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The contributions of scale-appropriate farm mechanization to hunger and poverty reduction: evidence from smallholder systems in Nepal

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Abstract
Purpose – This study examines the adoption drivers of scale-appropriate mechanization in Nepal's maize-based farming systems. The authors also assess the contribution of scale-appropriate mechanization to the United Nations Sustainable Development Goals (SDGs) of zero hunger (SDG2) and no poverty (SDG1).

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Design/methodology/approach – Propensity score matching and doubly robust inverse probability-weighted regression adjusted methods were applied to estimate the effects of mini-tiller adoption. These methods control the biases that arise from observed heterogeneities between mini-tillers users and nonusers.
Findings – The study findings show that farm size, labor shortages, draft animal scarcity, market proximity, household assets and household heads' educational level influence the adoption of mechanization in Nepal. Mechanized farms exhibited enhanced maize productivity, profits and household food self-sufficiency. Reduced depth and severity of poverty were also observed. Nevertheless, these effects were not uniform; very small farms (≤0.41 ha) facing acute labor shortages benefited the most.
Research limitations/implications – The study results suggest that policymakers in developing nations like Nepal may wish to expand their emphasis on scale-appropriate mechanization to improve farm productivity and household food security, reduce poverty and contribute to the SDGs.
Originality/value – This first-of-its-kind study establishes the causal effects between scale-appropriate farm mechanization and SDG1 (no poverty) and SDG2 (zero hunger) in a developing nation.

Keywords Sustainable Development Goals, Sustainable agricultural mechanization, Agricultural productivity and profitability, Household food security, Poverty, Impact heterogeneity

Paper type Research paper

1. Introduction

Smallholder farming systems in many developing countries face acute labor shortages due to an accelerating trend of rural labor outmigration (Yang *et al.*, 2013; Wang *et al.*, 2016). Consequently, rural wages have sharply increased, affecting farm enterprise productivity and profitability (Paudel *et al.*, 2019a, b; Zhang *et al.*, 2014). Due to labor shortages, many smallholders cannot manage their crops within optimal time windows. Policymakers have consequently begun to refocus on encouraging scale-appropriate farm mechanization to overcome acute labor shortages and high production costs and create jobs in rural areas through mechanization services provision (Paudel *et al.*, 2019a, b; Van Loon *et al.*, 2020; Yang *et al.*, 2013) [1]. Mechanization in smallholder farming systems decreases the cost of production by offsetting the cost effects of labor shortages and reducing human drudgery and often increases farm productivity (Pingali, 2007; Kienzle *et al.*, 2013). Scale-appropriate mechanization has consequently been proposed to improve on-farm efficiency, agricultural productivity and food security; hence, it has the potential for the structural transformation of rural economies, especially in areas where smallholder-based (<2 ha) farming systems are most common, outmigration is most intense and mechanization is yet to hold (Baudron *et al.*, 2015; Paudel *et al.*, 2019a, b). Therefore, scale-appropriate mechanization attempts to identify equipment and machinery business options that are well matched to small farm sizes and smallholders' technical, social, environmental and economic circumstances (Krupnik *et al.*, 2013; Justice *et al.*, 2021) [2].

Given the potential role of scale-appropriate farm mechanization in improving rural livelihoods and structural transformation of rural economies, it is imperative to quantify its impact on agricultural productivity, profitability, food security and rural poverty. This study investigates the extent to which the adoption of small-scale mechanization contributes to the United Nations (UN) Sustainable Development Goals (SDGs) of zero hunger (SDG2) and no poverty (SDG1). This study focuses on the target indicators of 1.1 and 2.3 as part of SDG1 and SDG2, respectively (UN, 2015). Within SDG1, target indicator SDG1.1 highlights the eradication of extreme poverty for the farmers earning less than US$ 1.25 per day. SDG2's target indicator SDG2 [3] highlights to double agriculture productivity and farm income by 2030. To this end, this case study first characterizes the drivers of scale-appropriate mechanization adoption in Nepal's smallholder-dominated and maize-based farming systems, where rural outmigration has become an acute concern (Krupnik *et al.*, 2021). The study then assesses the impacts of mechanization on agricultural productivity, cost of production, farm profits, household food security and poverty. Since smallholder farms dominate over two-thirds of the agricultural systems globally (FAO, 2014) and interest in scale-appropriate farm mechanization is growing rapidly (Belton *et al.*, 2021), empirical quantification of mechanization interventions is expected to aid in designing the policies that are effective and productive to meet the SDG targets.

Small-scale farm mechanization technologies like mini-tillers (Paudel *et al.*, 2020a, b), reapers (Paudel *et al.*, 2018), threshers (Devkota *et al.*, 2015), rice transplanters (Alam *et al.*, 2019), two-wheel tractors (Aryal *et al.*, 2019) and irrigation pump sets (Foster *et al.*, 2021) have already been widely adopted in many countries. They can increase efficiency for smallholder farmers by saving labor, time and money and contribute to their livelihoods and food security. Such technologies are gaining interest due to their implications for household labor dynamics, labor efficiencies and cost of cultivation (Biggs *et al.*, 2011; Fischer *et al.*, 2018; Belton *et al.*, 2021). Adopting such mechanization technologies can contribute to the structural transformation of agrarian economies (Do *et al.*, 2023).

Mechanization in Nepal is crucial due to its diverse production agroecology. Nepal has three district agroecological production domains (i.e. the mountains, mid-hills and terai). Among the three distinct domains, the mid-hills occupy the largest cultivated area (MoAD, 2017). In the hills, farm mechanization faces logistical challenges due to rugged topography (i.e. issue of access) and a prevalence of small farms, terraced farming and fragmented landholdings, factors that compound issues of economic viability (Krupnik *et al.*, 2021). Although larger horsepower four-wheel tractors are highly used for rural transport, rugged terrain significantly limits their use for agriculture in the hills. While 12- to 19-horsepower two-wheel tractors are traditionally used on farms near roads in the valley bottoms or ridge tops, light-weighted 5- to 9-horsepower mini-tillers are appropriate machines that can fit in the hill geographies.

Moreover, Nepal's national average agricultural landholding is 0.7 ha, and only about 4% of households hold more than 2 ha (CBS, 2011; Krupnik *et al.*, 2021). Second, there is a lack of timely and affordable availability of agricultural labor due to outmigration from rural areas. Nepal is also increasingly becoming a labor-exporting country. Over 4m international labor permits were granted between 2008 and 2018. In 2018, Nepal received over US$ 8.79bn in remittances, contributing almost one-third of the gross domestic product. While remittances have contributed to economic development, agricultural productivity in Nepal has stagnated. The comparative trend analysis in Appendix (Figure A1) shows a positive association between labor outmigration and rural wage rates.

The trends of labor outmigration, rising rural wage rates and low agricultural productivity have been linked to farmland abandonment (Subedi *et al.*, 2021), especially in the mid-hills (Krupnik *et al.*, 2021). The delay in labor availability and high labor prices can consequentially delay crop management operations and affect farm productivity and profitability. Combined with additional challenges, these issues have affected the domestic production of staple cereals and contributed to the expenditure of Nepal's foreign reserves. For example, in 2017, Nepal imported rice (0.54m tons worth US$ 232m), wheat (0.14m tons worth US$ 38m) and maize (0.35m tons worth US$ 91m) (FAO, 2019).

While some studies have investigated the gender and social equality dimensions of mechanization (Doss, 2013; Paudel *et al.*, 2019b, 2020a, b), others have studied the impacts of labor migration on rural livelihoods and food security (Gartaula *et al.*, 2012). However, recent empirical research on scale-appropriate mechanization and its impact on household food security and agrarian poverty is scarce. Although the other types of scale-appropriate machinery are spreading in Nepal's hills (e.g. mini-maize shellers, rice threshers and small horsepower mills), this study focuses on light-weight mini-tillers that have spread rapidly, with over 30,000 units put into use in Nepal over the last decade (CSISA, 2021), to investigate how scale-appropriate mechanization contributes to livelihoods and the SGDs for smallholder maize growers in Nepal mid-hills.

We consequently investigate the following key policy questions: (1) What drives the mini-tiller adoption in the maize-based farming systems in Nepal hills? (2) Does the adoption of mini-tillers increase maize yields and profitability and decrease cultivation costs? (3) Does mini-tiller adoption enhance household food security and alleviate rural poverty? Finally, (4) Is there a heterogeneous effect of mini-tiller adoption across different socio-economic strata? Findings from this study will provide evidence for mechanization research and development and guide policymakers on the significance of scale-appropriate mechanization for smallholders' food security and rural poverty. Moreover, this study could contribute to the literature since this is the first paper to provide the empirical linkages between farm mechanization and UN' SDGs, particularly with SDG1 (no poverty) and SDG2 (zero hunger). Finally, this paper could inform the policymakers in Nepal and other developing countries on the potential impact of investing in farm mechanization. For example, Nepal's agricultural mechanization policy promulgated in 2014 and associated interventions have included subsidy provisions to promote mechanization (Gauchan and Shrestha, 2017). This study could inform similar policies on the potential impacts of such public investment on agricultural productivity, food security and rural poverty.

