The Effects of nonfarm activities on farm households’ food consumption in rural Cambodia

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This article analyzes the effects of participation in nonfarm activities on farm households’ food consumption in rural Cambodia. An endogenous switching model is built on data from the Cambodia Socio-Economic Survey conducted in 2009 to evaluate whether rural farm households make food consumption gains from participation in such activities. This model accounts for selection bias resulting from unobserved factors that potentially affect both farm households’ decision to participate in nonfarm activities and food consumption. The model also controls for structural differences between participants in nonfarm activities and nonparticipants that most previous studies do not account for. The results suggest that by engaging in nonfarm activities, rural farm households make positive gains in per capita food consumption, thus confirming the hypothesis that engagement in nonfarm activities exerts positive effects on household food consumption. 

Keywords: nonfarm activities; farm households; food consumption; Cambodia

Introduction

Over the past two decades, Cambodia has recorded remarkable economic growth. This growth, which was mainly driven by tourism and agriculture, made a tremendous contribution to reducing poverty from 50% in 2004 to 20% in 2011 (ADB 2013). Still, inequality in income and food consumption between rural and urban populations has increased, with urban households enjoying higher income and consumption levels. The nationwide undernourishment prevalence declined from 37% in 2004 to 33% in 2009; however, rural undernourishment, especially among the poorest households, slightly increased (NIS 2011), raising concern over food security issues among rural farmers and the poorest population. This result suggests that more attention should be paid to rural economic development. Although Cambodia has a higher potential for agriculture, nonfarm activities can play a crucial role in developing the rural economy, especially in alleviating poverty. It is well recognized that farm households’ engagement in nonfarm activities is a pathway out of poverty in rural areas of developing countries (IFAD 2011).

Generally, in addition to profits from agricultural production, other income sources from nonfarm activities such as self-employment and salary-paid employment contribute to farm households’ level of income. The revenue from nonfarm activities largely contributes to the alleviation of extreme poverty in rural Cambodia (Tong 2011). This demonstrates that agriculture per se fails to lift farm households out of the poverty trap in rural Cambodia. Cambodia’s greater integration into international trade, the tourism boom and urban development have created jobs for Cambodian farm households and stimulated the nonfarm sector. Moreover, over the last few decades, the development of physical infrastructure has improved urban–rural road connectivity, which also facilitates agricultural households’ engagement in nonfarm activities. Given the potential for nonfarm activities to reduce poverty in Cambodia, it is worth analyzing the effects of working off the farm on rural farm households’ food security in terms of food consumption.

Engagement in nonfarm activities is farm households’ self-insurance mechanism to increase and stabilize household incomes (Alasia et al. 2009). Several studies analyze the economic impacts of participation in nonfarm employment on farm households at the household level by evaluating the impacts on farming practice, household expenditure or household incomes (see e.g., McNally 2002; de Janvry and Sadoulet 2001; Mishra and Sandretto 2001; Goodwin and Mishra 2004; de Janvry, Sadoulet, and Zhu 2005; Chang and Mishra 2008; Owusu, Awudu, and Seini 2011; Akaakohol and Aye 2014; Scharf and Rahut 2014). The findings show that farm households engaging in nonfarm employment tend to enjoy higher household incomes and produce agricultural products more efficiently, suggesting the vital role of nonfarm activities in raising farm households’ incomes and improving farming practice.

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Hence, farm households’ participation in nonfarm activities would very likely increase and stabilize household food consumption over a prolonged period of time. However, to appropriately quantify the potential for nonfarm activities to improve rural food security in terms of food consumption in developing countries such as Cambodia, one needs an unbiased and consistent estimation of the effects of such activities.

Some studies assess the economic effects of nonfarm employment on farm households by employing a propensity score matching approach to account for selection bias (see e.g., Owusu, Awudu, and Seini 2011; Olugbire et al. 2011). Still, this approach cannot control for the unobserved confounders that influence both the treatment and outcome and, thus, potentially produces inconsistent and biased estimates of the economic effects of nonfarm activities. Standard treatment models that control for nonrandom sample selection can be used to address this issue (see e.g., Chang and Mishra 2008). The models are, however, estimated under the assumption that the impacts are uniform across different subsamples; nonetheless, there may be inherent differences between nonfarm participants and nonparticipants. In this case, the structure of household consumption patterns would very likely be systematically different, especially if factors affecting the decisions to participate or not participate in nonfarm activities equally influence the consumption level. Therefore, the uniform effects assumption can hide an inherent interaction between the decisions regarding nonfarm activities and factors affecting the consumption level, potentially resulting in unreliable outcomes (Rao and Qaim 2011).

The basic objective of the current paper is to analyze the effects of nonfarm activities on farm households’ food consumption in rural Cambodia by building an endogenous switching model on data from the Cambodia Socio-Economic Survey (CSES) conducted in 2009. The model treats nonfarm participation and nonparticipation as regimes to address potential endogeneity due to endogenous bias in the decisions concerning the regimes and inherent differences between participants and nonparticipants. Then, using the model, the effects can be estimated by controlling for both observed and unobserved factors that determine both the decisions regarding the regimes and household food consumption. Furthermore, the model accounts for potential systematic differences between the participants and the nonparticipants in terms of consumption functions. This study contributes to the literature by analyzing the effects of nonfarm participation on household food consumption and addressing these econometric challenges using cross-sectional data. As mentioned earlier, the focus of the current study on the effects of nonfarm activities on household food consumption is motivated by its implication for the achievement of poverty alleviation. It is also the first study to analyze the effects of nonfarm activities on farm households in rural Cambodia. The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature, Section 3 describes the empirical framework and data used for the analysis, Section 4 presents the results and Section 5 concludes the study.

**Literature review**

The contribution of household income diversification through working off the farm and increasing household earnings is supported by many empirical studies (see, e.g., Reardon, Delgado, and Matlon 1992; Mishra and Sandretto 2001; de Janvry and Sadoulet 2001; Goodwin and Mishra 2004; de Janvry, Sadoulet, and Zhu 2005; Chang and Mishra 2008; Owusu, Awudu, and Seini 2011; Olugbire et al. 2011). The findings of these studies indicate that through engaging in nonfarm employment, farmers are able to increase their household incomes and reduce their vulnerability. Participation in nonfarm activities is the farmers’ strategy for diversifying their household earnings portfolio to sustain their household income and stabilize their household consumption over a prolonged period of time (Reardon, Delgado, and Matlon 1992). These effects substantially contribute to poverty reduction in rural developing countries, as identified by Lanjouw and Lanjouw (2001) and Lanjouw and Shariff (2004). In addition to spurring household incomes and alleviating the severity of poverty, nonfarm employment can reduce income inequality among rural households (de Janvry, Sadoulet, and Zhu 2005).

