

# Impacts of agricultural value chain development in a mountainous region: Evidence from Nepal

by  
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ISBN 978-92-9266-091-8

Printed May 2021

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## Acknowledgements

Funding for the survey design and data collection activities was provided by IFAD as part of the larger impact assessment of the High-Value Agriculture Project in Hill and Mountain Areas (HVAP) in Nepal. The Solar Irrigation for Agricultural Resilience (SoLAR) project at IWMI contributed to Kashi Kafle's research time for data analysis and writing. The authors are grateful to Boris Bravo-Ureta, Florian Neubauer, Athur Mabiso, Fabrizio Bresciani, Antonio Rota, Eva-Maria Egger, Giuseppe Maggio, Sinafikeh Gemessa, David Stifel and Robert Pickmans for their helpful comments and discussions during the earlier stages of this research. We thank the IFAD research series editor, Aslihan Arslan, and Mario González Flores (Inter-American Development Bank) for very useful comments that further improved the paper during the peer review process. Kwabena Krah, Krishna Thapa and Margaret Cornelius provided excellent research assistance. Thanks go to IFAD's Bashu Babu Aryal and Mehri Ismaili, and the project staff for technical and logistical support during field visits in Nepal. Finally, we thank Andreas Kutka and Mohamed Abouaziza for setting up a data quality check system during the survey. All remaining errors are by the authors (all of whom were IFAD staff during the survey design and data collection).

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## Abstract

This analysis investigates the potential mechanism and the practical significance of the impacts of agricultural value chain development in a geographically challenging rural area of a developing country. We use data from a carefully designed primary survey administered in the hill and mountainous region in Western Nepal. Using the inverse probability weighted regression adjustment method, we show that linking small-scale producers with regional and local traders can help increase agricultural income. We unpack the potential mechanism of the impact pathway and show that the increase in agricultural income is a consequence of higher agricultural revenues, owing to a higher volume of sales at lower prices. We argue that value chain intervention in rural areas, where land is not fully exploited, can lead to acreage expansion or crop switching, which eventually results in higher supply at lower output prices. The positive impact on household income is practically significant in that it translated into improved food security, dietary diversity and household resilience. These findings are robust to various specifications. Targeted value chain interventions that strengthen and stabilize small-scale producers' access to markets can contribute to rural poverty reduction via an increase in agricultural income.

# 1. Introduction

Sufficient, timely and stable access to a well-functioning agricultural market is a necessary condition for efficient and profitable agricultural production systems (Mishra et al., 2018; Minten and Kyle, 1999; Reardon and Minten, 2011). Multiple mechanisms could explain how limited access to markets leads to a reduction in agricultural productivity, which further increases poverty and vulnerability (Barrett, 2008). Poor access to markets leads to higher transaction costs (mainly associated with transportation and information costs in our setting) (Key and Runsten, 1999), lower output prices, higher input costs and lack of access to credit (Burke, Bergquist and Miguel, 2019). Interventions that boost access to markets can help increase farm revenues by lowering transaction costs and improving access to market information such as price information, thus having direct implications for household welfare (Chamberlin and Jayne, 2013; Barrett, 2008). In addition, improved access to markets can diversify income-generating opportunities for small-scale producers by creating new production and marketing opportunities (Joshi et al., 2004). By offering both improved market access and greater income-generating opportunities, stable access to markets can provide an additional incentive for small-scale producers to grow high-value crops such as fruits and vegetables, which are otherwise too risky. They are highly perishable and failing to get them to market in time could incur substantial losses.

Improving small-scale producers' access to markets and market information is a key element for agricultural development and rural poverty reduction (Jensen, 2007; Aker, 2010; Mu and van de Walle, 2011; BIRTHAL et al., 2015). Reduced transaction costs can have a direct implication for poverty reduction through increased farm revenues (Besley and Burgess, 2000; Barrett, 2008; Chamberlin and Jayne, 2013), because the transaction cost is a form of market friction that prevents market access for small-scale producers (de Janvry, Fafchamps and Sadoulet, 1991; Key, Sadoulet and de Janvry, 2000). In the past, the majority of agricultural development projects focused primarily on demand-side approaches (de Janvry and Sadoulet, 2020). In recent years, increasingly more interventions have taken a value chain approach, which links producers with buyers and other stakeholders (Cavatassi et al., 2011; Biggeri et al., 2018; Kuijpers, 2020). In this emergent literature, the mechanisms for improved agricultural productivity, income and household welfare are not yet clear.

One strand of literature shows that reducing transaction costs can increase small-scale producers' participation in agricultural value chains, which eventually raises farm income by increasing agricultural productivity (Key and Runsten, 1999; Alene et al., 2008; Markelova et al., 2009). Other studies have shown how the linkage between producers and traders can increase market access and value chain participation of small-scale producers (Michelson, Reardon and Perez, 2012; Barrett et al., 2012; Wang, Wang and Delgado, 2014).

While the existing body of evidence credits reduced transaction cost for the positive impacts on livelihood outcomes, it is unclear how the reduction in transaction cost affects agricultural prices and sales. In addition, interventions specifically designed to improve market access for small-scale producers in geographically challenging hilly and mountainous areas are limited, and the policy implications associated with interventions in rugged terrain could be very different from those occurring in a homogenous landscape. Hence, a knowledge gap also exists concerning if and how value chain interventions in mountainous areas are able to increase the agricultural revenue of small-scale producers and contribute to an increase in household income.

Even though many believe that stable and improved market access increases revenue through higher output prices, in the context of rough terrain, where most of the land is unexploited or underused, market access could drive down output prices by increasing farm supply via acreage expansion or crop switching. The question then becomes, what are the underlying mechanisms by which the improved access to agricultural markets can be translated into higher incomes? We hypothesize that improved linkages between small-scale producers and markets increase agricultural revenue (and household income) by increasing the volume of sales at slightly lower output prices. In addition, we argue that the project-led income growth is translated into practically meaningful outcomes such as improved household food security, dietary diversity and resilience.

The High-Value Agriculture Project in Hill and Mountain Areas (HVAP) in Nepal presents a unique opportunity to answer these questions by: (i) estimating the impacts of a comprehensive market intervention in an extremely rough topography; and (ii) unpacking the potential mechanism driving the impacts. The setting of the study is in Far-Western Nepal, a region characterized by extreme poverty and severe food insecurity, primarily due to its rugged terrain, which has hindered road network development and market access. The region has the poorest road network in the country, with more than 80 per cent of the population living farther than 2 km from the nearest road (Transport and ICT, 2016). The people living in this region often face much higher input prices and lower output prices compared with those in regional market hubs (Pyakuryal, Thapa and Roy, 2005). High transaction costs and extremely difficult terrain in which to move goods to regional markets have discouraged producers from expanding their production (Shrestha, 2020).

In addition, low agricultural productivity and lack of market access have contributed to extreme poverty, chronic food insecurity and malnutrition (Asian Development Bank, 2018). The lack of market access has made agriculture less attractive as a source of income, contributing to mass migration of farm workers to the Middle East, South East Asia and other regions requiring low-skill labour (Rapsomanikis, 2015). Despite the good potential for high-value crops due to favourable agroclimatic conditions, most producers grow cereals for home consumption, and subsistence farming has long been the norm (Mishra et al., 2018). As a result, domestic agriculture is far from meeting local food demand, and food purchases from the market have drastically increased, making up to 58 per cent of the value of food consumption in rural areas (Reardon et al., 2014). As the mountainous and hilly areas are home to about half of the country's population (Sharma, 2006), enhancing market access in these areas is key to improving livelihoods and providing a pathway out of poverty.

In 2011, the Government of Nepal implemented HVAP, a value chain development project for high-value crops across seven hilly and mountainous districts in Karnali Province.<sup>1</sup> The objective of the project was to link small-scale producers with regional and national markets via a large and coordinated intervention. The goal was to reduce local food prices, increase agricultural revenue and improve food security. According to the results from this study, not only did the intervention increase farm income but it also reduced local food prices, making food products more accessible to vulnerable households.

The study results are based on the data from a carefully designed household survey, in which over 3,000 households were interviewed in 2018. Data were gathered only once after the intervention ended, but counterfactual households were carefully chosen to be able to identify the impacts of the intervention on livelihood outcomes. As the intervention was rolled out in 2011, we used the data from the National Population and Housing Census 2011 to ensure similarities between project and counterfactual villages in the baseline. Multiple key informant interviews were conducted in early 2018 to identify producer organizations (POs) that did not receive the intervention but would have qualified for it had there been greater resources to expand intervention coverage in 2011. We used matching and regression adjustment methods to estimate the impacts.

