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ARTICLE

Value chain development of bay leaf in Nepal: an impact assessment

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ABSTRACT
We assessed an impact of bay leaf value chain intervention programme on household welfare in mountain agroforestry context. We used primary survey data from project and comparison villages and propensity score matching for creating a valid counterfactual. Results indicate that households in the project villages planted 75 per cent more bay leaf trees, produced 170 per cent more bay leaves and sold more quality products at higher prices than households in comparison villages; per-capita household income increased by NPR 5000–7300, share of bay leaf income in total household income increased by 8–10 per cent and level of poverty declined by 6–8 per cent. Households with female respondents benefited more in some aspects but not so in others, especially in enrolling children in school.

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Bay leaf; household welfare; livelihoods; propensity score matching; value chain

Introduction

Nepal is a mountainous country with rugged terrain; hills and mountains occupy more than three-quarters of the surface area. The majority of upland farmers have small landholdings and depend on subsistence rain-fed agriculture with multiple crops, agroforestry and livestock (Niroula and Thapa 2007; Altieri 2002; Barbier 2010). Their livelihoods also depend substantially on the collection and sale of a range of non-timber forest products (NTFPs) (Rasul, Karki, and Sah 2008). Rural farmers generally have poor market access as a result of a lack of essential knowledge, lack of infrastructure such as roads for transportation and poor communications (Jacoby 2000). In particular, they lack an established market for agroforestry products, even though these products could be a significant source of additional income.

Often, middlemen receive substantial profit margins, while the poor and unorganised farmers receive only low returns (Dewees and Scherr 1996; Marshall, Newton, and Schreckenberg 2003), and the farmers are often harassed and cheated by traders and middlemen using their market power (Pokhrel and Thapa 2007). Furthermore, as most farmers produce on a small scale and sell any surplus locally, they tend not to have any grading or other value addition techniques (Tiwari et al. 2008).

Taken together, the poor market access and low value addition discourage smallholder farmers from commercialising their agricultural and agroforestry practices. For smallholder rural farmers in the Himalayan region, securing an appropriate value for their NTFPs can be crucial for livelihoods (Russell and Franzel 2004; Bacon 2005; Barham and Chitemi 2009; Mitchell and Coles 2011).

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Supplemental data for this article can be accessed here

Increasing the productivity of agroforestry and improving market access with better product quality can significantly enhance economic opportunities in the rural context (Leakey 2001; Sunderlin et al. 2005; Leakey et al. 2005; Mahapatra, Albers, and Robinson 2005; Rasul, Karki, and Sah 2008; Timko, Waeber, and Kozak 2010).

The value chain (VC) approach emphasises a range of activities and market linkages to help farmers enhance the quality of products and bring them to market at a higher price, thus increasing household income (Gold, Godsey, and Josiah 2004; Te Velde et al. 2006; Choudhary, Kunwar, and Rasul 2015; Mateows 2015). These activities can be used to add value at every step to agroforestry products by systematically improving product quality through grading, processing, packing and storing, as well as connecting farmers more directly to the market (Kaplinsky and Morris 2001; Kirimi et al. 2011; Bolwig et al. 2011; Mohan 2016). Developing a strategic marketing approach through VC development helps farmers to obtain a fair price for their products (Gold, Godsey, and Josiah 2004; Ortmann and King 2007). In many developing countries, VC interventions have enabled farmers to add value to agroforestry products, increased market price, established regulated intermediaries and reduced intermediaries' profit margin. Collective action has also increased farmers' self-motivation and improved market access for smallholder producers of agroforestry products (Islam 2014; Gyau et al. 2014; Choudhary et al. 2014).

Notwithstanding the growing emphasis on using VC approaches and improving farmer–market linkages, there are few published studies evaluating the potential of VC approaches to increase farmers' income in mountain areas, where access and connectivity to markets are poor. Following a detailed review of the literature on VCs, Humphrey and Navas-Alemán (2010, 29) argued that 'there is not enough evidence on poverty alleviation impacts from these interventions [value chain] to claim that they are effective or efficient in helping the poor'. The majority of published studies for the Himalayan region focus on initial design, implementation and uptake, but there is little empirical evidence on the extent to which projects have helped increase household welfare or reduced poverty.

In this paper, we evaluate the effect on household welfare 5 years post-completion of a VC intervention for production and marketing of Indian bay leaf (*Cinnamomum tamala*) in a mid-hills district in Nepal. The study used cross-sectional household survey data collected in 2014 from project and comparison villages 5 years after completion of the intervention in 2009 to examine the extent to which it had contributed to increasing income and enhancing the well-being of farmers.

The paper is organised as follows: The next section discusses the methodology used for the analysis including the study context and value chain pathways showing the linkages among the intervention, outcome, outputs and the expected impacts. Section following this section presents the main results and robustness check with discussion. The final section concludes highlighting the main contribution and caveats. Supplementary materials are available from journal's website.

Methodology

The study area

The study area is situated in the mid-hills of Udayapur district in eastern Nepal. The total population of the district in 2011 was 66,557 (NPHC 2011), in 44 village development committee units and one municipality. Most of the villages are located in remote areas without road access. The main economic and livelihood activities are farming, livestock, agroforestry and small business, with bay leaf farming as a supplementary source income to some households.

The VC intervention project

The bay leaf VC intervention project was carried out from January 2007 to December 2009. Some of the farmers in the study area had already been engaged in small-scale farming and trading of NTFPs, particularly bay leaf, for several years. However, they had little knowledge about sustainable harvesting, storing, grading, packing or marketing, and there was no cooperative or collection centre in the area. Farmers were bringing their low-quality bay leaf products to distant roadside collection points to sell at a low price with less than 10 per cent gross margin (Choudhary et al. 2014). The lack of market access and low returns meant that the scale of production was small (International Centre for Integrated Mountain Development [ICIMOD] 2011).

