.175
Explanatory variables		
Time-variant variables		
movement restricted within village tracts	Yes = 1	0.199
within state/region	Yes = 1	0.956
movement restriction index (=2 if within village tracts)	Count	1.138
indebtedness (owe loans to dealers / banks)	Yes = 1	0.396
inability to receive loan payment extension	Yes = 1	0.350
delayed payment by customers	Yes = 1	0.840
imminent risk of financial asset exhaustion	Yes = 1	0.527
financial constraints index (sum of above four variables)	Count	2.124
rainfall percentile	Percentile (1 = 100%)	45.554
violent events in the township during the survey month	Count	0.919
planting season	Yes = 1	0.570
dummy variable for main machines used during the survey round		
tractors	Yes = 1	0.552
combine harvesters	Yes = 1	0.448
Time-invariant variables		
Regions		
Ayeyarwady	Yes = 1	0.391
Bago	Yes = 1	0.124
Magway	Yes = 1	0.365
Mandalay	Yes = 1	0.039
Sagaing	Yes = 1	0.073
Yangon	Yes = 1	0.006
Kayin	Yes = 1	0.003
Number of full panel observations (combined)		1,850
Average numbers of panel rounds		3.8

Source: Authors.

Table 6. Effects of mechanization fees on size-land productivity relationship (short-run)

Columns Variables	(a)	(b)	(c)	(d)	(e)	(f)
	ln (Yield)		Yield (standard deviation)		Profit per acre (standard deviation)	
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Mechanization fee * ln (Area)	0.012* (0.007)	0.012* (0.007)	0.030** (0.014)	0.029** (0.014)	0.041*** (0.014)	0.044*** (0.014)
ln (Area)	-0.332*** (0.061)	-0.364*** (0.054)	-0.470*** (0.116)	-0.558*** (0.090)	-0.244* (0.130)	-0.299** (0.117)
Mechanization fee	-0.008 (0.008)	-0.009 (0.008)	-0.023* (0.013)	-0.025* (0.013)	-0.057*** (0.018)	-0.055*** (0.019)
ln (Labor per area)	-0.041 (0.027)		-0.065 (0.046)		-0.058 (0.049)	
ln (Fertilizer per area)	0.019*** (0.005)		0.041*** (0.009)		0.026*** (0.009)	
ln (Own equipment per area)	0.023 (0.032)		0.076 (0.077)		0.106 (0.072)	
ln (Other expenditures per area)	0.014** (0.006)		0.011 (0.010)		-0.106*** (0.015)	
Irrigation	0.017 (0.026)		0.058 (0.061)			
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Sample size	4,696	4,696	4,696	4,696	4,696	4,696
p-value	.000	.000	.000	.000	.000	.000

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

Table 7. Effects of mechanization fees on size-land productivity relationship (long-run; IPW-GMM)

Columns Variables	(a)	(b)	(c) = (a) – (b)	(d)	(e)	(f) = (d) – (e)
	Dependent variable = ln (Yield)			Dependent variable = profit per acre (standard deviation)		
	Above threshold[a] of 4wt mech fee Coef. (std.err)	Below threshold of 4wt mech fee Coef. (std.err)	Difference (std.err)	Above threshold of 4wt mech fee Coef. (std.err)	Below threshold of 4wt mech fee Coef. (std.err)	Difference (std.err)
ln (Area)	0.188** (0.074)	-0.011 (0.055)	0.199** (0.084)	0.312* (0.161)	-0.021 (0.088)	0.333* (0.178)
ln (Labor per area)	0.100** (0.046)	0.019 (0.028)	0.081 (0.057)	0.141 (0.121)	0.104* (0.055)	0.037 (0.138)
ln (Fertilizer per area)	-0.022 (0.019)	0.058*** (0.020)	-0.080*** (0.027)	-0.069* (0.041)	0.064* (0.036)	-0.133** (0.050)
ln (Own equipment per area)	0.263*** (0.062)	0.074 (0.051)	0.189** (0.076)	0.604*** (0.132)	0.030 (0.073)	0.574*** (0.154)
ln (Other expenditures per area)	0.204*** (0.064)	0.099** (0.046)	0.105 (0.079)	-0.141 (0.136)	-0.305** (0.101)	0.163 (0.155)
Irrigation	0.266*** (0.079)	0.153*** (0.049)	0.112 (0.098)	0.698*** (0.189)	0.234** (0.092)	0.463** (0.237)
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Average	6.960*** (0.024)	7.066*** (0.037)	-0.106** (0.043)	-0.239*** (0.066)	0.072** (0.035)	-0.311*** (0.084)
Sample size	686	1662		686	1662	
p-value	.000	.000		.000	.000	

