Technology and Technical Efficiency Gaps Correcting for Selectivity Bias: A Preliminary Analysis from a Value Chain Project in Nepal

by Florian Neubauer, Tisorn Songsemsawas, Joanna N. Kámiche-Zegarra, and Boris E. Bravo-Ureta

TECHNOLOGY AND TECHNICAL EFFICIENCY GAPS CORRECTING FOR SELECTIVITY BIAS: A PRELIMINARY ANALYSIS FROM A VALUE CHAIN PROJECT IN NEPAL

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Abstract

Strengthening linkages between smallholder producers and markets is a potential pathway to increase agricultural productivity, welfare and food security for smallholder producers in developing countries. Our study investigates the impact of an integrated value chain intervention in Nepal which connected producer organizations with markets and provided marketing-related training activities. Using primary survey data consisting of 1,952 households (955 treatment and 997 control), we match project (treatment) and non-project (control) households to ensure common support and balance across the two groups. We then use selectivity-corrected stochastic production frontier analysis to account for differences in unobservable characteristics. Our results indicate that strengthened linkages result in higher frontier output, but no improvements in technical efficiency. A possible explanation is that project beneficiaries probably require additional complementary access to production inputs to fully harness the benefits of the improved linkages.

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JEL Codes: D24, O13, Q13

1. Introduction

During the past few decades, the number of people living below the international poverty line of $1.90/day declined from 36% to 10% across the globe (World Bank, 2018). Nonetheless, at least 736 million people still live in extreme poverty. Many of these people have small farms, live in rural areas and rely on agriculture as their main source of income, which has direct implications on their welfare and food security. Smallholder producers often face numerous production constraints and market frictions such as limited access to markets, credit, information as well as production and post-harvest technologies (Alene et al., 2008; Markelova et al., 2009; Minten et al., 2020). One approach to improve their agricultural productivity is through strengthening agricultural value chains by offering market access opportunities and diversifying livelihood strategies (Barrett et al., 2012; Reardon et al., 2009).

Despite their potential and rapid transformation, the mid-stream segment of agricultural value chains (i.e., processing, packaging, and transporting) is often under researched and has attracted limited attention in policy discussions (AGRA, 2019; Reardon, 2015). High transaction costs are often identified as the major obstacles preventing smallholder producers from accessing markets along value chains (Alene et al., 2008; de Janvry et al., 1991). Therefore, investing in value chains could improve agricultural productivity and welfare of smallholder producers, particularly for those living in remote locations where transaction costs are relatively high, particularly those related to transportation and information. Furthermore, such investments could help address market failures by promoting farm diversification towards high-value crops and by encouraging value addition and off-farm sales (de Janvry and Sadoulet, 2020; Swinnen and Kuijpers, 2019).

Many rural households in developing countries depend on food bought on markets beyond their own production; hence, value chains are crucial for increasing income of smallholder producers (Reardon et al., 2014). This is clearly the case in Nepal, the setting for our study, where 58% of the total value of food consumption stems from items purchased in surrounding markets. We use data collected from the High Value Agriculture Project in Hill and Mountain Areas (HVAP) in Nepal, a value chain project implemented in the Western Hills of the country between 2011 and 2018 to demonstrate how investing in agricultural value chains could improve productivity and livelihoods among smallholder producers.

Improved market linkages allow smallholder farmers to diversify production beyond staples toward high-value commodities. Producing high-value commodities could contribute to income generation, job creation, and poverty alleviation among smallholder producers (Joshi et al., 2004; Weinberger and Lumpkin, 2007). While these topics have been researched in previous studies, the available work typically ignores that producers self-select into joining value chain interventions, which raises the concern that participation is very likely driven by unobservable characteristics such as ability or managerial skills.

Existing evidence shows that value chain investments can enhance the well-being of participating producers (Barrett et al., 2012; Reardon et al., 2009). What is less clear is to what extent value chain investments can contribute to narrowing technology and managerial performance gaps, where the former is measured by a jump in the production frontier and the latter by changes in technical efficiency (TE) (Bravo-Ureta et al., 2012). González-Flores et al. (2014) investigate the impact of *Plataformas de Concertación* on productivity growth of subsistence farmers in Ecuador[1]. They find that the program increases yield but lowers TE of treated compared to control households. Dong et al. (2019) employ the SC-SPF methodology in a similar context, where the aim is to bring farmers closer to agricultural information and other actors along the vegetable value chain. They look at participation in professional cooperatives in China and report that cooperative members have higher TE and income compared to non-members.

Our goal is to provide rigorous evidence of the impact of strengthened linkages between smallholder producers and markets on two components of productivity: (1) technological change (TC) as measured by a jump in the production frontier; and (2) TE differentials between HVAP beneficiary (treatment) and non-beneficiary (control) groups. Thus, we make three contributions to the literature. First, we adopt a novel econometric approach which accounts for selectivity bias from observed and unobserved characteristics. We use propensity score matching (PSM) to control for self-selection from observable characteristics (Ho et al., 2007). Then, we apply the SC-SPF methodology to ensure that our parameter estimates are unbiased and consistent (Bravo-Ureta et al., 2012; Greene, 2010).

Second, we contribute to the growing pool of studies which apply the SC-SPF methodology in the context of agriculture in the developing world. This pool includes studies on rice production (Abdul-Rahaman et al., 2021; Abdul-Rahaman and Abdulai, 2018; Bravo-Ureta et al., 2020; Villano et al., 2015), certified wheat adoption (Baglan et al., 2020), apple cooperatives (Ma et al., 2018), and vegetable production (Dong et al., 2019). Further, the SC-SPF methodology has been applied to study other agricultural practices including integrated pest management (Rahman and Norton, 2019), land tenure certification (Lawin and Tamini, 2019), natural resource management

[1] Plataformas de Concertación is a multi-stakeholder platform to increase participation of farmers in value chains of high-value commodities in Bolivia by promoting new technology adoption, offering skill-enhancing trainings, and creating linkages to markets (Cavatassi et al., 2011).

(De los Santos-Montero and Bravo-Ureta, 2017), conservation agriculture (Abdulai and Abdulai, 2017), and irrigation infrastructure (Bravo-Ureta et al., 2020).

