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Non-farm employment, food poverty and vulnerability in rural Vietnam

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Abstract

This study sheds light on the effects of non-farm employment on household food poverty and vulnerability among rural households in Vietnam using data from the Vietnam Household Living Standard Survey of 2010. Vulnerability to food poverty constitutes a certain probability that a non-poor household will become food-poor or that a food-poor household will remain in poverty in future. The results suggest that non-farm employment exerts a positive and statistically significant effect on the reduction in household food poverty and vulnerability. Specifically, participating in non-farm employment will help decrease the probability of falling into food poverty in future by roughly 19%. We also document that 31% of non-food-poor households in rural areas suffered from vulnerability to food poverty, indicating their high probability of falling into food poverty in future. Additional results from regional evaluation suggest that the North-west region of Vietnam is most vulnerable to food poverty and has an urgent need of targeted government development policies; improving access to non-farm employment could help mitigate vulnerability.

Keywords Households · Non-farm employment · Poverty · Rural Vietnam · Vulnerability to food poverty

JEL Classification C21 · C26 · I32 · O18 · R20

1 Introduction

After its 1986 political and economic reform (*Doi Moi*), Vietnam remarkably progressed in decreasing poverty, transforming from one of the world's poorest nations to a lower-middle-income country (World Bank 2012). The nation's agricultural development has been

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an important engine in achieving broad rural prosperity and food security by contributing to economic growth through different channels, such as the provision of employment and food. Additionally, a large proportion of Vietnam's poor were involved with the agriculture sector, and, thus, it could be asserted that developing the nation's agriculture would be a crucial element in alleviating its poverty (World Bank 2016). However, agriculture is not always a panacea to decrease poverty, as it is fraught with many challenges that have invariably narrowed its prospects for fighting food poverty. Specifically, the sector suffers from natural and economic risks, such as disasters and price changes. Hence, these risks will indirectly affect Vietnam's food security through its agriculture production, endangering the nation's stability. Moreover, such risks will intensively affect rural regions and the ethnics, which are regarded as the nation's most vulnerable.

Although chances to gain agricultural productivity still exist, pessimism exists regarding the possibilities to generate employment from the agricultural sector in the long term (World Bank 1998). Notably, agricultural workers in rural areas are more than four times more likely to be poor compared with people working in other sectors (World Bank 2016). Further, Brandt and Benjamin (2004) reveal that higher agricultural productivity did not increase the number of rural households in Vietnam; this demonstrates that, from 1993 to 1998, the proportion of farming incomes to total incomes among rural households declined from 46 to 33% in northern Vietnam, and from 43 to 38% in the south.

A core feature of the structural changes in the Vietnamese rural economy is the gradual reduction in the dependency on agricultural areas, whether income sources or employment. This change reflects both 'push' and 'pull' regimes. The 'push' regime is caused by the diminishing return to labour and land, which leads to stagnant farm income that compels farmers to participate in non-agricultural sectors. In contrast, the 'pull' regime is promoted through productivity growth in agriculture, which then generates higher household incomes that allow farmers to continuously expand their agricultural products towards more non-farm products and services. Clearly, these structural changes expose the positive effects of non-farm employment, whether direct or indirect, on food security. The movement into non-farm employment will enable rural households to increase and diversify their income. For the household as a farming enterprise, their non-farm income is also an important source of investment in their agricultural business to potentially provide them a higher income. Further, this increasing income diversification from non-farm employment will either create smoother food consumption overtime or ameliorate food shortage risks to cope with unexpected crop failures, helping them maintain food security (Qureshi et al. 2015). As most of the world's poor live in rural areas, and given its beneficial effects, non-farm employment has become an important source of income for them. Non-farm activities even account for as much as 35–50% of rural households' income in developing countries (World Bank 2016).

However, concerns still exist regarding non-farm employment's effects on households' food security. Specifically, the labour movement from agricultural to non-agricultural sectors during structural changes in the rural economy will lead to labour shortages in agricultural production. Many labourers have left their agricultural jobs to pursue non-farm employment. This movement of labour and resources away from farming will decrease food and crop production, which will then potentially threaten food security and vulnerability. Hence, policymakers face a challenging dual task in either enhancing the economic and structural transformation in rural areas, or facilitating food security. Another concern is that many rural areas in industrial zones are challenged by an increasing number of young labourers attempting to seek employment in manufacturing by abandoning agricultural production. Their motivation to transfer to these sectors could be partially influenced by the employment trends in manufacturing communities. They may perceive working off-farm as more desirable than farming given the increase in opportunities for employment outside the farm sector. This could be a reasonable option given the limited agricultural resources such as land and capital shortages in industrial zones. Consequently, these workers' movement to non-farm sectors could be beneficial. However, moving to non-farm sectors when agricultural production is still sufficient, such as with abundant agricultural land, could put the actual worth of non-farm employment into question.

Additionally, Vietnam is located in Southeast Asia and is one of the countries that has suffered the most from climate change and natural disasters. These disasters will endanger the food poverty of non-food-poor households on the threshold of food poverty and at a high risk of experiencing food poverty in future.

In this case, poverty measurements may not be a proper indicator for measuring the risk of future food poverty. Household food poverty is said to exist when food consumption expenditure falls below the established food poverty line. In other words, this expenditure is reflected in the *ex post* assessment of a household's well-being. The current food poverty status of a household might not be an accurate guide to anticipate the *ex ante* risk of a non-food-poor household becoming food-poor in future. However, the concept of 'vulnerability' to poverty better anticipates risk. Vulnerability is the certain probability that a non-poor household will become food-poor or that a food-poor household will remain in food poverty in future (Chaudhuri et al. 2002; Calvo and Dercon 2008). Vulnerability is distinguished from poverty by the way the former assesses the probability of being poor in future than of having been below the poverty threshold in the past. Accordingly, people are considered vulnerable to food poverty if they have more than an even probability of being food-poor in future. Therefore, assessing how non-farm employment would affect the vulnerability of entering food poverty, or the probability of falling into food poverty, as a non-food-poor household, this would facilitate better, forward-looking anti-poverty interventions. Sustainable development is 'the development that meets the needs of the present without compromising the ability of future generations to meet their own needs' (World Commission on Environment and Development 1987). Hence, future perspectives are considered the focus of sustainable development. The analysis of the effect on food poverty and vulnerability to food poverty would partly provide policy implications for us to ensure future food security as part of our overall sustainable development.

This study addresses these concerns by empirically investigating the effects of non-farm participation on food poverty (FP) and the vulnerability to food poverty (VFP), with a focus on rural Vietnam. Our main hypotheses explore not only whether non-farm participation will reduce FP and VFP in rural Vietnam, but also the factors that determine non-farm participation. The study is conducted through three main objectives: First, it examines non-farm activities' effects on food poverty through their impacts on food consumption. Second, it analyses non-farm employment's effects on the VFP. To do so, the VFP concept and the relationship between FP and VFP will first be clarified. Subsequently, non-farm activities' impacts on VFP will be investigated based on the correlation between FP and VFP. Third, the study also investigates the determinants of non-farm participation, which will lead to policy implications to enhance non-farm participation in rural areas.

An econometric approach is taken to achieve these three main objectives, as follows: First, we investigate the relationships between non-farm activities and FP and VFP by comprehensively addressing the issues with either endogeneity or selection bias. The instrumental variables (IV) method is then employed to solve any endogeneity issues. Heckman's selection model is also employed for a robustness check by controlling for issues with either endogeneity or a selection bias. Moreover, heteroscedasticity issues also arise, as the assumption of constant variance might not hold when using cross-sectional data; this problem is overcome by employing a three-stage feasible general least squares (FGLS) method to examine non-farm activities' effects on anticipated food consumption. Second, we investigate the relationship between household FP and VFP by employing either cross-tabulations or Pearson's product moment correlation coefficient. Additionally, the receiver operating characteristics curve (ROC) is applied to examine the degree at which vulnerability signals poverty.

The remainder of this paper is structured as follows: Sect. 2 captures the main relevant literature. Sections 3 and 4 present the conceptual and analytical frameworks, respectively. Section 5 describes the data and provides a descriptive analysis. Section 6 discusses the study's results and primary findings, and Sect. 7 concludes.