Source: Authors. *** 1% ** 5% * 10%.
Note: [a]Threshold = 66.7 percentile.

Table 8. Results of Table 6 separated by rainfall and irrigated plots

Columns Variables	(a)	(b)	(c)	(d)	(e)	(f)
	ln (Yield)		Yield (standard deviation)		Profit per acre (standard deviation)	
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Rainfed plots						
Mechanization fee * ln (area)	0.022** (0.010)	0.022** (0.010)	0.040** (0.019)	0.040** (0.019)	0.041** (0.018)	0.042** (0.018)
ln (Area)	-0.225*** (0.076)	-0.302*** (0.068)	-0.204 (0.128)	-0.407*** (0.094)	0.189 (0.140)	0.035 (0.114)
Mechanization fee	-0.009 (0.011)	-0.007 (0.012)	-0.023 (0.015)	-0.019 (0.016)	-0.051*** (0.018)	-0.046*** (0.018)
Other inputs	Included		Included		Included	
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Sample size	2,602	2,602	2,602	2,602	2,602	2,602
p-value	.000	.000	.000	.000	.000	.000
Irrigated plots						
ln (Area)	-0.483*** (0.089)	-0.469*** (0.078)	-0.798*** (0.188)	-0.752*** (0.147)	-0.680*** (0.206)	-0.597*** (0.182)
Mechanization fee	0.006 (0.008)	0.003 (0.008)	-0.002 (0.018)	-0.007 (0.018)	-0.036 (0.029)	-0.037 (0.029)
Mechanization fee * ln (area)	0.005 (0.009)	0.003 (0.009)	0.023 (0.024)	0.020 (0.024)	0.040 (0.026)	0.046* (0.026)
Other inputs	Included		Included		Included	
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Sample size	2,096	2,096	2,096	2,096	2,096	2,096
p-value	.000	.000	.000	.000	.000	.000

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

Table 9. Correlates of Malmquist TFP growth rates (effects of one-standard deviation changes)

Variables	Coef. (std.err)
ln (Area)	–0.538** (0.218)
Mechanization fee	0.022 (0.030)
ln (Area)*Mechanization fee	0.042** (0.021)
COVID case	0.018 (0.017)
Rainfall anomalies	–0.020 (0.021)
Temperature anomalies	–0.017 (0.013)
Pests or disease (yes = 1)	–0.040*** (0.011)
Animal damage (yes = 1)	0.023 (0.032)
Intercept	1.106*** (0.014)
Sample size	2,348
p-value (H_0: jointly insignificant)	.000

Source: Authors' estimations. *** 1% ** 5% * 10%.
Standard errors are robust to unknown heteroskedasticity.

Table 10. Long-run IPW-GMM using satellite and census-data as additional IV to mitigate potential plot-size measurement errors (Agricultural area per worker at township level)