Third, our work provides an in-depth assessment of TE related to high-value crops. Existing studies on TE focus primarily on the production of staple crops (Abdulai and Abdulai, 2017, 2017; Bravo-Ureta et al., 2020; Lawin and Tamini, 2019; Villano et al., 2015). Our study complements those focusing on high-value crops (Ma et al., 2018), and in particular analyses related to linking high-value crop producers with markets (Dong et al., 2019; González-Flores et al., 2014; Mishra et al., 2018). Given the Government of Nepal's growing interest in high-value crop production, findings in this work could provide useful information about areas requiring investments and support to improve agricultural productivity and TE of smallholder producers.

Our results show that improved linkages between farmers and markets contribute to higher agricultural productivity of farmers and provide evidence of increasing returns to scale for production inputs including land, labor, and purchased inputs. Further, the technology gap expands between farmers in the treatment group relative to the control group, suggesting shifts in the production frontier due to the project. However, our results indicate lower TE for treatment households, a finding that has two likely explanations. First, while treated farmers have benefitted from the project in terms of productivity, they could still be adjusting to the new technology, suggesting that additional trainings and support might be required (González-Flores et al., 2014). Second, lacking complementary inputs due to cash and credit constraints as well as the need for additional training might have kept beneficiaries from fully harnessing project benefits, which are findings also documented in Bravo-Ureta et al. (2020).

The rest of this paper is organized as follows. In Section 2, we provide an overview of the context and setting of our study. Section 3 describes the data, methods, as well as the empirical framework. Section 4 gives an overview of the results. We discuss the policy implications of our work in Section 5 before we conclude in section 6.

2. Context and setting

Agriculture plays an important role in Nepal's economy, its development, and in achieving the Government's goals of poverty reduction and improved food security (Kafle et al., 2020). Agriculture contributed about a quarter to Nepal's GDP in 2018 and three quarters of all households in the country are employed in agriculture (Roka, 2017; World Bank, 2020).

HVAP is a project conducted in the Western Hills of Nepal, where the challenging landscape poses great difficulty for smallholder producers to diversify their livelihood strategies and access input and output markets. The project covered seven highly vulnerable districts: Achham, Dailekh, Jajarkot, Jumla, Kalikot, Salyan, and Surkhet. Achham is part of Sudurpashchim Pradesh, and the remaining six districts are located in the province of Karnali Pradesh (Figure 1). In 2011, the region received the second lowest Human Development Index value of all regions within Nepal at 0.447 (Government of Nepal and United Nations Development Programme, 2014). Life expectancy at birth was 57.2 years, the adult literacy rate was just above 50%, and the mean years of schooling among adults were 3.07 years. All of these were well below the national averages.

[FIGURE 1 HERE]

As part of the efforts to reduce poverty and food insecurity, the Government of Nepal worked with development agencies to link smallholder producers with markets through the HVAP project. HVAP developed inclusive value chains and strengthened service markets in the hill and mountainous area of Nepal (IFAD, 2009) [2]. It worked mainly with producer organizations (POs) and main actors along seven value chains: apple, ginger, vegetable seeds, off-season vegetables, turmeric, *timur* (Sichuan pepper), and goats.

Our study focuses on Component 1 of HVAP, inclusive value chain development. It established contractual agreements between POs and agribusinesses, strengthened PO capacity, provided market information, delivered support services, built and rehabilitated infrastructures, and offered training on skill development to PO members. Component 2 consists of training activities offered to smallholder producers in topics related to business literacy, post-harvest processing, marketing, entrepreneurship, and market information. Networking sessions were also offered to connect project participants with input dealers and traders.

Strengthened linkages between producers and markets as well as improved PO capacity are the main channels through which HVAP is anticipated to improve agricultural productivity of its target groups. Contractual agreements between POs and agribusinesses should help reduce transaction costs when selling agricultural products to markets (Markelova et al., 2009; Mojo et al., 2017). Training activities related to capacity building provided to POs are expected to help their members improve productivity (Dong et al., 2019; González-Flores et al., 2014; Ma et al., 2018). Further, together with improved linkages and PO capacity, project investments in market facilities such as collection centers and cold storages could significantly reduce post-harvest losses of crops (Mu and Walle, 2011; Shrestha, 2020).

The possible mechanism whereby HVAP could contribute to augmenting the technology set and TE of its target groups is as follows. A jump in the production frontier is expected to be driven by the strengthened linkages between POs and markets leading to increased value of

[2] More details about HVAP activities and implementation can be found in (Kafle et al., 2018).

production, information regarding improved farming practices, and more access to various inputs such as seeds, fertilizer, pesticides. Higher TE is expected to come from capacity building training offered to POs and their members designed to enhance managerial performance and entrepreneurship. Changes in TE may also be driven by smallholder producers' motivation to raise their managerial efforts in response to the greater production potential afforded by improved market linkages.

3. Data, methodology and empirical framework

3.1 Data

We develop a mixed-method approach combining statistical procedures with local information from project staff to create the counterfactual group. First, we worked with the project staff to prepare a full list of supported POs along with critical information (e.g., location, PO members, etc.). Second, we used data from the 2011 National Population and Housing Census, which were collected before HVAP was implemented. The data are available up to the village development committee (VDC) level[3]. HVAP was mainly implemented at the PO level within each VDC. As the project treatment VDCs were identified based on socio-economic characteristics of the population, we used PSM to match treatment VDCs with potential control VDCs based on socio-economic characteristics. This process resulted in a list with three possible control VDCs for each treatment VDC. Third, we asked project staff to apply their local knowledge so as to reduce this list by pairing each treatment VDC to the most similar control VDC.

[3] The current constitution of Nepal, which was adopted in 2015, necessitated the reform of administrative divisions. Through this reform, the Rural Municipality system replaced the VDC system. However, our research design follows the VDC system which was in use when HVAP started its implementation in 2011 with the aim of replicating the targeting strategy of HVAP to build the counterfactual.

Next, we selected control POs within the identified suitable control VDCs from the previous step. We asked the project staff and local stakeholders to help identify up to three potential control POs for each treatment PO by replicating the process to recruit treatment POs.

