

Can Skill Diversification Improve Welfare in Rural Areas? Evidence from Bhutan

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1. Introduction

Seventy-five percent of the world's most vulnerable and impoverished populations reside in rural areas and have income sources that are primarily derived from agriculture activities (World Bank, 2008). How to effectively raise the income of this population and reduce poverty and vulnerability remains a contentious issue in development. Given that rural populations are constrained by low skills and agricultural activities are highly risky, training programs for non-agricultural activities have been promoted based on the premise that skill diversification can create additional opportunities for income generation that will improve the circumstances of the rural poor. The extensive evaluations of training programs in developed and developing countries, however, have revealed that program design is crucial to ensuring the effectiveness and success of such programs (Betcherman et al, 2004).

This paper examines the impact of the three month training component of the Rural Skills Development Project (RSDP) in Bhutan. This project was designed to diversify income sources of rural households beyond agriculture and to reduce expenses spent on housing repairs by training villagers in carpentry, masonry, plumbing, and electrical wiring. The absence of a valid baseline survey and the non-randomised nature of beneficiaries to the project imposed significant challenges in assessing the program impacts. Time and cost considerations also resulted in an endline survey of Bhutanese households that had a control group that was drawn from the same villages as the trainees. To resolve these limitations, we used a match estimator that includes a proxy for motivation to create the match between the treatment and control group to estimate the causal impacts of the training. Potential pitfalls to our estimates that could arise from unobserved selection bias and spillover effects were examined in detail and supplemented with qualitative analysis to support the validity of our results.

We make several important contributions to the literature. First, as most evaluations have been based primarily in urban environments we provide important insights into the effects of training in a rural environment. Secondly, we focus on a wider array of outcome variables which we believe is important as

the justification for implementing the project was not solely to raise incomes, but also to reduce housing costs and diversify incomes outside of agriculture. Finally, we examine distributional issues related to the project impact and specifically the impact that the training has on competitive and non-competitive labor markets. Taking into account competition within a labor market and how it may influence the effectiveness of a training program appears to be absent in previous studies.

The analysis shows limited evidence of income increases, housing repair costs decreases, and increases in psychosocial outlook due to the training program. However, there is evidence that the training program allowed for diversification of income sources into skills outside of agriculture by increasing the amount of income received from the skill areas covered by the training program. Income diversification mainly occurred for females, those who are less educated, and those who were trained in carpentry or masonry. Most notably, in geographic areas that were non-competitive, meaning trainees accounted for a smaller percent of the population, the training did lead to significantly higher household per capita incomes. These findings are significant as it suggests that having too many people in the labor market within a small geographic area may be counterproductive without an explicit mechanism to connect trainees to the labor market or provide work opportunities. Finally, as women are much less likely to participate in the training, encouraging greater equality in the skill development process may require providing more female-friendly training that has flexibility in training time and venues as well as training in other skill areas.

The remainder of the paper is organised as follows. Section 2 provides background on RSDP. Section 3 describes the related literature. Section 4 describes the research design including the choice of the control group and the data gathered for the evaluation process. Section 5 describes the empirical approach and results for a variety of specifications and sub-populations. Section 6 aims to validate the results by eliminating unobserved selection and spillover effects as possible factors. Section 7 discusses the findings and provides qualitative evidence for our findings. Finally section 8 concludes.

2. Rural Poverty in Bhutan and the Rural Skills Development Project

In Bhutan, where 80 per cent of the population relies on subsistence farming, and rural poverty at 30.9 per cent stands in contrast to an urban poverty rate of only 1.7 per cent, as of 2007, trying to implement effective policies and programs to reduce rural poverty and have more inclusive growth remains a critical development challenge (Asian Development Bank, 2009). The majority of the rural population relies on largely unproductive subsistence agriculture for their income and daily consumption needs. Moreover, many rural Bhutanese are exposed to considerably difficult climate and terrain where generating income from agriculture is nearly impossible for a good part of the year. Due to limited income generating opportunities and the high incidence of poverty in rural areas, there has been an increasing rate of urban migration especially among the youth population. This has contributed to an urban unemployment rate of 33 per cent among youth (ages 15-24 years) as the demand for labor has not kept pace with the supply (Ministry of Labour and Human Resources, 2008). The high rate of urban youth unemployment and the disparities in poverty incidence between urban and rural areas are increasingly seen as a threat to social stability and economic development within Bhutan. Thus, raising the incomes of the rural poor is potentially crucial to ensuring continued stability in the development process.

RSDP was a \$1.99 million project implemented by the Royal Government of Bhutan in collaboration with the Asian Development Bank (ADB) running from February 2007 to December 2010. RSDP was designed to mitigate the degree of poverty among rural Bhutanese by diversifying income opportunities outside of agriculture during the off season and providing cost savings on expenditures required for minor repairs.¹ As a result, this project was seen as an important step in increasing the economic and social welfare of the rural population.

RSDP provided training in four basic construction skills of carpentry, masonry, plumbing, and electrical wiring to poor villagers to increase their net income. Training was provided in 3 stages. The first two stages took place over three months. Stage 1 was comprised of theory lessons where participants reviewed basic concepts related to the skills. Stage 2 involved practical demonstration where participants were introduced to building and took part in construction of a toilet structure. Stage 3 provided on-the-job (OJT) training where participants were involved in school hostel construction over a period of approximately four to six months. For all stages, training was held for seven hours each day, excluding one hour for lunch. The average attendance rate was high at nearly 98 per cent. Stipend compensation for the first two stages was approximately Nu. 4,100 per month or about Nu. 180 per day (\$3.6), while Stage 3 participants received Nu. 6,000 per month or about Nu. 270 per day (\$5.4).²

The training was provided in all 25 gewogs³ across the 3 districts of Bumthang, Haa, and Trashigang from February 2007 to November 2010. Potential candidates for training cited their interest in a particular skill program while trainers and the project team subsequently selected candidates based on demand. There were a pre-allocated number of seats for each skill area. To ensure sufficient participation to build a toilet in Stage 2 and a hostel in Stage 3, some participants who volunteered for a specific trade that were over the quota were offered to enter training for their second priority skill area. For the training program to occur in a gewog the project management required recruitment of a minimum of 35 trainees for participation in Stage 1 and Stage 2. Participants for Stage 3 were selected from those who completed the first two stages and were interested in further developing their skills. In most gewogs participation targets were not met under a voluntary basis and pressure was placed on villagers to participate in the program so that the 35 trainee threshold for the program to occur in a given gewog could be reached. However, interviews with villagers indicated that many were not fully aware of the existence of the training program at inception and sometimes was the main driving factor for lack of participation.