Columns Variables	(a)	(b)	(c) = (a) – (b)	(d)	(e)	(f) = (d) – (e)
	Dependent variable = ln (Yield)			Dependent variable = profit per acre (standard deviation)		
	Above threshold[a] of 4wt mech. fee Coef. (std.err)	Below threshold of 4wt mech. fee Coef. (std.err)	Difference (std.err)	Above threshold of 4wt mech. fee Coef. (std.err)	Below threshold of 4wt mech. fee Coef. (std.err)	Difference (std.err)
ln (Area)	0.185** (0.075)	-0.045 (0.059)	0.230** (0.091)	0.289* (0.165)	-0.031 (0.099)	0.320** (0.095)
ln (Labor per area)	0.101** (0.045)	0.010 (0.032)	0.061 (0.058)	0.153 (0.119)	0.089 (0.058)	0.064 (0.135)
ln (Fertilizer per area)	-0.026 (0.019)	0.030 (0.021)	-0.040 (0.028)	-0.062 (0.042)	0.051 (0.036)	-0.113** (0.051)
ln (Own equipment per area)	0.254*** (0.062)	0.073 (0.056)	0.225*** (0.081)	0.597*** (0.138)	0.040 (0.078)	0.557*** (0.164)
ln (Other expenditures per area)	0.219*** (0.063)	0.146*** (0.051)	0.002 (0.079)	-0.179 (0.137)	-0.256** (0.111)	0.077 (0.158)
Irrigation	0.288** (0.081)	0.179*** (0.048)	0.109 (0.101)	0.655*** (0.187)	0.224** (0.092)	0.431* (0.233)
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included
Sample size	686	1662		686	1662	
p-value (H_0: variables jointly insignificant)	.000	.000		.000	.000	
p-value (H_0: not overidentified)[b]	.453	.656		.453	.656	
p-value (H_0: underidentified)[b]	.000	.000		.000	.000	

Source: Authors. *** 1% ** 5% * 10%.
Note: [a]Threshold = 66.7 percentile.
[b]These tests are added since satellite-based IV accounts for an additional IV, unlike Table 7 in which models were exactly identified.

Table 11. Long-run IPW-GMM using satellite and census-data as additional IV to mitigate potential plot-size measurement errors (Rice area per worker at township level)

Columns Variables	(a)	(b)	(c) = (a) – (b)	(d)	(e)	(f) = (d) – (e)
	Dependent variable = ln (Yield)			Dependent variable = profit per acre (standard deviation)		
	Above threshold[a] of 4wt mech fee Coef. (std.err)	Below threshold of 4wt mech fee Coef. (std.err)	Difference (std.err)	Above threshold of 4wt mech fee Coef. (std.err)	Below threshold of 4wt mech fee Coef. (std.err)	Difference (std.err)
ln (Area)	0.231* (0.074)	0.010 (0.060)	0.220** (0.095)	0.311* (0.173)	-0.036 (0.092)	0.347* (0.193)
ln (Labor per area)	0.079* (0.045)	0.010 (0.032)	0.069 (0.057)	0.143 (0.120)	0.093* (0.055)	0.050 (0.136)
ln (Fertilizer per area)	0.005 (0.017)	0.043** (0.021)	-0.037 (0.027)	-0.067* (0.040)	0.065* (0.035)	-0.132*** (0.049)
ln (Own equipment per area)	0.282*** (0.062)	0.076 (0.055)	0.205** (0.084)	0.619*** (0.139)	0.030 (0.075)	0.589*** (0.164)
ln (Other expenditures per area)	0.138** (0.065)	0.101** (0.049)	0.037 (0.081)	-0.163 (0.130)	-0.295*** (0.105)	0.132 (0.152)
Irrigation	0.179** (0.079)	0.183*** (0.050)	-0.004 (0.100)	0.689** (0.184)	0.230** (0.091)	0.459** (0.229)
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included
Sample size	686	1662		686	1662	
p-value (H_0: variables jointly insignificant)	.000	.000		.000	.000	
p-value (H_0: not overidentified)	.311	.406		.311	.406	
p-value (H_0: underidentified)	.000	.000		.000	.000	

Source: Authors. *** 1% ** 5% * 10%.
Note: [a]Threshold = 66.7 percentile.
[b]These tests are added since satellite-based IV accounts for an additional IV, unlike Table 7 in which models were exactly identified.

