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Evaluating the Impacts of Traditional Biomass Energy Use on Agricultural Production in Sichuan, China

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Abstract

As crop straw and firewood are generated as by-products of food production systems, they are perceived to be sustainable energy sources that do not threaten food security by Chinese government for a long time. However, the time spent on collecting straw and firewood may create a burden on rural household, as it could reduce the available labor inputs for agricultural production, which in turn, possibly brings negative impact on food security. Building on an integrated agriculture-energy production system, a Symmetric Normalized Quadratic (SNQ) multi-output profit function (which includes labor allocations as quasi-fixed factors) is estimated to investigate the impacts of traditional biomass energy use on agricultural production in this paper. The negative signs of the calculated cross-price elasticities of supply (agricultural products and biomass energy) confirm that the relationship between biomass collection and agricultural production is competition. Moreover, the cross-price elasticities of biomass collection with respect to inputs are positive, implying that indirect link between biomass collection and agricultural production perhaps lies in household consumption decisions. The important implication of this study is that potential policy interventions for developing biomass energy in rural China could aim at enhancing food security by improving household motivation of engaging in agricultural production and slowing down the competition between biomass collection and agricultural production. It is suggested that government should attach more importance to simultaneously promote the prices of agricultural products and control the prices of intermediate inputs.

Keywords: biomass collection, agricultural production, labor allocation, China

JEL Codes: O13, Q01, Q12, Q41

1. Introduction

Biomass, which is related mostly to agriculture and forestry, is an important source of renewable energy in rural China. While the largest contributing sources are estimated to be the residues from annual crop production and forest logging like straw and firewood, much of them are presently used for cooking and heating in rural households (IRENA, 2014). According to the national statistics of China (MOA, 2010), the theoretical resources amount of crops straw with 15% water content was 0.82 billion ton, while the available resources amount of that for energy use was about 687 million ton, including 265 million ton maize straws, 205 million ton rice straws and 150 million ton wheat straws. Moreover, totally 0.155 billion ton woody biomass resources derived from deforestation wastes, wood processing and firewood forests were used as feedstock for energy production by the end of 2010 (CRES, 2011). As these residues are generated as by-products of food production systems, they have been perceived to be sustainable energy sources that do not threaten food security by Chinese government for a long time (Fernandez, 2016). Despite all this, due to lack of access to modern technologies such as gasification, briquetting and co-combustion of coal and biomass, a large number of rural households have to convert biomass to energy at low efficiencies by directly burning it. Biomass collection, in this context, involves operations of gathering and packaging biomass in or near the field, and transporting it to a specific site (in most cases, households place the collected biomass near their houses) for temporary storage (Zafar, 2015). The time spent on collecting biomass may create a burden on household who decides to use traditional biomass energy such as crops straw and firewood, as it could reduce the available labor inputs for agricultural production, which in turn, may deal negative impacts on food security (Li et al., 2001; van der Kroon et al., 2013). Therefore, it is of great importance to better understand the effects of traditional biomass energy use on agricultural production in China.

Currently in Sichuan Province, household energy consumption in rural areas still depends on traditional biomass energy generated from firewood and crop residues, due to the slow progress of energy transition toward modern fuels (Guta, 2014; Chen et al., 2016). By the end of 2013, the proportion of traditional biomass energy, i.e. crop straw and firewood, in rural energy consumption was 44% (SCREO, 2013). Excessive firewood collection leads to deforestation, while the utilization of crop straw potentially has negative effects on soil quality (Mathye, 2002; Chen el al., 2006). However, the existing evidence regarding the relationship between traditional biomass energy and agriculture is still insufficient to provide a clear picture of agriculture-energy interactions at micro level in rural Sichuan. Hence, the main purpose of this paper is to investigate how traditional biomass energy use affects agricultural production with a focus on biomass collection.

In recent years, a large number of researches have analyzed the agriculture-energy linkages resulting from the integration of food, feed and fuel production, with focus on the effects of crop-based biofuel on agriculture (Kgathi and Mfundisi, 2009; Timilsina et al., 2010; Babcock, 2011; Alka et al., 2014; Guta et al., 2015). The majority of them are qualitative analysis (Dodder et al, 2015). The results demonstrate that the utilization of crop-based biofuel impacts agricultural production, both directly and indirectly. The direct influences come from the competition between energy crop cultivation and agricultural production for resources such as land, labor and water (von Lampe, 2007; Baier et al., 2009), whereas the indirect effects are reflected through the mechanism of price transmission between biofuel prices and food prices (Havey and Pilgrim, 2011; Ajanovic, 2011; Zilberman et al., 2013). Moreover, considering the relationship between biomass collection and agricultural production, most existing empirical studies have only examined the influence of firewood collection on household agricultural production (Kgathi, 1997; Heltberg et al., 2000; Fisher et al., 2005; Chen et al., 2006). As suggested by van Horen and Eberhard (1995), an increase in labor time spent on firewood collection may adversely influence the labor budget and in turn, negatively affect agricultural production. That is to say, due to the limited time endowment, household members especially women and children, who have to spend extensive amounts of time on firewood collection, are usually constrained from engaging in other income generating activities such as working off-farm and agricultural production (Li et al., 2001; van der Kroon et al., 2013). Nonetheless, few rigorous empirical studies have been conducted on the interaction between crop straw collection and agricultural production. Although biomass collection is expected to compete with agricultural production, the understanding and the empirical evidence of the impacts of biomass collection on agricultural production are still relatively limited. Thus, the present article aims to fill the gaps in past literature by integrating biomass (including crop straw and firewood) collection into agricultural production. A major contribution of this paper is the analysis of household labor allocation between biomass collection and agricultural production, and of household responses to factors such as prices of agricultural products and intermediate inputs, and opportunity costs of time. A Symmetric Normalized Quadratic (SNQ) multi-output profit function, which includes labor allocation as quasi-fixed factors, is derived from a model of household production behaviors and estimated by triangulating several econometric approaches.

A basic hypothesis of this paper is that biomass collection competes with agricultural production for labor resources. Based on the economic theory of duality, we propose to test the hypothesis through investigating household production responses to the changes in the prices of outputs and inputs. Here, we assume that households in the study region (in Sichuan Province) are price taking and profit maximizing and competitive producers, and the market for traditional biomass energy (i.e. crop straw and firewood) is absent. The structure of this paper is organized as follows: The theoretical framework developed on an agricultural household model is provided in Section 2. Section 3 gives the model specifications and estimation strategies adopted for empirical analysis. In Section 4, the data and variables used in this paper are described. Section 5 presents the estimation results of the models, and the main findings and policy implications are summarized in Section 6.

