Impacts of agricultural value chain development on poverty reduction in Nepal: Mechanism and practical significance

Work in Progress

Kashi Kafle (k.kafle@cgiar.org)
Tisorn Songsermsawas (t.songsermsawas@ifad.org)
Paul Winters (p.winters@ifad.org)

Selected Paper prepared for presentation at the 2019 Agricultural and Applied Economics Association Annual Meeting, Atlanta, Georgia, July 21-July 23

Impacts of agricultural value chain development on poverty reduction in Nepal: Mechanism and practical significance

Kashi Kafle[1], Tisorn Songsermsawas[2*], Paul Winters[2]

Abstract

This analysis evaluates a real world complex intervention to study the impacts of an agricultural value chain development program on income, assets and mechanism and practical significance of the income growth, in hill and mountainous regions of Nepal. The intervention was not designed for the study and no baseline data existed to compare the final outcomes. Data came from a carefully designed household survey administered to 3,028 households (50% beneficiaries and other 50% non-beneficiaries) across seven districts in Western Nepal. Using matching, regression adjustment, and doubly robust methods, we find that improving agricultural value chain by linking smallholder producers with traders and service providers increases household income. The impacts on poverty reduction come through increased household income (36.8%) which in turn comes via increased volume of agricultural produce sales, despite a significant decrease in output prices. Examination of the practical significance of the income growth reveals that the project-led income growth improves food security, dietary diversity, and household resilience. Selection bias from unobservables are not controlled for due to lack of baseline data, but robustness checks confirm the results are consistent across different specifications. The impacts are greater among the farmers who primarily produce the commodities supported by the intervention.

Key words: Nepal, high value commodities, value-chain development, impacts, poverty-reduction
JEL codes: O12, O22, Q12

---

[1] K. Kafle is an economist at International Water Management Institute (IWMI), T. Songsermsawas is an economist at International Fund for Agricultural Development (IFAD), and P. Winters is an Associate Vice-President of IFAD.
*Corresponding author, t.songsermsawas@ifad.org
Acknowledgements: The authors are grateful to Sara Savastano, Romina Cavatassi, Alessandro Garbero, Rui Benfica, Athur Mabiso, Fabrizio Bresciani, Antonio Rota, and Eva-Maria Egger (IFAD), David Stifel (Lafayette College), Robert Pickmans (UC Berkeley) for their helpful comments. Thanks go to the IFAD Nepal Country office team, and the High Value Agriculture Project in Hill and Mountain Areas (HVAP) for technical and logistical support during field visits. Finally, we thank Andreas Kutka for setting up a system for data quality check.

1. Introduction

Access to stable and well-functional agricultural market or value-chain is an entry point to efficient and profitable agricultural production system. Like many other developing countries, one of the challenges Nepalese farmers face is lack of access to agricultural markets. Nepal's hilly and mountainous terrain makes it even more difficult to connect smallholder framers with input and output markets. Majority of agricultural development programs often focus on increasing agricultural productivity or reducing post-harvest losses but improving smallholders' access to markets and market related information has not received much traction. Even though the existing body of literature overwhelmingly agrees that increase in agricultural production improves food security and reduces poverty, the positive impacts might not be sustainable without a sustained access to agricultural markets. Poor market institutions and poor access to markets often lead to high input prices and low output prices which directly increase input cost and decrease farm revenue, respectively. In addition, lack of or poor access to output markets can lead to excess supply which further reduces market prices leading to a rapid fall in agricultural production.

Multiple pathways explain as to how poor access to markets leads to reduction in agricultural productivity, which further increases poverty and vulnerability. Lack of or poor access to market institutions leads to higher transaction costs, lower output prices received by farmers, higher input costs, and lack of credit. Smallholder farmers in developing countries often face substantial transactions costs when accessing markets (Key and Runsten 1999). Improved access to markets is hypothesized to increase farm incomes through lower or no transaction costs and better access to market information such as prices. Policies or interventions that improve smallholder farmers' access to markets may help increase farm revenues and thus have direct implications on household welfare outcomes (Chamberlin and Jayne 2013). Empirical evidence on how interventions specifically designed to improve market access for smallholder farmers contribute to household welfare is limited.

In this analysis, we study the impacts of an agricultural value chain development program in Nepal, the High Value Agriculture Project in Hill and Mountain Areas (HVAP). HVAP interventions targeted smallholder farmers across seven districts in hilly and mountainous region in western Nepal. The intervention supported seven different value-chains of high value agricultural commodities – apple, turmeric, ginger, *timur* (Sichuan pepper), off-season vegetables, vegetable seeds, and meat goats. Other project activities included linking smallholder farmers with different actors in the respective value-chain for each commodity – input suppliers, traders, local retailers, domestic suppliers and exporters, district commerce and industries, and agricultural extension workers. We estimate the impacts of the intervention on poverty indicators – income and asset growth. In addition, we explore mechanisms that lead to positive impact on income growth. We hypothesize that agricultural revenue increases because 1) the intervention reduces the agricultural transaction cost and farmers are able to sell more of their products, and 2) the intervention has loosened the market constraints and increased the farm gate prices (thought reduced transaction cost). Moreover, we assess the practical significance of the income growth on livelihood outcomes by estimating the relationship between project-led income growth and household food security, dietary diversity, and resilience.

Our analysis makes important contributions to the literature. First, we rigorously evaluate a complex real world intervention – value chain development intervention focusing on high value commodities – to estimate project impacts on poverty indicators; the intervention was not designed for the study. Second, we unpack the mechanism behind the project-led income growth and also assess the practical significance of the income growth by examining the relationship between income growth and household food security, dietary diversity, and resilience. Finally, following a growing interest in the results of agricultural value chain projects, we respond to the call made by international financial organizations including the World Bank and the Inter-American Development Bank for impact evaluations of agricultural projects. Market access is crucial for alleviating poverty and hunger by allowing farmers to access productivity-improving

inputs and generating higher agricultural revenue (Chamberlin and Jayne 2013). Thus, understanding how value chain interventions can improve and facilitate market access would help inform future design of projects or interventions to ensure that they lead to positive and significant impacts. In addition, our analysis is among a few in the literature to evaluate an agricultural value chain development program that brings all actors of the value chain – smallholder producers, retailers, related government offices, and the local financial institutions – together.

The rest of the paper is organized as follows. In Section 2, the details of the HVAP intervention are provided along with the project theory of change. Sampling strategies and sample size details are provided in Section 3. Section 4 describes the data and analytical methods used in the analysis. In Section 5, descriptive and econometric results are presented. Section 6 concludes.

2. The Intervention

The High Value Agriculture Project in Hill and Mountain Areas (HVAP) is a project supported by the International Fund for Agricultural Development (IFAD). HVAP was implemented by the Ministry of Agriculture and Livestock Development of the Government of Nepal. The project was signed in 2009 but implementation of project activities did not start until early 2011. Project activities completed in September 2018. The intervention was targeted to smallholder farmers residing in very rough geographic terrain in western Nepal – namely Surkeht, Dailekh, Salyan, Jajarkot, Kalikot, Jumla, and Acham districts. Shaded area in Figure 1 shows districts covered by the project, but it is important to note that the project did not cover the districts entirely; only certain parts of each district were covered as guided by the selection procedure (see section 2.1).

--Figure 1 here—

The primary goal of HVAP was to reduce poverty and improve food security in geographically most challenging rural areas of Nepal through an inclusive value chain and improved and functional service market for high value agricultural commodities.[2] Traditional agriculture is not a viable option in these districts due to the rough terrain. Therefore, HVAP concentrated on value chain development for high-value agricultural commodities suitable for the agro-climatic zone – namely apple, ginger, turmeric, *timur* (Sichuan Pepper), off-season vegetables, vegetable seeds, and meat goat. Even though seven different value chains were supported choice of the value-chain differed by agro-ecology of the project areas and none of the project districts received supports for all seven value chains.