However, the extent to which nonfarm employment contributes to improvements in farm households’ livelihoods depends on returns from that employment. Moreover, the latter may have impacts on the distribution of household incomes because it is farm households’ strategy for diversifying household incomes portfolio. For example, Scharf and Rahut (2014) investigated the distributional and welfare impacts of engagement in nonfarm work on farm households in the rural Himalayas by estimating a system of structural equations and accounting for the heterogeneity of the decision of whether to engage or not engage in nonfarm work. The findings show that low-return nonfarm work is associated with lower income inequality, while high-return nonfarm activities have a disqualifying impact on household income distribution. Furthermore, participation in high-return nonfarm activities has a positive correlation with better household welfare in terms of expenditure on all necessary goods and services, confirming a positive effect of high-return nonfarm employment on household well-being. In addition, the authors found that poor farmers tend to rely on low-return nonfarm employment that does little to contribute to the improvement in household welfare. By using an ordinary least square (OLS) regression model to examine the effects of nonfarm activities on household consumption expenditure
in Nigeria, Akaakohol and Aye (2014) found that nonfarm activities, household head’s age and education level, and access to credit have significant positive impacts on household consumption expenditure.

The evaluation of the economic effects of nonfarm activities on farm households is a difficult assignment, especially when using household-level cross-sectional data, due to some econometric challenges such as self-selection bias and endogeneity problems. Some studies attempt to reduce these issues using nonparametric or semi-parametric econometric techniques. For example, Owusu, Awudu, and Seini (2011) assessed the impacts of nonfarm employment on farmers’ household revenue and food security by using data from the 2007 household survey in the rural northern region of Ghana and controlling for selection bias. In doing so, the authors applied a propensity score matching approach that allowed them to compare the income and food security of the nonfarm employment participants with those of the nonparticipants. They found that farm households’ engagement in nonfarm employment produces a significant positive effect on household revenue and food security. The authors also concluded that the findings support the view that nonfarm income is the key to poverty reduction in rural communities of developing countries. Olugbire et al. (2011) investigated the effects of nonfarm work (self-employment and wage-paid employment) on farm households’ income and poverty in Nigeria by using the propensity score matching model, as did Owusu, Awudu, and Seini (2011), to address the selection bias and endogeneity issues. Their findings suggest that nonfarm wage-paid employment households’ income is significantly higher than self-employment households’ income. Moreover, the results reveal that the welfare impact of wage-paid employment participation is stronger than that of self-employment participation. However, the haves reap more benefits from wage-paid employment than do the have-nots. A limitation of the propensity score matching approach is that the evaluation of the effects is carried out only with observed characteristics. That is, the approach cannot control for unobserved characteristics that influence both the treatment and outcome and, thus, may yield biased and inconsistent estimates of the effects of nonfarm activities.

To address this issue, one can adopt standard treatment models that account for nonrandom sample selection. For example, Chang and Mishra (2008) used a two-stage procedure and controlled for potential sample selection bias to analyze the effects of nonfarm work decisions by operator and spouse on household food expenditure. The authors found that the spouse’s decision concerning nonfarm work is significantly interrelated with that of the operator. The former is negatively correlated with food expenditure, while the latter has a positive correlation with food expenditure. Yet, the models cannot control for inherent differences between the nonfarm participants and nonparticipants. That is, the structure of household expenditure would very likely be systematically different, especially if factors influencing the decisions of whether to participate or not participate in nonfarm activities equally affect the expenditure. This equal effect would therefore conceal an inherent interaction between the decisions concerning nonfarm activities and factors affecting the expenditure, potentially resulting in biased and inconsistent estimates in the outcome equation (Rao and Qaim 2011).

There are few empirical studies that evaluate the economic impacts of participation in nonfarm activities on farm households by addressing endogeneity arising from the endogenous bias of the decision to work off the farm and inherent differences between the nonfarm employment participants and the nonparticipants using cross-sectional data. Furthermore, analyzing the implication of nonfarm activities for the achievement of poverty reduction should not overlook the effects of such activities on household food consumption, which has been taken for granted by many relevant studies. To properly evaluate the potential for nonfarm activities to improve household food security in terms of food consumption in rural Cambodia, one necessarily needs an unbiased and consistent estimation of the effects of such activities. This article aims to reduce the bias and inconsistent estimation by controlling for unobserved characteristics across farm households and systematic differences between participants and nonparticipants.

**Empirical framework and data**

This section begins with a discussion of econometric approaches to the empirical analysis and ends with a description of the source of data used in the analysis. A rigorous econometric approach is used to analyze factors determining the farm households’ decision to engage in nonfarm activities and to evaluate the impacts of such activities on household food consumption per capita.

**Econometric approaches**

(a) **Determinants of nonfarm work participation**

Following the conventional framework of household choice, a farm household decides to diversify into nonfarm work if nonfarm wage/income is higher than the reservation wage/income from on-farm work and leisure. This suggests that the likelihood of participating in nonfarm activities is determined by both household socio-economic characteristics and farm characteristics. To capture the relationship between these characteristics and farm households’ decision to engage in nonfarm activities, a probit model is employed. Similar to Chang and Mishra (2008) and Ahearn et al. (2006), the probit model describing the household decision can be written as
of nonfarm activities. In econometrics, when unobserved effects are correlated with both the regressed (per capita food consumption) and a regressor (nonfarm participation), the coefficient on the latter is inconsistent and biased.

One can use a Heckman selection approach or standard treatment effect model to control for this selection bias. Still, these approaches cannot control for the potential systematic differences between the groups due to the assumption that the consumption functions differ between the participants and nonparticipants by only a constant term (Rao and Qaim 2011). Owusu, Awudu, and Seini (2011) and Olugbire et al. (2011) adopted the propensity score matching approach that can account for the systematic differences in observed characteristics. The approach may still yield biased and inconsistent estimates because it cannot control for unobserved factors that potentially affect both the decision of whether to engage in nonfarm activities and the consumption expenditure.

The endogenous switching model is adopted to address the above-mentioned econometric challenges. The model treats participation in nonfarm activities and nonparticipation as regimes and is specified as follows:

\[ I = \alpha Z + v \]  
\[ I^* = \begin{cases} 
1, & \text{if nonfarm participation} \\
0, & \text{otherwise} 
\end{cases} \]  
\[ y_1 = \beta_1 X_1 + u_1 \text{ if } I^* = 1 \]  
\[ y_0 = \beta_0 X_0 + u_0 \text{ if } I^* = 0 \]

where \( y_1 \) and \( y_0 \) represent household expenditure on food consumption per capita for nonfarm participants and nonparticipants, respectively; \( I \) is a latent variable, as defined in Equation (1); and \( \alpha, \beta_1 \) and \( \beta_0 \) are vectors of parameters to be estimated. Although the variable sets \( Z \) and \( X \) can overlap, at least one variable in \( Z \) does not appear in \( X \) to properly identify the outcome equations. \( v, u_1 \) and \( u_0 \) are error terms that are contemporaneously correlated and assumed to be jointly normally distributed with a zero mean vector and the following covariance matrix:

\[ \text{cov}(v, u_1, u_0) = \begin{bmatrix} \sigma_v^2 & \sigma_{vu_1} & \sigma_{vu_0} \\
\sigma_{vu_1} & \sigma_{u_1u_1} & \sigma_{u_1u_0} \\
\sigma_{vu_0} & \sigma_{u_1u_0} & \sigma_{u_0u_0} 
\end{bmatrix} \]  

where \( \text{var}(v) = \sigma_v^2, \text{var}(u_1) = \sigma_{u_1}^2, \text{var}(u_0) = \sigma_{u_0}^2, \text{cov}(u_1, u_0) = \sigma_{u_1u_0}, \text{cov}(u_1, v) = \sigma_{u_1v}, \text{and cov}(u_0, v) = \sigma_{u_0v} \). The variance \( \sigma_v^2 \) is assumed to be 1, as \( \alpha \) can be only estimated up to a scale factor (Maddala, Griliches, and Michael 1986; Rao and Qaim 2011). In addition, the covariance \( \sigma_{u_1u_0} \) is equal to zero because \( y_1 \) and \( y_0 \) are not observed together. Note that in a cross-sectional sample, \( y_1 \) and \( y_0 \) are only partially observed, with the former being only observed for the subsample of nonfarm participants and

