The Productivity Effects of Adopting Improved Organic Manure Practices in Nepal

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Owing to farmers' issues on accessibility and affordability of chemical fertilizers in Nepal, organic manure has been advocated as a more environmentally sustainable fertilizer input alternative. Using household survey data from Nepal, we analyze the adoption and productivity effects of improved organic manure practices. Our empirical strategy utilizes a recently developed control function approach in the endogenous switching regression model that allows for substantial heterogeneities accounting for potential self-selection problem due to observables and unobservables. Findings reinforce the crucial role of social capital as farm households' adoption decisions are significantly influenced by 1) having adopter neighbors or friends, 2) residing in proximity to the market, and 3) gaining easy access to agricultural extension services. Beyond environmental and social considerations, this study establishes economic motivations for the adoption decision. The results show that the adoption of improved organic manure practices increased crop yield by 17 percentage points. These practices did not only result in significantly higher yields among adopting farms, but counterfactual analyses indicate that non-adopting farms would have realized much better yield conditions had they implemented the technology. The study concludes with implications for policies and initiatives to expand the adoption and impacts of improved organic manure practices in Nepal.

Keywords: technology adoption, endogenous switching regression, control function, organic manure, crop yield, Nepal

INTRODUCTION

In both developed and developing economies, new production technologies have been credited for realizing improvements in crop yields and food security conditions (Duan et al., 2016). Achieving higher agricultural productivity requires adopting modern technologies and inputs such as improved seeds and varieties, integrated pests, soil, fertilizer, and water management practices. Among production inputs, chemical fertilizer is the key to raising agricultural productivity and allows producers to generate a higher annualized rate of economic returns (Duflo et al., 2011).

In Nepal, overall chemical fertilizer use has been lower than its peer countries, owing to accessibility and affordability issues (World Bank, 2017). In the face of constant pressure for its agricultural industry to meet the economy's increasing food and feed demands, the pressing challenge has been to find a viable fertilizer alternative to reconcile its low chemical fertilizer use. Improved organic manure practices such as improved farmyard manure (cattle shed improvement), compost and crop residue, and vermicompost could be alternatives to increase or maintain crop yield. Studies show that adopting these practices for certain growing conditions and management systems might close the yield gap with

farms that only use chemical fertilizers (Seufert et al., 2012). Of the several manure alternatives, vermicompost has received significant attention in recent years due to increased awareness of sustainable organic agriculture and its economic and environmental benefits (Bajeli et al., 2016).

Vermicomposting involves feeding earthworms with biodegradable waste to convert them into slow-release organic manure (Yami et al., 2003; Joshi et al., 2015). Like any other organic fertilizer, vermicomposting offers a host of environmental benefits. It serves as a valuable resource to supply plant nutrients and refill the soil's organic matter content, thereby maintaining soil fertility, soil organic carbon content, and crop yield (Vig et al., 2011; Sangeetha et al., 2012; Bajeli et al., 2016). It helps increase yield by providing better growth and reducing pest infestation (Joshi et al., 2015); it can be a substitute for chemical fertilizers (Bhat et al., 2018). In the light of today's rapid urbanization and increased rural-urban migration trends, solid waste management issues have become an important concern in large urban areas. Incorporating earthworms in the composting process could somehow solve waste management and reduce environmental loads (Bhat et al., 2018). Realizing the benefits of vermicomposting, Nepal's government launched its vermicompost production program in 2014. The program was designed to accelerate vermicompost technology diffusion and enhance vermicompost use (Amgai et al., 2017). Under the program, a subsidy is granted to any producer who constructed a vermicomposting bin on their farm. Around 25 organic fertilizer firms with 100600 Mton annual compost production capacity were established by 2016.

Despite the method's apparent benefits and government support, its adoption rate has been slow. The adoption decision is usually weighed against two considerations: economic viability and environmental sustainability (Wang et al., 2018). Certain studies contend that a shift to organic farming methods usually involves a gestation phase in the adoption when the crop yield effect is initially slow and variable in the shorter-term horizon (Khaliq et al., 2006), and growing methods are usually more labor-intensive (Wang et al., 2016). However, proponents of organic agricultural systems contend that economic incentives cannot solely influence farmers' adoption behavior as they also consider external environmental benefits accruing to the organic methods (Blackstock et al., 2010). Thus, it is imperative to identify and understand factors that affect the adoption of such a practice and its impacts on crop productivity to formulate more widespread adoption and diffusion policies. Only a few studies modeled yield response to vermicomposting in an experimental trial (for example, Panta and Yami, 2008). However, to the best of our knowledge, no study has empirically investigated the adoption of this practice and its impacts on crop yield using observational data.

This study fills such a research gap by analyzing farm household survey data from two districts of Nepal. This research has a two-fold objective: first, identifying principal determinants of adoption, and second, determining the effect of a household's adoption decision on crop yield.[1] Our analytical

framework is designed to address several estimation issues. The adoption status of farmers is endogenous due to self-selection into a treatment, thus causing selection bias. Selection bias may arise because farmers who adopt improved practice may share some common unobserved characteristics, such as management abilities and knowledge and skills, which correlate with yield. On the other hand, adopters are more likely to be systematically different from non-adopters in observed and unobserved characteristics that could affect crop yield. Failure to account for selection bias arising from the endogenous treatment indicator capturing the adoption decision (labeled as "*adoption*" in our empirical model) may result in inconsistent estimation. Therefore, we explicitly consider the problem of non-random selection into treatment following the control function approach in the endogenous switching regression model (CF-ESR) proposed by Murtazashvili and Wooldridge (2016).

