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# Nonfarm employment and household income among ethnic minorities in Vietnam

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This study examines the determinants of nonfarm participation and the effect of nonfarm employment on household income among ethnic minorities in the Northwest Mountains, Vietnam. The logistic regression analysis shows that education and the availability of local enterprises or trade villages, notably among other factors, have a significantly increasing impact on the likelihood of taking up wage employment, while the presence of paved roads gives households more chance to engage in nonfarm self-employment. Using a propensity score matching analysis, the study found that households that participated in wage or nonfarm self-employment have higher levels of per capita income than those without nonfarm employment. The findings imply that nonfarm employment offers a pathway out of poverty for ethnic minorities.

**Keywords:** ethnic minorities; nonfarm participation; propensity score matching; North-West; Vietnam

**JEL classification:** I32; O12; J15

## 1. Introduction

Vietnam has 54 distinct ethnic groups; each with its own language, lifestyle and cultural heritage. The most populous group is 'Viet' or 'Kinh', which accounts for 86% of the country's population (Tung & Trang, 2014). The majority of this group lives in inland deltas and coastal areas and enjoys higher living standards than ethnic minority groups. 'Hoa' or the Chinese group is a relative rich group that also resides in inland deltas and coastal areas (Imai, Gaiha, & Kang, 2011). The other 52 ethnic minority groups reside in upland and mountainous areas, ranging from the South to the North (Tung & Trang, 2014). These groups have a very limited access to infrastructure or health and educational facilities and they are much poorer than the ethnic majority group (Kinh/Hoa groups)[1](Imai et al., 2011).

Although ethnic minority groups make up less than 15% of Vietnam's total population, they contribute 47% of the poor in 2010, compared with 29% in 1998. It was estimated that 66.3% of ethnic minorities still lived below the poverty line compared with only 12.9% of the Kinh majority population in 2010 (World Bank [WB], 2012).[2] Ethnic minorities depend heavily on agriculture in association with land for subsistence and their ability to switch to nonfarm employment is very limited. The change in economic

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and employment structure from agriculture to other sectors in ethnic minority areas has taken place slowly, and not yet met with the trend of regional development and the development pace of the country (United Nations Development Programme [UNDP], 2012).

A growing body of empirical evidence has confirmed that nonfarm employment is a positive determinant of poverty alleviation and household welfare for both rural and peri-urban households in Vietnam (Tuyen, 2014). For instance, van de Walle and Cratty (2004) found that although access to land tends to considerably increase household wellbeing, the probability of falling into poverty is substantially lower among households who participate in nonfarm self-employment in rural Vietnam. As calculated by Pham, Bui, and Dao (2010), on average and *ceteris paribus*, the shift of a household from pure agriculture to pure non-agriculture raises expenditure per capita, and this outcome tends to steadily increase over time. In addition, participation in any types of nonfarm activities increases both income and expenditure per adult equivalent for households in Vietnam's peri-urban areas (Tuyen, Lim, Cameron, & Huong, 2014a).

Nevertheless, to the best of my knowledge, limited evidence exists for the determinants of nonfarm participation and impact of nonfarm employment on household welfare among ethnic minorities in Vietnam. Hence, the current study was conducted to fill in this gap in the literature. The main objective of this study is to examine the determinants of nonfarm participation and the impact of nonfarm employment on income among ethnic minority households in North West Mountains. The North West Mountainous region was selected for this study because it is the poorest region of Vietnam with a significant proportion of ethnic minorities living in mountainous areas, with very limited access to non-farm activities and other social and physical infrastructure (Cuong, 2012).

Using a micro-econometric approach combined with a propensity score matching analysis, the current study added to the extant literature by offering new empirical evidence of key factors affecting the participation in nonfarm activities and significantly positive impacts of nonfarm participation on household income among ethnic minorities in the Northwest Mountains area. These findings are very informative and useful because they provide Vietnam policy makers with evidence that nonfarm employment offers a pathway out of poverty for ethnic minorities in the sense that nonfarm activities have a strongly positive association with household income. This study improves our understanding about the role of nonfarm employment in the livelihood of ethnic minority households in the study area.