(b) Modeling effects of nonfarm participation on household food consumption

According to the standard agricultural household model, a farm household allocates labor and consumption levels by maximizing the utility subject to cash and production technology constraints. Because it generates additional income, participation in nonfarm activities is very likely to determine household food consumption. This study hypothesizes that participation in nonfarm activities exerts positive effects on household food consumption because it increases household earnings. To assess the effects of nonfarm engagement on household food consumption, a commonly used model in the literature on effect evaluation is written as follows:

\[ Y = \beta X + \gamma I + \varepsilon \]  

where \( Y \) is the household’s per capita food consumption expenditure; \( X \) includes household and farm characteristics and other factors, which are expected to affect the consumption expenditure; \( I \) is a dummy for participation in nonfarm activities; and \( \gamma \) is the coefficient capturing the effects of nonfarm participation on the consumption expenditure. However, this coefficient may be biased and inconsistent due to the self-selection of farm households into the nonfarm participant group. If, for example, participants are wealthier or live in an area with a high cost of living, their expenditure on food consumption is higher, irrespective of whether they participate in nonfarm activities. In addition, the farm households’ nonfarm skills and motivation for diversifying household earnings can also influence both their decisions of whether to participate or not participate in nonfarm activities and household food consumption levels. The coefficient on the nonfarm dummy (\( I \)) would, in this case, also include the effects of these unobserved factors and, thus, produce an overestimate of the effects of nonfarm activities.

where \( I \) is the probability that a farm household works off the farm in addition to its primary farm work (also known as the latent variable). It equals 1 for a farm household that engages in at least one nonfarm work activity and 0 for a farm household that does not engage in any nonfarm work activities. \( \alpha \) is the vector of parameters to be estimated, and \( v \) is the error term under the assumption that \( v \sim N(0, 1) \). \( Z \) includes household characteristics, farm characteristics, agroecological risks and public transportation condition, which are expected to determine the likelihood of engaging in nonfarm activities.

\[ I = \alpha Z + v \]  
\[ I^* = \begin{cases} 
1, & \text{if nonfarm participation} \\
0, & \text{otherwise} 
\end{cases} \]  
\[ y_1 = \beta_1 X_1 + u_1 \text{ if } I^* = 1 \]  
\[ y_0 = \beta_0 X_0 + u_0 \text{ if } I^* = 0 \]
the latter being only observed for the subsample of nonparticipants.

When there are unobserved effects, the error term \( v \) of the selection equation is correlated with the error terms \( u_1 \) and \( u_0 \) of the outcome equations. That is, the expected values of \( u_1 \) and \( u_0 \) would be nonzero conditional on regime selection. Therefore, endogeneity can be tested with estimates of the covariance terms \( \sigma_{u_1v} \) and \( \sigma_{u_0v} \). If \( \sigma_{u_1v} = \sigma_{u_0v} = 0 \), the model exhibits exogenous switching; if either \( \sigma_{u_1v} \) or \( \sigma_{u_0v} \) is nonzero, the model shows endogenous switching (Maddala, Griliches, and Michael 1986). In this case, one needs to test for significant coefficients of the correlation between \( u_1 \) and \( v \left( \rho_{u_1v} = \sigma_{u_1v}/\sigma_{u_1}\sigma_v \right) \) and between \( u_0 \) and \( v \left( \rho_{u_0v} = \sigma_{u_0v}/\sigma_{u_0}\sigma_v \right) \) (Lokshin and Sajaia 2004). Using these correlations, the expected values of the error terms \( u_1 \) and \( u_0 \) conditional on regime selection can be written as:

\[
E(u_1|I = 1, X_1) = E(u_1|v > -\alpha Z) = \frac{\phi(Z\alpha)}{\Phi(Z\alpha)} \sigma_{u_1v} \lambda_1
\]

\[
E(u_0|I = 0, X_0) = E(u_0|v \leq -\alpha Z) = \frac{-\phi(Z\alpha)}{1 - \Phi(Z\alpha)} \sigma_{u_0v} \lambda_0
\]

where \( \phi \) is the standard normal probability density function and \( \Phi \) is the cumulative distribution function of the standard normal distribution. \( \lambda_1 \) and \( \lambda_0 \) are the Inverse Mills Ratios (IMRs) predicted at \( Z\alpha \) for participants and nonparticipants, respectively (Greene 2008).

In addition to the endogeneity test, \( \rho_{u_1v} \) and \( \rho_{u_0v} \) allow economic interpretations based on their signs. If the coefficients \( \rho_{u_1v} \) and \( \rho_{u_0v} \) have opposite signs, farmers decide whether to participate in nonfarm activities based on the comparative advantage (Maddala 1983; Fuglie and Bosch 1995; Rao and Qaim 2011). That is, participants enjoy above-average consumption levels once they participate in nonfarm activities if \( \rho_{u_1v} < 0 \), whereas nonparticipants enjoy above-average consumption levels when they do not participate if \( \rho_{u_0v} > 0 \). Alternately, if \( \rho_{u_1v} \) and \( \rho_{u_0v} \) have the same signs, ‘hierarchical sorting’ is evidenced (Fuglie and Bosch 1995), suggesting that the participants consume above-average levels regardless of whether they participate in nonfarm activities but they are better off participating than not participating. Similarly, the nonparticipants consume below-average levels in either case but they are better off choosing not to participate in nonfarm activities.

Furthermore, the coefficients \( \rho_{u_1v} \) and \( \rho_{u_0v} \) can indicate model consistency under the condition \( \rho_{u_1v} < \rho_{u_0v} \) (Trost 1981). This condition also implies that the participants’ consumption levels are above what they otherwise would be if they did not participate in nonfarm activities.

(c) Estimation approach

Once either \( \sigma_{u_1v} \) or \( \sigma_{u_0v} \) takes a nonzero value, one can estimate the model by using a two-stage procedure. In the first stage, a probit model of regime choice is estimated, providing the estimates of \( \alpha \), on which the IMRs \( \lambda_1 \) and \( \lambda_0 \) can be predicted according to Equations (7) and (8). In the second stage, the outcome equations are estimated by including the predicted IMRs as regressors. The estimated coefficients of IMRs yield the estimates of \( \sigma_{u_1v} \) and \( \sigma_{u_0v} \). However, due to the estimation of the IMRs, the residuals \( u_1 \) and \( u_0 \) cannot be employed to compute the standard errors of estimates in the second stage (Maddala 1983; Fuglie and Bosch 1995). Simultaneously estimating the selection and outcome equations with the full information maximum likelihood (FIML) procedure is more efficient for the endogenous switching regression (Lokshin and Sajaia 2004; Rao and Qaim 2011; Di Falco, Veronesi, and Yesuf 2011; Clougherty and Duso 2015). Because the endogenous switching model resembles a sample selection model, it should be noted that the coefficients \( \beta_1 \) and \( \beta_0 \) in Equations (4) and (5) measure the marginal effects of explanatory variables on household food consumption unconditional on households’ actual regime choice. That is, the effects of \( X \) on the respective subsample \( y \) (\( y_1 \) for participant group or \( y_0 \) for nonparticipant group).