Results show that the intervention raised annual household income by more than 32 per cent, which was mainly driven by an increase in agricultural revenue of more than 57 per cent. We unpack this increase in agricultural (both crop and livestock) revenue to investigate whether the boost in income was mainly driven by output prices or quantities. We found that project households received lower per unit output prices, particularly for the commodities supported by the project. However, this decrease in output price was more than offset by the significant increase in the quantity sold, indicating that the increase in agricultural revenue (or household income) was a result of higher sale volumes. One possible mechanism is that the intervention led to acreage expansion or crop switching to high-value crops. Analyzing the practical significance of

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<sup>1</sup> The project covered six districts in Karnali Province and a few villages from Achham district, which lies in Sudurpashchim Province.



the project impacts, we found that the project helped improve household food security, dietary diversity and household resilience.

Our analysis makes three important contributions. First, our results are consistent with findings in the existing literature that, even in hilly and mountainous terrain, agricultural value chain development interventions are effective in increasing agricultural revenue (Reardon et al., 2009; Barrett et al., 2012; Quisumbing et al., 2015). Second, we add to the literature by showing that the increase in agricultural revenue largely came from an increase in the volume of sales of the commodities supported by the project. It was not the result of higher output prices. This finding is novel and we argue that improved market access probably led to acreage expansion, which then reduced prices but farm revenue went up due to economies of scale. Third, we demonstrated that the increase in agricultural revenue, which came via higher sale volumes, indeed translated into improved food security, dietary diversity and household resilience. We argue that targeted value chain interventions that strengthen and stabilize smallholders' access to markets can increase income and food security (Reardon et al., 2009; Barrett et al., 2012; Herrmann, Nkonya and Faße, 2018; Liverpool-Tasie et al., 2020).

The rest of the paper is organized as follows. Section 2 discusses the details of the intervention. Section 3 explains the conceptual framework, econometric methods and the identification strategy. Section 4 describes the sampling design. In section 5, descriptive and econometric results are presented. Section 6 concludes.

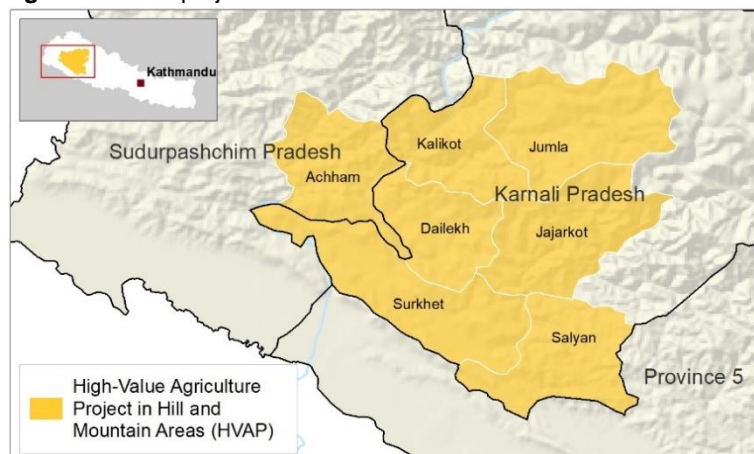
## 2. Setting

The Government of Nepal, in collaboration with the International Fund for Agricultural Development (IFAD) and the SNV Netherlands Development Organisation, implemented a value chain development programme for high-value agricultural commodities across seven districts in Karnali Province. It was a coordinated effort to reduce poverty and improve food security in the country's most challenging hilly and mountainous areas. The project started in 2011 and ended in 2018. During its lifetime, the project supported about 107,860 small-scale producers and 456 POs. The project aimed at reducing poverty and increasing food security through an inclusive value chain and improved and functional service market for high-value agricultural commodities. Specific activities included establishing contractual agreements between POs and agribusinesses; strengthening institutional capacity by providing market information, support services and infrastructure; and providing skill-development training to producers (IFAD 2009).

The intervention is closely aligned with Nepal's Agriculture Development Strategy 2015 to 2035, which aims at improving agricultural productivity in rural areas by promoting high-value agriculture (Government of Nepal 2015). Traditional agriculture is not always a viable option in these districts owing to the rough terrain. Therefore, the project concentrated on value chain development of high-value agricultural commodities suitable for the agroclimatic zone – namely apple, ginger, turmeric, *timur* (Sichuan pepper), off-season vegetables, vegetable seeds and meat goats. The commodities selected to be supported are high-value crops with marketing potential for both domestic and export markets (particularly neighbouring countries such as China and India), as the project areas are situated in an important trade corridor in Nepal connecting to China and India. Though seven different value chains were supported, the choice of the value chain commodity supported differed according to the agroecology of the project areas, and none of the project districts received support for all seven value chains. Neither POs nor the individual producers were mandated to grow only project-supported commodities. In addition, they could also grow crops or trees not supported by the project.

The project specifically targeted small-scale producers residing in very rough geographic terrain across seven districts – namely Surkhet, Dailekh, Salyan, Jajarkot, Kalikot, Jumla and Achham. The 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 were covered due to resource limitations. The project spanned 14 municipalities and 24 rural municipalities (126 villages and 2 municipalities in the old administrative system, which was phased out in 2015).

**Figure 1.** HVAP project areas



Producers were required to form a PO to be eligible for project activities. The project consisted of two major components: (i) inclusive value chain development; and (ii) service market strengthening. Under the 'inclusive value chain development' component, small-scale producers were linked with input suppliers and traders in regional and national markets along the value chain. For social inclusiveness, the project specifically targeted female producers and ethnic minorities – *Dalit*, *Janajati* and other marginalized groups.<sup>2</sup>

Under the 'service market strengthening' component, the project provided training to small-scale producers. This involved a comprehensive business literacy class for both female and male producers. The business literacy classes (BCL) were organized in cooperation with the Ministry of Agriculture and Livestock and agricultural extension offices, as well as the District Chamber of Commerce and Industry. BCL participants were provided with practical information about marketing, operating small agricultural enterprises and networking with value chain actors, including input suppliers and 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 exercises about running agricultural enterprises, price formation strategies, etc. The project also assisted with forming self-help groups and cooperatives to strengthen production and marketing activities. The cooperatives were capacitated to work as collection centres in their locality. In addition, the project helped in building cold storages in major market outlets, primarily in district headquarters. Another important aspect of the 'service market strengthening' component was linking producers with input suppliers. However, the project did not provide direct support for the supply of production inputs such as fertilizers, seeds, seedlings or irrigation.

Inputs and activities supported by the HVAP could benefit its target groups in the following ways. First, improved linkages between POs and markets should help reduce transaction costs faced by producers when selling their agricultural products (Alene et al., 2008; Markelova et al., 2009). Second, capacity building and skill-enhancing training related to production and marketing should help producers improve their productivity and receive higher returns to their outputs (Davis et al., 2012; Emerick et al., 2016; Kondylis, Mueller and Zhu, 2017; Verkaart et al., 2017). Third, investment in market infrastructures such as collection centres and cold storages could help reduce post-harvest losses and vulnerability due to market shocks (Mu and van de Walle, 2011; Shrestha 2020). And finally, adopting the social inclusion approach to engage women and other vulnerable groups in the value chain increases empowerment, social capital and social support within target communities (Quisumbing et al., 2015; Malapit et al., 2020).

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<sup>2</sup> From the set of eligible POs, a predetermined number of POs were selected from each of the seven districts based on the following rule. Eligible POs that consisted of more female producers and minority groups were given first priority. The remaining number of POs were selected based on the order by which applications were received. However, it is not clear how many POs applied and how many of them were eligible for the project.