2. Data

This assessment is based on the maize-growing farm households' survey in Nepal mid-hills. The data were collected with farm households through direct interviews with the farmers. Maize is a major cereal crop in Nepal hills. Maize can be grown in all of Nepal's ecological production domains, up to an elevation of 2,700 meters above sea level, including all 77 districts of Nepal. About 80% of the maize in Nepal is rainfed. The crop is cultivated on almost 1m hectares, with 68% in the mid-hills (Paudel *et al.*, 2022). In 2017, total maize production in Nepal was 2.3m tons. The national average yield of maize was 2.5 tons per hectare (as of 2017), with a yield gap of about 3.0 tons per hectare (MoAD, 2017). Maize is used as food, feed and industrial raw material in Nepal, but 80% is for direct human consumption in the hills.

Trained enumerators deployed a structured questionnaire on an electronic device (http://surveybe.com/). Intentional skips and validation rules were applied to reduce the survey's entry mistakes and time duration. Household demographics, crops cultivated, income sources (both on-farm and off-farm), consumption expenditures and inputs and outputs for maize cultivation were included in the questionnaire. Data were collected from October to November 2017, after the maize harvest in the mid-hill region. A total of six districts, namely Doti, Surkhet, Palpa, Nuwakot, Kavre and Illam, were selected purposively considering their maize growing area, the intensity of mini-tiller adoption and after consultation with the district-level agricultural governmental offices. From the selected districts, 34 subdistricts (village development committees – VDCs) were selected purposively based on the high maize area and the number of mini-tillers adopted in each VDCs. Lastly, 1,004 farm households were chosen randomly for the survey. Among the sample households, 376 were mini-tiller users and 628 were nonusers. Nevertheless, around 740 farms (73.71%) cultivated maize in that particular year, and as such, maize-cultivating households' data are used in the analysis. Among the 740 maize-growing households, 13% were mini-tiller renters (who take the mini-tiller services), 24% were owner adopters and 63% were nonadopters. Here, we combined mini-tiller renters and owners as adopters to get insights into the mini-tiller's impacts on outcome variables. The districts and locations of the sample are shown in Figure 1.

3. Methodology

3.1 Estimating poverty index

We used several outcome indicators to assess the impacts of mechanization interventions: maize productivity, land preparation cost, labor cost, total variable costs, gross margin, household food self-sufficiency and poverty. Following Foster *et al.* (1984), three widely used poverty indicators, namely, incidence, depth and severity, were used to measure different dimensions of poverty. The headcount index, or incidence of poverty, is the proportion of the population living below the poverty line of US$ 1.25 a day. The poverty gap, or depth of

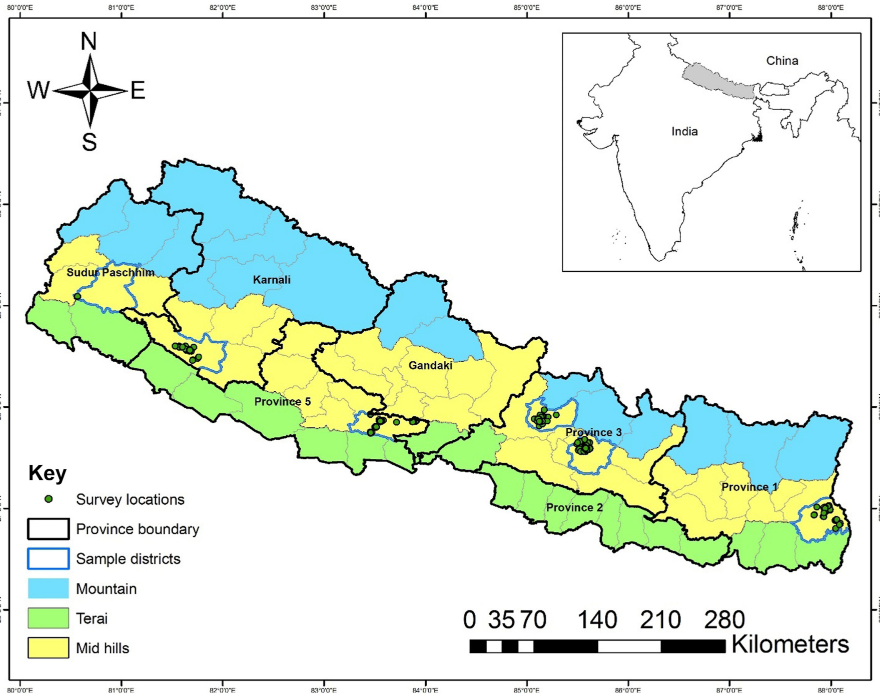

Figure 1. Map of Nepal showing the sample districts and survey locations

poverty, is the income shortfall relative to the poverty line across the population. The severity of poverty, or the square poverty gap, is the level of inequality among the poor. Given our research focus, we used SDG's target of achieving an income of US$ 1.25 per person per day (or US$ 456.25 per annum) as an income-based poverty line threshold to assess the impact of mechanization on poverty. More specifically, following Foster *et al.* (1984), we estimated the incidence, depth and severity of poverty as follows:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{q}\left[\frac{\mu - y_i}{\mu}\right]^\alpha$$

where P_α is the poverty measures; N is the total number of sample households; q is the number of poor households; μ is the poverty line and y_i is the income of the household i. The different values of α provide different poverty indicators. The value of $\alpha = 0$ means the P_0 measures the incidence of poverty or the proportion of the population living below the income-based poverty line of US$ 456.25 per annum. Moreover, the value of $\alpha = 1$ means the P_1, measures the depth of the poverty gap, which is the income gap to the poverty line across the population. Finally, the value of $\alpha = 2$ means that P_2 measures the severity or square poverty gap, which is the level of inequality among the sampled households. The decrease in poverty indicators indicates that adopting mechanization would positively affect poverty reduction (Do *et al.*, 2019).

3.2 Propensity score matching

Ideally, to evaluate the impacts of certain technology, such as mini-tiller use by smallholders, is to conduct a randomized control trial (RCT). However, RCTs are costly to implement, especially those associated with capital equipment. The other methods to assess the impacts of technological interventions include Heckman's two-stage sample selection model (Heckman *et al.*, 1997) and switching regressions (e.g. Lokshin and Sajaia, 2004) that require a suitable instrument to control the endogeneity (Nguyen *et al.*, 2018). However, finding a suitable instrument that satisfies the exclusion restriction was impossible due to our study's diverse nature of outcome variables. In the absence of instrumental variable approaches, propensity score matching (PSM) was applied, following Caliendo and Kopeinig (2005). However, PSM minimizes selection bias from observed heterogeneities but does not deal with unobserved sources of heterogeneity (Paudel *et al.*, 2020a, b). However, these unobserved heterogeneities often leave visible traces in observed data that can be detected through different bounding tests (Rosenbaum, 2002). We used different bounding tests, model specification tests, sensitivity analysis and matching algorithms aligned with the PSM literature to address the latter point.

Since we used PSM to assess the impacts on outcome indicators, the primary interest was the average treatment effect on the treated (ATT), which can be estimated as follows:

$$ATT = E[Y_{1j}|MT_j = 1] - E[Y_{0j}|MT_j = 1] \tag{1}$$

where Y_{1j} is the observed outcome variable (e.g. maize yield) for the jth mini-tiller adopting farm and Y_{0j} is the maize yield for the same jth household before adopting the mini-tiller.

The underlying estimation problem in Equation (1) can be expressed as a treatment effect model of the form:

$$y_{jt} = \alpha_j + \tau_i + \beta' x_{jt} + \delta MT_j + \varepsilon_{jt} \tag{2}$$

$$MT_j^* = \gamma' \omega_j + u_j$$

$$MT_j = \begin{Bmatrix} 1, if\ MT_j > 0 \\ 0, Otherwise \end{Bmatrix} \tag{3}$$

$$Prob(MT_j = 1) = F(\gamma' \omega_j) \tag{4}$$

$$Prob(MT_j = 0) = 1 - F(\gamma' \omega_j) \tag{5}$$

where MT_j^* is a latent unobserved variable, MT_j is observed as a dummy variable; $MT_j = 1$, representing mini-tiller adopters (i.e. treatment group), while $MT_j = 0$, representing nonadopters (i.e. control group); x_j is the vector of farm-level attributes determining the outcome of the mini-tiller adoption, and ω_j determines the probability of mini-tiller adoption. α_j and τ_i capture the individual and time-specific effects, respectively; β and γ are parameters that measure the relationship between the dependent and independent variables, respectively; ε and u are the random components of the respective equations. The functional form F takes the form of a normal, logistic or probability function.