Under normality assumption, we estimate the selection corrected yield function using a two-step control function procedure. The first stage utilizes the probit model for the adoption decision. In the second stage, the selection correction term (generalized residual term) derived from the first stage is used as a control function. Finally, we build a counterfactual analysis and compare the expected crop yield under the actual and counterfactual conditions of adoption and non-adoption. We evaluate heterogeneous treatment effects of adoption decisions using estimates from the second step to identify the crop yield differences between adopters and non-adopters. Our preferred specification indicates that the adoption of improved practice is associated with an approximately 17 percent increase in crop productivity. The improved organic manure practice did not only result in significantly higher yields among adopting farms, but counterfactual analyses indicate that non-adopting farms would have realized much better yield conditions had they implemented the technology.

This study offers important empirical evidence relevant to ongoing discussions of the relative strengths of organic production methods. While the environmental benefits of manures eradicate such risks as soil deterioration, greenhouse emissions, and water contamination commonly associated with chemical fertilizer applications (Makkar et al., 2022), we explain its economic viability through yield potential. Findings offer important implications for Nepal's and other developing countries' farmers and policyholders who aspire to realize higher farm productivity and rural farm incomes that coincide with environmentally sustainable and sound growing practices.

Country and Industry Context

Agriculture plays a substantial role in Nepal's economy. It accounts for a third of the nation's GDP and two-thirds of its labor force. The sector's performance is key to overall economic growth, poverty alleviation, and improving national productivity (MoAD, 2018). Notably, Nepal has made considerable progress toward overall poverty reduction and food security in recent years, yet uneven dispersion of economic activities and benefits results in the persistence of poverty and food insecurity conditions in its rural areas. Around 77% of the national population still earns less than $2 a day (World Bank, 2015).

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[1]Our measure of crop yield is productivity, which is defined as the total crop harvested per hectare of cropland. In this article, productivity and yield are used interchangeably.

Most Nepalese farmers are smaller holders, with nearly half of the farm households operating less than 0.5 hectares of land under an integrated farming arrangement. Farming is still predominantly for subsistence, and the adoption rate of advanced farm technology is marginal. The agricultural sector's weak performance and slow growth rates (averaging 2.8% per year) have dragged down overall economic growth (World Bank, 2017), as agriculture is the country's largest employer.

Chemical Fertilizer Use

Chemical fertilizer applications in Nepal increased substantially from 5.64 kg/ha in 2006 to 74.08 kg/ha in 2016. Despite such an upward trend in average fertilizer use, the country's chemical fertilizer use is still much lower than the utilization rates in other South Asian countries (estimated around 160 kg/ha) (World Bank, 2017).

Several factors explain the relatively lower levels of chemical fertilizer use in Nepal. First, the Nepalese chemical fertilizer industry is still facing significant supply constraints. Market demand consistently exceeds supply; thus, the appropriate products are usually unavailable to the farmers. For instance, according to Kyle et al. (2017), only 25% of Nepalese households could purchase fertilizer in sufficient quantities. These individuals must walk quite a long distance and then wait in line to avail of even small fertilizer amounts. Second, farmers are not well-informed by technical advisers from the industry and other institutions about the proper choices for fertilizers appropriate to their respective farming situations. Third, low-income smallholder farmers typically face credit constraints as credit delivery systems in the country's farm sector are often riddled with anomalous lending decisions. Specifically, allegations surface that loans for chemical fertilizers often go to politically connected people. Fourth, although Nepal's government has set up price subsidies for chemical fertilizers designed to alleviate the farmers' cost burden, market reality dictates that the resulting subsidized fertilizer price is still much higher than other countries' prices, such as those in India. The government's fertilizer price subsidy program has been criticized as "regressive." Strong allegations contend that only wealthier farmers and those with more land often benefit most from the government's price subsidies (Donovan, 2004). Besides, Nepal's agro-climatic zones result in some heterogeneity in patterns of chemical fertilizer use among farmers. For example, the hilly regions representing more than half of total cultivated land only account for a fourth of total fertilizer use.

METHODOLOGY

Data Sources

The data set comes from a face-to-face household survey conducted from October to December 2015 in *Chitwan* and *Lalitpur* districts in Nepal's central region. This region grows rice, maize, wheat, potato, and oilseeds, representing more than 90% of the total grain production and cultivated area (MoAD, 2018). Mixed cropping is the most common type of farming, and farmers grow two to three crops annually, depending upon whether the land is irrigated. Rice-wheat-maize or rice-vegetables-maize is the major cropping pattern in irrigated land, while the rice-wheat-fallow or rice-fallow-maize is the primary pattern in the rainfed condition (MoAD, 2018). In selecting survey households, we used a multi-level stratified sampling approach. We first identified the *Chitwan* and *Lalitpur* districts as the main improved organic manure practicing areas, given their high intensity of improved manure users. Afterward, we purposely selected four village development committees (VDCs)[2] from each district with guidance from the District Agriculture Extension Officer.

The household survey was conducted in two stages. First, we did a reconnaissance survey to better understand the use, production, and crops grown in the survey areas. We also did in-depth key informant interviews with farmers, extension staff, and cooperatives officials. This first stage's information was used to improve the survey instrument, identify the survey areas, and refine the sampling framework. We then randomly surveyed approximately 25–35 farm households from each VDC. The share of sample size allocated to each VDC was proportional to the number of adopters. Finally, a sample of 480 farm households (240 from each district), comprising of 200 non-adopters and 280 adopters, was chosen for the study. After employing further data cleaning protocols, the final sample size was reduced to 444 households. In this study, the primary variable of interest is a binary indicator of adoption, denoting whether a farm household produced and/or applied any of three improved organic manure practices: improved farmyard manure (FYM), vermicompost, and other composts, in their farms a year before the survey year. Non-adopters did not use any of the three improved organic manure practices to produce any of their crops.

The household survey questionnaires were structured and pre-tested. The survey provides comprehensive information about household demographic characteristics, farm activities, social networks, access to information, crop production details (input use, yield, and revenue), land and livestock ownership, organic manure use, preparation methods, and market information.