After obtaining the final roster of treatment and control POs to be included in our sample, we worked with the project staff to obtain a list of households in each PO. This list focused on households that meet the project's eligibility criteria based on well-being, income, and landholding[4]. We use this final list as the sampling frame to randomly select approximately 12-13 households from each PO to be part of our sample.[5]

The full dataset consists of 235 POs (117 treatment and 118 control) and contains information from 3,020 households (1,500 treatment and 1,520 control). The data were collected as part of a primary survey conducted in the Western Hills between May and July 2018. The data collected cover information for the 12-month period preceding data collection, which includes two cultivation seasons. The survey was a multi-module document designed to collect socio-economic characteristics, land ownership and use, agricultural and livestock production and other livelihood information.

Given the focus in this paper and to reduce the heterogeneity of the production systems, we center our analysis on 178 POs (91 treatment and 87 control) located in the mid-hill zone. The sample includes 1,952 households (955 treatment and 997 control) from five districts (Achham, Dailekh, Jajarkot, Jumla, and Surkhet). The other two districts (Kalikot and Salyan) are in the high-hill zone where the production systems are not directly comparable to those that are prevalent in

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[4] A household's well-being status is determined based on a subject assessment done at the community level. Each household's well-being can be classified as extremely poor, moderately poor, near poor, and not poor. Households classified as extremely poor, moderately poor, or near poor are considered eligible. For income, the annual per capita income for eligible households must be less than 2,000 Nepalese Rupees (Rs.; approximately US$17). 1 US$ is approximately 120 Rs. For land, the landholding size of eligible households must be less than 0.5 hectares.

[5] More detailed information about the sample design is discussed in (Kafle et al., 2020).

the mid-hill districts[6]. We further focus our analysis on households that reported crop production during the 12-month recall period. The indicator of interest in our study is total value of agricultural production (both crop and livestock combined)[7]. We winsorize this variable at the top 1% of the distribution to account for extreme values (Fink et al., 2020).

3.2. Methodology and empirical framework

We employ PSM to control differences in observable characteristics between the treatment and control groups (Caliendo and Kopeinig, 2008). Using a probit model, we calculate propensity scores and restrict the sample to those observations that satisfy the overlap condition (common support). Thus, we discard control observations that have a lower propensity score than the lowest treatment observation, and treatment observations that have propensity scores higher than the highest control. We then use radius matching, which pairs each treatment observation to all control observations that fall within a certain pre-defined caliper, where the latter is defined as the maximum allowable distance the between propensity scores of two observations. Following the matching, we check if the two samples are balanced by employing t-tests as well as using the standardized percentage bias as proposed by (Rosenbaum and Rubin, 1985). As is common practice, we implement the matching process using 1-to-1 nearest neighbor (NN) without replacing as a robustness check[8], which yields qualitatively similar results.

We then estimate conventional SPF models for the pooled sample (control and treatment observations) and separately for the treatment and control groups. Recognizing that selection into participation based on unobservable characteristics is likely, we adopt the selectivity corrected-

[6] Households in the five districts of the mid-hill zone represent approximately 80% of our overall sample.
[7] The total value of annual production variable is computed by multiplying output level with constant prices of each commodity by season computed at the median of the data.
[8] We note that the 1-to-1 option we use is one of the most restrictive alternatives, if not the most restrictive, usually leading to a smaller matched sample, as each control observation can only be used once to construct the counterfactual.

stochastic production frontier (SC-SPF) model developed by Greene (2010), which was adapted for impact evaluation of development projects by Bravo-Ureta et al. (2012). Therefore, the framework includes two separate models to be estimated: first, a probit sample selection model with a binary participation variable as the dependent variable, a vector of time-invariant explanatory variables, and an error term; second, a stochastic frontier model with agricultural output as the dependent variable, a vector of explanatory variables, as well as a two-sided error term. The important distinction to early frontier studies that corrected for selectivity bias lies in the assumption about the correlation between the error terms of the sample selection and stochastic frontier models. While Kumbhakar et al. (2009) assume that selectivity issues stem from the correlation between the error term in the probit selection model with the inefficiency component of the error in the SPF, Greene (2010) assumes that the correlation is between the error in the probit with the noise in the SPF.

Meta-analyses of agricultural efficiency studies show that the translog and Cobb-Douglas (C-D) functional forms are most commonly used in TE studies (Bravo-Ureta et al., 2017, 2007; Ogundari, 2014). Moreover, comparisons of TE scores obtained from CD and translog specifications tend to be highly correlated (Bravo-Ureta et al. 2020; Baccouche and Kouki, 2003). We employ the C-D functional form given that it is globally compliant with assumptions coming from the economic theory of production (Corbo and Meller, 1979; O'Donnell, 2018).

The specification of the SPF model to be estimated is:

$$lnY_{ij} = \alpha_0 + \sum \beta_j \, lnX_{ij} + \sum \gamma_j \, H_{ij} + \sum \delta_j F_{ij} + \sum \lambda_j \, Z_{ij} + \sum \pi_j \, D_{ij} + \varepsilon_{ij}, \qquad (2)$$
$$\varepsilon_{ij} = v_{ij} - u_{ij}$$

where lnY_{ij} is the log of total annual value of agricultural production for farmer i in group j (treatment or control), the Roman letters indicate vectors of traditional purchased inputs (X_{ij}), household characteristics (H_{ij}), farm characteristics (F_{ij}), environmental variables (Z_{ij}), as well as dummy variables representing the district a farmer lives in (D_{ij}). All Greek letters are parameters to be estimated, and v_{ij} and u_{ij} are the two-sided and the one-sided error terms.

The SC-SPF algorithm includes the joint estimation of the SPF (equation 2) model and a probit (or logit) selectivity equation (equation 3), whose specification in this paper is as follows:

$$TREAT_i = \alpha_0 + \sum \alpha_{ik}\, CV_{ik} + w_i, \qquad (3)$$

where $TREAT_i$ is a binary variable indicating project participation, CV_{ik} is a set of covariates, α are the parameters to be estimated, and w is the error term which is normally distributed. The model is estimate twice, reversing the definition of the *TREAT* variable to *Control* in the second estimation.