HVAP project activities were targeted to smallholder farmers but the project required the farmers to form producer groups or cooperatives – collectively called producer organizations (POs) – to be eligible to participate in project activities. The project covered a total of 456 POs across the seven districts. The project consisted of two major components: *inclusive value chain development* and *service market strengthening*. Under the 'inclusive value chain development' component, the project adopted a unique approach to link smallholder producers with input suppliers and traders in domestic market along the value chain. To make sure the intervention is inclusive of all social groups, the project specifically targeted women farmers and ethnic minorities – *Dalit*, *Janajati*, and other marginalized groups. Each producer organization was required to have representation of women and ethnic minorities proportional to the population of the concerned community.

Under the 'service market strengthening' component, the project supported small producers through training and forming self-help groups or cooperatives to strengthen

[2] HVAP intervention is closely aligned with Nepal's Agriculture Development Strategy 2015 to 2035 (ADS) which aims to improve agricultural productivity in rural areas by promoting high-value agriculture (Government of Nepal 2015).

production and marketing activities as well as building collection centres locally and cold storage in major market outlets, primarily district headquarters. Training involved a comprehensive business literacy class for both female and male members of the POs. The business literacy classes (BCL) were organized in cooperation with the District Department of Agriculture and Livestock as well as District Chamber of Commerce and Industry. BCL participants were provided practical information about marketing, operating small agricultural enterprises, building network with value chain actors including input suppliers as well output markets. BCL classes were delivered by specially trained project staff and each class consisted of a one-hour session followed by another hour of demonstration or practical exercise about running agricultural enterprise, price formation strategies etc.

The project covered 14 municipalities and 24 rural municipalities (126 villages and 2 municipalities in the old administrative system which was phased out in 2017) across six districts in Karnali Province and Accham district [3]. A total of 15,629 households and 101,959 individuals across 467 POs were directly covered by the project activities.

2.1. Eligibility criteria

Selection of project beneficiaries was not random. An eligibility rule was established to select POs and households as well as identify the types of commodities (value chain) to support for each PO. Table 1 presents the eligibility rules in details. Type of commodities was determined by the travel time to the nearest market. POs that were less than three-hour travel from a market received support for off-season vegetables, POs that were between three to six hours from a market received support for ginger, turmeric, or apple based on the agro-climatic conditions, and the POs that were farther than six hours travel time from a market received support for meat goat, *timur*, or vegetable seeds, again based on the agro-climatic conditions.

[3]Accham district is not in the Karnali Province. However, a few villages in Achham that are close to Karnali Province were covered by HVAP.

--Table 1 here –

Beneficiary households were selected based on three different well-being characteristics – a participatory ranking of well-being, net income level, and landholding size. Farmers were asked to gather at a place and rank each of their well-being status collectively into four categories – extremely poor, moderately poor, near poor, and not poor. Households that fell under the first three categories were eligible for the project. Households with per-capita annual income less than 2000 Rupees were also eligible, so were the households with landholding size of 0.5 Ha or less.

2.2. Theory of change

We hypothesize that the HVAP intervention leads to poverty reduction via multiple pathways: 1) increased agricultural productivity, 2) reduction in transaction costs, and 3) increased income through higher and stable agricultural prices and sales. First, as a result of various capacity building and skill development training related to agricultural and livestock production and marketing, agricultural productivity is expected to increase and producers can expect to receive better prices for their agricultural produces (Davis et al. 2012; Emerick et al. 2016; Kondylis, Mueller and Zhu 2017; Verkaart et al. 2017). Also, increased output demand leads to increase in agricultural productivity.

Second, establishing or strengthening linkages between farmers and traders, and between small and large enterprises can reduce the transactions costs related to agricultural marketing (Key and Runsten 1999; Alene et al. 2008; Markelova et al. 2009). A low transaction cost can have a direct implication on poverty reduction through increased farm revenue (Besley and Burgess 2000; Barrett 2008; Chamberlin and Jayne 2013). Since the transactions cost is believed to be a form of market friction which prevents smallholder participation in agricultural value chains (de Janvry, Fafchamps and Sadoulet 1991; Key, Sadoulet and de Janvry 2000),

interventions that reduce agricultural transaction costs (both in input markets and output markets) can increase farm revenues.

Third, the HVAP intervention is designed to minimize middlemen's role in agricultural marketing. The project linked small producers with input suppliers and output markets along the agricultural value chain, provided periodic information about agricultural prices, and improved the 'bargaining power' of the small farmers by bringing them together as a produce group. It is expected that these activities cut down middlemen's role and farmers receive higher and stable prices and sales throughout the year. Several studies have shown that linkages between farmers and traders can increase market access and value chain participation of small farmers in different context (Michelson, Reardon and Perez 2012; Barrett et al. 2012; Wang, Wang and Delgado 2014), so we aim to confirm the linkage in the case of Nepal. In addition, establishing or upgrading market structures such as collection centres and cold stores helps to stabilize market prices and reduce vulnerability (Mu and van de Walle 2011). Price stability, better access to markets, and higher farm gate prices lead to poverty reduction through stable and higher farm income.

Finally, the social inclusion and gender balancing approach of the project helps to empower women and marginalized communities, enhance social capital, increase social support, and reduce social inequality within the project communities and beyond.

3. Sampling strategy

3.1. Sample size determination

Power calculations were used to determine the sample size required for the study. We used a method developed by the World Bank that incorporates expected minimum change in the outcome variable, its standard deviation, the critical values of the confidence interval and statistical power, and the minimum number of units to be sampled within each cluster (Winters,

Salazar and Maffioli 2010; World Bank 2007). Equation 1 was used to calculate the required sample size (N):

$$N = \frac{4\,\sigma^2\left(Z_a + Z_\beta\right)^2}{D^2}[1 + \rho(m-1)] \qquad (1)$$

where σ is the standard deviation of the baseline outcome variable, Z_a is the critical value of the confidence interval, Z_β is the critical value of the statistical power, *D* is the minimum expected change in the baseline outcome variable, ρ is the intra-cluster correlation (ICC) of the unit of analysis, and *m* is the number of units to be sampled within each cluster.

Means and standard deviations for outcome variables were constructed using 2011 Census data and the minimum expected change (*D*) for each outcome variable was calculated based on existing literature and project's long-run targets. Among other parameters, we assumed the analysis will have 80% statistical power and 95% confidence level so Z_a =1.96, and Z_β=1.28. Following the standard practice of 10 to 15 sampling units per cluster, we sampled at least 13 households per cluster (m) keeping the ICC constant at 0.05. We calculated different sample sizes varying the parameters in Equation 1 for different outcome variables. A sample size of 3,000 households would be able to detect the minimum expected change on key outcomes variables – 4% decrease in poverty, 10% increase in agricultural productivity, and 20% increase in meat goat production.

3.2. Sample selection

As the districts covered by HVAP were widely distributed across the Province, and each district differed from other districts in various aspects including composition of ethnic groups, agro-ecological conditions, and type of agricultural value chain, we employed a multi-stage stratified sampling to assure representative sample from all districts, and value chains. There

were a total of 32 unique district-value chain pairs (for example Achham-Goat, Dailekh-Goat, Jumla-Apple etc.), and our sampling design accounted for such heterogeneity. Figure 2 presents our sampling design for project sample. A similar approach was used for control sample selection also.