ESTIMATION STRATEGY

A household's decision to adopt the improved technology and its impacts on crop yield is modeled in a two-stage framework. The first stage captures the adoption decision. We model the adoption decision in a random utility framework under the assumption that a farmer decides whether to adopt this practice based on expected utility considerations. A farm household i uses improved organic manure if the expected utility from the adoption (U_{i1}^*) is higher than that of the non-adoption case (U_{i0}^*). In other words, if we account for the expected utility difference between these two options by a latent continuous variable D_i^* $(D_i^* = U_{i1}^* - U_{i0}^*)$, a farmer decides to adopt improved technology only if $D_i^* > 0$. However, the actual utility

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[2]VDC were the smallest administrative unit of Nepal during the household survey.

level of D_i^* is unknown to the researcher, but household characteristics are observed. Therefore, we can specify the latent variable as a function of variables, denoted as z_i, which affect the expected utility of adoption as:

$$D_i^* = z_i\gamma + \omega_i, D_i = 1\left[D_i^* > 0\right]i = 1, 2, \ldots N \qquad (1)$$

where D_i is a binary adoption indicator that takes a value of 1 for household i who chooses to adopt and 0 otherwise; $1[.]$ is an indicator function that is equal to 1 if the statement inside the bracket is true and 0 otherwise; and $\omega \sim N(0, \sigma_\omega^2)$, and $i = 1, 2, \ldots N$ are the number of households.

In the second stage, we model the effect of technology adoption on crop productivity. Let y_i represent farm productivity, which is a linear function of household characteristics X_i and the adoption decision, D_i. In particular, y_i is assumed to be generated as

$$y_i = X_i'\beta + \theta D_i + \epsilon_i \qquad (2)$$

where β represents a vector of parameters to be estimated, θ is the coefficient associated with a binary indicator of adoption D_i, and τ_i is random disturbance terms, that is $\tau_i \sim N(0, \sigma_\epsilon^2)$. The most common way to examine the impact of adopting improved practice on crop yield would be to estimate **Eq. 2** by ordinary least squares (OLS). The OLS estimates, however, may yield imprecise estimates since the decision to adopt may be based on individual self-selection and is potentially endogenous i.e., $cov(D_i, \epsilon_i) \neq 0$. Selection bias may occur because farmers who adopt improved technology share common unobserved characteristics, such as innate managerial skills, technical abilities, individual preferences, and social networks, which could also be correlated with outcomes (Abadie and Cattaneo, 2018). Similarly, adopting farmers may have systematically distinctive characteristics from non-adopters. Such features affect the cost of adoption and/or expected return, leading to heterogenous technology adoption behaviors. Therefore, the selection **Eq. 1** becomes more severe in the presence of heterogeneous treatment effects when the correlation between ω_i and D_i may arise through τ_i, or the idiosyncratic gains from adoption (Blundell and Dias, 2009).

Several approaches have been proposed to address this estimation issue, such as 1) selection models (Heckman and Robb, 1986; Powell, 1994), 2) instrumental variable models (Heckman and Vytlacil, 2005; Heckman et al., 2006), and 3) matching methods (Heckman and Navarro-Lozano, 2004). To account for the endogeneity problem discussed above, we utilize the endogenous switching regression (ESR) model developed by Heckman (1976), where the coefficient on a binary endogenous treatment is allowed to differ across units in both observed and unobserved characteristics. The ESR can be estimated with the two-step method using a control function (CF) or simultaneously via full information maximum likelihood (FIML-ESR). The FIML-ESR implemented in Stata by Lokshin and Sajaia (2004) has increasingly been used in multiple studies to deal with self-selection in **Eq. 1** technology adoption (Asfaw et al., 2012; Manda et al., 2019; Kassie et al., 2020), 2) cooperative membership (Ma and Abdulai, 2016), and 3) climate change adaptation (Di Falco

et al., 2011; Di Falco and Veronesi, 2014; Dhakal et al., 2022). Maximum likelihood (ML) is a widely used technique with some limitations. The ML produces more efficient estimators and asymptotically correct standard error estimates under the appropriate assumption (Wooldridge, 2010). However, ML estimators tend to be more vulnerable to misspecification (Greene, 2007, p.421). Under certain circumstances, such as dealing with a small sample size, the ML estimation can be computationally complicated and costly to implement, thus limiting its use (Nguimkeu et al., 2019). For instance, correlations between the outcomes equation and selection equation errors might not be strongly identified, resulting in multiple local maxima or, at times, leading to non-convergence problems.

In contrast, the two-step method always results in convergence. The CF approach, combined with instrumental variables, produces consistent estimation in the presence of endogenous regressors under standard identification assumptions (Wooldridge 2015). It considers the non-linear interaction between an endogenous regressor and the error terms. Besides, unlike the FIML-ESR, the CF-ESR approach provides a direct marginal effect of endogenous treatment on outcomes and consistent estimates in the presence of unobserved heterogeneity between adopters and non-adopters (Murtazashvili and Wooldridge, 2016). Considering these issues, we employ the CF-ESR model proposed by Murtazashvili and Wooldridge (2016)[3].