The paper is structured into four sections. The next section describes data source, measurements of poverty, econometric models and a propensity score matching (PSM) analysis used in this study. The third section presents estimation results and discussion. Finally, conclusion and policy implications are presented in the fourth section.

## 2. Data and methods

### *2.1. Data source*

The data from the Northern Mountains Baseline Survey (NMBS) 2010 were used for this study. The survey was conducted by the General Statistical Office (GSO) of Vietnam from July to September in 2010 to collect the baseline data for the Second Northern Mountains Poverty Reduction Project. The main objective of the project is to reduce poverty in the Northern Mountains area. The project has invested in social and physical infrastructure in poor areas and also has helped the poor expand agricultural and non-agricultural production. Six provinces in the North West region (see Appendix 1) were covered in the project, including Hoa Binh, Lai Chau, Lao Cai, Son La, Dien Bien and Yen Bai (Cuong, 2012).

The survey covered 120 communes that were randomly selected from six aforementioned provinces. The sample size included 1800 households from various ethnicities, such as Tay, Thai, Muong, H'Mong and Dao. Both commune and household data were collected for the survey. The household data include characteristics of household members, education and employment, healthcare, income, housing, fixed assets and participation of households into targeted programmes. The commune data consist of information about the characteristics of communities such as demography, population, infrastructure, nonfarm job opportunities and targeted programmes in the communes. The commune data can be merged with the household data.

### *2.2. Poverty measurements*

Foster, Greer, and Thorbecke (FGT) decomposable poverty measures were used to compute the incidence, depth and severity of poverty (Foster, Greer, & Thorbecke, 1984). These measures were most widely used for measuring poverty (Coudouel, Hentschel, & Wodon, 2002). The FGT class of poverty measures is calculated as: $P_{\propto} = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{W-Yi}{W}\right)^{\propto}$, where $N$ represents the size of the total population (or sample); $Y_i$ denotes income per capita of the $i$th household; $W$ is the poverty line; $q$ is the number of poor households (those with per capita income below $W$); $\propto$ is Poverty Aversion Parameter Index which has the values of 0, 1 and 2 representing the incidence of poverty, depth of poverty and severity of poverty (Foster et al., 1984).

When $\propto = 0$, then FGT is reduced to $P_0 = \frac{q}{N}$, which is the headcount index (incidence of poverty) measuring the proportion of the population with per capita income below the poverty line. By far, this measure is most commonly used because of its straightforwardness and simple calculation (WB, 2005).

If $\propto = 1$, then the FGT class of poverty measure $(P_1)$ is computed as: $P_1 = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{W-Yi}{W}\right)^{1}$, which is the poverty gap index or the depth of poverty. This measures the extent to which individuals fall below the poverty line (the poverty gap) as a percentage of the poverty line. It should be noted that this measure is the mean proportionate poverty gap in the population (where the non-poor have zero poverty gap). This provides information about how far off the poor are from the poverty line. Hence, the poverty gap index has a virtue as it indicates the level of poverty (WB, 2005).

When $\propto = 2$, the FGT class of poverty measure $(P_2)$ becomes: $P_2 = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{W-Yi}{W}\right)^{2}$, which is the squared poverty gap or the poverty severity index. This averages the squares of the poverty gaps relative to the poverty line. This measures the variation in income distribution among households below the poverty line (Ravallion, 1992). The poverty severity index takes into account not only the distance separating the poor from the poverty line (the poverty gap), but also the inequality among them. That is, a larger weight is placed on poor households who are further away from the poverty line (Coudouel et al., 2002).

### *2.3. Modelling determinants of nonfarm participation*

First, households were split into three groups, namely those with wage employment, those with nonfarm self-employment and those without nonfarm employment.[3] The first group includes households that received income from wage work and other sources but not nonfarm self-employment. The second group is represented by those with income earned from nonfarm self-employment and other sources except for wage employment. The third group consists of households that did not take up wage work or nonfarm self-employment. Once households were divided into three different groups, statistical analyses were then used to compare the means of household characteristics and assets between the groups. As noted by Gujarati and Porter (2009), there are distinct statistical techniques for investigating the differences in two or more mean values, which commonly have the name of analysis of variance. However, a similar objective can be obtained by using the framework of regression analysis. Therefore, regression analysis using an Analysis of Variance (ANOVA) model was applied to compare the mean of household characteristics and assets between the two groups. In addition, a chi-square test was applied to discover whether a statistically significant association existed between two categorical variables such as the type of households and their participation in credit markets.

