Farm production efficiency and natural forest extraction: Evidence from Cambodia

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Abstract

Farm production and natural forest extraction remain principal livelihood strategies of local people in many rural areas of the developing world. In this paper, we apply stochastic frontier analysis to evaluate farm production efficiency and simultaneous equations modelling to estimate the interrelationship between farm production efficiency and natural forest extraction. We use a two-year panel dataset of 430 rural households in Stung Treng province of Cambodia. We find that natural forest extraction is decreasing in farm production efficiency. Our results suggest that improving farm production efficiency, via the promotion of rural education and privatization of farm land, should be considered an integral component of natural forest conservation policy.

Key words: Rural livelihood; non-separability; stochastic frontier analysis; simultaneous equations model; panel data; instrumental variable.

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1. Introduction

It is estimated that a significant number of people, approximately 300 million (WWF, 2014) to 800 million (Chomitz, 2007), live in or near natural forests (Perge and McKay, 2016). Many of these people in developing countries are poor and are largely excluded from public services, partly because these areas are typically remote and badly connected to the rest of the economy (Liu et al., 2016; Parvathi and Nguyen, 2018). Therefore, farming and extraction of natural forests remain their principal livelihood strategies (Edirisinghe, 2015). This is because other livelihood activities such as non-farm self-employment or off-farm wage-employment opportunities are often limited in these areas. However, farming activities of rural households in the developing world are often inefficient (Gedara et al., 2012; Manjunatha et al., 2013; Koirala et al., 2016), and thus might not be able to provide adequate food and sufficient income to farmers and their families. Consequently, rural smallholders may still depend on natural forests either as an economic mainstay or as a supplementary source of household income (Walelign, 2017).

At the same time, natural forests continue to degrade at alarming rates in these regions (Dinh et al., 2017), although recent conservation efforts might have slowed down the speed of deforestation and forest degradation (FAO, 2010). Therefore, increasing farm production efficiency and reducing natural forest degradation are still major development and conservation concerns. Many empirical studies have examined key determinants of farm production efficiency (Omonona et al., 2010; Nguyen et al., 2012; Ho et al., 2017) or ways to reduce natural forest degradation (see reviews by Wunder et al., 2014; O'Donnell et al., 2014) separately. But we found only one study which explores the interrelationship between these two issues, namely Illukpitiya and Yanagida (2010). These authors develop separate farm level models for measuring farm technical efficiency and forest dependency and then analyse the relationship between these two results. While this is a step forward, the approach suggested is still restrictive because it does not account for potential simultaneity and endogeneity biases. Farming and extracting forest products are connected through smallholders' input allocation decisions and through potential technical interdependencies. In addition, there are differences in rural households' characteristics and in their economic conditions and these factors might affect both households' productive efficiency and their forest extraction.

Therefore, an improved insight into the empirical interrelationship between farming efficiency and forest extraction takes on an added significance in the context of conservation management. In a number of developing countries ownership of natural forests rests with the state and a system of protected forest areas such as forest national parks or forest natural reserves has been established as a means of forest biodiversity conservation (Hayes, 2006; van Rensburg and Mulugeta, 2016). Such forest conservation strategies might not be able to reduce rural households' participation in (illegal) hunting and logging, and collecting non-timber forest products from these protected areas (Le Gallic and Cox, 2006) because forests are an important livelihood resource (Kura et al., 2017). Although the extraction of natural forests by rural households living in close proximity to forests might be less depletive than logging activities by timber companies there is evidence that even indigenous people can degrade forest resources (Nguyen et al., 2015).

Against this background, our paper aims to address the following questions: (i) how to take into account the non-separability of farming efficiency and foraging activities in farm level modelling? (ii) what are the factors promoting or hindering farm production efficiency in forest peripheries? and (iii) to what extent how does an increase in farm production efficiency reduce natural forest extraction by smallholders? This understanding is policy relevant as it can contribute to the formulation of successful rural development and natural forest conservation initiatives.

To answer these questions, we first present a theoretical economic model that accounts for the interrelationship between farm production efficiency and natural forest extraction. We then empirically test the interrelationship with a two-year panel dataset of rural households collected in 2013 and 2014 in Strung Treng province of Cambodia. We apply an econometric framework that allows us to control for simultaneity and endogeneity biases. The information provided by the framework developed in this paper is expected to be useful to guide policy makers and practitioners in designing effective programs for rural development and natural forest conservation. To our understanding, this is the first effort to investigate the interrelationship between, and the determinants of, farm production efficiency and natural resource extraction in a simultaneous econometric framework.

Cambodia is one of the least developed countries in the world and is characterized by a relatively low Gross Domestic Product (GDP) and a high dependence on natural resources (De Lopez, 2003; Scheidel et al., 2013) such as water and forests (Nguyen et al., 2015). Decentralisation has long been propagated as a means to enhance local engagement with governance structures of forest systems in Asia but is still of limited relevance in Cambodia (Shyamsundar and Ghate, 2014; Persson and Prowse, 2017). The country has started to experience rapid economic growth, after years of conflict and political isolation. However, agriculture remains the key economic sector accounting for 34% of the GDP and 51% of total employment (UNDP, 2014). The Cambodian farming sector is in the early stage of the transition process towards commercialization. The majority of farmers still practice small-scale subsistence farming with traditional, labour-intensive methods and minimal input use (Sharma et al., 2016). Also, the significant granting of economic land concessions to foreign and domestic agribusinesses causes a decline in the availability of land for smallholders (Bühler et al., 2015; Jiao et al., 2015). Moreover, the adoption and diffusion of technology in the Cambodian farming sector remains low (Ebers et al., 2017). This situation creates a need to increase the production efficiency of Cambodian small-scale farming. The country is rich in forest resources with a national forest cover of about 54% in 2015, a decline from 73% in 1990 (World Bank, 2015). Although natural forest extraction is one of the rural livelihood strategies (Nguyen et al., 2015), forest resources have been degraded over time in this country (Travers et al., 2015).

The remainder of the article is organised as follows. Section 2 presents the theoretical background for the study. Section 3 describes the study design, including the study area, data collection, and data analysis. Section 4 analyses and discusses the results. Section 5 summarizes and concludes.

2. Theoretical background

2.1 Farm production efficiency

Farm production efficiency evaluates the economic performance of a farm that faces resource scarcity. There are always two important components in farm efficiency analysis (Hoang and Nguyen, 2013). The first component estimates farm production efficiency scores and their variation across farms. The second component analyses the determinants of farm production efficiency in order to provide farmers and their advisors with useful information on how to improve efficiency.