Consider the following ESR model

$$y_i = (1 - D_i)X_i\beta_0 + D_iX_i\beta_1 + (1 - D_i)\epsilon_{i0} + D_i\epsilon_{i1} \qquad (3)$$

where D_i is an endogenous binary indicator for adoption, (the endogenous switching indicator for individual i), X_i is a vector of exogenous covariates, with the first element being unity, and ϵ_{i0} and ϵ_{i1} are unobservables. It can be derived by simple substitution from a counterfactual framework:

$$y_i = (1 - D_i)y_i^0 + D_iy_i^1 \qquad (4)$$
$$y_i^0 = X_i\beta_0 + \epsilon_{i0} \qquad (5)$$
$$y_i^1 = X_i\beta_1 + \epsilon_{i1} \qquad (6)$$

where y_i^0 and y_i^1 are the counterfactual outcomes, and a binary variable D_i can be correlated with $(\epsilon_{i0}, \epsilon_{i1})$. To estimate the ESR model, **Eq. 4** can be written as

$$y_i = X_i\beta_0 + D_iX_i\gamma + \epsilon_{i0} + D_i\vartheta_{i1} \qquad (7)$$

were $\vartheta_{i1} = \epsilon_{i1} - \epsilon_{i0}$ and $\gamma = \beta_1 - \beta_0$. Without the presence of $D_i\vartheta_{i1}$, we could estimate **Eq. 7** by standard instrumental variable estimators. In this case, the standard instrumental variable estimators will be inconsistent. The problem with applying the instrumental variable method in the above equation is that the term $D_i\vartheta_{i1}$ is assumed to be correlated with explanatory variables X even under a strong independence assumption because of the endogeneity of D_i

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[3]Unlike Murtazashvili and Wooldridge (2016), we assume all covariates (except a binary treatment status *adaptation*) in the ESR model to be exogenous.

(Murtazashvili and Wooldridge, 2016). However, we can identify **Eq. 7** using a CF for D_i.

Control Function Approach

The control function approach involves two-step estimation procedures. The first step involves the estimation of the probit model of D_i on z_i as

$$P(D_i = 1|z_i) = \Phi(z_{1i}\pi_1 + X_i\pi_2) \tag{8}$$

where z_{1i} are instrumental variables so that $z_i = f(X_i, z_{1i})$, π_1 and π_2 are coefficients.

In order to achieve identification, we should satisfy the exclusion restriction that requires at least one excluded exogenous variable (z_{1i}) in the probit model for D_i. The excluded exogenous variable(s) should affect the adoption decision but not directly affect the yield. In other words, the effect of the instrumental variables on the outcome should come only through the adoption decision.

This approach also requires evidence of $\pi_1 \neq 0$ for the instrument(s) to be valid, and a rank condition must be imposed to ensure consistency. In this analysis, three instrument variables are considered for the exclusion restriction: distance to market, self-reported adoption status of friends and neighbors, and access to agricultural extension services. These instruments have been used in several previous studies, such as distance to market (Suri, 2011), self-reported adoption status of friends and neighbors (Krishnan and Patnam, 2014; Wossen et al., 2019), and access to extension contact (Di Falco et al., 2011; Di Falco and Veronesi, 2014; Huang et al., 2015). These exclusion restriction variables are used as proxies for the source of information and motivation that explicitly affect the adoption decision and influence the adoption decision.

In the second step, generalized residuals are obtained as

$$\hat{r}_i = D_i\lambda(z_i\hat{\pi}) - (1 - D_i)\lambda(-z_i\hat{\pi}) \tag{9}$$

where γ, π_1 and π_2 are coefficients, and other terms are as defined previously.

Subsequently, our preferred estimating equation would be

$$y_i = X_i\beta_0 + D_iX_i\gamma + \rho_0\hat{r}_i + \rho_1D_i\hat{r}_i + \epsilon_i \tag{10}$$

which is estimated by two-stage least squares using instrumental variables $(z_i, D_iz_i, \hat{r}_i, D_i\hat{r}_i)$ and where β_0 γ ρ_0, ρ_1 are the parameters. We use the Huber/White sandwich estimator for the robust heteroskedasticity standard errors and standard errors clustered at the village level.

In the final step, **Eq. 10** is estimated separately when $D_i = 1$ and $D_i = 0$ to get different estimations for adopters ($y_i^{(1)}$) and non-adopters ($y_i^{(0)}$), where Inverse Mills Ratio are $\lambda(z_i\hat{\pi})$ and $\lambda(-z_i\hat{\pi})$, respectively. In doing so, the estimating equation would be

$$y_i^{(1)} = X_i\beta_1 + (\rho_0 + \rho_1)\hat{r}_i + \epsilon_i \tag{11}$$

$$y_i^{(0)} = X_i\beta_0 + \rho_0\hat{r}_i + \epsilon_i. \tag{12}$$

Heterogeneity Analysis

This study investigates the treatment effects of improved organic manure practice adoption on crop productivity. The three most used treatment parameters to explore the impact of adoption in the program evaluation literature are the average treatment effect (ATE), the average treatment effect on treated (ATT), and the average treatment effect on untreated (ATU). The ATE measure would be the average outcome if individuals were randomly assigned to treatment, and ATT measures the average effects on individuals specifically assigned to treatment. ATT then is the appropriate parameter to identify the impact of adoption on adopting households. If, however, the interest focuses on the impact of adoption on households of a certain type as if they were randomly selected, then ATE is the parameter of interest to recover. The ATE, ATT, and ATU measures are defined using conventions introduced by Wooldridge (2015), as follows:

$$ATE = E(y_i^{(1)} - y_i^{(0)}). \tag{13}$$

From **Eq 11**, **12** ATE can be written as

$$ATE = X\beta_1 + (\rho_0 + \rho_1)\hat{r}_i - X\beta_0 + \rho_0\hat{r}_i = (\beta_1 - \beta_0)X + \rho_1\hat{r}_i \tag{14}$$

The $y_i^{(1)}$ and $y_i^{(0)}$ are not directly observed, but $\hat{y}_i^{(1)}$ and $\hat{y}_i^{(0)}$ can be estimated from the above equation as follows:

$$\widehat{ATE} = N^{-1}\sum_{i=1}^{N}\left[\hat{y}_i^{(1)} - \hat{y}_i^{(0)}\right] \tag{15}$$