2 Literature review

Three strands of prior literature indicate highly controversial, inconclusive evidence of the economic effects of non-farm participation. Economic theories ambiguously evaluate the relationship in terms of the effects' signs and magnitudes (Taylor and Lybbert 2015). In contrast, several studies indicate beneficial economic effects (Owusu et al. 2011; Reardon and Berdegue 2001; Tran 2015), while others suggest less beneficial effects (Leones and Feldman 1998) or even no effects or mixed results for household expenditures (Bardhan and Udry 1999; Van De Walle and Cratty 2004). Specifically, on the positive side, most studies indicate that non-farm employment is potentially important in breaking poverty traps through direct effects. For example, increasing rural households' income enables them to overcome farm credit limitations, which increases the absorption of surplus labour and diversifies income (Oseni and Winters 2009; Reardon and Berdegue 2001). Non-farm participation leads to significantly higher expected household food consumption, which, in turn, lowers their probability of being food-poor in future (Zereyesus et al. 2017). Do et al. (2019) also show that participating in non-farm activities did not increase household food availability in rural Cambodia, but significantly improved food access, use and stability. Rahman and Mishra (2020) find positive effects of non-agricultural livelihood on various food security indicators—especially that it improves dietary diversity in households. Van De Walle and Cratty (2004) also indicate a considerably lower probability of experiencing poverty among rural households that participated in non-farm employment in Vietnam. Skilled non-farm employment especially is likely to have a larger effect on vulnerability alleviation than unskilled labour in this sector (Imai et al. 2015). Pham et al. (2012) suggest that promoting non-farm employment through larger investments in education, health services and rural infrastructure would reduce rural poverty. However, they argue that opportunities for non-farm employment diversification would benefit the non-poor more than the poor (Pham et al. 2012). Hoang et al. (2014) show that, when an additional member of the household participates in non-farm activities, household expenditure increases by over 50% over a 6-year period (2002–2008). Their analysis also documents that the increase in non-farm hours is not accompanied by any loss of agricultural income even if additional non-farm working hours lessen the hours spent on agricultural production. On the negative side, Leones and Feldman (1998) assert that non-farm activities could threaten agricultural production. Their argument reveals that, in the absence of surplus labour and when the labour market is small, the movement of labour towards non-farm activities will decrease farming labour and agricultural output. According to Cazzuffi et al. (2020), although agricultural commercialisation is significant to household welfare improvement, it has negative effects on the food consumption per capita.

Despite rural non-farm activities' importance in household income and food security, not much is known about their effects on farm performance, and, particularly, relative to smallholder agricultural production's efficiency and productivity in developing countries. Given these controversial, differing conclusions regarding non-farm participation's effect on food security, this study contributes to the literature by investigating non-farm participation's effects on household food poverty and vulnerability to food poverty in rural Vietnam. We specifically focus on issues with endogeneity regarding the participation in non-farm works as well as heteroscedasticity by deriving a VFP index. It is also the first study to investigate the effects of non-farm participation on vulnerability to food poverty in rural Vietnam.

3 Conceptual framework

3.1 Non-farm employment and its determinants

Rural non-farm employment is known to include all income-generating activities which are not agricultural, but are located in rural areas (Ferreira and Lanjouw 2001; Reardon and Berdegue 2001). In addition to this, Tacoli (1998) defines rural non-farm employment as those activities that take place on the farm, but not derived from or related to crop production. Based on a sectoral approach, Barrett et al. (2001) categorise rural non-farm employment as primary production, secondary (manufacturing) activities, and tertiary (service activities) activities on rural farms.

In this study, we define rural non-farm employment as any activity in rural areas other than farm wage employment and farm self-employment. Under this concept, rural non-farm employment entails a diversity of activities—from self-employment in household-based industries to micro- or small- and medium-sized enterprises or even large-scale agro-processing facilities managed by large multinational enterprises. More precisely, it includes trade, agro-processing, mining, manufacturing, construction and transport. These activities may vary by regional and local characteristics such as infrastructure, intensity of industrialisation, available resource endowments and even credit accessibility. A striking characteristic of the rural non-farm sector is the heterogeneity in activities; the groups' earnings vary by the returns across occupations and seasonality (Lanjouw 2007). Hence, some sources of non-farm employment do not always increase the expected earnings of the household; however, they increase the volatility in earnings and consumption (Barrett et al. 2001).

The motivation of rural household members to participate in non-farm employment is mainly driven by two main factors: 'pull' factor—for example, having higher incomes via better returns and lower risk in the non-farm sector compared with the on-farm sector; and 'push' factor, such as constraints in land holdings, risky farming, high-volatility consumption under shocks, as well as the inability to receive higher income from farming works. The motivation of workers to enter the non-farm sector is also dependent on the state of the infrastructure and human capital. In this study, we also include the variables 'paved road' and 'market' as the proxies for the market and infrastructure of the commune. Moreover, women often decide to participate in non-farm public employment because they believe it to be more stable and secure than agricultural sector in communes with poor agricultural base (Atamanov and Van den Berg 2012). The increasing intensity of industrial manufacturing could also be popularising non-farm employment. This intensity is expected to generate more complex networks of non-farm employment, that is, the size of non-farm workers in the region. A larger network of non-farm workers would undoubtedly have spillover effects and motivate farmers to enter the non-farm labour market.

3.2 Food poverty and food poverty line

There are several compelling reasons for studying food poverty. First, while the role of non-farm employment in poverty in Vietnam has been investigated, the literature has largely ignored its role in food poverty. Our new findings contribute to this gap and help cultivate a better understanding of this issue. Second, food poverty is an important and inseparable dimension of poverty. The strategy for poverty alleviation must be integrated with the policies for reducing food poverty. Third, there is growing interest in investing in household food consumption than to reduce poverty itself. A common challenge in collecting household survey data when addressing household welfare is that individuals tend to reluctantly report their true income; this leads to a measurement error bias in the estimation. Regarding consumption—especially food consumption—there are fewer reasons to hide or give misleading reports. Thus, using food consumption as the indicator of household well-being is better than using poverty measurements, as it reduces measurement error biases.

Food poverty commonly pertains to the phenomenon of household-level hunger. Households suffering from food poverty do not have enough food to meet the energy and nutrient needs of all their members. In this study, households are considered as food-poor if their log of food consumption falls below the log of food poverty line. Specifically, the food poverty line can be measured as follows:

$$\ln f_i = \omega_1 + \omega_2 C_i \text{ and} \tag{1}$$

$$P = e^{\widehat{\omega_1} + \text{RDA}\widehat{\omega_2}}, \tag{2}$$

where f_i is the daily food consumption per adult of household i; C_i is the daily calories consumption per adult of household i; RDA is the Recommended Dietary Allowance of calories. For the case of Vietnam, we use an RDA value of 2700,[1] following the moderate daily energy intake by work categories per adult, as suggested by the Vietnam National Institute of Nutrition (Nguyen and Pham 2008). P is the food poverty line, which refers to the required food expenditure to gain the RDA of calories. $\widehat{\omega_1}$ and $\widehat{\omega_2}$ are the estimates of ω_1 and ω_2, respectively, which are used to calculate the food poverty line in Eq. (2).

3.3 The vulnerability to food poverty

Three major approaches define vulnerability: the vulnerability as uninsured exposure to risk, vulnerability as low expected utility and vulnerability as expected poverty (VEP). Among these, VEP regards vulnerability as the probability that a household will either experience or remain in poverty in future (Chaudhuri et al. 2002). In other word, VEP is

[1] The RDA value equal to 2700 (kcal/day) per adult in our study is the moderate energy intake required for group of male with age from 19 to 30 years, as suggested by Vietnam National Institute of Nutrition.

used to predict probability of future food consumption being lower than a specific probability threshold. Moreover, the VEP approach is more widely used with cross-sectional data. To reinforce its compatibility, this study uses the VEP concept as its primary approach to examine VFP. Based on this approach, the VEP measurement is constructed as follows: First, the VFP of household i at time t (V_{it}) is defined as the probability that the household will be food-poor at time t:

$$V_{i,t} = \Pr\left(\ln f_{i,t+1} < \ln P \mid X_{i,t}\right), \tag{3}$$

where $f_{i,t+1}$ indicates the food consumption of household i at time $t+1$ and P is the appropriate food poverty line of household i. In the case of cross-sectional data, food consumption expenditures can be derived as:

$$\ln f_{i,t} = X_i\alpha + \varepsilon_i, \tag{4}$$

where X_i is a vector of household and community characteristics; α is a vector of parameters of interest; and ε_i is the stochastic error term, with a zero mean and normal distribution. We estimate the equation by employing FGLS technique, as described in Sect. 4.3. Thus, the estimated coefficients can be used to measure the value of vulnerability:

$$\hat{V}_{i,t} = \text{prob}\left(\ln f_{i,t+1} < \ln P \mid X_{i,t}\right) = \boldsymbol{\Phi}\left(\frac{\ln P - \ln \hat{E}(\ln f_{i,t} \mid X_{i,t})}{\sqrt{\hat{\sigma}^2_{\varepsilon,i}}}\right), \tag{5}$$

where $\hat{V}_{i,t}$ measures the estimated vulnerability to food poverty, which is the probability that the food consumption expenditure of household i will fall below a given food poverty line. The $\boldsymbol{\Phi}$ here is the cumulative density function of the standard normal distribution, while $\hat{\sigma}_{\varepsilon,i}$ refers to the estimated standard error. More details of how to construct vulnerability index are presented in Sect. 4.3. This study applies a threshold of 0.5 to indicate VFP, and this threshold is popular among other scholars in previous studies (Pritchett and Sumarto 2000; Chaudhuri et al. 2002). Further, Pritchett and Sumarto (2000) suggest that when a household's current consumption equals the poverty line, it encounters a zero mean shock that would reach one period ahead at a vulnerability of 0.5. Therefore, households are considered vulnerable if their vulnerability index is above 50%.

4 Analytical framework

4.1 Instrumental variable estimation model

An endogeneity issue will occur in the study's first stage when we examine non-farm activities' impacts on households' food expenditures using the following probit model:

$$f_i = \beta_0 + \beta_1 \text{NF}_i + \beta_2 X_i + \varepsilon_i, \tag{6}$$

where f_i indicates the food consumption; NF_i is a variable of non-farm activities; X_i is a vector of household characteristics, or regional characteristics and other community-level determinants; and ε_i is the error term, which is assumed to be characterised by a bivariate normal distribution with mean zero and a finite covariance matrix. This describes how farm households either effectively allocate their labourers or their motivation to participate in non-farm employment.

