Nonfarm Employment and Poverty Reduction in Rural Ghana: A Propensity-Score Matching Analysis

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Abstract
This article investigates the impact of nonfarm employment on farm household income and way out of poverty, using farm household data from Brong-Ahafo region of Ghana. A propensity score matching model is used to evaluate the impact participating in both wage and self-employment. Separate estimates are also provided for males and females. The results from the study show that nonfarm employment has a positive and robust effect on farm household income and a negative and significant effect on the likelihood of being poor. Self-employment was found to have much higher impacts than wage employment, reflecting the fact that most employment opportunities in the rural areas are in the former sector.

Keywords: Non-farm employment; Poverty; Matching

1. Introduction

Despite agriculture being the main stay of most rural economies in sub-Saharan Africa, nonfarm sources of income contribute significantly to overall income of rural households and are very relevant in the poverty reduction strategies of these economies. Reardon et al. (1994) report an average share of 42% of non-farm income in total rural household income in Africa, 32% in Asia and 40% in Latin America. More recent estimates by Haggblade et al. (2002) show that local nonfarm income contributes between 30% to 45% of rural household incomes in the developing world. Available evidence also

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suggests that the significance of non-farm income has increased over the last few decades (Reardon et al., 2000). Given that output and income from agriculture are subject to high variability and risk, nonfarm income may help smoothen consumption and improve livelihood security (Lanjouw, 1999).

As part of an income diversification strategy, nonfarm activities among farm households are pursued through employment in the rural non-farm labor market; self-employment in the local non-farm sector; and employment in the migration labor market. As pointed out by Reardon (1997), in spite of the increasing evidence of the significance of the nonfarm sector to farm households in Africa, there is still scanty empirical evidence on farm household participation in the nonfarm sector in both wage employment and self-employment. This contrasts strongly with the vast literature on the nonfarm sector in rural Asia and Latin America (e.g., Leones and Feldman, 1998; Micevska and Rahut, 2008).

Moreover, the empirical studies on Africa have been largely limited to analyzing the nature and determinants of participation in nonfarm activities, with very little empirical evidence on the impact of participation in the non-farm sector on farm household income and poverty (Barrett et al., 2001; Jolliffe, 2004; van den Berg and Kumbi, 2006). Studies examining the effects of nonfarm income on total farm household incomes and poverty have focused on the income-equity effects of nonfarm income. However, work on the direct impact of nonfarm employment on farm household income and poverty is very scarce (Reardon et al., 2000).

The purpose of this article is to examine the impact of nonfarm employment on total farm household income and poverty among farm households in the Brong-Ahafo region

of Ghana. Specifically, we investigate the impact of nonfarm employment, disaggregated

by wage employment and self-employment on total household income and poverty. We

also provide separate estimates for male headed and female headed households. In view

of the non-experimental nature of the data employed in the analysis, a propensity score

matching model is employed to account for selection bias that normally arises when

participation is not randomly assigned and self-selection into participation occurs. This

paper differs from other studies in the sense that it disaggregates nonfarm employment

into wage and self-employment, and also employs a matching model that is suitable for

non-experimental data.

The remainder of the article is organized as follows: The empirical specification is

outlined in Section 2, which also contains a description of the propensity score matching

approach. Section 3 provides a description of the data. Section 4 discusses the empirical

results on the implementation of the matching procedure. Section 5 provides some

concluding comments.