To model the determinants of participation in a given nonfarm activity (wage employment or nonfarm self-employment), we used a logit model with the dependent variable being a binary variable that has a value of one if a household engaged in some sort of nonfarm activity and a value of zero otherwise. The logit model takes the form (Gujarati & Porter, 2009):

$$\Pr(Y = 1|X) = \frac{Exp(\beta'_s X'_s)}{1 + Exp(\beta'_s X'_s)}$$

where the coefficients $\beta'_s$ are the parameters that need be estimated in the model and $X'_s$ are the explanatory variables. This model estimates the probability that some event occurs, which is in this case the probability of a household participating in a nonfarm activity (self-employment or wage employment). Since the maximum likelihood estimation (MLE) of the Logit model is based on the distribution of $Y$ given $X$, the heteroscedasticity in $Var(Y|X)$ is automatically accounted for (Wooldridge, 2013).

Following the framework for micro policy analysis of rural livelihoods proposed by Ellis (2000), a household's participation in nonfarm activities was hypothesised to be determined by a vector of the characteristics of households and community or region. The definitions, measurements and expected signs of explanatory variables are given in Table 1. Specifically, our specification included household size and dependency ratio, the proportion of male working members, the age, education and gender of household heads. Some other socio-economic characteristics, namely land, access to credit and fixed assets were also included in the models. In addition, we controlled for some commune characteristics such as population density, and the presence of nonfarm opportunities and paved roads. Finally, controls were also added to account for natural calamities and diseases of domestic animals and crop plants at the commune level.

### 2.4. *Measuring the impact of nonfarm participation on household income*

Propensity Score Matching (PSM) was used to measure the impact of nonfarm participation on household income in the current study. The PSM has become a popular approach to estimate causal treatment effects (Caliendo & Kopeinig, 2008). The main advantage of this approach is that one can draw on existing data sources, so that it is quicker and cheaper to implement. In addition, the PSM does not rely on any functional

Table 1. Definition and measurement of variables included in the models.

| Explanatory variables | Definition and measurement | Expected signs |
|---|---|---|
| Household size | Total household members (persons) | +/− |
| Dependency ratio[b] | Proportion of dependents in the households | +/− |
| Age | Age of household head (years). | +/− |
| Ratio of male working members | Proportion of male members who worked in the last 12 months | + |
| Gender[a] | Whether or not the household head is male (male=1; female=0). | +/− |
| Primary education[a] | Whether or not the household head completed the primary school | + |
| Lower secondary[a] | Whether or not the household head completed the lower secondary school | + |
| Upper secondary and higher[a] | Whether or not the household head completed the upper secondary school or higher level | + |
| Agricultural land | The size of farmland per capita (1000 $m^2$ per person) | − |
| Residential land | The size of residential land per capita (10 $m^2$ per person) | +/− |
| Fixed assets | Total value of all fixed assets (log of VND 1000). | + |
| Credit[a] | Whether or not the household received any loan during the last 24 months before the time of the survey | + |
| Paved road[a] | Whether or not there is any paved road to the commune in which the household lived. | + |
| Nonfarm job opportunities[a] | Whether or not there is any production/services unit or trade village located within such a distance that the people in the commune can go there to work and then go home every day. | + |
| Population density | Number of people per one square kilometre | + |
| Natural calamities[a] | Whether or not there is any natural calamity such as fires, floods, storm landslides, earthquakes that occurred in the commune in which the household lived in the last 3 years | +/− |
| Diseases[a] | Whether or not there is any disease of domestic animals or crop plants that occurred in the commune in which the household lived in the last 3 years | +/− |

Note: [a]means dummy variables.
[b]this ratio is calculated by the number of female members aged under 15 and over 59, and male members aged under 15 and over 65, divided by the number of female members aged 15–59 and male members aged 15–64.
Source: Author's analysis

forms linking the outcome to nonfarm participation. This method allows controlling for potential bias such as self-selection on observed characteristics into nonfarm participation (Caliendo & Kopeinig, 2008).