### 3. Methods

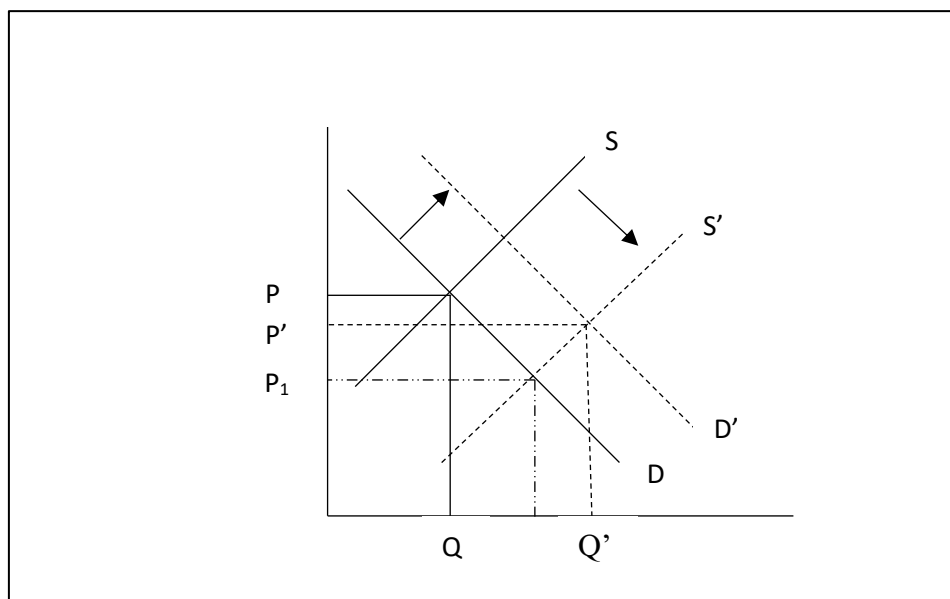
#### 3.1. Conceptual framework

We hypothesize that the project leads to increased agricultural revenue, which in turn comes from increased volume of sales at stable prices. Since most areas covered by the project were a rough terrain and barely had access to markets and roads, pre-intervention producers were producing little and selling some products locally and some to middlemen. The intervention linked producers with regional and national traders by physically bringing the two parties together and exchanging contact numbers, production details and potential market demand. This activity gave producers reliable market access. We argue that producers respond to the direct access to market and price information by (i) increasing the volume of sales; and (ii) switching to commodities that have higher value and marketing potential.

When producers that were not connected to markets get access to markets and price information, initially output prices go up and input prices go down, resulting in reduced input cost and higher revenues. This leads to an increase in supply of the commodities in question, either via the expansion of production acreage by existing producers or via the entrance of new producers. The shift in supply then drives the prices down. In response, market demand increases. Improvement in markets shifts the demand curve upwards until a new equilibrium price is established. Figure 2 illustrates this phenomenon.

**Figure 2.** Potential impact on output prices and sales

In figure 2, pre-intervention, suppose the price was  $P$  and quantity produced was  $Q$ . The intervention first shifts the supply curve right ( $S$  to  $S'$ ) and transactions happen at price  $P_1$ . Eventually, market demand shifts upwards in response to the project activities and a new equilibrium is reached at price  $P'$  and quantity  $Q'$ . Producers receive a lower price than the pre-intervention price ( $P$ ) but the sell volume drastically increases from  $Q$  to  $Q'$ . Unfortunately, our analysis is unable to test this empirically due to the lack of baseline data. We elicit this phenomenon, rather indirectly, by estimating the project impacts on (i) household income; (ii) output prices; and (iii) sale volumes separately. Each of these outcome variables ( $Y_i$ ) is directly influenced by the project activities ( $T$ ) and other sociodemographic covariates ( $X$ ). Equation 1 illustrates this.



$$Y_i = f(T, X) \quad \forall i = 1, 2, \dots, n \tag{1}$$

### 3.2. Econometric models

We use both parametric and non-parametric methods to estimate the average treatment effects (ATE) and treatment effects on the treated (ATT). Ordinary least squares (OLS) is used to estimate ATE on incomes, prices and sale volumes as well as other livelihood outcomes. Inverse probability weighted regression adjustment (IPWRA) is used to estimate ATT, non-parametrically. In the absence of baseline data, these estimators control for selection on observable attributes only. Selection bias from unobservable attributes is not controlled for, but we perform several robustness checks. Equation 2 shows the estimating equation for the OLS estimator.

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i \quad (2)$$

$Y_i$  is an outcome of interest,  $T_i$  is the binary indicator for project,  $X_i$  is the vector of observable characteristics of household  $i$ , and  $\varepsilon_i$  is the error term. Standard errors are clustered at the household level because most production decisions and practices are made by the individual household. The coefficient  $\beta$  is the estimate of the project impacts on outcome  $Y$ .

The IPWRA estimator combines the inverse probability weighted (IPW) and the regression adjustment (RA) estimators. The regression adjustment method adds one more term in the OLS equation (2) – the interaction between the project indicator and mean corrected control covariates ( $X_i - \bar{X}$ ). It has been used previously to estimate impacts of agricultural interventions (Godtland et al., 2004; Rejesus et al., 2011). Specifically, the regression specification is as follows:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \delta (X_i - \bar{X}) T_i + \varepsilon_i \quad (3)$$

In Equation 3,  $\bar{X}$  is the vector of the average of the observable characteristics of household  $i$ , and  $\beta$  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  $\bar{X}$  with  $\bar{X}_i$  in equation 3 (where  $\bar{X}_i$  is the average over treatment households only) yields the ATT estimate.

The inverse probability weighted (IPW) estimator gets rid of the confounding factors by creating a pseudo-population. It uses the inverse of the estimated propensity score as weight (Wooldridge, 2010; Hirano et al., 2013). The propensity score can be estimated using probit and then used to compute the treatment effects as follows:

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

IPWRA models the likelihood of project participation and estimates the project impacts contingent on the likelihood (Wooldridge, 2007; Wooldridge, 2010). A major advantage of this approach is that only one of the two estimation equations needs to be specified correctly, and thus has the 'double-robust' property. This estimator is similar to the regression adjustment estimator but it uses inverse probability as weights for all control covariates. 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.

Our preferred method for this analysis is the inverse probability weighted regression adjustment method for its doubly robust properties. Both the matching and regression adjustment methods may have issues of selection bias because both of these methods can account for observable characteristics only. Counterfactual selection is key to truly identify the impacts of an intervention ex-post. Next, we discuss how the careful selection of a counterfactual group enables us to identify the impacts.

### 3.3. Identification strategy

One of the threats to identification in ex-post impact evaluations is the lack of baseline data. Finding a valid counterfactual group is key to identifying the impacts, but in the absence of baseline data we could not rely only on quantitative approaches. As such, we adopted a mixed-method approach from the design stage of the impact evaluation. Availability of the National Population and Housing Census 2011 data worked in our favour, specifically because the intervention also started in 2011. While the census data themselves could not serve as the 'baseline' data to represent pre-project conditions, there was only so much we could do to leverage the information available. The census data were aggregated and made available only up to the village development committee (VDC) level.<sup>3</sup> The intervention was implemented at the PO level, even though the ultimate target groups were private households. The POs, in most cases, were a collection of households from different parts of a VDC, though in a handful of cases a few households from neighbouring VDCs were included too. Against this backdrop, the counterfactual selection process proceeded as follows.

First, we obtained the full list of project POs, as well as the VDCs and districts each PO belonged to. Using the census data, we put together a list of non-project VDCs in each district. The VDC-level information available in the census data was used to identify non-project VDCs that were similar to project VDCs in 2011. Nearest neighbourhood matching was run for each district to match the project and non-project VDCs. In each district, the matching variables included binary indicators for agricultural household, landholding size, female land ownership, home ownership, housing characteristics (types of roof, wall and floor), access to services (source of consumption water, type of toilet), access to energy (sources of lighting and cooking), household size and literacy rate.

Non-project VDCs that did not fall within the common support with the project VDCs were dropped. A longlist of non-project VDCs was prepared with up to two replacement VDCs for each of the project VDCs (second and third best match). The list of project VDCs and their matched pairs of non-project VDCs was then sent to project staff and community leaders for validation. For each project VDC, the project staff and community leaders were asked to rank the non-project VDCs from the list as best matched, second best matched and least matched based on their subjective assessment of similarities and differences between the VDCs. The final list of matched non-project VDCs was compiled based on both quantitative and qualitative matching. This list was remarkably similar to the one obtained from the matching procedure.

The second step was the selection of counterfactual POs. Even though the project and non-project VDCs were remarkably similar, we had to make sure the counterfactual POs and households from the non-project VDCs were also very similar to the project households. In the absence of the pre-existing baseline data, we applied the project eligibility criteria that were used to select project POs and households in 2011. We tracked down the project staff who had led the beneficiary selection in 2011, and they helped us to replicate the same process in non-project VDCs, hypothetically. Before describing the process for selection of counterfactual POs and

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<sup>3</sup> Nepal underwent a massive administrative restructure in 2017. The VDC system was replaced with the Rural Municipality system in 2017. However, since the HVAP project started in 2011 and the impact evaluation was designed around project selection criteria used in 2011, we followed the old VDC system in this paper.

households, we describe the project eligibility criteria that were also used to identify suitable project commodities (table 1).