2.1. Nonfarm employment and household income

The relationship for examining the impact of nonfarm employment on farm household

income assumes a linear specification for household income as a function of a vector of

explanatory variables (Z_i) and a participation dummy variable (D_i). The farm household

income (Y_{ij}) regression can be expressed as

$$Y_{ij} = \beta Z_i^{'} + \alpha D_i + \xi_i \qquad (1)$$

where Y_{ij} is farm household income for male headed households ($i = 1$) and female headed

households ($i = 2$), participating in overall nonfarm employment ($j = 1$), wage

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employment in the nonfarm sector ($j = 2$) and self-employment in the nonfarm sector ($j = 3$); ξ_i is a normal random disturbance term and D_i is a 0 or 1 dummy variable for participation in nonfarm employment; $D_i = 1$ if the individual participates in nonfarm employment, and $D_i = 0$, otherwise. The vector, Z_i, summarizes individual and household characteristics such as demographic characteristics, human capital, and asset structure. As shown in the empirical literature on nonfarm employment, whether an individual participates in the nonfarm labor market or not is dependent on the individual and household characteristics. Thus, the decision of individuals to participate in the nonfarm labor market is based on the individual's self-selection rather than random assignment (Huffman, 1991).

Following the empirical literature on off-farm work decisions of agricultural households, it is assumed that the participation decision of the individual is influenced by a comparison between the reservation wage (W_{ij}^R) and the potential market wage (W_{ij}^m) in the nonfarm sector. If the potential market wage of an individual's nonfarm time is greater than the shadow value of time, a positive number of nonfarm hours will be observed for the individual. Thus, participation in nonfarm employment occurs if $W_{ij}^m - W_{ij}^R > 0$. Given that we do observe participation or non-participation, Huffman and Lange (1989) note that an index function can be specified with an unobserved variable, T_{ij}^* such that $T_{ij}^* = \gamma X_i' + \mu_i$

$$
\begin{aligned}
T_{ij} &= 1 \ \text{ if } \ T_{ij}^* > 0 \\
T_{ij} &= 0 \ \text{ if } \ T_{ij}^* \le 0
\end{aligned}
\tag{2}
$$

where X_i is a vector of individual and household characteristics and μ_i is an error term. It is important to note from outcome equation (1) and treatment equation (2) that the relationship between participation in nonfarm employment and farm household income may be interdependent. As noted by Reardon (1997), participation in nonfarm employment can help households earn higher incomes, while wealthier households can easily overcome barriers to participation in nonfarm activities. The implication of this is that treatment assignment is not random, with the group of participants being systematically different. If unobservable factors influence both error terms in the participation (μ_i) and household income (ξ_i), equations, selection bias occurs, resulting in correlation of the error terms in the two specifications. The error term of the outcome variable and the treatment variable then become correlated such that $corr(\mu, \xi) = \rho$. In this case, any standard regression technique such as OLS applied to the regression models produces biased results when $\rho \neq 0$.

The Heckman two-step approach is used to address selectivity bias but this approach relies on the strong distributional assumption that the error terms in the treatment and outcome specifications are jointly normally distributed, with zero means and constant variances. In addition, the exclusion restriction required for the Heckman procedure is an untestable assumption and often difficult to meet, as it is difficult to find variables that affect the probability of participation in nonfarm employment, but not household income other than through their effect on participation (Bryson et al., 2002). The problem of self-selection can be overcome by resorting to statistical matching which involves pairing participants and non-participants that are similar in terms of observable characteristics (Dehejia and Wahba, 2002).

2.2. The propensity score matching technique

To examine this causal effect of non-farm employment participation on household income and poverty, the *p*-score matching approach is employed. The propensity score $p(X)$ is the conditional probability of receiving a treatment given pre-treatment characteristics (Rosenbaum and Rubin, 1983). Thus,

$$p(X) \equiv Pr\{T = 1 \mid X\} = E\{T \mid X\} \tag{3}$$

where $T = \{0,1\}$ is the indicator of exposure to treatment (non-farm employment participation) and X is the vector of pre-treatment characteristics.

The parameter of interest in the estimation of propensity score is the Average Treatment Effect on the Treated (ATT) which can be estimated as

$$\delta \equiv E\{Y_i^1 - Y_i^0 \mid T_i = 1\} = E\{E\{Y_i^1 \mid T_i = 1, p(X_i)\} - E\{Y_i^0 \mid T_i = 0, p(X_i)\} \mid T_i = 1\} \tag{4}$$

where $p(X_i)$ is the *p*-score, Y_i^1 and Y_i^0 are the potential outcomes in the two counterfactual situations of receiving treatment (participation in non-farm employment) and no treatment (non-participation in non-farm employment).