4. Results

4.1 Descriptive statistics

We discard three control observations that were off support and apply radius matching, which is more lenient than the often used 1-to-1 NN[9]. Three control and two treatment units were not matched, and we discard them from the sample. Table 1 shows the descriptive statistics of our sample before and after PSM. The results for the unmatched sample already indicate that control and treatment groups are statistically similar in most of their characteristics. This is due to the careful sample design, which helped to reduce most observable differences preemptively. There are still some statistically significant differences in education, access to credit, and access to

[9] We also apply the 1-to-1- nearest neighbor approach without replacement as a robustness check

extension, but the relative biases between treatment and control groups for these variables are much smaller after matching.

[TABLE 1 HERE]

However, the average differences between the means of treatment and control groups diminished, and the statistical significance remained unchanged. To complement the t-tests, which are sensitive to sample size, we calculate the change in standardized percentage bias, which is shown on the right-hand side of the table. These results suggest a high-quality matching as the standardized percentage bias for all covariates gravitates towards zero for the matched sample. Rubin's R, a measure of the average standardized percentage bias, shows a bias reduction from 39.5% to 6.5%, which is significantly lower than the suggested threshold of 25% (Rubin, 2001).

4.2 Estimation results of conventional SPF and SC-SPF models

The results of the OLS model, and both the conventional SPF as well as SC-SPF models are shown in Table 2. The coefficients can be interpreted as partial production elasticities given the C-D specification of the production frontier.

[TABLE 2 HERE]

The individual parameter estimates are robust across models, although the point estimates of the traditional inputs land, labor, and purchased inputs are slightly lower for the SC-SPF models. Overall, they lie within the expected range (between zero and one) and are statistically significant. The sum of the partial elasticities of the traditional inputs lies between 1.099 for the treatment group in the SC-SPF model in column (5) and 1.386 for the pooled sample in the conventional SPF model in column (2). The OLS model has the highest sum with 1.413 in column (1).

Across specifications, partial production elasticities indicate increasing returns to scale and are statistically significant, which are in line with the findings in González-Flores et al. (2014).

However, the magnitudes of the coefficients we estimate differ from those reported in their paper. The highest elasticity is for purchased inputs, which is consistent with the fact that smallholder producers in developing countries are often cash or credit constrained so they can only open limited amounts (Kalirajan, 1991; Karlan et al., 2014). Since the farmers in our sample use very small amounts of purchased inputs, the marginal returns to purchased input use can be very high. This is a finding also noted in González-Flores et al. (2014). Conversely, cultivated land provides the least contribution to total value of production. A possible explanation is due to the steep terrain around the project area.

Unsurprisingly, the parameter for the binary variable *flat slope* (1: flat, 0: steep) is positive and highly significant, except for the control group in the conventional model and both selectivity corrected models. In a regular setting, the positive and significant altitude coefficient for the treatment group could be surprising, since one would expect that higher altitude is detrimental to productivity for all farmers. However, in our setting farmers in higher altitudes are more likely to have livestock production along with crop production, which is a lucrative business. In addition, some horticulture crops like apples are more suitable to be cultivated in the cooler higher altitudes and most farmers in lower elevations cultivate less lucrative vegetables.

Experience, proxied by age, seems to only matter for the control group in the SC-SPF model, which could indicate that new technologies could bridge the gap between less and more experienced farmers. The parameter for gender is positive and highly significant in the treatment group but not significant in the control group. While it could be that male-headed households can adapt quicker to new technology, it could also hint at the need to optimize project activities to make them more gender inclusive and supportive of female farmers. Similarly, access to extension is positively associated with higher productivity, but only for the treatment group. Education has a strong and significant effect on output across all groups and specifications. Surprisingly, access to credit has a negative impact on production, but adverse weather events have a significant negative effect, as expected. In addition, we do not observe any significant differences in outcomes between households that belong to ethnic minority groups and those who do not.

The results of the SC-SPF models show that selection bias due to unobservable characteristics is present, as indicated by the significant Rho coefficient for the control group. Therefore, unobservable characteristics like ability, aspiration, and motivation are likely to have influenced a particular set of households to self-select into treatment.

TE scores from the SPF models are shown at the bottom of Table 2. Using the conventional SPF model, we find a significant gap in TE between treatment and control groups, with treated farmers operating at 53% efficiency, while control farmers have a higher TE at 69%. This gap persists when controlling for unobservable characteristics in the SC-SPF models, with treated producers operating at 50% and control producers at 67%. Two possible explanations could be behind this finding. First, households who benefitted from the project have to overcome a short-run adjustment period while they learn to take full advantage of the new technologies and this is similar to findings reported by González-Flores et al. (2014). This suggests the importance of verifying this argument in a follow-up study. Second, qualitative information indicates that access to improved inputs and post-harvest technologies, such as cold storage, remain challenges for treatment households. Similarly, in a study of Filipino rice production, Bravo-Ureta et al. (2020) find that there is no significant improvement on TE among treatment households, which is potentially due to insufficient training and limited access to complementary inputs due to remaining cash and credit constraints after the project.

5. Policy implications

Our work builds on earlier studies related to the enabling factors and barriers to technology adoption and technical efficiency improvements among smallholder producers in developing countries (Abdul-Rahaman and Abdulai, 2018; Bravo-Ureta et al., 2020; De los Santos-Montero and Bravo-Ureta, 2017; González-Flores et al., 2014; Ma et al., 2018; Villano et al., 2015).

We note two implications for policy makers to improve smallholder producers' technology and managerial performance. First, while interventions at single stages of the value chain can have positive effects, our results support a more holistic approach with interventions along the whole value chain to have more sustainable effects (Kafle et al., 2020). Implementing such designs is often difficult due to limited access to financial services, input and output markets, and post-harvest technologies, but it should be considered wherever possible.