--Figure 2 here—

In the first stage, we stratified the project area to seven sub-populations (districts), and listed all POs covered by HVAP in each district (Strata). Then we used the pre-determined project sample size and the minimum number of sampling units per cluster to determine the required number of clusters; that is dividing 1500 by 13 gave us the cluster sample size of 117, after rounding. As we had 467 clusters in total, the cluster sample represented 25% of the cluster population. To assure proportional representation of all clusters in the final sample, we sampled 25% of clusters (POs) from each strata (District) by using simple random sampling with proportional allocation. This exercise gave us the distribution of 117 project clusters across project strata.

In the second stage, we listed all the households in the selected clusters. Then, we calculated the number of households to be sampled from each stratum (district) based on the number of sample households per cluster. We then randomly selected households from each selected cluster. As the required sample size was not an exact multiple of cluster sample size, we sampled 12 to 13 households per cluster to meet the required sample size.

Following the project sample selection, we used similar approach to select the control sample. First, propensity scores matching with three nearest neighbours were used to identify non-project POs similar to project POs. In the absence of baseline data, we used 2011 population census data to construct the propensity scores for project and non-project POs. After matching project and non-project POs based on propensity scores we validated the matched pairs using local knowledge of project staff and village leaders. Control households were then

selected using the same sampling strategy used to select project households (see Figure 2). Since HAP project selection was purposive with different selection criteria (see Table 1), we used the similar criteria to select 'control' households from non-project POs that were matched with project POs. In the absence of baseline data, recall method was used to elicit whether a household would have met the HVAP eligibility criteria in 2011.

4. Data and methods

4.1. Data

The data used in this analysis come from a primary household survey we conducted in rural Nepal between May and July 2018. A carefully designed household survey was implemented to 3,020 smallholder households across seven project districts in western Nepal. Table 2 outlines the number of households and producer organizations (POs) by project status. The full sample consisted of 1,500 project households from 117 POs and 1,520 non-project households from 118 POs in areas not covered by the project. We designed the survey to collect information on household income, demographics, food security indicators, asset ownership, access to credit, access to markets, and details on agricultural production, land holding size, and marketing of agricultural produces.

--Table 2 here--

The data is representative of various ethnic groups present in the area. For simplicity, *Dalit*, *Janajati*, and other ethnic minority (DJEM henceforth) are aggregated together. The DJEM group represents approximately 26% of the households in our sample. Of the DJEM sample, Kami and Magar are the dominant groups constituting 10.7% and 9.3% of the full sample. The proportion of other ethnic groups is distributed as follows; 2.5% *Damai/Dholi*, 1.7% *Sarki*, 0.6% *Gurung*, and a total of 0.6% *Tamang, Newar, Tharu,* and *Rai.*

4.2. Propensity score matching

Since we have no baseline data, we opted to use propensity score matching to match project and control households based on observables and find common support to arrive to the final sample used in the analysis. After the matching process which eliminated households outside of common support, we are left with 2,874 total households (1,417 project households and 1,457 control households). To make sure project households from one district are not matched with control households from another district, matching was done within each district, separately. Results show that the Rosenbaum and Rubin bias reduced from 18.7% before matching to 2.8% after matching, which is lower than the maximum tolerable threshold of 25% suggested by Rubin (2001).

The relative ratio between the variances of all covariates in project and control groups is 0.94, which is also within the suggested bound between 0.8 and 1.25. Following the standard practice in the matching literature (Leuven and Sianesi 2018), the matched sample is trimmed at the second and 98th percentiles of the estimated propensity score. Table 3 presents some key descriptive statistics of project and control households and a test of the null hypothesis that there is no difference in project and control means, both before and after the matching process. Results in Table 3 show that most observable characteristics are statistically similar across project and control groups. Those characteristics that are statistically different across the two groups before matching remain different in post-matching sample too but the magnitude of difference has decreased.

--Table 3 here—

4.3. Econometric methods

We use matching and regression adjustment methods to identify the average treatment effects (ATE) and treatment effects on the treated (ATT). In the first step of our analysis, we improve the quality of the counterfactuals by matching project households and control

households based on a number of household-level characteristics. Treated and control households that fall under the common support are used to estimate treatment effects. In the absence of baseline data, our analysis controls for selection on observable attributes only. Selection bias from unobservable attributes are not controlled for but we perform several robustness checks.

First, we use the propensity score matching (PSM) method.[4] In the PSM framework, impacts of the project (T_i) on household i can be written as follows:

$$\delta_i = \frac{Y_{i1}}{m_i} - \frac{Y_{i0}}{m_i},$$

where δ_i is the impact of the project (or average treatment effects), Y_{i1} refers to the outcome of interest for project household i, Y_{i0} is the outcome of interest for household i in the absence of the project, and m_i is the number of observations in each cluster (in this case $m_i = 12$). Treatment effects on the treated (ATT) can be estimated using following expression:

$$ATT_{PSM} = E(\delta_i | T = 1) = E(Y_{i1} - Y_{i0} | T = 1) \quad (2)$$

The key identifying assumption in this case is that the project status is independent of the outcomes of interest, contingent on the observable characteristics (Rosenbaum and Rubin, 1983). Mathematically, if X_i is a vector of observable characteristics, then $T_i \perp (Y_{i0}, Y_{i1}) | X_i$.

Second, we employ a regression-adjustment method to complement the PSM results and consistently estimate treatment effects while controlling for selection into project participation based on observable characteristics. Our regression adjustment method is similar to the one used in Godtland et al. (2004) to estimate the impact of farmer field schools on potato production in Peru and in Rejesus et al. (2011) to estimate the impacts of an improved

[4] We employ alternative matching approaches to ensure that our PSM results are robust to different specifications and validate the PSM results.

irrigation technology on rice production in The Philippines.[5] Specifically, the regression specification is as follows:

$$Y_i = \alpha + \beta T_i + \gamma \boldsymbol{X}_i + \delta(\boldsymbol{X}_i - \overline{\boldsymbol{X}})T_i + \varepsilon_i \quad (3)$$

where Y_i is an outcome of interest, $\boldsymbol{X}_i$ is the vector of observable characteristics of household i, $\overline{\boldsymbol{X}}$ is the vector of the average of the observable characteristics of household *i*, and ε_i is the error term. In Equation (3), β is the ATE estimate, which is mathematically represented as

$$\beta_{ate,\ RA} = \frac{1}{N}\sum_{i=1}^{N}[E(Y_i|X_i, T_i = 1) - E(Y_i|X_i, T_i = 0)]$$

Replacing $\overline{\boldsymbol{X}}$ with $\overline{\boldsymbol{X}}_1$ in equation 3 (where $\overline{\boldsymbol{X}}_1$ is the average over treatment households only) yields the ATT estimate.

Third, we use inverse-probability-weighted (IPW) matching method which gets rid of the confounding factors by creating a pseudo-population. Following Wooldridge's (2010) exposition, we use inverse of the parametrically estimated propensity score but one could use the non-parametrically estimated propensity score as described in Hirano et al. (2013). The propensity score was estimated using probit model and then used to compute the treatment effects using IPW method as follows

$$\beta_{ate,\ IPW} = \frac{1}{N}\sum_{i=1}^{N}\frac{[T_i - \hat{p}(X_i)]Y_i}{\hat{p}(X_i)[1 - \hat{p}(X_i)]}$$

Finally, we use the doubly robust method which uses the inverse-probability-weighted regression-adjustment (IPWRA) estimator (Wooldridge 2007; Wooldridge 2010). This approach models the likelihood of project participation and estimates the project impacts contingent of the likelihood. A major advantage of this approach is that only one of the two estimation equations

[5] See also Wooldridge (2010) for more details about this approach.

needs to be specified correctly, and thus has the "double-robust" property. This method follows a similar to the regression-based method but it uses inverse probability weights. In this case, each observation in the dataset is assigned weights according to the following matrix:

$$\omega(t,x) = t + (1-t)\frac{\hat{P}(X)}{1-\hat{P}(X)},$$

where $\omega(t,x)$ is the weight applied, t represents $T_i = 1$, $\hat{P}(X)$ is the estimated propensity score, and X is a vector of covariates.