The VC intervention programme was implemented by the ICIMOD, a regional intergovernmental organisation working in the Hindu Kush Himalayan region, in coordination with the Federation of Community Forestry Users, Nepal (FECOFUN), the umbrella organisation for community forest user groups. FECOFUN played an important role in social mobilisation, identifying stakeholders and bay leaf farmers and implementation of advocacy activities. The programme was a pilot designed to increase understanding of how to integrate poor mountain people into a VC and increase the economic benefits for targeted farmers.

The present study, carried out 5 years post-intervention in 2014, was designed to evaluate the long-term impact and sustainability of the VC approach used in the intervention phase (2007–2009). The original intervention is described in detail in ICIMOD (2011) and Choudhary et al. (2014) and summarised here to facilitate understanding.

The process of VC development 'describes the full range of activities which are required to bring a product or service from conception, through the different phases of production (involving a combination of physical transformation and the input of various producer services), delivery to final consumers, and final disposal after use' (Kaplinsky and Morris 2001). The intervention started with social mobilisation, with particular attention paid to women, to inform farmers about the potential benefits of the programme. Five villages were selected for the VC activities based on several criteria such as upland farmers, remoteness, poverty status, lack of marketing facilities, farmers already collecting and selling bay leaf, the possibility of improving bay leaf quality through intervention and farmers' interest in the project. The farmers participated in targeted training on preparing bay leaf tree nurseries and harvesting, drying, grading, packing, and storing bay leaves in order to improve product quality. They also formed a farmers' cooperative to improve coordination and communication among the bay leaf producers and help establish direct contact with traders and markets, cutting out the role of unregulated intermediaries and increasing farmers' profit margins (ICIMOD 2011). The expected impact pathways of the VC intervention programme are shown in detail in Figure 1.

Village-level master trainers trained by the intervention programme facilitated and conducted the training events. Bay leaf collection centres were established in the villages where farmers were able to store graded bay leaf prior to marketing. As a part of the intervention, the project prepared guidelines in the local language on improving product quality and post-harvest handling of bay leaf and introduced a buy-back guarantee scheme in which the cooperative agreed to buy-back unsold bay leaf at a fixed price from the farmers to reduce the marketing risk. The project emphasised the involvement of women farmers at every step in the process. The intervention was intended to develop leadership, particularly among women farmers, with improved communication skills and coordination that would help strengthening the relationship between produces and traders.

Empirical approach

The intervention villages for VC intervention were selected based on several criteria such as upland farmers, remoteness, poverty status, possibility of improving bay leaf product quality through intervention and lack of marketing facilities. As the intervention programme was intended to improve the bay leaf product quality so that the farmers could receive better price for their product in the targeted villages, the selection criteria introduced sample selection biases.

To address the sample selection bias, we used propensity score matching (PSM) method. The PSM method minimises selection bias by matching observations between treatment and control groups using estimated propensity scores based on observed characteristics (covariates) of the

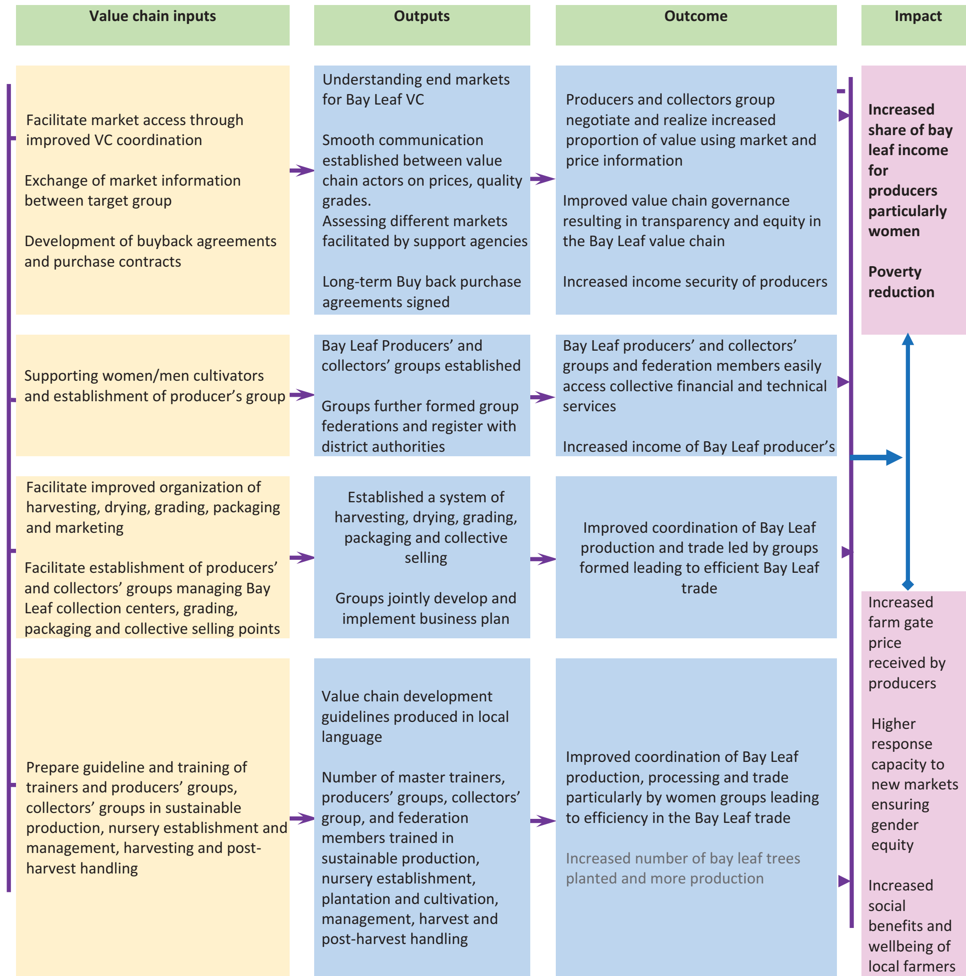

Figure 1. Impact pathways of bay leaf value chain intervention.

respondents (Rosenbaum and Rubin 1983; Heckman and Robb 1985). Studies suggest that in the absence of randomisation, PSM can be used as a way of achieving comparable results to experimental methods (Heckman, Ichimura, and Todd 1997; Smith and Todd 2005).