Second, there exists substantial variation in productivity outcomes of firms and households (Bloom et al., 2013; Rosenzweig and Udry, 2020). Particularly in agriculture, the returns to investments vary greatly even after controlling for technology, input use, and agro-climatic factors (Fan et al., 2000; Murgai et al., 2001). Differential access to information has been identified as one factor (Aker, 2010; Jensen, 2007). Farmer field schools could be one channel through which smallholder producers can access information (Waddington et al., 2014). In general, providing sufficient training and extension services along with the introduction of new technologies is crucial. Adopting new technologies can have an initial setback in efficiency; hence, supporting farmers in making the best use of them as quickly as possible can have substantial productivity gains. Social networks have also been found as an important channel to transmit information (Liverpool-Tasie and Winter-Nelson, 2012; Magnan et al., 2015; Thuo et al., 2014). However, the extent to which information is disseminated among peers could be limited in settings where social networks are clustered among close groups (Jäckering et al., 2019; Songsermsawas et al., 2016).

6. Conclusions

In this study, we present evidence of the productivity impacts of strengthening linkages between smallholder producers and markets by a value chain project in the hill and mountainous region of Nepal. The project focuses mainly on working along different stages of the value chain by establishing contractual agreements between POs and agribusinesses, strengthening PO capacity, providing market information, delivering support services, building and rehabilitating infrastructures, and offering training on skill development.

Given the cross-sectional structure of our data, our identification strategy encompasses PSM and the SC-SPF model (Bravo-Ureta et al., 2012; Greene, 2010) to account for differences in observable as well as unobservable characteristics between control and treatment groups. Our work shows that improved linkages with markets had a positive and significant impact on smallholder producers' productivity, which are consistent with previous findings (Barrett et al., 2012; González-Flores et al., 2014; Reardon et al., 2009). However, we find that TE is lower for the treatment than the control group, consistent with previous studies (Bravo-Ureta et al., 2020; Gebregziabher et al., 2012; González-Flores et al., 2014). This finding suggests that an increase in productivity due to improved value chains can occur without an increase in efficiency. Moreover, it is possible that an initial adaptation period to the new technology is the cause for the drop in TE but we cannot verify this due to a lack of adequate data (González-Flores et al., 2014). Cash and credit constraints which may have prevented farmers from purchasing high quality inputs can also be the cause for farmers not being able to take full advantage of their increased production possibilities induced by the project (Bravo-Ureta et al., 2020).

Therefore, our work indicates that additional research focusing on mechanisms to help small farms improve their productivity, particularly among the economically disadvantaged and vulnerable groups, is warranted. We further encourage more research on the impact of value chain projects on farmer’s productivity and technical efficiency in different contexts.

Figure 1

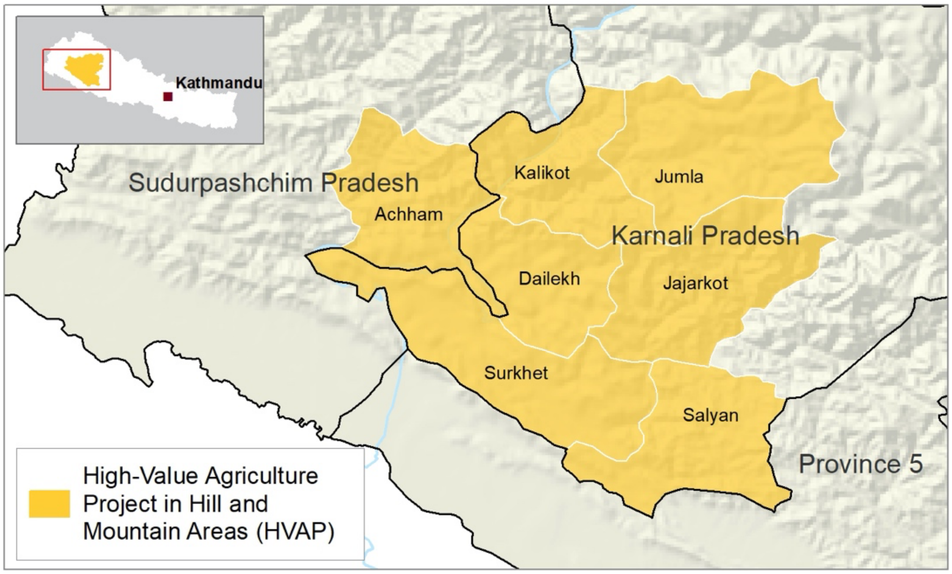

Table 1: Descriptive statistics

	T-tests								Standardized Percentage Bias	
	Unmatched				Matched				Unmatched	Matched
	Means				Means					
	Treated	Control	Difference	p-value	Treated	Control	Difference	p-value		
Covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Characteristics of the household head										
Age (yrs)	45.46	44.61	0.86	0.13	45.48	44.6	0.88	0.121	6.8	0.1
Sex (% male)	0.73	0.71	0.03	0.193	0.73	0.71	0.03	0.187	5.9	-0.5
Attended school (%)	0.57	0.59	-0.02	0.461	0.57	0.59	-0.02	0.444	-3.3	-1.9
Education (yrs)	4.39	4.75	-0.36	0.095*	4.38	4.74	-0.35	0.099*	-7.6	-2.8
Panel B: Household demographics										
Household size	4.99	5.07	-0.08	0.372	5.00	5.07	-0.07	0.44	-4.0	1.3
Dependency ratio	0.77	0.91	-0.13	0.000***	0.77	0.9	-0.13	0.000***	-16.7	0.8
Female household members (%)	0.54	0.55	-0.01	0.097*	0.54	0.55	-0.01	0.095*	-7.5	0.1
Literacy rate of household members (%)	0.68	0.68	0.00	0.975	0.68	0.68	0.00	0.949	0.2	0.0
Ethnic minority: Dalits (%)	0.32	0.3	0.02	0.297	0.32	0.3	0.02	0.352	4.7	-2.5
Access to credit (%)	0.54	0.57	-0.04	0.083*	0.54	0.57	-0.04	0.086*	-7.8	2.8
Access to extension (%)	0.33	0.21	0.12	0.000***	0.33	0.21	0.12	0.000***	27.2	0.1
Rubin's B									39.3	6.5
Number of observations	1,957				1,952					
of which treated and control	957	1,000			955	997				

