Impact of Nonfarm Participation on Household Welfare: Empirical Evidence from Pakistan

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Abstract

This article employs propensity score matching approach to estimate the impact of nonfarm participation on rural household welfare in Punjab province of Pakistan. For the study cross sectional data set was collected from 325 households from the southern Punjab province. The data was collected from both categories of farmers having participated in the nonfarm activities and not participated in the nonfarm activities. The propensity score matching approach was employed to correct for potential sample selection biased ness, which may arise due to systematic differences between the participants and non participants. A number of matching algorithms were employed to check the robustness of the results. The empirical results indicate that education play a significant role regarding nonfarm participation. The nonfarm participants' households have higher incomes and have lesser poverty levels in the range of 9-18 percent.

Key Words: Nonfarm; Poverty; Income; Propensity Score Matching; Pakistan.

Introduction

Worldwide, rural households are engaged in a variety of nonfarm activities to generate income (Lanjouw and Lanjouw, 2001; World Bank, 2003). In some cases nonfarm employment can be a coping strategy to deal with lack of access to sufficient land or with income shocks in agriculture. In other cases, rural households may find it profitable to reduce their farming activities and engage increasingly in nonfarm employment (Micevska and Rahut, 2007).

In the developing countries nonfarm participation contributes about 30 percent to 45 percent of the rural household income (Haggblade et al., 2002). As the incomes from agriculture are subject to high variability and risk, nonfarm income may help smoothen consumption and improve livelihood security (Lanjouw, 1999).

Many empirical studies have reported that nonfarm activities occupy an important place in rural economies throughout the developing world (Hazell and Haggblade (1993); Adams and He (1995); Bakht (1996); Sen (1996); Lanjouw (1999)). Similarly, Reardon (1997) reported that the typical rural household in Africa has more than one member employed in a non-farm enterprise and the share of nonfarm income varies from 20 percent to 50 percent. Similarly Islam (1997) reported that the share of the non-farm sector in rural employment in developing countries varies from 20 percent to 50 percent. The main reason of rural poverty is high underemployment in agriculture combined with a scarcity of non-farm opportunities.

The nonfarm income can also help in ensuring household food security. The nonfarm income provides the cash that enables a farm household to purchase food during drought or after a harvest shortfall. Nonfarm income is also a source of farm household savings, used for food purchase in difficult times (Barrett and Reardon, 2011). Over the last two decades, the nonfarm economy has increasingly become the central focus of attention in rural development policy, due to positive contribution to poverty reduction and food security (Reardon 1998; Ellis, 1998; Lanjouw and Lanjouw, 2001; Davis, 2003). Participation in nonfarm activities is one of the livelihood strategies among poor rural households in many developing countries (Mduma and Wobst, 2005).

The nonfarm sectors in Pakistan, like many other developing countries covers a wide spectrum of activities. The pursuit of this diversification leads one to explore the potentials of the whole range of nonfarm activities. There is a considerable body of literature on poverty in Pakistan. This literature, however, has largely ignored the importance of nonfarm sector in poverty alleviation. Only few recent studies, based on relatively small sample size, have examined linkages between rural nonfarm sector and poverty (Adam and He, 1995). In Pakistan poverty has generally been higher in the rural areas than in the urban areas (Arif et al., 2000).

The objective of the current paper is to estimate the impact of nonfarm participation on rural household income and poverty status. For that the reminder of this paper is organized as follows. In section 2 conceptual framework and empirical models are presented. Section 3 presents the details about data set, sampling procedure and description of variables. In section 4 empirical results regarding impact of nonfarm participation are presented. In section 5, paper concludes with policy recommendations.

Conceptual Framework

In the current paper we start from a simple model. We assume that the household tends to increase its income level by having participation in the nonfarm activities. The farmers' participation in the nonfarm activities can be represented as D_i. Where D_i is equal to 1 in case of participation and 0 in case of non participation. However, the participation in the nonfarm activities is influenced by a number of factors such as farmer's personal, socioeconomic and farm level characteristics (X_i). The relationship between household income and the participation in nonfarm activities can be represented as

$$Y_i = \beta X_i + \gamma D_i + \mu_i \qquad (1)$$

Where Y_i is the farm household income participation in nonfarm activities, whereas X_i is a vector of household and farm level characteristics, in the equation D_i is the participation dummy = 1 for participation and 0 otherwise.