By project end, 831 trainees completed Stage 1 and Stage 2 of the training. Of these, 280 completed Stage 3 across the three target districts. In addition, 81 trainees, of which 71.6 per cent were female, received training in hair dressing. Table 1 shows the completion of training activities for the different stages for the three different districts. It shows that most stage 1 and 2 activities had been completed in Haa and Trashigang districts by November 2009, but that many of the stage 3 activities in Trashigang where the majority of trainees occurred did not complete until July of 2010.

Given plans to scale up the approach in other gewogs after project completion, assessing whether the project achieved its intended goals is important. By identifying which populations can benefit the most from these training programs and where there are constraints to participation it is possible to help guide how to effectively expand future training programs so as to maximize the impacts and to have greater equality in the development process.

3. Related Literature

The methods and means to effectively raise the income and overall welfare of the poor and vulnerable in rural areas are debatable. While the primary focus on raising rural incomes has been through increases in agriculture productivity, there is a growing body of evidence that diversification into non-farm activities can have large benefits for poor rural households and can serve as an engine of growth for the rural economy. The origins of advocating investment in agriculture activities to reduce poverty has arisen primarily from cross-country studies such as Loayaza and Raddatz (2010), de Janvry and Sadoulet (2009), and Christiaensen et al (2010) who have found that greater increases in agriculture GDP generally tends to have a greater effect on reducing poverty than other sectors. However, these findings based on aggregate data may arise from the fact that agriculture is dominated by poorer households and therefore has less insight into what are truly effective options to alleviate poverty in rural areas.

In comparison, findings on the effects of sectoral investment at a microeconomic and country-specific level are more disparate. Manufacturing and tertiary sector in China are found to contribute less to poverty reduction than agriculture by Ravallion and Chen (2007) and Montalvo and Ravallion (2010). However, while agriculture growth is cited as playing a major role in contributing to poverty reduction in Indonesia, growth in rural services is found as a significant contributor to reduced poverty using regional aggregate data by Suryahadi et al (2009). Evidence on India provided by Lanjouw and Murgai (2009), finds only small growth in the self-employed non farm sector in rural India. Moreover, Foster and Rosenzweig (2004) find that rural industrialization is a substitute for added productivity in the farm sector in India which suggests that trying to promote both farm and non-farm sectors in rural areas may not be an optimal strategy.

Yet, while there is support for the idea that investment in agriculture is important for helping the rural poor, there are a number of studies that advocate non-farm activities as a pathway out of poverty. Kinda and Loening (2010) and Babatunde and Qaim (2009) suggest that while agriculture holds a large potential for growth it cannot solely meet the challenge of rural employment. A large number of studies have found significant evidence to support policies and programs focused on non-agricultural activities in rural areas. Deininger et al. (2007) finds that the value added in the non-farm formal sector in Sri Lanka amounts to almost 80 per cent of agricultural GDP. Adams (2002) finds that increases in aggregate non-farm income has a greater impact on reducing inequality and poverty in Egypt than increases in agriculture income. However, this is likely driven by Egypt's institutional characteristics where highly productive agricultural land has limited access mandating that the poor enter non-farm activities to increase their incomes. Barrett et al (2005) finds that diversification in Africa especially those associated with work not related to unskilled labor results in higher income and greater income mobility. Barrett (2005) examines diversification strategies in Africa and arrives at the conclusion that those that devote themselves solely to agricultural production must rely on a low-return strategy of complete dependence on the agricultural sector and often find themselves in a poverty trap. Escobal (2001) finds that 51 per

cent of net income of rural households comes from off-farm activities in Peru. Access to public assets such as roads, and private assets such as education and credit, are important factors in diversification. The finding is that increasing access to these assets will help rural households to increase their employment in non-farm sector. These findings support the claim that the non-farm sector holds considerable potential for growth and poverty reduction.⁴

Besides sectoral factors that contribute to increased welfare, identifying the types of programs and policies that are effective in raising incomes of the poor is important. In particular, training programs are increasingly used by development organizations to improve the welfare of the poor. However, the findings are typically mixed especially when comparing between the results of experimental and non-experimental evaluations. The findings from experimental evaluations typically provide less support for training programs as an effective strategy to raise employment and incomes. Card et al (2011) evaluated a training program based on random assignment that was targeted at young adults between the ages of 18-29 in the Dominican Republic. They find no positive impact on employment with only minor evidence of an impact on hourly wages and the probability of having health insurance coverage. Attanasio et al. (2011) evaluates a relatively short term training program requiring three months of in-classroom training and three months of on-the-job-training to young adults between the ages of 18-25 in urban areas based on randomised assignment of program offering. In contrast, they find the program did raise earnings and employment for both men and women in Colombia with lower bound estimates for internal rates of return of 13.5 per cent for women and 4.5 per cent for men. Betcherman et al (2004) provides an extensive review of studies that have examined the impacts of training programs. With the exception of training programs that explicitly facilitated labor market linkages they found that most training programs had small or no effects. Ibarra and Rosas Shady (2009) reviewed seven different rigorous evaluations of training programs intended to increase employment opportunities for youth in Latin America that primarily provided demand driven training courses creating a more direct linkage with labor market opportunities. Five of the seven countries showed significant improvements in employment prospects

due to the training. This suggests that training, and even short-term training, can potentially help increase employment outcomes and incomes of disadvantaged populations.