Table 2

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**Conventional SPF**			**SC-SPF**	
		Pooled	Treated	Control	Treated	Control
Treated	0.346***	0.332***				
	(0.0333)	*(0.0324)*				
Cultivated area (ha)	0.291***	0.238***	0.175***	0.339***	0.184***	0.299***
	(0.0318)	*(0.0316)*	*(0.037)*	*(0.0536)*	*(0.0342)*	*(0.043)*
Labor (person days)	0.366***	0.329***	0.314***	0.349***	0.275***	0.296***
	(0.0375)	*(0.0361)*	*(0.0435)*	*(0.06)*	*(0.0407)*	*(0.0498)*
Purchased inputs (dummy)	0.637***	0.686***	0.626***	0.533***	0.64***	0.459***
	(0.106)	*(0.102)*	*(0.13)*	*(0.155)*	*(0.154)*	*(0.1689)*
Purchased inputs (max, NPR)	0.105***	0.112***	0.116***	0.082***	0.121***	0.073***
	(0.0130)	*(0.0125)*	*(0.0154)*	*(0.0197)*	*(0.0185)*	*(0.0209)*
Black soil (dummy)	0.0465	0.0331	0.0343	0.0763	0.086	0.095
	(0.0370)	*(0.0357)*	*(0.0473)*	*(0.0528)*	*(0.0603)*	*(0.0601)*
Flat slope (dummy)	0.0484	0.0456	0.0346	-0.0264	0.028	-0.033
	(0.0405)	*(0.0389)*	*(0.0499)*	*(0.06)*	*(0.0632)*	*(0.0717)*
Altitude	0.0001***	0.0001***	0.0002***	0.0001***	0.0002***	-0.0001
	(0.00004)	*(0.00004)*	*(0.00005)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Experience (age of household head)	0.0016	0.002	-0.0003	0.005**	0.000	0.005**
	(0.0015)	*(0.0015)*	*(0.00201)*	*(0.0021)*	*(0.0025)*	*(0.0024)*
Gender of household head	0.0605	0.0608	0.149***	-0.0501	0.146**	-0.067
	(0.0411)	*(0.0396)*	*(0.0531)*	*(0.0587)*	*(0.0633)*	*(0.0651)*
Education of household head	0.0126***	0.0127***	0.0134**	0.0158***	0.014**	0.015**
	(0.0042)	*(0.00404)*	*(0.00539)*	*(0.0059)*	*(0.0068)*	*(0.0072)*
Ethnic minority (dummy)	0.0264	0.00514	0.00349	-0.0156	0.033	0.015
	(0.0365)	*(0.0353)*	*(0.0459)*	*(0.0533)*	*(0.059)*	*(0.0596)*
Access to credit	-0.121***	-0.116***	-0.0557	-0.158***	-0.081	-0.177***
	(0.0337)	*(0.0324)*	*(0.0425)*	*(0.0477)*	*(0.0547)*	*(0.0536)*
Access to extension	0.0798**	0.0692*	0.0889**	0.0502	0.11*	0.103
	(0.0388)	*(0.0372)*	*(0.0446)*	*(0.0603)*	*(0.0586)*	*(0.0687)*
Weather shock (dummy =1: more than 1 extreme weather event)	-0.135*	-0.161**	-0.202**	-0.129	-0.146	-0.147
	(0.0730)	*(0.0703)*	*(0.102)*	*(0.0958)*	*(0.1512)*	*(0.1195)*
Constant	8.484***	9.2***	9.527***	9.398***	9.535***	9.9884***
	(0.208)	*(0.205)*	*(0.27)*	*(0.352)*	*(0.3897)*	*(0.389)*
Observations	1,952	1,952	955	997	955	997
R-squared	0.454					
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Rho					0.286	-0.52*
TE		56%	54%	70%	50%	67%

Standard errors in italics and parantheses, *** p<0.01, ** p<0.05, * p<0.1

References

Abdulai, A.-N., Abdulai, A., 2017. Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. Environment and Development Economics 22, 177–201. https://doi.org/10.1017/S1355770X16000309

Abdul-Rahaman, A., Abdulai, A., 2018. Do farmer groups impact on farm yield and efficiency of smallholder farmers? Evidence from rice farmers in northern Ghana. Food Policy 81, 95–105. https://doi.org/10.1016/j.foodpol.2018.10.007

Abdul-Rahaman, A., Issahaku, G., Zereyesus, Y.A., 2021. Improved rice variety adoption and farm production efficiency: Accounting for unobservable selection bias and technology gaps among smallholder farmers in Ghana. Technology in Society 64, 101471. https://doi.org/10.1016/j.techsoc.2020.101471

AGRA, 2019. Africa agriculture status report: The hidden middle: A quiet revolution in the private sector driving agricultural transformation (Issue 7) (Technical report). Alliance for a Green Revolution in Africa (AGRA), Nairobi, Kenya.

Aker, J.C., 2010. Information from markets near and far: Mobile phones and agricultural markets in Niger. American Economic Journal: Applied Economics 2, 46–59. https://doi.org/10.1257/app.2.3.46

Alene, A.D., Manyong, V.M., Omanya, G., Mignouna, H.D., Bokanga, M., Odhiambo, G., 2008. Smallholder market participation under transactions costs: Maize supply and fertilizer demand in Kenya. Food Policy 33, 318–328. https://doi.org/10.1016/j.foodpol.2007.12.001

Baglan, M., Mwalupaso, G.E., Zhou, X., Geng, X., 2020. Towards cleaner production: Certified seed adoption and its effect on technical efficiency. Sustainability 12, 1344. https://doi.org/10.3390/su12041344

Barrett, C.B., Bachke, M.E., Bellemare, M.F., Michelson, H.C., Narayanan, S., Walker, T.F., 2012. Smallholder participation in contract farming: Comparative evidence from five countries. World Development 40, 715–730. https://doi.org/10.1016/j.worlddev.2011.09.006

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., Roberts, J., 2013. Does management matter? Evidence from India. Q J Econ 128, 1–51. https://doi.org/10.1093/qje/qjs044

Bravo-Ureta, B.E., Greene, W., Solís, D., 2012. Technical efficiency analysis correcting for biases from observed and unobserved variables: an application to a natural resource management project. Empir Econ 43, 55–72. https://doi.org/10.1007/s00181-011-0491-y

Bravo-Ureta, B.E., Higgins, D., Arslan, A., 2020. Irrigation infrastructure and farm productivity in the Philippines: A stochastic Meta-Frontier analysis. World Development 135, 105073. https://doi.org/10.1016/j.worlddev.2020.105073

Bravo-Ureta, B.E., Jara-Rojas, R., Lachaud, M.A., Moreira, V.H., Bravo-Ureta, B.E., Jara-Rojas, R., Lachaud, M.A., Moreira, V.H., 2017. A meta analysis of farm efficiency: Evidence from the production frontier literature (Technical report). Zwick Center for Food and Resource, University of Connecticut.