Table 12. Effects of mechanization fees on size-land productivity relationship (short-run)

Columns Variables	(a)	(b)	(c)	(d)
	ln (Value per acre of 3 main crops)		ln (Rice production value per acre – all varieties combined)	
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
Mechanization fee * ln (Area)	0.104*** (0.039)	0.101*** (0.039)	0.044* (0.021)	0.044** (0.021)
ln (Area)	-0.442*** (0.103)	-0.439*** (0.103)	0.010 (0.026)	0.011 (0.025)
Mechanization fee	-0.074 (0.065)	-0.073 (0.065)	0.005 (0.017)	0.005 (0.017)
Other inputs		Included		Included
Other controls	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included
Constant	Included	Included	Included	Included
Sample size	3,832	3,832	4,696	4,696
p-value	.000	.000	.000	.000

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

Table 13. Long-run IPW-GMM using satellite and census-data as additional IV to mitigate potential plot-size measurement errors (Rice area per worker at township level)

Columns Variables	(a)	(b)	(c) = (a) – (b)	(d)	(e)	(f) = (d) – (e)
	Dependent variable = ln (Value per acre of 3 main crops)			Dependent variable = ln (Rice yield at household level)		
	Above threshold[a] of 4wt mech fee Coef. (std.err)	Below threshold of 4wt mech fee Coef. (std.err)	Difference (std.err)	Above threshold of 4wt mech fee Coef. (std.err)	Below threshold of 4wt mech fee Coef. (std.err)	Difference (std.err)
Unconditional model						
ln (Area)	-0.061 (0.125)	-0.367*** (0.091)	0.305* (0.159)	0.008 (0.026)	-0.048* (0.029)	0.056* (0.033)
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included
Conditional model						
ln (Area)	-0.099 (0.127)	-0.342*** (0.103)	0.243 (0.167)	0.002 (0.026)	-0.054** (0.026)	0.056* (0.033)
Other inputs	Included	Included	Included	Included	Included	Included
Other controls	Included	Included	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included
Sample size	772	1158		1107	1241	
p-value (H_0: variables jointly insignificant)	.000	.000		.000	.000	

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

Table 14. Effects of mechanization fees on size-land productivity relationship (short-run)

Columns Variables	(a) Whether using tractors through hiring (percentage point change) Coef. (std.err)	(b) Tractor hiring spending per acre (standard deviation) Coef. (std.err)	(c) Quantity of fertilizer used per acre (standard deviation) Coef. (std.err)	(d) Total spending per acre (% change / 100) Coef. (std.err)
Mechanization fee * ln (Area)	-0.002 (0.005)	-0.009 (0.019)	0.016* (0.010)	-0.011 (0.007)
ln (Area)	-0.008 (0.023)	-0.022 (0.041)	-0.286*** (0.051)	-0.174** (0.029)
Mechanization fee	-0.008 (0.007)	0.344*** (0.026)	-0.018 (0.017)	0.015 (0.010)
Other controls	Included	Included	Included	Included
Year dummy	Included	Included	Included	Included
Constant	Included	Included	Included	Included
Sample size	4,696	4,696	4,696	4,696
p-value	.000	.000	.000	.000

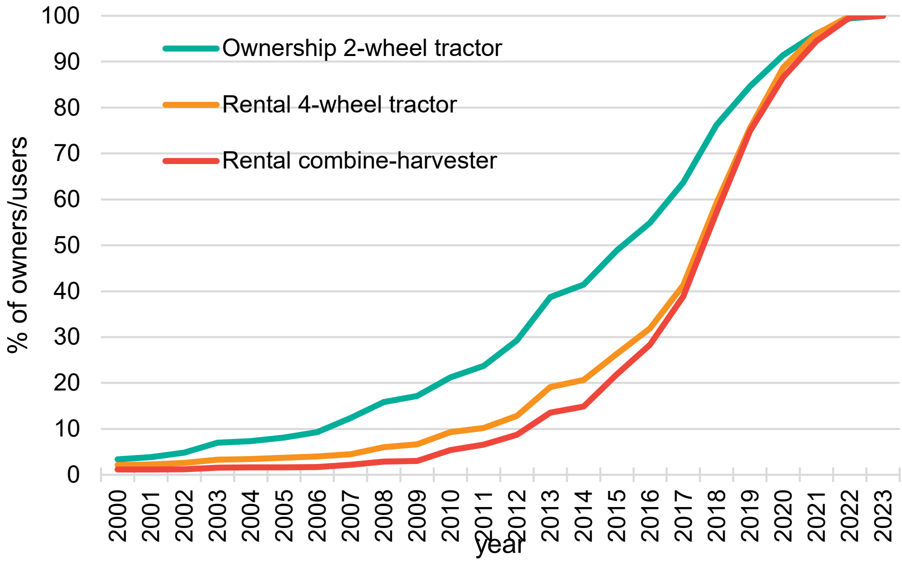
Source: Authors. *** 1% ** 5% * 10%.