In principle, farm production efficiency can be estimated either with parametric or with non-parametric techniques, including the Data Envelopment Analysis (DEA) or Stochastic Frontier Model (SFM). The SFM is more suitable to the farming sector because farmers operate in uncertain environments and are exposed to various production risks (Hardaker et al., 2004). Aigner et al. (1977) and Meeusen and van den Broeck (1977) use the SFM as follows:

$$q_i = \mathrm{x}_i^{'}\beta + v_i - u_i \tag{1}$$

where q_i represents the output of farm i, $\mathrm{x}_i^{'}$ represents the input vector and β is the vector of unknown parameters. The symmetric random error v_i accounts for statistical noise and production risks that are beyond the control of the farmer (noise effect). The non-negative random variable u_i is associated with the production factors that are under the control of the farmer (inefficiency effect).

The graphic representation illustrates the basic features of the SFM (Figure 1). Figure 1 shows the production frontier for two farms i = {A, B}, using the simplified example of one input x_i to produce one output q_i. Both farms could improve their efficiency by moving to the technically feasible output given their respective input levels. The stochastic frontier output varies around the deterministic frontier because of the noise effect. In the case of farm A, the noise effect is positive. As a consequence, the stochastic frontier output q_A^* lies above the deterministic frontier. But since the inefficiency effect is greater than the noise effect, the observed output q_A lies under the deterministic frontier. In the case of farm B, both the noise and the inefficiency effect are negative. Thus, the stochastic frontier output and the observed output both lie under the deterministic frontier. Empirically, the noise effect is equally distributed around the deterministic frontier while the inefficiency effect tends to lie below. The features of the model generalize to the multi-input, multi-output case (Coelli et al., 2005).

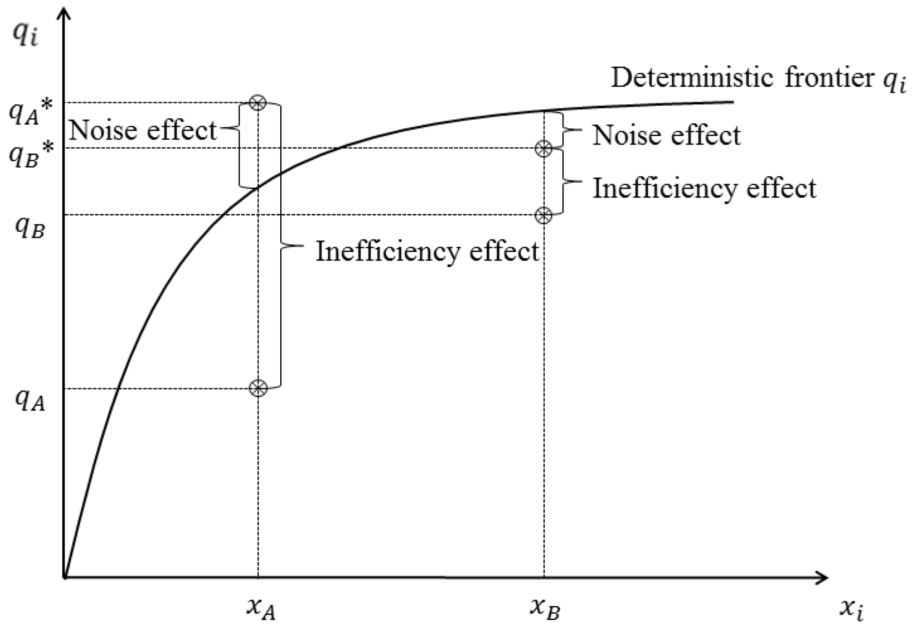

Figure 1: The stochastic frontier model for efficiency analysis (Source: Coelli et al., 2005)

Importantly, most of the SFM have been developed to allow the inclusion in equation (1) of exogenous factors, such as farming conditions and household characteristics. These factors are different from the factor inputs but influence the farming efficiency by scaling the distribution of u_{it} and/or v_{it} in equation (1), where *t* is the time period.

In the first application of the SFM, Aigner et al. (1977) assume a half-normal distribution of the inefficiency effect u_i. This specification is easy to estimate, because it has a single parameter. Yet, it assumes that most observations are clustered around full efficiency (Kumbhakar et al., 2015). However, the observed farmers may show more variation in efficiency, since they use different inputs and have different access to resources (Hoang and Nguyen, 2013; Karunarathna and Wilson, 2017). The truncated-normal distribution suggested by Stevenson (1980) considers this variation in efficiency by allowing a non-zero mode. Accordingly, in our application u_i is assumed to be $iidN^+(\mu, \sigma_u^2)$.

2.2 Farm production efficiency and natural forest extraction

In this section, we develop a conceptual interrelationship between farm production efficiency and natural forest extraction by rural farm households. As reported by Illukpitiya and Yanagida (2010), high rates of natural forest extraction might be caused by rural households who primarily depend on inefficient farming for their livelihoods, even though natural forests are property of other entities, i.e. the state. High rates of natural forest extraction could also be due to weak law enforcements. Therefore, we hypothesize that higher farm production efficiency is associated with a reduced need, or rather economic incentive, for rural households to (illegally) exploit protected forest resources.

Assume that the household maximizes monetary income (*I*) from agricultural produce, R_a, and from collected forest resources, R_f, like timber and other non-timber forest products[1]. Let S denote given local socio-economic and biophysical conditions that are

[1] Households will also maximize off-farm and other sources of income like remittances. But we examine the interrelationship between agricultural income and forest environmental income and hence restrict and simplify our analysis to this aspect.

beyond the farmer's control. Let v x 1 be a vector of inputs (*N*) used excluding farm land at corresponding price p_N. The household then maximizes

$$I = \max_{R_a, R_f, N} \quad (p_a R_a + p_f R_f) - (p_N N_a + p_N N_f) \tag{2a}$$

$$s.t. \qquad F(\Gamma R_a, R_f, N_a; S) \leq 0 \quad with \quad 0 < \Gamma \leq 1 \tag{2b}$$

$$G(R_f, N_f; S) \leq 0 \tag{2c}$$

$$N_a + N_f \leq N \tag{2d}$$

The model above allows the input mix, *N*, to be allocated to the production of R_a and R_f taking into account the local conditions *S*. Equation (2b) shows that income maximisation is subject to the available farm production technology and affected by the efficiency, Γ, with which the household uses the technology. The value for $1 - \Gamma$ shows the inefficiency effect, i.e. the extent in which the agricultural output for the farm household is less than the maximum possible output as denoted by the agricultural production frontier $F(R_a, R_f, N_a; S)$. R_f is included in the agricultural production function to represent that the forest might provide material for agricultural activities, for example for fencing. It also captures potential negative effects, such as forest wildlife contributing to crop damage and crop loss, and farmers adjusting their agricultural inputs accordingly (see Wossink and Swinton, 2007; Watve et al., 2016). Finally, equation (2d) indicates there is an upper limit on the input mix available to the rural household.

From equations (2a) - (2d) it follows that the two outputs R_a or R_f are interlinked at the household level. This linkage arises primarily because of competition for the same inputs, the case of which is especially representative for farm households in remote areas. In addition there are potential technical interdependences in the production process. Due to these interrelations we can no longer solve the income maximising behaviour for the two outputs independently.