Two important properties of the *p*-score matching are the balancing property and conditional independence assumption (CIA). Testing for this property is important to ascertain if household behavior within each group is actually similar. Related to the balancing property of *p*-score is the conditional independence assumption (CIA), which states that participation in non-farm employment is random and uncorrelated with household income and poverty status, once the set of observable characteristics, *X*, are controlled for. A further requirement is the common support condition which requires that persons with the same values of covariates X have positive probabilities of being

both participants and non-participants (Heckman, LaLonde, and Smith, 1999). Thus, all individuals in the common support region actually can participate in all states ($0 < P(T = 1 | X) < 1$).

2.3. Implementation of the *p*-score

This section discusses the estimation of the *p*-score, choice of matching algorithm, overlapping or common support condition, and assessment of matching quality. Caliendo and Kopeinig (2008) note that the logit model which has more density mass in the bounds could be used to estimate the propensity score $p(X)$.

The next stage is to choose the matching algorithm which best estimates the *p*-score. The choice of matching method involves a trade-off between matching quality and its variance. Various matching estimators have been suggested in the literature. These include the nearest neighbor matching, radius matching, and the kernel matching. The nearest neighbor matching uses only the participant and its closest neighbor. As pointed out by Abadie and Imbens (2006), the nearest-neighbor matching estimators for average treatment effects allows individual observations to be used as a match more than once and compared with matching without replacement. Kernel-based matching on the other hand uses more non-participants for each participant, thereby reducing the variance but possibly increasing the bias.

2.4. Matching quality

The matching quality depends on the ability of the matching procedure to balance the relevant covariates. The standardized bias proposed by Rosenbaum and Rubin (1985) is

used method to quantify the bias between treated and control groups. Sianesi (2004) has also proposed a comparison of the pseudo-R^2 before and after matching. To ensure that there are no systematic differences in the distribution of the covariates between both groups, the pseudo-R^2 should be fairly low after matching. Sensitivity analysis can also be undertaken to check if the influence of an unmeasured variable on the selection process is so strong to undermine the matching procedure. Since it is not possible to estimate the selection bias in practice with non-experimental data, we employ the bounding approach suggested by Rosenbaum (2002).

The bounds on the odds-ratio that either of the two matched individuals will receive treatment is denoted by $1/\Gamma \leq P(X_i)(1 - P(X_j))/P(X_j)(1 - P(X_i)) \leq \Gamma$. In this case, $\Gamma = 1$, represents the scenario without any hidden bias, where both matched individuals have the same probability of participating in non-farm employment (Hujer et al., 2004). Sensitivity analysis for insignificant effects is not meaningful and should normally not be considered.

3. Data description

This article employs data from a household survey conducted in 2003 in two administrative districts—Techiman and Nkoranza–in the Brong Ahafo region of Ghana. A stratified random sample of 400 farm households were selected from six villages— Aworopata, Twimea-Nkwanta, Nkwaeso and Woraso, Ayerede and Dromankese—in the two districts. The two districts were purposely selected to provide representation of the different agro-climatic conditions and economic incentives for non-farm employment opportunities in the administrative districts of Brong Ahafo region.

Participation in non-farm employment in general, and in self-employment and wage employment were all measured as dummy variables indicating 1 if the farmer participated in these activities and zero otherwise. Total household income as noted by Reardon and Taylor (1996) can be categorised into income from non-farm employment (in this article, self-employment and wage employment incomes), on-farm work, income from livestock and transfers received by the household. The share of non-farm income in total household income is 30% with self-employment income share alone being 81%. The share of non-farm income in the total household income for the non-participants is 40%. The average household income for the participants was ¢8,690,000 (US $1022.35) and for non-participants was ¢8,200,000 (US $964.71).[3]