The empirical analysis regarding participation in the nonfarm activities and the farmers' net returns is carried out by employing the propensity score matching approach.

Propensity Score Matching Approach

The method of matching has achieved popularity more recently as a tool of evaluation. It assumes that selection can be explained purely in terms of observables characteristics. Propensity score matching can be implemented with both cross-sectional and longitudinal dataset. Matching deals with the selection process by constructing a comparison group of individuals with observable characteristics similar to those of treated. Applying the method is, in principle, simple. For every individual in the treatment group a matching individual is found from among the non-treatment group. The choice of match is dictated by observable characteristics. What is required is to match each treatment group individual with individual sharing similar characteristics. The mean effect of treatment can then be calculated as the average difference in outcomes between the treated and non-treated.

The matching method is a non-parametric approach and is more general in the sense that no particular specification has to be assumed. The main purpose of the matching is to re-establish the conditions of an experiment when no such data are available.

It follows that the expected treatment effect for the treated population is of primary significance. This effect may be given as

$$\tau\,|_{I=1} = E(\tau \mid I=1) = E(R_1 \mid I=1) - E(R_0 \mid I=1) \qquad (2)$$

where τ is the average treatment effect for the treated (ATT), R_1 denotes the value of the outcome for adopters of the new technology and R_0 is the value of the same variable for non-adopters. As noted above, a major problem is that we do not observe $E(R_0 \mid I = 1)$. Although the difference $[\tau^e = E(R_1 \mid I = 1) - E(R_0 \mid I = 0]$ can be estimated, it is a potentially biased estimator.

In the absence of experimental data, the propensity score-matching model (PSM) can be employed to account for this sample selection bias (Dehejia and Wahba, 2002). The PSM is defined as the conditional probability that a farmer adopts the new technology or participate in nonfarm activities, given pre-adoption/ participation characteristics (Rosenbaum and Rubin, 1983). To create the condition of a randomized experiment, the PSM employs the unconfoundedness assumption also known as conditional independence assumption (CIA), which implies that once Z is controlled for, technology adoption is random and uncorrelated with the outcome variables. The PSM can be expressed as,

$$p(Z) = \Pr\{I = 1 \mid Z\} = E\{I \mid Z\} \tag{3}$$

where $I = \{0,1\}$ is the indicator for adoption and Z is the vector of pre-adoption characteristics. The conditional distribution of Z, given $p(Z)$ is similar in both groups of adopters and non-adopters.

Unlike the parametric methods, propensity score matching requires no assumption about the functional form in specifying the relationship between outcome and predictors of outcome. The drawback of the approach is the strong assumption of unconfoundedness. As argued by Smith and Todd (2005), there may be systematic differences between adopters and non-adopters outcomes even after conditioning because selection is based on unmeasured characteristics. However, Jalan and Ravallion (2003) pointed out that the assumption is no more restrictive than those of instrumental variable (IV) approach employed in cross-sectional data analysis. In a study by Michalopoulos et al. (2004) to assess which non-experimental method provides the most accurate estimates in the absence of random assignment, they conclude that propensity score methods provided a specification check that tended to eliminate biases that were larger than average. On the other hand, fixed effects model did not consistently improve the results. The second assumption of the propensity score matching is the common support condition that matching can only be performed over the region of common support.

Data and Description of Variables

The present study was carried out in the Punjab province of Pakistan, which is the most populous province having almost 60 percent of the country population living there. The name Punjab literally translates from the Persian words *Panj* meaning five and *Ab* meaning water. Thus Punjab can be translated as five waters- and hence the land of the five rivers, referring to the *Jhelum*, *Chenab*, *Ravi*, *Beas* and *Sutlej* (Pakistan Encyclopedia, 2009).