The first step in PSM analysis is to estimate the propensity score for each household with nonfarm participation (participant) and household without nonfarm participation (non-participant) on the basis of observed characteristics. Normally, a logit or probit function is used for this purpose and there is no strong advantage in using the logit over the probit model (Heinrich, Maffioli, & Vazquez, 2010). The second step is to compare the mean income of participants with that of the matched (similar) non-participants. In other words, the purpose of the PSM is to search for comparable non-participation households among all non-participation households to form a control group, and then compare the mean income of the treatment and control groups. The underlying point of this PSM is that control and treatment units with the same propensity score have the same probability of assignment to the treatment as in randomised experiments (Dehejia & Wahba, 2002).

Let NF be an indicator variable equal to 1 if a household participates in a nonfarm activity (wage employment or self-employment) and zero otherwise. In the treatment literature, NF is an indicator that receives the 'treatment'. The propensity score $P(T_1)$ is defined as the conditional probability of receiving the treatment given pre-treatment characteristics.

$$P(T_1) \equiv Prob(D_1 = 1/T_1 = E(D_1/T_1; P(T_1 = F(T_1) \tag{1}$$

where $T_1$ includes a vector of the characteristics of a household *i; E* is the expectation operator; and $F(T_1)$ represents normal or logistic cumulative distribution frequency. The assumption of the conditional independence of the score result expands the use of the propensity scores for the estimation of the conditional treatment effect. The predicted propensity scores are employed to quantify the treatment effect.

The average treatment effect on the treated (ATT) is a parameter of interest in the analysis of propensity score matching. Hence, we use the ATT to evaluate the impact of nonfarm participation on household income. The ATT is calculated through matching participants and non-participants that are closest in terms of propensity scores. In this paper, the treated group is referred to as households with nonfarm employment and the ATT is computed as follows:

$$\mathrm{ATT} = E[Y_{1i} - Y_{oi}|D_i = 1] = E[Y_{1i}|D_i = 1] - \mathrm{E}[\mathrm{Y}_{oi}|D_i = 1] \tag{2}$$

where $E(Y/1)/D = 1$ represents the expected income of households with nonfarm employment and $E(Y/0)$ expresses the counterfactual income of households without nonfarm participation. The counterfactual estimates represent what the income of households with nonfarm employment would be, if they have not engaged in nonfarm activities.

Several matching algorithms have been proposed in the literature to match participants and nonparticipants with the same propensity scores. Following Smith and Todd (2005) and Morgan, Frisco, Farkas, and Hibel (2008), we used Kernel matching to match treatment and comparison observations in this study.[4]

## 3. Results and discussion

### *3.1. Background on household characteristics and assets*

The data in Table 2 reveal that income from crops contributed the largest share of total household income for the whole sample. Combined, the income from crops, livestock, forestry, and aquaculture accounted for about 80% of total income. This suggests that agriculture plays an important role in the livelihood of the ethnic minorities in Northwest Mountains. Income from nonfarm employment (wage and self-employment) contributed 13.3% of the total income, while 9.4% was contributed by other sources. Looking at the income structure of each group, the crop income share of the poor is, on average, much larger than that of the non-poor. However, the non-poor derived more income from forestry, livestock and aquaculture than the poor. The non-poor had much more income from nonfarm activities, including both wage and nonfarm self-employment than the poor. Also, the non-poor earned more income from other sources than the poor. These figures suggest that the poor tend to rely much more on crop production than the non-poor. As shown in Table 2, households without nonfarm employment are much poorer than those

Table 2. Income structure and poverty by household group.