Assuming the existence of an interior solution[2] the optimal choice of the decision variables, N_a, N_f, R_a, and R_f is characterised by the first order conditions. At optimal levels of inputs and outputs we have $-pN+\lambda_1\frac{\mathrm{d}F}{\mathrm{d}N_a}+\lambda_3=0$ and $-pN+\lambda_2\frac{\mathrm{d}G}{\mathrm{d}N_f}+\lambda_3=0$ where the $\lambda's$ are the Lagrange multipliers associated with equations (2b) - (2d). The marginal agricultural product of input N_a, $\frac{\mathrm{d}F}{\mathrm{d}N}$, is composed as follows

$$\frac{\mathrm{d}F}{\mathrm{d}N_a}=\Gamma\left(\frac{\partial F}{\partial R_a}\frac{\partial R_a}{\partial N_a}+\frac{\partial F}{\partial R_a}\frac{\partial R_a}{\partial R_f}\frac{\partial R_f}{\partial N_a}\right). \tag{3}$$

Thus if farm production efficiency, $\Gamma,$ is large it increases the marginal agricultural product of N_a assuming all else is constant.

The focus of this study is on how a change in farm production efficiency affects the extraction of forest products, R_f. The expression for the marginal cost of forest extraction, λ_2, provides insight into this relationship. From the first order conditions we have

$$\lambda_2=\lambda_1\Gamma\left(\frac{\partial F}{\partial R_a}\frac{\partial R_a}{\partial N}+\frac{\partial F}{\partial R_a}\frac{\partial R_a}{\partial R_f}\frac{\partial R_f}{\partial N}\right)\Big/\frac{dG}{dN_f} \tag{4}$$

[2] Conditions for an interior solution are that *F* and *G* are continuous and differentiable over the whole domain and are convex.

From the farm household's perspective the opportunity cost λ_2 of extracting one more unit of forest resources goes up with a higher productive efficiency Γ. In equation (4) an increase in efficiency will lead to higher marginal cost λ_2 through the increase in $\frac{dF}{dN}$ (see equation (3)). Equation (4) shows that, through the interdependencies, a higher agricultural efficiency will necessarily increase the marginal cost of extracting forest resources, R_f, such as timber, game and other wild food. Marginal cost determines supply according to micro-economic theory. So it holds that, everything else equal, the higher a farm household's agricultural efficiency the lower this household's incentive to extract forestry output.

To summarise, under rational behaviour we expect a negative relationship between a higher farming efficiency and the amount of natural forest extraction at the farm household level. The extent of this relationship is an empirical matter. The econometric analysis needs to account explicitly for the technical interdependencies and the allocation of the input mix.

3. Study design

3.1 Study site and data collection

Our data collection was conducted in 2013 and 2014 in Stung Treng province of Cambodia (Figure 2). This province is remote (500km from the nation's capital - Phnom Penh) and comprises of 129 villages in five districts. The province was selected because its economy is largely based on agriculture and extraction of forest and water resources (NIS, 2013). The majority of households (85%) are engaged in small-scale farming (NCDD, 2009). The most important crop in the province is rice. The province is rich in natural forests which include the Virachey National Park, the Stung Treng Ramsar Reserve and part of the Prey Long protected forest reserve. These protected forests are in principle *de jury* state property and managed by governmental authorities. In reality, the enforcement of the existing regulations regarding natural forest extraction is very weak in Cambodia (Travers et al., 2011; Rudi et al., 2014). This leads to a decline of these diverse natural forests which negatively impacts on local livelihoods as well as the local economy (Ehara et al., 2016). As reported by Clement et al. (2014) Cambodian protected forest areas were designated primarily based on habitat types, historical records, and very limited field work. In general, most protected areas contain established villages since the location of settlements was not known when they were designated.

We used a two-step procedure for data collection based on the guidelines of the United Nations Department of Economic and Social Affairs (UN, 2005). The village is identified as the primary sampling unit. In the first step, 30 of the 129 villages of the province were selected by sampling proportional to a village's size (measured as the number of households in the village). The information about the size of each village was obtained from the

Cambodian National Census 2008 (NIS, 2008). In the second step, twenty households of each village were randomly drawn from the village list of households.

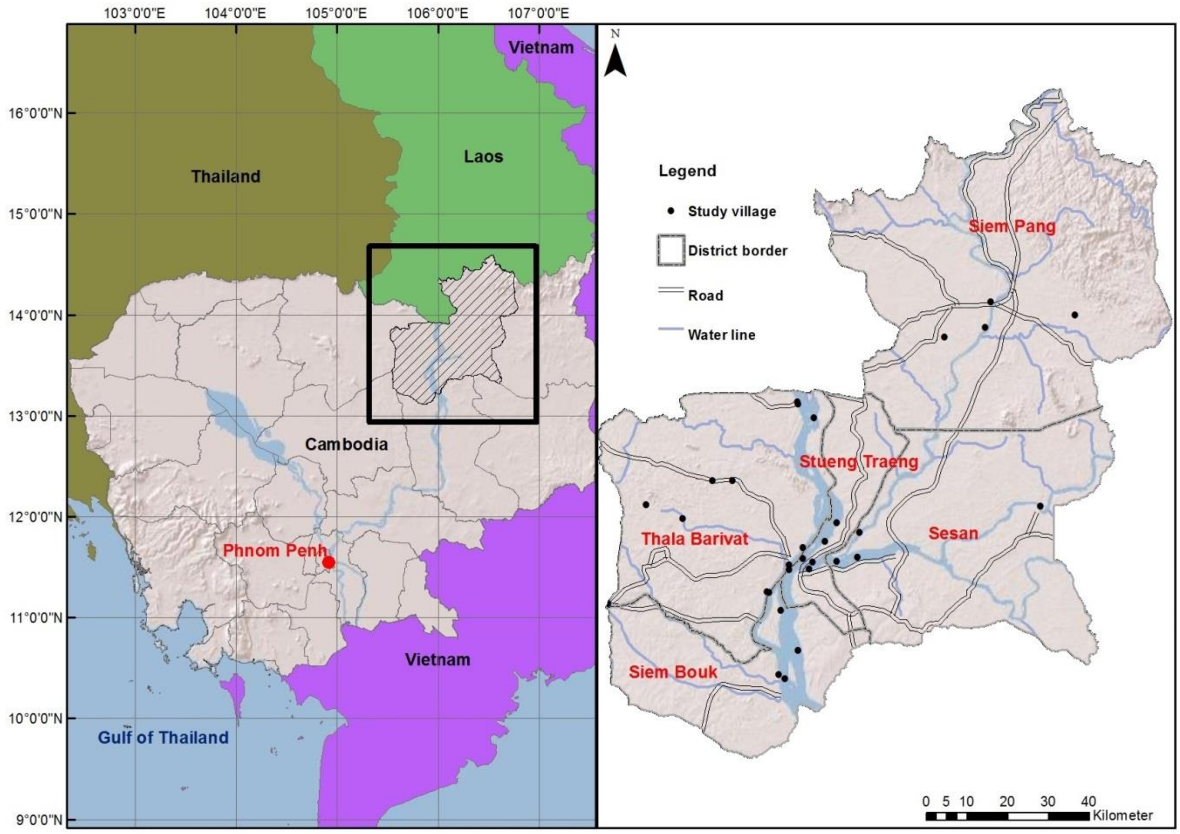

Figure 2: Maps of Cambodia (left) and the Stung Treng province (right) (Source: Nguyen et al., 2015)