2. Theoretical framework

In order to address the focused issue, an agricultural household model including household labor allocation to production activities is elaborated. Before further analysis, two basic assumptions for this study are set. The first one is that intra-household economic activities on the production side are only composed of biomass collection and agricultural production. The second one is that farm households allocate their limited labor endowment to agricultural production, biomass collection and off-farm work to generate income to support their consumption. Hence, biomass production will be integrated into the agricultural household model for investigating how a household makes decision on biomass energy use, and how it would, in turn, influence agricultural production.

Firstly, the agricultural production of the household is assumed to be continuous and monotonic in its labor input L_{ai}, twice-differentiable and strongly concave. It is represented by the function:

$$q_{ai} = F_{ai}(L_{ai}; B_i) \ with \ F'_{ai} > 0, F''_{ai} < 0 \tag{2.1}$$

Where B is a set of all inputs except labor (i.e. land, water, and all the other inputs) which is assumed to be exogenous.

Now, we introduce the household biomass collection into our household model. In rural Sichuan, the most important types of biomass energy are crop straw collected from the farm and firewood collected from forest. Then, we define biomass resources here as crop residues and firewood. We assume that the labor supplied to biomass collection is $L_{bi}(\geq 0)$, and define household biomass collection function as:

$$q_{bi} = F_{bi}(L_{bi}; Z_i) \ with \ F'_{bi} > 0, F''_{bi} < 0 \tag{2.2}$$

Where Z is an exogenous vector of household characteristics pertaining to the accessibility and availability of biomass resources such as the distance from the forest or the field to the house, the transportation cost, and the stock of biomass resources.

In previous literatures using the household models, the biomass collection was usually integrated into the agricultural household model by adding a separate production function (Wiedenmann, 1991; Heltberg et al. 2000; Köhlin and Parks, 2001; Fisher et al. 2005; Chen et al. 2006; Charles and James, 2008). In this approach, there is an implicit assumption that labor allocation decisions are separable and can be made independent of allocation decisions on agricultural production and biomass collection (Weaver, 1983). However, in Sichuan Province, the labor allocated between agricultural production and biomass collection cannot be distinguished by any physical indicator such as gender and age. The members of the household engaged in farm work, in most cases, are also responsible for biomass collection. They often collect firewood on their way to and from the fields or collect crop straw after harvesting and take it home. The simple aggregation of the production functions in past studies lacks the information on the internal relationship between agricultural production and biomass collection. Rural households usually rely on the market to provide signals through the price system to choose the proportions of available labor inputs that should be allocated to each activity (Debertin, 2012). In other words, household labor allocation should on the basis of the decisions regarding these two activities. Therefore, the above separable labor allocation assumption will not be hold in this study. In order to better simulate household production behaviors in our study region, a multiple output production function will be considered (Weaver, 1983).

Then, we can derive a multiple output production function that embodies the behavioral relationship as well as technical relationship based on the single-input productions (2.1) and (2.2):

$$f_i(q_{ai}, q_{bi}) = g_i(L_i; B_i, Z_i); \quad L_i = L_{ai} + L_{bi} \tag{2.3}$$

Where the function $f(\cdot)$ is concave in q_{ai} and q_{bi}. This shows the behavioral relationship that defines the transformation curve for the agricultural products and collected biomass (Debertin, 2012). The function $g(\cdot)$ reflects the technical relationship that specifies possible combinations of the output q_{ai} and q_{bi} produced from the mix of labor inputs L_{ai} and L_{bi} (Debertin, 2012), and it may be concave in L_i (the total labor input for intrahousehold production activities).

Using the implicit function theorem, we can write:

$$q_{ai} = F_{ai}[L - F_{bi}^{-1}(q_{bi})] = h_i(q_{bi}, L_i; B_i, Z_i) \tag{2.4}$$

And we can also obtain:

$$L_i = F_{ai}^{-1}(q_{ai}) + F_{bi}^{-1}(q_{bi}) \tag{2.5}$$

The total differentiation of (2.5) with respect to q_{ai} and q_{bi} yields:

$$dL_i = \frac{dF_{ai}^{-1}(q_{ai})}{dq_{ai}} dq_{ai} + \frac{dF_{bi}^{-1}(q_{bi})}{dq_{bi}} dq_{bi} = (1/MPL_{ai})dq_{ai} + (1/MPL_{bi})dq_{bi} \tag{2.6}$$

Assuming that L_i is invariable, therefore we have:

$$dL_i = (1/MPL_{ai})dq_{ai} + (1/MPL_{bi})dq_{bi} = 0 \Rightarrow \frac{dq_{ai}}{dq_{bi}} = -\frac{MPL_{ai}}{MPL_{bi}} \tag{2.7}$$

The equation (2.7) gives the behavioral relationship between agricultural and biomass collection. The expression dq_{ai}/dq_{bi} represents the slope of the product transformation curve at a particular point. It is the rate of product transformation of biomass collection for agricultural production ($RPT_{q_{ai}q_{bi}}$) and indicates the rate at which agricultural products can be substituted for the biomass outputs as the labor input bundle is reallocated (Debertin, 2012). Along the production transformation curve, $RPT_{q_{ai}q_{bi}}$ is equal to the negative ratio of individual marginal products. According to our assumptions that $F_a' > 0$ and $F_b' > 0$, this rate is unambiguously negative. This implies that, for agricultural products and biomass collection, one must be reduced in order to obtain more of the other, given a fixed available amount of labor inputs L_i.

As the objective of the household is to maximize its real income from agricultural production, biomass collection and off-farm work, it then can be expressed as a profit maximization problem:

$$\begin{aligned} &Max\pi_i = g_i(L_i; B_i, Z_i) - w_i^*(L_{ai} + L_{bi}) + w_i L_{oi} + E_i \\ &= f_i(q_{ai}, q_{bi}) - w_i^*(L_{ai} + L_{bi}) + w_i(T(a)_i - L_{ai} - L_{bi}) + E_i \quad w.r.t.\ L_{oi}, L_{ai}, L_{bi} \end{aligned} \tag{2.8}$$

With slight modification, the first-order conditions for household labor allocation are obtained as:

$$\frac{\partial \pi_i}{\partial L_{oi}} = w_i \tag{2.9}$$

$$\frac{\partial \pi_i}{\partial L_{ai}} = \frac{\partial q_{ai}}{\partial L_{ai}} - w_i^* = 0 \Rightarrow MPL_{ai} = w_i^* \tag{2.10}$$

$$\frac{\partial \pi_i}{\partial L_{bi}} = \frac{\partial q_{bi}}{\partial L_{bi}} - w_i^* = 0 \Rightarrow MPL_{bi} = w_i^* \tag{2.11}$$

The conditions from (2.9) to (2.11) imply that the optimum of labor allocation between agricultural production and biomass collection will occur at the points where the marginal output equals to the shadow wage of household labor. Then we can solve the household profit maximization problem and obtain the reduced form of household optimal labor allocation functions as follow:

$$L_{ni}^* = L_i^*(w_i^*, w_i, T(a)_i, E_i, B_i, Z_i)\ (n = a, b, o) \tag{2.12}$$

The labor allocated to off-farm work (o), agricultural production (a), and biomass collection (b) can be expressed as a function of market wage rate, shadow wage rate, household time endowment, non-labor income, inputs and services for agricultural production, and the factors affecting biomass collection.