| Income share | All | Non-poor | Poor |
|---|---|---|---|
| Wage employment | 0,105 | 0,167 | 0,070 |
| Nonfarm self-employment | 0,018 | 0,030 | 0,010 |
| Crop | 0,620 | 0,450 | 0,720 |
| Livestock | 0,089 | 0,125 | 0,070 |
| Forestry | 0,060 | 0,096 | 0,040 |
| Aquaculture | 0,014 | 0,015 | 0,010 |
| Other | 0,094 | 0,117 | 0,080 |
| Poverty | All | Participants | Non-participants |
| Poverty headcount | 0.66 | 0.56 | 0.76 |
| Poverty gap | 0.27 | 0.23 | 0.31 |
| Poverty severity | 0.13 | 0.11 | 0.14 |

Source: Author's own calculation from the 2010 NMBS using the poverty line that is based on the income per person per month of 400,000 VND. 1 USD was equal to about 19,000 VND in 2010. Participants include households that participated in wage or nonfarm self-employment or both. Non-participants are households that did not engage in any nonfarm activity.

with nonfarm employment by any measure of poverty. The above findings suggest that the differences in poverty between the two groups might come from the differences in income sources.

Table 3 indicates that there are significant differences in the mean values of a lot of household characteristics between three groups of households. Households without nonfarm employment had a smaller size than those with nonfarm self-employment, but they had a much higher dependency ratio than that of those with wage employment. There was no difference in the age of households between the groups. However, the heads of households with wage work had higher levels of education than those of households without nonfarm employment. Households that took up wage employment also participated in credit markets more frequently than those that did not engage in any nonfarm activity. Nevertheless, the difference in education and credit participation was not detected between households with nonfarm self-employment and those without nonfarm participation.

As reported in Table 3, households that undertook nonfarm self-employment owned much less arable land than those who did not engage in any nonfarm activity. Households with wage employment had more residential land than those without nonfarm employment. It can be seen in Table 3 that there are some statistically significant associations existing between the type of households and the characteristics of the communes. The engagement in nonfarm self-employment is found to be positively correlated with the presence of paved roads. A similar association is also detected between the participation in wage work and the availability of nonfarm job opportunities. Population density seems to be positively related to wage employment but negatively associated with nonfarm self-employment. Finally, there is a positive link between natural disasters and wage employment but a negative relationship between diseases and nonfarm self-employment. Noticeable differences in some household and commune characteristics between the groups were expected to be closely linked with the participation in nonfarm activities.

### *3.2. Determinants of the participation in nonfarm activities*

Table 4 reports the estimation results from the logit model. It is evident that many explanatory variables are statistically significant at 10% or lower level, with their signs

Table 3. Descriptive statistics of household characteristics by group.

| Explanatory variables | Households without nonfarm employment Mean | SD | Households with wage employment Mean | SD | Households with nonfarm self-employment Mean | SD |
|---|---|---|---|---|---|---|
| *Household characteristics* | | | | | | |
| Household size | 5.30 | (2.10) | 5.00** | (1.85) | 6.00*** | (2.31) |
| Dependency ratio | 0.96 | (0.73) | 0.73*** | (0.62) | 0.90 | (0.70) |
| Proportion of male working members | 0.53 | (0.19) | 0.55* | (0.20) | 0.52 | (0.15) |
| Age of household head | 41 | (14.00) | 41.30 | (12.17) | 41.00 | (12.00) |
| Gender of household head[a] | 0.92 | (0.27) | 0.94 | (0.24) | 0.97** | (0.17) |
| Credit participation[a] | 0.36 | (0.48) | 0.44*** | (0.50) | 0.40 | (0.49) |
| *Education* | | | | | | |
| Primary education[a] | 0.20 | (0.40) | 0.26*** | (0.44) | 0.20 | (0.40) |
| Lower secondary[a] | 0.11 | (0.31) | 0.21*** | (0.41) | 0.10 | (0.30) |
| Upper secondary and higher[a] | 0.02 | (0.14) | 0.10*** | (0.30) | 0.02 | (0.14) |
| *Assets/wealth* | | | | | | |
| Arable land | 3,971 | (9,540) | 4,023 | (1,153) | 2,684* | (3,626) |
| Residential land | 510 | (481) | 562* | (849) | 431* | (410) |
| Value of fixed assets | 22,287 | (24,870) | 23,817 | (25,983) | 30,893 | (36,376) |
| *Commune characteristics* | | | | | | |
| Paved road[a] | 0.23 | (0.42) | 0.23 | (0.42) | 0.30* | (0.46) |
| Nonfarm job opportunities[a] | 0.15 | (0.36) | 0.34*** | (0.47) | 0.11 | (0.32) |
| Population density | 122 | (318) | 166** | (399) | 104*** | (167) |
| Natural calamities | 0.57 | (0.49) | 0.68*** | (0.47) | 0.60 | 0.49 |
| Diseases | 0.20 | (0.40) | 0.16* | (0.36) | 0.05*** | 0.22 |
| Observations | 1027 | | 467 | | 158 | |