**Table 1.** 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, <i>timur</i> and vegetable seeds
Well-being ranking	Eligible if household falls into first three categories: Extreme poor, moderately poor or near poor
Income level	Eligible if per adult equivalent 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 project design documents.

The type of commodities supported was determined by the travel time from the location of the PO to the nearest market. POs that were located less than three hours from the nearest market received support for off-season vegetables due to their high perishability. Those located between three to six hours from the nearest market received support for ginger, turmeric or apple, based on the agroclimatic conditions. POs that were farther than six hours' travel time from the nearest market received support for meat goats, *timur* or vegetable seeds, again based on the agroclimatic conditions. Each PO received the project activities for only one commodity. We followed the same eligibility criteria set forth by the project to identify non-project POs that were best matched with project POs.

At the start of the project in 2011, the project staff had identified existing informal POs and then turned them into formal (and sometimes larger) POs. The project POs had the following attributes: (i) having 25-40 households as members; (ii) having the potential to produce one of the targeted commodities; and (iii) having a sizable representation of women and ethnic minorities proportional to the population of the VDC. We followed the same criteria to replicate the process in selecting non-project POs. For each project PO, we asked the project staff in consultation with local leaders to identify up to three potential non-project POs in the best-matched non-project VDC. Non-project POs did not necessarily have to focus on the same type of commodities as project POs, but should have the potential to cultivate the same commodities to ensure their comparability. We had to identify three potential non-project POs for each project PO because existing informal POs in non-project VDCs were smaller than the project POs, so we could run into the problem of insufficient counterfactual households. In a few cases, non-project POs that were smaller in size (less than 25 households) were merged with a similar PO within the same VDC. After the list of potential counterfactual POs was amassed, it was validated by both the project staff and community leaders, who also confirmed that the set of non-project POs would have been included in the project, had there been an expansion of the intervention.

The final stage was the selection of the counterfactual households. For the actual intervention, households were selected based on three well-being attributes: subjective assessment of well-being, net income level and landholding size. Participatory rural appraisal (PRA) was used to rank the well-being level of all the households in a PO, subjectively. The four well-being categories were: extremely poor, moderately poor, near poor and not poor. Households within the first three categories (extremely poor, moderately poor, and near poor) were deemed eligible for the project. However, if the subjective assessment of well-being had left out households with annual per capita income of Rs. 2,000 (roughly US\$20) or less, or landholding size of 0.5 ha. or less, these

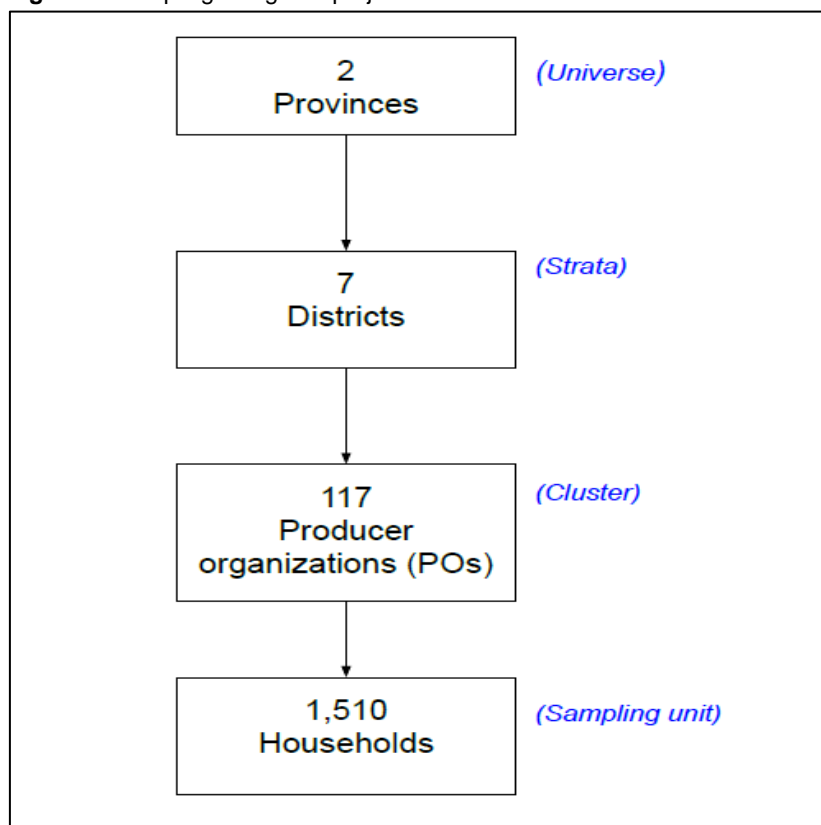
households were also made eligible for the project.<sup>4</sup> For the selection of counterfactual households, a team of social mobilizers was sent to the non-project VDCs to essentially replicate the household selection process. It was not always possible to conduct PRA and replicate the subjective well-being ranking, but income level and landholding-size criteria were closely followed in determining eligibility for counterfactual household selection.

## 4. Data

### 4.1. Sample selection

Project VDCs were widely distributed across seven districts, both in terms of the number of POs and types of commodities supported. The districts differed from each other in various aspects, including demographic composition, agroclimatic conditions and topography. We used a multistage stratification to assure a representative sample from all districts and value chains. There were 32 unique district-value chain pairs in total (for example, Achham-goat, Dailekh-goat, Jumla-apple, etc.), and our sampling design accounted for such heterogeneity. Figure 3 presents our sampling design for the selection of project POs.

**Figure 3.** Sampling design for project areas



The stratification at the district level divided the project area into seven sub-populations (districts), and consisted of all project POs in each district. Then we used the predetermined project sample size and the minimum number of sampling units per cluster (in this case, a PO) to determine the required number of clusters. That is, dividing the required sample size of 1,500 by 13, which gave us the cluster sample size of 117, after rounding.<sup>5</sup> As we had 456 clusters in total, the cluster sample represented 25 per cent of the cluster population. More detailed information about the sample size calculations is provided in the next section (Section 3.3). To assure proportional representation of all clusters in the final sample, we sampled 25 per cent of clusters from each

<sup>4</sup> One Nepalese rupee is approximately equal to US\$0.01.

<sup>5</sup> We provide details about the sample size calculation to determine the sample size required to ensure sufficient statistical power in section A of the appendix.



district by using simple random sampling with proportional allocation. This process gave us the distribution of 117 project clusters across project strata.

Then we calculated the number of households to be sampled from each district based on the number of sample households per cluster. We 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 from the list of PO members prepared by the project staff to meet the required sample size.

## 4.2. Data

Data were collected through a comprehensive household and agriculture survey between May and July 2018. The survey was administered to 3,020 households across the seven project districts. Table 2 outlines the number of households and POs (clusters) by project status. The full sample consisted of 1,500 project households from 117 clusters and 1,520 non-project households from 118 clusters.