The PSM method estimates the average treatment effect (ATE) of an intervention programme in three steps: (1) estimation of the propensity scores of treatment and control observations based on observed characteristics (X_i); (2) matching the observations from control and treatment groups based on the propensity scores; and (3) estimating ATEs non-parametrically as the mean difference of the outcome variable between matched pairs of observations from the treatment (Y^1) and the control or comparison (Y^0) groups. More formally, the 'ATE' of an intervention programme on the entire population is given by

$$\mathrm{ATE} = E\left(Y^1 - Y^0\right) \tag{1}$$

In practice, we were only interested in the effect of the intervention programme on the treated population. The average effect of the treatment on the treated population (ATET) is given by

$$\text{ATET} = E\left(Y^1 \; - \; Y^0 | T = 1\right) \tag{2}$$

where $T = 1$ refers to the treatment. Equation (2) can also be written as

$$\text{ATET} = E\left(Y^1 | T = 1\right) \; - E\left(Y^0 | T = 1\right) \tag{3}$$

However, we cannot observe the second term in Equation (3) which refers to the average outcome in the treated group had they not received the treatment. Instead, we observe $\mathrm{E}\left(\mathrm{Y}^0 | \mathrm{T} = 0\right)$, which is the average outcome in the control group in the absence of treatment. If we replace the unobservable term $\mathrm{E}\left(\mathrm{Y}^0 | \mathrm{T} = 1\right)$ in Equation (3) with an observable term $\mathrm{E}\left(\mathrm{Y}^0 | \mathrm{T} = 0\right)$, we get

$$\delta \; = E\left(Y^1 | T = 1\right) \; - E\left(Y^0 | T = 0\right) \tag{4}$$

The difference between Equation (3) and Equation (4) is the selection bias that we would get by using Equation (4) instead of Equation (3) in an impact evaluation using observational data. In a random assignment of a treatment, the bias is expected to be zero, on average.

Data and variables

The overall aim of the study was to assess the impacts of the VC intervention carried out from 2007 to 2009, using cross-sectional data collected in 2014. A three-pronged approach was used to collect data: a household survey, focus group discussions with farmers and key informant interviews with office bearers in the relevant offices in Udayapur district and other stakeholders. The information from the focus group discussions and interviews was used in designing the household survey.

For the household survey, a random sample of 162 of the 280 farm households who had participated in the intervention was selected in the project villages based on proportion of population size. For comparison, a random sample of 100 farm households was selected from the 328 households in total in four neighbouring villages with similar socio-economic and geographic characteristics (25 in each village). The usable sample size is slightly smaller (157 for intervention and 93 for control household) due to missing values for some of the variables. The interview was conducted in local language. The interviewees were either the head of household (generally male) or another responsible household member (usually female). The data collected included information on the household characteristics as well as information related to bay leaf production and sales. For some of the variables, the information was collected for five-year span (2009–2013), and for other variables, information for the survey year (2014) was collected. Table 1 displays the variables in these two groups.

The number of bay leaf trees planted and production of bay leaf were recorded for each year in the whole five-year period (2009–2013) using the recall method. We believe that the recall bias for these variables is low as farmers are likely to remember how many new trees they had planted each year, how they were growing and how much bay leaf they had produced (sold) in a given year. Studies also suggest very little evidence of large recall bias in agriculture affecting data quality (Beegle, Carletto, and Himelein 2012). As rural famers have limited sources of cash income and virtually no surplus of crops, they are likely to remember these variables fairly accurately. During the household survey, the survey team visited some of the plantation areas and verified the farmers claim in order to avoid social desirability bias.

The data for the survey year included variables such as household total income; income from bay leaf; skills learned from the programme for improving bay leaf production and marketing; subjective information on household perceptions of improvement in bay leaf farming skills such as planting, harvesting, grading, drying, packing and storing; and the relationship with bay leaf traders after the intervention.

The number of bay leaf trees planted and weight of bay leaves produced were used as indicators of sustainability of the intervention. Bay leaf trees start producing sufficient leaves for

Table 1. Definition of major variables and mean and standard deviation of comparison and treatment groups.

Variables	Definition of variables	Comparison group Mean	Comparison group SD	Treatment group Mean	Treatment group SD
Socio-economic characteristics		[N1 = 93]		[N2 = 157]	
Female	If respondent is female	0.56	0.50	0.35	0.48
Household size	Total household members	6.22	2.31	6.31	2.44
Janajati	If ethnicity is 'Janajati'	0.87	0.34	0.99	0.08
Respondent age	Respondent age (years)	42.65	14.42	41.81	14.28
Girls	If child gender is female	0.57	0.50	0.36	0.48
Children age	Children above 4 years	10.43	3.08	10.50	3.19
No education	If respondent is illiterate	0.55	0.50	0.35	0.48
Primary school	If respondent has primary schooling	0.32	0.47	0.45	0.50
Middle school	If respondent has middle school education	0.06	0.25	0.10	0.30
High school and above	If respondent has high school education	0.06	0.25	0.10	0.29
Farming own land	If household is farming own land	0.76	0.43	0.54	0.50
Livestock farmer	If occupation is livestock	0.03	0.18	0.03	0.16
Other occupation	Other occupations	0.08	0.27	0.03	0.16
Outcome variables (for survey year)					
Improved grading	Grading skill improved	0.24	0.43	0.91	0.28
Improved access market	Access to market improved	0.01	0.12	0.84	0.37
Use Bay leaf income on child education	Bay leaf income expenses on child education	0.11	0.11	0.23	0.23
Share of bay leaf income	Share of bay leaf income	0.29	0.46	0.31	0.46
Use Bay leaf income for household-goods	Bay leaf income expenses on household goods and appliance	0.27	0.45	0.33	0.47
Poverty status of household	Percentage of households below poverty line	0.46	0.50	0.38	0.49
Current school enrolment	If child is currently going school	0.96	0.19	0.95	0.22
Bay leaf farming as secondary occupation	Adopting bay leaf farming as a secondary occupation	0.33	0.47	0.31	0.46
Per-capita income	Per-capita income in 10 thousand	1.83	1.92	0.31	2.44
Outcome variables from 5-year recall		Comparison [N3 = 465]		Treatment [N4 = 785]	
Number of bay leaf trees planted	Total number of bay leaf trees planted	33.57	107.66	66.42	240.01
Total production of bay leaf	Total amount of bay leaf production in kilogram	202.40	301.89	569.70	1857.00