The province is mainly a fertile region along the river valleys, while sparse deserts can be found near the border with Balochistan province and India. The region contains the Thal and Cholistan deserts. The Indus River and its many tributaries traverse the Punjab from north to south. The landscape is amongst the most heavily irrigated on earth and canals can be found throughout the province. Weather extremes are notable from the hot and barren south to the cool hills of the north. The foothills of the Himalayas are found in the extreme north as well.

Most areas in Punjab experience fairly cool winters, often accompanied by rain. By mid-February the temperature begins to rise; spring time weather continues until mid-April, when the summer heat sets in. The onset of the southwest monsoon is anticipated to reach Punjab by June. Despite its dry climate, extensive irrigation makes it a rich agricultural region. Its canal-irrigation system (established by the British) is the largest in the world. Wheat is the main food crop, while cotton and rice are important cash crops that contribute substantially to the national exchequer. Other crops include sugarcane, millet, corn, oilseeds, pulses, fruits and vegetables. Livestock and poultry production also contribute substantially to Pakistan agriculture.

Punjab contributes about 68% to annual food grain production in the country, about 51 million acres (210,000 km square) is cultivated and another 9.05 million acres (36,600 km square) are lying as cultivable waste in different parts of the province. Attaining self-sufficiency in agriculture has shifted the focus of the strategies towards small and medium farming, stress on rainfed areas, farm-to-market roads, electrification for tube-wells and control of water logging and salinity.

In Pakistan majority of the population i.e. 63 percent lives in the rural areas. The rural population is heavily dependent upon agricultural sector for their livelihood. There are limited non farm opportunities for the rural population. These opportunities include involvement in some business activities, service sector and also the involvement in the labour activities on some other farm. The data employed in the current analysis was collected through a field survey of 325 farmers from the Southern part of the Punjab province of Pakistan. Stratified random sampling technique was employed to select the farmers in the districts of Bahawalpur, Bahawalnagar, Vehari, Khanewal, Multan, Lodhran and Rahim Yar Khan. The districts were further divided into sub-districts and villages respectively for homogenous data collection. The sample ensured representation of the farmers both participating in the nonfarm activities and not participating in the nonfarm activities. The data collected included information on village infrastructure, household background, socioeconomic characteristics of the farmer, land holding, credit source and assets. The description of the variables is presented in table 1. The table indicates that average age of the farmers' was 42 years. The education level of the household was about 9 years of the schooling. About 62 percent of the farmers were self household head and in other cases they have some relationship with the household head i.e. father, brother, son and cousin etc. Among the surveyed households only 44 percent of the households have good quality soil and vice versa. The mean land holding in the study area was about 32 acres. The mean family size was about 10 family members per household. About 66 percent of the household have own tube well, similarly about 64 percent

Table 1 Data and description of variables

Variable	Description	Mean	Std. Dev
Bahawalpur	1 if farmer belongs to Bahawalpur district, 0 otherwise	0.172	0.382
Bahawalnagar	1 if farmer belongs to Bahawalnagar district, 0 otherwise	0.095	0.294
Khanewal	1 if farmer belongs to Khanewal district, 0 otherwise	0.135	0.342
Vehari	1 if farmer belongs to Vehari district, 0 otherwise	0.156	0.364
Multan	1 if farmer belongs to Multan district, 0 otherwise	0.061	0.240
Lodhran	1 if farmer belongs to Lodhran district, 0 otherwise	0.184	0.388
Rahim Yar Khan	1 if farmer belongs to Rahim Yar Khan, 0 otherwise	0.193	0.395
Age	Age of farmer in number of years	41.972	12.41
Education	Education level of farmer in number of years	9.02	12.143
Head	1 if farmer is head of household, 0 otherwise	0.618	0.485
Soil fertility	1 if good soil fertility, 0 otherwise	0.436	0.496
Land holding	Number of acres owned by the farmer	31.52	12.57
Family size	Number of family members in the household	9.52	3.29
Tube well	1 if household own a tube well, 0 otherwise	0.661	0.473
Tractor	1 if household own a tractor, 0 otherwise	0.643	0.479
Car	1 if household own a car, 0 otherwise	0.215	0.411
TV	1 if household own a tv, 0 otherwise	0.747	0.435
Credit access	1 if household have access to credit facility, 0 otherwise	0.338	0.473
Membership	1 if farmer have organization membership, 0 otherwise	0.156	0.364
Off farm work	1 if farmer is involved in off farm work, 0 otherwise	0.20	0.400
Household	Income of the household in rupees	46415	3210.5
Poverty	Poverty level of the household measured in head		
	Count index	0.230	0.276