3. Empirical specification and strategy

The basic hypothesis of this research is that agricultural production competes with biomass collection for labor resources. Based on the theoretical framework provided in Section 2, we propose to test the hypothesis through investigating the product supply and input demand relationships. Here, we assume that the households in our study region are clearly price taker and profit maximizing and competitive producers. A two-stage estimation strategy developed on the basis of previous literature (Henning and Henningsen, 2007; Tiberti and Tiberti, 2015) is adopted. We firstly estimate the shadow wage of household labor through modeling the intra-household production system and then include the estimated shadow wage in a multi-output profit function to investigate the relationship between agricultural production and biomass collection.

3.1 Shadow wage estimation

3.1.1 Household participation decisions

As the shadow wage rate of household labor is endogenous and mainly determined within household, it can be expressed as a function of household characteristics affecting household preferences and choices (Singh et al, 1986). Therefore, functions in (2.12) can be transformed to:

$$L_{ni}^{*} = L_{i}^{*}(w_i, T(a)_i, E_i, B_i, Z_i, a_i)\ (n = a, b, o) \tag{3.1}$$

Considering the first-order Taylor series expansion for function (3.1):

$$Y_{ni} = \alpha_{n0} + (\frac{\partial L_{ni}}{\partial w_i})w_i + \sum_{j=1}^{J} (\frac{\partial L_{ni}}{\partial X_{ij}})X_{ij} + \varepsilon_{ni} \tag{3.2}$$

Where ε_{ni} is the error term; $X = [X_1, \cdots X_J]$ represents exogenous explanatory variables other than market wage rate. Let us denote $\alpha_{n1} = \partial L_{ni} / \partial w_i$ and $\alpha_{nj} = \partial L_{ni} / \partial X_{ij}$, and then we can create three estimable participation equations in the form as:

$$Y_{ni} = \alpha_{n0} + \alpha_{n1} w_i + \alpha_{nj} X_{ij} + \varepsilon_{ni} \quad (n = a, b, o) \tag{3.3}$$

It can be seen from (3.3) that the dependent variables are decisions on participation in one of the three activities ($Y_{ni} = 1$ if household participates in one activity, otherwise $Y_{ni} = 0$).

Among independent variables, w_i is the market wage rate. Theoretically, the functions in (3.1) reveal that market rate is one of the most important determinants for household participation decision on off-farm work. When the market rate increases, households are more likely to participate in off-farm work. With respect to other explanatory variables in X , the other income E_i is measured by non-labor income. In our study, it mainly consists of subsidies provided from government (such as subsidies for superior crop varieties, direct subsidies to grain cultivation, subsidies for pig breeding, and compensations for health insurance, etc.), reimbursements from various insurances, remittances and other returns from investment in capital market. The household size and demographic characteristics (such as the fractions of children and elderly people) are used as proxies for its time endowment $T(a)_i$. Larger households could have more labor resources, while the fractions of children and elderly people also reflect the amount of available labor resources that can be provided by the household. Normally, households with larger fractions of children and elderly people are less likely to allocate labor to off-farm work. For the other inputs in agricultural production (B_i), we firstly choose the areas of arable land owned by the household as it can significantly influence the household decision regarding participation in agricultural production. We do not use the total value of intermediate inputs as an explanatory variable in our econometric model, because household allocation decision can affect intermediate inputs using activities, especially the use of fertilizers and pesticides, according to the findings of many previous works of research (Lamb, 2001; Mathenge and Tschirley, 2007). Instead, we use the weighted price of fertilizers and pesticides as a proxy for the amount of intermediate inputs since the households are more likely to purchase cheaper fertilizers and pesticides. Meanwhile, considering biomass collection, the distance from house to the nearest biomass collecting spot is selected to represent the accessibility and availability of biomass resources. It is also supposed to negatively influence household labor allocation to biomass collection. Particularly, for the omission of this variable caused by non-participation in biomass collection, we assume that these households face the average distance and substitute regional sample mean for the missing data.

We also include household head characteristics such as age, gender and educational level in our model, because these characteristics affect the quality of household labor, and then influence the marginal products of land and other intermediate inputs, which in turn brings effects to household participation decisions on different activities. Finally, the household location dummies are added into the regression to capture the effects of regions on household labor participation decisions.

In order to estimate the participation equations, we employ a multivariate probit model and then use the method of simulated maximum likelihood (SML) to obtain the estimate results of the model.

3.1.2 Production decisions

We then estimate the shadow wage rate of household labor using production function. According to the multi-output production function obtained using implicit function theorem in (2.3) and considering the easiness of estimation and interpretation, the simultaneous agriculture-energy production relationship for household i can be represented by a system of two equations derived from the Cobb-Douglas transformation function as follows (Just et al., 1983; Debertin, 2012):

$$\ln TOA_i = \sigma_1 \ln TOB_i + \sigma_2 \ln L_{ai} + \sum \xi_m \ln B_{mi} + \sum \rho_k d_{ki} + v_i$$

$$\ln TOB_i = \lambda_1 \ln TOA_i + \lambda_2 \ln L_{bi} + \sum \rho_j d_{ji} + \mu_i \qquad (3.4)$$

Where μ_i and v_i are the error term.

In this model, the agricultural output (variable name TOA, measured by the total value of agricultural products, i.e. the quantities of crops produced by household i multiply the prices of these crops.) is modeled as a function of the quantity of biomass (denoted as TOB, measured by the total amount of the biomass collected by household i [1].), the quantity of labor input (L_a, the total hours spent on farm), a vector of other inputs (B_m, including the areas of arable land AL and the total value of intermediate inputs TCI [2].), and other variables (d_k), such as household local dummies (r_1 and r_2) that also can influence households' agricultural production. In contrast, the amount of collected biomass is hypothesized as a function of the total value of agricultural outputs, the labor input (L_b, the total hours spent on biomass collection), and other influencing factors d_j (including the distance to biomass collecting spots DB and household location dummies).