Yet, very little exists in the literature on the effectiveness of training programs in rural environments. As education and incomes are much lower in rural areas, and the local labor markets are smaller, one could expect very different findings than those in urban environments and it is not necessarily straightforward that training rural populations in skills outside of agriculture will improve their circumstances. This study which examines the impacts of a short-term training program for rural households in Bhutan will greatly complement past studies in understanding not just whether training programs work, but whether rural workers have the capacity and capabilities to take advantage of such a training program without an explicit component that also helps to provide job opportunities.

4. RSDP Survey

a. Research Design

The challenge in conducting this study was an absence of a valid baseline study, the non-randomised nature of the participation in the training program, and time and cost constraints. This ultimately determined our design of survey, sampling selection, and subsequent empirical methodology.¹ We developed an extensive endline household survey to capture detailed characteristics of the respondents and households and measure the project impacts over a variety of economic, social, and psychosocial outcomes.⁵ This survey was run from late September to mid November of 2010.

Our approach was to gather a census survey of all trainees between the ages of 18-40 years of age. This age range covers 90 per cent of the trainee population. We also surveyed a set of non-trainees that were

characteristically similar in age and gender profiles under the assumption that this control group could serve as an appropriate counterfactual to the set of trainees. We required that this control group was between 18-40 years of age and were roughly 33 per cent female. To remain within the time and cost constraints, we derived a control group from within the gewogs covered by the project.⁶ Surveying was largely done by calling trainee and control group members into the gewog offices in return for a compensation of Nu. 100 to take a survey that took on average 75 minutes to complete. For trainees that were out of their gewog during the survey period, an effort was made to conduct phone interviews.

b. Sample and Descriptives

To focus on moderately longer-term impacts, we imposed the restriction that trainees had completed the training program at least 12 months prior to the survey and focused on trainees that had only completed stage 1 and 2. We dropped stage 3 trainees as very few had completed training 12 months prior to the survey.⁷ Table 2 shows survey rates for trainees in our sample. We were able to survey 74 per cent of all trainees. Survey rates differ considerably dependent on trainee characteristics with higher survey rates for females than males, for those less than 25 years of age, and over the skills of masonry and plumbing compared to carpentry and electrical.

Our final sample consists of 451 non-trainees and 320 trainees. Table 3 summarizes the characteristics of trainees and non-trainees over key variables. This table shows there are differences between control group population and the trainee population. The control group has an average age that is three years older, a larger percentage of females and married individuals, and lower levels of education suggesting that there are selection effects at work. Some of the outcome measures of interest show that non-trainees appear somewhat worse off than trainees with lower household per capita incomes and higher costs of household repairs. In general, the surveyed population is poor with yearly average household per capita

income of Nu. 9,076 (\$181) for non-trainees and Nu. 11,376 (\$226) for trainees. Moreover, the cost of household repairs at around Nu. 5,000 per year account for almost 10 per cent of a household's budget.

5. Empirical Methods and Results

Our objective is to identify the impacts of participation of individual, i , in stage 1 and 2 of the skills training program, T_i , on a series of social and economic outcomes, y_i . This is done by creating a counterfactual comparison group, $y_i(0)$, for those who participated in the program, $y_i(1)$. As the non-randomised nature of the program makes selection bias a relevant concern we investigate the effects of the training program primarily relying on a non-parametric matching estimator to estimate the average treatment effect (ATE), $\tau^{ATE} = E[y_i(1) - y_i(0)]$, and average treatment effect on the treated (ATT), $\tau^{ATT} = E[y_i(1) - y_i(0) | T_i = 1]$.

5.1 Matching Estimator

Matching estimators attempt to resolve the endogenous nature of participation in the training program. However, in the context of an endline survey, it relies heavily on the assumption that (i) all observables adequately capture participation into the training program such that there is no unobserved effect that both drives the participation decision and the resulting outcomes and (ii) observables capture characteristics of the individuals prior to the treatment. Given these assumptions hold true, then it is possible to obtain an unbiased estimate of the ATE and ATT. The matching estimator used is based on a bias-adjusted nearest neighbor match estimator proposed by Abadie and Imbens (2006, 2011). This relaxes restrictions imposed by the original parametric propensity score match estimator of Rosenbaum and Rubin (1983). This estimator is computed via non-parametric methods with each trainee matched to the five closest non-trainees based on the relevant variables.

Variations in the variables to construct matches were investigated. Household size, sex, age, education, and civil status were ultimately chosen for inclusion in our model based on their significance in determining the outcomes of interest and the high likelihood that they did not change due to selection into the program. As our control group is drawn from the same villages as the treated group unobserved motivation and innate skills related to work performance is a concern as they are often correlated with higher participation rates and better outcomes.⁸ This implies that the estimates may be biased away from zero and cause us to falsely find that the program had an effect. Our survey asked several questions on willingness to participate in a hypothetical training program for six weeks at a stipend compensation of Nu. 160 per day and willingness to travel for work that could potentially proxy for motivation. Answers displayed in Table 4 show that trainees are more motivated to participate in a training program and are more willing to travel further for work opportunities. We therefore included the indicators on stated willingness to travel for work to proxy for motivation and limit the selection bias. These variables are interacted with the sex indicator as the decision to enter training, earnings potential, and outlook are believed to differ substantially between males and females. Kernel density estimates of a propensity score estimated from a probit model of the probability to participate in the training based on the set of variables chosen for estimating the match estimator are shown in Figure 1. It shows a high degree of overlap between the set of trainees and the set of non-trainees indicating that it may be possible to construct a relevant counterfactual control group.

5.1.1 Impacts on the Average Trainee

Table 5 shows results of the ATE and ATT using the matching estimator. Column 1 estimates the ATE for the basic match estimator with biased-adjusted standard errors and exact matching on sex and years of education variable, but excludes the willingness to travel for work variables. Column 2 includes the willingness to travel for work variables as criteria for matching. Column 3 and 4 are like column 1 and 2 respectively, except it estimates the ATT. Column 5 imposes on top of the criteria of column 4 that the

matches are exact over the civil status variable. Column 6 additionally imposes over the estimate of column 5 that all matches only occur within the area of common support defined by a regression based propensity score and trims .05 from the minimum and maximum values. Both column 1 and 3 are for comparison purposes to show what the exclusion of the proxy for motivation from the match may have on the estimated impacts. It shows that the exclusion of this proxy results in a finding that household per capita income significantly increased due to the training program. However, columns 2, 4, 5 and 6 are likely more valid estimates as it tries to account for selection bias in the estimates by including the proxy for motivation in the match.