As mentioned earlier, to properly identify the model, it is necessary to use variables that directly determine the decision to engage in nonfarm activities but not the outcomes as selection instruments. The study uses a dummy for availability of public transportation in the village as the identification restriction. The availability of public transportation in the village captures the village transportation condition. Then, the study hypothesizes that the availability of public transportation in the village would increase the farm households’ likelihood of engaging in nonfarm activities. The hypothesis is built on the fact that the availability of public transportation in the village can facilitate the ability to travel back and forth between home and workplaces. Following Di Falco, Veronesi, and Yesuf (2011), a simple falsification test is conducted to establish the admissibility of the instruments: if a selection instrument is valid, it will have an impact on the participation decision but not on the nonparticipants’ food consumption per capita. In the appendix, Table A suggests that the dummy for availability of public transportation can be considered as a valid identification instrument because it is a statistically significant driver of the decision of whether to engage in nonfarm activities but not of nonparticipants’ per capita consumption.

(d) Estimation of effects of nonfarm participation on household food consumption

The particular interest of the current study is to quantify the effects of nonfarm activities on farm household food consumption per capita.
consumption. To do this, one needs to compare the participants’ conditional expected consumption derived from the endogenous switching regression model with the counterfactual case that the same participants have chosen not to participate. The conditional expected value of food consumption by a farm household with characteristics $X$ and $Z$ that participates in nonfarm activities is derived as follows (Maddala 1983):

$$E(y_1|I = 1) = \beta_1 X_1 + \sigma_{uv} \lambda_1$$

(9)

where $\sigma_{uv} \lambda_1$ accounts for sample selection arising from the fact that a farm household participating in nonfarm activities differs from other households with characteristics $X$ and $Z$ because of unobserved characteristics (Fuglie and Bosch 1995). The conditional expected value of food consumption that the same farm household would enjoy without participation is derived from the following (Maddala 1983):

$$E(y_0|I = 1) = \beta_0 X_1 + \sigma_{uv} \lambda_1$$

(10)

The consumption gain, which is defined as the change in per capita food consumption due to nonfarm participation, can then be computed as follows (Maddala 1983):

$$E(y_1|I = 1) - E(y_0|I = 1) = (\beta_1 - \beta_0) X_1 + (\sigma_{uv} - \sigma_{mv}) \lambda_1$$

(11)

In the literature on impact assessment, this consumption gain is called the average treatment effect on the treated (ATT), which accounts for all factors potentially leading to consumption differences. This treatment effect on the treated results from the differences in the coefficients in Equations (9) and (10) ($\beta_1 - \beta_0$ and $\sigma_{uv} - \sigma_{mv}$). If a farm household self-selects to participate in nonfarm activities or not participate based on the comparative advantage, $\sigma_{uv} - \sigma_{mv}$ would be positive, and participation in nonfarm activities would produce bigger benefits in terms of food consumption under self-selection than under random assignment (Maddala 1983; Rao and Qaim 2011). In this case, a simple comparison between mean consumption in the participant group $E(y_1|I = 1)$ and that in the nonparticipant group $E(y_0|I = 0)$ would result in an upward bias of the treatment effect, which is accounted for in Equation (11).

**Variables**

The dependent variable in the selection equation is a binary variable for participation in nonfarm activities. It equals 1 for a farm household that engages in at least one nonfarm work activity and 0 for a farm household that does not engage in any nonfarm work activities. The dependent variable in the outcome equations is household expenditure on per capita food consumption within seven days.

The explanatory variables consist of household characteristics, farm characteristics, availability of irrigation infrastructure in the village, availability of public transportation in the village and agroecological risks. These variables are summarized in Table 1. Household characteristics include household head’s age, gender, education level, household members over the age of 64 years and household members under the age of 15 years. Age is used to capture life cycle effects on participation in nonfarm activities and household food consumption. After reaching a certain age, a person would gradually start losing job opportunities and consuming less food. Education level is an indicator of human capital; those with a high education level would have more job opportunities. Additionally, well-educated individuals would have easier access to a large amount of information and be able to build networks in the community better (Azam, Imai, and Gaiha 2012). Hence, the education level would stimulate the farm households’ participation in nonfarm activities, as found by Lanjouw and Shariff (2004) and de Janvry, Sadoulet, and Zhu (2005). The variables of household members over the age of 64 years and under the age of 15 years are used to capture the effects of dependents on the likelihood of engaging in nonfarm activities and household food consumption. The number of dependents can produce mixed effects on the farm households’ nonfarm engagement (Shi, Heerink, and Qu 2007). On the one hand, with more dependents in a farm household, high household incomes are needed to satisfy food consumption and other necessary expenditures, stimulating household income diversification. On the other hand, the farm households with more dependents need to spend more time taking care of these dependents, reducing the time available for nonfarm activities. However, older members may help care for children, possibly allowing the parents to engage in either on-farm or nonfarm employment. Nevertheless, more dependents in a household would reduce household food consumption per capita if the household enjoyed low household earnings.

Landholding in hectares is used to capture the effects of farm characteristics. The landholding variable is employed instead of a cultivated land area variable because the latter has a higher potential for endogeneity, although land markets in rural Cambodia are inactive, as argued by Azam, Imai, and Gaiha (2012). Labor employed on larger farms is less flexible, and households holding a larger area of land are likely to be discouraged from engaging in nonfarm employment (Benjamin 1994; Mishra and Goodwin 1997). Landholding would therefore have negative effects on nonfarm participation; however, it is difficult to hypothesize about the effects on household food consumption due to the potentially mixed effects. In Cambodia, there are only two seasons (six months of the dry season and six months of the wet season) for farming per year. In the dry season, farmers tend to face a water shortage due to limited irrigation infrastructure development.
Therefore, the availability of irrigation infrastructure in the village, especially in dry seasons, is likely to influence farmers to increase their on-farm investments without diversifying into nonfarm activities.

A dummy for yield damage caused by excessive rainfall and/or flood, drought, rot, birds/other insects and/or rodents is used to capture the effects of agroecological risks. Farmers reported yield quantity loss from such agroecological factors from the previous year to the time of interview. Because some farmers produced multiple crops, the use of aggregate quantities of damaged crops to capture such effects is impracticable. Moreover, due to the unavailability of information on rainfall levels, the study constructs the yield damage dummy, with the value equal to 1 if a farmer suffered post-harvest damage caused by excessive rainfall and/or flood, drought, rot, birds/other insects and/or rodents and 0 if the farmer did not suffer such damage. Because the risks negatively affect agricultural returns, they would affect the farm households’ decision regarding on-farm and nonfarm activities and household welfare in terms of food consumption (Kaur et al. 2011). As mentioned in Section 3, the dummy for availability of public transportation in the village is used as the identification instrument in the model. The availability of public transportation in the village can facilitate traveling back and forth between home and workplaces and connect rural economies to the entire economy of Cambodia. This creates nonfarm employment opportunities for the farm households and, thus, likely motivates farm households to engage in nonfarm employment.