Once the system of equations (3.4) has been estimated, the shadow wage of household labor can be calculated using the following formula:

$$w_i^* = MPL_{ai} = \frac{\hat{\sigma}_2 T\hat{O}A_i}{(1 - \hat{\sigma}_1 \hat{\lambda}_1) L_{ai}} \qquad (3.5)$$

Where $T\hat{O}A_i$ is the predicted value of agricultural output, and $\hat{\sigma}_1$, $\hat{\sigma}_2$ and $\hat{\lambda}_1$ are the estimated coefficients associated with outputs and labor allocated in agricultural production, respectively.

As the market for biomass energy is almost absent in our study region, the prices of biomass energy (crops straw and firewood) cannot be directly observed. Therefore, according to the equilibrium condition $MPL_{ai} = MPL_{bi} = w_i^*$, we use the shadow wage derived from (3.5) to calculate the shadow prices of crop straw and firewood as:

$$Shadow\ price = \frac{w_i^* (CNY\ per\ hour) \times Collecting\ time\ (Hours)}{Total\ amount\ of\ collected\ biomass\ (kg)} \qquad (3.6)$$

The Ordinary Least Squares (OLS) estimates of the production system may be biased for three main reasons. Firstly, unobserved information such as the ability and management level of the household reflected in the error terms are likely to be correlated with the endogenous

[1] Since the biomass or biomass energy is non-tradable. In order to unify the units of firewood and crop straw to standard coal equivalent (Kgsce), we divide the quantities of them by their conversion coefficients. The data of conversion coefficients for all types of energy are collected from China Energy Statistic Yearbook(2009)

[2] Due to the unavailability of the data, we use the total cost of fertilizer, pesticides and plastic films instead.

variables, particular the variable inputs (labor and intermediate inputs) in both of the equations, which may lead to omitted variable bias. Secondly, the two output variables are jointly determined. Thus, the single-equation estimation may suffer from simultaneity bias, due to the correlation between the disturbance of each equation and the output variables. Moreover, since the output variables are also the dependent variables of the equations in the system, the error terms among the equations are also expected to be correlated (Greene, 2012), which may cause the problem of inefficient estimation. Thirdly, the observed data can only reflect the situation of the households who decide to participate in corresponding production activities. Under this circumstance, the conditional means of error terms over the non-zero output population are not equal to zero, implying that the potential sample selection bias should be corrected in our model estimation.

The first problem could be mitigated by including observable household characteristics such as age, gender and educational level as proxies for management ability for both of the production activities.

The second problem is solved by using estimation methods for simultaneous equations. In this research, IT3SLS (iterative three-stage least squares) is applied to estimate the system of production functions. The IT3SLS method combines the procedure of the 2SLS (two-stage least squares) and SURE (Seemingly unrelated estimation) and produces the system estimates from a three-stage process (Zellner, 1962). In the first and second stages, an instrumental-variables approach is adopted to develop instrumented values for all endogenous variables (the output variables in the system) and to obtain a consistent estimate for the covariance matrix of the equation disturbances. All other exogenous variables in the system are used as instruments. In the third stage, generalized least squares (GLS) estimation is performed using the covariance matrix estimated before and with the instrumented values in place of right-hand-side endogenous variables (Greene, 2012). And then, this process iterates over the estimated disturbance covariance matrix and parameter estimates until parameter estimates converge.

The third problem can be solved by the standard two-stage Heckman (1979) sample selection model. In the first stage, the results of the multivariate probit regression model, which is estimated to determine the probabilities that a given household will participate in agricultural production and biomass collection, are used to calculate the inverse mills ratio (IMR) for each household. In the second stage, parameter estimates of the production system are obtained by augmenting the regression with the IMRs using 3SLS (Heckman, 1979). Based on the equations in (3.3), the IMRs for the household i who chooses to participate in either activity can be computed as follows:

$$IMR_{in} = \phi(w_i, X_{i,j}, r1, r2) / \Phi(w_i, X_{i,j}, r1, r2) \quad (n = a, b, o) \tag{3.7}$$

Additionally, to deal with the zero-value variables that have undefined logarithm, we modify them by replacing them with a “sufficiently small” value (MaCurdy and Pencavel, 1986; Jacoby, 1992; Soloaga, 1999).

3.2 Household profit maximization problem

In order to further investigate the impacts of biomass collection on agricultural production, we estimate a multi-output profit function to obtain the full coefficients of the profit function as well as the price elasticities with respect to all outputs and inputs in the second step. Regarding the specification of profit function, a number of plausible functional forms have been discussed in previous works of literature. They include the translog (TL), generalized Leontief (GL), normalized quadratic (NQ), symmetric normalized quadratic (SNQ) and many other forms (Christensen et al., 1973; Lau, 1972; 1978; Diewert and Wales, 1987; 1988; 1992; Diewert and Ostensoe, 1988; Kohli, 1993; Villezca-Becerra and Schumway, 1992). As described in Kohli (1993), the SNQ profit function treats all outputs and inputs symmetrically (NQ profit function can be considered as a special case of SNQ profit function). It is necessarily linearly homogeneous in prices and quantities, and as a fully flexible functional form, it can be easily imposed monotonicity and convexity properties (Kohli, 1993). Therefore, we adopt a symmetric normalized quadratic (SNQ) profit function defined as follows (Diewert and Wales, 1987, 1992):

$$\pi(p,z)=\sum_{i=1}^{n}\alpha_i p_i+\frac{1}{2}W^{-1}\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij}p_i p_j+\sum_{i=1}^{n}\sum_{j=1}^{m}\delta_{ij}p_i z_j+\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{m}\gamma_{ijk}p_i z_j z_k \qquad (3.8)$$

With π =profit, p_i =netput prices, z_i =quantities of non-allocable quasi-fixed inputs, $W=\sum_{i=1}^{n}\theta_i p_i$ =price index for normalization, θ_i =weights of prices for normalization, and α_i , β_{ij} , δ_{ij} and γ_{ijk} =coefficients to be estimated.

Given the above specification, the estimation equations (output supply and input demand equations) used to analyze household production decisions are obtained by the first derivation of the profit function using Hotelling's Lemma ($q_i=\partial\pi/\partial p_i$):

$$x_i=\alpha_i+W^{-1}\sum_{j=1}^{n}\beta_{ij}p_j-\frac{1}{2}\theta_i W^{-2}\sum_{j=1}^{n}\sum_{k=1}^{n}\beta_{jk}p_j p_k+\sum_{j=1}^{m}\delta_{ij}z_j+\frac{1}{2}\sum_{j=1}^{m}\sum_{k=1}^{m}\gamma_{ijk}z_j z_k \qquad (3.9)$$

Where x_i =netput quantities or quantity indices.