Total usable number of observations is 250 as some 10 observations are dropped due to incomplete information. Recall information for 5 years of number of bay leaf trees planted and production of bay leaf $N = 1250$. The distribution of sample size is as indicated in the table.
Source: Field survey 2014.

harvesting 5 years after plantation and remain productive for more than 25 years. Thus, the number of trees planted was mainly an indicator of future potential, and the quantity produced an indicator of how well producers were managing the existing trees. Success in adding value to bay leaf products was measured using two outcomes: improved grading skills and improved access to market. We also examined whether the intervention had prompted more households to start bay leaf farming and/or production as a secondary occupation. Improvement in grading skills, knowledge and access to markets was measured using survey questions in which respondents were asked to compare the current state of these outcomes with past practices before intervention.

Livelihood improvement was assessed by measuring various indicators of household welfare. The major variables were household income, assessed in per-capita basis, and share of bay leaf income in total income. We also looked at the impact on household poverty and changes in household expenditure on consumer goods and child schooling, as well as any change in school enrolment – as an indicator of possible impact on children's future earning potential (Becker 1962).

Table 1 shows the means and standard deviations of household characteristics and outcome variables for project and comparison villages. The household-level demographic variables were reasonably similar in project and comparison villages, providing some confidence in their comparability. Household size, respondent's age, children's age and school enrolment were not significantly different. Differences in the socio-economic variables were expected as the intervention was intended to improve livelihoods, and the post-intervention survey would be expected to reflect changes brought about by the activities.

Figure 2 shows the average number of bay leaf trees planted by the households in each year of the five-year period between the intervention and the survey. The graph shows an increasing trend in planting bay leaf trees in both types of village, but with a much greater increase in the project villages, indicating that the intervention had some success in encouraging farmers to plant bay leaf trees.

Propensity score estimation

The main issue that we face while evaluating an impact of an intervention is that we never observe the actual counterfactual information. Without a proper counterfactual, we cannot attribute the difference in the outcomes between project and comparison households to the VC intervention programme alone as other confounding factors may also have played a role. In non-experimental setting, PSM method enables a counterfactual group to be created that provides information on what would have happened to the households in the project villages if there had been no VC intervention programme (Kelley, Ryan, and Gregersen 2008; Cavatassi et al. 2011; Wu et al. 2010; Getachew and Jaleta 2011).

While matching, we first used a logit model to predict the propensity scores (probability of intervention) for each household based on observable characteristics such as age, gender, education, ethnicity, interaction between gender and education and a higher-order term of the respondent's age. For reference purpose, the logit estimates are presented in supplementary materials (Table S7). The propensity scores were then used to match households from project and comparison villages to examine the impact of the intervention.

It is necessary to have a conditional independence and significant overlap or common support between the households from project and comparison sites with the given propensity scores in order to use PSM for impact evaluation (Caliendo and Kopeinig 2008). The overlap indicates that there are comparable households in both groups with similar observable characteristics. In our case, the estimated propensity scores ranged from 0.02 to 0.78 in the comparison villages and from 0.14 to 0.80 in the project villages, with a considerable overlap (common support) between households in the two groups of villages (Figure 3). Only 3 per cent of the households did not have common support. These 'off-support' observations could be dropped to improve matching

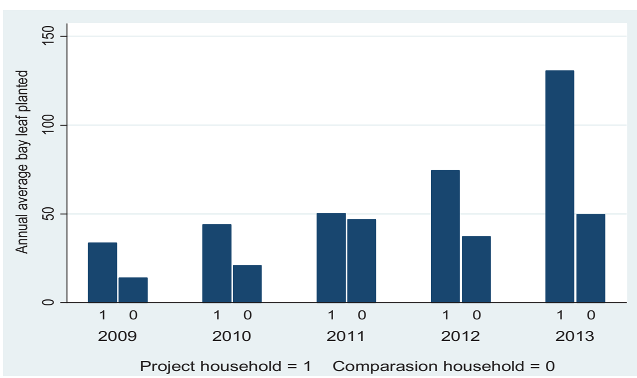

Figure 2. Average number of bay leaf trees planted in 2009–2013 (Household average).

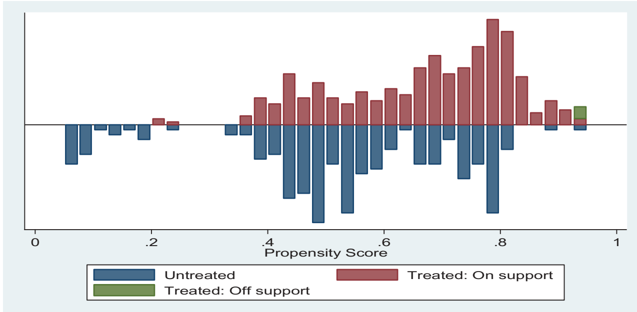

Figure 3. Estimated propensity scores and common support.

before estimating the impact of the intervention. Dropping 'off-support' observations means removing information related to households where there is no comparable household across the project and comparison village (Caliendo and Kopeinig 2008). The approach is akin to dealing with extreme outliers in statistical analysis.