Source: Survey Results.

of the farmers have own tractor. Only 22 percent of the households have own vehicle (car), contrary majority of the households 75 percent own a TV. About 34 percent of the households have access to credit facility. Only 16 percent of the households have organization membership. Nearly 20 percent of the households were involved in nonfarm work and vice versa. The average household income was about 46415 rupees per month. For estimation of the poverty head count index was employed and the results indicate that about 23 percent of the households lives below the poverty line.

Empirical Results

The empirical analysis was carried out by employing STATA statistical software. The logit estimates regarding participation in the nonfarm activities are presented in table 2. Regarding inclusion of variables in the nonfarm participation model guidance was taken from the previous studies like Caliendo and Kopeinig (2008) pointed out that to obtain the unconfounded effect of adoption on outcome, only variables that influence both adoption and outcomes and are not affected by adoption should be used in the propensity score model when matching is performed. Smith and Todd (2005) also argued that the choice of variables should be guided by economic theory, sound knowledge of previous research and the institutional setting within which treatment and outcomes are measured. Similarly Bryson et al. (2002) described that only those variables that affect participation and outcomes should be included, variables that affect neither participation nor outcomes are clearly irrelevant.

In Pakistan the farmers participate in the nonfarm activities within the same village (same community) or in some other village nearby where the nonfarm activities participation opportunities are available to the farmer. Some farmers also travel to nearby cities for participation in nonfarm activities. The most common nonfarm opportunities available to the farmers are involvement in some business activities, involvement in service sector, but majority of the farmers in the study area are involved

Table 2 Propensity score matching estimates regarding nonfarm participation (logit estimates)

Variable	Coefficient	z-values
Age	-0.015	-0.82
Education	0.043**	2.06
Household head	0.190	0.52
Soil fertility	0.326*	1.94
Household size	0.050**	2.21
Land holding	-0.067*	-1.92
Tube well (dummy)	0.135	0.40
Tractor (dummy)	-0.358	-0.98
TV (dummy)	-0.194	-0.53
Car (dummy)	-0.456	-1.06
Credit (dummy)	-0.277	-0.83
Constant	-0.743	-0.83
Number of observations	325	
Pseudo R^2	0.1025	
χ^2	33.34	
Prob > χ^2	0.000	

Note:District dummies were also included in the model, although not reported. The results are significantly different from zero at ***1, **5 and *10 percent levels respectively.

in the labour activities.