In all cases, there is limited evidence that the training program had any effect on incomes or other outcomes such as housing repair costs, loan amounts, and self-perceived status of trainees more than one year after completion of the training program. The only outcome that is robustly significant to our variations in specification is the percentage share of household income coming from construction related employment.

5.1.2 Impacts on Different Subgroups of Trainees

Even if there are relatively few impacts overall, it is possible that different subgroups may have benefitted from the training program. We examine the impact on different subgroups to see whether the training program should use more targeted strategies to maximize its impact. Table 6 provides the ATT of the distributional impacts of the training among different sub-populations as well as the different skill areas for the outcomes of household per capita income, housing repair costs, and percent of household per capita income obtained from the different skill areas. These estimates are based on the basic match estimator from Table 5 of column 4. Similar to the overall results, the findings show no evidence of any significant impacts of the training program on household per capita income or in the cost of housing

repairs for the different sub-groups. However, the training had an impact on the diversification of incomes primarily for females, low-educated individuals, and those trained in carpentry and masonry.

5.1.3 Impacts on Trainees in Non-Competitive and Competitive Labor Markets

The impact of the training may also have a differential effect depending on the percentage of trainees within a geographic area. This may arise if a labor market becomes too competitive or saturated with too many workers of a certain skill set. This would lower the expected income that can be obtained from that skill area unless demand for that skill rises. We combine our data with 2010 voter eligibility data from the Election Commission of Bhutan at the chiwog level (sub-area of a gewog) and construct an indicator for the percent of trainees within a chiwog. We re-estimate ATT effects for the nearest neighbor matches on a sample where individuals resided in non-competitive labor markets (chiwogs where trainees comprise < 2 per cent of the population) and on a sample where individuals resided in competitive labor markets (chiwogs that had trainees comprising > 2 per cent of the population). We added several indicators for average incomes in a gewog to better control for gewog resources that can affect outcomes. This roughly splits our sample into equal halves with approximately 350 observations per sample.

Table 7 display results from this analysis. It shows that there is a significant increase in household per capita income for trainees in non-competitive labor markets (column 1), but not competitive labor markets (column 3). These results are robust to trimming the top .05 and bottom .05 of the sample using an estimated propensity score as seen in column 2 and 4. In non-competitive labor markets the training is also shown to have significantly led to a diversification of incomes, by increasing the percent of household per capita income that comes from one of the skill areas served by the training.¹¹ In comparison, the training appears to have no impact on percent of household per capita incomes that come from the four skill areas for trainees residing in competitive labor markets. However, trainees in competitive labor markets are found to have lower household per capita expenditure and reduced amounts

spent on loans. Given that the current average per capita income of a trainee is Nu. 11,376 and the estimated rise in income for trainees in non-competitive labor markets is approximately Nu. 3,000 this accounts for over a 33 per cent increase in household per capita income.

6. Robustness Checks

The validity of our results relies heavily on the assumption that unobserved selection bias and spillover effects are not contaminating our control sample that is used as our counterfactual for our trainee sample. This section discusses whether these are likely factors driving our results.

6.1 Unobserved Selection Bias

There is a lack of evidence that the training program had any effect on the average trainee who participated in the training program except on the basis of raising the percentage of household per capita income obtained from construction related skills as opposed to other sources of income. While the estimates consistently showed no effect over most outcome measures and various modeling assumptions it is plausible that trainees are not randomly selected given our variables chosen for matching or that the proxy for motivation, the willingness to travel for work, was changed by entry into the training program. While we believe that such a motivation indicator should remain the same we re-examine the impact of the training program within the context of maximum likelihood estimation of treatment-effects (MLE-TE) and two-stage least squares (2SLS) to estimate the local-average treatment effect (LATE).⁹ In this analysis we attempt to identify the training effects using a person's stated belief on the importance of the construction skill area as an instrument for opting into the training program.

We impose exclusion restrictions in the treatment equation when estimating using maximum MLE-TE and 2SLS. We use the respondent's perceived belief in the value of construction related activities offered

by the training program as indicators that would affect participation in the training program, but does not affect actual outcomes of the household. It is hypothesized that this variable should be excluded from the main regression equations because after including motivation factors, which we proxy by the stated willingness to travel for work, this should not explicitly enter the main outcome equations.¹⁰ This instrument is shown to be significantly correlated with entry into the training program at the 10 per cent significance level. This estimation provides the local average treatment effect (LATE) which models the effect of treatment of the marginal individual who decides to enter treatment due to an increased belief that construction related activities are useful.¹² It therefore has a useful policy interpretation in that, if this effect is significant, it suggests that greater outreach and encouragement on the value of having construction related skills would lead to significant changes in outcomes for the marginal participant who decides to enter the training program.

Table 8 shows that for the marginal trainee who decides to participate in the training program, because of perceived belief that the training is useful, there is no significant increase in household per capita income, total cost of household repairs, or even a rise in percent of household per capita income from these skill areas.

6.2 Spillover Effects

Our models have attempted to address the selection bias that arises when unobserved motivational factors determine selection into the training and subsequent outcomes. However, the absence of any effect on household incomes, cost of housing repairs, or other outcomes could be due to spillover effects that arise from using a control group that are obtained from the same village as the treatment. Spillovers could also explain why we observe significant increases in household per capita incomes in chiwogs with non-competitive labor markets compared to chiwogs with competitive labor markets.

For example, spillovers would invalidate our use of a control group if trainees were sharing knowledge obtained from the training with non-trainees. This would allow non-trainees to use these skills to also earn income and lower the cost of house repairs and would be a positive indirect benefit of the program. Spillovers could also lead to reduced differences in total cost of household repairs if trainees were providing non-trainee households with free or bartered labor or higher costs of household repairs if more trainees make it easier to access construction related services. Thus, in the presence of spillovers we would expect to underestimate the true impacts of the program.