5. Results

In this section, first we provide descriptive statistics of key outcome and independent variables. Then we provide the estimated project impacts on poverty indicators – household income and asset ownership. Next, we explore potential mechanisms for the positive impacts on income and asset growth and the practical significance of the project-led income growth. Throughout the analysis, all components of income are calculated using a 12-month recall period preceding the survey. In addition, all income indicators are presented in the logarithmic scale, so the point estimates on income variables are interpreted as percentage changes. We use four difference estimating models to estimate the treatment effects – Propensity Score Matching (PSM), Regression Adjustment (RA), Inverse Probability Weighting (IPW) and a doubly robust method that combined IPW and RA. Results look similar across these models, but our preferred estimating model is IPWRA for it's doubly robust properties.

Table 4 presents summary statistics for key outcome variables – total income, agricultural incomes, non-agricultural incomes, dietary diversity, food consumption score, food security indicator and household asset index. Column 1 presents statistics for project sample, column 2 presents the statistics for control sample and column 3 presents p-value for the test of the null hypothesis that project and control means are different. On average, project households had a total income of 188 thousand rupees per year compared to 153 thousand rupees per year for

control households. The difference is statistically significant indicating that the project might have led to significant income growth. Similar results hold for aggregated agricultural income and both livestock and crop income. In contrast, non-agricultural income is higher among control households than project households, though the difference is not statistically significant. No sub-categories of non-agricultural income for project sample is statistically different from control sample indicating that project led growth in household income entirely came from the growth in agricultural income.

The last two panels in Table 4 present statistics for dietary diversity, food security indicators, and household resilience (measured by asset index)[6]. Both household dietary diversity and food consumption indicators are significantly greater among project sample than control sample indicating that the project might have led to diversified diets. Similarly, project households are less food insecure (measured by FIES score) and more resilient (measured by asset index) than control households.

--Table 4 here—

Table 5 presents the project impacts on total household income and individual components of household income, by type of income source. Growth in total household income among project households is 36.8% more than in control households. In absolute terms, household income for project households increases by 56,466 rupees per year relative to control households. The estimated growth in household income (36.8%) exceeds the project goal of increasing income by 30%. The growth in household income primarily came from growth in crop and livestock incomes coupled with significant decrease in remittance flow. This finding is

[6] Household resilience can be and will be measured by using household's ability to recover from shocks. This measure is still under construction.

very encouraging because it provides critical evidence that HVAP interventions are effective in deterring migration and promoting agricultural transformation at the same time.

Crop income increases by about 50% among project households and livestock income grew by about 93%. We have no baseline data to compare the estimated growth against a pre-project income level, but one could guess the pre-project agricultural income levels were probably very low. The growth in crop and livestock income means that compared to control households, project households earned 15,333 rupees more per year from crop cultivation and 19,231 rupees more per year from livestock keeping. Result indicates that livestock production contributes more to household income growth than crop production.

--Table 5 here—

Among other income components, wage income and income from social transfers are slightly higher for project households and income from self-employment/enterprise and sales of goods and services are slightly lower for project households than control households, but none of them are statistically significant. The amount of remittances received by project households is 31.5% (9,011 rupees per year) lower than the remittances received by control households. This finding, although only suggestive due to the absence of a true baseline dataset, complements to the finding in the literature about the crowding out of private transfers by public transfers (Angelucci 2015; Nepal 2016), which in this case is the support from the HVAP project.

Table 6 presents the project impacts on asset indicators. Asset indicators are weighted indexes where weights are calculated using the first principal component from the principal component analysis (PCA). We do not attempt to interpret the magnitude of the impacts, rather focus on the direction of change. While there is no significant impact on housing quality index (or housing characteristics), the intervention had significant positive impacts on durable assets, agricultural assets, and livestock ownership (measured by the tropical livestock unit, TLU).

Results show that agricultural assets grew by up to 0.18 units compared to the control mean of 2.53, and the tropical livestock unit for project households increased by about 0.23 units compared to the control mean of 2.7. Given that households accumulate assets as a saving strategy, growth in asset index implies that the intervention helped improve household wellbeing and resilience.

--Table 6 here—

5.1. Mechanism behind income growth - prices

Results in Table 5 indicate that the intervention had a large significant impact on household income, primarily agricultural income. This part of the analysis unpacks the mechanism behind the growth in income. We have two hypotheses: 1) the intervention has reduced the agricultural transaction cost and farmers are now able to sell more of their products to traders, and 2) the intervention has loosened the market constraints and increased the farm gate prices (again thought reduced transaction cost). Results in Table 7 and Table 8 indicate that the first hypothesis is in place – i.e. the growth in income comes from increased sale volume. In the early years of the intervention, the growth in income might have come from higher farm gate prices (through reduced transaction cost), but we have no way to verify that. Increase in prices in the beginning might have led to increase in agricultural supply which eventually reduced the prices but farmers were able to sale more. So, the growth in income observed in later years probably comes through high sale volumes at lower prices – economy of scale.

--Table 7 here –

Table 7 presents project impacts on prices of project and non-project commodities. The first panel presents project impacts on project commodities – apple, ginger, turmeric, *timur*,

vegetables, and meat goat. Results show the intervention have reduced the unit prices of most project commodities. For example, controlling for household, housing, and demographic characteristics, the intervention reduced meat goat prices by 615 rupees per one goat, and *timur* prices by 105 rupees per kg. The second panel in Table 7 presents impacts on prices of selected non-project commodities. Unlike project commodities, prices for non-project commodities are still higher among project households than control households. The intervention increased the prices of cereals (rice, wheat, maize), animal products (milk and eggs), and chickens as well, although the price increase was statistically significant for maize, wheat, and eggs only.

We know from Table 7 that the increase in income did not come via higher prices farmers received. If prices were the avenue to income growth, then we would have seen decrease in income and increase in poverty. Table 8 tests our second hypothesis that income increases via economies of scale in agricultural produce sales – farmers are operating in small margin but they are now able to make more by selling more. Results in Table 8 confirms our hypothesis. The volume of sales for each of the project commodities is significantly greater among project households than control households. The volume of sales for selected non-project commodities were also higher among project commodities, but the differences were not statistically significant.

---Table 8 here---

Results in Tables 7 and 8 collectively indicate that the project-led growth in income primarily came from increase in sale volume. The project contributed to lower prices of project commodities which in turn can have further positive effects on poverty reduction through price effects. In addition, we test other hypotheses to explore the potential mechanisms behind the positive impacts on poverty reduction. Using distance to the nearest agricultural market and selling centre as a proxy for market access, we find that project households have better access to markets compared to control households (Results not presented here). Project households were

five percent more likely to sell their produce to a trader during the wet season and six percent more likely to sell to a trader during the dry season than control households.

5.2. Practical significance of income growth

In this section we explore whether the positive impacts on income, assets, and market access translate into improved food security, dietary diversity, and household resilience. Results in Table 9 show that project households reported to have consumed more food items compared to control households. A one percent increase in household income increases the dietary diversity of project households by 0.12 food groups. Therefore, a 36% increase in household income means that project households would consume four more good groups than control households, holding all else constant. The intervention itself also has a positive impact on household dietary diversity (column 2), but the impact is not statistically significant when income is added in the model (column 1). This indicates that project's impacts on dietary diversity mostly emerges through growth in income. Similar results hold for household food consumption score (FCS) and food insecurity indicator. A one percent increase in income increases the share of households with acceptable food consumption status by 1.6% and reduces household food insecurity by 4%. These findings are consistent with evidence in the literature on the linkage between agriculture and food security (Jodlowski et al. 2016; Upton, Cissé and Barrett 2016; Kafle, Winter-Nelson and Goldsmith 2016).