Two questionnaires with structured interviews[3], one for the households and the other for the village heads, were used to collect data. The household questionnaire contains sections on education, health and employment status of household members, agricultural production, household expenditure and income, and remittances, with a separate subsection on natural forest extraction (e.g. hunting, collecting, and logging). These income-generating activities were recorded along with information on types of extracted products, places of extraction, distance from home to extracting grounds and to markets, intensity of extraction, payments in cash or in kind for permission to extract, cost of extraction (e.g. fuels and materials), and the

[3] Both village and household questionnaires are available and can be provided upon request.

quantity and value of total outputs. As for all income relevant variables, the reference period in the questionnaire was one year, i.e. that data on all income items for the past 12 months was collected. The household questionnaire was addressed to the household head. The village questionnaire captures village-related data, i.e. on road conditions around the village and was addressed to the village head.

The data collection was conducted in April and May of 2013 and 2014 which resulted in a two year total sample of 1200 households. For the purpose of this study, we excluded all households of which the head is employed as local staff in governmental institutions or works as a trader of various types of goods (and so is not engaged in farming). We also excluded the households with missing important variables. Thus, our final sample includes 430 households in both years, resulting in a final sample of 860 observations.

3.2 Data analysis

3.2.1 Estimating farm production efficiency

We use the SFM to estimate farm production efficiency with the log linear form of the Cobb Douglass function for the farm production. The output value of annual crops (in 2013 PPP$ per ha) is the dependent variable[4]. The independent variables include farm land area (*farm_land*) (in ha) and the expenditures (also in 2013 PPP$ per ha) for seeds or seedling (*seed*), mineral fertilizer (*mineral_ferti*), organic fertilizer (*organic_ferti*), machinery (*harvest_mach*), family labour (*family_labour*), hired labour (*hired_labour*), and other inputs (*other_expen*) (see Table A1 in the appendix section for more details). A perfect multicollinearity between the input variables was not detected by the Variance Inflation Factor (VIF) test (see Table A2 in the appendix section).

[4] PPP: Purchasing Pover Parity

Since we have panel data, we performed Hausman tests and chose the True Random-Effects (TRE) model (Greene, 2005) (see Table A3 in the appendix section). This model extends Pitt and Lee (1981) to include skewed stochastic terms of inefficiency. This model is specified as follows:

$$\text{Ln } O_{jt} = \text{Ln } P_{jt}\,\beta + \alpha_{jt} + v_{jt} - u_{jt} \tag{5}$$

where O_{jt} represents the output of agricultural crops (in 2013 PPP$ per ha) and P_{jt} denotes a vector of inputs used in the production process for farm *j* in year *t* as specified above; β is the parameter to be estimated; α_{jt} denotes farm-specific and time-variant heterogeneity; v_{jt} is the error term; u_{jt} represents production inefficiency, is nonnegative, and is assumed to be an exponential distribution.

To estimate farm production efficiency we first measure the value of u_{jt}. We use the conditional mean function following Jondrow et al. (1982) to disentangle the inefficiency component u_{jt} after fitting the frontier to the data. Thereby we calculate farm production efficiency using the function $E[u_{jt} \mid e_{jt}]$ where $e_{jt} \equiv v_{jt} - u_{jt}$ as below:

$$E[u_{jt} \mid e_{jt}] = \frac{\omega_{jt}\gamma_{jt}}{1+\gamma_{jt}^2}\left[\frac{\varphi\left(\frac{e_{jt}\gamma_{jt}}{\omega_j}\right)}{1-\varphi\left(\frac{e_{jt}\gamma_{jt}}{\omega_{jt}}\right)} - \frac{e_{jt}\gamma_{jt}}{\omega_{jt}}\right] \tag{6}$$

We follow Hadri et al. (2003) and test whether we need to account for heteroscedasticity in the statistical and efficiency estimations of the production function. The results of the test showed that the average farm production efficiency is downward biased by about 2% for the homogenous True Random-Effects (TRE) model on heteroscedastic TRE data. Therefore, we estimate farm production efficiency using both the heteroscedastic TRE model on heteroscedastic TRE data (TRE1) and the homoscedastic True Random-Effects on heteroscedastic TRE data (TRE2). However, we present and interpret the results of only the

TRE1. The results of TRE2 are in the appendix section (see Table A4 in the appendix section).

3.2.2 Examining determinants of farm production efficiency and natural forest extraction

We focus on the central question of whether an increase in farm production efficiency results in a decrease in natural forest extraction. We use forest environmental income as a proxy for the extraction. Forest environmental income is defined as the income earned from the extraction activities in natural forests (logging, hunting, and collecting non-timber forest products, see Sjaastad et al., 2005 and Angelsen et al., 2014 for the concept of environmental income). In this regard, our forest environmental income does not include non-pecuniary benefits from natural forests such as water provision (Nguyen et al., 2013) or environmental amenities (Rajapaksa et al., 2017). If these ecosystem services were accounted for, the forest environmental income would be higher.

Given the interdependences between farm production efficiency and forest environmental income as presented in Section 2, we use a simultaneous equations model in which forest environmental income is a function of farm production efficiency and vice versa. This model is thus able to account for the potential interdependences between farm production efficiency and natural forest extraction. Since we have panel data, the simultaneous equations model and the structural equations model are run with fixed-effects in order to eliminate the effects of unobservable and time-invariant factors. More specifically, the simultaneous equations model with fixed-effects is specified as follows:

$$F_{jt} = \beta_0 + T_{jt}\,\beta_1 + X_{jt}\,\beta_2 + R_{jt}\,\beta_3 + \gamma_j + \varepsilon_{jt} \quad (7)$$

$$T_{jt} = \Omega_0 + F_{jt}\,\Omega_1 + X_{jt}\,\Omega_2 + Z_{jt}\,\Omega_3 + \omega_j + \mu_{jt} \quad (8)$$

where F_{jt} refers to forest environmental income of household *j* in year *t*. T_{jt} denotes farm production efficiency and X_{jt} represents household and farm characteristics. R_{jt} is a set of instrumental variables that affect forest environmental income but does not affect farm production efficiency. Z_{jt} is a set of instrumental variables that affect farm production efficiency but does not affect forest environmental income. In simultaneous equations models the instrumental variables help to control for the endogeneity issues (Greene, 2005). γ_j and ω_j are the unobservable time-invariant individual effects. ε_{jt} and μ_{jt} are the error terms.