In this research, we have four groups of netputs $(n=4)$, i.e. agricultural output (a), biomass output (b), labor input (l), and other intermediate inputs (o)[3]. Arable land is specified as the only quasi-fixed input. The price data were obtained from our field survey. Due to the facts that each group has many different individual output and input categories and the variations in price of the same commodities are quite small, therefore, except labor input, within other three groups, it is necessary to aggregate the price and quantity data of different individual outputs and inputs. In this study, we set up household-specific price index by calculating the

[3] Totally, we set up a system of four equations (two outputs equations and two inputs equations).

sum of weighted prices of each category using output value structure in each group. The price (index) of each group of netput can be defined as (Lewbel, 1989):

$$p_i = \sum_{i=1}^{n} p_n s_n \quad (n = 1,2 \cdots N) \tag{3.10}$$

Where s_n is the share of the value of netput n in netput group i and p_n is the producer price of netput n (As we do not have the price data of all types of intermediate inputs for each household, we use the sum of weighted prices of fertilizer, pesticide and plastic films which was calculated using the average price and consumption structure data of the sampled households instead.). For the households that do not participate in either of the two productive activities, the corresponding production data are missing. We keep their outputs quantities zero and assume that these households face the average prices and replace the missing data with the sample mean. In particular, for agricultural output (x_{ai}) and intermediate inputs (x_{oi}), the aggregated quantity indices are computed through dividing their total value by their weighted prices.

Moreover, we employ the following formula outlined by Diewert and Wales (1992) to calculate the weights θ_i:

$$\theta_i = \frac{|\bar{x}_i| p_i}{\sum_{i=1}^{n} |\bar{x}_i| p_i} \tag{3.11}$$

Once the SNQ profit function has been estimated, we define the price elasticity as:

$$E_{ij} = \frac{\dfrac{\partial q_i}{q_i}}{\dfrac{\partial p_j}{p_j}} = \frac{\partial q_i}{\partial p_j} \cdot \frac{p_j}{q_i} \tag{3.12}$$

Then, we will use these price elasticities to further analyze the relationship between agriculture production and biomass collection.

According to Microeconomic theory, we must consider the conditions imposed on our SNQ profit function before estimating it. Homogeneity in netput prices is imposed by the functional form and symmetry requires $\beta_{ij} = \beta_{ji}, \quad \forall i, j = 1, \cdots, n$ (Henning and Henningsen, 2007). In addition, in order to be consistent with the solutions to the profit maximization problem, the profit function has to be convex in netput prices (Varian, 1978). This implies that the Hessian matrix of the profit function must be positive semidefinite (Arnade and Kelch, 2007). Therefore, we applied the three-stage procedure proposed by Koebel et al. (2000; 2003) to impose convexity on the SNQ profit function. Firstly, we calculate the Hessian matrix after estimating the unrestricted netput equations in (3.9). Then, we minimize the weighted difference between the unrestricted Hessian matrix and a Hessian matrix that is restricted as positive semidefinite by the Cholesky factorization. In the last stage, we estimated the restricted coefficients by adopting an asymptotic least squared (ALS) framework (Gourieroux et al., 1985; Kodde et al., 1990; Henning and Henningsen, 2007).

As the shadow wage of household labor (p_l^*) and the shadow price of biomass energy (p_b^*) are unobservable and endogenously determined in the production system, an estimating process of instrumental variable regression should be employed in our estimation. Here, we use the average age and educational years of employed household members[4] as instrumental variables for the shadow wage and shadow price. These two variables are exogenous in our model, and the characteristics of the employed household members can affect the quality of household labor, thus influencing household labor allocation and production decisions. Because of the fact that these variables are considered to be correlated with household production system, and therefore, they are appropriate instrumental variables. In order to estimate our SNQ profit function, we firstly regress the shadow wage (p_l^*) and shadow price (p_b^*) on these instrumental variables and all the other exogenous variables respectively. Then the predicted value of these two endogenous variables will be used as augmented variables in the constrained IT3SLS at the second step.

Using the iterative three-stage least square (IT3SLS) estimation method, we jointly estimate the SNQ profit function and the four netput equations with the data collected from our household survey. As described already, restrictions are imposed on the system to insure profit maximization. The estimations and calculations for the SNQ profit function are carried out by the statistical software "R" with the add-on package "micEconSNQP".

[4] The employed household members include self-employed members working on farm and those employed off-farm in a specific household.

4. Data

4.1. Sample description

The data used in this paper were collected in a household survey conducted from August 2013 to February 2014. 556 rural households were randomly selected from 6 counties of 3 cities in Sichuan Province.

As it is shown in Table 1, for the whole sample, 524 households engage in agricultural production, accounting for 94.2% of the total, while 409 households collect biomass, occupying 73.6% of all those surveyed. On average, the value of annual agricultural outputs is 17,208 CNY[5], whereas the amount of biomass collected by households is 3635 Kgsce[6] per year. Moreover, the average time allocated to agricultural production is 717 hours per year, while the average time spent on collecting biomass is 236 hours annually. Regarding to agricultural production, households from Yibin (hilly areas) have the highest participation rate (96.2%), whereas households located in Deyang (plain areas) have the lowest one (91.9%). However, households from Aba (mountainous areas) spent longest time (796 hours per year) on farm work, while those from Deyang spent the shortest time (613hours per household per year). Accordingly, the total value of agricultural outputs in Aba is the largest (21,678 CNY per year), whilst that in Deyang is the smallest (14,329 CNY per year).

Turning to biomass collection, the participation rate differs among different areas. In Aba, the participation rate is the highest (92.4%) and it took the longest time (380hours per year) for households to collect the largest amount of biomass (5354kgsce per year). In constrast, Deyang has the lowest participation rate (45.6%), resulting in the fact that the time (74 hours per year) allocated to biomass collection is the shortest, and the amount of biomass collected by households is the smallest.