Notes: SD: standard deviations.
*Mean statistically significant at 5%.
**Mean statistically significant at 10%.
***Mean statistically significant at 1%
[a]Means dummy variables. [b]Measured in 1000 VND. Value of fixed assets measured in 1 billion VND. 1 USD was equal about 19,000 VND in 2010. Households without nonfarm employment were used as the reference group in ANOVA models.
Source: Author's own calculation

as expected.[5] Households with more dependent members are indicative of labour shortage, which reduces the likelihood of undertaking wage employment. Additional household members raise the odds of engaging in nonfarm self-employment by about 10%. Having more male working members increases the probability of taking up wage employment. The finding is consistent with Pham et al. (2010) that men are more likely than women to take up wage work in Vietnam rural. Households headed by older heads are less likely to engage in nonfarm self-employment. Education has a significantly positive effect on the choice of wage employment; and the effect increases with the level of education. Holding all other variables constant, the odds of participating in wage employment for households with the head having a primary diploma are about 93% higher than the odds of those whose heads have not completed this education level. Similar findings were also found in Shandong Province, China by Huang, Wu, and Rozelle (2009) and in Vietnam by Tuyen et al. (2014a) that young and better-educated members are more likely to participate in nonfarm activities. The findings suggest that households with low educational levels may be hindered from taking up some sort of nonfarm employment. However, education is found not to be correlated with the

Table 4. Logit estimates with odd ratios for determinants of nonfarm participation.

| Explanatory variables | Wage employment vs. farm employment | Nonfarm self-employment vs. farm employment |
|---|---|---|
| Household size | 1.0109 | 1.0975* |
| | (0.037) | (0.052) |
| Dependency ratio | 0.7039*** | 0.7923 |
| | (0.073) | (0.114) |
| Proportion of male working members | 2.4609*** | 0.6135 |
| | (0.847) | (0.335) |
| Age of household head | 1.0063 | 0.9869 |
| | (0.006) | (0.008) |
| Gender of household head | 0.9425 | 1.5135 |
| | (0.264) | (0.753) |
| Primary education | 1.9265*** | 1.0184 |
| | (0.305) | (0.239) |
| Lower secondary education | 2.7256*** | 0.9764 |
| | (0.489) | (0.304) |
| Upper secondary and higher | 7.0503*** | 1.2613 |
| | (2.103) | (0.835) |
| Arable land | 1.0084 | 0.9274** |
| | (0.006) | (0.035) |
| Residential land | 0.9996 | 0.9972 |
| | (0.001) | (0.003) |
| Credit participation | 1.4161*** | 1.0795 |
| | (0.181) | (0.202) |
| Fixed assets | 0.9153* | 1.3598*** |
| | (0.048) | (0.133) |
| Paved road | 1.0459 | 1.4288* |
| | (0.159) | (0.288) |
| Nonfarm job opportunities | 2.2523*** | 0.7208 |
| | (0.336) | (0.205) |
| Population density | 1.0003** | 0.9996 |
| | (0.000) | (0.000) |
| Natural calamities | 1.5817*** | 0.7632 |
| | (0.264) | (0.153) |
| Diseases | 0.9866 | 0.2031*** |
| | (0.215) | (0.082) |
| Constant | 0.2284** | 0.0174*** |
| | (0.138) | (0.019) |
| Pseudo $R^2$ | 0.1059 | 0.0728 |
| Prob > $\chi^2$ | 0.0000 | 0.000 |
| Observations | 1,352 | 1,068 |

Notes: Estimates are odd ratios and robust standard errors in parentheses.
*Mean statistically significant at 5%
**Mean statistically significant at 10%
***Mean statistically significant at 1%, respectively. [a]means dummy variables.
Source: Author's own calculation

choice of nonfarm self-employment, implying that in terms of formal education, there has been relative ease of entry into this employment. The same finding was also recorded in rural Ghana by Ackah (2013).