### Data

The data from the CSES conducted in 2009 by the National Institute of Statistics (NIS) are used in the current study’s empirical analysis. The survey was sampled based on the preliminary data from the General Population Census conducted in 2008 using a three-stage cluster procedure. Villages and enumeration areas were selected in the first and second stages, respectively; households were selected in the last stage. A total of 12,000 households within 24 provinces (all provinces in Cambodia) were selected as the sample, which is the largest sample size among the CSESs. However, 29 households were dropped due to their absence at the time of the enumerators’ visit. Then, the remaining 11,971 households participated in the survey. Although the NIS has conducted the CSES annually since 2007, the 2009 data-set represents the nationwide sample of the household survey. Because it has the largest sample size, the 2009 data-set is employed for the analysis in lieu of an updated data-set. Because the study is interested in rural Cambodia, Phnom Penh city (the capital of Cambodia) and other provincial capital cities are excluded from the observations such that the focus is only on rural farmers in Cambodia. After excluding the capital and the provincial capital cities and deleting some missing observations, the final sample count is 5762 households.

### Empirical analysis

This section starts with a description of summary statistics of main variables used in the analysis and a descriptive statistical analysis of the differences between farmers who work off the farm and those who do not. The section ends by presenting the econometric analysis results.

### Descriptive statistics analysis

Table 2 summarizes the statistics of variables used in the econometric analysis. The table demonstrates that, on
average, approximately 22% of the farm households diversify into nonfarm employment, and approximately 87% of the households are male-headed. Moreover, approximately 16% have access to irrigation infrastructure in the wet season due to the availability of irrigation infrastructure in the village, and approximately 52% live in a village with public transportation.

Table 3 presents general differences between the nonfarm participants and nonparticipants. The summary statistics in the table indicate some remarkable differences between the participants and nonparticipants, which are confirmed by simple statistical tests of differences in means. There is a significant difference between the farm households that participate in nonfarm activities and those that do not in terms of the household head’s gender. On average, approximately 76% of the nonfarm participant households are male-headed, while approximately 79% of the nonparticipant households are male-headed. The heads of nonfarm participant households completed, on average, a seven-year formal education, while the heads of nonparticipant households completed, on average, a six-year formal education. This result shows that those households headed by a better-educated person are more likely to engage in nonfarm activities. There is also a significant difference in relation to village public transportation availability, with approximately 58% of the nonfarm participant households and 49% of the nonparticipant households living in a village with public transportation. With an average food consumption expenditure per capita of 32,068.030 riels (US$ 8) per week, the nonfarm participant households’ per capita expenditure on food consumption is significantly higher than the nonparticipant households’ expenditure, with an average of 29,138.470 riels (US$ 7.28). This result suggests that the nonfarm participant households are likely to enjoy higher levels of food consumption per family member than the nonparticipant households.

Table 2. Summary statistics of variables used in regression.

| Variables                        | Obs. | Mean   | SD    | Min  | Max  |
|----------------------------------|------|--------|-------|------|------|
| Household head’s gender          | 5762 | 0.872  | 0.334 | 0    | 1    |
| Household head’s age             | 5762 | 3.745  | 0.312 | 2.708| 4.466|
| Household head’s age squared     | 5762 | 14.122 | 2.321 | 7.334| 19.944|
| Household head’s education level | 5762 | 1.596  | 0.536 | 0    | 2.944|
| Household members > 64           | 5762 | 0.203  | 0.487 | 0    | 3    |
| Household members < 15           | 5762 | 1.607  | 1.256 | 0    | 8    |
| Landholding                      | 5762 | 0.062  | 1.118 | −6.502| 5.709|
| Availability of irrigation       | 5762 | 0.158  | 0.364 | 0    | 1    |
| Yield damage                     | 5762 | 0.720  | 0.449 | 0    | 1    |
| Availability of public transportation | 5762 | 0.516  | 0.500 | 0    | 1    |
| Nonfarm participation            | 5762 | 0.219  | 0.414 | 0    | 1    |
| Food consumption per capita      | 5762 | 10.159 | 0.539 | 7.567| 12.789|

Note: Because some households possess land area of less than one hectare, some values of the natural log of landholding are negative, thus producing negative mean value of the natural log of landholding.

Table 3. Characteristics of participants and nonparticipants in nonfarm activities.

| Variables                        | Participants (n = 1262) | Nonparticipants (n = 4500) | Difference in Means |
|----------------------------------|------------------------|---------------------------|---------------------|
|                                  | Mean                   | SD                        | Mean                | SD                  |                                  |
| Food consumption per capita      | 32,068.030             | 20,919.080                | 29,138.470          | 19,212.040          | 2929.556***                      |
| Household head’s gender          | 0.763                  | 0.425                     | 0.795               | 0.404               | −0.032***                        |
| Household head’s age             | 46.732                 | 12.998                    | 44.890              | 14.557              | 1.842***                         |
| Household head’s education level | 7.109                  | 3.820                     | 5.731               | 2.772               | 1.379***                         |
| Household members > 64           | 0.181                  | 0.449                     | 0.228               | 0.511               | −0.047***                        |
| Household members < 15           | 1.449                  | 1.276                     | 1.570               | 1.292               | −0.121***                        |
| Landholding                      | 1.716                  | 8.809                     | 1.761               | 6.978               | −0.045                           |
| Availability of irrigation       | 0.138                  | 0.345                     | 0.146               | 0.353               | −0.008                           |
| Yield damage                     | 0.700                  | 0.459                     | 0.728               | 0.445               | −0.028**                         |
| Availability of public transportation | 0.583                  | 0.493                     | 0.494               | 0.500               | 0.089***                         |

Note: Per capita food consumption is per capita expenditure on food consumption in Cambodian currency (Riel) within seven days.

**Test statistic significance at 5% level.
***Test statistic significance at 1% level.
Econometric analysis

The descriptive analysis indicates significant differences in per capita household expenditure on food consumption between the nonfarm participant households and nonparticipants. However, to properly evaluate the effects of participation in nonfarm activities on farm households’ food consumption per capita, as outlined in Section 3, an endogenous switching regression model is used. The consumption equations are jointly estimated with the selection equation explaining farm households’ engagement in nonfarm activities.

(a) Determinants of nonfarm work participation

In Table 4, the first column presents the independently estimated results of a normal probit, while the second column presents the results of the probit model jointly estimated with the consumption equations by using the FIML procedure. The likelihood of participating in nonfarm activities is significantly dependent on the farm household head’s education level and age. Farm households with better-educated heads are very likely to engage in nonfarm activities. This result is consistent with the above descriptive statistics analysis and with the findings of many studies (see, e.g., Lanjouw and Shariff 2004; de Janvry, Sadoulet, and Zhu 2005; Akaakohol and Aye 2014). This is plausible because education can help farm households better adjust to nonfarm labor market requirements. In general, better-educated farmers are more innovative and entrepreneurial (Rao and Qaim 2011) and, thus, more likely to be active in generating income not only from farming activities but also from nonfarm activities. Additionally, the coefficient of age is significantly positive, revealing that older farmers are very likely to engage in nonfarm activities, which may be associated with their experience. Yet, the coefficient of age-squared term is significantly negative, suggesting that as the head grows older, s/he gains more experience and has growing employment opportunities but that s/he starts to gradually lose the opportunities after turning a certain age.