Table 15. Associations of fatal violent events and mechanization fees and other supply-side issues (effects on standard deviation)

Columns Variables	(a) Mechanization fees	(b)	(c)	(d)	(e)	(f)	(g)
		Face higher prices than previous year					
		Machines	Attachments and spare parts (imported)	Attachments and spare parts (locally manu-factured)	Fuels/ diesels	Repair services/ mechanics	Operators
	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)	Coef. (std.err)
ln (Violent incidents)	0.145** (0.040)	0.709*** (0.089)	0.726*** (0.091)	0.626*** (0.069)	1.047*** (0.130)	0.452*** (0.051)	0.347*** (0.048)
movement restriction index	-0.041 (0.036)	0.053 (0.056)	0.134*** (0.046)	0.237*** (0.050)	0.130*** (0.049)	0.056 (0.051)	-0.050 (0.055)
financial constraints index	0.021 (0.016)	0.087*** (0.025)	0.078*** (0.024)	0.100*** (0.025)	0.033 (0.022)	0.152*** (0.024)	0.100*** (0.030)
rainfall percentile	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Machine type dummy (tractor vs. combine harvester)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Planting season (yes = 1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Planting season * state/region dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,592	1,850	1,850	1,850	1,850	1,850	1,850
P-value (H0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000

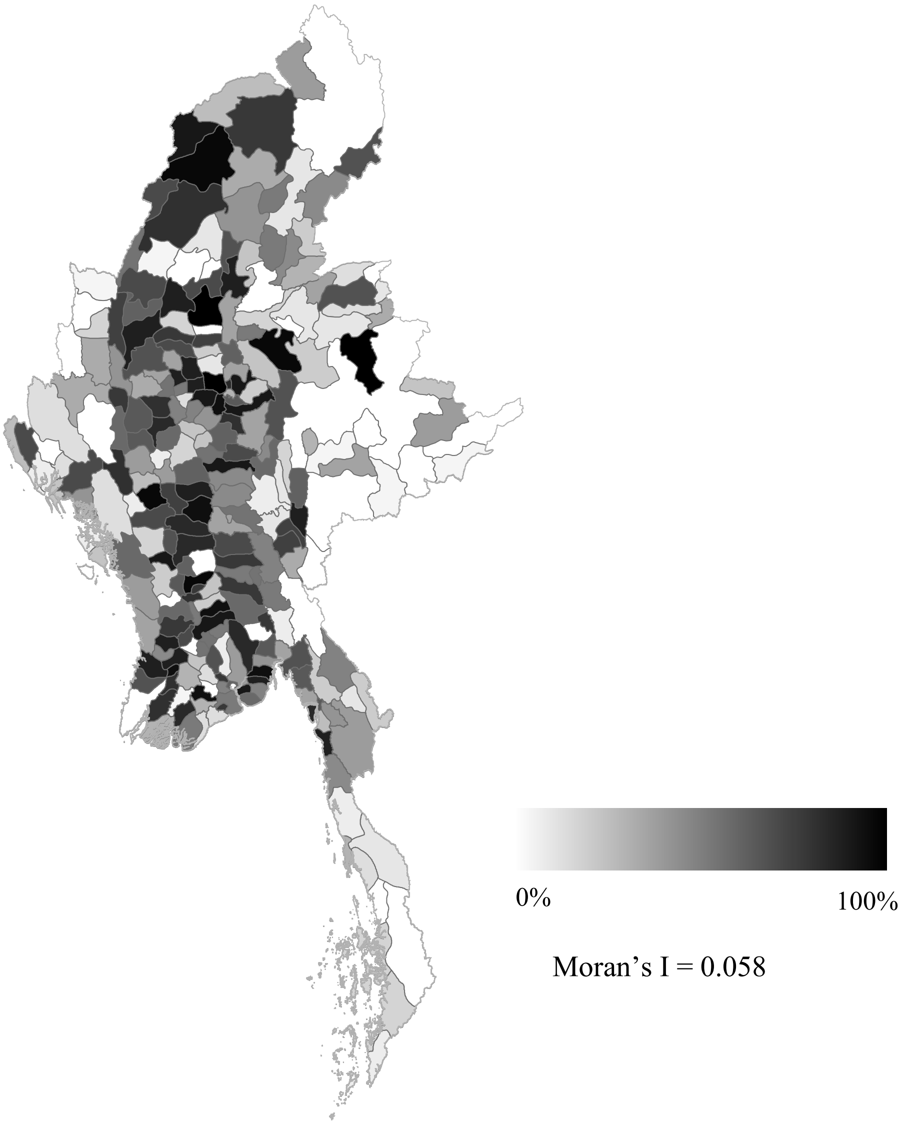
Source: Authors. *10% **5% ***1%

Figure 1. Year of acquisition of 2-wheel tractor (for owners) or start of use of mechanization services (for users)



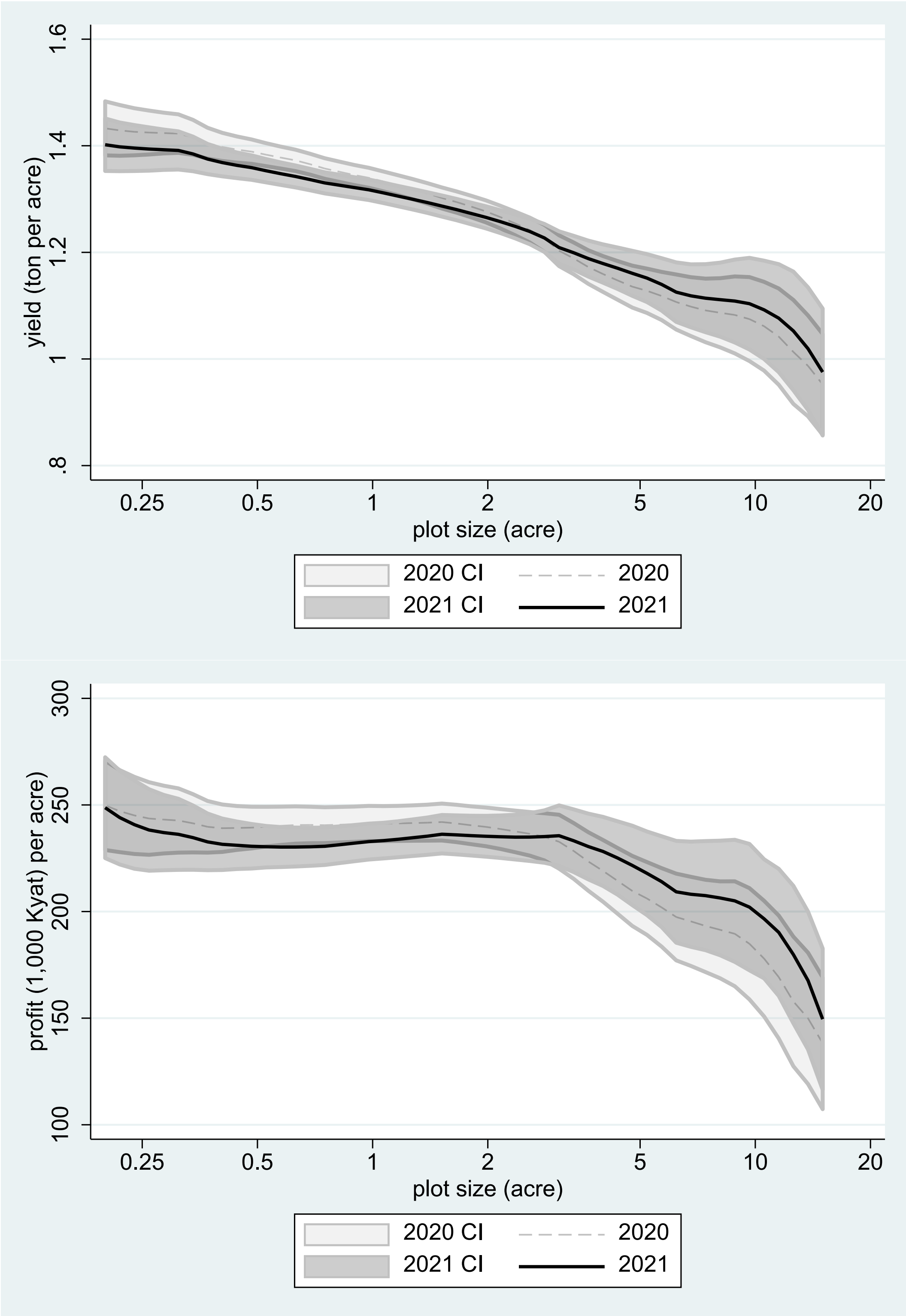
Source: Authors.