Bravo-Ureta, B.E., Solís, D., Moreira López, V.H., Maripani, J.F., Thiam, A., Rivas, T., 2007. Technical efficiency in farming: a meta-regression analysis. J Prod Anal 27, 57–72. https://doi.org/10.1007/s11123-006-0025-3

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. J Economic Surveys 22, 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x
Corbo, V., Meller, P., 1979. The translog production function. Journal of Econometrics 10, 193–199. https://doi.org/10.1016/0304-4076(79)90004-6
de Janvry, A., Fafchamps, M., Sadoulet, E., 1991. Peasant household behaviour with missing markets: Some paradoxes explained. The Economic Journal 101, 1400. https://doi.org/10.2307/2234892
de Janvry, A., Sadoulet, E., 2020. Using agriculture for development: Supply- and demand-side approaches. World Development 133, 105003. https://doi.org/10.1016/j.worlddev.2020.105003
De los Santos-Montero, L.A., Bravo-Ureta, B.E., 2017. Productivity effects and natural resource management: Econometric evidence from POSAF-II in Nicaragua. Natural Resources Forum 41, 220–233. https://doi.org/10.1111/1477-8947.12133
De los Santos-Montero, L.A., Bravo-Ureta, B.E., 2017. Productivity effects and natural resource management: econometric evidence from POSAF-II in Nicaragua. Nat Resour Forum 41, 220–233. https://doi.org/10.1111/1477-8947.12133
Dong, Y., Mu, Y., Abler, D., 2019. Do farmer professional cooperatives improve technical efficiency and income? Evidence from small vegetable farms in China. Journal of Agricultural and Applied Economics 51, 591–605. https://doi.org/10.1017/aae.2019.22
Fan, S., Hazell, P., Thorat, S., 2000. Government spending, growth and poverty in rural India. Am J Agric Econ 82, 1038–1051. https://doi.org/10.1111/0002-9092.00101
Fink, G., Jack, B.K., Masiye, F., 2020. Seasonal Liquidity, Rural Labor Markets, and Agricultural Production. American Economic Review 110, 3351–3392. https://doi.org/10.1257/aer.20180607
Gebregziabher, G., Namara, R.E., Holden, S., 2012. Technical Efficiency of Irrigated and Rain-Fed Smallholder Agriculture in Tigray, Ethiopia: A Comparative Stochastic Frontier Production Function Analysis. Quarterly Journal of International Agriculture 203–226.
González-Flores, M., Bravo-Ureta, B.E., Solís, D., Winters, P., 2014. The impact of high value markets on smallholder productivity in the Ecuadorean Sierra: A Stochastic Production Frontier approach correcting for selectivity bias. Food Policy 44, 237–247. https://doi.org/10.1016/j.foodpol.2013.09.014
Government of Nepal, United Nations Development Programme, 2014. Nepal human development report 2014: beyond geography, unlocking human potential. Government of Nepal, National Planning Commission, Kathmandu.
Greene, W., 2010. A stochastic frontier model with correction for sample selection. J Prod Anal 34, 15–24. https://doi.org/10.1007/s11123-009-0159-1
Ho, D.E., Imai, K., King, G., Stuart, E.A., 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Polit. anal. 15, 199–236. https://doi.org/10.1093/pan/mpl013
IFAD, 2009. President's report: Proposed loan and grant to the Government of Nepal for the High-Value Agriculture Project in Hill and Mountain Areas. IFAD, Rome, Italy.
Jäckering, L., Gödecke, T., Wollni, M., 2019. Agriculture–nutrition linkages in farmers' communication networks. Agricultural Economics 50, 657–672. https://doi.org/10.1111/agec.12516

Jensen, R., 2007. The digital provide: information (technology), market performance, and welfare in the South Indian fisheries sector. Q J Econ 122, 879–924. https://doi.org/10.1162/qjec.122.3.879

Joshi, P.K., Gulati, A., Birthal, P.S., Tewari, L., 2004. Agriculture diversification in South Asia: Patterns, determinants and policy implications. Economic and Political Weekly 39, 2457–2467.

Kafle, K., Krah, K., Songsermsawas, T., 2018. High-value agriculture project in Hill and Mountain Areas (HVAP): Impact assessment report (Technical report). IFAD, Rome, Italy.

Kafle, K., Songsermsawas, T., Winters, P., 2020. Agricultural value chain development in Nepal: Understanding mechanisms for poverty reduction (Working paper). IFAD, Rome, Italy.

Kalirajan, K.P., 1991. The importance of efficient use in the adoption of technology: A micro panel data analysis. J Prod Anal 2, 113–126. https://doi.org/10.1007/BF00156342

Karlan, D., Osei, R., Osei-Akoto, I., Udry, C., 2014. Agricultural decisions after relaxing credit and risk constraints. The Quarterly Journal of Economics 129, 597–652. https://doi.org/10.1093/qje/qju002

Kumbhakar, S.C., Tsionas, E.G., Sipiläinen, T., 2009. Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. J Prod Anal 31, 151–161. https://doi.org/10.1007/s11123-008-0081-y

Lawin, K.G., Tamini, L.D., 2019. Tenure security and farm efficiency analysis correcting for biases from observed and unobserved variables: Evidence from Benin. Journal of Agricultural Economics 70, 116–134. https://doi.org/10.1111/1477-9552.12275