The coefficient of household members over the age of 64 years is significantly negative, suggesting that the farm households with older members (over the age of 64 years) are more likely to be discouraged from participating in nonfarm work. This is because farmers may face a deficiency in labor force when some family members age and, thus, are more likely to lose nonfarm job opportunities. Landholding has a significantly negative correlation with participation in nonfarm activities, demonstrating that the farm households owning larger land are more likely to prefer on-farm work to diversifying into nonfarm activities. Labor employed on larger farms is not flexible; thus, larger landholding is very likely to reduce an individuals’ likelihood of engaging in nonfarm activities (Benjamin 1994; Mishra and Goodwin 1997). The availability of public transportation in the village has a significantly positive correlation with participation in nonfarm activities. Public transportation can help facilitate the ability to travel back and forth between home and workplace and create nonfarm employment opportunities for active farmers, likely inducing farm households to engage in nonfarm employment.

(b) Determinants of household food consumption

The nonfarm participant households’ and nonparticipant households’ food consumption is, as outlined in Section 3, explained based on household food consumption.

Table 4. Determinants of nonfarm work participation.

| Variables                        | Independently Estimated Probita | Jointly Estimated Probitb |
|----------------------------------|--------------------------------|--------------------------|
|                                  | Coef.  | SE    | P-value | Coef.  | SE    | P-value |
| Household head’s gender          | −0.068 | 0.058 | .238    | −0.067 | 0.058 | .247    |
| Household head’s age             | 9.504*** | 1.654 | .000    | 9.562*** | 1.659 | .000    |
| Household head’s age squared     | −1.130*** | 0.222 | .000    | −1.137*** | 0.223 | .000    |
| Household head’s education       | 0.331*** | 0.038 | .000    | 0.330*** | 0.037 | .000    |
| Household members > 64           | −0.145*** | 0.047 | .002    | −0.147*** | 0.047 | .002    |
| Household members < 15           | −0.021 | 0.017 | .200    | −0.021 | 0.017 | .204    |
| Landholding                      | −0.114*** | 0.017 | .000    | −0.112*** | 0.017 | .000    |
| Availability of irrigation       | −0.052 | 0.052 | .319    | −0.051 | 0.052 | .327    |
| Yield damage                     | −0.032 | 0.043 | .453    | −0.034 | 0.043 | .428    |
| Availability of public transport | 0.122*** | 0.039 | .002    | 0.140*** | 0.038 | .000    |
| Constant                         | −20.924*** | 3.071 | .000    | −21.049*** | 3.079 | .000    |
| Observation                      | 5762   |      |         | 5762   |      |         |
| Prob. > Chi-squared              | .000   |      |         | .000   |      |         |
| Pseudo $R^2$                     | .65    |      |         | .65    |      |         |

*Probit model is estimated independently from the consumption regime equations. **Probit model is jointly estimated with the consumption regime equations by using the FIML procedure reported in Table 4.
***Test statistic significance at 1% level.
Table 5. Determinants of household food consumption.

| Variables            | Participants (n = 1262) | Nonparticipants (n = 4500) |
|----------------------|-------------------------|-----------------------------|
|                      | Coef.  | SE  | P-value | Coef.  | SE  | P-value |
| Households’ gender   | -0.035 | 0.040 | .392    | -0.043 | 0.021 | .039    |
| Households’ age      | 0.650  | 1.429 | .649    | 0.490  | 0.507 | .334    |
| Households’ age squared | -0.125 | 0.185 | .499    | -0.070 | 0.069 | .310    |
| Households’ education | 0.106*** | 0.036 | .003    | 0.096*** | 0.014 | .000    |
| Households members > 64 | 0.021  | 0.034 | .536    | -0.050*** | 0.017 | .003    |
| Households members < 15 | -0.117*** | 0.012 | .000    | -0.126*** | 0.006 | .000    |
| Landholding          | 0.024* | 0.014 | .092    | -0.013*** | 0.007 | .046    |
| Availability of irrigation | -0.033 | 0.037 | .380    | 0.018 | 0.018 | .319    |
| Yield damage         | -0.024 | 0.030 | .430    | 0.009  | 0.015 | .542    |
| Constant             | 9.772*** | 2.850 | .001    | 9.332*** | 0.932 | .000    |
| \( \ln(\sigma_{u,v}) \) | -0.688*** | 0.067 | .000    | -0.814*** | 0.012 | .000    |
| \( \ln(\sigma_{v}) \) | -0.462** | 0.206 | .025    | -0.136 | 0.108 | .205    |
| \( \rho_{u,v} \)     | 0.814*** | 0.012 | .000    | 0.0427** |
| \( \rho_{v} \)       | Log likelihood       | -6361.84                |

Note: Dependent variable is the natural log of per capita expenditure on food consumption. These outcome equations are jointly estimated with the selection equation reported in Table 3 by using the FIML.

*Test statistic significance at 10% level.
**Test statistic significance at 5% level.
***Test statistic significance at 1% level.

The estimated results also demonstrate that there are systematic differences across the two regimes. For example, the household heads’ education level has a significant and positive correlation with the food consumption per capita for both regimes, but the coefficient is higher for the nonfarm participants than that for the nonparticipants. This result suggests that the effects of education are greater among the nonfarm participants. This is because better educated participants may be more productive in farming than their counterparts in the nonparticipant group. The results confirm the important role of education and/or technical training in contributing to the improvement in rural household food security in terms of per capita food consumption. Of note, because the coefficient represents unconditional effects, the difference is not due to participation in nonfarm activities. Moreover, the findings show that education jointly determines the likelihood of nonfarm participation and household food consumption.

The number of family members under the age of 15 years has a significantly negative relationship with the per capita food consumption for both regimes, while the number of family members over the age of 64 years is significantly and negatively correlated with the food consumption per capita only for the nonparticipants. This result can somewhat explain the fact that inactive members do little to contribute to the household incomes portfolio and largely rely on active members. Furthermore, the results indicate that landholding has a significantly positive correlation (at the 10% level) with the per capita food consumption for the participants and a significantly negative correlation (at the 5% level) for the nonparticipants. This finding suggests that the nonfarm participants can use their own land for farming in a more productive way than the nonparticipants, possibly because of their higher levels of human capital and ability to use more fertilizers. As noted in the
descriptive statistics analysis, the heads of nonfarm participant households are better educated than those of nonparticipant households. In addition, the nonfarm participants are very likely to enjoy higher agricultural returns on labor due to a decrease in excessive labor on the farm. By contrast, for nonparticipants, there may be negative returns on labor when they are employed by a farm of typical size. Because for nonparticipants labor remains in the farm sector, the possibility of disguised unemployment cannot be ruled out. According to the Lewis model, the presence of disguised labor in agriculture reduces farm output below its potential, thus producing negative effects on household food consumption. Furthermore, the inverse relationship between landholding and household food consumption for the nonparticipants may reflect the inverse relationship between land size and productivity.