--Table 9 here---

The last panel in Table 9 presents relationship between household income and resilience. As of now, resilience is measured with household asset index only but analysis using additional measures of resilience (e.g. ability to recover from shocks) is underway. Results on household asset index show that the intervention increased household resilience both directly through

training and capacity building activities and through income growth. The impact of income growth is about double the direct project impact on household asset index.

6. Conclusion

This analysis studies the impacts of an agricultural value chain development program in Nepal – the High Value Agriculture Project in Hill and Mountain Areas (HVAP). HVAP interventions targeted smallholder farmers across seven districts in hilly and mountainous region in western Nepal. The intervention supported seven different value-chains of high value agricultural commodities – apple, turmeric, ginger, *timur* (Sichuan pepper), off-season vegetables, vegetable seeds, and meat goats. Other project activities included linking smallholder farmers with different actors in the respective value-chain for each commodity – input suppliers, traders, local retailers, domestic suppliers and exporters, district commerce and industries, and agricultural extension workers. We estimate the impacts of the intervention on poverty indicators using matching on observables, inverse-probability weighting, and a doubly-robust regression adjustment method. Our findings show a strong positive impact on both income and asset growth. Motivated by the findings, we provide additional analysis to explore potential mechanisms behind the positive impacts on income growth and practical significance of the income growth.

Our analysis provides rigorous evidence on whether market access support to smallholder farmers leads to poverty reduction. Results show that annual household income (in the 12 months preceding the time of data collection) grew by about 37% among project households. This increase is equivalent to an increase of approximately US$500 a year. This was driven mainly by increases in crop income and livestock income which increase by 50 percent and 93 percent, respectively. Beneficiary households also saw growth in asset ownership – in all of durable assets, livestock assets, as well as agricultural assets. The project also improved market access in that compared to non-beneficiaries, beneficiary farmers were five percent more likely to

sell their produce to a trader during the wet season and six percent more likely to sell to a trader during the dry season.

We explore the mechanisms behind income growth by estimating the relationship between the intervention and out prices and volume of sales. We also investigate the practical significance of income growth by examining the relationship between project-led income growth and household dietary diversity, food security, and resilience. We discovered that income growth primarily comes through economies of scale in agricultural production and sales. The intervention led to decrease in output prices for project supported commodities but significant increase in volume of sales. Our hypothesis of agricultural income (revenue) growth via higher agricultural prices is not substantiated but our second hypothesis that agricultural revenue increases due to increase in sale volume is confirmed indicating that the HVAP intervention has led to income growth by creating more market demand for agricultural produces. The intervention might have increased food security by reducing agricultural prices in project areas.

Our analysis of the practical significance of the income growth confirms that the intervention has reduce food insecurity, increased household dietary diversity, and improved household resilience. Project impacts on food security, dietary diversity, and resilience are primarily mediated via project led income growth.

The findings have important policy implications. First, interventions that support market activities and link different actors of the agricultural value chain together can have positive impact on agricultural production and product marketing. Linking of small producers with local and regional traders can reduce the transaction cost which ultimately increase supply and bring down the prices. The increase in supply and stable market demand increases agricultural revenue which increased household income. Our findings from the analysis of mechanism and practical significance of the income growth imply that policies that support agricultural value chain can reduce poverty, improve food security and nutrition, and improve household resilience in the long run.

The analysis provides multiple lessons for researchers and policymakers who are keen to design similar projects elsewhere. The project design was concentrated to a small number of value chains that were interlinked. The focused project design must have led to project activities customized and catered to specific local needs of smallholder farmers in the target group. As it turns out, the focused approach facilitates channelling of resources and services to ensure strong and positive project results. Second, the project worked with small and cohesive groups of farmers (25 to 40 members in a group). The reasonably small size of farmer groups allows project staff to engage closely with each group and monitor project activities to accommodate the needs of each group and its members. Third, the project used a mix of top-down and bottom-up approaches to link producers to traders, government agencies, commerce and finance departments, and scientists to address the absence of product and input markets, marketing facilities, credit, and policy support. This combined approach provided farmers with access to technical help, credit, as well as a sustained link to agricultural markets and traders, which are key to stable and efficient agricultural production system.

Tables

Table 1. HVAP project eligibility criteria

Targeting criteria	Eligibility rule
Travel time to markets (one-way)	
< 3 hours	Eligible for fresh vegetables
3 - 6 hours	Eligible for ginger, turmeric, and apple
6 - 12 hours	Eligible for goat, *timur*, and vegetable seeds
Well-being ranking	Eligible if households fall into first three categories: Extreme poor, Moderately poor, or Near poor
Income level	Eligible if per capita income is less than Rs. 2,000 a year
Landholding size	Eligible if landholding size is 0.5 Ha or less per household

Source: Author's illustrations based on HVAP project design documents

Table 2. Sample distribution across districts by project status

Districts	Producer Organizations (POs)			Households		
	Project	Control	Total	Project	Control	Total
Achham	7	6	13	91	78	169
Dailekh	17	18	35	221	234	455
Jajarkot	15	15	30	192	195	387
Jumla	15	15	30	193	193	386
Kalikot	15	16	31	193	206	399
Salyan	11	15	26	139	189	328
Surkhet	37	33	70	471	425	896
Total	**117**	**118**	**235**	**1,500**	**1,520**	**3,020**

Notes: Authors' illustration.

Table 3. Descriptive statistics before and after matching and test of the null hypothesis of no difference in project and control means

Variable	Before matching			After matching		
	Project	**Control**	**P-value**	**Project**	**Control**	**P-value**
Household head characteristics						
Age of head (years)	45.76	44.718	0.022**	45.705	44.770	0.046**
	(12.23)	(12.816)		(12.285)	(12.749)	
Schooling of head (=1 if ever attended school)	0.523	0.544	0.238	0.519	0.537	0.315
	(0.500)	(0.498)		(0.500)	(0.499)	
Education of head (=1 if literate)	4.103	4.655	0.002***	4.124	4.592	0.009***
	(4.663)	(5.046)		(4.642)	(4.971)	
Sex of head (=1 if male)	0.728	0.742	0.380	0.731	0.744	0.408
	(0.445)	(0.438)		(0.444)	(0.436)	
Household demographics						
Household size	5.092	5.125	0.652	5.066	5.108	0.570
	(2.016)	(2.009)		(1.945)	(1.964)	
Num. of children (0 to 14 years)	1.700	1.832	0.006***	1.708	1.818	0.023**
	(1.288)	(1.334)		(1.270)	(1.308)	
Num. of youth (15 to 34 years)	1.764	1.725	0.351	1.740	1.722	0.665
	(1.140)	(1.159)		(1.106)	(1.156)	
Num. of adults (35 to 64 years)	1.411	1.325	0.007**	1.399	1.334	0.046**
	(0.858)	(0.880)		(0.855)	(0.874)	
Num. of seniors (>65 years)	0.218	0.244	0.177	0.220	0.234	0.443
	(0.505)	(0.529)		(0.505)	(0.512)	
Share of female in household	0.537	0.534	0.586	0.537	0.533	0.608
	(0.176)	(0.174)		(0.175)	(0.173)	
Dependency ratio	0.776	0.892	0.000***	0.790	0.878	0.003***
	(0.744)	(0.848)		(0.751)	(0.829)	
Literacy rate (if age 5 years+)	0.650	0.648	0.861	0.649	0.648	0.957
	(0.228)	(0.239)		(0.229)	(0.238)	
Land ownership	0.980	0.984	0.466	0.980	0.984	0.426
	(0.140)	(0.127)		(0.142)	(0.127)	
DJEM household (=1 if yes)	0.256	0.258	0.905	0.256	0.257	0.941
	(0.436)	(0.437)		(0.436)	(0.437)	
Observations	**1498**	**1518**		**1415**	**1455**	

Notes: Point estimates are estimated means. Asterisks *, **, and *** indicate level of significance at 10%, 5%, and 1% level, respectively.