The independent variables are identified based on the Sustainable Livelihoods Framework (Ashley and Carney, 1999) which includes human, financial, physical, social, and natural capital. Human capital is represented by the age (*age*), gender (*gender*), and education level (*education*) of the household head[5], the household size (*hh_size*), and household labour (*hh_labour*). Physical capital is represented by the number of tractors (*tractor*) and the number of motorbikes (*motorbike*) that the household owns. Social capital is represented by the number of mobile phones (*mobile*) used by household members and the number of socio-political groups (*SPO*) that household members participate in. Financial capital is represented by the share of remittances (*remit_share*) that the household received of their total household income and by a binary variable that represents whether the household has access to agricultural loans (*agri_credit*). Natural capital is represented by the share of owned farm land (*own_land_share*) and the share of irrigated farm land (*irrig_land_share*) in total farm land, and the mean distance (*forest_dist*) from home to extracting grounds in natural forests[6]. We

[5] We also used a dummy variable to represent the ethnicity of the household head (1 = Khmer, the majority ethnic group, and 0 otherwise). 337 households (78% of the sample) belong to the Khmer group. However, as the ethnicity does not change over time because our panel data are balanced this variable was dropped during the estimation of the simultaneous and structural equations models with fixed effects.

[6] Farmland area (*farm_land*) also belongs to natural capital; however, as it is used to estimate farm production efficiency, and farm production efficiency is included in the forest environmental income functions of both models, it is excluded these models.

also use a dummy variable for road conditions (*road_con*) to represent the accessibility to the village (see Table A1 in the appendix section). A perfect multicollinearity among these independent variables of this simultaneous equations model and the following structural equations model was also not detected by the VIF test (see Table A5 in the appendix section).

We use variable *forest_dist* as the instrumental variable that affects forest environmental income but does not affect farm production efficiency (R_{jt}). Thus, it is included in the forest environmental income function but is excluded in the farm production efficiency function. We also use variables *own_land_share* and *irrig_land_share* as the instrumental variables that affect farm production efficiency but do not affect forest environmental income (Z_{jt}). These two variables are included in the farm production efficiency function but are excluded in the forest environmental income function (see Table 5).

As we simultaneously model the variables forest environmental income (F_{jt}) and farm production efficiency (T_{jt}), these variables are endogenous. Therefore, we apply a three-stage least squares method. This method accounts for the correlation between the endogenous dependent variables and the error terms of equations (7) and (8). It also enables us to generate more efficient parameter estimates for these equations than a two-stage least squares or a seemingly unrelated regression equations model (Zellner and Theil, 1962).

As a test of robustness, we also estimate a structural equations model in which forest environmental income is a function of farm technical efficiency but not vice versa. We follow Roodman (2011) to specify the structural equations model with fixed-effects as follows:

$$F_{jt} = \beta_0 + T_{jt}\,\beta_1 + X_{jt}\,\beta_2 + R_{jt}\,\beta_3 + \gamma_j + \varepsilon_{jt} \qquad (9)$$

$$T_{jt} = \sigma_0 + X_{jt}\,\sigma_1 + Z_{jt}\,\sigma_2 + \nu_j + \rho_{jt} \qquad (10)$$

where σ are the parameters to be estimated. ν_j are the unobservable time-invariant individual effects. ρ_{jt} is a random error term (see the results in Table A8 in the appendix).

To validate the simultaneous equations model and the structural equations model, we performed the following tests: (i) we used the Hansen-Sargan test of overidentifying restrictions and the results did not reject the null hypothesis, which means the overidentifying restrictions are valid; (ii) we used the Breusch-Pagan Lagrange Multiplier test for independent equations and the results rejected the null hypothesis which implies that the two equations are dependent (related); (iii) we used the Likelihood Ratio (LR) test and the Wald test for the overall system heteroscedasticity and the results rejected the null hypothesis which indicates that there is an overall system heteroscedasticity (see Table A6 in the appendix section). We also used the Hall-Pagan Lagrange Multiplier test for single equation heteroscedasticity. The results showed that there is heterogeneity in the forest environmental income function in both the simultaneous and structural equations models (see Table A7 in the appendix section). Therefore, in the simultaneous equations model the standard errors are bootstrapped with 1,000 replications and clustered at the village level; and in the structural equations models the standard errors are clustered at the village level.

4. Results and discussion

4.1 Livelihood conditions of rural households

The descriptive statistics in Table 1 illustrate the livelihood conditions of rural households in the study site. Each household has an average farm land area of about 2ha, of which 97% are its owned land. However, only about 8% of the farm land is irrigated. The mean distance to natural forests is about 3km. The majority of rural households (about 90%) are male-headed and the average age of household heads is 45 years. The average education level of household heads is low (3 years). Each household has an average size of 6 members, of which 50% are labourers. Only about 11% of households have agricultural loans and the share of remittances in total household income is only about 3.5%. About 90% of the villages have limited accessibility part of the year due to the weather conditions in the rainy season.

Table 1: Descriptive statistics of the variables representing livelihood assets/capital of rural households

Variable	Mean	Standard deviation
Natural capital		
farm_land (ha)	2.01	1.60
own_land_share (%)	97.11	16.06
irrig_land_share (%)	7.70	25.45
forest_dist (km)	3.05	4.29
Human capital		
age (year)	44.63	13.67
gender (% of male-headed households)	89.88	30.17
education (year)	2.96	2.91
hh_size (no. of persons)	5.61	2.02
hh_labour (no. of labourers)	2.99	1.36
Social capital		
SPO (no. of socio-political groups)	0.63	0.48
mobile (no. of mobile phones)	1.19	1.30
Physical capital		
tractor (no. of tractors)	0.31	0.47
motorbike (no. of motorbikes)	0.72	0.69
Financial capital		

agri_credit (% of households having agri. loan)	10.58	30.78
remit_share (%)	3.47	10.73
Village variables		
road_con (%)	9.19	28.90

Table 2 illustrates the structure of farming systems in the study site. The most important crop is rain-fed paddy rice. It is cultivated by 92% of households on about 70% of farm land. The next important crop is cassava, followed by pulses, nuts, and corn. The most important farm input is family labour. This is plausible as Cambodian farmers are facing limited access to input markets due to the low level of rural infrastructure development. Family labour is the only input that is used intensively in Cambodia. This is in line with the World Bank (2015) observing that farmers in Cambodia mostly rely on traditional, labour-intensive methods. As a consequence, the output value of crop production is only about 1200$/ha, which is relatively low compared with the neighbouring countries, for example Vietnam (Nguyen et al., 2017) or Thailand (Ebers et al., 2017).