Liverpool-Tasie, L.S.O., Winter-Nelson, A., 2012. Social learning and farm technology in Ethiopia: Impacts by technology, network type, and poverty status. The Journal of Development Studies 48, 1505–1521. https://doi.org/10.1080/00220388.2012.693167

Ma, W., Renwick, A., Yuan, P., Ratna, N., 2018. Agricultural cooperative membership and technical efficiency of apple farmers in China: An analysis accounting for selectivity bias. Food Policy 81, 122–132. https://doi.org/10.1016/j.foodpol.2018.10.009

Magnan, N., Spielman, D.J., Lybbert, T.J., Gulati, K., 2015. Leveling with friends: Social networks and Indian farmers' demand for a technology with heterogeneous benefits. Journal of Development Economics 116, 223–251. https://doi.org/10.1016/j.jdeveco.2015.05.003

Markelova, H., Meinzen-Dick, R., Hellin, J., Dohrn, S., 2009. Collective action for smallholder market access. Food Policy, Collective Action for Smallholder Market Access 34, 1–7. https://doi.org/10.1016/j.foodpol.2008.10.001

Minten, B., Tamru, S., Reardon, T., 2020. Post-harvest losses in rural-urban value chains: Evidence from Ethiopia. Food Policy 101860. https://doi.org/10.1016/j.foodpol.2020.101860

Mishra, A.K., Shaik, S., Khanal, A.R., Bairagi, S., 2018. Contract farming and technical efficiency: Evidence from low-value and high-value crops in Nepal. Agribusiness 34, 426–440. https://doi.org/10.1002/agr.21533

Mojo, D., Fischer, C., Degefa, T., 2017. The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. Journal of Rural Studies 50, 84–94. https://doi.org/10.1016/j.jrurstud.2016.12.010

Mu, R., Walle, D. van de, 2011. Rural roads and local market development in Vietnam. Journal of Development Studies 47, 709–734. https://doi.org/10.1080/00220381003599436

Murgai, R., Ali, M., Byerlee, D., 2001. Productivity growth and sustainability in Post-Green Revolution agriculture: The case of the Indian and Pakistan Punjabs. The World Bank Research Observer 16, 199–218.
O'Donnell, C., 2018. Productivity and efficiency analysis: An economic approach to measuring and explaining managerial performance. Springer.
Ogundari, K., 2014. The paradigm of agricultural efficiency and its implication on food security in Africa: What does meta-analysis reveal? World Development 64, 690–702. https://doi.org/10.1016/j.worlddev.2014.07.005
Rahman, Md.S., Norton, G.W., 2019. Adoption and impacts of integrated pest management in Bangladesh: Evidence from smallholder bitter gourd growers. Horticulturae 5, 32. https://doi.org/10.3390/horticulturae5020032
Reardon, T., 2015. The hidden middle: the quiet revolution in the midstream of agrifood value chains in developing countries. Oxford Review of Economic Policy 31, 45–63. https://doi.org/10.1093/oxrep/grv011
Reardon, T., Barrett, C.B., Berdegué, J.A., Swinnen, J.F.M., 2009. Agrifood industry transformation and small farmers in developing countries. World Development 37, 1717–1727. https://doi.org/10.1016/j.worlddev.2008.08.023
Reardon, T., Tschirley, D., Dolislager, M., Snyder, J., Hu, C., White, S., 2014. Urbanization, diet change, and transformation of food supply chains in Asia (Technical report). Michigan State University.
Roka, H., 2017. The status of smallholder farmers in Nepal's Agricultural Development Strategy (2015–2035). Agrarian South: Journal of Political Economy 6, 354–372. https://doi.org/10.1177/2277976017745197
Rosenbaum, P.R., Rubin, D.B., 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician 39, 33. https://doi.org/10.2307/2683903
Rosenzweig, M.R., Udry, C., 2020. External validity in a stochastic world: Evidence from low-income countries. Review of Economic Studies 87, 343–381. https://doi.org/10.1093/restud/rdz021
Rubin, D.B., 2001. Using propensity scores to help design observational studies: Application to the tobacco litigation. Health Services & Outcomes Research Methodology 2, 169–188. https://doi.org/10.1023/A:1020363010465
Shrestha, S.A., 2020. Roads, participation in markets, and benefits to agricultural households: Evidence from the topography-based highway network in Nepal. Economic Development and Cultural Change 68, 839–864. https://doi.org/10.1086/702226
Songsermsawas, T., Baylis, K., Chhatre, A., Michelson, H., 2016. Can peers improve agricultural revenue? World Development 83, 163–178. https://doi.org/10.1016/j.worlddev.2016.01.023
Swinnen, J., Kuijpers, R., 2019. Value chain innovations for technology transfer in developing and emerging economies: Conceptual issues, typology, and policy implications. Food Policy 83, 298–309. https://doi.org/10.1016/j.foodpol.2017.07.013
Thuo, M., Bell, A.A., Bravo-Ureta, B.E., Lachaud, M.A., Okello, D.K., Okoko, E.N., Kidula, N.L., Deom, C.M., Puppala, N., 2014. Effects of social network factors on information acquisition and adoption of improved groundnut varieties: the case of Uganda and Kenya. Agric Hum Values 31, 339–353. https://doi.org/10.1007/s10460-014-9486-6

Villano, R., Bravo-Ureta, B., Solís, D., Fleming, E., 2015. Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. J Agric Econ 66, 129–154. https://doi.org/10.1111/1477-9552.12081
Waddington, H., Snilstveit, B., Hombrados, J., Vojtkova, M., Phillips, D., Davies, P., White, H., 2014. Farmer field schools for improving farming practices and farmer outcomes: A systematic review. Campbell Systematic Reviews 10, i–335. https://doi.org/10.4073/CSR.2014.6
Weinberger, K., Lumpkin, T.A., 2007. Diversification into horticulture and poverty reduction: A research agenda. World Development 35, 1464–1480. https://doi.org/10.1016/j.worlddev.2007.05.002
World Bank, 2020. World Development Indicators [WWW Document]. URL https://databank.worldbank.org/source/world-development-indicators (accessed 7.14.20).
World Bank, 2018. Poverty and Shared Prosperity 2018 : Piecing Together the Poverty Puzzle. World Bank, Washington DC.