According to previous studies, examining the relationship between non-farm income and food consumption expenditures might expose endogeneity issues (Babatunde and Qaim 2010; Ferreira and Lanjouw 2001; Ruben and Van Den Berg 2001). Theoretically, endogeneity issues may be caused by the presence of any bias stemming from measurement errors, simultaneous causality and omitted variables. This study excludes the case involving measure errors, as household respondents are unlikely to erroneously report their working status, regardless of non-farm employment status. Therefore, two highly likely causes of endogeneity remain: simultaneous causality and omitted variables. The former occurs under the simultaneous influence of non-farm participation and food consumption expenditures. As higher food consumption can enhance the household's labour productivity, this will consequently increase the household's participation in non-farm activities. Simultaneously, non-farm participation might increase households' food consumption expenditures through its potential impact on household income. In contrast, the omitted-variable bias appears when a model incorrectly ignores one or more relevant variables. While variables correlate with non-farm participation, these are included in the error term as they are not observable. The decision to participate in non-farm employment might be influenced by such unobservable factors as the intergenerational exchange of knowledge, skills or other unobserved abilities.

Without seriously considering endogeneity, this issue could lead to inconsistent estimates. Therefore, it is substantially important to account for this issue; one of the most effective methods to do so involves the instrumental variable (IV) method. This can help us obtain consistent estimates in the presence of bias caused by simultaneous causality and omitted variables. This study applies the IV method through three steps: First, a probit model of non-farm activities (NF_i) is fit to the instrument (I_i).[2] Second, we regress the probit model (NF_i) on its predicted outcome ($\widehat{NF_i}$) and other household characteristics (X_i). Subsequently, the fitted value of non-farm activities as taken from this step will be used in the FGLS regression to solve for heteroscedasticity. The valid instrumental variable must correlate with the non-farm participation variable (NF_i), but not with the disturbances in the equations (Greene 2017). In other words, it must be excludable and exogenous from the equation of interest. The instrumental variable's validity should be checked across all specifications. Further, high F-statistics from the first-stage regression of non-farm participation would be an important reference in checking validity—specifically, those F-statistics should, over the rule of thumb (Stock and Yogo 2005).

Choosing a suitable IV for the model is difficult, as this variable should be characterised by its changes as associated with the changes in the endogenous variable—or the non-farm participation variable (NF_i) in this study—but this cannot change the dependent variables, which are households' food consumption and vulnerability. This study incorporates commonly used non-farm networks as the IV for non-farm participation, as these are measured by the contacts with other participants in non-farm employment. Non-farm networks are widely recognised as one of the most influential factors driving non-farm work participation (e.g. Taylor et al. 2003; Zhang and Li 2003; Lihua 2013; Oseni and Winters 2009; Tuladhar et al. 2014; Hoang et al. 2014). Moreover, Kajisa (2007) asserts that non-farm networks are critical in connecting and supporting household members' non-farm

[2] The list of explanatory variables for this probit model is the same as the list of explanatory variables for non-farm participation in the 1st stage in Table 8.

Table 1 Instrumental variable model: post-estimation tests. *Source*: Authors' calculation

IV (Non-farm networks)	Dependent variable: household food consumption			
First-stage regression test	Critical value			
	5%	10%	20%	30%
2SLS size of nominal 5% Wald test	16.38	8.96	6.66	5.53
LIML size of nominal 5% Wald test	16.38	8.96	6.66	5.53
Kleibergen-Paap rk Wald F statistic	*Minimum eigenvalue statistic = 395.19*			
Summary statistics	R^2 = 0.323; Adjusted. R^2 = 0.319; Partial R^2 = 0.076; Prob > F = 0.0000			
Test of endogeneity				
Durbin (score) chi2(1)	4.542 (P = 0.0331)			
Wu–Hausman	4.517 (P = 0.0336)			

employment. Brünjes and Revilla Diez (2016) study indicates that family contacts are important in the process of discovering non-farm participation in all sectors. By providing non-farm employment information through household members' relatives and neighbours, non-farm networks will decrease their costs of searching for non-farm work as well as the costs of accessibility to non-farm employment. Hence, the non-farm network variable could be the proper instrumental variable for this study, satisfying the theoretical requirement of instrument variable selection.

We measure non-farm networks as the previous period's share of community-level non-farm participation, which is 2008. Clearly, non-farm networks are only expected to affect food consumption through households' non-farm participation, and, therefore, this variable can be excluded. It is important to confirm whether endogeneity exists before determining how to solve the issue itself. For example, a Wu–Hausman test reveals a small P value; consequently, we can reject the hypothesis H_0, in that the variables are exogenous, or we can confirm endogeneity's existence in our model. Next, a first-stage regression test is conducted to check whether our instrumental variable (non-farm networks) correlates with the endogenous variable, but not with the disturbances in the equations; in other words, this test aims to determine the instrument's strength. Stock and Yogo (2005) posit that this test is crucial, as weak instruments might cause an inconsistent estimation of the instrumental variable while distorting hypothesis tests of the estimated parameters.

As Table 1 indicates, the first-stage regression test provides statistics of the two-stage least squares (2SLS) size and limited information maximum likelihood (LIML) size from a nominal 5% Wald's test as well as Kleibergen-Paap rk Wald F minimum eigenvalue statistics. This indicates the instrument is strong, as the Kleibergen-Paap rk Wald F statistic of 395.19 is much higher than the critical value of 16.38 at a 5% rejection rate. The LIML again affirms this conclusion.

4.2 Treatment effects model for endogenous treatments

We employ the treatment effects model for endogenous treatments for the robustness check; this model is a variant of the Heckman sample selection model (Heckman 1979). It is widely used to measure the average treatment effect (ATE) as well as other parameters through the two-step consistent estimator of a linear regression model or through maximum likelihood estimation. Conventional treatment effects basically allow us to estimate experimental-type causal effects from observational data. For our study, since an unobserved variable affects the treatment that a person receives—thereby, affecting the outcome—we were confronted with the problem of endogeneity and could not receive the accurate estimates of effects under the conventional treatment effects estimators. The treatment effect model for endogenous treatments is designed to address this problem. Besides, it also helps to account for the sample selection bias in models. The level of selection bias will be captured by adjusting the inverse Mills ratio.

The treatment effect model includes two main equations: the selection Eq. (7) and the outcome Eq. (8). The selection equation demonstrates the estimation of non-farm participation, and the outcome equation shows the estimation of food consumption and vulnerability. The selection equation is identified as follows:

$$\begin{aligned} \mathrm{NF}_i^* &= Z_i\delta + \mu_i \text{ and} \\ \mathrm{NF}_i &= 1 \text{ if } \mathrm{NF}_i^* > 0 \text{ and } \mathrm{NF}_i = 0 \text{ otherwise,} \end{aligned} \tag{7}$$

where NF_i^* is the latent variable and Z_i is a vector of exogenous variables that determine the treatment (the non-farm participation). The value of NF_i equals 1 if the household participates in the non-farm activities and 0 otherwise—that is, NF_i is 1 if at least one member from the i th household participates in the non-farm activities and 0 otherwise. The outcome equation is indicated as follows:

$$f_i = X_i\beta + \mathrm{NF}_i\gamma + \varepsilon_i. \tag{8}$$

The terms ε_i and μ_i are assumed to be the unobserved and bivariate normal error terms with zero mean, respectively. We substitute selection Eq. (7) into outcome Eq. (8) to obtain the outcome models for both participants and non-participants:

$$\text{If } \mathrm{NF}_i^* > 0,\ \mathrm{NF}_i = 1 \text{ then } f_{1i} = X_i\beta + (Z_i\delta + \mu_i)\gamma + \varepsilon_i; \tag{9}$$

$$\text{If } \mathrm{NF}_i^* \le 0,\ \mathrm{NF}_i = 0 \text{ then } f_{0i} = X_i\beta + \varepsilon_i. \tag{10}$$

Hence, Eq. (9) expresses the participant's outcome model, while the non-participant's outcome model is reflected in Eq. (10). Based on this assumption, we can derive the inverse Mills ratio (λ_i). From Eqs. (9) and (10), we have:

$$E\left(f_{1i}|\mathrm{NF}_i = 1\right) = X_i\beta + \gamma + E\left(\varepsilon_i|\mathrm{NF}_i = 1\right) = X_i\beta + \gamma + \lambda_{1i} = X_i\beta + \gamma + \frac{\emptyset\left(\alpha Z_i\right)}{\Phi\left(\alpha Z_i\right)}. \tag{11}$$

$$E\left(f_{0i}|\mathrm{NF}_i = 0\right) = X_i\beta + E\left(\varepsilon_i|\mathrm{NF}_i = 0\right) = X_i\beta + \lambda_{0i} = X_i\beta - \frac{\emptyset\left(\alpha Z_i\right)}{1 - \Phi\left(\alpha Z_i\right)}. \tag{12}$$

In these cases, the inverse Mills ratio (λ_i) is:

$$\lambda_i = E\left(\varepsilon_i|\mathrm{NF}_i = 0\right) = \begin{cases} \lambda_{1i} = \frac{\emptyset(\alpha Z_i)}{\Phi(\alpha Z_i)} & \text{if} \quad \mathrm{NF}_i = 1 \\ \lambda_{0i} = \frac{\emptyset(\alpha Z_i)}{1-\Phi(\alpha Z_i)} & \text{if} \quad \mathrm{NF}_i = 0 \end{cases}. \tag{13}$$

The inverse Mills ratio (λ_i) calculates the expected value of the contribution of the unobserved covariates to the participation decision, which is conditional on the observed participation (Heckman 1979).