Table 2: Values of output and inputs of farming

	Mean	Standard deviation	Share of cultivating households (%)
Output			
crop_value (PPP$/ha)	1223.78	1363.36	
Inputs			
farm_land (ha)	2.01	1.60	
- Rice	1.41	1.18	92.3
- Cassava	0.37	0.93	26.1
- Pulses & nuts	0.17	0.74	10.6
- Corn	0.04	0.20	7.0
- Others	0.02	0.27	1.9
seed (PPP$/ha)	18.43	168.73	
mineral_ferti (PPP$/ha)	11.31	172.77	
organic_ferti (PPP$/ha)	20.54	281.61	
harvet_mach (PPP$/ha)	22.65	65.81	
family_labour (PPP$/ha)	570.46	1206.16	
hired_labour (PPP$/ha)	59.25	204.90	
other_expen (PPP$/ha)	24.29	44.64	

Natural forest extraction is an income source for rural households. Forest environmental income is about 870$/year and accounts for about 17.5% of total annual household income (see Table A9 in the appendix section). Various types of forest products are collected by rural households. These include honey, red ants' eggs, lizards, frogs, toads, molluscs, snakes, birds, deer, wild pigs, resin, mushrooms, herbs, bamboo shoots, lotus, other vegetables, fruits, and wood. These products are grouped into (i) small animal, (ii) game, (iii) vegetables, resin and fruits, and (iv) wood (Table 3).

Table 3: Natural forest extraction and use

Product	No. of extracting households	Distance to extracting ground (km)	Forest environmental income (PPP $)		
			Total	For sale	For consumption
Small animals	132	2.7	310	141	169
Game	25	6.3	1245	842	403
Vegetables, resin & fruits	601	2.5	664	556	108
Wood	590	3.5	641	510	131

The most popular collected products are vegetables, resin, fruits, and firewood, which are extracted throughout the year. On average, the distance to the extracting ground in natural forests is 3km (Table 1). The distance to harvest vegetables, resin and fruits is about 2.5km, but households have to travel a longer distance for higher monetary products, for example, to hunt game (6.6km) or to log (3.5 km). This indicates that households must go far to look for environmental resources of high monetary value. This is consistent with the findings of Angelsen et al. (2014) and Nguyen et al. (2015) that forest products are becoming scarce, and thus extraction is subject to increasing opportunity costs (e.g. in terms of traveling time and labour). Extracted forest products are used for both home consumption and for sale. While small animals are used mainly for home consumption, other products such as vegetable, resin, fruits and wood are used more for sale.

Table 4: Forest environmental income by household income quartile

Income quartile	No. of households	Forest environmental income (PPP $)				
		Total	Small animals	Game	Vegetables, resin & fruits	Wood
1st	215	191	12	8	109	61
2nd	215	561	48	20	312	181
3rd	215	960	50	35	527	348
4th	215	1756	77	78	671	930
Total	**860**	**867**	**47**	**35**	**405**	**380**

Table 4 shows that that the richer households in our sample extract forest resources much more than the poorer households when households are classified into income quartiles. The annual forest environmental income of the 1st income quartile (the poorest households) is 9 times smaller than that of the 4th income quartile (the richest households). For all extracted products considered in our survey, the rich are found to have higher forest environmental income than the poor. Specifically we find that the income from vegetable, resin and fruits of the richest quartile is 6 times higher than that of the poorest quartile but this increases to 10 and 15 times higher when considering the income from game and wood, respectively. Although all extraction activities in natural forests without permission/agreement of relevant authorities are considered “illegal”, extraction of vegetables, resin, and fruits is tolerant and accepted, while logging and hunting games are really “illegal”. Thus, the findings from Table 4 indicate that (i) the poor mainly extract non-wood forest products (which is tolerated) while the rich mainly extract wood (which is illegal), and as a consequence (ii) the rich are likely to contribute more to the degradation of natural forests than the poor.

4.2 Farm production efficiency

Table 5 reports the estimated coefficients and standard errors of the SFM. All expenditures for inputs except for seeds, organic fertilizers and agricultural machinery have a significant and positive effect on the value of output (P<0.1). The result is plausible as most farmers in Cambodia still rely on traditional seeds and labour-intensive farming techniques, although they start purchasing more mineral fertilizers (Ebers et al., 2017). The predicted production efficiency is about 60% which indicates that rural households can still increase their production by about 40% through a more efficient use of production factors.

Table 5: Farm efficiency estimates from the heteroscedastic True Random-Effects (TRE) stochastic frontier model on heteroscedastic TRE data (Model TRE1)

	Coefficient	Standard error
farm_land (ln)	0.376***	0.033
seed (ln)	0.010	0.010
mineral_ferti (ln)	0.036***	0.012
organic_ferti (ln)	0.016	0.016
harvest_mach (ln)	0.003	0.008
family_labour (ln)	0.831***	0.017
hired_labour (ln)	0.033***	0.009
other_expen (ln)	0.012*	0.008
constant	2.615***	0.139
Usigma		
Zu	-0.203**	0.100
constant	-1.056***	0.160
Vsigma		
Zv	0.076	0.081
constant	-0.867***	0.114
Theta		
constant	0.276***	0.068
farm_efficiency		
- mean (%)	59.57	
- standard deviation	15.76	
No. of observations	860	
No. of groups	430	
Log likelihood	-1133.15	
Wald chi^2	6089.38	
Prob. > chi^2	0.000	

* Significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 3 shows the distribution of production efficiency scores. About 11% of households have efficiency scores of less than 40%, while only 4% of households have more than 80%. Most households (85%) have efficiency scores from 40% to 80% (see also Table A10 in the appendix section). The distribution of farm production efficiency scores is similar to that reported for other developing countries and for rice production in Cambodia (Ebers et al., 2017).