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[5] CNY=Chinese Yuan

[6] Kgsce=Kilogram of standard coal equivalent

Table 1: General Information of household participation in agricultural production and biomass collection in study region

	Aba (Mountainous areas)	Yibin (Hilly areas)	Deyang (Plain areas)	Total sample
Sample size	185	186	185	556
Household participation in two activities (Number)				
Households participating in agricultural production	175 (94.6)	179 (96.2)	170 (91.9)	524 (94.2)
Households participating in biomass collection	171 (92.4)	153 (82.3)	85 (45.6)	409 (73.6)
Households participate in neither activities	3 (1.6)	2 (1.1)	12 (6.5)	17 (3.1)
Summary of household working activities (per household per year)				
Total value of agricultural products (CNY)	21678	15625	14329	17208
Total amount of collected biomass (kgsce)	5354	4515	1031	3635
Total hours spent on agricultural production	796	742	613	717
Total hours spent on biomass collection	380	255	74	236

Note: The values in parentheses are the shares in subsample or total sample.
Source: Author's Own Household Survey (2013)

4.2 Variable description

The variables used in estimating our econometric models are listed in Table 2. The variables employed to estimate household shadow wage rate can be categorized into household head characteristics, household demographic characteristics, household productive characteristics and other external factors. In terms of household head characteristics, the average age of the heads of the surveyed households is 51.74 years, and their average schooling year is 6.42 years. The share of the male household heads in the total sample is about 0.93. For household demographic characteristics, the average family size of the households in our sample is 4.12. The mean values of the fractions of children and elderly people in household members are 0.11 and 0.12, respectively. Considering productive variables, the mean value of the annual agricultural outputs for the sampled households is 17,207.65 CNY, while the amount of collected biomass is 3634.93 Kgsce per year. Averagely, the surveyed households spend 716.91 hours on agricultural production, while allocating 236.31 hours to biomass collection per year. Moreover, on average, the area of arable land possessed by the surveyed household is about 4.01 Mu[7]. Meanwhile, the mean cost of the intermediate inputs is about 4560.98 CNY. The average weighted price of fertilizers and pesticides is 6.27 CNY per kg. Among other external factors, the average market wage rate for the samples households is 8.29 CNY per hour, and the average non-labor income level is 2789.01 CNY per year. Additionally, in our sample, the number of households from the mountainous and plain areas both amount to 33.27% and 33.45% of the households are from hilly areas. The biomass collecting spot is on average 2.14 km away from the house of the household.

Moving on to the variables used in estimate the multi-output profit function, the mean value of the total hours spent on domestic production activities is about 953.23 hours for each household. The calculation results of price indices and quantity indices of the netputs are also shown in Table 2.

Table 2: Description of variables used in empirical analysis

Variables	Mean	Std. Dev.
Total value of intermediate inputs (CNY)	4560.98	15827.21
Total value of agricultural outputs (CNY)	17207.65	46668.22
Total amount of collected biomass (Kgsce)	3634.93	4464.77
Age of household head (Years)	51.74	11.54
Age squared of household head	2810.22	1245.77
Gender of household head (share of male)	0.93	0.26
Educational level of household head (Years)	6.42	3.48
Family size (Unit)	4.12	1.37
Fraction of children (≤14)	0.11	0.16
Fraction of elderly people (≥65)	0.12	0.23
Arable land areas (Mu)	4.01	3.69
Weighted price of fertilizers and pesticides (CNY per kg)	6.27	6.53
Market wage rate (CNY per hour)	8.29	5.07
Non-labor income (CNY)	2789.01	4484.31
Distance to biomass collecting spot (km)	2.14	4.41
Total hours allocated to agricultural production (Hours)	716.91	507.08
Total hours allocated to biomass collection (Hours)	236.31	320.52
Quantity index of agricultural outputs (kg)	55562.34	187089.9
Total hours allocated to two activities (Hours)	953.23	655.11
Quantity index of Intermediate inputs (kg)	850.71	886.11
Price index of agricultural products (CNY per kg)	1.27	1.93
Price index of intermediate inputs (CNY per unit)	7.34	22.79
Average age of employed household members (Years)	44.69	10.73
Educational level of employed household members (Years)	6.72	2.69
Y_{ai} (=1, if household participates in agricultural production)	0.94	0.23
Y_{bi} (=1, if household participates in biomass collection)	0.74	0.44
Y_{oi} (=1, if household participates in off-farm work)	0.87	0.34
r_1 (=1, if the household is from mountainous areas)	0.3327	0.4713
r_2 (=1, if the household is from plain areas)	0.3327	0.4713
Sample size	556	

Source: Author's own household survey

[7] 1 Ha= 15 Chinese Mu

5. Estimation results

Table 3 lists the estimation results of the multivariate probit model that explains how households make decisions regarding participation in different activities. The estimates of ρs (Rho, correlation between the errors) that maximizes the multivariate probit likelihood function are 0.1095, -0.0114 and 0.0291, respectively. Specifically, the correlation coefficient between agricultural production and biomass collection (Rho (b, a)) is positive and significantly greater than zero at the level of 5%. This indicates that the random disturbances in participation equations of agricultural production and biomass collection are affected in the same direction by random shocks. In other words, household participation decisions on these two activities are not statistically independent. The correlation coefficients between off-farm work and the two intra-household production activities are insignificant, implying that the household participation decision regarding off-farm work does not statistically depend on participation decisions about intra-household production activities. This also means that we can separately analyze the relationship between biomass collection and agricultural production without considering off-farm labor allocation. The significant log pseudo likelihood statistic suggests that the independent variables taken together influence household participation decisions. According to the estimated parameters, households that have higher wage rate are more likely to participate in off-farm work and less likely to collect biomass. These results are in line with our expectation.

As expected, non-labor income has a significant negative impact on household participation decision regarding agricultural production and off-farm work. Households with higher no-labor income level are less likely to allocate time to on-farm work and off-farm work and T a more likely to allocate time to biomass collection. The price index of intermediate inputs has a significant negative impact on off-farm work. That means raising the intermediate input price reduces household likelihood to participate in off-farm employment. The areas of arable land owned by households can also significantly influence household participation in off-farm work. Households possessing more arable land are less likely to find jobs outside their farms.

Table 3: Multivariate Probit Estimates of household participation functions of agricultural production, biomass collection and off-farm work