The effect of adoption on the adopting farm household (i.e., ATT) is given by

$$ATT = E(y_i^{(1)} - y_i^{(0)}|D_i = 1). \tag{16}$$

The ATT can thus be estimated as

$$\widehat{ATT} = N^{-1}\sum_{i=1}^{N}y_i(D_i = 1)\left[\hat{y}_i^{(1)} - \hat{y}_i^{(0)}\right] \tag{17}$$

On the other hand, the effect of adoption on the non-adopting households (ATU) is given by

$$ATU = E(y_i^{(1)} - y_i^{(0)}|D_i = 0). \tag{18}$$

The ATU is estimated as

$$\widehat{ATU} = N^{-1}\sum_{i=1}^{N}y_i(D_i = 0)\left[\hat{y}_i^{(1)} - \hat{y}_i^{(0)}\right] \tag{19}$$

RESULTS

We first report summary statistics of variables used in our analysis. We then estimate **Eq. 10** for the full sample and **Eq. 11** and **Eq. 12** for adopting and non-adopting households, respectively, to examine the extent to which the estimated effect is heterogeneous across adoption status.

Summary Statistics

Figure 1 presents the distribution of crop yield by adoption status. As the plots indicate, adopters have higher crop productivity when the distribution shift to the right than non-adopters.
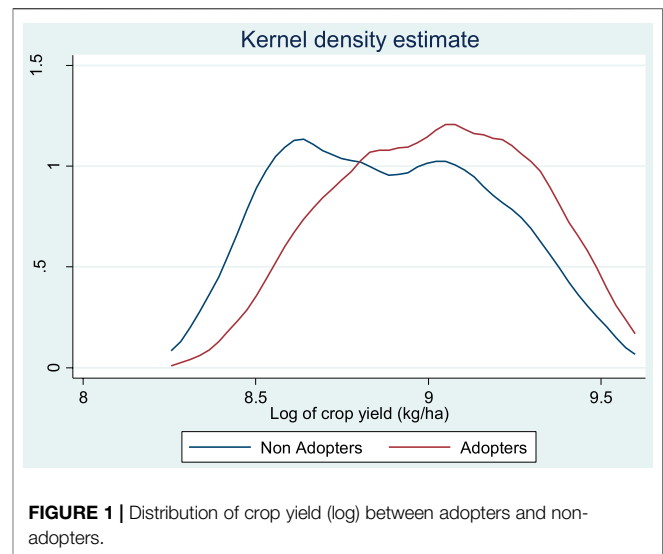
Table 1 presents the summary statistics and statistical significance tests on equality of means and proportions for continuous and dummy variables, respectively, among adopters and non-adopters. This study's choices of dependent variables are drawn from approaches employed in the existing literature on technology adoption and crop yield (Kassie et al., 2015; Manda et al., 2019; Kassie et al., 2020, for example). This study's analytical model includes household characteristics (such as sex, age, educational attainment, household size, and social networks), membership in cooperatives and agricultural groups, access to credit and training, wealth indicators (in terms of land holdings and livestock ownership), and production input costs (manure and fertilizers, labor, irrigation and machinery, seeds, and planting) to control for the observed heterogeneity between adopters and non-adopters. We hypothesize that household characteristics and input costs affect farmers' adoption decisions and crop productivity levels. In this study's sample, around 60% of the households adopt improved practices to produce crops (**Table 1**).

The average age of the sample household head is 41 years, whereas 62% are female-headed. There is no significant difference in the observed age and gender of the household head. The average livestock ownership measured in tropical livestock units (LTU[4]) is 2.38. Household size and livestock numbers between adopting and non-adopting households are not significantly different. The mean cultivated land area (owned) of sample households is 0.399 ha, and the average adopters' cultivated land area is significantly larger than that for non-adopters. We find statistically significant differences between adopters and non-adopters for most of the other explanatory variables. In general, adopters are more likely to be educated, trained, and cooperative or group members. Moreover, they have better access to credit, extension services, and marketing centers. In terms of input costs (control variables), adopters tend to spend significantly more on manure and fertilizers, while non-adopters are more likely to spend more on irrigation and machinery. Adopting households also register significantly higher crop productivity levels compared to non-adopting households. The summary statistics suggest that adopters are largely positively self-selected, and the impact of improved manure practices on yield seems to be positive.

Determinants of Adoption

Data columns 1 and 2 in **Table 2** present the first stage-probit estimates and their marginal effects on adopters and non-adopters. The estimated coefficients help find factors that significantly influence the farm household's decision to adopt. However, the probit model's estimated coefficients are not directly interpretable; therefore, marginal effects are evaluated to quantify the marginal change in the probability of adoption with a unit change in each response variable.

Results show that most of the covariates hypothesized to influence adoption decisions register the expected results. Five

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[4]TLU = =0.7*(Buffalo + +Cattle)+ 0.1*Goat+0.2*Pig+0.01*Poultry.

FIGURE 1 | Distribution of crop yield (log) between adopters and non-adopters.

sources of heterogeneity largely explain the households' decision to adopt. These include demographics (age and sex), sources of information (access to extension services, improved skill, knowledge, and training), social and human capital (access to credit, cooperative/group membership, and educational attainment), location, and self-reported adoption status of neighbors/friends. The resulting coefficient estimates identify three main factors that determine the farm household's decision to adopt practices: 1) having adopter neighbors/friends, 2) residing in proximity to the market, and 3) gaining easy access to extension services. These variables appear to pave the way for the wider and more effective dissemination of relevant information for the adopting household's assimilation of the improved technology. For instance, households residing near the market would have more information on improved organic manure practices and are 20% more likely to adopt the technology. Households also receive information about improved technologies and inputs from university extension services and their neighbors/friends, which altogether play a vital role in influencing decisions on technology adoption. The findings indicate that having access to extension services and being in adopters' neighborhoods can reduce farm households' constraints on adopting the technology and increase the likelihood of adoption by 6% and 56%, respectively. This result is consistent with the findings of other studies on technology adoption that document how farmers learn about how innovative technology from their neighbors/friends on social networks (Conley and Udry, 2010). Empirical evidence indicates that most information on input use come from neighbors/friends and extension agents (Asfaw et al., 2012; Krishnan and Patnam, 2014; Wossen et al., 2019). Households may also acquire knowledge and information about improved manure practices by participating in cooperatives or agricultural groups. Results show that membership in cooperatives/groups is positive and significant, indicating that farm households are around 27% more likely to adopt improved technology than non-members. This result conforms with the findings of previous adoption studies

TABLE 1 | Descriptive statistics and mean differences in variables between adopters and non-adopters.