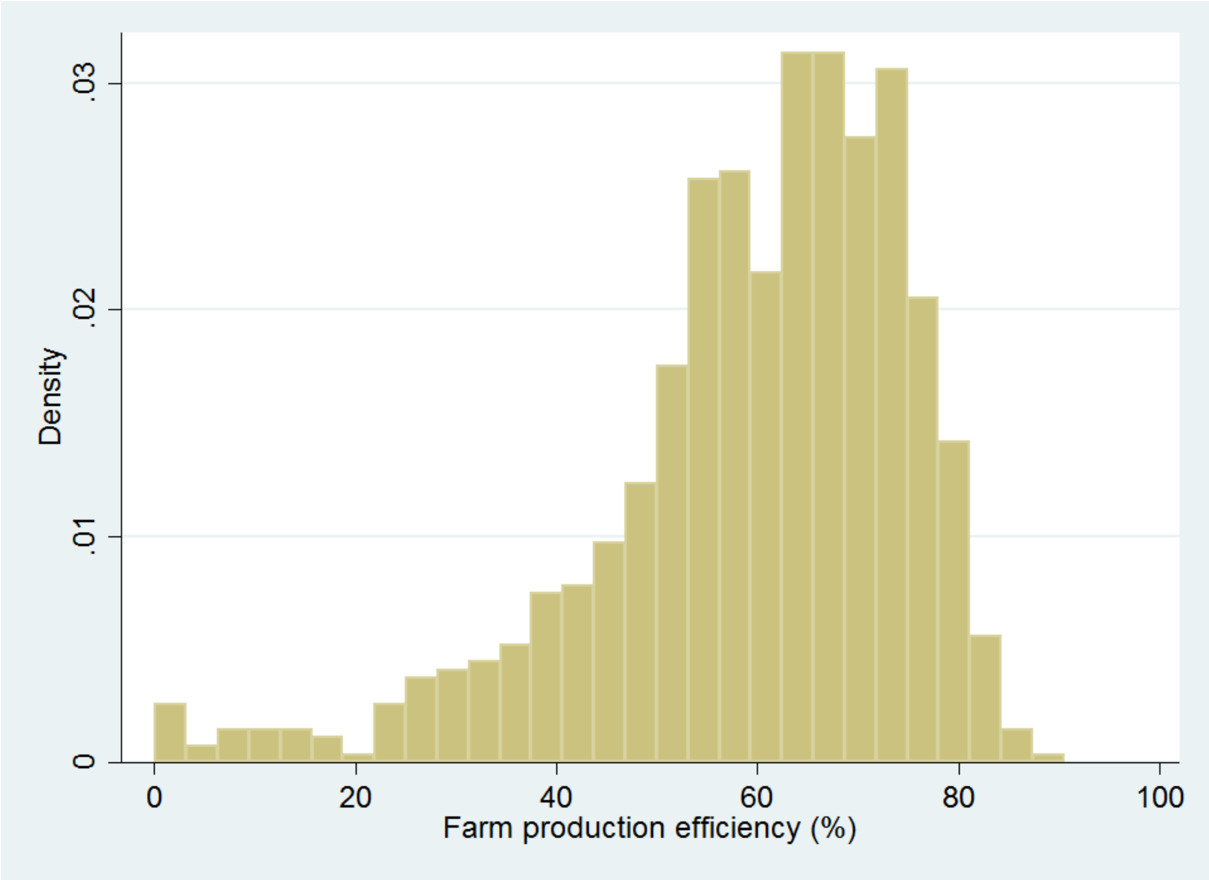

Figure 3: Distribution of farm production efficiency

4.3 Interrelationship between farm production efficiency and forest environmental income

Table 6 presents the estimations for the determinants of farm production efficiency and forest environmental income and shows the interrelationship between them. The results demonstrate that forest environmental income is a decreasing function of farm production efficiency. Thus, increasing farm production efficiency would reduce the pressure on forest degradation caused by extraction. In other words, making agriculture more efficient is one of the ways to avoid increased pressure on tropical forests. This finding is useful for policy makers and practitioners when designing effective programs for rural development and natural forest conservation since tropical forests around the world are often surrounded by rural communities whose primary livelihood is dependent on agriculture and on natural forest extraction.

Table 6: Determinants of farm production efficiency and forest environmental income

	Simultaneous Equations Model[a]			
	farm_efficiency		*forest_income*	
	Coefficient	Standard error	Coefficient	Standard error
farm_efficiency			-81.285*	45.148
forest_income	-0.003*	0.002		
Natural capital				
own_land_share	0.034***	0.013		
irrig_land_share	-0.008	0.016		
forest_dist			84.546***	30.802
Human capital				
age	-0.425**	0.205	-23.570	40.554
gender	-10.135**	4.893	-737.204	673.597
education	3.775***	0.862	246.574	225.119
hh_size	0.048	1.482	-16.840	190.336
hh_labour	-0.964	1.550	80.072	180.316
Social capital				
SPO	4.981**	2.354	619.724**	255.896
mobile	-0.141	0.665	-6.610	82.135
Physical capital				
tractor	3.860	3.142	1297.450***	287.075
motorbike	1.356	1.519	165.245	211.188
Financial capital				
agri_credit	1.610	3.778	271.310	487.842
remit_share	-9.884	7.034	-1151.431	912.697
Village variables				
road_con	-4.152*	2.328	-217.841	301.080
constant	75.256***	12.018	5426.706	4086.802
No. of observations	860			
Wald chi^2	67.28			
Prob. > chi^2	0.000			

[a] Estimation via three-stage least squares (3SLS) (Zellner and Theil, 1962), robust standard error bootstrapped with 1,000 replications and clustered at the village level in parentheses; see the results of the structural equations model in the appendix
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Other factors that have statistically significant effects on farm production efficiency are age, gender and education level of household heads, number of socio-political groups that households are members of, owned land share, and physical accessibility to the villages as captured by the road conditions. In addition, we find that forest environmental income has a small, but statistically significant effect on farm production efficiency.

Regarding the characteristics of household heads, age and gender have efficiency decreasing effects, while the education level has an efficiency increasing effect. In our study site, young farmers are more likely to adopt new technologies such as new seed varieties and female-headed households are significantly more efficient in farming activities. This is consistent with Mishra et al. (2017) who report that female-headed farm households in the Philippines, despite having limited access to land, have higher values of rice production than their male counterparts. Education level tends to improve the ability to manage information. Having memberships of socio-political groups can facilitate the exchange of information related to farming; as a consequence, it might increase farming efficiency (Ebers et al., 2017). On the other hand, the memberships also lead to a higher level of forest extraction (Nguyen et al., 2015). Regarding the effect of owned land share, our finding is in line with the literature that land ownership significantly increases farming efficiency (Rahman and Rahman, 2009; Manjunatha et al., 2013). The effect of road condition on farm production efficiency is negative. This might be because better road conditions can motivate higher educated household members to look for off-farm wage employment opportunities elsewhere. This is known as “brain drain” effect (Okoye, 2016). Migrants are considered being talented young people who are the most significant agricultural innovators. Their out-migration is thus assumed to cause a shortage of agricultural labour and decrease agricultural productivity (Snarr et al., 2011; Obeng-Odoom, 2017). The negative effect of forest environmental income on farming efficiency can also be explained in a similar way. The more household labour is used for natural forest extraction, the less household labour is available for farming activities. As a consequence, it decreases farming productivity.

Regarding forest extraction, forest environmental income is significantly and positively correlated with the distance to extracting ground in natural forests, the number of tractors and socio-political group memberships. The positive effect of the distance to extracting grounds in natural forests confirms our earlier finding (Table 3) and is consistent with Angelsen et al. (2014) who find that environmental resources are becoming scarce and extractors must go further to find them. In other words, extractors must go further away from home to look for higher monetary forest products. This is also in line with Nguyen et al. (2015) who report that forest resources are decreasing in our study area. The authors report that the increasing scarcity of the resources over the last 20 years was confirmed by 83% of the respondents who had been living in the villages for at least 20 years. They also show that farmers use tractors for logging in Cambodia. We also find that the share of remittances in total household income would reduce forest environmental income. This is because remittances increase household income (Nguyen et al., 2017). Our finding is consistent with López-Feldman and Chávez (2017) who report that in Mexico remittances decrease the likelihood that a household participates in natural resource extraction. Thus, increasing off-farm wage employment opportunities can also contribute to reducing natural forest extraction.