Table 3. continued…

Variable	Before matching			After matching		
	Project	**Control**	**P-value**	**Project**	**Control**	**P-value**
Housing characteristics						
Number of rooms	3.368	3.404	0.524	3.368	3.401	0.566
	(1.416)	(1.617)		(1.415)	(1.611)	
Improved wall (1=Yes, 0=No)	0.072	0.082	0.292	0.071	0.082	0.295
	(0.259)	(0.275)		(0.258)	(0.274)	
Improved roof (1=Yes, 0=No)	0.783	0.752	0.041**	0.786	0.749	0.020**
	(0.412)	(0.432)		(0.410)	(0.434)	
Improved floor (1=Yes, 0=No)	0.079	0.092	0.234	0.079	0.089	0.326
	(0.271)	(0.289)		(0.270)	(0.285)	
Access to toilet (1=Yes, 0=No)	0.774	0.748	0.094*	0.773	0.748	0.121
	(0.418)	(0.434)		(0.419)	(0.434)	
Access to safe drinking water (1=Yes, 0=No)	0.533	0.492	0.023**	0.537	0.489	0.009***
	(0.499)	(0.500)		(0.499)	(0.500)	
Access to electricity (1=Yes, 0=No)	0.372	0.399	0.123	0.369	0.400	0.087*
	(0.483)	(0.490)		(0.483)	(0.490)	
Observations	**1498**	**1518**		**1415**	**1455**	

Notes: Point estimates are estimated means. Asterisks *, **, and *** indicate level of significance at 10%, 5%, and 1% level, respectively.

Table 4. Summary statistics of key outcome variables

Income variables (,000 *Nepali Rupees*)	**Project Sample**	**Control Sample**	**P-value**
	(1)	**(2)**	**(3)**
Total household income	188.31	153.42	0.00***
	(185.16)	(177.40)	
Agricultural income	90.06	51.27	0.00***
	(107.55)	(72.18)	
Crop income	57.53	30.74	0.00***
	(61.78)	(36.72)	
Livestock income	27.96	19.25	0.00***
	(46.44)	(37.73)	
Non-agricultural income	101.28	102.92	0.78
	(161.24)	(158.73)	
Wage income	28.46	26.62	0.45
	(65.41)	(64.16)	
Self-employment and self-enterprise income	17.98	19.11	0.62
	(59.90)	(61.02)	
Income from sales of goods and services	21.78	21.81	0.99
	(71.94)	(71.47)	
Transfer and pension income	7.13	6.92	0.68
	(13.33)	(12.87)	
Remittance income	25.96	28.58	0.32
	(68.86)	(70.87)	
Dietary diversity and food security			
Household dietary diversity	6.60	6.47	0.01***
	(1.34)	(1.46)	
Food consumption is acceptable (FCS>42)	0.788	0.739	0.00***
	(0.409)	(0.439)	
Household is food insecure	0.417	0.516	0.00***
	(0.493)	(0.500)	
Empowerment and resilience			
Household asset index	1.095	0.994	0.01***
	(1.026)	(1.000)	
Women's empowerment index	-	-	-
Number of observations	**1415**	**1455**	

Notes: Point estimates are means. Standard errors are in parentheses. Level of significance *** p<0.01; ** p<0.05; and * p<0.1. FCS denotes Food Consumption Score. In Nepal, a FCS of 42 or higher is considered acceptable food consumption.

Table 5. Project impacts on agricultural income, non-agricultural income, and total household income

Income variables (*Nepali Rupees*)	**(1) IPWRA**	**(2) IPW**	**(4) PSM**	**(5) RA**	**(6) Control mean**
Log (Total household income)	0.368***	0.364***	0.371***	0.368***	153,440.4
	(0.048)	(0.048)	(0.051)	(0.048)	
Agricultural income					
Log (Crop income)	0.499***	0.499***	0.489***	0.499***	30,728.55
	(0.089)	(0.089)	(0.093)	(0.089)	
Log (Livestock income)	0.929***	0.938***	0.919***	0.932***	20,701.72
	(0.176)	(0.189)	(0.177)	(0.176)	
Non-agricultural income					
Log (Wage income)	0.269	0.387**	0.270	0.271	26,614.86
	(0.167)	(0.169)	(0.166)	(0.166)	
Log (Self-employment and self-enterprise income)	-0.132	-0.143	-0.137	-0.133	19,085.22
	(0.135)	(0.141)	(0.136)	(0.135)	
Log (Sales of products, goods, and service income)	-0.0536	-0.0657	-0.0594	-0.0551	21,777.32
	(0.138)	(0.145)	(0.139)	(0.138)	
Remittances and social transfers					
Log (Remittance income)	-0.315*	-0.334*	-0.321*	-0.309*	28,607.55
	(0.166)	(0.180)	(0.166)	(0.166)	
Log (Transfer and pension income)	0.215	0.162	0.208	0.217	6,917.63
	(0.160)	(0.170)	(0.160)	(0.159)	
Control covariates	Yes	Yes	Yes	Yes	
Number of observations	**2,874**	**2,874**	**2,874**	**2,874**	**1,457**

Notes: Level of significance *** p<0.01; ** p<0.05; and * p<0.1. Standard errors are in parentheses. IPWRA denotes Inverse Probability Weighted Regression Adjustment, IPW denotes Inverse Probability Weighting, PSM denotes Propensity Score Matching, and RA denotes Regression Adjustment.

Table 6. Project impacts on agricultural assets, housing quality, and durable assets

Asset indexes	**(1) IPWRA**	**(2) IPW**	**(4) PSM**	**(5) RA**	**(6) Control mean**
Agricultural assets					
Productive asset index (PCA)	0.164***	0.161***	0.163***	0.164***	2.53
	(0.034)	(0.038)	(0.034)	(0.034)	
Tropical Livestock Unit (TLU)	0.232***	0.239***	0.229***	0.233***	2.70
	(0.062)	(0.064)	(0.062)	(0.062)	
Non-agricultural assets					
Durable asset index (PCA)	0.097***	0.103***	0.093***	0.096***	0.99
	(0.034)	(0.035)	(0.034)	(0.034)	
Housing quality index (MCA)	0.007	0.006	0.006	0.007	0.23
	(0.006)	(0.007)	(0.006)	(0.006)	
Control covariates	Yes	Yes	Yes	Yes	
Number of observations	**2,874**	**2,874**	**2,874**	**2,874**	**1,457**

Notes: Level of significance *** p<0.01; ** p<0.05; and * p<0.1. Standard errors are in parentheses. IPWRA denotes Inverse Probability Weighted Regression Adjustment, IPW denotes Inverse Probability Weighting, PSM denotes Propensity Score Matching, and RA denotes Regression Adjustment.