Variable	Agricultural production (Y_{ai})		Biomass collection (Y_{bi})		Off-farm work (Y_{oi})	
	Coefficient	Std.Dev.	Coefficient	Std.Dev.	Coefficient	Std.Dev.
Age of household head	-0.1453**	0.0723	0.0531	0.0485	-0.0248	0.0441
Age squared of household head	0.0014**	0.0007	-0.0004	0.0005	0.0002	0.0004
Gender of household head	-0.0938	0.3472	-0.4138	0.2773	0.2412	0.2724
Educational level of household head	-0.0072	0.0303	-0.0458**	0.0219	-0.0041	0.0275
Family size	0.0799	0.0719	0.0643	0.0598	0.4365***	0.0747
Fraction of children (≤14)	-0.6252	0.6014	0.3226	0.5366	-1.1832**	0.5279
Fraction of elderly people (≥65)	0.1732	0.4400	0.6679	0.4086	-1.1086***	0.3436
Arable land areas	0.0789	0.0491	0.0067	0.0242	-0.0323*	0.0184
Market wage rate (log)	-0.1129	0.1419	-0.2182**	0.1066	0.1434*	0.0742
Non-labor income (log)	-0.2085**	0.0807	0.0947	0.0581	-0.1292*	0.0665
Price index of fertilizers and pesticides (log)	-0.1144	0.0920	0.1431	0.1039	-0.2165*	0.1105
Distance to biomass collecting spot	0.0547	0.0569	0.6374***	0.1179	0.0298	0.0354
Mountainous areas	-0.0859	0.3128	-0.1299	0.2436	-0.2744	0.2453
Plain areas	-0.1572	0.2438	-1.0145***	0.1755	-0.0638	0.2047
_cons	6.8066***	2.1738	-1.3185	1.4729	1.4401	1.3916
Log pseudolikelihood	-496.59624					
Rho (b,a)	0.1905**	0.0885				
Rho (o,a)	-0.0114	0.1225				
Rho (o,b)	0.0291	0.0951				
Wald chi2 (42)	228.00***					
No. of Obs	556					

Note: The significance levels are: *10%, **5%, ***1%. The missing location dummy is hilly area

In terms of the demographic characteristics, households with larger size and smaller fractions of children and elderly people are more likely to work off-farm. With respect to the household head characteristics, we find that households with older heads are less likely to work on farm, whereas households with higher educational level are less likely to collect biomass. In addition, household location plays a vital role in determining household participation in biomass collection. Households located in plain areas are less likely to participate in biomass collection than those located in hilly areas.

Table 4: Estimation results of the system of production functions using IT3SLS

Variable	Agricultural production		Biomass collection	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Total value of agricultural outputs (log)			0.0524	0.0803
Amount of collected biomass (log)	-0.0597	0.1232		
Hours worked on farm (log)	0.6241***	0.0935		
Hours worked on biomass collection (log)			0.3634***	0.0464
Total value of intermediate inputs (log)	0.0171	0.0146		
Areable land areas (log)	0.2763***	0.0810		
Age of household head	0.0360	0.0288	0.0116	0.0303
Age squared of household head	-0.0004	0.0003	-0.0002	0.0003
Gender of household head	0.0790	0.1771	0.1280	0.1803
Educational level of household head	0.0488***	0.0150	0.0182	0.0154
Distance to biomass collecting spots			0.0083	0.0123
Mountainous areas	0.3989***	0.1203	-0.1524	0.1381
Plain areas	0.2810	0.1791	-0.4265**	0.1806
IMR	0.3777	0.2778	-0.4154	0.2697
_cons	3.5683***	1.4237	5.5164***	0.9951
R^2	0.3677		0.2835	
No. of Obs.	394		394	
Endogenous variables[a]	ln_TOA, ln_TOB			

Note: The significance levels are: *10%, **5%, ***1%. The missing dummy for regions is Hilly area. a. All the other variables in this system are treated as exogenous to the system and uncorrelated with the disturbances. The exogenous variables are taken to be instruments for the endogenous variables

Table 4 presents the iterative three-stage least squared (IT3SLS) estimates of the production system. The R^2 for the two equations are 0.3677 and 0.2835. The inverse Mills ratio (IMR) is insignificant in both equations, indicating that sample selection bias would not happen if the system of production functions was estimated without taking household participation decisions on biomass collection into consideration.

With respect to the parameters of the production system, most of them have the expected signs. For the agricultural production, the inputs of labor and arable land have significantly positive impacts on the outputs. The educational level of the household head has a significant effect on farm production, supporting the widely accepted role of human capital in improving agricultural production (Henning and Henningsen, 2007; Tiberti and Tiberti, 2015). In addition, households located in mountainous areas produce more agricultural products than those from hilly areas. On the other hand, in biomass collection function, the labor input also has a significant and positive influence. The estimated parameters also indicate that households who are from plain areas collect less biomass than those from hilly areas. In addition, the coefficients of the output variables on right-hand-side of the two equations to some extent imply the relationship between agricultural production and biomass collection. Given fixed labor inputs, spending more time on biomass collection decreases the outputs of agricultural production. Conversely raising the yields of agricultural production could also increase the collecting amount of biomass. This could be possibly attributed to the fact that biomass collection occupies labor resources for agricultural production. Nonetheless, agricultural production provides biomass resources. Furthermore, due to the fact described in Section 2 that in Sichuan Province, household members usually collect biomass on the way to and from the fields, participating in agricultural production may increase the opportunity to pick up biomass.

After getting the parameter estimation results of the production system, the shadow wage of household labor and the shadow prices of the biomass energy are calculated using (3.5) and (3.6). According to the results, the average wage rate of household labor (p_l^*) is about 10.75 CNY/Hour, whereas the shadow price of biomass (p_b^*) is around 0.81 CNY/kgsce. Table A1 (See Annex) reports the estimates of the SNQ production function with restriction of curvature. The hausman test statistic indicates the endogeneity problem caused by including shadow wage in our model and our instrumental variables are not weak. Given our estimation results, we calculate the price elasticities of outputs and inputs according to (3.12) using sample means.

Table 5: Estimated price elasticities of outputs and inputs

	P_a	P_b^*	P_l^*	P_o
x_a	0.0420	-0.0219	-0.0067	-0.0133
x_b	-0.5247	0.2798	0.1212	0.1237
x_l	0.0463	-0.0348	-0.0755	0.0640
x_o	0.1504	-0.0584	0.1051	-0.1971

Note: The elasticities are calculated using R package “micEconSNQP”. The subscript a represents agricultural outputs; b denotes amount of collected biomass; l is labor inputs and, o refers to intermediate inputs.