We used the two-step estimation method. While in the first step, Eq. (3) was estimated using a conditional logit model to generate propensity scores for each sample household. Based on the weights of the propensity score, the matched treatment and control groups were identified in the second step to derive the treatment effects (Nguyen *et al.*, 2020; Ho *et al.*, 2022). Moreover, we used three popular matching algorithms, namely, nearest neighbor matching (NNM), kernel matching (KM) and caliper matching (CM) (Caliendo and Kopeinig, 2005) and statistical matching suggested by Dehejia and Wahba (2002). Moreover, the distribution of covariates should be balanced among control and observed subsample groups. Rosenbaum (2002) suggested that the mean standardized bias should be below 20% to qualify for the matching procedure.

Furthermore, Sianesi (2004) suggested a covariate balancing test so that the biases among covariates are minimized after matching, and there exists a substantial overlap between control and treated subsamples (Sianesi, 2004; Lee, 2013). A reduction in values of pseudo R^2, likelihood ratio and mean standardized biases (<20%) would indicate that the matching criteria are satisfied (Rosenbaum and Rubin, 1985). Moreover, the distributions of the propensity score between treated and control subsamples were visualized to check the condition for the common support. Households with a substantial overlap of propensity scores between control and treated subsamples were retained for the meaningful comparison. However, Smith and Todd (2005) suggested that estimated ATT using PSM might be sensitive to model specifications. We consequently conducted the sensitivity analysis by including higher-order variables, such as the square of family members, farm size and farmers' level of education in the model, following Dehejia (2005), and the treatment effects were reestimated. Finally, a robustness check of PSM findings was conducted using the doubly robust inverse probability weighted regression adjusted (IPWRA) method following (Ma *et al.*, 2021; Zhou and Ma, 2022).

3.3 Variables used for empirical analysis

Since this study assesses the impacts of mechanization intervention using PSM, similar to other observational studies, see for example; Thanh and Duong (2022) and Duong *et al.* (2021), we need three sets of variables: treatment, control and outcome. The treatment variable is the mini-tiller users and nonusers, which is a binary (yes = 1 or no = 0), and our data show that almost 274 (37%) farm households that grow maize are mini-tiller users and 466 (63%) are nonusers [4]. The other control and outcome variables are described in the following section.

Control variables: The description of control variables for the mini-tiller user and nonuser is presented in Table 1. We used DFID's (Department for International Development) sustainable livelihood framework to construct the control variables as specified in the literature (DFID, 1999). Based on this framework, the household's vulnerability could be reduced by improving human, natural, social, physical and financial assets. Here, we compared such assets across mini-tiller adopters and nonadopters. The average landholding in the study area is around 0.42 hectares. However, farm size among the mini-tiller adopters (0.54 ha) is marginally higher than among nonadopters (0.35 ha). Most adopters are male-headed households with farming as a primary occupation, with the head of household having more years of formal education and a higher mean age than the general population. A higher percentage of mini-tiller adopters were also members of cooperatives and groups (social institutions) and had greater access to agricultural credit due to the role of social institutions and agricultural credit in easing the liquidity to purchase mini-tillers. Moreover, most adopting households were closer to market centers. That proximity could be related to a higher rate of mineral fertilizer application in maize and the use of high-yielding varieties such as maize hybrids.

The difference between mini-tiller users and nonusers is also reflected in the ownership of household assets – a higher percentage of users own mobile devices, irrigation pumps, televisions and concrete-constructed houses. Although adopters also own higher livestock assets, most were for dairy production and reported inaccessibility of bullocks (draft animals) for tillage and land preparation. While the number of household members was higher in the adopter's category, the number of household members who out-migrated was higher among nonadopters. However, despite having a higher rate of out-migrated family members in the nonadopter category, off-farm income was significantly higher among the adopters. Those households with a small number of out-migrant members, therefore, still appear to be committed to agriculture; hence, they tend to adopt mini-tiller more than those with more migrant members. Finally, a higher percentage of adopters reported difficulty finding agricultural laborers for maize cultivation which could be associated with mini-tiller adoption.

Outcome variables: Since our analysis deals with the impacts of mechanization in the maize-based farming system, we used inputs and output for maize cultivation along with

Variables	Overall farms (N = 740) Mean	SE	Adopters (N = 274) Mean	SE	Nonadopters (N = 466) Mean	SE	Difference (%)
Human capital							
Household size (no)	5.688	0.076	5.945	0.130	5.536	0.092	7.383***
Age of household head (years)	48.757	0.399	49.774	0.644	48.159	0.506	3.353**
Education of household head (years)	5.974	0.157	7.109	0.258	5.307	0.192	33.968***
Gender of the household head (1 = male, 0 = female)	0.845	0.013	0.923	0.016	0.798	0.019	15.668***
The household's caste (1 = nonmarginalized caste, 0 = marginalized caste)	0.549	0.018	0.745	0.026	0.433	0.023	71.757***
Years of farming (years)	25.826	0.428	26.708	0.691	25.307	0.545	5.537
Natural capital							
Farm size (ha)	0.420	0.015	0.541	0.023	0.349	0.018	55.181***
Number of livestock owned (tropical livestock units or TLUs)†	2.081	0.047	2.248	0.089	1.983	0.054	13.392***
Financial capital							
Off-farm income NPR ('000)	294.807	9.886	300.475	18.918	291.474	11.092	3.088***
Access to agricultural credit (1 = yes, 0 = no)	0.972	0.006	0.985	0.007	0.964	0.009	2.271*
Social capital							
Membership in groups or cooperatives (1 = yes, 0 = no)	0.697	0.017	0.821	0.023	0.624	0.022	31.500***
Occupation of the household head (1 = farming, 0 = others)	0.588	0.018	0.646	0.029	0.554	0.023	16.678***
Nearest inputs market distance (km)	7.890	0.295	3.317	0.224	10.578	0.400	−68.642***
Difficult in finding labors (1 = yes, 0 = no)	0.701	0.017	0.745	0.026	0.676	0.022	10.142*
Bullock availability for maize land preparation (1 = difficult, 0 = easy)	0.272	0.016	0.445	0.030	0.170	0.017	162.644***
Number of household members migrated (no)	0.345	0.021	0.255	0.030	0.397	0.028	−35.648***
Used open pollinated varieties of maize seed (1 = yes, 0 = no)	0.080	0.010	0.080	0.016	0.079	0.013	1.125
Used hybrid maize seed (1 = yes, 0 = no)	0.428	0.018	0.584	0.030	0.337	0.022	73.323***
On-farm labor wage rate (NPR)	636.426	7.585	660.766	12.748	622.114	9.377	6.213
Physical capital							
Mobile phone ownership (1 = yes, 0 = no)	0.953	0.008	0.971	0.010	0.942	0.011	3.051*
Own pumps, engines, or vehicles (1 = yes, 0 = no)	0.297	0.017	0.445	0.030	0.210	0.019	111.724***
Own television (1 = yes, 0 = no)	0.927	0.010	0.982	0.008	0.895	0.014	9.711***
House type (1 = concrete, 0 = others)	0.169	0.014	0.288	0.027	0.099	0.014	192.082***
NPK fertilizer applied (kg/ha)††	69.960	3.532	95.140	6.555	55.154	3.922	72.499***
Farmyard manure applied (1 = yes, 0 = no)	0.931	0.009	0.912	0.017	0.942	0.011	−3.147

Note(s): ***Significant at 1% level, **significant at 5% level and *significant at 10% level. SE stands for standard errors. †TLU stands for tropical livestock unit (Pica-ciamarra *et al.*, 2007). Exchange rate 1 US$ = NPR 107 during the survey year (NRB, 2022). ††Total amount of fertilizer represents nitrogen, phosphorus and potash

Table 1.
Attributes of mini-tiller adopters, nonadopters and overall farms in the Nepal mid-hills

the household food security and poverty indicators as outcome variables. The comparison of outcome variables for mini-tiller users and nonusers is presented in Table 2. While the average per hectare land preparation cost for the maize cultivation in the study area is