4.3 Heteroscedasticity

Previous empirical studies show that heteroscedasticity may occur when using cross-sectional data for analysis; thus, the assumption of constant variance may not hold. The Breusch–Pagan/Cook–Weisberg test for heteroscedasticity, with P value smaller than 0.05, indicates that the null hypothesis is rejected and there is significant evidence of heteroscedasticity. Using the cross-sectional data, we can determine the function of log of household food consumption $\ln Y_{i,t}$:

$$\ln f_{i,t} = X_i\alpha + \varepsilon_i. \tag{14}$$

Further, the variance of the food consumption function could be described as the function of household characteristics X_i:

$$\sigma^2_{\varepsilon,i} = \beta X_i + \theta_i. \tag{15}$$

Amemiya (1977) suggests using a three-stage FGLS to solve the heteroscedasticity problem. We can estimate α and β from Eqs. (14) and (15), respectively. First, we conduct the ordinary least square (OLS) procedure to estimate Eq. (14). Second, we can estimate Eq. (16) by using the estimated residuals from Eq. (14):

$$\hat{\varepsilon}^2_{\mathrm{OLS},i} = \beta X_i + \theta_i, \tag{16}$$

where θ_i is the random error term. The estimated value from Eq. (16) is then used to transform this equation to

$$\frac{\hat{\varepsilon}^2_{\mathrm{OLS},i}}{\hat{\beta}X_{i,\mathrm{OLS}}} = \beta\left(\frac{X_i}{\hat{\beta}X_{i,\mathrm{OLS}}}\right) + \frac{\theta_i}{\hat{\beta}X_{i,\mathrm{OLS}}}. \tag{17}$$

Next, Eq. (17) is estimated using the OLS procedure to obtain an asymptotically efficient estimate $\hat{\beta}_{\mathrm{FGLS}}$. The value of $\hat{\beta}_{\mathrm{FGLS}}X_i$ is the efficient estimate of $\sigma^2_{\varepsilon,i}$. Hence, we have the following equation:

$$\hat{\sigma}_{\varepsilon,i} = \sqrt{\hat{\beta}_{\mathrm{FGLS}}X_i}. \tag{18}$$

Using the estimated value of $\hat{\sigma}_{\varepsilon,i}$ to transform Eq. (14), we have

$$\frac{\ln f_{i,t}}{\hat{\sigma}_{\varepsilon,i}} = \alpha\left(\frac{X_i}{\hat{\sigma}_{\varepsilon,i}}\right) + \frac{\varepsilon_i}{\hat{\sigma}_{\varepsilon,i}}. \tag{19}$$

The estimates of Eq. (19) provide us with an asymptotically efficient and consistent estimate of α. Equation (19) shows that dividing the reported standard error by the standard error taken from Eq. (18) yields the standard error of estimated coefficient $\hat{\alpha}_{\mathrm{FGLS}}$. With the estimate of $\hat{\beta}_{\mathrm{FGLS}}$ and $\hat{\alpha}_{\mathrm{FGLS}}$, we can estimate the expected log of food consumption for each household and its variance with the following equations:

$$\hat{E}\left(\ln f_{i,t} \mid X_{i,t}\right) = \hat{\alpha}_{\mathrm{FGLS}} X_i. \tag{20}$$

$$\hat{V}\left(\ln f_{i,t} \mid X_{i,t}\right) = \hat{\sigma}^2_{\varepsilon,i} = \hat{\beta}_{\mathrm{FGLS}} X_i. \tag{21}$$

With an assumption that the log of food consumption has normal distribution, it is possible to use these estimates to measure the household's vulnerability level, as follows:

$$\hat{V}_{i,t} = \mathrm{prob}\left(\ln f_{i,t+1} < \ln P \mid X_{i,t}\right) = \Phi\left(\frac{\ln P - \hat{\alpha}_{\mathrm{FGLS}} X_{i,t}}{\sqrt{\hat{\beta}_{\mathrm{FGLS}} X_{i,t}}}\right). \tag{22}$$

4.4 Cross-tabulations, the correlation coefficient and receiver operating characteristic curve

We investigate the relationship between FP and VFP by conducting cross-tabulations and calculating the correlation coefficient and receiver operating characteristic (ROC) curve. The cross-tabulations are also known as a 'contingency table analysis' and occur based on incidences of FP and VFP. The Pearson correlation coefficient r is often used to measure the strength of the linear association between two variables, which can be identified by the formula below:

$$r = \frac{N\sum_{i=1}^{N} x_i y_i - \sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{\sqrt{N\sum_{i=1}^{N} x_i^2 - \left(\sum_{i=1}^{N} x_i\right)^2}\sqrt{N\sum_{i=1}^{N} y_i^2 - \left(\sum_{i=1}^{N} y_i\right)^2}}, \tag{23}$$

where N denotes the number of observations and x_i and y_i are the two examined variables. The Pearson correlation coefficient r often lies between − 1 and + 1. In the case that the coefficient equals precisely − 1 or + 1, this reflects perfect negative or positive correlations, respectively. When the coefficient equals zero, no correlation exists between the two variables.

The ROC curve is commonly used in engineering and disease diagnoses to investigate the extent to which a given signal acts as an indicator for an underlying condition (Streiner and Cairney 2013). Hence, this study uses the ROC curve to examine the degree to which vulnerability can signal FP. The curve is calculated through the following process: Households classified as both food-poor and vulnerable are called 'true positive' (TP), and households that are both non-vulnerable and non-poor are called 'true negative' (TN). Households that are grouped as non-vulnerable but food-poor in time $t + 1$ are regarded as 'false negative'; otherwise, they belong to a 'false positive' group, which is vulnerable but not food-poor in time $t+1$. The sensitivity rate of the signal (SSOS) is calculated as follows:

$$\mathrm{SSOS} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}). \tag{24}$$

The specificity rate of the signal (SPOS) is measured as:

$$\mathrm{SPOS} = 1 - \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}). \tag{25}$$

The ROC curve as plotted with the vertical and horizontal axes is the SSOS and SPOS rates, respectively. The area under the ROC curve is a measure of the degree to which one variable could signal other variables.

5 Data and descriptive statistics

5.1 Data

Data is drawn from a 2010 survey on living standards in Vietnam: The Vietnam Household Living Standards Survey (VHLSS). The survey was conducted in 2010 by Vietnam's General Statistics Office (GSO) to provide comprehensive information on household characteristics. Its sample size of 36,756 households is representative at the national, regional, urban, rural and provincial levels (GSO 2010). The survey was conducted during four periods through face-to-face interviews with heads of household and key community officials in each area; it is widely used in analysing living standards and poverty in Vietnam. This study's data were primarily taken from the Vietnamese Income and Expenditure Survey, which is a subset of the VHLSS, and include information on income and expenditures for food and non-food items from 9399 households in 3129 communities.

A questionnaire from this survey includes information on household consumption, expenditures, farm and non-farm income, socioeconomic characteristics, and various contextual and institutional variables. This study obtain edits final 4484 observations by excluding the following: households in urban areas; households that did not provide employment information for each family member; households located in areas without information on non-farm opportunities or paved roads to the community, as well as information on village markets; and households with information missing from the following characteristics: the head of household's age and educational background.

5.2 Descriptive statistics

Table 2 displays the summary statistics of the explanatory variables for rural Vietnam's food consumption function in 2010. On average, the 2010 daily food consumption expenditure per adult was approximately 12,000 VND for basic foods and ranged from 500 to 79,000 VND. Each adult consumed approximately 3390 calories daily on average, which surpasses the standard daily adult requirement of 2700 calories.[3] Regarding non-farm participation, approximately 54 per cent of respondent households have members who participate in non-farm work. The average ages of the household head and spouse are 46 and 43 years, respectively. A majority of the households, or 73%, belong to the Kinh ethnic group. Regarding community characteristics, non-farm networks and opportunities are indicators for the density of community-level non-farm works, with high proportions of non-farm networks and opportunities in each village. The mean of non-farm networks, or 0.41%, indicates that at the village level, approximately 41% of the population on average has non-farm employment. In contrast, non-farm opportunities' score of 0.71 indicates that

[3] The number of calories is measured by converting the food consumption in kilograms into calories. 'Appendix 1' provides further details.