One of the technical requirements for PSM is to satisfy the balancing test for covariates, with households in the intervention and comparison sites compared statistically based on observable characteristics (Lee 2013). Supplementary materials (Table S1) show the results of the balancing test for PSM (kernel), including the mean differences between the household characteristics in project and comparison villages, the percentage bias before and after matching and the reduction in percentage bias as a result of the matching.

After PSM, the average percentage bias was reduced from 17 per cent to less than 4 per cent. The individual bias was also reduced significantly for all covariates from a maximum of about 45 per cent to less than 6 per cent. The small size of the bias after matching indicates that the matching was successful in reducing selection bias while creating a valid counterfactual. Nevertheless, as matching is based on observables, a small possibility of unobservable heterogeneity between households remains. We also used an alternative matching method (Mahalanobis) to examine the sensitivity of the matching biases. Both matching methods (Kernel and Mahalanobis) provided similar results. The biases after Mahalanobis matching are shown graphically in supplementary materials (Figure S1). In all cases, we have used matching with replacement due to small sample (N = 250).

In addition to Kernel and Mahalanobis matching, we used treatment effect estimators with PSM, regression adjustment and inverse-probability-weighted regression adjustment methods in order to see how sensitive the results were with alternative estimators. In all cases, we estimated the effect of the VC intervention, that is, the average treatment effect on the treated (ATET). The ATET measures the size of the impact of VC intervention on the given outcome for the treatment sample. As a baseline model, we also estimated weighted least-squared (WLS) regression with the propensity scores used as weights since the WLS method also addresses selection bias in the case of non-randomly selected treatment and comparison groups (Khandker, Koolwal, and Samad 2010).

Results and discussion

Impact on bay leaf tree plantation and production

As a starting point, we discuss the average effect of the intervention programme on the treated sample (ATET) for the number of bay leaf trees planted and the amount of bay leaf production. The results (Table 2) indicate that, on average, households in the project villages planted 19–26 more bay leaf trees annually and produced 323–374 kg more bay leaves than households in the comparison villages. In

Table 2. Impact on planting and production of bay leaf.

	PSM		Treatment effect estimators			
	Kernel	Mahalanobis	PSM	RA	IPWRA	WLS
Variable	[1]	[2]	[3]	[4]	[5]	[6]
Number of bay leaf trees planted						
ATET	26.26**	25.45*	18.91*	24.87**	24.95**	21.43**
SE	(11.12)	(13.42)	(11.07)	(10.93)	(10.77)	(9.57)
Total production of bay leaf in kilogram						
ATET	335.45***	374.86***	330.35***	324.00***	322.72***	359.22***
SE	(73.99)	(75.07)	(68.76)	(67.68)	(67.80)	(70,43.50)

*, ** and *** indicate significant at 10 per cent, 5 per cent and 1 per cent levels, respectively.

ATET: average treatment effect in project villages; SE: standard error; PSM: propensity score matching; RA: regression adjustment; IPWRA: inverse-probability-weighted regression adjustment; WLS: weighted least-squared regression.

For models [3], [4] and [5], robust standard errors are reported. As the data were collected from nine clusters, usual clustered robust SE for smaller number of clustered is not recommended (Wooldridge 2003; Cameron and Miller 2015). N = 1250 for ATETs.

relative terms, bay leaf tree plantation increased by 75 per cent and bay leaf production increased by 170 per cent in the project villages as a result of the intervention. These effects were statistically significant and consistent across all the matching methods used for the analysis indicating that the intervention programme was successful in helping farmers to plant more bay leaf trees and produce more bay leaf, as indicated in the impact pathways diagram (Figure 1).

Since the survey was conducted 5 years after the intervention was completed, the increase in bay leaf tree plantation can be seen as an indicator of the sustainability of the intervention programme. Planting trees has probably been encouraged both by the availability of saplings from the bay leaf nurseries and by the increased profit margins. Our discussions with farmers indicated that both the low price and the difficulties in marketing had previously discouraged farmers from planting bay leaf trees. During the 2014 survey, we saw that the households in the project villages were planting bay leaf trees along terrace edges and on marginal farmland as a buffer to prevent soil erosion, indicating that planting of bay leaf trees complimented rather than replaced other agriculture.

Impact on product quality and marketing

The intervention also sought to help farmers add value to their bay leaf product through grading, to gain better market access and to adopt bay leaf farming as a secondary occupation. In the absence of actual information on product quality and grading, we used the household survey to record the perceived knowledge on grading and marketing. Table 3 shows the effect of the intervention on grading skills and knowledge, improved access to market and adoption of bay leaf farming as a secondary profession.

Results using the six different estimators indicated that households in the project villages were 72–74 per cent more likely to have improved knowledge and skills on grading bay leaf and 81–83 per cent more likely to have better access to the bay leaf market, with similar results for all matching methods (Table 3). Further, 3–10 per cent more households opted for bay leaf farming as a secondary occupation in the project villages than in the comparison villages. Taken together, the findings indicate that the effects of the intervention were significant and sizable. It increased the level of knowledge and skills on bay leaf farming and knowledge about and access to markets, which enabled households to produce and sell better-quality bay leaf. The product buy-back scheme and the training provided in planting, harvesting and processing bay leaf encouraged additional farmers to adopt bay leaf farming as a secondary occupation.

Table 3. Impact on value chain-related outcome variables.