(c) Effects of nonfarm participation on household food consumption

To evaluate the effects of the nonfarm participation on household food consumption per capita, the conditional expected food consumption per capita by the nonfarm participant households \(E(y_1|I = 1)\) is compared to what they would have enjoyed if they did not participate in nonfarm activities \(E(y_0|I = 1)\). The difference in food consumption conditional on nonfarm participation is computed following Equation (11) and reported in Table 6. It is also possible to compute the counterfactual hypothetical effects for the nonparticipants. However, due to the absence of a selection effect for the nonparticipants, that is, the nonparticipants are not different from random farmers; the counterfactual hypothetical effects are not taken into account.

The conditional expected food consumption per capita by the nonfarm participant households \(E(y_1|I = 1)\) is approximately 24,542.98 riels, while the conditional expected per capita food consumption that the same participant households would have enjoyed if they did not participate in nonfarm work \(E(y_0|I = 1)\) is approximately 23,817.71 riels. Therefore, when participating in nonfarm activities, on average, farm households can make food consumption gains of approximately 725.26 riels per household member. This result reveals that participation in nonfarm activities can allow rural farm households to increase their per capita food consumption and, thus, improve their household food security. Because nonfarm employment generates supplementary household incomes, it can provide participants with additional capital for investments in agricultural technology, which is a productivity-enhancing factor. In addition to income generation, the farm households’ engagement in nonfarm employment can reduce the possibility of disguised unemployment as a result of excessive labor force on the farm, improving farm productivity and, thus, increasing the farm’s output level.

Conclusion

The article assesses the effects of engagement in nonfarm activities on the food consumption of the farm households in rural Cambodia by using data from the CSES conducted in 2009. The paper employs the endogenous switching model, which explains the farm household food consumption and accounts for selection bias and systematic differences between participants in nonfarm activities and nonparticipants. The results confirm that the nonfarm participation decision and household food consumption are affected by unobserved characteristics of farm households. There are also structural differences between the nonfarm participants and the nonparticipants; for instance, landholding has positive effects on the nonfarm participants’ food consumption but negative influences on the nonparticipants’ consumption.

By accounting for the self-selection bias and inherent differences between the nonfarm participants and the nonparticipants, the per capita food consumption gains from participation in nonfarm activities are positive, albeit small. The nonfarm participants can gain, on average, approximately 725.26 riels per household member due to participation. Therefore, by engaging in nonfarm activities as an income diversification strategy, rural farm households are more likely to enjoy higher food consumption levels. Increased and stable earnings of rural farm households can increase and smooth household food consumption and improve food security. Households participating in nonfarm income-generating activities, especially in higher return nonfarm employment, enjoy higher levels of household incomes and food security than those that do not participate in such activities (Chang and Mishra 2008). Thus, to improve rural farm households’ welfare in terms of household food consumption through nonfarm activities, an emphasis should be placed on rural nonfarm economy.

At the policy level, to promote the rural nonfarm economy, special attention should be paid to programs that enhance agribusiness, small-scale industry development, education and training, agricultural markets and agricultural public sector investment targeted at rural localities. The industrial development should focus on input-intensive technologies that enhance not only productivity but also

| Table 6. Effects of nonfarm participation on household food consumption. |
|-----------------|-----------------|-----------------|
| \(E(y_1|I = 1)\) | 1262            | 24,542.98       | 4031.425 |
| \(E(y_0|I = 1)\) | 4500            | 23,817.71       | 3695.085 |
| ATT             | 725.263***      |                  |          |

Note: The expected values of per capita food consumption by individual households are transformed from log terms.

***Test statistic significance at 1% level.
agricultural marketing. The development of the rural nonfarm sector requires public investment in rural infrastructure, such as roads and bridges, telecommunications, education, energy and water. The government may also directly promote the sector by designing programs that provide credit, training and necessary inputs to rural households. In addition to government participation, the development of the nonfarm sector requires the participation of private firms and not-for-profit organizations to strengthen rural small-scale industries through entrepreneurial skills training and other necessary services to small private manufacturing units (IFAD 2011). In general, policies to promote the development of the rural nonfarm sector should be formulated at three levels. At the national level, policies should focus on a friendly business environment. At the regional level, the focus should be on the provision of physical and social infrastructure that facilitates the connectivity of economic activities. Finally, at the local level, the emphasis should be on training, migration facilitation and public transportation, which motivate households to engage in nonfarm activities (IFAD 2011).

Finally, further studies should obtain accurate data on different types of nonfarm employment by the operator and spouse and analyze their effects on rural farm households’ food consumption. The effects, especially effects of the households’ time allocated to nonfarm activities, may differ by gender because farm couples play different roles in terms of labor allocation within the household.

Notes
1. Following previous studies, the probit model has been used to empirically analyze the nonfarm labor supply decisions (see e.g., Huffman and Lange 1989; Lim-Appleigate, Rodriguez, and Oliffe 2002; Ahearn et al. 2006; Chang and Mishra 2008; Démurger, Fournier, and Yang 2010).
2. Because the endogenous switching regression model resembles a sample selection model, the selection in the first stage is responsible for the selection bias arising from unobserved factors such as wealth, skills and motivation that potentially affect both the farm households’ decision to participate in nonfarm activities and food consumption levels. Generally, in the selection model, the probit model is estimated because of the assumption that the error term $v$ is normally distributed with a zero mean and variance $\sigma^2_v$ normalized to 1 (see e.g., Heckman 2001).
3. The amount is converted into US dollar at the exchange rate of 1 USD = 4000 riels.