Table 2 Variable definitions of the model. *Source*: Author's calculation

Code	Variables	Definition	Mean	SD	Min	Max	Expected signs
Household characteristics							
HAGE	Head's age	Age of household head (year)	45.83	12.51	18	99	+/−
SAGE	Spouse's age	Age of household heads' spouse (year)	43.43	12.34	15	94	+/−
ETH	Ethnics	Whether or not the ethnics of household head is of Kinh ethnicity	0.73	0.44	0	1	
HEDU1	No education	Whether the head of household is illiterate or not (yes = 1; no = 0)	0.34	0.47	0	1	−
HEDU2	Primary school education	Whether the head of household completed primary school education or not (yes = 1; no = 0)	0.26	0.44	0	1	+
HEDU3	Lower secondary school education	Whether the head of household completed lower secondary school education or not (yes = 1; no = 0)	0.38	0.49	0	1	+
HEDU4	Upper secondary school education and higher	Whether the head of household completed upper secondary school education and higher or not (yes = 1; no = 0)	0.017	0.13	0	1	+
DEPE	Dependency ratio[b]	The proportion of households 'dependents	0.60	0.57	0	4	+/−
SIZE	Household size	Total members of household (person)	4.31	1.47	2	12	+/−
GEN	Gender	Whether the household head is male or not (male = 1; female = 0)	0.95	0.22	0	1	+/−
ADLT	Adult[d]	The number of adults in the household (person)	3.86	1.28	2	10.6	+/−
FARM	Non-farm employment	Whether or not the household participated in non-farm activities (non-farm household = 1; otherwise = 0)	0.54	0.49	0	1	+
Assets							
MOBI	Mobile	Whether or not the household has mobile phones (yes = 1; no = 0)	0.87	0.33	0	1	+
COMP	Computer	Whether or not the household has computers (yes = 1; no = 0)	0.057	0.23	0	1	+
LAND	Lands holding	The size of farmland per capita (m2 per person)	10,891.68	57,639.07	8	2,848,072	+/−

Table 2 (continued)

Code	Variables	Definition	Mean	SD	Min	Max	Expected signs
TOIL	Toilet facility	Quality of toilet facility (yes = 1; no = 0)	0.30	0.46	0	1	+
HOMA	House material	Quality of house material (yes = 1; no = 0)	0.20	0.40	0	1	+
WATE	Clean water accessibility	Whether or not the household has access to clean water (yes = 1; no = 0)	0.061	0.24	0	1	+
ELEC	Electricity accessibility	Whether or not the household has access to electricity (yes = 1; no = 0)	0.94	0.23	0	1	+
Food consumption/expenditure							
FDAY	Food consumption	The daily food expenditure per adult of each household (thousand Vietnam Dong—VND)	11.59	5.27	0.56	79.12	
CDAY	Caloric consumption	Total daily caloric consumption per adult of each household (Cal)	3390	11,174.07	69.30	183,548	+
Commune characteristics							
DURE1	North-east[a]	Whether or not the household is located in the North-east region (yes = 1; no = 0)	0.18	0.38	0	1	+/−
DURE2	North-west[a]	Whether or not the household is located in the North-west region (yes = 1; no = 0)	0.22	0.42	0	1	+/−
DURE3	North Central[a]	Whether or not the household is located in the North-east region (yes = 1; no = 0)	0.077	0.27	0	1	+/−
DURE4	Red River Delta[a]	Whether or not the household is located in the North Central region (yes = 1; no = 0)	0.13	0.34	0	1	+/−
DURE5	Central Highlands[a]	Whether or not the household is located in the Red River Delta region (yes = 1; no = 0)	0.15	0.35	0	1	+/−
DURE6	Mekong River Delta[a]	Whether or not the household is located in the Mekong River Delta region (yes = 1; no = 0)	0.095	0.29	0	1	+/−
DURE7	South Central Coast[a]	Whether or not the household is located in the South Central Coast region (yes = 1; no = 0)	0.094	0.29	0	1	+/−
DURE8	South Coast[a]	Whether or not the household is located in the South Coast region (yes = 1; no = 0)	0.053	0.22	0	1	+/−

Table 2 (continued)

Code	Variables	Definition	Mean	SD	Min	Max	Expected signs
NFAO	Non-farm job opportunities	Whether or not there are any manufactures/services units within such a distance that the community in the village can work at every day and then return home. (yes = 1; no = 0)	0.71	0.45	0	1	+
FNET	Non-farm network[c]	The village level's non-farm participation share	0.41	0.23	0	1	+
ROAD	Paved road	Whether or not there is any paved road to the commune in the village (yes = 1; no = 0)	0.87	0.33	0	1	+
MARK	Market	Whether or not there is any intra-village and inter-village market in the commune in which the household resides (yes = 1; no = 0)	0.62	0.48	0	1	+
Observations			4484				

[a]This means dummy variables

[b]This proportion is measured by dividing total number of non-working age members (male members aged under 15 and over 65 years and female members aged under 15 and over 59 years) with the total number of working age members (male members aged 15–65 years and female members aged 15–59 years)

[c]This proportion is measured by dividing total number of people who have non-farm employment by the total population at the commune level in previous period

[d]The number of adults is calculated using the scale of 1 for adults and 0.65 for children following the method of Litchfield and Justino (2004) when evaluating adults regarding their food consumption level. This scale will more accurately reflect the consumption level of household, since it also considers the consumption of children rather than only measuring the consumption of adults

Table 3 The incidence of food poverty and vulnerability to food poverty in Vietnam. *Source*: Authors' calculation

Food poverty	Vulnerability to food poverty	Vulnerability to food poverty/food poverty ratio
48.57	53.10	1.093

Table 4 The relationship between food poverty and vulnerability to food poverty. *Source*: Authors' calculation

	Vulnerable	Non-vulnerable	Total (%)
Food-poor	61.88% (low-mean vulnerable)	38.12%	100
Non-food-poor	31.04% (high-volatility vulnerable)	68.96% (non-vulnerable)	100
Total	46.90%	53.10%	100
Person Chi2(1) = 427.8945			
Pr = 0.000			

Households are considered poor if their log of food expenditure is below the log of the food poverty line (log $P = 2.379$). Households are considered vulnerable if their vulnerability index is above 50%

71% of all villages have either manufacturing or services businesses that provide non-farm work for local people in the village.

Of all villages surveyed, 87% have paved roads in their communities, and 62% of all villages have intra- and inter-village markets in the community. This indicates a particular level of development in the community's infrastructure and markets, which should positively impact food consumption. The regional differences represent the particular community characteristics and agricultural systems in each region. Specifically, the sample indicates that 18%, 22%, 7.7%, 13%, 15%, 9.5%, 9.4% and 5.3% of the households are located in the North-east, North-west, North Central, Red River Delta, Central Highlands, Mekong River Delta, South Central Coast and South Coast regions, respectively.

6 Estimation results and discussion

6.1 Food poverty and the vulnerability to food poverty

Table 3 indicates that 48.57% of the Vietnamese rural population are food-poor, while 53.10% are vulnerable to food poverty; the ratio of VFP to FP is 1.093. These high incidences of FP and VFP expose an important issue in reducing FP. Further, Table 4 reveals the relationship between FP and VFP through a cross-tabulating analysis. Following Chaudhuri et al. (2002), we categorise the FP and VFP using the three-way classification of households. The 'non-vulnerable group' is the group that has a VFP level below the threshold of 0.5, and their estimated mean consumption is higher than the food poverty line. The second group constitutes households with a vulnerability level above the vulnerability threshold, but their mean consumption is higher than the food poverty line. This group is called 'high-volatility vulnerability', and it represents people who are not consumption-poor, but are vulnerable to food poverty because of their

Table 5 The result of receiver operating characteristics. *Source*: Authors' calculation

Receiver operating characteristics				
Observations	Area	SE	[95% Conf. Interval]	
4484	0.655	0.0071	0.641	0.669

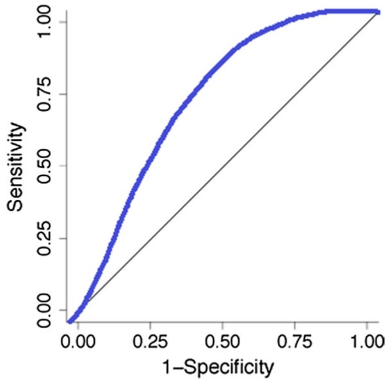

Fig. 1 The receiver operating characteristics curve of vulnerability and poverty. *Source*: Author's calculation

highly volatile consumption. Therefore, this group needs more income and consumption stabilisation interventions. The final group is called the 'low-mean vulnerable'; they have a mean consumption level lower than the food poverty line, and their vulnerability levels are higher than the vulnerability threshold. Specifically, these households are either food-poor or vulnerable to food poverty, indicating that they have a high probability of remaining food-poor in future. Their vulnerability is primarily rooted in the fact that, with their low mean consumption, even if their food consumption variability decreases, they are still highly vulnerable to food poverty. Therefore, for this group, a long-term strategy of poverty alleviation is necessary to ensure that this group get over the poverty line. Table 4 demonstrates that the proportion of the 'low-mean vulnerable' population that is food-poor and vulnerable to food poverty is 61.88%, which is much higher than the 'high volatility vulnerable' population (31.04%) who are non-food-poor and vulnerable to food poverty. Thus, those who are food-poor are more vulnerable to food poverty than those who are not. The high proportion of 'low-mean vulnerable' refers to the chronically poor; it is highly imperative to enact long-term poverty alleviation strategies in these cases. The 'high volatility vulnerable' group refers to the transient poor that need more income or consumption stabilisation intervention.

Further, Pearson's chi-squared result equals 427.89, and the observed differences are significant, proving that FP and VFP are codependent. Specifically, the chi-squared independent test reveals that FP and VFP are positively correlated, and its estimates are significant at a 5% level.