The poverty indicator used was per capita expenditure, whereby households with per capita expenditure less than US $1 per day were considered as poor (World Bank, 2001; Elbers et al, 2003). Using this poverty index, Coulombe (2005) notes, is the same as the one used in the poverty profile based on Ghana Living Standard Survey (GLSS4). The poverty outcome was measured as a binary variable and about 49% of the sampled farmers fell below the stipulated poverty line.[4] Since gender plays an important role in the poverty dynamics in Ghana, the gender stratification was used to account for specific sub-population within the full sample. Caliendo and Kopeinig (2008) have pointed out that matching should normally be based on variables that influence both treatment assignment and outcomes and are not affected by the treatment. Selection of variables relies on previous empirical work on the determinants of participation in nonfarm employment.

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[3] Exchange rate: US $1=¢8500 in 2003. ¢ = Cedis, the official currency of Ghana in 2003.
[4] A farmer is poor if his/her per capita expenditure per day falls below US $1.

4. Empirical Results

The results from the propensity score analysis are reported here.[5] The analysis was conducted for the entire sample and then differentiated by gender. As indicated earlier, the propensity score only serves as a device to balance the observed distribution of covariates across the treated and untreated groups. A detailed discussion of the results of the propensity score estimations is therefore not undertaken here. The common support condition was imposed and the balancing property was set and satisfied in all the estimated regression models at 1% level of significance.

The effects of non-farm employment on household income and poverty were estimated by nearest neighbor matching method with replacement. The results are presented in Table 2. The matching results generally indicate that non-farm employment has a positive and significant effect on household income and way out of poverty. For the full sample, the causal effect of participation in non-farm employment is 5.58, which is the average difference between incomes of similar pairs of households that belong to different participation status. The magnitude of the coefficient suggests that the average treatment effect of participating in non-farm employment increases the individual's household earnings by ¢5,578,100 (US $656). The coefficient for poverty indicates that participants in non-farm employment are less likely to be poor by about 46% (on average). The reduction in mean absolute standardized bias from 27.1% to 9.9% indicates a substantial reduction in bias as a result of employing the matching technique.

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[5] In the interest of brevity, the descriptive statistics of the variables used in the logit regression models, the results of p-score as well as the distributions of the propensity scores before and after the matching are not reported here but are available upon request from the authors.

Similarly, the causal effect of 6.58 for in self-employment indicates that the average treatment effect of participating in non-farm employment increases the individual's household earnings by ¢6,580,000 (US $774). Participants in self-employment are less likely to be poor by 36% points (on average). A reduction in mean absolute bias of 23.1% to 9.3% is an indication that by the chosen matching algorithm and propensity score estimation, the covariates are balanced. Although there appears to be no significant difference in income between participants and non-participants in wage employment, there is still a significant impact (*albeit* at the 10% level of significance) on poverty reduction.

Also presented in Table 2 are the separate estimates for males and females. The participation in non-farm employment by males generally leads to a positive and significant increase in household income, as well as a lower probability of being poor. The causal effects are also positive and robust for self-employment, but insignificant for wage employment. Only female participation in self-employment exerts a significant impact of household income and poverty status, indicating that only self-employment makes a significant difference between participants and non-participants.

The bounding approach suggested by Rosenbaum (2002) was employed to conduct a sensitivity analysis. The critical levels of e^{λ} are presented in Table 2. These values indicate the levels at which the causal inference of the significant impact of non-farm employment may be questionable. Given that sensitivity analysis for insignificant effects is not meaningful, Rosenbaum bounds were calculated for treatment effects that are significantly different from zero. For positive selection bias, those that are most likely to

participate in non-farm employments would tend to have higher household incomes and poverty reduction even in the absence of participation (Becker and Caliendo, 2007).