To test for the possibility of spillover effects, where i indexes the household, c the chiwog, and g the gewog, we run a probit model on the probability of earning income from one of the skill areas, $P(y_{icg}^{skill} > 0)$, on the percent of trainees within a chiwog, p_{cg}^{tr} , individual characteristics, X_{icg} , and indicators for average income within a gewog, μ_g given that an individual is a non-trainee, $T_{icg} = 0$. Namely,

$$P(y_{icg}^{skill} > 0) = \Phi(\alpha + \gamma p_{cg}^{tr} + \rho X_{icg} + \sigma \mu_g + \varepsilon_{icg} > 0 | T_{icg} = 0) \quad (1)$$

If there are spillover effects then we should find that the non-trainee sample is more likely to have obtained income from one of the skill areas if they are living in a chiwog with a higher density of trainees. That is $\gamma \Phi(.) > 0$. We find no evidence that there is any relationship between the density of trainees in a chiwog and obtaining income from the skill area provided by the training program as seen in Table 9.

We also perform a second test for the possibility of spillover effects where each outcome measure of interest was regressed on an indicator for trainee, T_{icg} , the percentage of trainees within a chiwog, p_{cg}^{tr} , plus the standard control variables, X_{icg} , included in the match estimates. Gewog fixed effects, μ_g , are included to account for average outcomes values within a gewog. Standard errors were clustered by chiwog. Specifically we ran a regression as follows:

$$y_{icg} = \alpha + \beta T_{icg} + \gamma p_{cg}^{tr} + \delta T_{icg} p_{icg}^{tr} + \rho X_{icg} + \mu_g + \varepsilon_{icg} \quad (2)$$

If there are spillover effects, then we would expect that $\delta < (>)0$, if $\beta > (<)0$. This implies that in the presence of spillovers, and after controlling for other factors that drive the outcomes of interest, we should expect to observe that trainees in chiwogs where there are a higher percentage of trainees there is less of an impact on outcomes than in chiwogs where there is a smaller percentage of. Table 9 shows coefficient estimates for δ , the interaction between trainee indicator and density of trainees in chiwog. It shows that there is no evidence that trainees are differentially affected by the percentage of trainees in chiwogs for all outcomes with the exception of percentage of household per capita income from the skill area. Given that the results from equation (1) showed that non-trainees in more competitive markets were no more likely to have made income from construction related skills suggests that the findings are more consistent with a story of competitive effects rather than a story of spillovers.

In addition, spillovers are unlikely to exist for several other reasons: First, the typical villages covered by the project are significantly spread out over a sizable land area making information flow difficult and raises the cost of training other villagers. Secondly, for 86 chiwogs, trainees accounted for an average of 2.2 per cent of the voting age population with the highest percentage chiwogs accounting for < 11 per cent of the population. Thirdly, previous studies, such as Godtland et al (2004), have found that diffusion of knowledge and transference of skills are low in the short-term. As trainees in our sample had completed the training on average 1.25 years before the survey, this is still considered a relatively short-term examination of the training effects. Thus, we believe that spillover effects are not driving our results.

7. Discussion

The overall results on the impact of the training showed limited economic, social, and psychosocial impacts. These conclusions appear robust to varying specifications with no evidence that these weak results are driven by potential spillover effects. However, significant impacts of the training program on household per capita income were found for trainees that reside in non-competitive labor markets. Thus, the training is potentially useful in raising incomes given that the labor market is not saturated with too many people holding the same skills. In labor markets where there is an oversupply of people that have been trained in a given skill area equilibrium wages may become depressed and job opportunities more limited and thus may negate much of the monetary benefits of the program. As most individuals remained in their village it reflects the lack of opportunities that can be generated based purely on local market demand for this type of work within a given gewog or district.

That the average trainee was able to diversify their incomes, but not increase their overall income, coincides with anecdotal reports that a large amount of rural villagers merely substituted agriculture activities for construction related activities. This is in part because the agriculture season and peak construction season occurs during similar months. More generally, it highlights the difficulties that rural workers may face in trying to obtain decent work opportunities. Without having an explicit mechanism that allows trainees to access employment opportunities in these skills the current stage 1 and 2 training program will have little benefit for the average trainee in a competitive market.

Yet, providing an explicit mechanism for trainees to access a larger labor market for their skills may not be sufficient. Intensifying the learning materials and providing more training to build the skills and confidence of trainees to be competitive in a larger labor market may be necessary. In our attempt to survey trainees who also went through Stage 3 training, we were only able to track down 27 per cent. This is potentially indicative of the benefits of the longer term training program as the trainees who were

not reached were mostly indicated as employed in contract work by relatives and friends in their home village.

Table 8 provides qualitative support for these claims. Over half of all trainees suggested that the training program could be improved through providing better work opportunities and 52 per cent of trainees from stage 1 and 2 training cited that the training program could be longer. This suggests that increasing the length of the training program and providing job placement services and entrepreneurship support to facilitate the trainees to start up their own business may also greatly facilitate rural households in reaping more immediate benefits from the training program.

8. Conclusion

There exists a variety of programs to raise the incomes of the rural poor. The potential for non-agriculture activities to have greater value added while serving as an alternative source of income has garnered support as a way to alleviate poverty and vulnerability to poverty of the rural poor. The rural skills development program in Bhutan was a short-term training program that was designed with this purpose in mind. It trained the rural poor in practical construction skills with the intention of raising overall incomes, diversifying incomes outside of agriculture activities, and reducing the costs of household repairs.

This study relied purely on an endline survey and was faced with limitations on the control population. Thus, to examine the effects of the training program on different social and psychosocial outcomes relies on heavy assumptions to identify the causal impact of the training program on the average trainee. This underscores the need for the process of serious program evaluation to begin at the start of the project. Had a sufficient baseline existed and a randomisation component been included it would have been

possible to rely less on the modeling assumptions and more on simple specifications to arrive at more definitive estimates on the magnitudes of the effects.