**Table 2.** Sample distribution across districts by project status

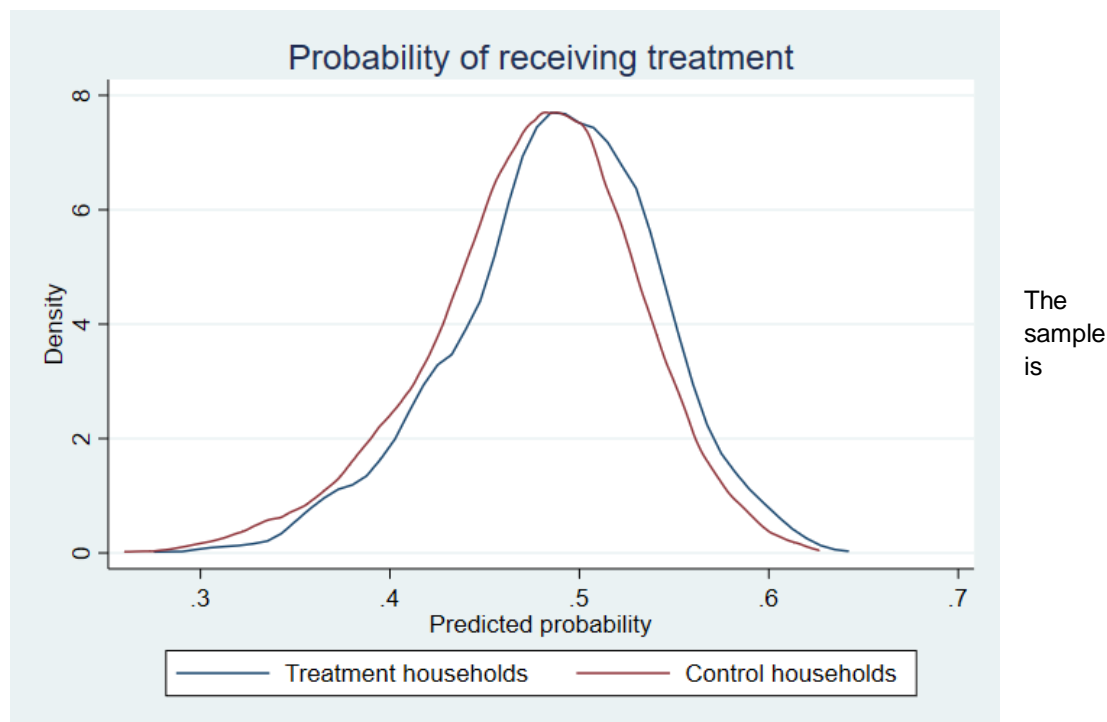
Districts	(1) POs			(2) Households		
	Project	Control	Total	Project	Control	Total
Achham	7	6	13	91	78	169
Dailekh	17	18	35	221	234	455
Jajarkot	15	15	30	192	195	387
Jumla	15	15	30	193	193	386
Kalikot	15	16	31	193	206	399
Salyan	11	15	26	139	189	328
Surkhet	37	33	70	471	425	896
<b>Total</b>	<b>117</b>	<b>118</b>	<b>235</b>	<b>1,500</b>	<b>1,520</b>	<b>3,020</b>

Notes: Authors' illustration.

Propensity score matching was used to match project and control households based on observables. The rest of the analysis is based on the households that fell under the common support. The matching was done at district level, so project households from one district were not matched with control households from another district. Due to this matching, the Rosenbaum and Rubin bias reduced from 23.3 per cent to 7.0 per cent – much lower than the maximum tolerable threshold of 25 per cent (Rubin, 2001). As suggested in Leuven and Sianesi (2018), the matched sample was trimmed at the second and 98<sup>th</sup> percentiles of the propensity score. The final sample consists of 2,710 households (1,300 project households and 1,410 control households). Figure 4 shows the kernel densities of the propensity scores of households in treatment and control groups after matching and trimming. This figure confirms that our strategy to create the counterfactual group has been successful in ensuring that households in the control group are as statistically comparable to those in the treatment group as possible.



**Figure 4.** Kernel densities of propensity scores



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

The survey collected information on multiple aspects, including household incomes, demographics, food security indicators, asset ownership, access to credit, access to markets and prices. Details on agricultural production, landholding size and marketing of agricultural produce were also collected. Most of this information was self-reported by the respondents and covers up to 12 months preceding the survey. As such, the data are subject to recall and self-reporting errors.

### 4.3. Price and sale indices

Output prices and sale volumes are specific to different crops. Rather than estimating the impacts on prices and volumes of every single commodity, we grouped commodities into two distinct groups – project commodities and non-project commodities – and created aggregated indices of prices and sale volumes for each group. We then estimated the project impacts on price index (and sale volume index) of project commodities and non-project commodities, separately. First, price and sale volume for each commodity were normalized by dividing with local averages, i.e.  $\omega_i = \frac{p_i}{\bar{p}}$ . Then the aggregated index for prices (or sale volumes) was created by taking the average of the normalized prices (or sale volumes) of all the commodities over the full sample, i.e.  $Index = N^{-1} \sum_{i=1}^n \omega_i$ . The same process was repeated for project and non-project commodities.

### 4.4. Descriptive results

Table 3 presents summary statistics of explanatory variables for project and control households before and after matching. Summary statistics are accompanied by p-values for the test of the null

hypothesis that there is no difference in project and control means.<sup>6</sup> Many observable characteristics are statistically similar across project and control groups, while the others are not. On average, household heads in the project group tend to be older, while those in the non-project group are more likely to have attended school. Further, households in the project group tend to have a higher dependency ratio and larger landholding. Other housing characteristics and the sources of energy also exhibit differences between households in project and non-project groups. However, these differences are small enough, and are not likely to affect self-selection into participation in the project. Overall, the summary statistics presented in table 3 confirm that our identification strategy to replicate the targeting strategy of the HVAP by combining statistical approaches with local information has resulted in a good counterfactual group. That is, we have been able to select non-project POs and households that are statistically comparable to those of project POs and households to measure the impact of strengthened market linkages.

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<sup>6</sup> We first match treatment and control households separately by district. Then, to confirm that they have common support when pooling observations from all districts together, we match them again. Table 3 presents results from the matching when pooling observations from all districts together.

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

Variables (binary, unless otherwise indicated)	Panel A				Panel B			
	Before matching				After matching			
	Project	Control	P-value	% Bias	Project	Control	P-value	% Bias
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>A: Household head characteristics</b>								
Age (years)	45.51	44.79	0.139	5.7	45.50	45.55	0.908	0.5
Ever attended school (=1 if yes)	0.515	0.533	0.339	3.7	0.515	0.515	0.969	0.2
Schooling (years)	4.082	4.543	0.012**	9.7	4.082	4.017	0.716	1.4
Sex (=1 if male)	0.726	0.742	0.339	3.7	0.725	0.713	0.480	1.4
Married (=1 if yes)	0.889	0.898	0.470	2.8	0.889	0.887	0.871	0.6
<b>B: Household demographics</b>								
Household size	5.047	5.124	0.304	4.0	5.049	5.013	0.630	1.9
Share of female members in household (%)	0.537	0.535	0.768	1.1	0.537	0.536	0.926	0.4
Dependency ratio	0.806	0.873	0.025**	8.6	0.806	0.801	0.863	0.7
Literacy rate (=1 if yes for age 5 years+)	0.644	0.648	0.618	1.9	0.644	0.644	0.979	0.1
Land size owned (ha)	0.489	0.477	0.458	2.9	0.489	0.484	0.750	1.3
Minority households (=1 if yes)	0.262	0.257	0.750	1.2	0.261	0.252	0.584	2.1
Housing index	0.288	0.287	0.935	0.3	0.288	0.284	0.665	1.7
Altitude (m)	1,310.1	1,364.2	0.031**	8.3	1,310.6	1,322.9	0.628	1.9
Dist. market (km)	3.956	4.341	0.053*	7.4	3.959	4.122	0.401	3.1
Irrigation (=1 if yes)	0.499	0.440	0.032**	11.9	0.498	0.488	0.599	2.1
Relative bias (%)				23.3				7.0
Variance ratio (V(T))/V(C)				0.98				1.00
<b>No. of obs.</b>	<b>1,301</b>	<b>1,410</b>			<b>1,300</b>	<b>1,410</b>		

Notes: Level of significance \*\*\* p<0.01; \*\* p<0.05; and \* p<0.1. Variables are binary unless otherwise indicated. Housing index is calculated using multiple correspondence analysis.

Table 4 presents summary statistics for outcome variables: total income, agricultural incomes, non-agricultural incomes, prices and sales indices, dietary diversity, food consumption score, food security indicator and household asset index. All income-based variables are presented in levels in table 4, but are analyzed in logarithmic scale for the impact estimates. Dietary diversity was calculated based on the approach of the Food and Agriculture Organization of the United Nations (FAO) (Kennedy, Ballard and Dop, 2011), food consumption score (FCS) was calculated as suggested in WFP (2008) and food security was measured with FAO's food insecurity experience scale (FIES) (Cafiero, Viviani and Nord, 2018). The household asset index was calculated using the factor analysis approach (Sahn and Stifel, 2003).

In table 4, column 1 presents statistics for the project sample, column 2 presents the statistics for the control sample and column 3 presents the p-value for the test of the null hypothesis that project and control means are not different. On average, project households had a per adult equivalent income of US\$396 per year compared with US\$339 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 the project sample are statistically different from the control sample, indicating that project-led growth in household income came entirely from the growth in agricultural income.