Table 7. Project impacts on market prices faced by the farmers

Prices (Rupees/kg)	**(1)**	**(2)**	**(3)**	**(4)**	**N**
Project commodities	**OLS**	**RA**	**IPWRA**	**Control mean**	**Households**
Apple	0.626	2.52	1.59	44.65	343
	(1.365)	(1.91)	(1.75)	(0.98)	
Ginger	10.47	-6.89	-5.71	28.33	108
	(18.48)	(15.92)	(20.71)	(3.62)	
Turmeric	-25.92**	-5.87	-5.87	30.23	67
	(10.38)	(11.24)	(11.24)	(5.16)	
Timur	-16.16	-97.13***	-104.67***	500.00	84
	(21.44)	(36.45)	(36.97)	(0.00)	
Beans	4.366	7.47*	8.44	90.29	224
	(4.258)	(4.50)	(6.30)	(2.81)	
Potato	-3.58***	-2.16**	-2.62***	30.89	384
	(0.796)	(1.01)	(0.84)	(0.72)	
Tomato	-5.051**	-2.52	-2.34	41.85	233
	(2.108)	(2.23)	(3.08)	(1.80)	
Cabbage	-2.005	4.38	3.95	28.41	169
	(2.099)	(5.82)	(5.74)	(1.94)	
Meat goats (Rupees/count)	-580.6**	-638.5***	-614.8***	5146.89	1160
	(234.0)	(236.33)	(234.26)	(166.81)	
Non-project commodities					293
Rice	2.626*	0.90	0.73	19.80	
	(1.497)	(1.46)	(1.48)	(0.92)	
Maize	4.324***	4.45***	4.45***	21.25	827
	(0.529)	(0.54)	(0.54)	(0.26)	
Wheat	3.311***	6.60***	6.61***	26.61	393
	(1.011)	(1.09)	(1.08)	(0.39)	
Eggs (Rupees/ dozen)	3.911**	4.41**	4.65***	225.66	562
	(1.738)	(1.85)	(1.80)	(1.53)	
Milk (Rupees/litre)	0.972	1.34	1.31	58.00	562
	(1.059)	(1.05)	(1.02)	(0.97)	
Chicken (Rupees/count)	-13.99	-5.62	0.11	326.50	598
	(29.51)	(30.48)	(29.61)	(17.76)	
Controls	Yes	Yes	Yes		

Notes: Level of significance *** p<0.01; ** p<0.05; and * p<0.1. Standard errors are in parentheses. OLS denotes Ordinary Least Squares, IPWRA denotes Inverse Probability Weighted Regression Adjustment, and RA denotes Regression Adjustment.
Controls include household size, number of children, number of youth, number of adults, dependency ratio, age, gender, and education of the household head, indicators for improved roof, walls, floor, access to toilet, access to safe drinking water, access to electricity, indicator for land ownership, and land holding size

Table 8. Volume of sales for project and non-project commodities and test of the null hypotheses of no difference

Quantity of sales (kg)	**(1)**	**(2)**	**(3)**		**N**
Project commodities	**Full sample**	**Project**	**Control**	**P-value**	**Households**
Apple	1331.02	1538.56	629.54	0.00***	219
	(2014.35)	(2233.87)	(540.83)		
Ginger	668.23	740.89	327.89	0.00***	108
	(563.63)	(579.19)	(316.24)		
Turmeric	330.42	400.27	176.75	0.00***	64
	(364.79)	(407.91)	(168.87)		
Timur	83.39	89.26	53.61	0.13	85
	(111.39)	(117.40)	(69.45)		
Beans	211.11	235.87	129.02	0.02**	164
	(422.88)	(475.43)	(123.16)		
Potato	1028.97	1147.59	596.63	0.00***	353
	(1384.49)	(1479.68)	(835.28)		
Tomato	647.63	699.74	442.55	0.05**	232
	(1015.21)	(1074.29)	(710.91)		
Cabbage	861.68	893.88	708.17	0.36	173
	(1397.30)	(1484.40)	(872.47)		
Meat goats (count)	2.29	2.74	1.84	0.00***	2147
	(4.00)	(4.69)	(3.10)		
Non-project commodities					
Rice	920.73	990.97	753.23	0.33	44
	(852.31)	(934.46)	(613.87)		
Maize	315.41	337.92	293.12	0.27	201
	(284.06)	(310.33)	(255.00)		
Wheat	512.82	551.68	399.23	0.31	51
	(542.23)	(579.34)	(414.05)		
Eggs (dozen)	79.48	59.26	100.26	0.22	588
	(400.94)	(214.86)	(527.46)		
Milk (litre)	75.14	66.71	83.80	0.53	588
	(329.34)	(232.00)	(406.02)		
Chicken (count)	14.36	17.30	11.63	0.19	1124
	(71.73)	(83.69)	(58.48)		

Notes: Point estimates are means. Standard deviations are in parentheses. Level of significance *** p<0.01; ** p<0.05; and * p<0.1.

Table 9. Relationship between project-led income growth and dietary diversity and food security

Livelihood outcomes	**OLS**			**Control mean**
	(1)	**(2)**	**(3)**	
Household dietary diversity (11 food groups)				6.47
Project	0.042	0.086*	-	
	(0.049)	(0.049)		
Log (Annual household income)	0.124***	-	0.126***	
	(0.019)		(0.019)	
Controls	Yes	Yes	Yes	
Food consumption is acceptable (Food Consumption score>42)				0.739
Project	0.039**	0.045***	-	
	(0.016)	(0.016)		
Log (Annual household income)	0.016***	-	0.018***	
	(0.0060)		(0.006)	
Control	Yes	Yes	Yes	
Household is food insecure				0.516
Project	-0.078***	-0.092***		
	(0.018)	(0.018)		
Log (Annual household income)	-0.040***	-	-0.044***	
	(0.0068)		(0.0068)	
Control	Yes	Yes	Yes	
Household resilience (asset index)				0.994
Project	0.046*	0.079***	-	
	(0.027)	(0.027)		
Log (Annual household income)	0.093***	-	0.095***	
	(0.010)		(0.010)	
Control	Yes	Yes	Yes	
Number of households	**2869**	**2869**	**2869**	

Notes: Level of significance *** p<0.01; ** p<0.05; and * p<0.1. Standard errors are in parentheses. OLS denotes Ordinary Least Squares. Controls include household size, number of children, number of youth, number of adults, dependency ratio, age, gender, and education of the household head, indicators for improved roof, walls, floor, access to toilet, access to safe drinking water, access to electricity, indicator for land ownership, and land holding size.