Variable name	Full sample	Adopters	Non-adopter	Mean difference
	(1)	(2)	(3)	(4)
Female household head (1/0)	0.622	0.624	0.618	0.006
	(0.023)	(0.030)	(0.037)	
Age of household head (year)	45.144	45.489	44.629	0.860
	(0.597)	(0.775)	(0.939)	
Log household size	1.720	1.742	1.686	0.055
	(0.019)	(0.022)	(0.032)	
Livestock ownership (TLU)	2.375	2.450	2.263	0.187
	(0.083)	(0.112)	(0.124)	
Land area (ha)	0.399	0.449	0.324	0.125***
	(0.016)	(0.019)	(0.026)	
Log irrigation and machinery cost (NPR)	8.127	8.005	8.309	-0.304**
	(0.053)	(0.077)	(0.063)	
Log manure and fertilizer cost (NPR)	8.805	8.980	8.542	0.438***
	(0.044)	(0.053)	(0.073)	
Log labor cost (NPR)	9.186	9.259	9.076	0.183
	(0.049)	(0.063)	(0.079)	
Log seed and planting materials cost (NPR)	7.437	7.504	7.337	0.166
	(0.055)	(0.073)	(0.084)	
Agricultural training/meeting (1/0)	0.608	0.809	0.474	0.335***
	(0.023)	(0.030)	(0.031)	
Knowledge on improved manure practice (1/0)	0.698	0.722	0.663	0.059
	(0.022)	(0.028)	(0.036)	
Credit (1/0)	0.667	0.865	0.534	0.331***
	(0.022)	(0.026)	(0.031)	
Formal education (1 = yes)	0.671	0.820	0.449	0.370***
	(0.022)	(0.024)	(0.037)	
Cooperative/group members (1/0)	0.676	0.764	0.617	0.148***
	(0.022)	(0.032)	(0.030)	
Outstanding loan (1/0)	0.437	0.383	0.517	−0.133
	(0.024)	(0.030)	(0.038)	
Neighbor/friends adoption (1/0)	0.572	0.789	0.247	0.542***
	(0.024)	(0.025)	(0.032)	
Distance to market (km)	2.541	3.030	1.809	1.221***
	(0.079)	(0.110)	(0.083)	
Extension contact	2.716	3.353	1.764	1.589***
	(0.080)	(0.107)	(0.076)	
Log of crop yield (kg/ha)	8.964	9.017	8.886	0.130***
	(0.014)	(0.017)	(0.022)	
Adoption (1/0)	0.599			
	(0.023)			
N	444	266	178	

Note: Robust standard errors clustered at the village development committee are in parentheses, TLU, Tropical livestock unit. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. NPR stands for Nepalese Rupee, exchange rate: 1 US $ = Nepalese Rupees 107 at the time of survey (https://www.nrb.org.np/).

(Ma and Abdulai, 2016; Wossen et al., 2017). Similarly, education, access to credit, training, and knowledge about improved manure practices are positively and significantly associated with the adoption. Our findings thus lend support to previously validated positive effects of education (Huffman, 2020; Mukherjee, 2020), access to credit (Croppenstedt et al., 2003; Barrett et al., 2004; Mukherjee, 2020), and training (Nakano et al., 2018; Kumar et al., 2020). However, the estimated coefficient of the female household head dummy is negative and significant, thus suggesting that women are about 33% less likely to adopt than their male counterparts. Some studies attribute this trend to women's usual lack of access to resources, extension information, infrastructure, education, and credit services (Satyavathi et al., 2010; Rola-Rubzen et al., 2020).

Validity of Instruments

Instrumental variables (IVs) are expected to significantly affect technology adoption. Living in closer proximity to the market, having frequent contact with extension staff, and having neighbors or friend adopters increase the probability of adoption. These instrument variables provide information about the benefit of using compost and increase the likelihood of adoption.

The confirmation of the validity of this study's instruments is presented in **Supplementary Appendix SA1**. As noted by Bound et al. (1995), the "cure can be worse than the disease" when the excluded instruments are only weakly correlated with the endogenous variables. Weak IVs can lead to inconsistent and unreliable estimates. To test the relevancy condition (to identify

TABLE 2 | Probit, OLS, and control function approach to estimate crop yield function.