The middle two panels in table 4 present statistics for dietary diversity, food security indicators and household resilience (measured by asset index).<sup>7</sup> Both household dietary diversity and food consumption indicators are significantly greater among project households than among control households, 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.** Summary statistics of outcome variables

<b>Income variables (US\$ per adult equivalent/year)</b>	<b>(1) Project sample</b>	<b>(2) Control sample</b>	<b>(3) P-value</b>
Total income	396.48 (11.80)	338.60 (12.64)	0.001***
Agricultural income	182.82 (6.25)	106.63 (5.38)	0.000***
Crop income	116.91 (3.96)	61.44 (2.25)	0.000***
Livestock income	65.92 (4.08)	45.08 (4.14)	0.000***
Non-agricultural income	214.75 (9.92)	232.77 (11.33)	0.235
<b><i>Dietary diversity and food security</i></b>			
Household dietary diversity (out of 13 food groups)	6.59 (0.037)	6.47 (0.039)	0.031**
Food consumption is acceptable (=1 if FCS>42)	0.782 (0.011)	0.738 (0.012)	0.007***
Household is food insecure (=1 if yes)	0.425 (0.014)	0.520 (0.013)	0.000***
<b><i>Resilience</i></b>			
Household asset index	1.09 (0.029)	0.99 (0.026)	0.006***
<b><i>Output prices and sales</i></b>			
Price index: project commodities	0.97 (0.016)	1.05 (0.023)	0.011**
Price index: non-project commodities	1.02 (0.017)	0.96 (0.015)	0.137
Quantity sold: project commodities	1.10 (0.042)	0.74 (0.036)	0.000***
Quantity sold: non-project commodities	1.20 (0.199)	0.95 (0.162)	0.332
<b>Households</b>	<b>1,300</b>	<b>1,410</b>	

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

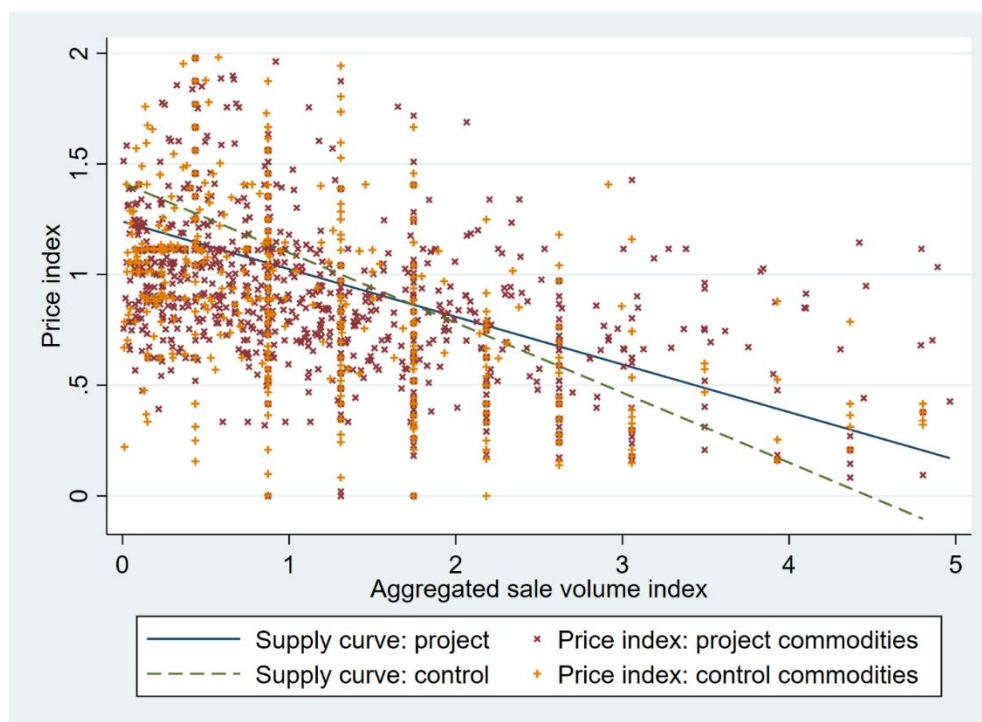
The last panel in table 4 presents a summary of output prices and sales indices. The price index for project commodities is significantly lower for project households than control households, but the opposite is true for non-project commodities. The quantity of sales of project commodities was significantly higher for project households than for control households. The quantity sold of non-

<sup>7</sup> Household resilience can be and will be measured by using the household's ability to recover from shocks. This measure is still under construction.

project commodities was not different between project and control households. This indicates that the intervention contributed to significantly higher sales of project commodities at lower prices.

This observation is consistent with our hypothesis that the project leads to increased agricultural revenue through higher sales at stable prices. To demonstrate this, we drew a supply curve for project and non-project commodities. As hypothesized in figure 3, the supply curve for project commodities shifted rightward compared to the supply curve for non-project commodities (figure 5). This confirms that the intervention served as a supply curve shifter, which eventually brought down the equilibrium prices for a much higher quantity of sales.

**Figure 5.** Supply curves for commodities supported by the project



## 5. Results

In this section, we provide the estimated project impacts on household income for the full sample and various sub-samples, including female-headed and minority households. Next, we explore potential mechanisms for the positive impacts on income by estimating the project impacts on output prices and sale volumes. Finally, we assess the practical significance of the project-led income growth on food security, dietary diversity and household resilience.

### 5.1. Econometric results

Table 5 presents the project impacts on total annual per adult equivalent income. Results are presented for the full sample as well as for female-headed and minority households. In each case, results from both OLS and IPWRA estimators are available. The project helped increase per adult equivalent income (or household income for that matter) regardless of household socio-economic status. Overall, the project increased total household income by 33 per cent, but the increase is smaller for minority households (23 per cent) and female-headed households (19 per cent).<sup>8</sup> In absolute terms, annual per adult equivalent income for project households is Rs. 6,946 (US\$58) higher than control households. The estimated increase in income exceeds the project goal of increasing income by 30 per cent.

<sup>8</sup> We also ran alternative regressions by adding the interaction term for project and female-headed households, and for project and minority households in the estimating model. Results are qualitative similar compared to the results from the sub-sample analysis.

We also calculated net income (total income, crop income and livestock income) by subtracting the total cost from the gross income. Crop production cost was a sum of the average cost for fertilizers, pesticides, seeds and hired labour. Livestock production cost was the sum of the average cost for vaccination and veterinary services, fodder and feed, reproduction, shelter and other equipment. As expected, the impacts on the net incomes are qualitatively similar to the impacts on gross income; the magnitudes of the impacts on net incomes are slightly smaller. We prefer to report the impact estimates for the gross income over the net income because the cost information is likely subject to more measurement errors.

Coefficient estimates on control variables are as expected. Per adult equivalent income is positively correlated with the household head's age, marital status and education level, but it is negatively correlated with female headship, household size and dependency ratio. Among other covariates, per adult equivalent income is also positively correlated with household literacy rate, land size, share of female household members, number of rooms in the dwelling and other improved dwelling characteristics, and access to irrigation.

**Table 5.** Project impacts on income

Income (US\$ per capita/year)	(1) Full sample		(2) Minority households		(3) Female-headed households	
	OLS	IPWRA	OLS	IPWRA	OLS	IPWRA
Log (Total income)	0.34*** (0.04)	0.33*** (0.04)	0.25*** (0.08)	0.23*** (0.08)	0.20*** (0.08)	0.19** (0.08)
Log (Agricultural income)	0.53*** (0.05)	0.51*** (0.05)	0.62*** (0.09)	0.61*** (0.09)	0.43*** (0.10)	0.42*** (0.10)
Log (Crop income)	0.47** (0.05)	0.47*** (0.05)	0.56*** (0.09)	0.56*** (0.09)	0.37*** (0.10)	0.37*** (0.10)
Log (Livestock income)	0.47*** (0.08)	0.44*** (0.08)	0.51*** (0.15)	0.49*** (0.16)	0.22 (0.16)	0.19 (0.16)
Log (Non-agricultural income)	-0.12 (0.09)	-0.14 (0.09)	-0.29* (0.17)	-0.29 (0.18)	-0.22 (0.16)	-0.21 (0.16)
Log (Remittance transfers)	-0.20*** (0.08)	-0.19** (0.08)	-0.10 (0.15)	-0.12 (0.15)	-0.07 (0.19)	-0.05 (0.19)
<b>No. of obs.</b>	<b>2,710</b>		<b>702</b>		<b>721</b>	

*Notes:* Each coefficient estimate in this table comes from a separate individual regression equation. Altogether, there are 36 coefficient estimates from 36 different regressions. For OLS, point estimates on control covariates are available but they are suspended for brevity. Level of significance \*\*\* p<0.01; \*\* p<0.05; and \* p<0.1. Robust standard errors, clustered at the household level, are in parentheses. Control variables include age, school attendance, schooling years, sex and marriage status of household head; household size; share of female household members; dependency ratio; literacy rate within household; landholding size; ethnic minority status; housing index; altitude; distance to market; and access to irrigation.