References
ADB (Asian Development Bank). 2013. Cambodia Diversifying Beyond Garment and Tourism, Country Diagnostic Study. Manila: Economic Research Department, Asian Development Bank.
Ahearn, M., H. El-Osta, S. Hisham, and J. Dewbre. 2006. “The Impact of Coupled and Decoupled Government Subsidies on the Off-farm Labor Supply Participation of US Farm Operators.” American Journal of Agricultural Economics 88 (2): 393–408.
Akakohol, M. A., and G. C. Aye. 2014. “Diversification and Farm Household Welfare in Makurdi, Benue State, Nigeria.” Development Studies Research 1 (1): 168–175.
Alasia, A., A. Weersink, R. Bolllman, and J. Cranfield. 2009. “Off-farm Labour Decision of Canadian Farm Operators: Urbanization Effects and Rural Labour Market Linkages.” Journal of Rural Studies 25 (1): 12–24.
Azam, M. S., K. S. Imai, and R. Gaia. 2012. “Agricultural Supply Response and Smallholders Market Participation – The Case of Cambodia.” Discussion Paper DP2012-09, Kobe, Japan: Research Institute for Economics and Business Administration, Kobe University.
Benjamin, C. 1994. “The Growing Importance of Diversification Activities for French Farm Households.” Journal of Rural Development 10 (4): 331–342.
Chang, H. H., and A. Mishra. 2008. “Impact of Off-Farm Labor Supply on Food Expenditures of the Farm Household.” Food Policy 33 (6): 657–664.
Clougherty, J., and T. Duso. 2015. “Correcting for Self-selection Based Endogeneity in Management Research: A Review and Empirical Demonstration.” Discussion Paper 1465, Berlin: Deutsches Institut für Wirtschaftsforschung.
Démurger, S., M. Fournier, and W. Yang. 2010. “Rural Households’ Decisions Towards Income Diversification: Evidence from a Township in Northern China.” China Economic Review 21 (2010): S32–S44.
Di Falco, S., M. Veronesi, and M. Yesuf. 2011. “Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia.” American Journal of Agricultural Economics 93 (3): 829–846.
Fuglie, K. O., and D. J. Bosch. 1995. “Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-Regression Analysis.” American Journal of Agricultural Economics 77 (4): 891–900.
Goodwin, B., and A. Mishra. 2004. “Farming Efficiency and the Determinants of Multiple Job Holding by Farm Operators.” American Journal of Agricultural Economics 86 (3): 722–729.
Greene, W. H. 2008. Econometric Analysis. Upper Saddle River, NJ: Prentice Hall.
Heckman, J. J. 2001. “Microdata, Heterogeneity and the Evaluation of Public Policy: Nobel Lecture.” Journal of Political Economy 109 (4): 673–748.
Huffman, W. E., and M. D. Lange. 1989. “Off-Farm Work Decisions of Husbands and Wives: Joint Decisions Making.” Review of Economics and Statistics 71 (August 1989): 471–480.
IFAD (International Fund for Agricultural Development). 2011. Agriculture: Pathways to Prosperity in Asia and the Pacific. Published by the United Nation’s International Fund for Agricultural Development. http://www.ifad.org/pub/ape/pathways.pdf
de Janvry, A., and E. Sadoulet. 2001. “Income Strategies Among Rural Households in Mexico: the Role of Off-Farm Activities.” World Development 29 (3): 467–480.
de Janvry, A., E. Sadoulet, and N. Zhu. 2005. “The Role of Non-Farm Incomes in Reducing Rural Poverty and Inequality in China.” UC Berkeley Department of Agricultural and Resource Economics, UCB. CUDARE Working Paper No. 1001. http://escholarship.org/uc/item/7ts2z766
Kaur, Smrit, Vani S. Kulkarni, Raghav Gaiha, and Manoj K. Pandey, eds. 2011. “Prospects of Non-Farm Employment and Welfare in Rural Areas.” In Routledge Handbook of South Asian Economies, edited by R. Jha. http://ideas.repec.org/p/pas/asarcc/2010-05.html
Lanjouw, J. O., and P. Lanjouw. 2001. “The Rural Non-Farm Sector: Issues and Evidence from Developing Countries.” *Agricultural Economics* 26 (2001): 1–23.

Lanjouw, P., and A. Shariff. 2004. “Rural Non-Farm Employment in India: Access, Income and Poverty Impact.” *Economic and Political Weekly* 39 (40): 4429–4446.

Lim-Applegate, H., G. Rodriguez, and R. Offert. 2002. “Determinants of Non-Farm Labour Participation Rates Among Farmers in Australia.” *Australian Journal of Agricultural and Resource Economics* 46 (1): 85–98.

Lokshin, M., and Z. Sajaia. 2004. “Maximum Likelihood Estimation of Endogenous Switching Regression Models.” *Stata Journal* 4 (3): 282–289.

Maddala, G. S. 1983. *Limited-dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

Maddala, G. S., eds. 1986. “Dis-equilibrium, Self-Selection, and Switching Models.” In *Handbook of Econometrics*, edited by Z. Griliches and D. I. Michael, 1633–1682. North-Holland: Elsevier.

McNally, S. 2002. “Are Other Gainful Activities on Farms Good for the Environment?” *Journal of Environmental Management* 66 (1): 57–65.

Mishra, A. K., and B. K. Goodwin. 1997. “Farm Income Variability and the Supply of Off-Farm Labor.” *American Journal of Agricultural Economics* 79 (3): 880–887.

Mishra, A., and C. Sandretto. 2001. “Stability of Farm Income and the Role of Nonfarm Income in U.S. Agriculture.” *Review of Agricultural Economics* 24 (1): 208–221.

NIS (National Institute of Statistics). 2011. *Food Security Trend Analysis Report, Cambodia Socio-Economic Survey 2004 and 2009*. Phnom Penh: National Institute of Statistics, Ministry of Planning of Cambodia.

Oluibre, O. O., A. O. Falusi, A. I. Adeoti, A. S. Oyekale, and O. A. Adeniran. 2011. “Non-farm Income Diversification and Poverty Reduction in Nigeria: A Propensity-Score Matching Analysis.” *Continental Journal of Agricultural Science* 5 (3): 21–28.

Owusu, V., A. Awudu, and A. Seini. 2011. “Non-Farm Work and Food Security among Farm Households in Northern Ghana.” *Food Policy* 36 (2): 108–118.

Rao, E. J. O., and M. Qaim. 2011. “Supermarkets, Farm Household Income, and Poverty: Insights from Kenya.” *World Development* 39 (5): 784–796.

Reardon, T., C. Delgado, and P. Matlon. 1992. “Determinants and Effects of Income Diversification Amongst Farm Households in Burkina Faso.” *Journal of Development Studies* 28 (2): 264–296.

Scharf, M., and D. B. Rabut. 2014. “Nonfarm Employment and Rural Welfare: Evidence from Himalaya.” *American Journal of Agricultural Economics* 96 (4): 1183–1197.

Shi, X., N. Heerink, and F. Qu. 2007. “Choices Between Different Off-Farm Employment Sub-Categories: An Empirical Analysis for Jiangxi Province, China.” *China Economic Review* 18 (4): 438–455.

Tong, K. 2011. “Migration, Remittances and Poverty Reduction: Evidence from Cambodia.” *Cambodia Development Review* 5 (4): 7–12.

Trost, R. P. 1981. “Interpretation of Error Covariances with Nonrandom Data: An Empirical Illustration of Returns to College Education.” *Atlantic Economic Journal* 9 (3): 85–90.

## Appendix

### Table A. Parameter estimates – test for validity of the selected instrument.

| Variables                          | Coef.   | SE   | P-value | Coef.   | SE   | P-value |
|------------------------------------|---------|------|---------|---------|------|---------|
| Household head’s gender            | −0.042**| 0.021| .046    | −0.068  | 0.058| .238    |
| Household head’s age               | 0.370   | 0.494| .455    | 9.504***| 1.654| .000    |
| Household head’s age squared       | −0.057  | 0.067| .402    | −1.130***| 0.222| .000    |
| Household head’s education         | 0.089***| 0.013| .000    | 0.331***| 0.038| .000    |
| Household members > 64             | −0.046***| 0.016| .005    | −0.145***| 0.047| .002    |
| Household members < 15             | −0.125***| 0.006| .000    | −0.021  | 0.017| .200    |
| Landholding                        | −0.011* | 0.006| .091    | −0.114***| 0.017| .000    |
| Availability of irrigation         | 0.019   | 0.018| .297    | −0.052  | 0.052| .319    |
| Yield damage                       | 0.011   | 0.015| .476    | −0.032  | 0.043| .453    |
| Availability of public transport   | −0.018  | 0.013| .187    | 0.122***| 0.039| .002    |
| Constant                           | 9.589***| 0.901| .000    | −20.924***| 3.071| .000    |
| Observation                        | 4500    |      |         | 5762    |      |         |
| Adj R-squared                      | 0.118   |      |         | 0.000   |      |         |
| Prob > chi2                        |         |      |         | 0.065   |      |         |
| Pseudo R²                          |         |      |         | −2831.2 |      |         |

*Test statistic significance at 10% level.

**Test statistic significance at 5% level.

***Test statistic significance at 1% level.