Variables	Overall farms (N = 740) Mean	S.E	Adopters (N = 274) Mean	S.E	Nonadopters (N = 466) Mean	S.E	Difference (%)
Seed cost (NPR/ha)	4676.36	186.60	5634.36	327.18	4113.08	221.54	36.99***
Fertilizer cost (NPR/ha)	4542.24	231.28	6248.32	433.91	3539.09	253.29	76.55***
Land preparation cost (NPR/ha)	17024.66	309.74	13179.27	350.44	19285.69	412.35	−31.66***
Labor cost (NPR/ha)	27145.26	703.42	22773.93	880.34	29715.53	971.00	−23.36***
Total variable cost (NPR/ha)†	66072.72	1108.72	59393.92	1525.52	69999.74	1486.39	−15.15***
Maize yield (kg/ha)	3158.65	75.98	3428.77	137.71	2999.82	88.75	14.30***
Gross revenue (NPR/ha)††	76813.53	1830.05	81898.68	3185.93	73823.54	2212.76	10.94**
Gross margin (NPR/ha)†††	10740.80	1838.88	22504.76	3133.43	3823.80	2206.05	488.54***
Households with food self-sufficient for ≥12 months (%)	31.62	1.71	50.00	3.02	20.81	1.88	140.21***
Incidence of poverty (%)	21.49	1.51	21.53	2.49	21.46	1.90	0.34
Poverty gap (%)	7.33	0.65	6.67	1.02	7.74	0.85	−13.83
Square poverty gap (%)	3.68	0.43	3.26	0.69	3.93	0.57	−17.22

Note(s): ***Significant at 1% level, *significant at 5% level. SE stands for standard errors. Exchange rate 1 US$ = NPR 107 during the survey year (NRB, 2022). †Total variable cost is the summation of all the costs (seed, land preparation, fertilizer and labor costs). ††Gross revenue is obtained by multiplying grain yield with farm gate price. †††Gross margin is the difference between gross revenue and total variable costs

Table 2. Maize enterprise budgets and outcome variables for mini-tiller adopters and nonadopters in the mid-hills of Nepal

around NPR 17,025 (US$ 159 per ha), the land preparation cost for the mini-tiller adopters was 32% lower than for the nonadopters [5]. Mini-tillers are primarily used for agricultural land preparation and tillage, while the nonadopters have used bullocks and hired labor, increasing land preparation costs. Moreover, mini-tiller users' seed and fertilizer costs are higher than nonusers'. The fertilizer application rate was higher among adopters, and they also tended to utilize hybrid maize seeds, which could be the reason for the adopter's higher rates of investment in seed and fertilizer. However, mean per hectare labor costs for maize cultivation were still 23% lower at US$ 213 for adopters versus US$ 278 for nonadopters. Naturally, due to the lower labor and land preparation cost, the total variable costs for the mini-tiller users were 15% lower on average (US$ 555 versus US$ 654 per hectare) than for nonadopters. However, the seed and fertilizer costs were higher for the adopters.

Moreover, the maize yield achieved by the mini-tiller adopters was 3,429 kg/ha, which is 14% higher than that achieved by nonadopters. The higher maize yield and low cost of production among mini-tiller adopters led to higher per hectare gross revenue and gross margin (profit) for the mini-tiller adopters, which were, respectively, 14% (NPR 81,899 or US$ 765 per ha) and 11% (NPR 22,505 or US$ 210 per ha) higher for the adopters. Reduced production costs, gain in profits and increase in maize productivity positively affected the household food security status [6]. While 50% of adopters reported that they could support their household food self-sufficiency from their household production, only 21% of the nonadopters reported achieving food self-sufficiency. Moreover, the incidence of poverty or the headcount was almost similar across the adoption categories. However, although the poverty gap and severity were slightly lower for the mini-tiller adopter category, the observed difference was statistically insignificant. Finally, the differences in inputs and all farm-level attributes may affect maize productivity, costs, profits, food security and poverty indicators. Hence, it justifies the use of PSM to control these attributes. Other factors could affect mini-tiller adoption decisions, which are described in the next section.

4. Results and discussion

4.1 Drivers of mini-tiller adoption

The results on potential mini-tiller adoption drivers are presented in Table 3. The coefficient of farm size is positive and suggests that large farms are likely to adopt mini-tillers. However, the negative coefficient of farm size squared suggests that larger farm sizes reduce the probability of mini-tiller uses when the cultivated area exceeds 2.65 hectares [7]. The mini-tiller is a suitable machinery for the smallholder farmer; as a result, its adoption increases to a certain level of farm size; however, beyond a certain land size, the mini-tiller is not more attractive because of the need for a higher-capacity farm machinery. Other factors associated with mini-tiller adoptions positively include the educational level of household heads, belonging to a nonmarginalized caste [8], family size and household assets (such as television and concrete building/house). The model shows that farms relying on off-farm income, applying more farmyard manure in maize, and farms with more migrant members are negatively associated with mini-tiller adoption. As expected, farm households closer to market centers, facing labor shortages, and with fewer draft animals for agricultural land preparations are the mini-tiller adopters.

	Coefficient	Std. error	Marginal effects
Farm size (ha)	4.628***	0.861	0.670***
Farm size squared	−1.747***	0.370	−0.253***
Age of household head (years)	0.002	0.022	3E-04
Education of household head (years)	0.125***	0.037	0.018***
Gender of the household head (1 = male)	0.387	0.387	0.051
Households' caste (1 = nonmarginalized caste)	0.889***	0.257	0.126***
Years of farming (years)	0.013	0.019	0.002
Household size (no)	0.155**	0.078	0.022**
Occupation of the household head (1 = farming)	0.318	0.260	0.045
Number of migrated household members (no)	−0.535**	0.233	−0.077**
Groups or cooperatives membership (1 = yes)	0.328	0.303	0.046
Access to credit (1 = yes)	0.023	0.807	0.003
Mobile phone ownership (1 = yes)	−0.349	0.620	−0.056
Own pumps or vehicles (1 = yes)	0.442*	0.274	0.068
Own television (1 = yes)	1.619**	0.671	0.148**
Household type (1 = concrete)	0.655**	0.319	0.108*
On-farm labor wage rate (NPR)	0.008***	0.001	0.001***
Log of off-farm income (NPR)	−0.078**	0.038	−0.011**
Log of NPK fertilizer applied (kg/ha)	−0.024	0.025	−0.003
Farmyard manure applied (1 = yes)	−0.920*	0.522	−0.167
Used open pollinated maize seed (1 = yes)	0.006	0.483	0.001
Used hybrid maize seed (1 = yes)	0.297	0.268	0.044
Nearest inputs market distance (km)	−0.365***	0.041	−0.053***
Numbers of livestock owned (TLU)	−0.133	0.097	−0.019
Difficulty experienced in finding labor (1 = yes)	0.447	0.294	0.061*
Difficulty experienced in finding draft animals (1 = yes)	0.933***	0.273	0.154***
Model intercept	−8.137***	1.585	
LR χ^2	502.1		
Prob > χ^2	0.000		
Pseudo R^2	0.515		
Log likelihood	−236.682		
Model correctly classified adopters and nonadopters (%)	86.49		
No of observations	740		

Note(s): ***Significant at 1% level, **significant at 5% level and *significant at 10% level

Table 3. Drivers of mini-tiller adoption for maize farming in the mid-hills of Nepal

Our findings on the drivers of scale-appropriate mechanization are in line with those of earlier studies on farm mechanization. For example, scholars reported that farm size in smallholder farming systems is an essential driver for both mechanization adoption (Ghosh, 2010) and demand (Paudel *et al.*, 2019a, b). Moreover, farmers with more household assets and wealth are more likely to adopt mini-tillers, and the findings are supported by literature on technology adoption (Kassie *et al.*, 2013; Paudel *et al.*, 2019a). Our analysis shows that farmers owning more draft animals are less likely to adopt mini-tillers since the livestock are used for land preparation, and potentially, households with more livestock, especially draft animals, are less likely to use the mini-tillers. At the same time, farmers that face difficulty finding the draft animal and farm labor for maize cultivation appear to have a greater potential to adopt mini-tiller users, which echoes previous studies in the region (Paudel *et al.*, 2019a, b). Finally, our results show that market proximity is positively linked to mini-tiller adoption, as indicated in the previous studies on technology adoption (Kassie *et al.*, 2011). Farm households closer to markets have likely increased access to mini-tiller traders, fuel supplies, mechanics, spare parts and access to credit and information needed to purchase mini-tillers.

4.2 Impact of mini-tiller adoption

There was a substantial difference in observed attributes between mini-tiller adopters and nonadopters (Table 1), which could result from biased estimates of outcome variables (Table 2) if we did not match observed attributes between the two groups. Hence, it is essential to use PSM. So, in the second stage, based on the propensity score generated from the conditional logit model, mini-tiller adopters were matched with nonadopters and the ATTs were estimated. We used three matching algorithms as specified in the analytical framework. The matching criteria were evaluated to control the observed distribution of covariates among mini-tiller adopters and nonadopters. After matching, the covariate balancing test shows a substantial bias reduction for many covariates (Appendix–Figure A2). The distribution of propensity scores presented in Appendix (Figure A3) shows a substantial overlap between the mini-tiller control (nonusers) and treated (users), indicating common support. Furthermore, the mean absolute standard bias reduced after matching, with less than the required limit of 20% across three matching algorithms (Table A1). Moreover, the reduction in values of pseudo R^2 and likelihood ratios test suggests a low bias among covariates after matching.