Hence, based on the previous studies the variables included in the model are age, education, land holding, soil fertility and household assets etc. The age coefficient is negative indicating that mostly young farmers participate in nonfarm activities and vice versa. The results of age are in line with the previous studies, as Smith (2000) noted that mostly the younger household members migrate in search of nonfarm income earning activities. A key determinant of participation in more remunerative nonfarm activities is education. Education is an important advantage to alleviate poverty if nonfarm activities are to compensate for asset disadvantage. Getting rural household out of poverty requires investment in rural education, as well as efforts to increase access of rural youth to schooling and to prepare them to access well-remunerated non-agricultural employment. This is particularly important if the expanding nonfarm sector increasingly favors employment that requires skills and education. The education coefficient is positive and significant at 5 percent level of significance indicating that higher education levels increases farmers participation levels. This can also be incurred from the results that the educated farmers have higher opportunities to participate in nonfarm activities as they get more chances than the non educated farmers. Similar results were also reported by the previous studies; Micevska and Rahut (2007) and Ruben and van den Berg (2001) showed that educated and wealthier households take advantage of their human and physical capital by participating more in nonfarm activities. The household head was included as dummy variable and the coefficient is positive although non-significant. Soil fertility was included as dummy variable and the coefficient is positive and significant at 10 percent level of significance implying direct relationship between nonfarm participation and soil fertility. The household size is positive and significant at 5 percent level of significance indicating that as the number of persons in the household increases chances of nonfarm participation also increases and vice versa. The results regarding family size are in line with the previous studies as structure of rural families play a significant part in determining the access by individuals to non-farm opportunities. Reardon (1997) observe that family size and structure affect the ability of a household to supply labour to non-farm sector. Larger families and those with multiple conjugal units supply more labour to the rural nonfarm sector, as sufficient family members remain in the home or on the farm to meet labour needs for subsistence. The land holding is negative and significant at 10 percent level of significance indicating that more the land holding less the chances of nonfarm participation and vice versa. The results regarding land ownership are in line with the previous studies as share of nonfarm income was found to fall with land size, meaning poor households were pushed into non-farming due to land scarcity and excess of labour (Reardon et al., 2001; Davis et al., 2007). In the current study a number of household assets are included in the model, to show the impact of assets ownership regarding nonfarm participation. The tube well coefficient is positive and non significant. The tractor coefficient is negative and non significant. The TV coefficient is negative and non significant. Similarly the car coefficient is negative and non significant. The value of pseudo R^2 is 0.1025, the value of R^2 indicates that about 10 percent variation in the dependent variable is due to independent variables included in the model. The χ^2 value is significant at 1 percent level of significance, hence indicating the robustness of the variables included in the model.

A number of different matching algorithms i.e. Nearest Neighbour Matching[1] (NNM), Kernel Matching[2] (KM), Radius Matching[3] (RM) and Mahalanobis Metric Matching (MMM) are employed to analyze the impact of nonfarm participation on household income and poverty status, the results are presented in table 3. As the most important variable of interest in table 3 is the average treatment affect for the treated (ATT) i.e. difference in outcome of the participants and non participants. The impact on two important outcome variables related to household welfare i.e. income and poverty was estimated. The results for income are positive and significant in all the four matching algorithms. The results for income are in the range of rupees 1852 to highest of rupees 3271 indicating that participants have higher income levels as compared to non participants. The results indicated that nonfarm participants

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[1] The nearest neighbor algorithm matches similar individual in the participation group to similar individual in the non participation group.

[2] The Kernel matching takes the weighted average of all the non participants and then matches with the individuals in the participation group.

[3] The radius matching is actually a variant of nearest neighbor matching

Table 3 ATT results for nonfarm participation

Matching Algorithm	Outcome	Caliper/ATT Bandwidth	t-value	Critical level of hidden bias		Number of Treated	Number of Control
Nearest Neighbor Matching	Income	0.01	2563.08*	1.92	1.45-1.50	55	141
Nearest Neighbor Matching	Poverty	0.01	-0.16**	-2.07	1.50-1.55	52	152
Kernel Matching	Income	0.05	3245.07***	3.26	1.30-1.35	56	202
Kernel Matching	Poverty	0.05	-0.09	-0.62	-	51	219
Radius Matching	Income	0.03	1852.83*	1.85	1.20-1.25	58	213
Radius Matching	Poverty	0.03	-0.14*	-1.69	1.45-1.50	52	247
Mahalnobis Metric Matching	Income	0.07	3271***	2.78	1.15-1.20	31	89
Mahalnobis Metric Matching	Poverty	0.07	-0.18*	-1.77	1.20-1.25	35	92

Note: ATT stands for average treatment affect for the treated. The results are significantly different from zero at ***1, **5 and *10 percent levels respectively.

have higher income levels as compared to non participants. This can be concluded from the empirical results that higher income levels have positive welfare impact on the residents on rural households in Pakistan. The results for poverty are negative and significant in case of NNM, RM and MMM while non significant in case of KM. The results for poverty vary in the range of 0.09-0.18 indicating that nonfarm participation can help to reduce household poverty in the range of 9 percent to 18 percent, or in other words the participant households have less poverty level as compared to non participants. The results are very much in line with the previous studies like that of de janvry et al. (2005) have reported for China.