Our conclusions are inevitably constrained by the process of evaluation and we recognise that there are potential limits to our method of evaluation that are impossible to resolve within the constraints imposed by the available data. A number of researchers such as LaLonde (1986) and McKenzie et al (2011) have shown that propensity score matching tends to overestimate the effects that are found using experimental methods. Moreover, Heckman et al (1997) has found that bias due to omitted variables is significant in typical parametric methods of matching, but non-parametric methods can potentially resolve this bias given baseline and endline data. In the absence of spillovers, our data may represent a possible upper bound on the benefits that can be achieved from such a short-term training program.

Nevertheless, by addressing selection and spillover effects and supplementing it with some qualitative analysis we believe our results are valid. Our analysis revealed a number of potential challenges and constraints to achieving highly positive economic, social, and psychosocial impacts for the general rural villager who decides to enter the short-term training program. Our finding that the training was beneficial in raising incomes for trainees who resided in non-competitive labor markets, but not in competitive labor markets highlights the need for program design to better assess the labor market and ensure that it does not become over saturated. If the labor market situation is not taken into account then the training program may have little effect on the average rural trainee.

Still, if diversification of incomes into non-agriculture activities is believed to help in reducing vulnerability to poverty then the program has partially achieved one of its objectives. However, refining the curriculum and extending the training time to provide more time for trainees to really develop their skills may help improve the success of the training. Having an explicit mechanism for trainees to enter the larger labor market through job placement services and providing entrepreneurship support can further

help to increase employment opportunities that lead to greater rises in income for trainees and can in turn lead to greater improvements in psychosocial outlook.

Finally, there are significant distributional implications based on the population set that decided to voluntarily participate in the program. As females are significantly less likely to participate even after controlling for education, household size, and village characteristics, having greater inclusiveness across genders may entail providing more flexible training times and venues that accommodate the needs of women and a selection of courses that are more appealing to the female population. By refining both the training program and the targeting of the program it may help to better accelerate the speed at which it is possible to reduce poverty and vulnerability to poverty of the rural poor and increase equality in the development process.

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ENDNOTES

1. The off season for farming depends on the particular district.
2. All conversions are based on an exchange rate of Nu. 50 to \$1.
3. Each district is broken into smaller areas known as gewog, similar to the concept of sub-districts. Each gewog comprises 4-10 chiwogs, which is equivalent to a cluster of villages. Each chiwog consists of approximately 200 – 400 households.
4. A report reviewing some anecdotal evidence on rural non-farm economy is Davis (2004).
5. The survey can be obtained from the authors upon request. Household per capita income measures were constructed from detailed responses to income generating activities in the main and secondary occupations of each household member over the course of the past year, as well as income obtained from other sources such as rentals, remittances, and sale of assets. For agriculture income, specific details were asked on cropping patterns and the amount sold of each crop in the last year. The main part of our survey was modeled after the Bhutan Living Standard Survey.

6. The terrain in Bhutan is very challenging making it difficult and costly to send enumerators to comparable villages. Had time and cost considerations not been a factor we would have surveyed a control group of individuals who are outside of the pilot gewogs and have similar characteristics to trainees. This set of trainees should be drawn from similar sized villages and should be a set we can claim would have otherwise been interested in participating in RSDP had RSDP been offered in the village.

7. The attempt to survey stage 3 trainees to obtain information on their current status resulted in reaching only 27%. It was indicated to be due to stage 3 trainees having contract employment on hydropower projects and other construction projects outside of the districts. Marriage and migration to urban centers to pursue other occupations was also cited in some cases.

8. Having panel data (that is baseline and endline data) would have helped in estimation as we would have been able to control for unobserved characteristics via individual fixed effects. This bias is believed to be reduced in instances where gewog heads placed pressure on villagers to participate in the program suggesting that some of the trainees may not be as different from the set of control group drawn from the same villages lessening selection bias on the basis of motivation.

9. The MLE-TE regression model is a maximum likelihood estimator that assumes joint normality of the error terms for the selection, modeled via probit, and outcome equation. It explicitly addresses the bias caused by correlation of the regression variables with omitted variables by adding a term to the regression that represents the non-zero expectation of the error term. Given the specification equations are correctly modeled and the errors are joint normal then this approach will essentially resolve the bias stemming from unobservables that may arise in the propensity score matching methods. However, joint normality is a fairly restrictive assumption especially in smaller sample sizes in the context of this model. On the other

hand the 2SLS regression model the first stage via linear probability model. And the error from both the first stage and the second stage are assumed to be independent.

10. The validity of this instrument is debatable within the context of our analysis if the training program affected the perceived belief on the importance of construction skills.

11. Analysis of sub-groups were not considered for competitive and non-competitive labor markets as the reduced sample size makes it difficult to obtain a sufficient number of matches between treatment and control groups.

12. Imbens and Angrist (1994) show that only under very restrictive assumptions will the LATE actually coincide with the ATE.

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Table 1
Dates of Training Activities by District

Districts	Stage 1&2		Dates	
	Start	End	Start	End
Haa (Dawakha LSS)	Sep 2008	Dec 2008	Feb 2009	Jun 2009
Haa (Sombeykha CPS)	Jan 2009	Feb 2009	Feb 2009	Apr 2009
Haa (Gakiling)	Jul 2010	Aug 2010	Sep 2010	Dec 2010
Trashigang (Thungkhar LSS)	Sep 2009	Nov 2009	Apr 2010	Jul 2010
Trashigang (Bikhar LSS)	Sep 2009	Nov 2009	Feb 2010	Apr 2010
Trashigang (Joenkhar CPS)	Sep 2009	Nov 2009	Jan 2010	Mar 2010
Bumthang	Mar 2010	Jun 2010	Jul 2010	Nov 2010

Notes:

Lower secondary school (LSS), Central primary school (CPS)

Table 2
Trainee Counts

variable	Counts		% Surveyed
	Actual	Surveyed	
Total	432	320	0.74
District: Haa	128	101	0.79
District: Trashigang	304	219	0.72
Skill: plumbing	70	66	0.94
Skill: masonry	163	121	0.74
Skill: carpentry	127	77	0.61
Skill: electrical	72	56	0.78
Male	283	203	0.72
Female	149	117	0.79
Age < 25	129	105	0.81
Age >= 25	303	215	0.71

Notes:

Trainees are ages 18-40 years who have completed training at least 12 months prior to the survey, and were only in stage 1 and 2 of the training program.