The ATTs for the mini-tiller adopters are shown in Table 4, and only the matched samples with common support are presented for meaningful comparison [9]. Results show that the use of mini-tillers reduced maize land preparation cost, labor cost and total variable cost that range from NPR 5,377 to 6,424 (US$ 50–60) per ha, NPR 6,424 to 8,185 (US$ 60–76) per ha and NPR 9,037 to 10,501 (US$ 84–98), respectively. However, the adoption of mini-tillers enhanced maize yield and gross margin (profitability) by 20–25% (573–673 kg/ha) and NPR 19,852–23,477 (US$ 186–219) per ha, respectively. The decrease in land preparation cost, the total cost of production and increased maize productivity and profitability enhanced the households' probability of being more food self-sufficient by 24–26%. Moreover, the increase in productivity, gains in gross margin (profits), reduced labor, land preparation and overall maize cultivation costs and concurrent increase in food self-sufficiency enabled households to reduce their depth and severity of poverty that range from 6.61 to 9.30% and 4.30–5.58%, respectively. However, there were no significant effects of mini-tiller uses in reducing headcount poverty (data not shown).

Our findings on the impacts of mini-tiller use on maize yield and farm profitability support Paudel *et al.* (2019a), who reported that mini-tiller uses enhanced rice productivity by almost 27% in the hill ecologies of Nepal. While the declining numbers of draft animals (Rao and Birthal, 2008) and labor scarcity (Maharjan *et al.*, 2013a; Maharjan *et al.*, 2020) have forced farmers to delay land preparation and intercultural operations resulting in low agricultural productivity (Maharjan *et al.*, 2013b; Khanal, 2018; Paudel *et al.*, 2019a), the increase in

Matching algorithms	Outcome variables	Treated	Control	ATT	SE	*t*-stat	Critical level of hidden bias (Γ)	No of control samples	No of treated samples†
Kernel-based matching (KBM)	Maize yield (kg/ha)	3393.06	2717.82	675.23**	315.09	2.14	1.25–1.30	466	233
	Land preparation cost (NPR/ha)	13114.00	18490.82	−5376.82***	1538.71	−3.49	5.95–6.00		
	Total labor cost (NPR/ha)	21090.03	29275.07	−8185.04**	3626.48	−2.26	2.85–2.90		
	Total variable cost (NPR/ha)	57224.35	66741.83	−9517.48*	5669.87	−1.68	2.20–2.25		
	Gross margin (NPR/ha)	23964.06	487.07	23476.99***	7354.22	3.19	2.85–2.90		
	Food self-sufficiency (%)	48.50	21.53	26.97***	7.54	3.05	1.95–2.00		
	Poverty gap (%)	7.06	13.67	−6.61**	3.25	−2.03	2.60–2.65		
	Square poverty gap (%)	3.38	7.42	−4.03*	2.17	−1.86	3.95–4.00		
Nearest neighbor matching (NNM)	Maize yield (kg/ha)	3393.06	2776.76	616.30*	354.82	1.74	1.30–1.35	466	233
	Land preparation cost (NPR/ha)	13114.00	19430.47	−6316.47***	1362.31	−4.64	6.65–6.70		
	Total labor cost (NPR/ha)	21090.03	28143.87	−7053.84*	3798.07	−1.86	2.20–2.25		
	Total variable cost (NPR/ha)	57224.35	67725.32	−10500.97*	5606.45	−1.87	1.85–1.90		
	Gross margin (NPR/ha)	23964.06	1825.02	22139.04***	8630.90	2.57	2.05–2.10		
	Food self-sufficiency (%)	48.50	24.18	24.32***	7.97	3.57	1.90–1.95		
	Poverty gap (%)	7.06	16.36	−9.30**	3.97	−2.34	3.05–3.10		
	Square poverty gap (%)	3.38	8.96	−5.58*	2.95	−1.89	4.20–4.25		
Caliper matching (CM)	Maize yield (kg/ha)	3393.06	2819.75	573.30*	332.27	1.73	1.20–1.25	466	233
	Land preparation cost (NPR/ha)	13114.00	19538.23	−6424.23***	1425.89	−4.51	9.05–9.10		
	Total labor cost (NPR/ha)	21090.03	27842.99	−6752.96**	3361.05	−2.01	2.55–2.60		
	Total variable cost (NPR/ha)	57224.35	66261.18	−9036.83*	5204.44	−1.74	2.00–2.05		
	Gross margin (NPR/ha)	23964.06	4111.88	19852.18***	8057.24	2.46	1.75–1.80		
	Food self-sufficiency (%)	48.49	23.43	25.06***	7.06	3.55	2.85–2.90		
	Poverty gap (%)	7.06	15.10	−8.04***	3.03	−2.66	2.95–3.00		
	Square poverty gap (%)	3.38	8.45	−5.07***	2.02	−2.51	4.50–4.55		

Note(s): ***Significant at 1% level, **significant at 5% level and *significant at 10% level. SE stands for standard errors. ATT: average treatment effect on the treated. SE: standard error. Exchange rate 1 US$ = NPR 107 during the survey year (NRB, 2022). †Samples with common support are only presented for the meaningful comparison

Table 4.
Impact of mini-tiller adoption on outcome variables

productivity and profitability observed in our study can be attributed to timely crop establishment and inter-cultural operations, namely through the use of the mini-tiller for land preparation and weeding, due to machinery adoption. Conversely, our results on the impacts of mini-tillers in enhancing household food self-sufficiency and rural poverty are unique. This could be the first study that empirically links scale-appropriate mechanization with food security and poverty indicators.

Based on the Rosenbaum bounds, the sensitivity analysis to detect the presence of bias arising from unobserved heterogeneity is given in Table 4, Column 8 [10]. The critical gamma (Γ) value ranged between 1.20–1.25 and 9.05–9.10, indicating the relative robustness of these results to unobserved factors. For example, with respect to the impacts of mini-tillers on maize yield, the estimated critical value of gamma ($\Gamma = 1.30$) indicates that a 30% change in the odds of mini-tiller adoption is required before the estimated impacts of mini-tillers adoption on maize yield become statistically insignificant. However, critical values close to 1 indicate large potential sensitivity to such hidden bias. This suggests that our results are robust and could not be affected by unobserved heterogeneity. Hence, we conclude that the treatment effects are robust and not affected by hidden biases.

Smith and Todd (2005) suspected that estimates generated from PSM might be sensitive to model specifications. To rule out this concern, we conducted sensitivity analysis by adding three higher-order covariates in the model, such as the quadratic form of family size and household heads' education, and the ATTs were recalculated. In the first model, we added the square of household size, and in the second model, we added the square of education, while in the third model, we included both household size and education of household head squares (Appendix Table A2). The reestimated ATTs are shown in Appendix (Table A3). The treatment effects did not change significantly even after changing the model specifications and adding more conditional variables. The estimated ATTs are similar to those presented in Table 4, suggesting that our results are robust and are not sensitive to the changes in model specifications.

4.3 Robustness check

We used the doubly robust IPWRA method to check the robustness of our findings from PSM, and the results are presented in Table 5. Results show that the adoption of mini-tillers significantly reduced land preparation costs (US$ 77 or NPR 8,280 per ha), labor costs (US$ 76 or NPR 8,140) and the total cost of maize cultivation (US$ 119 or NPR 12,790 per ha) and enhanced the maize productivity (846 kg/ha) and farm profit (US$ 265 or NPR 28,390). Moreover, increased maize productivity improved household food self-sufficiency significantly by 28% and reduced the depth and severity of poverty by 5 and 4%, respectively. These results are qualitatively similar to the PSM results presented in Table 4 and indicate the robustness of our findings. Moreover, IPWRA results have a doubly robust property and guarantee that the estimated treatment effects are unbiased (Ma *et al.*, 2021; Zhou and Ma, 2022).

Table 5. Robustness check using doubly robust inverse probability weighted regression adjusted (IPWRA) method

Outcome variables	ATT	Std. error	Other controls
Maize yield (kg/ha)	845.87***	304.15	Yes
Land preparation cost ('000 NPR/ha)	−8.28***	0.85	Yes
Total labor cost ('000 NPR/ha)	−8.14***	1.03	Yes
Total variable cost ('000 NPR/ha)	−12.79***	2.24	Yes
Gross margin ('000 NPR/ha)	28.39***	5.53	Yes
Food self-sufficiency (%)	28.04***	5.57	Yes
Poverty gap (%)	−5.10***	1.56	Yes
Square poverty gap (%)	−4.47***	0.98	Yes

Note(s): ***Significant at 1% level. Exchange rate 1 US$ = NPR 107 during the survey year (NRB, 2022). ATT: average treatment effect on the treated. Five of the observations were removed from the data due to very low propensity score and difficulty in findings overlaps among control samples

4.4 Heterogenous effects of mini-tiller adoption

Technology adoption may not always have a homogeneous effect on an entire population; hence, impact heterogeneity is expected. To understand the differential impacts of mini-tiller adoption, we stratified our matched data into farm size categories, household caste and labor availability. The results of impact heterogeneity on outcome indicators are presented in Table 6. These results are based on the matched samples within the common support region.