Regarding the role of household assets in the determination of participation in nonfarm activities, the results show that land is negatively associated with nonfarm self-employment.

This implies that households with less land are more likely to take up nonfarm self-employment as a way to supplement farm income. This finding is in line with that in several previous studies in Vietnam's rural and peri-urban areas (e.g., Minot, Epprecht, Anh, & Trung, 2006; Tuyen, Lim, Cameron, & Huong, 2014b; van de Walle & Cratty, 2004). Surprisingly, access to credit is not statistically correlated with nonfarm self-employment. We found evidence that fixed assets are positively associated with participating in nonfarm self-employment, but negatively linked with engaging in wage employment.

In accordance with previous literature on nonfarm participation, the finding of the paper shows that nonfarm participation by households is significantly affected by some community characteristics (Escobal, 2001). For example, holding all else constant, living in a commune with the presence of nonfarm job opportunities would raise the odds of a household taking up wage employment by about 125%. Also, the availability of paved roads increases the odds of engaging in nonfarm self-employment by around 43%. The occurrences of different shocks have different effects on the engagement in wage employment and nonfarm self-employment. While the presence of natural calamities increases the odds of adopting wage work by about 58%, the occurrence of diseases of domestic animals or crop plants reduces the odds of undertaking nonfarm self-employment by around 80%. This might be explained by the fact that households that suffered from natural disasters were compelled to take up wage employment as a way of supplementing their income.

### 3.3. *The impact of nonfarm participation on household income*

Descriptive statistics of the observable variables for households with and without nonfarm participation in Table 3 clearly indicate that there are substantial differences between groups of households. This implies that there is the possibility for a selection bias in the sample, which requires matching of households with similar characteristics from the two groups before computing the income effect. A test of the balancing property was implemented and the results show that this requirement was satisfied. This indicates that the distribution of the conditioning variables is not different across the treatment and comparison groups in the matched samples. This also indicates that the self-selection bias (due to observed characteristics) has been eliminated, satisfying the matching requirements for calculating treatment effects.

The kernel matching results in Table 5 reveal that participation in any nonfarm activity would have a positive and significant impact on household income per capita.

Table 5. The impact of nonfarm employment on household income per capita.

| | Monthly household income per capita(1000 VND) |
|---|---|
| Wage employment | |
| Average outcome, treated ($N$=437) | 521.000 |
| Average outcome, control ($N$=907) | 360.000 |
| Difference in average outcome, ATT | 161.000$^{***}$(19.500) |
| Nonfarm self-employment | |
| Average outcome, treated ($N$=153) | 434.000 |
| Average outcome, control ($N$=902) | 347.000 |
| Difference in average outcome, ATT | 87.000$^{***}$(31.000) |

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. 1 USD was equal about 19,000 VND in 2010. Estimates using Kernel Matching method and bootstrapped standard errors are in parentheses with 1000 replications.
Source: Author's own calculation

Specifically, the estimates of the average treatment effect indicate that households that took up wage work would have, on average, more monthly income per capita than 161,000 VND (8.5 USD) than those who did not undertake any nonfarm employment. Similarly, the average treatment effect on the treated (ATT) suggests that households with nonfarm self-employment would earn, on average, a higher monthly income per capita of 87,000 VND (4.6 USD) than those without nonfarm participation. Overall, the result is consistent with previous studies using the same method in rural Vietnam and other developing countries. For example, Pham et al. (2010) found that controlling for other factors, households that participated in nonfarm activities (either wage or nonfarm self-employment) had higher expenditure per capita than those without nonfarm participation in rural Vietnam. Similar findings were also found in rural Ghana by Ackah (2013), rural Nigeria by Shehu and Sidique (2014) and rural Ethiopia by Ali and Peerlings (2012).