Figures

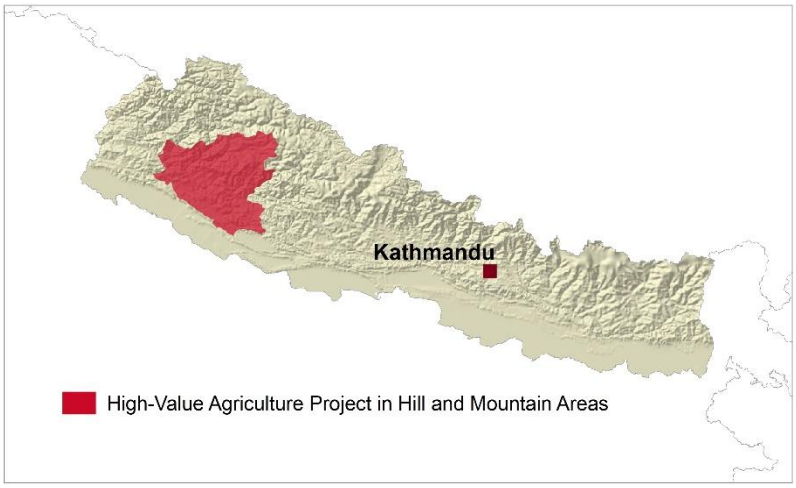

Figure 1: HVAP project areas on the map of Nepal

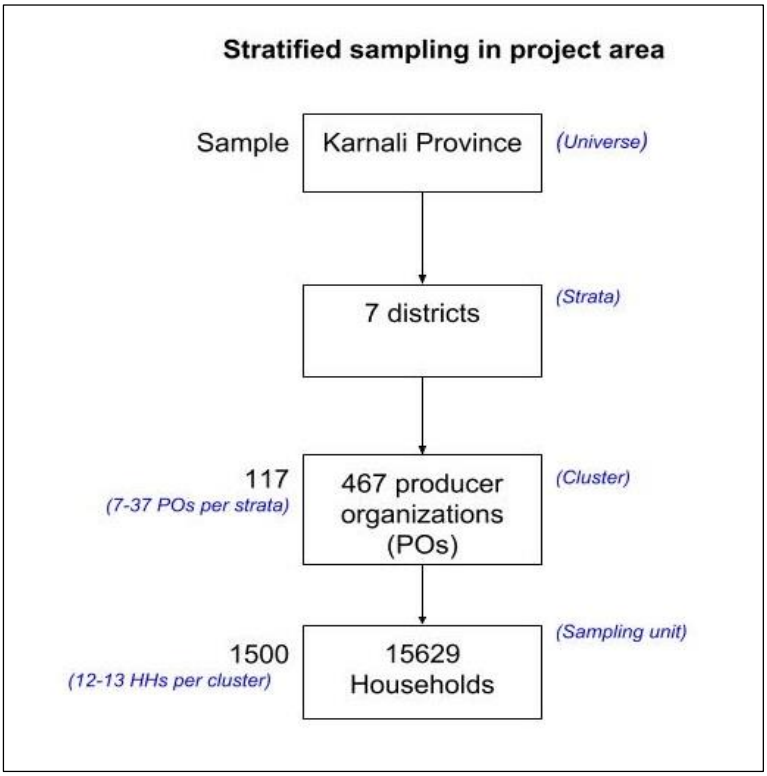

Figure 2: Sampling design for HVAP project areas

References

Alene, A.D., V.M. Manyong, G. Omanya, H.D. Mignouna, M. Bokanga, and G. Odhiambo. 2008. "Smallholder market participation under transactions costs: Maize supply and fertilizer demand in Kenya." *Food Policy* 33(4):318–328.

Angelucci, M. 2015. "Migration and Financial Constraints: Evidence from Mexico." *Review of Economics and Statistics* 97(1):224–228.

Barrett, C.B. 2008. "Smallholder market participation: Concepts and evidence from eastern and southern Africa." *Food Policy* 33(4):299–317.

Barrett, C.B., M.E. Bachke, M.F. Bellemare, H.C. Michelson, S. Narayanan, and T.F. Walker. 2012. "Smallholder Participation in Contract Farming: Comparative Evidence from Five Countries." *World Development* 40(4):715–730.

Besley, T., and R. Burgess. 2000. "Land Reform, Poverty Reduction, and Growth: Evidence from India." *The Quarterly Journal of Economics* 115(2):389–430.

Booysen, F., S. van der Berg, R. Burger, M. von Maltitz, and G. du Rand. 2008. "Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries." *World Development* 36(6):1113–1130.

Chamberlin, J., and T.S. Jayne. 2013. "Unpacking the Meaning of 'Market Access': Evidence from Rural Kenya." *World Development* 41:245–264.

Davis, K., E. Nkonya, E. Kato, D.A. Mekonnen, M. Odendo, R. Miiro, and J. Nkuba. 2012. "Impact of Farmer Field Schools on Agricultural Productivity and Poverty in East Africa." *World Development* 40(2):402–413.

Emerick, K., A. de Janvry, E. Sadoulet, and M.H. Dar. 2016. "Technological Innovations, Downside Risk, and the Modernization of Agriculture." *American Economic Review* 106(6):1537–1561.

Godtland, E.M., E. Sadoulet, A. de Janvry, R. Murgai, and O. Ortiz. 2004. "The Impact of Farmer Field Schools on Knowledge and Productivity: A Study of Potato Farmers in the Peruvian Andes." *Economic Development and Cultural Change* 53(1):63–92.

Government of Nepal. 2015. "Agriculture Development Strategy (ADS) 2015-2035, Ministry of Agricultural of Development."

de Janvry, A., M. Fafchamps, and E. Sadoulet. 1991. "Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained." *The Economic Journal* 101(409):1400.

Jodlowski, M., A. Winter-Nelson, K. Baylis, and P.D. Goldsmith. 2016. "Milk in the Data: Food Security Impacts from a Livestock Field Experiment in Zambia." *World Development* 77:99–114.

Kafle, K., A. Winter-Nelson, and P. Goldsmith. 2016. "Does 25 cents more per day make a difference? The impact of livestock transfer and development in rural Zambia." *Food Policy* 63:62–72.

Key, N., and D. Runsten. 1999. "Contract Farming, Smallholders, and Rural Development in Latin America: The Organization of Agroprocessing Firms and the Scale of Outgrower Production." *World Development* 27(2):381–401.

Key, N., E. Sadoulet, and A. de Janvry. 2000. "Transactions Costs and Agricultural Household Supply Response." *American Journal of Agricultural Economics* 82(2):245–259.

Kondylis, F., V. Mueller, and J. Zhu. 2017. "Seeing is believing? Evidence from an extension network experiment." *Journal of Development Economics* 125:1–20.

Leuven, E., and B. Sianesi. 2018. *PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing*. Available at: https://econpapers.repec.org/software/bocbocode/s432001.htm [Accessed June 21, 2019].

Markelova, H., R. Meinzen-Dick, J. Hellin, and S. Dohrn. 2009. "Collective action for smallholder market access." *Food Policy* 34(1):1–7.

Michelson, H., T. Reardon, and F. Perez. 2012. "Small Farmers and Big Retail: Trade-offs of Supplying Supermarkets in Nicaragua." *World Development* 40(2):342–354.

Mu, R., and D. van de Walle. 2011. "Rural Roads and Local Market Development in Vietnam." *Journal of Development Studies* 47(5):709–734.

Nepal, A. 2016. *Impact of the Poverty Alleviation Fund Program on Migration and Remittances in Nepal*. Urbana, IL: University of Illinois.

Rejesus, R.M., F.G. Palis, D.G.P. Rodriguez, R.M. Lampayan, and B.A.M. Bouman. 2011. "Impact of the alternate wetting and drying (AWD) water-saving irrigation technique: Evidence from rice producers in the Philippines." *Food Policy* 36(2):280–288.

Upton, J.B., J.D. Cissé, and C.B. Barrett. 2016. "Food security as resilience: reconciling definition and measurement." *Agricultural Economics* 47(S1):135–147.

Verkaart, S., B.G. Munyua, K. Mausch, and J.D. Michler. 2017. "Welfare impacts of improved chickpea adoption: A pathway for rural development in Ethiopia?" *Food Policy* 66:50–61.

Wang, H.H., Y. Wang, and M.S. Delgado. 2014. "The Transition to Modern Agriculture: Contract Farming in Developing Economies." *American Journal of Agricultural Economics* 96(5):1257–1271.

Winters, P., A. Maffioli, and L. Salazar. 2011. "Introduction to the Special Feature: Evaluating the Impact of Agricultural Projects in Developing Countries." *Journal of Agricultural Economics* 62(2):393–402.

Winters, P., L. Salazar, and A. Maffioli. 2010. "Desgining Impact Evaluations for Agricultural Projects." No. IDB-TN-198, Inter-American Development Bank.

Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Wooldridge, J.M. 2007. "Inverse probability weighted estimation for general missing data problems." *Journal of Econometrics* 141(2):1281–1301.

World Bank. 2007. "Data for Impact Evaluation." Doing Impact Evaluation No. N. 6, The World Bank.