Specifically, the project increases agricultural income by 51 per cent, crop income by 47 per cent and livestock income by 44 per cent. These increases in agricultural incomes are greater in minority households and smaller in female-headed households than the overall impacts.<sup>9</sup> Results clearly indicate that the growth in household income primarily came from growth in crop and livestock incomes. The project has negative impacts on non-agricultural incomes – project households had a 14 per cent reduction in non-agricultural incomes, but the point estimate is not statistically significant. Interestingly, project households saw a significant decrease in remittance

<sup>9</sup> Agricultural income is the sum of crop income and livestock income. The sum of the changes in crop and livestock incomes is greater than the change in agricultural income because these incomes are log transformed, and  $\Delta \log(x + y) \neq \Delta \log(x) + \Delta \log(y)$ .

flow compared with control households (a decrease of 19 per cent). The increase in agricultural income accompanied by a decrease in remittance income implies that perhaps the intervention was effective in deterring migration and promoting agricultural production at the same time.

## 5.2. Mechanism behind income growth – prices

The results in table 5 indicate that the intervention had a large significant impact on household income, primarily via increased agricultural income. This part of the analysis unpacks the mechanism behind the growth in income. Results in table 6 indicate that the growth in income largely came from increased sale volumes at slightly lower market prices. 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 test that. An increase in prices in the beginning might have led to an increase in agricultural supply, which eventually reduced the prices but producers were able to sell more. Therefore, the growth in income observed in later years probably came through high sale volumes at lower prices, providing evidence of economy of scale.

**Table 6.** Impacts on output prices and sales

Outcome variables	(1) Full sample		(2) Minority households		(3) Female-headed households	
	OLS	IPWRA	OLS	IPWRA	OLS	IPWRA
<b>A: Prices</b>						
Price index: Project commodities	-0.09*** (0.03)	-0.09** (0.03)	-0.12** (0.06)	-0.11** (0.06)	-0.08 (0.07)	-0.07 (0.06)
Price index: Non-project commodities	0.05** (0.02)	0.05** (0.02)	-0.02 (0.05)	-0.02 (0.05)	0.12** (0.06)	0.12** (0.06)
<b>B: Volume of sales</b>						
Sales index: Project commodities	0.38*** (0.06)	0.36*** (0.05)	0.34*** (0.10)	0.34*** (0.10)	0.14* (0.08)	0.14* (0.07)
Sales index: Non-project commodities	0.32 (0.26)	0.26 (0.25)	0.92 (0.78)	0.55 (0.88)	0.24 (0.60)	0.03 (0.06)
<b>No. of obs.</b>	<b>2,710</b>		<b>702</b>		<b>721</b>	

*Notes:* Each coefficient estimate in this table comes from a separate individual regression equation. For OLS, point estimates on control covariates are available but they are suspended for brevity. Level of significance \*\*\* p<0.01; \*\* p<0.05; and \* p<0.1. Robust standard errors are in parentheses. Control variables include age, school attendance, schooling years, sex and marriage status of household head; household size; share of female household members; dependency ratio; literacy rate within household; landholding size; ethnic minority status; housing index; altitude; distance to market; and access to irrigation.

Table 6 presents project impacts on prices of project and non-project commodities. The first panel presents project impacts on the price index of project commodities – apple, ginger, turmeric, *timur*, vegetables and meat goats. The intervention has reduced the unit prices of the project commodities by about 0.09 units (a reduction of 9 per cent). Since the dependent variable is an aggregated index, it is tricky to make sense of the magnitude of the impact. Appendix table A1 presents project impacts on individual commodity prices. Controlling for household characteristics, housing qualities and demographic characteristics, the intervention reduced meat goat prices by Rs. 615 (US\$5) per one goat and *timur* prices by Rs. 105 (US\$0.9) per kg. The intervention also reduced prices for vegetables, specifically turmeric, potato and tomato.

The second panel in table 6 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 price index for non-project commodities by about 0.05 units (an increase of 5 per cent). Looking at the individual commodities presented in appendix table A1, prices of cereals (rice, wheat, maize) went up by about Rs. 5 per kg, and eggs by Rs. 5 per dozen. Prices went up for chickens and milk as well, but these increases were not statistically significant.

Taken together, results in table 6 indicate that the increase in agricultural income did not come via higher prices producers received. The project did increase the prices for some non-project commodities, but the increase is not enough to offset the decrease in prices of project commodities. If prices were the primary avenue to income growth, then we would have seen a decrease in household income. Further, we test our second hypothesis that the increase in income came via economies of scale in agricultural sales. A possible explanation is that producers are operating by a small margin but they are now able to make more by selling more. Results confirm our hypothesis. The project contributed to an increase in volumes of sales of project commodities. Compared to the control households, the aggregated sale volume index was 0.38 units greater for project households (an increase of 40 per cent). The volume of sales of non-project commodities was no different between project and control households. Additional results (unreported here, but available upon request) indicate that treatment households are significantly more likely to cultivate at least one of the project-focused commodities than control households. The share of cultivated land areas allocated to project commodities are significantly higher for project households than for the control group.

We unpack impacts on the sale volume index into individual commodities in appendix table A2. Results show that 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 are also higher among project commodities, but the differences are not statistically significant.

Results in table 6 collectively indicate that the project-led growth in income primarily came from an increase in sale volumes. The project contributed to lower prices of project commodities, which in turn can have further positive effects on increased income through price effects. In exploring the potential mechanisms behind the positive impacts on household income, we tested whether the improvement in market access (or reduction in transaction cost) had a role. Using distance to the nearest agricultural market and selling centre as a proxy for market access, we find that project households have had better access to markets compared to control households (results not presented here). Project households were 5 per cent more likely to sell their produce to a trader during the wet season and 6 per cent more likely to sell to a trader during the dry season than control households.

### **5.3. Practical significance of income growth**

In this section, we explore whether the positive impacts on income have translated into improved food security, dietary diversity and household resilience. Results in table 7 show that project households reported to have consumed more food items compared with control households. A 10 per cent increase in household income increases the dietary diversity of project households by 1.2 food groups. Therefore, a 33 per cent increase in household income means that project households would consume approximately four more food groups than control households, holding all else constant. The intervention itself also has a positive impact on household dietary diversity, but the negative and significant coefficient on the interaction term reveals that the project's direct impact on food security subsides as income grows more. This indicates that the project's impacts on dietary diversity mostly emerges through the increase in income.

Similar results hold for the household FCS and FIES indicators. A 1 per cent increase in income increases the share of households with acceptable food consumption status by 4 per cent and reduces household food insecurity by 9 per cent. These findings are consistent with evidence in the literature on the linkage between increased agricultural income and food security (Jodlowski et al., 2016; Upton, Cissé and Barrett, 2016; Kafle, Winter-Nelson and Goldsmith, 2016). The last row in table 7 presents the relationship between household income and resilience. Resilience is measured with a household asset index. The intervention increased household resilience both directly, perhaps through training and capacity building activities, and through income increase.



**Table 7.** Practical significance of the project impacts

Outcome variables	(1)		(2)		(3)	
	Full sample		Minority households		Female-headed households	
	OLS	IPWRA	OLS	IPWRA	OLS	IPWRA
<b>Livelihood outcomes</b>						
Household is food insecure (1=Yes, 0=No)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09** (0.04)	-0.08** (0.04)	-0.06 (0.04)	-0.06 (0.04)
Food consumption score <sup>a</sup> (=1 if acceptable)	0.04*** (0.02)	0.04** (0.02)	0.05 (0.03)	0.05 (0.03)	0.05* (0.03)	0.06* (0.03)
Household dietary diversity (out of 13 food groups)	0.01** (0.01)	0.01* (0.01)	0.01 (0.02)	0.01 (0.02)	0.004 (0.01)	0.002 (0.01)
Household asset index	0.10*** (0.03)	0.09*** (0.03)	0.002 (0.06)	-0.0004 (0.06)	0.004 (0.05)	0.03 (0.05)
<b>No. of obs.</b>	<b>2,710</b>		<b>702</b>		<b>721</b>	

*Notes:* Each coefficient estimate in this table comes from a separate individual regression equation. For OLS, point estimates on control covariates are available but they are suspended for brevity. Level of significance \*\*\* p<0.01; \*\* p<0.05; and \* p<0.1. Robust standard errors are in parentheses. Control variables include age, school attendance, schooling years, sex, and marriage status of household head; household size; share of female household members; dependency ratio; literacy rate within household; landholding size; ethnic minority status; housing index; altitude; distance to market; and access to irrigation.