The positive and significant results for household income and negative and significant results for the poverty levels indicate that nonfarm participation besides increasing household income can help to reduce the poverty levels in the rural households, which can increase the household welfare in the long run.

The critical level of hidden bias is also presented in the table 3. The critical level of hidden bias varies in the range of 1.15-1.55. The critical level of hidden bias indicates that participants and nonparticipants vary in their odds of participation in the range of 15-55 percent. This does not indicate that in the presence of hidden bias the results will be questionable; this only indicates the level up to which the participants and non participants will vary. The number of treated and the number of control are also presented in the table 3. The number of treated indicates the individual in the participation group, while the number of control indicates the individual in the control group.

As the main purpose of the propensity score matching is to balance the covariates before and after matching for that a number of different matching tests are employed like median absolute bias before and after matching, value of R^2 before and after matching and the joint significance of covariates before and after matching. In all the matching algorithms i.e. NNM, RM, KM and MMM, the median absolute bias is quite high before matching and is quite low after matching, indicating

Table 4 Indicators of covariate balancing before and after matching

Matching Algorithm	Caliper	Median absolute bias (before matching) %	Median absolute bias (after matching) %	(Total) % bias reduction	Pseudo R^2 (unmatched)	Pseudo R^2 (matched)	$P > \chi^2$ (unmatched)	$P > \chi^2$ (matched)
Nearest Neighbour Matching	0.01	18.51	5.77	68.827	0.436	0.001	0.000	0.832
Nearest Neighbour Matching	0.01	17.93	6.82	61.936	0.544	0.003	0.000	0.705
Kernel Based Matching	0.05	16.44	3.76	77.128	0.721	0.005	0.000	0.915
Kernel Based Matching	0.05	13.55	7.81	42.361	0.419	0.003	0.000	0.472
Radius Matching	0.03	15.76	9.54	39.453	0.837	0.006	0.000	0.718
Radius Matching	0.03	17.58	8.41	52.161	0.526	0.008	0.000	0.632
Mahalanobis Metric Matching	0.07	12.73	6.83	46.347	0.268	0.085	0.000	0.521
Mahalanobis Metric Matching	0.07	9.62	4.67	51.455	0.378	0.056	0.000	0.832

that after matching the covariates have been balanced. The percentage bias reduction is in the range of 39-77 percent indicating that considerable amount of bias has been reduced after matching and the participants and non participant are very similar to each other. The value of R^2 is another indicator of covariate balancing. The value of R^2 is quite high before matching and is quite low after matching indicating that after matching there is not much difference between participants and non participants. The joint significance of covariates should always be accepted before matching and should always be rejected after matching that after matching the participants and non participants are quite similar and there are no systematic differences between participants and non participants.

Conclusions

The nonfarm participation determinants indicate that education play an important role regarding nonfarm participation. The farmers having higher education levels were enjoying the higher participation in the nonfarm activities and vice versa. This can be concluded from the empirical results that participation in the nonfarm activities have positive and significant impact on household welfare. The participants of the nonfarm work have higher household income as compared to non participants. The higher income levels can help to reduce the household poverty levels as the empirical results of the current study also indicates that poverty levels were lower among the households participating in the nonfarm activities as compared to household not participating in the nonfarm activities. As the agriculture sector is vulnerable to risk, hence the participation in nonfarm activities can also be a risk coping strategy. The policy implications of these findings can be the that in rural areas more nonfarm opportunities needs to be created, so that farmers are able to increase their incomes besides reducing the poverty levels. The less education levels is one of key barrier regarding entering in the nonfarm participation.

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