Table 3
Summary Statistics of Key Variables

Variable	Non-trainee				Trainees			
	Mean	SD	Min	Max	Mean	SD	Min	Max
HH per capita income (Nu.)	9076	12881	0	88333	11376	13756	0	95000
HH per capita expenditures (Nu.)	3266	7634	0	129043	2844	4634	0	41433
Total cost of HH repairs (Nu.)	5701	25747	0	505069	4946	11333	0	88216
Loan amount - present (Nu.)	16485	59197	0	900000	12561	37348	0	500000
Change loan amount 3 years prior (Nu.)	9327	68030	-500000	900000	4503	43559	-300000	500000
% HH per capita income from skill area	0.06	0.23	0	1.87	0.17	0.29	0	1
Change status from 3 years ago	0.91	1.41	-5	9	0.95	1.29	-5	6
Prospects now compared to 3 years ago	4.77	1.56	1	10	4.74	1.51	1	9
# assets livestock	0.23	0.46	0	2	0.16	0.37	0	2
Change # assets livestock from 3 years ago	0.09	0.39	-2	2	0.03	0.4	-2	2
# HH assets	7.64	2.48	0	15	7.87	2.38	0	14
Change # HH assets from 3 years ago	0	0.16	-1	1	0.02	0.16	-1	1
Received income from skill area	0.09	0.28	0	1	0.32	0.47	0	1
HH size	4.8	2.38	1	31	4.94	1.94	1	14
# of HH > 15 years of age	0.71	0.25	0	1	0.73	0.23	0	1
Respondent: female	0.49	0.5	0	1	0.37	0.48	0	1
Respondent: age	32	6	18	40	28	6	18	40
Years of education	1.58	3.36	0	16	2.01	3.18	0	13
Respondent: married	0.71	0.45	0	1	0.62	0.49	0	1
Approximate observations	451				320			

Notes:

Trainees and non-trainees are ages 18-40 years. Trainees completed training at least 12 months prior to the survey, and were only in stage 1 and 2 of the training program.

Table 4
Behavioral factors affecting participation in training

	Categories	Non-Trainee	Trainee
Observations		451	112
Willing to participate in training		0.70	0.76
	Distance willing to travel for work		
Outside district		0.27	0.38
Within gewog		0.08	0.09
Within district		0.18	0.19
Within village		0.17	0.10

Notes:

See Table 3 notes.

Table 5
Estimated Impact of Training on Different Outcomes

Outcome Variable	Matching Estimator					
	ATE (1)^a	ATE (2)^b	ATT (3)^a	ATT (4)^b	ATT (5)^c	ATT (6)^d
HH per capita income (Nu.)	1838.40*	1616.77	2529.65**	1858.67*	1538.65	1701.15
	[1063.52]	[1035.52]	[1077.94]	[1124.08]	[1158.96]	[1146.32]
HH per capita expenditures (Nu.)	-365.90	-545.50	-686.57	-570.13	-653.96	-987.27
	[548.95]	[507.53]	[601.73]	[563.87]	[473.57]	[600.15]
Total cost of HH repairs (Nu.)	-771.87	-945.62	312.71	492.33	-196.26	-962.25
	[1429.72]	[1398.90]	[1173.11]	[1153.67]	[1435.84]	[1499.91]
Loan amount - present (Nu.)	-3283.66	-3463.82	-3394.57	-2965.99	-2366.02	-3865.98
	[3657.61]	[3526.45]	[3354.87]	[3103.64]	[3106.24]	[3193.25]
Change loan amount 3 years prior (Nu.)	-6969.52	-6078.94	-6914.65*	-5560.17	-5470.93	-6774.89*
	[4237.31]	[4156.06]	[3719.27]	[3651.31]	[3613.45]	[3778.38]
% HH per capita income from skill area	0.085***	0.087***	0.070***	0.062**	0.058**	0.063**
	[0.022]	[0.023]	[0.025]	[0.026]	[0.026]	[0.025]
Change status from 3 years ago	0.023	0.013	0.054	0.031	0.082	0.069
	[0.111]	[0.105]	[0.117]	[0.109]	[0.114]	[0.117]
Prospects now compared to 3 years ago	-0.099	-0.142	-0.113	-0.185	-0.146	-0.172
	[0.126]	[0.121]	[0.131]	[0.122]	[0.126]	[0.128]

Notes:

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. See table 3 note.

All estimates are computed via STATA nnmatch function with bias-adjusted standard errors, where each trainee match to closest 5 non-trainees in sample based on match variables.

Average treatment effect (ATE) and average treatment effect on treated (ATT)

a. Column 1 and 3: Match variables are household size, sex, age, years of education, civil status, and sex interacted with all other variables. Exact matching on sex and years of education.

- b. Column 2 and 4: Match variables as in column 1 with willingness to travel for work indicators.
- c. Column 5: Match variables as in column 2. Exact matching also on civil status.
- d. Column 6: Match variables as in column 5 with observations trimmed with propensity score that are .05 from the minimum and maximum values of common support defined by the propensity score.

Table 6
Estimated Impact of Training on Log Household Per Capita Income for Different Sub-Groups

Outcome Variable	HH per Capita Income	Cost of Housing Repairs	% HH Per Capita Income Skill Area
Female	2051.72 [1543.31]	75.24 [1142.47]	0.100*** [0.031]
Male	1743.36 [1566.68]	1476.24 [1188.46]	0.044 [0.037]
Age < 25	2422.02 [1935.16]	-2711.98 [2460.59]	0.044 [0.048]
Age >= 25	1415.89 [1359.11]	614.73 [1467.64]	0.054* [0.030]
Highest Education: Jr High or Above	2395.88 [2716.56]	-3964.89 [6719.49]	0.026 [0.054]
Highest Education: Elementary	1265.16 [1237.60]	931.24 [950.93]	0.070** [0.029]
Skill: Carpentry	2012.18 [1307.15]	1215.45 [1078.38]	0.084*** [0.032]
Skill: Masonry	897.9 [1459.15]	2124.59 [1340.25]	0.090** [0.037]
Skill: Electrical	2615.52 [2407.63]	320.77 [1859.70]	0.058 [0.047]
Skill: Plumbing	683.47 [1903.94]	-2329.8 [3149.85]	0.027 [0.035]

Notes:

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

See table 5 notes. Average treatment effect on treated (ATT) estimated.