<sup>a</sup> In Nepal, a food consumption score of 42 or higher is considered acceptable food consumption.

It is encouraging to report that the income increase resulting from the intervention is translated into practically significant outcomes such as an increase in food security and household resilience. Qualitative information collected from our fieldwork could provide some explanations for the encouraging econometric results. First, the project design was concentrated on a small number of value chains that were interlinked. The focused project design led to project activities that were customized and that catered to the specific local needs of small-scale producers in the target group. Second, the project worked with small and cohesive groups of producers (25 to 40 members in a PO). The reasonably small size of POs allowed 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 regional and national 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 producers with access to technical help and credit, as well as a sustained link to agricultural markets and traders, which are key to stable and efficient agricultural production systems.

## 6. Conclusion

This analysis studied the impacts of strengthened linkages between small-scale producers and markets within the context of the value chain development project. The intervention supported by the HVAP targeted small-scale producers across seven districts in the hilly and mountainous region in Western Nepal. It 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 small-scale producers 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 estimated the impacts of the intervention on household income using OLS and IPWRA – a non-parametric estimator known for its doubly robust properties. Our findings showed a strong positive impact on household income, which primarily emerged from growth in agricultural revenue. Building on this finding, our analysis unpacked the potential mechanisms behind the positive impacts on income growth and its practical significance.

Results showed that the project helped raise per adult equivalent income (in the 12 months preceding the time of data collection) by about 33 per cent. At the prevailing market exchange rate, this increase was equivalent to approximately US\$58 per person per year. Further analysis showed the increase in income was smaller among female-headed and minority households. For all groups, though, the increase in income was driven primarily by increases in crop income and livestock income, which increased by 47 per cent and 44 per cent, respectively.

We explored the mechanisms behind income growth by estimating the relationship between the intervention, output prices and volume of sales. We discovered that income growth primarily came through economies of scale in agricultural production and sales. The intervention led to a decrease in output prices for project-supported commodities but, at the same time, there was a significant increase in the volume of sales. Our hypothesis of agricultural income (revenue) growth via higher agricultural prices was not substantiated, but our second hypothesis that agricultural revenue increases due to an increase in sale volume was confirmed. This indicates that the intervention might have led to income growth by creating more market demand for agricultural produce by lowering or removing market frictions or transaction costs. The increase in market demand shifted the supply, thereby increasing the volume of sales at lower but stable prices.

We also investigated the practical significance of income growth by examining the relationship between project-led income growth and household dietary diversity, food security and resilience. The intervention increased household dietary diversity, reduced food insecurity and improved household resilience. These impacts were primarily mediated via project-led income growth. In addition, the intervention might have increased food security by reducing agricultural prices in project areas, but we have no way of testing that.

The findings have important policy implications. First, our results imply that interventions that support market activities and link different actors of the agricultural value chain together can increase income. The increase in income is driven by positive impacts on agricultural production and farm revenue. Significant increases in income among minority and female-headed households demonstrate the importance of an inclusive value chain approach. Second, such policies can improve food security and nutrition, and improve household resilience in the long run. Third, the results tell an important story about the potential mechanism behind the income growth. Regarding the mechanism, our findings are in contrast to previous findings that market interventions raise farm prices (Goyal, 2010; Mu and van de Walle, 2011). Linking small producers with regional and national traders can reduce the transaction cost, but it also reduces the farm prices by shifting the supply curve outwards. The increase in supply and stable market demand increases agricultural revenue, which increases household income.

Following the lessons learned and positive results of the HVAP, the Government of Nepal along with its development partners have scaled up the HVAP in the Agricultural Sector Development Programme (ASDP). ASDP is operating in six districts covered by the HVAP, as well as expanding to four new districts in higher mountain areas (IFAD, 2017). Since 2018, ASDP has been operating to increase economic opportunities for small-scale producers, improve community infrastructures and services, and foster social inclusion by using a market-driven approach.

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## 8. Appendix

### Sample size determination

Power calculation was used to determine the sample size required for the study. The sample size was calculated maintaining 80 per cent statistical power and 5 per cent type I error. Since the larger impact evaluation exercise had multiple outcomes of interest, the minimum required sample size was calculated for each of the outcome variables. Since the sample size varied by outcome variable, the largest number was chosen as the sample size for the study. This is a common practice in the literature (Winters, Salazar and Maffioli 2010; World Bank 2007). One advantage of this approach over others is that it uses information from the pre-existing data as well as the expected minimum change in the outcome variables in determining sample size. Equation 4 provides the formula:

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

where  $\sigma$  is the standard deviation of the baseline outcome variable,  $Z_\alpha$  is the critical value of the confidence interval,  $Z_\beta$  is the critical value of the statistical power,  $D$  is the minimum expected change in the baseline outcome variable,  $\rho$  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 the National Population and Housing Census 2011 (Central Bureau of Statistics, 2011) and the minimum expected change ( $D$ ) for each outcome variable was calculated based on existing literature and the project's long-run targets. Among other parameters, we assumed the analysis will have 80 per cent statistical power and 95 per cent confidence level so  $Z_\alpha = 1.96$  and  $Z_\beta = 1.28$ . 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 4 for different outcome variables. A sample size of 3,000 households would be able to detect the minimum expected change on key outcomes variables: a 4 per cent decrease in poverty, 10 per cent increase in agricultural productivity and 20 per cent increase in meat goat production.

**Table A1.** Project impacts on market prices faced by the farmers

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

Notes: Level of significance \*\*\* p<0.01; \*\* p<0.05; and \* p<0.1. Robust standard errors, clustered at the household level, are in parentheses. OLS denotes ordinary least squares, and IPWRA denotes inverse probability weighted regression adjustment.

Controls include household size; number of children, number of youths, 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 landholding size.

**Table A2.** Project impacts on volume of sales for project and non-project commodities

Sale volumes (kg)	(1)	(2)	(3)	N
	OLS	IPWRA	Control mean	Households
<i>Project commodities</i>				
Apple	715.5*** (204.1)	628.58*** (188.22)	637.02 (79.50)	200
Ginger	320.2* (166.0)	454.77*** (140.93)	262.78 (33.82)	102
Turmeric	185.2** (82.25)	661.92*** (129.66)	176.75 (37.76)	62
Timur	-2.10 (31.45)	-211.19** (93.28)	48.54 (19.82)	79
Beans	83.99 (59.86)	112.19** (51.42)	129.02 (19.98)	151
Potato	699.8*** (172.9)	680.45*** (130.29)	579.70 (100.15)	331
Tomato	396.9** (183.4)	532.33*** (120.29)	456.67 (107.84)	220
Cabbage	-206.5 (241.6)	677.10** (299.96)	677.96 (169.93)	163
Meat goats (count)	0.82*** (0.17)	0.78*** (0.17)	1.82 (0.10)	2039
<i>Non-project commodities</i>				
Rice	359.4 (261.7)	-128.0 (213.49)	753.23 (170.26)	42
Maize	31.54 (39.69)	30.89 (37.37)	296.49 (26.34)	189
Wheat	141.8 (173.5)	173.47 (120.31)	399.23 (114.84)	50
Eggs (dozen)	-52.06 (31.63)	-42.96 (28.50)	104.28 (32.75)	562
Milk (litre)	-24.45 (26.39)	-17.12 (24.65)	86.96 (25.19)	562
Chicken (count)	6.26 (3.96)	8.18* (4.21)	11.01 (2.49)	1056
Controls	Yes	Yes		




Notes: Level of significance \*\*\* p<0.01; \*\* p<0.05; and \* p<0.1. Robust standard errors, clustered at the household level, are in parentheses. OLS denotes ordinary least squares, and IPWRA denotes inverse probability weighted regression adjustment.

Controls include household size; number of children, number of youths, 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 landholding size.





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