We can apply the ROC curve to more strongly confirm the relationship between poverty indexes and vulnerability indexes. Practically, the ROC curve is built as a plot of the true and false positive rates with each feasible cut-point from the diagnostic examination, indicating the trade-off between the degree of specificity and sensitivity. The closer the curve gets to the left-hand and top borders, the more accurate the test's results are. As revealed in Table 5 and Fig. 1, the area under the ROC curve accounts for approximately 66%, which

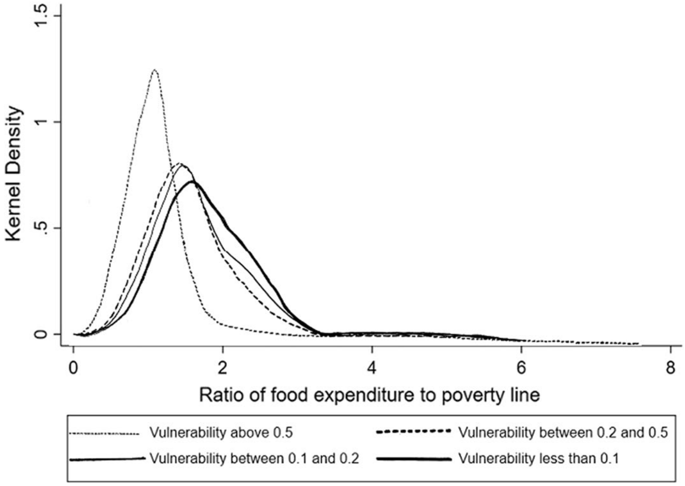

Fig. 2 The Kernel density estimates of the ratio of food expenditure to the poverty line. *Source*: Author's calculation

is a relatively high value. This indicates that the vulnerability index is a strong signal for the poverty index.

This conclusion is affirmed through Fig. 2, which illustrates the kernel density estimates for the ratio of food consumption to the poverty line. This figure shows that the higher the household's level of vulnerability, the lower the kernel density estimates for the ratio of food consumption to the poverty line. This indicates that a higher vulnerability index will lead to the higher likelihood of food poverty.

6.2 Non-farm participation's effect on food consumption and vulnerability to food poverty

Table 6 displays the regression results from both the OLS and IV estimations to estimate the determinants of log food consumption and vulnerability. It is recognised that even though the magnitudes of coefficient estimates change, the general estimation results of both regression methods (OLS and IV regression) do not change qualitatively. This implies that the sign of estimated results will still remain when the problem of endogeneity is controlled for.

This reveals that non-farm participation positively affects food consumption in all regression models. Further, the OLS estimates expose inconsistency because of endogeneity. The third step in the IV model applies the FGLS method to correct heteroscedasticity, which is consistent with solving these problems. Specifically, the estimated coefficients for non-farm participation from the IV model, with and without the FGLS methods as the third step, are 0.13 and 0.15, respectively. These are both significant at the 1% level, indicating that non-farm participation exhibits a moderately positive relationship with food consumption. This result parallels those from previous studies in other developing countries. For example, Reardon and Berdegue (2001) examine a case in Burkina Faso to prove that non-farm participation will increase food consumption. Similarly, Ersado (2006) discover that non-farm diversification positively impacts food expenditures. Owusu et al. (2011) also reveal that non-farm participation has a positive relationship with household income and

Table 6 Regression results of log food consumption per adult. *Source*: Authors' calculation

Explanatory variables	OLS estimates		IV model		
	Food consumption	Vulnerability	Food consumption		Vulnerability
			Without FGLS step	With FGLS step	
Household characteristics					
Non-farm participation	0.0325** (0.0134)	− 0.00849*** (0.00256)	0.132*** (0.0487)	0.151*** (0.0478)	− 0.191*** (0.0136)
Head's age	0.0039** (0.0016)	− 0.00529*** (0.000314)	0.0041** (0.00165)	0.0034** (0.00164)	− 0.00559*** (0.000458)
Spouse's age	− 0.0031* (0.0016)	0.0044*** (0.000318)	− 0.0028* (0.00168)	− 0.00214 (0.00167)	0.0039*** (0.000466)
Ethnics	0.139*** (0.0188)	− 0.212*** (0.00361)	0.156*** (0.0219)	0.116*** (0.0217)	− 0.168*** (0.0061)
No education	base category	base category	base category	base category	base category
Primary school education	0.0407*** (0.015)	− 0.0681*** (0.00292)	0.0381* (0.0153)	0.0424*** (0.0151)	− 0.0631*** (0.00427)
Lower secondary school education	0.0561*** (0.0154)	− 0.0807*** (0.00296)	0.0492*** (0.0158)	0.0491*** (0.0156)	− 0.0681*** (0.0044)
Upper secondary school education and higher	0.119*** (0.046)	− 0.146*** (0.00879)	0.0961** (0.0474)	0.0878 (0.0544)	− 0.103*** (0.132)
Dependency ratio	− 0.0672*** (0.014)	0.0961*** (0.00269)	− 0.064*** (0.0142)	− 0.0546*** (0.014)	0.0901*** (0.00396)
Household size	0.147*** (0.0189)	− 0.197*** (0.00362)	0.15*** (0.019)	0.139*** (0.0185)	− 0.204*** (0.0053)
Gender	− 0.0586** (0.0275)	0.0932*** (0.00526)	− 0.0505* (0.0278)	− 0.0541* (0.0276)	0.07825*** (0.00775)
Adult	− 0.251*** (0.0211)	0.338*** (0.00405)	− 0.2602*** (0.0216)	− 0.247*** (0.0209)	0.354*** (0.00602)
Assets					
Lands holding	2.42×10^{-7}** (1.01×10^{-7})	-2.86×10^{-7}** (1.93×10^{-7})	2.46×10^{-7}** (1.01×10^{-7})	7.14×10^{-7}** (1.83×10^{-7})	-2.93×10^{-7}** (2.81×10^{-8})

Table 6 (continued)

Explanatory variables	OLS estimates		IV model		
	Food consumption	Vulnerability	Food consumption		Vulnerability
			Without FGLS step	With FGLS step	
Toilet facility	0.0891*** (0.0145)	− 0.154*** (0.00279)	0.078*** (0.0155)	0.082*** (0.0151)	− 0.133*** (0.00432)
House Material	0.017 (0.016)	− 0.0148*** (0.0039)	0.0145 (0.0161)	0.00933 (0.0154)	− 0.009** (0.00447)
Computer ownership	0.212*** (0.026)	− 0.237*** (0.00508)	0.207*** (0.0268)	0.198*** (0.0266)	− 0.226*** (0.00745)
Mobile ownership	0.1392*** (0.020)	− 0.197*** (0.0039)	0.134*** (0.0206)	0.135 (0.0222)	− 0.187*** (0.00574)
Clean water accessibility	0.027 (0.0247)	− 0.0295*** (0.00473)	0.0215 (0.0249)	0.0119 (0.0233)	− 0.0194*** (0.00694)
Electricity accessibility	− 0.0201 (0.030)	0.0383*** (0.0058)	− 0.0306 (0.0308)	− 0.0305 (0.032)	0.0576*** (0.00857)
Commune characteristics					
North-east	0.0366 (0.0302)	− 0.0673*** (0.00585)	0.0317 (0.0307)	0.0366 (0.0347)	− 0.0582*** (0.00857)
North-west	− 0.0336 (0.0341)	0.0348*** (0.00654)	− 0.0278 (0.0344)	− 0.0198 (0.0386)	0.0241** (0.00957)
North Central	− 0.178*** (0.030)	0.236*** (0.00578)	− 0.189*** (0.0307)	− 0.185*** (0.0349)	0.257*** (0.00856)
Red River Delta	− 0.0121 (0.0299)	0.113*** (0.00541)	− 0.132*** (0.03)	− 0.125 (0.0341)	0.151*** (0.00835)
Central Highlands	− 0.0133 (0.0331)	− 0.00364 (0.00635)	0.00458 (0.0343)	0.0204 (0.0373)	− 0.0366*** (0.00956)
Mekong River Delta	− 0.0121 (0.0299)	− 0.0244*** (0.00574)	− 0.0178 (0.0302)	− 0.00964 (0.0341)	− 0.0139* (0.00835)

Table 6 (continued)

Explanatory variables	OLS estimates		IV model		
	Food consumption	Vulnerability	Food consumption		Vulnerability
			Without FGLS step	With FGLS step	
South Central Coast	− 0.159*** (0.031)	0.197*** (0.00594)	− 0.174*** (0.0319)	− 0.169*** (0.0364)	0.225*** (0.00889)
South Coast	base category	base category	base category	base category	base category
Non-farm job opportunities	0.0026 (0.014)	− 0.0142*** (0.00272)	− 0.00302 (0.0145)	0.003 (0.0143)	− 0.00386 (0.00404)
Paved road	0.0242 (0.0186)	− 0.0151*** (0.00357)	0.014 (0.0193)	0.00124 (0.018)	0.00373 (0.00538)
Market	0.0103 (0.0123)	− 0.0121*** (0.00236)	0.0102 (0.0124)	0.0121 (0.0122)	− 0.0118*** (0.00344)
R-square	0.2086	0.93	0.199	0.207	0.86
Observation	4484	4484	4484	4484	4484

Robust standard errors in parentheses; province-level indicators included, but not shown

*Mean statistical significance at 10%; ** at 5%; and ***at 1%

food security status, emphasising that non-farm participation is crucial to both food security and alleviating poverty in northern Ghana's rural areas. In fact, non-farm participation will increase household income while creating more diverse income. Subsequently, this helps to loosen households' budget constraints and increase their expenditures (Matshe and Young 2004; Owusu et al. 2011). Further, non-farm employment helps reduce vulnerability to food poverty. Specifically, the estimated coefficient results from the IV model equal − 0.191. That is, if households participate in non-farm activities, their probability of falling into food poverty is significantly less likely by 19%.