## 4. Conclusion and policy implication

Previous empirical information about nonfarm employment and its effects on household welfare in Vietnam's ethnic minority areas has been limited. This study has attempted to discover the determinants of participation in nonfarm activities and the impact of nonfarm employment on household income among ethnic minorities in Northwest Mountains, Vietnam. The main finding of the study is that households who participated in wage work or nonfarm self-employment had much higher income per capita than similar households who did not take up any nonfarm employment, even after controlling for the fact that households that had income from nonfarm sources are a nonrandom sample of ethnic minority households. In general, the findings of the paper are consistent with those of the extant literature on the role of nonfarm employment in household welfare in both Vietnam and other developing countries.

The current study found evidence that some household characteristics are strongly associated with nonfarm participation. Having more members increases the chance of taking up nonfarm self-employment. The likelihood of undertaking wage employment increases with the ratio of male working members. A key determinant of participation in higher return activities is education. Households with heads that have completed primary education have a higher probability of adopting wage work than those with heads not having completing this education level. Similar but much stronger impacts were also recorded for the case of having a lower secondary diploma and an upper secondary diploma or higher. Participation in nonfarm self-employment is not correlated with any level of education but it is negatively associated with land endowment and positively related to the value of fixed assets.

Similar to previous findings, the current study found evidence that some commune characteristics play an important role in determining the participation in nonfarm activities. Controlling for other factors, a commune with the presence of local enterprises or trade villages would give households living in that commune a higher chance of taking up wage employment. A commune having paved roads would increase the likelihood of participation in nonfarm self-employment. Shocks have different effects on nonfarm participation. While the occurrence of natural disasters increases the probability of adopting wage employment, the presence of diseases of domestic animals or crop plants reduces the chance of participating in nonfarm self-employment.

The findings of the current study lead directly to a discussion about what policy makers can do to reduce poverty in the study area. By providing a better understanding about what are the key determinants of nonfarm participation and the significantly positive impact of nonfarm employment on household income, the study offers useful information as to what sorts of policy interventions might be effective in combating poverty and improving welfare for ethnic minorities. The empirical evidence here suggests that promoting rural nonfarm activities, coupled with support for improving the access of poor households to these, are expected to be an effective way of reducing poverty in the Northwest Mountainous region. Increasing the chance for households to take up nonfarm employment could be obtained by improving the access of the poor to education, expanding nonfarm job opportunities and investing in local physical (hard) infrastructure in the form of building up paved roads in communes.

However, there are also a caveat in this study. While propensity score matching (PSM) can eliminate selection bias from observable characteristics, it fails to address the endogeneity problem resulting from unobservable household characteristics that may affect the participation in nonfarm activities and outcomes given that the current paper uses only cross-sectional data. Hence, this suggests a potential topic for future research, that post-intervention data should be collected from the same pool of households who participated in the pre-intervention data collection. With panel data, future studies can further examine the effect of changed occupation on the change of income using similar methodology.

## Disclosure statement

No potential conflict of interest was reported by the author.

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## Notes

1. Following previous studies (Cuong, 2012; van de Walle & Gunewardena, 2001), we defined Kinh/Hoa groups as the ethnic majority group in the current study.
2. This poverty rate was calculated based on the updated poverty line proposed by the General Statistical Office – World Bank (GSO-WB) in 2010 (expenditure per person per month of 653,000 VND).
3. However, there is another group including 66 households that participated in both wage and nonfarm self-employment. This group is excluded from the study because the propensity score matching analysis does not satisfy the requirement of balancing property.
4. Other matching algorithms have been also used to check the robustness and the results confirm that households with wage or nonfarm self-employment earned a significantly higher income than those without nonfarm employment.
5. Odd ratios (ORs) being larger than 1 and smaller than 0 indicate that the association between the dependent and explanatory variables are positive and negative, respectively.

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## Appendix 1. Map of the North West region, Vietnam