Covariates	Adoption (1/0)	dy/dx[b]	Log yield (kg/ha)	
	Probit		**OLS**	**Control function**
	(1)	**(2)**	**(3)**	**(4)**
Female household head (1/0)	−1.251***	−0.332***	0.074**	0.081***
	(0.402)	(0.112)	(0.029)	(0.029)
Age of household head (year)	0.133*	0.035*	0.000	−0.000
	(0.076)	(0.020)	(0.005)	(0.005)
Log household size	0.585	0.155	−0.030	−0.038*
	(0.383)	(0.106)	(0.029)	(0.029)
Livestock ownership (TLU)	0.130	0.035	0.002	0.003
	(0.109)	(0.028)	(0.007)	(0.007)
Land area (ha)	0.257	0.068	−0.065	−0.076**
	(0.560)	(0.150)	(0.043)	(0.041)
Log irrigation and machinery cost (NPR)	−0.106	−0.028	0.036**	0.040***
	(0.160)	(0.043)	(0.014)	(0.014)
Log manure and fertilizer cost (NPR)	−0.296	−0.079	0.062***	0.060***
	(0.222)	(0.057)	(0.016)	(0.016)
Log of labor cost (NPR)	0.177	0.047	−0.023*	−0.024
	(0.168)	(0.043)	(0.013)	(0.013)
Log seed and planting materials cost (NPR)	−0.184	−0.049	−0.002	−0.003
	(0.130)	(0.034)	(0.010)	(0.010)
Agricultural training/meeting (1/0)	1.896***	0.504***	0.095***	0.108***
	(0.452)	(0.107)	(0.031)	(0.033)
Knowledge on improved manure practice (1/0)	1.466***	0.389***	0.064**	0.059***
	(0.441)	(0.109)	(0.029)	(0.029)
Credit (1/0)	1.193***	0.317***	0.079***	0.089***
	(0.374)	(0.104)	(0.027)	(0.028)
Formal education (1/0)	1.326***	0.352***	0.163***	0.145***
	(0.404)	(0.116)	(0.032)	(0.034)
Cooperative/group members (1/0)	1.031**	0.274**	0.028	0.033*
	(0.428)	(0.107)	(0.027)	(0.027)
Outstanding loan (1/0)	−1.118***	−0.297***	−0.144***	−0.137***
	(0.375)	(0.105)	(0.031)	(0.031)
Neighbors/ friends adoption (1/0)	2.107***	0.560***		
	(0.397)	(0.109)		
Frequency of extension contact	0.227**	0.060**		
	(0.110)	(0.029)		
Distance to market (km)	−0.745***	−0.198***		
	(0.164)	(0.039)		
Adoption (1/0)			0.108***	0.158***
			(0.036)	(0.050)
Generalized residual (ρ)				−0.059***
				(0.033)
Constant	−2.683		8.110***	8.104***
	(2.770)		(0.216)	(0.214)
Observations	444		444	444
R^2	0.675[a]		0.635	0.640

Robust SE at the village development committee in parentheses in parentheses. TLU, tropical livestock unit. dy/dx, marginal effect.
*Significant at the 10% level;
**Significant at the 5% level; ***Significant at the 1% level.
[a]Pseudo R^2.
[b]Maginal effect, which is computed at the mean value of the X variables.

weak instruments), we regress the binary adoption variable on a set of excluded instruments. The result shows that instruments are jointly significant for explaining the adoption decision ($\chi^2 = 235.43$; $p < 0.001$ for the probit model and F-statistics = 113.08; $p < 0.001$ for the linear probability model). More importantly, Cragg-Donald's F-test statistics are large enough to reject the hypothesis that the excluded variables are weak instruments (see for details, Stock and Yogo, 2005).

Further, in order for the model to be identified, exclusion restrictions need to be enforced, whereby instruments must be highly correlated with the endogenous binary adoption decisions but not directly correlated with crop productivity. In other words, the IVs' impact on crop yield should come only through adoption decisions. However, the exclusion restriction can be violated if households learn productivity-improving methods from friends and neighbors. Intuitively, we argue that farm households are less likely to know about friends' and neighbors' unobserved characteristics. Moreover, the distance variables are random from the household location after controlling for other household characteristics.

TABLE 3 | Treatment effects of improved organic manure practice on crop yield.

Sub-samples	Decision stage		Treatment effects
	To adopt	No to adopt	
	(1)	(2)	(3)
Households that adopted	$\widehat{y_{11}} = 8693.601$	$\widehat{y_{10}} = 7522.625$	$\widehat{ATT} = 1170.976$***
Household did not adopt	$\widehat{y_{01}} = 8863.365$	$\widehat{y_{00}} = 7420.306$	$\widehat{ATU} = 1448.059$***
Heterogenous effects	$\widehat{y_{11} - y_{01}} = -174.764$	$\widehat{y_{10} - y_{00}} = 102.319$	$\widehat{ATT} - \widehat{ATU} = 277.083$ **
Local average treatment effect (LATE)	8763.664	7481.605	1282.059

ATT represents the effect of the adoption on the households that adapted. ATU represents the effects of improved organic manure practices on households that did not adopt
Significant at the 10% level;
**Significant at the 5% level;*
***Significant at the 1% level.*

We also carried out the "falsification test" (Di Falco et al., 2011) to test the validity of IVs. In this test, the crop yield among households that did not adopt is regressed (data column 2 of **Supplementary Appendix SA1**) on all IVs. The results support exclusion restriction as none of these IVs are significant.

Impacts of Improved Manure Practice Adoption on Crop Yield

The OLS estimates of the yield functions, controlling for various observables and inputs, are in column 3 of **Table 2**. The parameter estimates suggest a positive and significant effect of improved organic manure practice use on crop yield. The OLS results show households adopting improved technology have 11% higher crop yield[5] than non-adopting households after controlling for observed characteristics. However, the OLS estimates assume that adoption is exogenously determined while potentially endogenous due to sample selection. This approach does not consider the unobservable, such as innate ability and skills that are likely correlated with the adoption decisions and crop productivity, thus leading to inconsistent estimates.

Column 4 in **Table 2** presents the results of the CF-ESR setting. A notable result is the sign and significance of the coefficient of the generalized residual (ρ). The estimated generalized residual ($\hat{\rho}$) is statistically significant at the 1 percent level, which provides compelling evidence of self-selection in adoption decisions, thus indicating that adoption is endogenous. In particular, the negative sign of ρ suggests negative selection bias that farm households with lower-than-average crop yields are more likely to practice improved organic farming. It can also be contended that unobservable factors that raise observed crop yield tend to occur with observables that lower adoption decisions.