Other variables that also positively relate to food consumption include household size and markets' availability in the village. When the household size increases and more intra- and inter-village markets exist, the household will spend more money on food consumption. As another notable variable, the dependency ratio exposes the negative impacts on food consumption: the estimated coefficients for the impacts of the dependency ratio from the OLS regression and IV estimation models (without and with FGLS) are − 0.0672, − 0.064 and − 0.0546, respectively, and are all significant at the 1% level. If a household has more dependent members, it will experience a lower daily food consumption per adult; in another words, it will be likely more vulnerable to food poverty in future. This implication offers the same intuition as results from Christiaensen and Boisvert (2000), who examined a case in Mali to prove that households with more children experience a higher risk of poverty in future. Regarding household assets, the results from Table 6 indicate that landholding and sanitation facilities are positively associated with food consumption. This implies that households with better living condition clearly spend more on food.

The results also show that education has an important role in reducing food poverty and vulnerability. The better the education that the head of household has, the less likely that the household will be food-poor in future. Further, the vulnerability of female-headed households is, on average, lower than that of male-headed households. However, the positive value of the estimated coefficient of the gender variable is significant at the 5% level, indicating that male-headed households are more likely to be more vulnerable to food poverty. Possibly, food consumption of male-headed households faces higher volatility if this group experiences an adverse shock. This volatility leads to higher *ex ante* variance in food consumption ($\hat{\beta}X_i$), as demonstrated in Eq. (21). Consequently, such households are more vulnerable to both adverse shocks and more likely to be undernourished in future.

Landholding also has positive effects on food consumption and vulnerability reduction. Computer and mobile ownership is a proxy not only for household welfare, but also for the degree to which the household is connected with information and social networks. Interestingly, the households that own a computer are 22.6% less likely to fall into food poverty in future, indicating the importance of information and social networks in reducing vulnerability. More information provides more employment opportunities or production experience for households, which, in turn, increase income and stabilise food consumption. Quality of toilet facilities and quality of house material are proxies for housing condition. These variables have significantly positive effects on food consumption and vulnerability reduction, implying that the households with better housing conditions will enjoy higher food consumption.

As reported in Table 7, the mean vulnerability of households without non-farm participation is greater than those with non-farm participation, or 54.75% and 43.45%, respectively. This indicates that households are less likely to experience or remain in food poverty in future if at least one member participates in non-farm work than households with no one participating in non-farm work. Additionally, and as can be observed in Table 9 and

Table 7 Vulnerability to food poverty for household characteristics and non-farm participation. *Source*: Authors' calculation

	Observations	Mean vulnerability (%)	Standard deviation
Non-farm participation			
Yes		43.45	0.272
No		54.75	0.284
Gender			
Male	4253	49.77	0.282
Female	231	28.37	0.231
Ethics			
Kinh	3287	40.02	0.254
Others	1197	72.40	0.218
Region			
Mekong River Delta	804	36.69	0.243
Red River Delta	993	37.95	0.239
Central Highlands	346	49.49	0.305
North Central	583	66.05	0.243
North-east	666	48.82	0.293
North-west	426	70.37	0.249
South Central Coast	424	58.39	0.239
Non-farm job opportunities			
Yes	3213	43.45	0.271
No	1271	61.85	0.278
Paved Road			
Yes	3911	47.82	0.278
No	573	54.43	0.312
Market			
Yes	2776	45.44	0.270
No	1708	53.92	0.296

Graph 1, the North-west region is the most vulnerable, with a VFP index of 70.37%. In contrast, the Mekong River Delta and Red River Delta regions are among the least vulnerable, with vulnerability indexes of 36.69% and 37.95%, respectively. The mountainous North-west region is the home of 32 ethnic minority groups, with the highest average poverty rate in Vietnam of 60.1% in 2010 (World Bank 2012). The Red River and Mekong River Deltas are considered the two 'rice bowls' of Vietnam, as the heart of the country's rice production industry. Thus, these regions partially ensure food availability to their communities. The results from Table 9 also demonstrate that the Kinh ethnic group[4] is less vulnerable to food poverty than other ethnic groups. It is also notable that households located in the regions with roads into the community as well as intra- and inter-village markets exhibit lower vulnerability indexes than those without paved roads and markets. This might

[4] The Kinh people (Vietnamese: *người Việt* or *người Kinh*) are an ethnic group originating from present-day northern Vietnam. They are considered the country's majority ethnic group, as they comprise 86% of its population, and are officially known as Kinh to distinguish them from other ethnic groups in Vietnam (Mekong Development Research Institute 2014).

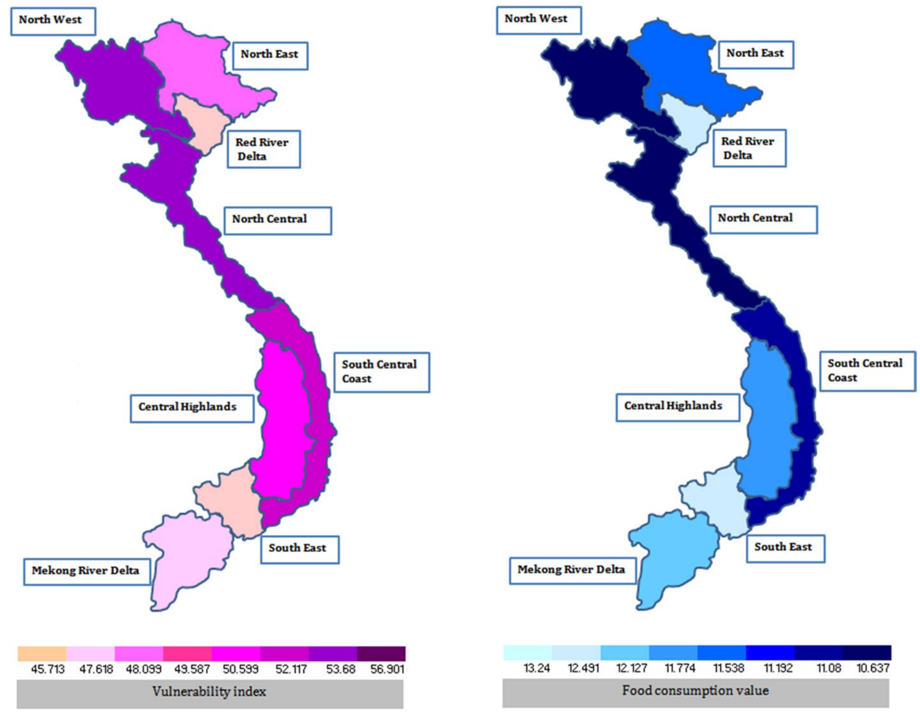

Fig. 3 The vulnerability index and food consumption value of rural households in Vietnam. *Source*: Author's calculation

be explained by the fact that improving the infrastructure system makes it easier to access markets; the exits to intra- and inter-village markets will increase both food trading and consumption, which are regarded as the drivers of food security. This result is consistent with previous studies, which confirm infrastructure's importance in decreasing poverty in general, and food poverty in particular (Gibson and Rozelle 2003).

Additionally, non-farm job opportunities also have relatively high impacts on the vulnerability index. Generally, villages with non-farm job opportunities will exhibit a vulnerability index of 43.45% which is less than the vulnerability threshold, while those without non-farm job opportunities will be more vulnerable to food poverty, with a vulnerability index of 61.85% (Fig. 3).

6.3 Robustness check using treatment effects model for endogenous treatments

A robustness check was conducted by employing treatment effects model for endogenous treatments, a version of Heckman's selection model to confirm the IV model's results. Table 8 reports the results from the selection and outcome equations.