	Propensity score matching		Treatment effects estimators			
	Kernel	Mahalanobis	PS Match	RA	IPWRA	WLS
Variable	[1]	[2]	[3]	[4]	[5]	[6]
Improved grading skill and knowledge						
ATET	0.73***	0.74***	0.74***	0.72***	0.72***	0.74***
SE	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)	(0.01)
Improved access to market						
ATET	0.81***	0.83***	0.83***	0.83***	0.83***	0.82***
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adoption of bay leaf farming as a secondary occupation						
ATET	0.03	0.10**	0.09***	0.04*	0.05**	0.10***
SE	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)

*, ** and *** indicate significant at 10 per cent, 5 per cent and 1 per cent levels, respectively. See Table 2 notes for details. N = 241 for ATETs.

Impact on household welfare and expenditure

The main goal of the bay leaf VC intervention was to improve the welfare of rural farmers by helping them gain more income from their produce, which also means bay leaf providing a larger share of household income. The increased income is expected to increase household consumption expenditure, reduce household poverty and increase school enrolment of children (Basu and Van 1998). However, the survey does not have information on total household consumption. In our case, we consider per-capita household income, change in poverty status and school enrolment of children as measures of household welfare.

Our results indicate that compared to the comparison villages, household per-capita income in the project villages increased by NRP 5000–7300, the share of bay leaf income in household total income increased by 9–10 per cent and the poverty rate went down by 6–8 per cent (Table 4). These findings confirm the information collected from the focus group discussions that farmers received a better price and had higher profit margins for bay leaf after enhancing product quality, increasing output and integrating production with marketing.

In both project and comparison villages, around 4–6 per cent of children were not enrolled in school, and the VC intervention programme did not affect school enrolment. The lack of improvement in child schooling may have a number of explanations. First, there could be a number of specific reasons why particular children are not in school, for example, distance to school, especially at secondary level in a rural area; children with educational or physical challenges; and older

Table 4. Impact on household welfare.

	Propensity score matching		Treatment effects estimators			
	Kernel	Mahalanobis	PS Match	RA	IPWRA	WLS
Variable	[1]	[2]	[3]	[4]	[5]	[6]
Household per-capita Income						
ATET	5700**	7300**	5800***	5000**	5200**	6800***
SE	(3000)	(3200)	(2300)	(2500)	(2400)	(2100)
Share of bay leaf income						
ATET	0.10***	0.09***	0.09***	0.09***	0.09***	0.10***
SE	(0.009)	(0.01)	(0.007)	(0.009)	(0.009)	0.008
Household poverty						
ATET	−0.08***	−0.08	−0.06***	−0.07***	−0.06**	−0.07***
SE	(0.02)	(0.05)	(0.02)	(0.02)	(0.02)	(0.01)
Current school enrolment of school-age children						
ATET	−0.007	−0.02	−0.017	−0.006	−0.009	−0.007
SE	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)

** and *** indicate significant at 5 per cent and 1 per cent levels respectively. SeeTable 2 notes for details. N = 241 for ATET.

children being considered to be of working age. It is also possible that when the value of bay leaf increases, school-age children got involved in bay leaf collection, as the immediate opportunity cost of attending school increases with increased earning potential from engaging in bay leaf collection. We also suspect that the school dropout rate may be higher in the study area.

We also examined household spending on consumer goods (rather than total expenditure) and child education to see whether the increased income had enhanced household welfare. Households in the project villages spent 6–14 per cent more on consumer goods (non-food) than those in comparison villages, but the amount spent on child education remained the same (Table 5). The finding is consistent with evidence from other studies that increased income not necessarily improves child schooling (Karki Nepal 2016).

Impact on women farmers

Since the VC development intervention was aimed to improve the market access and other welfare indicators of both men and women farmers, we also examined the potential benefit of bay leaf VC intervention for women respondents and their families. For this propose, we matched households with women respondent from project and comparison villages using propensity scores and estimated the same models. We presented results in Table 6. These results suggest that the women respondents' households in programme villages have planted more bay leaf trees, produced more bay leaves and improved grading skills and better market access compared to their counterparts in the comparison villages.

In the focus group discussions, women reported that they would have spent more time on improving product quality but might have faced greater difficulty in marketing in the absence of the intervention. The results suggest that the intervention was successful in helping rural women farmers for improving their income and market access. However, for these households, per-capita household income, poverty level and expenditure in consumer good and child schooling are not different from the reference group. To our surprise, the school enrolment of children is lower in these intervention households with female respondents. This finding provides some support to our suspicion that older children may have dropped out of school and engaged in bay leaf farming for this group of households, indicating that the intervention had a positive effect on both market access and earnings of female respondent's households, but it may possibly have negative consequences in child schooling. More research is needed to examine this issue further.

Robustness

The robustness of a PSM estimator can be examined by making marginal changes in the specification of the logit model (Dehejia 2005). In line with this, we examined the robustness of our results by re-estimating the propensity scores using different specifications for the logit model (dropping age squared, age and gender interaction and other main occupation) and using the new scores to

Table 5. Impact on household expenditures.

	Propensity score matching			Treatment effects estimators		
	Kernel	Mahalanobis	PS Match	RA	IPWRA	WLS
Variable	[1]	[2]	[3]	[4]	[5]	[6]
Use of bay leaf income on household consumer goods						
ATET	0.13***	0.14***	0.06***	0.10***	0.10***	0.13***
SE	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)
Use of bay leaf income on child education						
ATET	−0.01	−0.01	−0.08***	−0.0006	−0.0008	−0.01
SE	(0.02)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)

*** indicate significant 1 per cent level. See Table 2 notes for details. N = 241 for ATET.

Table 6. Impact on planting of bay leaf trees and production of bay leaf (women-only subsample).