Figure 2. General dispersion (less spatial correlation) of mechanization fee growth rate across space (percentage change between 2020 and 2021)



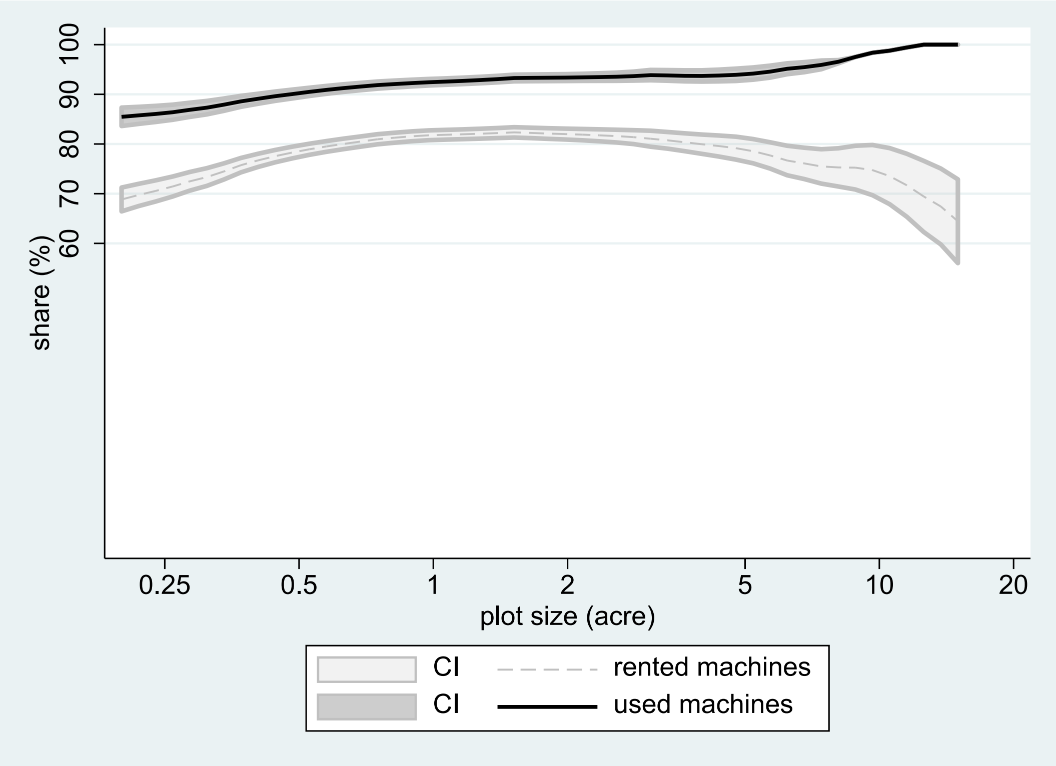
Source: Authors’ calculations based on IFPRI 2022.