It can be seen from Table 5 that all outputs and inputs are inelastic. The own-price elasticities of outputs indicate that if the weighted average price of agricultural products increases 1%, the agricultural outputs will rise by about 0.04%, whereas a 1% increase in the shadow price of biomass energy will increase the outputs of biomass collection by about 0.28%. Meanwhile, the own-price elasticities of inputs also suggest that a 1% increase in the shadow wage of household labor will decrease labor input for the productive activities by 0.08%, whereas a 1% increase in the weighted average price of intermediate inputs will reduce household demand for them by 0.20%. Considering the cross-price elasticities, the supply (agricultural products and biomass energy) cross-price elasticities are negative, revealing a competitive relationship between these two activities. In other words, an increase in price of either of the outputs leads more labor inputs to be invested in producing it, in turn, reducing the production of the other. This is also in line with the findings of our theoretical analysis in Section 2. Additionally, the cross-price elasticities for the inputs (labor and intermediate inputs) are positive, reflecting that the intermediate inputs such as fertilizers and pesticides are substitutes to labor-capital in our study region. This is to say, holding other variables constant, if the price of intermediate inputs increases, households will use less of them and simultaneously allocate more labor to production activities in order to keep the same quantities of outputs and vice versa. Moreover, if we compare the cross-price elasticities of intermediate inputs and labor (i.e. $\left|E_{x_o p_l^*}\right| > \left|E_{x_l p_o}\right|$), the labor-intensive feature of the production system in rural Sichuan Province is then confirmed. However, if we compare the own-price elasticities of the outputs with their cross-price elasticities respectively (i.e. $\left|E_{x_a p_a}\right| > \left|E_{x_a p_b^*}\right|$ and $\left|E_{x_b p_a}\right| > \left|E_{x_b p_b^*}\right|$), it demonstrates that both agricultural production and biomass collection are more likely to be driven by the market of agricultural products than the demand of biomass energy. Particularly, for agricultural production, the negative signs of the cross-price elasticities of outputs with respect to inputs are consistent with economic theory. In contrast, although fertilizers and pesticides are not directly invested in biomass collection, the positive signs of the cross-price elasticities to inputs imply that biomass collection is perhaps influenced by consumption decisions. When the price of other inputs increases, households have to spend more on purchasing them and cut down their expenditures on commercial energy under a given budget constraint. As the consequence, they collect more biomass for energy use to compensate for the consumption of commercial energy. On the other side, if the shadow wage increases, households will work on domestic production activities for longer duration instead of working off-farm, resulting in a decrease in their disposable incomes. Therefore, they have to use biomass as fuels to reduce the expense on commercial energy.

6. Conclusion

In this paper, we analyze the impacts of biomass collection on agricultural production in our study region. The results of our study show that the educational level of the household head, market wage rate and household location are key factors in determining household participation in these two activities. Households with higher educational level and market wage rate are less likely to engage in both of these two productive activities, while those located in plain areas are less likely to work on farm as well as to collect biomass. Particularly, an interesting result is that non-labor income level can significantly influence household participation decisions on agricultural production and biomass collection in opposite directions. An increase in household non-labor income decreases the likelihood to work on farm, while increasing household participation probability of biomass collection. A possible explanation for this is that the proportion of agriculture-related subsidies in non-labor income is quite small to encourage households to participate in agriculture production. Moreover, an increase in non-labor income could reduce household incentives to work for extra income, and therefore increase the time allocated to biomass collection.

More importantly, the estimation results of the SNQ profit function reveal that the supply cross-price elasticities of agricultural products and biomass energy are -0.02 and -0.52 respectively, confirming that the relationship between biomass collection and agricultural production is competitive. Specifically, biomass collection is likely to be driven by the markets of intermediate inputs. This also indicates that biomass collection could be influenced by household consumption decisions. It means that if the prices of intermediate inputs increase, households will cut down their expenditures on commercial energy to purchase more of them under a given budget constraint Therefore, they have to collect more biomass to meet their demands for energy. Moreover, we also found that higher shadow wage induces households to allocate more labor on farm instead of working outside, and hence decreases the disposable income that can be spent on commercial energy. Accordingly, biomass collection will increase.

One important implication of this study is that potential policy interventions for promoting biomass energy development in rural China could aim at enhancing food security by slowing down the competition between biomass collection and agricultural production. Simultaneously increasing the prices of agricultural products and decreasing the prices of intermediate inputs not only improve households' motivation of engaging in agricultural production, but also decrease biomass collection. Moreover, since non-labor income level is a crucial factor affecting household participation decisions on biomass collection and agricultural production, especially in mountainous areas, future policies should seek to establish a sound and effective subsidy system in rural areas by increasing the shares of agriculture-related subsidies, attempting to support agricultural production while reducing the probability of collecting biomass. Finally, indirect policy that improves household educational level should also be attached more emphasis in policy design. This could help to improve the efficiency and capacity of production.

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Annex

Table A1: Estimation Results of the normalized quadratic profit function with imposition of convexity

Parameter	Coef.[u]	T-Stat	Coef.[r]
α_a	37948.0339**	2.2065	50139.6383
α_b	-43.4072	-0.0365	1421.9070
α_l	-2104.5469	-1.1996	-4206.8905
α_o	-5585.7248***	-4.1370	-7045.2400
$\beta_{aa}(p_a p_a)$	-2202.7377**	-2.3939	2917.0882
$\beta_{ab}(p_a p_b^*)$	-1536.2492***	-2.7964	-1457.4017
$\beta_{al}(p_a p_l^*)$	2605.3060***	5.2161	-203.6292
$\beta_{ao}(p_a p_o)$	1133.6809**	2.4797	-1256.0572
$\beta_{bb}(p_b^* p_b^*)$	-429.1761	-2.7374	795.8768
$\beta_{bl}(p_b^* p_l^*)$	1146.4071***	6.2630	275.2318
$\beta_{bo}(p_b^* p_o)$	819.0182***	4.0979	386.2931
$\beta_{ll}(p_l^* p_l^*)$	-1648.3134***	-5.0531	458.5478
$\beta_{lo}(p_l^* p_o)$	-2103.3997***	-7.8839	-530.1505
$\beta_{oo}(p_o p_o)$	150.7006	0.5777	1399.9146
$\delta_{aAL}(z_{AL})$	6679.3614	1.3957	8125.4508
$\delta_{bAL}(z_{AL})$	42.7095	0.1323	182.6015
$\delta_{lAL}(z_{AL})$	-806.2899*	-1.6694	-1099.5683
$\delta_{oAL}(z_{AL})$	408.7647	1.1021	183.8917
$\gamma_{aALAL}(p_a z_{AL} z_{AL})$	-402.0526	-1.0679	-467.6394
$\gamma_{bALAL}(p_b^* z_{AL} z_{AL})$	6.5346	0.2597	0.1591
$\gamma_{lALAL}(p_l^* z_{AL} z_{AL})$	41.7793	1.1032	54.2255
$\gamma_{oALAL}(p_o z_{AL} z_{AL})$	-14.9734	-0.5167	-5.4900
Hausman test statistic	38.94***		
No. of Obs.	556		

Note: The system of SNQ profit function and netput equations are jointly estimated using R package "micEconSNQP". The significance levels are *10%, **5%, and ***1%. The missing dummy for regions is Hilly area. The superscript u refers to the estimated coefficients of unrestricted profit function, whereas r is those of restricted estimation. T-Stat refers to the estimate parameter to the left. Subscript a represents agricultural outputs; b denotes amount of collected biomass; l is labor inputs