These findings justify the use of the CF-ESR to account for selection bias to obtain consistent estimates. The two-step control function approach uses the two-step estimation procedure to address observed and unobserved heterogeneities between adopters and non-adopters. Our preferred specification suggests a positive and significant return to improved manure practice; adopting the technology leads to a 17% higher return in crop yield after controlling for confoundings. As such, sample selection results in an attenuation bias as the crop productivity impact of adoption is 6% higher when using a two-step control function approach than when using OLS. In the absence of sample selection, parameter estimates from OLS and the two-step models should be the same. The differential productivity impacts of adoption estimated with two approaches indicate substantial unobserved heterogeneities between adopters and non-adopters. Consistent with economic theory, input costs such as irrigation and machinery, fertilizers, and manures are significantly associated with increased crop yield per hectare.

The land area's estimated coefficient is negative and statistically significant, suggesting that productivity negatively correlates with cultivated land area. More specifically, the result indicates that a 1% increase in the cultivated land area decreases rice yield by 3%.[6] The inverse relationship between farm size and crop productivity is consistent with many existing studies (Huang et al., 2015) that small-sized farms are more productive.

We also report the estimated coefficients of the crop productivity equations for adopters and non-adopters separately (**Supplementary Appendix SA2**). The results show a substantial difference in yield equation coefficients between adopters and non-adopters. The difference in the estimated coefficients of covariates in the adopters and non-adopters equations supports heterogeneity across adopting and non-adopting households.

Heterogeneous Treatment Effects

Table 3 reports the expected productivity under actual and counterfactual conditions for adopters and non-adopters. The results show that adoption significantly increases crop productivity. The average predicted crop productivity of adopting farm households is about 8,764 kg/ha. In comparison, it is about 7,482 kg/ha for non-adopting farm households indicating an average yield advantage (LATE) of 1,282 kg/ha (around 17%). Specifically, farm households that did not adopt the technology would have increased their crop yield by 1,448 kg/ha (20% higher yield return) had they adopted the improved practice. In another counterfactual case, adopters

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[5]As dependent variable is expressed in logarithm the returns are calculated as $100 * (e^{(\beta)} - 1)$.

[6]Since land area is in hectare, we report the elasticity at means as 0.076*0.399*100%

would have produced about 1,171 kg/ha (14% less) if they had not adopted.

Similarly, yield improvement from adoption would have been significantly higher (277 kg/ha) for non-adopters than adopters had both groups adopted the technology; that is, the effect is bigger for non-adopting households with respect to adopting households. The positive and significant effects of technology adoption on crop productivity support the results of previous studies (Moyo et al., 2007; Kumar et al., 2020). Similarly, significant heterogeneous treatment effects offer other unobservable factors that make adopters systematically better producers than non-adopters, consistent with technology adoption literature (Abdulai and Huffman, 2014; Wossen et al., 2017). These findings indicate many opportunities for farmers to realize higher productivity by simply using these techniques.

Robustness Check

We checked our findings' validity by comparing the results from treatment effects models and propensity score matching (PSM). We also use the treatment effect model using Stata's canned routine for the comparison of our findings. The estimated coefficients and treatment effects (both ATT and ATE) are consistent with estimated parameters with CF-ESR (**Supplementary Appendix SA3**). We used the nearest neighbor matching (NNM) estimator for the propensity score matching. The NMM approach takes each adopter and searches for the non-adopter with the closest propensity score, and all adopters find a match with non-adopters (Caliendo and Kopeinig, 2008). The matched comparison group is understood to be counterfactual. The PSM method's average treatment effect is positive and significant, indicating higher productivity impacts of adoption. However, the ATE under this approach is slightly lower than that estimated by the CF-ESR (11% vs. 17%). The results suggest that inability to control for unobservable results in underestimating ATEs in the PSM. The PSM balances the observed distribution of covariates between adopters and non-adopters and accounts for only observed heterogeneity, while CF-ESR accounts for both observables and non-observables. These findings align with earlier studies suggesting the PSM's shortcomings in technology adoption literature (Andam et al., 2008; Shahzad and Abdulai, 2020).

CONCLUSION AND POLICY IMPLICATIONS

This article offers empirical support to the growing literature on the adoption behavior of farmers in developing economies. Its focus on improved organic manure practices helps solidify arguments for the greater relevance of organic production methods in general. Under this expanded perspective, this study reinforces the usual environmental, social, and economic motivations that may influence farmers' adoption decisions.

As the organic manure alternative weans, farm businesses from dependence on chemical production inputs, apparent gains

in environmental health and sustainability can strongly influence farmers' adoption behavior. Although not directly validated in this analysis, this underlying motivation is supplemented by social and economic arguments. In this study, the crucial role of social capital in adoption decisions is evident. More than just a validation of farmers' "free-riding behavior" where earlier adopters among peer farmers can help induce adoption decisions, the social dimension of adoption can reflect information sharing and collective empirical learning modes that socially cohesive and cooperative rural community systems in developing countries usually subscribe to. This contention is easily bolstered by the success of earlier rural development efforts that capitalized on the communities' pervading cultural norms and social networks. A case in point is the microfinance paradigm that confirms the sustained effectiveness of the group lending implemented for many decades now in many rural communities, especially in South Asia, that has effectively bolster poverty alleviation goals.

Beyond environmental and social considerations, this study also establishes economic motivations for adopting such alternative technology. Improved organic manure practice has not only resulted in significantly higher yields among adopting farms, but results of counterfactual analyses show that non-adopting farms would have realized much better yield conditions had they implemented the technology.

As Nepal's government continues to promote improved organic manure practice as a more affordable, practical production input, this study lays out encouraging parameters that prospective adopters may factor into their decisions. The composite effects of an alternative technology that reaps environmental, social, and economic benefits can only translate to a more sustainable farm economy, especially in a country like Nepal.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

CD: Conceptualization; Methodology; Project administration; Writing-original draft; Writing-review and editing. CE: Project administration; Resources; Supervision; Writing-original draft; Writing-review and editing.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.912860/full#supplementary-material

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