To assess the heterogenous effects of mini-tiller uses within different farm sizes, we stratified matched data into small and marginal farms around the mean farm size (0.42 ha). Results show that the productivity, profitability and food security impacts of mini-tiller

Table 6. Heterogenous effects of mini-tiller adoption on outcome variables across different socio-economic strata

Socio-economic strata	Outcome variables	Treated	Control	ATT	SE	*t*-stat	Critical level of hidden bias (Γ)	No of control samples	No of treated samples†
Farm size									
Marginal farms (≤0.42 ha)	Maize yield (kg/ha)	3873.31	2975.67	897.64**	384.29	2.34	1.45–1.50	378	111
	Gross margin (NPR/ha)	34579.24	−438.65	35017.89***	8870.76	3.95	2.70–2.75		
	Food self-sufficiency (%)	36.93	10.51	26.43***	7.87	3.36	1.90–1.95		
	Poverty gap (%)	4.59	13.05	8.46**	4.02	−2.10	3.15–3.20		
Small farms (>0.42 ha)	Maize yield (kg/ha)	2821.54	2397.00	424.54	555.48	0.76	–	88	112
	Gross margin (NPR/ha)	12435.53	4991.00	7444.53	12900.88	0.58	–		
	Food self-sufficiency (%)	58.04	45.54	12.50	14.61	0.86	–		
	Poverty gap (%)	8.49	19.41	−10.93	6.90	−1.58	–		
Caste of the households									
Nonmarginalized castes	Maize yield (kg/ha)	3527.95	2737.92	790.03*	429.26	1.84	1.45–1.50	202	166
	Gross margin (NPR/ha)	26916.40	6706.58	20209.83*	11038.77	1.83	1.65–1.70		
	Food self-sufficiency (%)	52.41	27.11	25.30**	10.20	2.48	2.10–2.15		
	Poverty gap (%)	6.92	18.18	−12.09**	5.55	−2.18	3.95–4.00		
Marginalized castes	Maize yield (kg/ha)	2953.68	2943.30	10.38	495.54	0.02	–	264	66
	Gross margin (NPR/ha)	14766.32	3047.83	11718.48	10777.79	1.09	–		
	Food self-sufficiency (%)	37.88	26.77	11.11	10.36	1.07	–		
	Poverty gap (%)	9.60	12.37	−2.76	4.74	−0.58	–		
Labor availability									
Difficulty experienced in finding labor	Maize yield (kg/ha)	3259.29	2744.08	515.21	366.27	1.41	1.10–1.15	315	169
	Gross margin (NPR/ha)	19617.51	925.39	18692.12**	8590.03	2.18	2.50–2.55		
	Food self-sufficiency (%)	50.89	24.65	26.23***	8.45	3.03	2.25–2.30		
	Poverty gap (%)	5.36	11.96	−6.61**	3.20	−2.06	2.15–2.20		
Ease finding labor	Maize yield (kg/ha)	3686.37	3544.06	142.31	659.03	0.22	–	151	53
	Gross margin (NPR/ha)	34497.98	19167.03	15330.94	12574.20	1.22	–		
	Food self-sufficiency (%)	43.40	32.70	10.69	14.03	0.76	–		
	Poverty gap (%)	10.30	16.42	−6.12	7.67	−0.80	–		

Note(s): ***Significant at 1% level; **significant at 5% level and *significant at 10% level. SE stands for standard errors. ATT: average treatment effect on the treated. SE: standard error. Exchange rate 1 US$ = NPR 107 during the survey year (NRB, 2022). The results presented in this table are from nearest neighbor matching with three neighbors and common support. †Samples with common support are only presented for the meaningful comparison adoption are significantly higher for marginal farms (i.e. ≤0.42 ha), while the results are statistically nonsignificant for the small farms (i.e. >0.42 ha). Adopting mini-tillers among marginal farms enhanced maize yield by 30% (898 kg/ha) and profitability by US$ 337 per ha. Moreover, the increase in maize productivity and profitability enabled small farms to enhance their household food security by 26% and reduced their depth of poverty by 8.5%. Our results show that marginal farms benefited more than small farms from mini-tiller adoption. Furthermore, the Γ value ranges from 1.45–1.50 to 3.15–3.20, suggesting that the causal inferences are unlikely to be affected, indicating our findings' robustness.

We assessed the heterogenous impacts of mini-tiller adoption concerning the caste of the households because most adopters were from nonmarginalized castes. These results suggest that maize productivity, profitability and household food security effects of mini-tiller adoption were significantly higher for nonmarginalized castes, while the treatment effects were statistically nonsignificant for marginalized castes. For the nonmarginalized caste, the adoption of mini-tillers increased the maize yield, profitability and household food security, respectively, by 29% (790 kg/ha), NPR 20,210 (US$ 194 per ha) and 25%. Moreover, the increase in productivity, profitability and household food security from the mini-tiller adoption reduced the depth of poverty by 12% for the adopters. These results indicate that households from nonmarginalized castes benefited the most from the mechanization compared with those from the marginalized caste. Moreover, the large value of gamma that ranges from 1.45–1.50 to 2.10–2.15 suggests that endogeneity is unlikely to affect the causal inferences.

We also estimated the differential impacts of mini-tiller adoption across households that reported difficulty finding labor versus those that did not report challenges finding laborers for maize cultivation. Our results suggest that mini tillers' impacts on increasing productivity, profitability, food security and reducing poverty were statistically significant among households that faced labor shortages. For the farms that did not encounter difficulties finding agricultural laborers, the mini-tiller's impact on productivity, profitability, food security and poverty was nonsignificant. Among the households that faced difficulty finding laborers, the adoption of mini-tiller enhanced the maize productivity by 19% (515 kg/ha), gross margin by US$ 175 per ha (NPR 18,692), household food self-sufficiency by 29% and reduced depth of poverty by 6.6%. These results indicate that scale-appropriate mechanization can positively affect farm households that suffer from acute labor shortages. Conversely, the nonsignificant effects on households without labor shortages are likely to be due to the increased availability of manual labor and animal traction for maize cultivation. Finally, the higher gamma value of that hidden bias is unlikely to affect the causal inferences, underscoring the robustness of our findings.

These results established a strong relationship of scale-appropriate mechanization with household food security, farm productivity, profitability and poverty, although corrective policy interventions may be required to extend these benefits to marginalized social groupings in pursuit of SGD10 (reducing inequalities). The results concur with previous studies suggesting inclusive and responsible mechanization policy, especially for engaging youth, women and socially marginalized communities to ensure visioning and foresight of agricultural innovation that adheres to scale-appropriate mechanization for the next few decades (Devkota *et al.*, 2020). However, achieving these results on a broader scale and contributing to SDGs will only have a significant effect if mini-tillers' large-scale adoption and scaling were realized throughout the country and with similar geographies in other countries. Achieving scale in adoption will be reliant on developing an enabling environment and favorable policy to encourage equitable access and farmers' use of these technologies, which will require political commitment, government support and actions to encourage the private sector to make machinery affordable.

4.5 Research limitations

Despite the valuable advantage of using PSM in our analysis, there is room for future improvement. First, the use of PSM accounts only for observed attributes of mini-tiller users and nonusers and does not account for latent or unobserved attributes. Many unobserved attributes could affect the smallholder farmers' decision to use the mini-tillers in Nepal hills, and such latent unobserved attributes or hidden biases could affect the causal inferences. Although we conducted Rosenbaum bounds tests to detect the presence of hidden bias from the observed data, in addition to the several sensitivity analyses, future research is needed, especially by accounting for such unobserved biases. Second, our data are from the hilly region of Nepal, and conducting such research in smallholder farming systems across other developing countries could provide the external validity of our results on the impacts of farm mechanization on the cost of crop production, productivity, profitability, food security and rural poverty.