The results compare favorably with findings from other studies and are generally insensitive to hidden bias. For the impact of non-farm employment on household income for the full sample, the sensitivity analysis suggests that at a level of $e^{\lambda} = 1.15$, causal inference of the significant impact of non-farm employment would have to be viewed critically. If individuals that have the same Z-vector differ in their odds of participation by a factor of 15%, the significance of the participation effect on income may be questionable. The critical value of 1.15 does not indicate that there is unobserved heterogeneity in the sample and that there is no effect of participation on income or poverty. What it indicates is that the confidence interval for the treatment effect would include zero, if an unobserved variable caused the odds ratio of treatment assignment to differ between treatment and control groups by 1.15 (Hujer et al., 2004). The results of the tests on the matching quality which are not presented here for the sake of brevity also show fairly low pseudo-R^2's and insignificant F-statistics after the matching, indicating that overall, these are satisfying results and that the matching procedure was successful in balancing the covariates between treated individuals and members from the comparison groups.

5. Conclusions

This study investigated the impact of non-farm employment on household income and poverty reduction, using a sample of farm households from the Brong-Ahafo region in Ghana. A propensity score matching model was employed to account for selection bias

that normally occurs when unobservable factors influence both participation in non-farm employment and household income. By explicitly referring to the causal relationship between participation in non-farm employment and household welfare, the paper seeks to address counterfactual questions that may be significant in predicting the impacts of policy changes. The paper provides separate estimates for the impacts of total non-farm employment, self-employment and wage employment, as well as for males and females.

The results show that non-farm employment has a positive and robust effect on household income and way out of poverty, a finding that is consistent with the widely held view that income from non-farm employment is crucial to food security and poverty alleviation in rural areas of developing countries. The estimates differentiated by employment type show that the gains from non-farm employment are higher for self-employment than wage employment. Self-employment was found to have a positive and significant impact on incomes and way out of poverty for both male and female headed households. While participation in wage employment did lower the probability of being poor for males, it did not appear to significantly influence the incomes of both male and female households. As argued by Reardon (1997), women in particular appear to be limited to the low-wage activities in the non-farm sector, resulting in lower earnings that do not necessarily help them out of poverty.

The findings indicate that the growing interest of policy makers in promoting non-farm activities, particularly in rural areas of developing countries is in the right direction. Besides being a valuable source of income for rural households, non-farm employment also helps to smooth incomes, which in turn smoothens consumption over long periods of time. Given that women face entry barriers to participation in self-employment, which

exerts a positive and robust effect on household income and way out of poverty, policy

measures could target them to improve their participation in this type of non-farm

activities. Such measures include increasing their access to assets such as information,

financial capital, education and infrastructure. These assets can help them overcome the

entry barriers to non-farm employment, particularly non-farm self-employment. It is

however significant to mention that development of the non-farm activities should

complement the effort to develop agriculture, since activities in the former depend

directly or indirectly on the latter.

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Table 2. Average treatment effects and sensitivity analysis

	Outcome	ATT	t-statistics	Critical value of Γ (hidden bias)
Full sample				
Non-farm employment	Household income	5.5781	3.64***	1.16
	Poverty	0.4638	-3.00***	1.30
Self-employment	Household income	6.5800	4.78***	1.21
	Poverty	0.3552	-2.99**	1.80
Wage-employment	Household income	4.2268	0.41	–
	Poverty	0.6190	-1.63*	1.30
Males				
Non-farm employment	Household income	5.7128	3.41***	1.18
	Poverty	0.4820	-1.76*	1.45
Self-employment	Household income	7.3394	3.42***	1.22
	Poverty	0.3108	-3.25***	2.7
Wage-employment	Household income	3.9433	1.54	–
	Poverty	0.6622	-3.59***	1.45
Females				
Non-farm employment	Household income	5.3829	0.75	–
	Poverty	0.4375	-0.36	–
Self-employment	Household income	5.8596	2.37**	1.20
	Poverty	0.3974	-1.70*	1.15
Wage-employment	Household income	4.9037	0.44	–
	Poverty	0.5161	-0.77	–

*** Denotes significant at 1%, ** denotes significant at 5%, * denotes significant at 10%.
Source: Own calculations