Match variables are household size, sex, age, years of education, civil status, and sex interacted with all other variables. Exact matching on sex and years of education (where applicable).

Table 7
Estimated Impact of Training on Different Outcomes

Outcome Variable	Matching Estimator ATT			
	Percent of Trainees in Chiwog			
	< 0.02 (1) ^a	< 0.02 (2) ^b	> 0.02 (3) ^a	> 0.02 (4) ^b
HH per capita income (Nu.)	3191.96** [1255.87]	3041.30** [1278.84]	2230.14 [1419.93]	2197.24 [1427.70]
HH per capita expenditures (Nu.)	-1492.48 [1195.96]	-1898.91 [1238.66]	-1046.30* [552.91]	-1109.07* [567.27]
Total cost of HH repairs (Nu.)	387.52 [1014.47]	30.96 [1031.93]	-530.85 [2561.85]	-1138.84 [2795.74]
Loan amount - present (Nu.)	386.81 [5090.65]	691.72 [5248.27]	-4685.67 [4124.03]	-6201.19 [4248.38]
Change loan amount 3 years prior (Nu.)	1753.78 [5384.00]	2911.53 [5590.30]	-11967.64** [5074.38]	-14393.53*** [5068.46]
% HH per capita income from skill area	0.134*** [0.032]	0.123*** [0.032]	0.032 [0.036]	0.036 [0.037]
Change status from 3 years ago	-0.171 [0.168]	-0.218 [0.171]	-0.057 [0.140]	0.04 [0.143]
Prospects now compared to 3 years ago	-0.237 [0.177]	-0.302* [0.180]	-0.229 [0.153]	-0.181 [0.157]

Notes:

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

See table 5 notes. Average treatment effect on treated (ATT) estimated.

a. Column 1 and 3: Match variables are household size, sex, age, years of education, civil status, and sex interacted with all other variables. Exact matching on sex and years of education.

b. Column 2 and 4: Match variables as in column 1 and 3 with observations trimmed with propensity score that are .05 from the minimum and maximum values of common support defined by the propensity score.

Table 8
Estimated Impact of Training on Different Outcomes

Outcome Variable	TE-MLE LATE (1)	2SLS LATE (2)
HH per capita income (Nu.)	9635.31 [20963.53]	15386.16 [18219.8]
HH per capita expenditures (Nu.)	-6067.35 [9843.43]	9543.12 [7891.51]
Total cost of HH repairs (Nu.)	36122.88 [37128.6]	-16900.7 [35111.26]
Loan amount - present (Nu.)	4319.23 [75481.16]	-11269.9 [56732.68]
Change loan amount 3 years prior (Nu.)	-21855.7 [88202.91]	-968886.8 [81347.42]
% HH per capita income from skill area	-0.88 [0.72]	0.23 [0.34]
Change status from 3 years ago	0.22 [2.01]	-3.43 [2.84]
Prospects now compared to 3 years ago	-3.38 [2.66]	-8.18 [5.48]

Notes:

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

See table 5 notes. Treatment-effect maximum likelihood estimate (TE-MLE) via STATA treatreg and two-stage least squares (2SLS).

Variables included in outcome equation are household size, sex, age, years of education, civil status, indicators for willingness to travel and sex interacted with all variables and average income in gewog.

Variables included in selection equation are as in c, but with instrument on stated belief in value of one of the skills provided by training program.

Standard errors clustered by chiwog.

Table 9
Tests of Spillover Effects

Marginal Effects Estimates	
	Equation (1) ^a : % Trainees in Chiwog
P(Income from skill > 0)	-0.222 [0.531]
Observations	342
	Equation (2) ^b : Training*% Trainees in Chiwog
Outcome Variable	(1)
HH per capita income	-12,516 [56,929]
HH per Capita Expenditures	2,391 [19,569]
Total Cost of HH Repairs	-45,664 [52,545]
Loan Amount - Present	36,780 [105,427]
Change Loan Amount	-46,326 [99,873]
% HH per capita income from skill area	-2.386** [0.977]
Change Status from 3 Yrs Ago	-1.28 [3.778]
Prospects Now Compared to 3 Yrs Ago	5.913 [3.979]
Approximate Observations	661

Notes:

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

See table notes.

a. Equation 1. Non-trainee sample only. Probit estimate of obtaining any income from skill area regressed on % of trainees plus household size, sex, age, years of education, civil status, indicators for willingness to travel and sex interacted with all variables, and average income wealth of gewog indicators.

b. Equation 2. Full sample. Standard regression estimate of outcomes regressed on trainee indicator, % of trainees in chiwog, and trainee interacted with % of trainees in chiwog, plus household size, sex, age, years of education, civil status, indicators for willingness to travel and sex interacted with all variables, and average income wealth of gewog indicators.

Table 10
Evaluation of Training Program

	Stage 1-2: Theory and Toilet	Stage 3: Hostel Construction
Observations	429	71
Rating (scale 1-10)	6.6	7.0
Better Work Opportunities	0.56	0.72
Length of Training Longer	0.52	0.56
Better Training Materials	0.19	0.14
Length of Training Shorter	0.17	0.18
Timeliness in Delivery of Tools	0.13	0.13
Timeliness of Stipend Payments	0.13	0.10
Occupational Health and Safety	0.10	0.06
Better Demonstration Tools	0.09	0.06
Quality of Trainer	0.09	0.10
Training Environment	0.07	0.06
Geographical Location	0.06	0.07
Curriculum Content	0.05	0.10

Note:

Contains all trainees surveyed independent of age or months since training.

Figure 1: Propensity Scores for Trainees and Non-Trainees