	Propensity score matching		Treatment effect estimators			
	Kernel	Mahalanobis	PSM	RA	IPWRA	WLS
Variable	[1]	[2]	[3]	[4]	[5]	[6]
Number of bay leaf trees planted						
ATET	25.89***	25.30	22.51**	30.64***	-	29.64***
SE	(10.39)	(15.66)	(10.90)	(9.36)		(9.78)
Total production of bay leaf in kilogram						
ATET	206.36***	180.89***	206.99***	207.45***	-	200.38***
SE	(23.58)	(28.13)	(22.38)	(23.34)		(24.08)
Improved grading skill and knowledge						
ATET	0.58***	0.52***	0.67***	0.59***	0.59	0.58***
SE	(0.09)	(0.12)	(0.08)	(0.07)	(0.07)	(0.07)
Improved access to market						
ATET	0.75***	0.75***	0.75***	0.75***	0.75***	0.75***
SE	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Adoption of bay leaf farming as a secondary occupation						
ATET	−0.02	0.03	0.03	0.01	0.02	−0.008
SE	(0.10)	(0.12)	(0.07)	(0.08)	(0.08)	(0.08)
Household per-capita Income						
ATET	0.18	0.14	0.02	0.16	0.15	−0.02
SE	(0.48)	(0.42)	(0.48)	(0.45)	(0.44)	(0.61)
Share of bay leaf income						
ATET	0.15***	0.14***	0.14***	0.15***	0.15***	0.15***
SE	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Household poverty						
ATET	−0.03	−0.04	0.04	−0.02	−0.02	−0.01
SE	(0.10)	(0.13)	(0.10)	(0.09)	(0.09)	(0.09)
Current school enrolment of school-age children						
ATET	−0.23***	−0.26***	−0.27***	−0.17**	−0.16**	−0.24***
SE	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.06)
Use of bay leaf income on household consumer goods						
ATET	0.11	0.10	0.06	0.08	0.08	0.11
SE	(0.09)	(0.12)	(0.10)	(0.09)	(0.09)	(0.09)
Use of bay leaf income on child education						
ATET	−0.04	−0.02	−0.01	−0.06	−0.06	−0.05
SE	(0.10)	(0.12)	(0.08)	(0.09)	(0.08)	(0.08)

** and *** indicate significant at 5 per cent and 1 per cent levels respectively. See Table 2 notes for details. IPWRA model did not converge in some cases, probably due to the small sample. (Female subsample has only 107 (55 treatment and 52 control) observations, and for ATETs, 86 observations are used. Some of the observations are dropped due to lack of common support in PSM.)

re-estimate the models. The results are shown in supplementary materials (Tables S2–S5). The estimated impacts on all the outcome variables were consistent in terms of magnitude and sign with the estimates shown in Tables 2–4.

We also used a placebo intervention to assess the robustness of the results. We first pooled both controlled and intervention villages together, generated a placebo intervention and randomly assigned ‘placebo control’ and ‘placebo intervention’ villages as in Karki Nepal (2015). We then estimated propensity scores for matching households in ‘placebo intervention’ and ‘placebo controlled’ villages. The results indicate that the placebo intervention had no effect on the number of bay leaf trees planted or the production of bay leaf (supplementary materials S7), which supports the main conclusion that the bay leaf VC intervention helped farmers to plant more bay leaf trees and produce more bay leaf. The effect of the placebo intervention on other outcome variables showed a similar pattern (results available on request).[1]

We also estimated clustered corrected standard errors, where SE(corrected) = SE(uncorrected) × VIF and $VIF = sqrt[1+(k-1) \times ICC]$. Here ICC refers to intra-clustered correlation, and k refers to average number of observations in each cluster. The VIF indicates the extent of bias that one would get without correcting for clustering. Table S6 provides both ICC and VIF for all outcome variables. After correcting the SEs, ATETs for number of bay leaf trees planted, production of bay leaf, improved grading skills and knowledge, improved access to market, effect on household poverty and use of bay leaf income for household consumer goods are still significant. This indicates that the impacts of the intervention estimated using PSM are consistent and robust and that the inferences drawn are causal.

Hidden bias

The matching that we used between project and comparison households is based on observed characteristics of the households. The matching method helps to reduce the *overt bias* coming from the observed characteristics of the households who either received the treatment or not (Rosenbaum 1991). However, households may also differ largely on unobserved characteristics, such as innate ability that they can use it to analyse given information and act differently. They may have the same level of education or landholding size, but choose to plant or not to plant bay leaf trees. Such characteristics cannot be measured or recoded in the observational data as these are unobservable characteristics of the households. In the presence of unobserved heterogeneity, outcomes may differ between groups even if the treatment has no obvious effect. In the presence of unobserved heterogeneity, which affects the outcomes in the absence of the intervention, our analysis may suffer from hidden biases where conclusion drawn may be flawed. In order to examine the extent to which our results are susceptible to hidden bias due to unobserved heterogeneity, we estimate (Table 7) Rosenbaum bounds for ATET as suggested in Rosenbaum (1991; 2005).

The parameter gamma (Γ) measures how much the observational study differs from experimental study or odds of receiving the treatment. For our analysis, we use $1 \leq \Gamma \leq 2$, where $\Gamma = 2$ indicates that the person may be twice as likely to receive a treatment compared to another person based on unobserved characteristics. This translates into the two-third probability of receiving the treatment and one-third probability of being in the control group (Rosenbaum 1991).

We present upper *p*-values from Rosenbaum bounds for hidden bias analysis as the lower *p*-values are always less than 0.01 for $\Gamma = 1$, and it gets smaller with larger value of Γ. The smaller upper *p*-value (say <0.01) indicates that the results that we obtain from observational study is not too different from experimental study or that hidden bias is not statistically significant. In our case, other than bay leaf farming as secondary occupation and household per-capita income, the hidden bias is insignificant, meaning that it is not a serious issue, and we can interpret the findings (ATETs) as causal effect of the intervention.

Table 7. Sensitivity analysis with Rosenbaum bounds.