5. Conclusion and policy implications

This study aimed to understand whether adopting scale-appropriate farm mechanization enhances agricultural productivity and household food security and reduces rural poverty in support of the UN's SDGs of ending global hunger and extreme poverty. We take Nepal as a case study to illustrate this topic as the country suffers rural labor shortages due to outmigration, and farming is becoming costly due to rising rural labor wages. We used farm survey data from maize-based farming systems in Nepal's mid-hills. PSM and doubly robust IPWRA methods were applied to estimate the effects of mini-tiller adoption. These methods control the biases that arise from observed heterogeneities between mini-tiller users and nonusers. We conducted sensitivity analysis and bounding tests to detect whether the presence of unobserved heterogeneities affects the results from PSM since PSM is susceptible to unobserved sources of heterogeneities. The analysis revealed that the unobserved heterogeneities did not alter the observed patterns of the mini-tiller's impact on agricultural productivity and rural poverty, suggesting the robustness of our findings.

We find that labor scarcity, draft animal shortages, market proximity and household assets are associated with mini-tiller adoption in Nepal. Moreover, adopting scale-appropriate mechanization helped reduce land preparation costs, labor costs and total cost of maize cultivation and improved maize yield in Nepal's mid-hills. The increase in maize productivity observed, in turn, enhanced household food self-sufficiency. Moreover, the decreased costs of maize cultivation increased farm profits and achieving food self-sufficiency enabled rural households to reduce poverty. Our analysis showed that adopting mechanization reduces the depth and severity of poverty for mini-tiller-adopting households. In this regard, this study is the first to estimate the impacts of small-scale mechanization on poverty and food insecurity. In Nepal, over two-thirds of the population relies on agriculture and one-fourth lives below absolute poverty. Under such a situation, where economic development is dependent on agriculture, our findings support initiatives prioritizing rural mechanization to achieve SGDs 1 and 2, no poverty and zero hunger, respectively.

This paper suggests some policy recommendations for developing countries like Nepal, where landholding is not suitable for large-scale farm equipment, the rural labor force is moving out of agriculture and agriculture is primarily for subsistence to promote scale-appropriate mechanization. The policies that support the spread of scale-appropriate mechanization have the potential to enhance agricultural productivity, farm profitability and household food security, reduce rural poverty and reduce farm drudgery. Moreover, the results warn to refrain from a blanket promotion of farm machinery and adopt a more targeted and segmented mechanization policy. This will help address the needs and preferences of the diverse groups of farmers, including women and marginalized ones, as the impacts are not uniform across all social and economic groups of farmers. We demonstrated that marginal farmers with $\leq$0.41 ha, households from nonmarginalized castes and farms facing labor shortages benefited the most from mechanization interventions. Thus, targeted mechanization policies for specific socioeconomic groups, such as marginalized castes and areas with acute labor shortages, will be needed to support inclusive development.

Notes

1. https://publish.illinois.edu/appropriatescalemechanizationconsortium/sample-page/
2. Scale-appropriate mechanization can be defined as the farm machines which fit to local agro-ecological, climatic and socioeconomic contexts.
3. These sub-districts (VDCs) in each of the district are transformed into rural municipalities with the recent political transformation in Nepal since 2017. However, the district structure has remained the same.
4. However, since we have purposively selected the samples, from the data provided by the mini-tiller selling private sectors, along with the high maize areas, in each district and sub-districts, this adoption rate may not represent for the hills ecologies of Nepal.
5. Since mini-tillers nonusers were using bullocks and labors for land preparation, we estimated the land preparation costs for nonusers by combining bullocks and cost of manual labor. However, there were two types of mini-tiller adopters: owner adopters and renters. We used the mean rental charge for the owner adopters to estimate land preparation costs, so that the cost is comparable between adopters and nonadopters.
6. We used household self-reported food self-sufficiency as an indicator for food security. Household food self-sufficiency is a subjective question asked to the household heads to get insights on how many months the household can sustain from their own farm level production. This is also a way of extremely identifying food insecure, transitionally food insecure and food secure households. Using such subjective assessment is common in impact assessment literature (Jaleta *et al.*, 2018).
7. The condition to fulfill the maximum farm size = 4.628/1.747 = 2.65 hectares (See, Table 3).
8. Nonmarginalized castes in this study mean Brahmin and Chettri, while the marginalized castes are the Vaishya and Shudra.
9. Some of the treated samples did not find the matching pairs based on their predicted propensity score and samples falling with in the common support are retained, while samples that did not find any common support are removed from the analysis.
10. Rosenbaum (1989) and Hujer *et al.* (2004) suggested that the sensitivity analysis of insignificant variable is not meaningful. Therefore, the Rosenbaum bounds test was conducted only for the variables that are significantly different after matching.

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Appendix

Matching algorithms	Pseudo R^2	Likelihood ratio χ^2	$P > \chi^2$	Mean bias	Median bias
Before matching	0.514	501.48	0.000	33.5	22.7
Nearest neighbor matching	0.096	62.11	0.001	12.1	9.3
Kernel-based matching	0.086	55.84	0.001	13.1	11.9
Caliper matching	0.081	52.08	0.002	11.7	10.7

Table A1. Statistical test for selection bias after matching

	Specification-1		Specification-2		Specification-3	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Farm size (ha)	4.638***	0.860	4.640***	0.861	4.661***	0.860
Farm size squared	−1.756***	0.368	−1.746***	0.370	−1.755***	0.367
Age of household head (years)	0.002	0.022	0.002	0.022	0.002	0.022
Education of household head (years)	0.126***	0.037	0.157*	0.088	0.176**	0.090
Gender of the household head (1 = male)	0.386	0.386	0.364	0.391	0.351	0.390
Households' caste (1 = nonmarginalized caste)	0.906***	0.258	0.889***	0.257	0.907***	0.258
Years of farming (years)	0.013	0.019	0.014	0.019	0.014	0.019
Household size (no)	−0.099	0.252	0.152	0.078	−0.132	0.258
Number of migrated household members (no)	−0.559**	0.233	−0.539**	0.234	−0.568**	0.235
Groups or cooperatives membership (1 = yes)	0.314	0.303	0.329	0.303	0.313	0.303
Access to credit (1 = yes)	0.059	0.807	0.052	0.809	0.110	0.810
Mobile phone ownership (1 = yes)	−0.340	0.616	−0.355	0.624	−0.347	0.621
Own pumps or vehicles (1 = yes)	0.439	0.275	0.445	0.274	0.443	0.275
Own television (1 = yes)	1.725***	0.679	1.636***	0.673	1.763***	0.683
Household type (1 = concrete)	0.644**	0.320	0.660**	0.320	0.650**	0.322
On-farm labor wage rate (NPR)	0.008***	0.001	0.008***	0.001	0.008***	0.001
Log of off-farm income (NPR)	−0.073**	0.038	−0.077**	0.038	−0.072*	0.038
Log of NPK fertilizer applied (kg/ha)	−0.026	0.025	−0.025	0.025	−0.028	0.025
Farmyard manure applied (1 = yes)	−0.915*	0.521	−0.892*	0.527	−0.873*	0.527
Used open pollinated maize seed (1 = yes)	0.021	0.484	−0.002	0.483	0.011	0.485
Used hybrid maize seed (1 = yes)	0.298	0.267	0.290	0.268	0.289	0.268
Nearest inputs market distance (km)	−0.367***	0.041	−0.366***	0.041	−0.369***	0.041
Numbers of livestock owned (TLU)	−0.115	0.098	−0.130	0.097	−0.108	0.099
Occupation of the household head (1 = farming)	0.337	0.261	0.299	0.264	0.311	0.264
Difficult in finding labor (1 = yes)	0.458	0.294	0.446	0.294	0.456	0.294
Difficult in finding draft animals (1 = yes)	0.940***	0.273	0.920***	0.274	0.921***	0.274
Household size × Household size	0.018	0.017	–	–	0.021	0.018
Education × Education	–	–	−0.003	0.007	−0.004	0.007
Model intercept	−7.639***	1.636	−8.219***	1.601	−7.710***	1.642
LR χ^2	503.17		502.26		503.54	
Prob > χ^2	0.000		0.000		0.000	
Pseudo R^2	0.516		0.515		0.516	
Log likelihood	−236.147		−236.602		−235.965	
Model correctly classified adopters and nonadopters (%)	86.62		86.62		86.76	
No of observations	740		740		740	

Note(s): ***significant at 1% level, **significant at 5% level and *significant at 10% level. SE stands for standard error

Table A2.
Logit model estimates for sensitivity analysis

Table A3. Average treatment effect on outcome variables under different specifications of selection models