Figure 3. Yield and profit - size relationships by year based on local polynomial regression



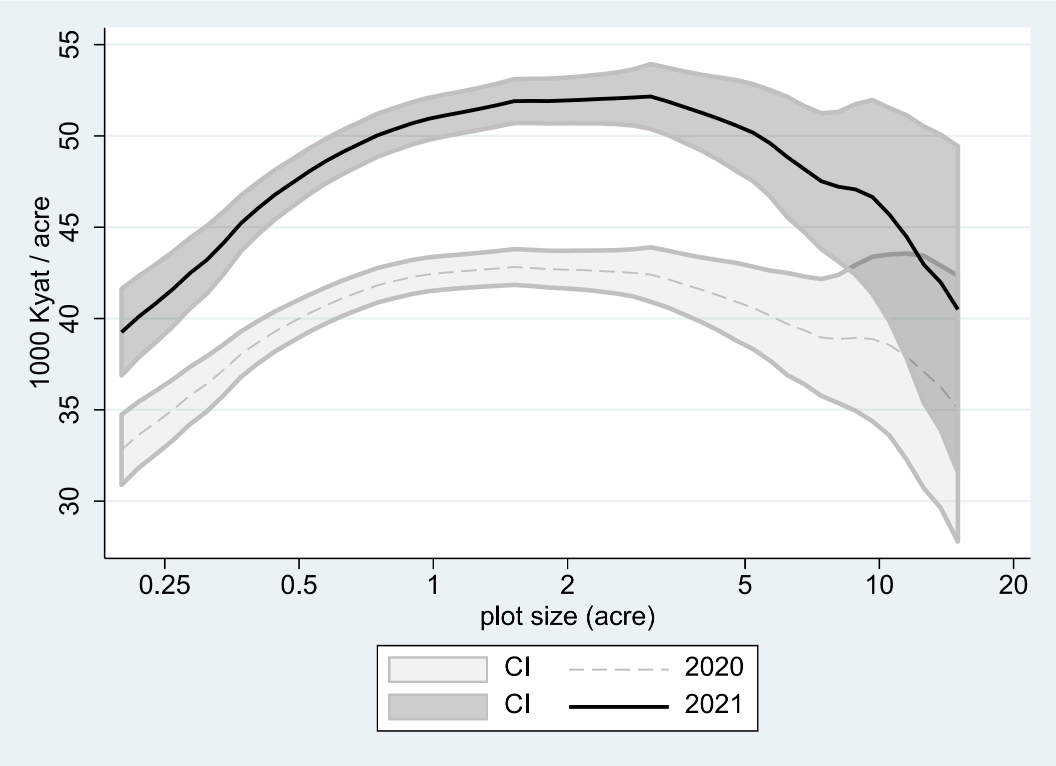
Source: Authors.
Note: CI = 90% Confidence Interval.

Figure 4. Share (%) of rice plots with machine uses by sources in 2021, by plot size



Source: Authors.
Note: CI = 90% Confidence Interval.

Figure 5. Machine rental costs per acre of rice plots, by plot size



Source: Authors.
Note: CI = 90% Confidence Interval.

Table 16. Correlates of mechanization fees in long-run model

Variables	Marginal effects	Std.err
Violent event in the township	0.036***	(0.010)
Age	-0.007	(0.010)
Gender of primary farm decision maker (female = 1)	-0.004	(0.009)
Education above standard 4	-0.009	(0.010)
Household member – adult male	-0.003	(0.009)
Household member – adult female	0.003	(0.009)
Household member – children	0.000	(0.009)
Farm size owned in ha	0.010	(0.009)
Asset	-0.015	(0.011)
Nonfarm income	-0.008	(0.009)
Nighttime light	0.028	(0.015)
Distance to input market	0.028***	(0.008)
COVID case	0.068***	(0.017)
Soil properties		
Soil alkalinity	-0.140***	(0.021)
Organic contents	0.015***	(0.020)
Soil texture	-0.158***	(0.018)
Salinity	0.221***	(0.026)
Sodicity	0.026	(0.017)
Poor drainage	-0.036**	(0.017)
Pests or disease	-0.005	(0.009)
Animal damage	-0.011	(0.010)
Historical average rainfall	0.274***	(0.021)
Historical average temperature	-0.098***	(0.017)
Rainfall anomaly	0.073***	(0.014)
Temperature anomaly	0.071***	(0.021)
State dummy	Included	

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

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

1201 Eye St, NW | Washington, DC 20005 USA
T. +1-202-862-5600 | F. +1-202-862-5606
ifpri@cgiar.org
www.ifpri.org | www.ifpri.info

IFPRI-MYANMAR

IFPRI-Myanmar@cgiar.org
www.myanmar.ifpri.info

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