The selection equation's results indicate the determinants of non-farm participation and reveal the following: Men are more likely than women to have more chances to participate in non-farm activities, and higher education is associated with the higher probability of involvement in the non-farm sector. This is because non-farm work differs from agricultural activities, in that the former requires a skill or capacity to participate; thus, limited

Table 8 Results of treatment effects model for endogenous treatments model

Explanatory variables	1st stage	2nd stage	
	Non-farm participation	Food consumption	Vulnerability
Household characteristics			
Non-farm participation		0.0454 (0.043)	− 0.104*** (0.0049)
Head's age	− 0.00426 (0.00628)	0.00396** (0.00163)	− 0.00545*** (0.000373)
Spouse's age	− 0.0109* (0.00638)	− 0.00306** (0.00166)	0.00416*** (0.000373)
Ethnics	0.424*** (0.0696)	0.136*** (0.0222)	− 0.189*** (0.00476)
No education	base category	base category	base category
Primary school education	0.0912 (0.0558)	0.0404*** (0.0155)	− 0.0655*** (0.00333)
Lower secondary school education	0.204*** (0.0574)	0.0552*** (0.016)	− 0.0741*** (0.00344)
Upper secondary school education and higher	0.882*** (0.22)	0.117** (0.0477)	− 0.123*** (0.0959)
Dependency ratio	− 0.0866 (0.0535)	− 0.0668*** (0.0138)	0.093*** (0.00347)
Household size	− 0.135* (0.0713)	0.147*** (0.0188)	− 0.2005*** (0.00476)
Gender	− 0.245** (0.0994)	− 0.0576** (0.0281)	0.0853*** (0.00631)
Adult	0.319*** (0.0795)	− 0.252*** (0.213)	0.346*** (0.00549)
Assets			
Lands holding	2.73×10^{-8}** (5.21×10^{-7})	2.43×10^{-7} (1.55×10^{-7})	-2.90×10^{-7} (5.49×10^{-8})
Toilet facility	0.241*** (0.0538)	0.877*** (0.015)	− 0.143*** (0.00294)
House material	0.103* (0.0589)	0.0173 (0.0163)	− 0.0118*** (0.00343)
Computer ownership	0.247** (0.115)	0.211*** (0.0258)	− 0.232*** (0.0076)
Mobile ownership	0.183** (0.0789)	0.138*** (0.0233)	− 0.192*** (0.00509)
Clean water accessibility	0.0572 (0.0986)	0.0263 (0.0251)	− 0.0242*** (0.00532)
Electricity accessibility	0.396*** (0.133)	− 0.0215 (0.0348)	0.0485*** (0.00842)
Commune characteristics			
North-east	0.605*** (0.111)	0.036 (0.0339)	− 0.0626*** (0.00598)
North-west	0.317** (0.129)	− 0.0328 (0.039)	0.0292*** (0.00754)
North Central	0.605*** (0.109)	− 0.179*** (0.0344)	0.247*** (0.00581)
Red River Delta	0.628*** (0.101)	− 0.114*** (0.0336)	0.133*** (0.00517)

Table 8 (continued)

Explanatory variables	1st stage	2nd stage	
	Non-farm participation	Food consumption	Vulnerability
Central Highlands	− 0.0333 (0.126)	− 0.011 (0.0367)	− 0.0209*** (0.00654)
Mekong River Delta	0.381*** (0.107)	− 0.128 (0.335)	− 0.0189*** (0.00557)
South Central Coast	0.454*** (0.111)	− 0.161*** (0.0358)	0.212*** (0.00608)
Non-farm job opportunities	0.0454 (0.0527)	0.00189 (0.0144)	− 0.00878*** (0.00319)
Paved Road	0.293*** (0.0729)	0.0229 (0.0182)	− 0.00518 (0.00463)
Market	− 0.0193 (0.0464)	0.0103 (0.0121)	− 0.0119*** (0.00271)
Non-farm networks	2.460*** (0.138)		
Inverse Mill's ratio (λ)		− 0.00829 (0.0265)	0.0647*** (0.00405)
Rho		− 0.0217 (0.0694)	0.774 (0.0356)
Sigma		0.381 (0.0053)	0.0837 (0.00217)
R-square			
Observation	4484		

Robust standard errors in parentheses; province-level indicators included, but not shown

*Mean statistical significance at 10%; **at 5%; and***at 1%

education and skills seem to be a barrier for people who wish to participate in off-farm employment. Households that possess electronic devices, such as mobile phones and computers, are more likely to not only catch up on information, but also build larger networks. Subsequently, they are more likely to gain non-farm employment.

The outcome equation's results reveal the determinants of households' food consumption and VFP. Non-farm participation significantly impacts the decrease in vulnerability, and participating in non-farm activities will decrease their probability of experiencing FP in the next period by approximately 11%.

Regarding the results of VFP, the estimated coefficient of inverse Mill's ratio (λ) is significant at the 1% level, indicating a selectivity bias in the model. The treatment effects for endogenous treatments model account for this issue and generate the consistent estimates. The negative sign of inverse Mill's ratio (λ) shows that, if the problem of selection bias had not been corrected, then it would have made the estimated coefficients biased in a downward direction.

Table 9 Conversion table calories for Vietnam. *Source*: Vietnam National Institute of Nutrition (2007)

Food	Kcal per 100 g	Food	Kcal per 100 g
Fragrant rice, specialty rice	344	Peanuts, sesame	568
Sticky rice	346	Fresh fruit	59
Corn	196	Convolvulus	25
Cassava	152	Kohlrabi	37
Sweet potatoes of all kinds	119	Cabbage	29
Noodles, bread, flour	249	Tomato	20
Pasta, noodles, instant noodles/porridge	349	Orange	38
Rice noodles, rice noodles, rice cake	110	Bananas	56
Vermicelli	332	Mango	62
Pork	260	Fish sauce, sauce	35
Beef	167	Salt	0
Buffalo meat	97	Honey	390
Chicken	199	Cake, jam, candy	376
Duck and other poultry meat	267	Condensed milk, milk powder	336
Grease, cooking oil	900	Ice cream, yogurt of all kinds	61
Fresh shrimp and fish	90	Fresh milk	74
Dried and processed shrimp and fish	208	Alcohol (all kinds)	167
Eggs (chicken, ducks)	166	Beer (all kinds)	11
Tofu	95	Soft drinks	42

7 Summary and conclusions

The previous empirical literature is limited regarding non-farm activities' impacts on households' FP and VFP in rural Vietnam. Therefore, this study attempts to investigate the impacts of non-farm participation on households' food poverty and the relationship between this FP and VFP; this leads to discerning the relationship between non-farm participation and the latter.

First, we find high incidences of food poverty and vulnerability in rural Vietnam. The 'low-mean vulnerable' group has a mean consumption level lower than the food poverty line, and its vulnerability levels are higher than the vulnerability threshold, accounting for approximately 62%, which is high. Specifically, these households are either food-poor or vulnerable to food poverty. That is, they have a high probability of remaining food-poor in future. Thus, long-term strategies of poverty alleviation are necessary to bring this group above the poverty line.

Second, this study finds that non-farm participation will increase food consumption. Consequently, this will help Vietnam's rural populations be less vulnerable to food poverty in future. Generally, this study's findings are consistent with previous studies on non-farm participation's role in decreasing poverty in Vietnam as well as other developing countries. The study also finds evidence that several household characteristics are highly associated with food consumption. Households with a higher number of dependent members appear to consume less food and are likely to be more vulnerable to food poverty in future. Third, and similar to previous findings, this study demonstrates that some community characteristics are important in households' food consumption. For example, households located in a village have better access to infrastructure, such as paved roads to the community and intra- and inter-village markets. This will increase the likelihood of food consumption and, therefore, decrease the risk of VFP.

The study also reveals the determinants of non-farm participation. As anticipated, our empirical analysis indicates that such household characteristics as education and household size are associated with increased non-farm participation.

Our findings lead to a discussion regarding the policies to implement to reduce food poverty and vulnerability. The evidence proving non-farm participation's importance suggests that policies that promote non-farm activities both provide and increase the opportunities for households to participate in non-farm employment. These opportunities should be an effective solution to reduce FP and VFP in rural Vietnam. Therefore, other potential solutions could be considered, such as promoting accessibility for the poor to education; investing and improving local physical infrastructures, such as augmenting and expanding villages' paved roads; and opening and expanding intra- and inter-village markets. Importantly, information of non-farm employment and social networks plays a crucial role in not only promoting non-farm employment, but also indirectly reducing vulnerability to food poverty. Hence, the government should facilitate the food-poor group with broader dissemination of market information, through, for example, the Internet, television and radio. Over time, this would help them easily access employment opportunities and, consequently, gain sustainable improvements in food security.

Vietnam's North-west region in particular has the highest vulnerability index, and hence, it is crucial to offer special support programs for the region's non-farm activities. These supporting programs include project-level interventions and credit programs. Specifically, project-level interventions in small rural enterprises could take many forms, as some are designed to support potential entrepreneurs in beginning new enterprises, while others support existing enterprises. Credit programs might operate through government-owned developments or commercial banks, private banks and non-government organisations. Schemes supporting small and medium-sized enterprises will be particularly essential in the rural non-farm economy, as these firms will be the dynamic engine to create a majority of non-agricultural jobs in rural areas.

Appendix 1: Technical note on measuring the food poverty line

This section explains the step of calculating the poverty line (P) used in Eqs. (1) and (2):

$$\ln f_i = \omega_1 + \omega_2 C_i$$
$$P = e^{\widehat{\omega_1} + \mathrm{RDA}\widehat{\omega_2}}$$

1. In the first step, we convert the food consumption in kilograms into calories consumption using the food composition table constructed by Vietnam National Institute of Nutrition in 2017 (Vietnam National Institute of Nutrition 2007). With the data of VHLSS in 2010, we compute the total calorie intake (Kcal) for 38 food items, representing the food basket of each household. From this, the calories consumption (C_i) for each household are measured. The value of C_i is then used in step 2 to regress Eq. (1) (Table 9).

2. The second step is to obtain the estimates of coefficient ω_2 and intercept ω_1 through the regression of the function of food consumption, with calories as the explanatory variables: $\ln f_i = \omega_1 + \omega_2 C_i$. We thus obtain the estimates results of coefficient and intercept: 1.85×10^{-6} and 2.35, respectively.
3. The third step is to calculate the poverty line based on the results of $\widehat{\omega_1}$ and $\widehat{\omega_2}$. Finally, we obtain $P = 10.538$ as the poverty line.

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