To summarize, Figure 4 visualizes our results on the relationships between the estimated farm production efficiency with observed farm income and with observed forest environmental income. The figure indicates that farm income is positively related with farm production efficiency whereas this relationship with forest environmental income is negative. Therefore, increasing farm production efficiency would enable farmers to focus more on farm production and thus reduce forest extraction. In addition, it would allow farmers to operate closer to the frontier output level without expanding farmland in forested areas. Our finding is consistent with Shively et al. (2001) who report that improved farming efficiency makes rural households wealthier due to increases in profit from farming; and as a consequence, they are less interested in the extraction of forest resources. As farming becomes more profitable, the opportunity cost of participating in extraction activities increases (Shively et al., 2001; Illukpitiya and Yanagida, 2010).

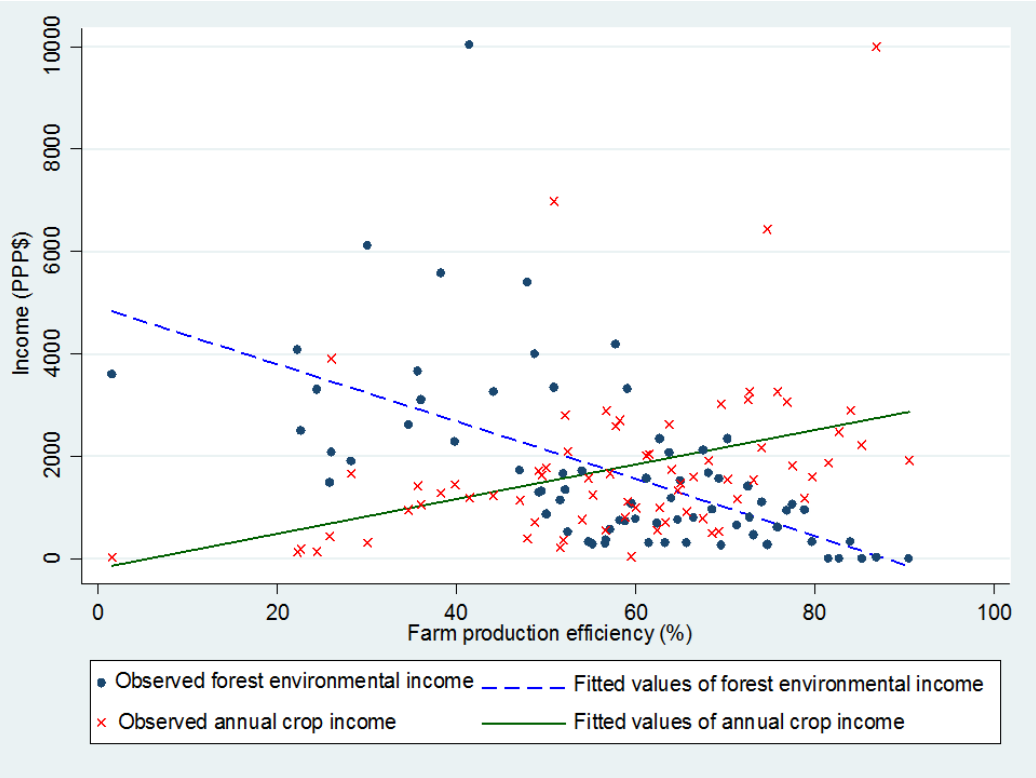

Figure 4: Interrelationship between farm production efficiency with annual crop income and forest environmental income

It should be noted that additional farm income can improve the household's purchasing power. Therefore, the household could substitute marketable goods for illegally collected goods, for example, the household can purchase wood instead of logging from protected forests. Another issue is that increased farm production efficiency could incentivize farmers to clear more forested land for farming activities (Shively et al., 2001). However, this assumption may not be applicable to countries where protected forests have been well demarcated (Illukpitiya and Yanagida, 2010). At our study site, although the extraction is still happening, the conversion of forested land to agricultural farm land is much more strongly regulated. However, this might still be popular in other regions of the country or in other developing countries (see Wunder et al. 2014). In this case, it is necessary to examine also the interdependence between an increase in farm production efficiency and the encroachment of forested land for agricultural production.

5. Summary and Conclusions

Farming and forest extraction remain principal livelihood strategies of rural population residing close to natural forests. However, there is a knowledge gap in the literature on the interrelationship between farm production efficiency and forest extraction activities. Hence the central objective of this study is to assess the impact of increased farm production efficiency of rural households in forest peripheries on their extraction of natural forests. Panel data of 430 farm households in Stung Treng province of Cambodia collected in 2013 and 2014 were used for the analysis. Farm production efficiency scores were estimated with stochastic frontier models. The interrelationship between farm production efficiency and forest environmental income was analyzed along with their determinants via simultaneous equations and structural equations models to control for simultaneity and endogeneity biases.

Our results indicate a mean estimated efficiency score of about 0.6, which implies that there is room for considerable efficiency improvements for the farmers in forest peripheries. We also find that younger and educated farmers who own their farm land and also participate in local social and political activities are likely to be more efficient in terms of agricultural production. We also observe that female farmers are generally more productive, although infrastructure conditions of the village such as the physical accessibility to the village also play an important role in farm efficiency.

The core result is that the interrelationship between farm production efficiency and forest environmental income is negative. Thus, as farm production efficiency increases, resulting in higher agricultural income, the extraction of forest resources will reduce. This finding is significant to address illegal forest exploitation by rural communities living near its perimeters. Results reveal that neither a long distance to forests diminish extraction activities, nor that membership in socio-political organizations curb forest resource use; and farmers having more tractors are keen to perform forest extraction activities like logging. Additionally, our results also suggest that it is not the poor who are to be blamed for over-extraction of the resources as they are less likely to engage in extraction activities with higher returns (e.g., logging) than wealthier households.

Hence, several conservation policy implications arise from these findings. Developing rural education and promoting land privatization would enable rural farmers in forest margins to improve agricultural efficiency. To further enhance conservation efforts, enforcing regulations to protect forests needs to be considered in conjunction with increasing economic benefits of wildlife to local farmers such as tourism-revenue sharing schemes. Moreover, generating additional off-farm employment opportunities in forest vicinities by facilitating rural investments is also advisable, for example wildlife-related employment. Given the importance of natural forests, access to the forests should be effectively regulated in order to prevent over-extraction and forest degradation. More specifically, as the poor extract more non-wood forest products and extract less wood, regulation of logging and hunting should be more strictly enforced.

Our research can be extended in several ways. Further research in other regions and over several time periods is needed to enrich the empirical evidence for Cambodia. Furthermore, as over-extraction of natural resources (especially through illegal hunting and logging) and encroachment of agricultural land into conservation areas might still happen in other parts of the country and in other developing countries, examining the interdependence between these two issues deserves further attention.

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