Gamma	1	1.2	1.4	1.6	1.8	2	ATET	SE
NBLT	<0.0001	0.0001	0.0182	0.2766	0.7666	0.9720	33.21***	11.6700
Production	<0.0001	<0.0001	0.0024	0.0914	0.4917	0.8753	368.43***	83.3300
Grading	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.75***	0.0600
Market access	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.81**	0.0400
Bay leaf farming	0.1945	0.4738	0.7279	0.8832	0.9565	0.9854	0.076	0.0750
HH PC	0.0463	0.2300	0.5214	0.7704	0.9112	0.9710	5200	3340
Income share	<0.0001	0.0008	0.0084	0.0412	0.1217	0.2546	0.10***	0.0250
Poverty	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	−0.1145	0.0800
Consumer goods	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.0002	0.1	0.0700
Schooling	<0.0001	0.0001	0.0002	0.0006	0.0011	0.0018	−0.0277	0.0760

Nearest neighbour matching estimator is used for estimating hidden bias. ** and *** indicate significant at 5 per cent and 1 per cent levels respectively.

Conclusion

In this study, we used PSM for ex-post data collected 5 years after the intervention to estimate the causal impact of a bay leaf VC intervention implemented in Udayapur district in Nepal to improve small upland farmer's household's income and welfare. Smallholder farmers were trained in establishing bay leaf nurseries, planting bay leaf trees and sustainable harvesting and improving the quality of bay leaf products by grading, storing and packaging before selling it in the markets. Farmers' groups and a cooperative were established to enhance capacity and bargaining power and gain a higher price for products through collective action. Each outcome variable was assessed using six estimators; robustness of the findings was examined by re-estimating the propensity scores using different specification for the logit equation and correcting standard errors for clustering.

The results indicate that households in the project villages planted 75 per cent more bay leaf trees, produced 170 per cent more bay leaves and sold more quality products at higher prices. As a result, per-capita household income increased by NPR 5000–7300, share of bay leaf income in total household income increased by 8–10 per cent and level of poverty declined by 6–8 per cent in project villages compared to comparison villages. Beneficiary households were not only able to plant more bay leaf trees, but also gained knowledge and skills on harvesting, grading, packaging and storing that motivated to improve product quantity and quality. Better quality and improved market access enabled farmers to achieve higher market prices, which led to the higher income. The knowledge and skill development and formation of the farmers' cooperative were key to the success of the intervention. The poor farmers were able to enhance their communication skills and integrate their subsistence economic activities more actively with the market. The assessment was made 5 years after project completion; thus, it clearly indicates that the gains were sustainable and increasing. When SEs are corrected for clustering, the ATETs for household income and share of bay leaf income on total household income turned to be statistically insignificant. This suggests that the SEs are downward bias without correcting for clustering, and for small sample with smaller number of clusters, correcting SEs for clustering is essential to avoid erroneous inference.

Against the conventional wisdom, the VC intervention had no effect on school enrolment. This issue is more obvious in the subsample of women respondent households where child school enrolment is significantly less in intervention villages compared to the reference group, showing some trade-off between higher bay leaf income and child school enrolment for the subsample of women respondents. It could be that schooling was thought not to be beneficial or accessible for some children; there might also be limited opportunities for sending children to better (more expensive) schools. Equally, children's education may not have been a priority in the rural settings when better opportunities arise for engaging the children. The result is consistent with other studies in which the increased income from development interventions did not automatically lead to higher investment in children's education (Karki Nepal 2015; Shah and Steinberg 2015; Rutherford et al. 2016). Development interventions that alleviate poverty without focusing on child education and human capital development may fail to break the intergenerational poverty cycle as less educated children are likely to have lower earning potential in future (Becker 1962).

This study contributes to the global literature by bringing robust empirical evidence about the long-term impact of a VC intervention. The findings have important policy implications for Nepal and other mountainous regions in developing countries where rural people live in isolated marginal areas with limited access to market. A well-designed VC approach can help reduce poverty and improve the livelihoods of rural farmers. Policymakers and development practitioners concerned with poverty alleviation should consider promoting VC interventions for locally available natural resources, with the provision of product buy-back schemes through cooperative, for livelihood improvement and poverty alleviation.

The results indicated that the bay leaf VC intervention programme was working well in the mountainous environment, and farmers in the intervention villages reported their satisfaction during the focus group discussions; several caveats, however, are in order. First, as the sample was small, the statistical power might not be sufficient to capture the effect on some outcome variables such as child education in women subsample. Second, the measurement errors for income and expenditure variables could be large, with a significant recall bias on the outcome variables as the intervention had started more than 6 years before the 2014 survey. Third, the PSM method matches households in programme and comparison villages based on observable characteristics, but the outcome variables may also be driven by unobservable characteristics such as risk-taking behaviour or interest in changing the existing agricultural practices. This issue remain, even though the Rosenbaum test does not show serious hidden bias. Finally, the intervention appeared to be effective in multiple areas including tree plantation, production, grading and marketing of the leaves and household poverty reduction. But the survey did not provide any information on the cost of achieving these outcomes and whether the intervention was cost effective. These caveats call for additional studies with larger sample sizes that take these issues into account before considering scaling up the VC intervention for agroforestry products in other areas.

Note

1. We also conducted two alternative placebo analyses. First, we used 'control' subsample and split into 'placebo control' and 'placebo treatment' groups. Then, we estimated ATETs for all outcome variables. The ATET differences between placebo control and placebo treatment for all outcomes were statistically insignificant. Second, we used 'farming own land' and 'livestock farmer' as placebo outcomes where we expect that these two variables may not be affected by the intervention. We re-estimated ATETs using these two variables are placebo outcomes. In both cases, the difference in ATETs between control and treatment groups was again statistically insignificant. Both of these results indicate that the treatment effect was statistically significant. These results are not included in the text but available upon request.

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