Specifications from Table A2	Outcome variables	ATT	SE	Pseudo-R^2 before matching	Pseudo-R^2 After matching	Likelihood ratio χ^2 Before matching	Likelihood ratio χ^2 After matching	Mean standardized bias Before matching	Mean standardized bias After matching	% bias reduction	Critical level of hidden bias (Γ)
Specification 1	Maize yield (kg/ha)	622.81*	350.75	0.515	0.103	502.33	66.21	32.5	13.1	59.69	1.20–1.25
	Land preparation cost (NPR/ha)	−6349.60***	1470.62	0.575	0.242	560.74	155.68	34.7	15.1	56.48	7.40–7.45
	Total labor cost (NPR/ha)	−7703.26**	3627.95	0.555	0.208	541.12	133.51	33.1	13.6	58.91	2.50–2.55
	Total variable cost (NPR/ha)	−10443.01*	5343.19	0.546	0.178	532.57	114.48	33.1	13.4	59.52	2.15–2.20
	Gross margin (NPR/ha)	23610.86***	8534.24	0.521	0.122	508.30	78.22	33.1	13.8	58.31	2.10–2.15
	Food self-sufficiency (%)	24.14***	7.87	0.532	0.146	518.51	94.05	34.0	14.0	58.82	2.15–2.20
	Poverty gap (%)	−8.75**	3.68	0.522	0.142	508.97	91.27	32.0	13.9	56.56	2.85–2.90
	Square poverty gap (%)	−5.52**	2.61	0.523	0.136	510.51	87.30	32.0	13.8	56.88	3.55–3.60
Specification 2	Maize yield (kg/ha)	733.42*	369.78	0.515	0.089	502.01	56.31	33.4	12.4	62.87	1.40–1.45
	Land preparation cost (NPR/ha)	−6574.83***	1380.01	0.576	0.212	561.56	134.86	35.6	14.3	59.83	7.95–8.00
	Total labor cost (NPR/ha)	−6767.14*	3526.30	0.555	0.188	540.94	119.61	34.1	12.5	63.34	2.20–2.25
	Total variable cost (NPR/ha)	−8832.65*	5024.80	0.547	0.156	533.59	99.24	34.0	12.2	64.12	1.80–1.85
	Gross margin (NPR/ha)	23452.02***	8761.05	0.521	0.105	507.81	66.49	34.1	12.8	62.46	2.00–2.05
	Food self-sufficiency (%)	26.35***	7.60	0.532	0.134	519.07	85.23	35.0	13.2	62.29	2.15–2.20
	Poverty gap (%)	−9.42***	3.67	0.521	0.128	508.64	81.22	32.9	13.1	60.18	3.00–3.05
	Square poverty gap (%)	−5.74**	2.75	0.523	0.122	510.18	77.57	32.9	12.9	60.79	4.15–4.20
Specification 3	Maize yield (kg/ha)	580.68*	344.45	0.515	0.083	502.01	52.99	33.4	13.1	60.78	1.15–1.20
	Land preparation cost (NPR/ha)	−6232.39***	1456.72	0.576	0.210	561.56	133.08	35.6	15.0	57.87	6.25–6.30
	Total labor cost (NPR/ha)	−7134.95*	3790.61	0.555	0.179	540.94	113.80	34.1	13.5	60.41	2.25–2.30
	Total variable cost (NPR/ha)	−10212.55*	5577.29	0.547	0.152	533.59	96.60	34.0	13.3	60.88	2.30–2.35
	Gross margin (NPR/ha)	21920.35***	8158.55	0.521	0.100	507.81	63.61	34.1	13.6	60.12	1.85–1.90
	Food self-sufficiency (%)	25.33***	7.94	0.532	0.132	519.07	83.96	35.0	14.1	59.71	1.80–1.85
	Poverty gap (%)	−8.70**	3.77	0.521	0.120	508.64	76.45	32.9	13.8	58.05	3.10–3.15
	Square poverty gap (%)	−4.58*	2.74	0.523	0.113	510.18	71.47	32.9	13.5	58.97	3.85–3.90

Note(s): ***Significant at 1% level, **significant at 5% level and *significant at 10% level. SE stands for standard errors, and nearest neighbor matching with three neighbors and common support is used for the estimation of specifications. Exchange rate 1 US$ = NPR 107 during the survey year (NRB, 2022)

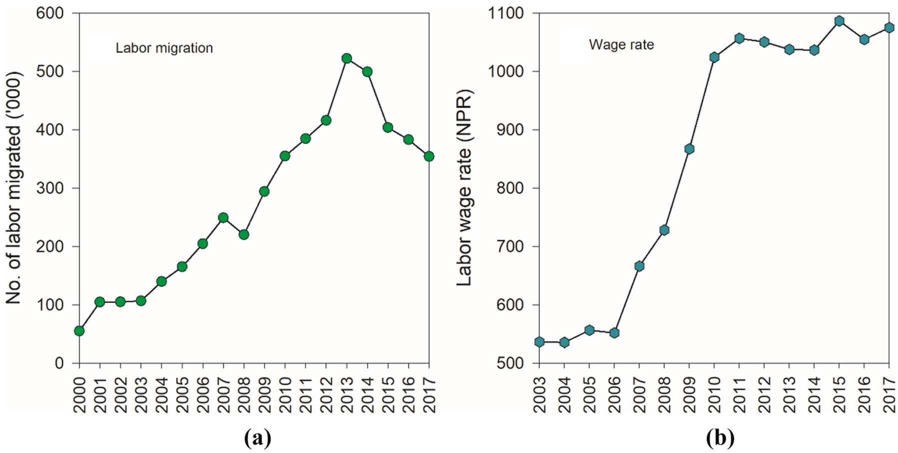

Figure A1.
The (a) trends of labor out-migration (MoLE, 2018) and increase in rural wage rates (b) in Nepal (MoF, 2018). Local currency values for inflation are adjusted considering year 2010

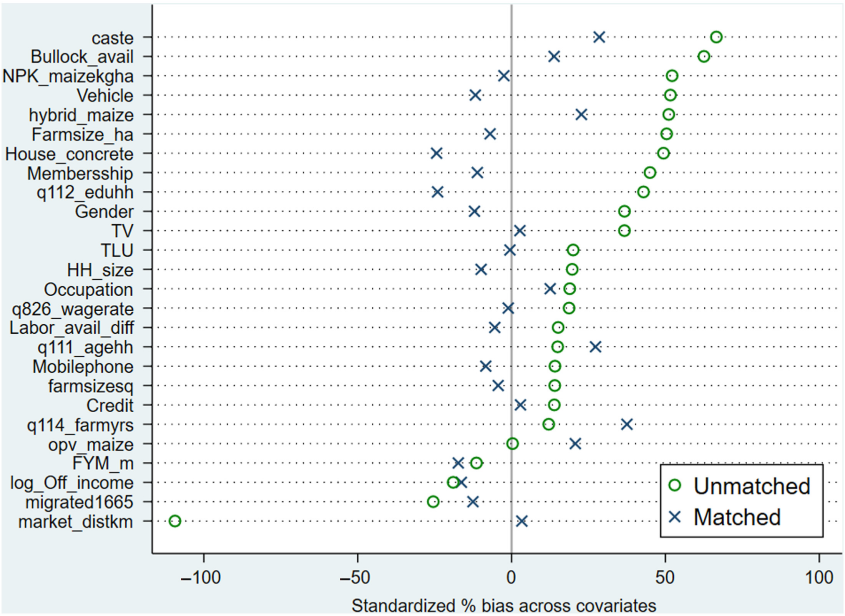

Figure A2.
Standardized bias before and after matching

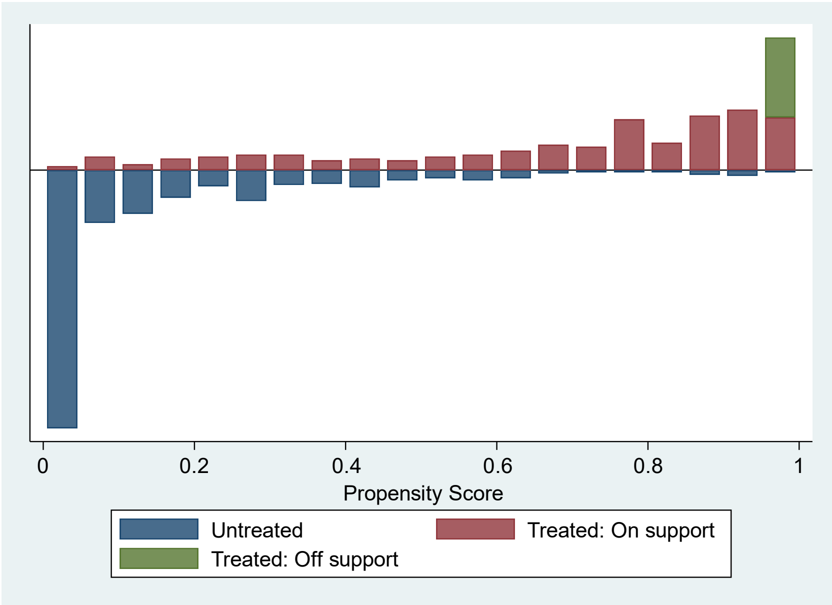

Figure A3.
Propensity score overlap between mini-tiller adopters (treated) and nonadopters (control) sub-samples

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