Estimation of Shadow Wage in Agricultural Household Model in Nepal *

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Abstract

In developing countries, where most of the families work on their own farms, wage or labor-related income cannot be observed directly. This paper contributes to the literature on gender wage difference in labor and development economics by developing a new approach to estimate the shadow wage of agricultural households in Nepal. Using a general functional form, we first derive the shadow wage from a theoretical model. Then, ward-level fixed effect is used to estimate the shadow wage by gender for Nepalese agricultural households. We find that productivity of women is higher at the mean, median and 75th quantile than that of men. Despite their higher productivity, females are underpaid at the mean and median in the labor market compared to their marginal productivity, calling for greater investments to involve female in the production process.

JEL classification: C18, J43.

Keywords: Shadow Wage, Separability, Agricultural Household

*The data set was obtained from Central Bureau of Statistics of Nepal.

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1 Introduction

Agriculture plays an important role in developing economies in part because a significant portion of the workforce is self-employed in it. The dominance of self-employment in the absence of observable wage labor markets poses difficulties for policy analysis related to agricultural households, as the marginal productivity of labor becomes difficult to measure. For self-employed individuals, the shadow wage, or opportunity cost of time, is determined from household production. The shadow wage is equal to the market wage in a functioning labor market. The shadow wage can be estimated in the absence of functioning labor markets (when the separability hypothesis fails) (Jacoby, 1993; Skoufias, 1994). [1]. It is derived from the first-order condition of the agricultural household utility maximization problem after profit has been incorporated into the budget constraint. The estimation of shadow wage can help facilitate in the understanding of the value of contributions to household production when individuals do not participate in formal labor markets.

Gender plays an important role in labor markets of developing countries. A gender wage gap is common in developing countries as well as developed countries. Wages for women are 60-75% of men's wages for similar type of jobs. A major reason for the wage gap can be either biological or social factors (Aly and Shields, 2010). In developing countries, women's participation in agriculture is common. Women in developing countries are usually restricted to traditional gender roles due to socio-cultural factors and the absence of functioning labor markets. Bardhan and Udry (1999) point out the importance of labor in gender differences of wages and occupational segmentation of women. In a patriarchal society including Nepal, wages and jobs may be gender-specific. Men and women internalize these standards and help perpetuate disparities.

In Nepal, where men and women carry traditional gender roles, failing to account for household output can lead to an underestimation of the role of women in household productivity. Women supply more hours in household works such as cooking, fetching water, child care among other household tasks. Figure 1 shows distribution of hours supplied by men and women in household works in Nepalese agricultural households. In addition, women in agricultural households, who are both producers and consumers, also supply similar amount of labor on their own farm as shown in Figure 2. The estimation of shadow wage helps us analyze the productivity of individuals which can help in the understanding of gender productivity

[1]We have performed test for separability following Le (2010) and rejected separability hypothesis. The separability results are available upon request.

gap in production process of agricultural households. This paper contributes to the estimation of shadow wages in Nepalese agricultural households by applying the semi-parametric production function introduced by Le (2009). We estimate the structural parameters of agricultural household labor supply from estimated reduced form equations using the classical minimum distance estimation approach.

Jacoby (1993), Skoufias (1994), Abdulai and Regmi (2000), Carter and Yao (2002), Le (2009), and Barrett, Sherlund, and Adesina (2008) are a few examples of studies that have estimated shadow wage. Barrett, Sherlund, and Adesina (2008) estimate structural household labor supply models in the presence of unobservable wages and possible deviation(s) in the marginal revenue product of self-labor from their shadow wage. Carter and Yao (2002) estimate shadow wages in the presence of market failures in land rental markets to constrained non-participant sub-samples of households, i.e., non-participating households who are in the region restricted to participate in land rental market in China.

We identify the shadow wage of men and women in Nepalese agricultural households using a structural model that incorporates the models in Jacoby (1993). Jacoby (1993) uses a pair of labor supply equations along with a specific functional form to estimate the shadow wage. He uses instruments to correctly estimate the production function (Cobb-Douglas and translog) in order to avoid bias in estimated marginal productivity. The model in our paper uses a semi-parametric production function. The semi-parametric functional form is a novel approach as it relaxes specific functional forms such as Cobb-Douglas, translog or log-linear. Instead, it uses a more general functional structure to derive the shadow wage. Unlike Jacoby, who uses instrumental variables, we obtain consistent estimates of reduced form parameters by estimating ward fixed effects to control community level unobserved variables that influence shadow wage. We also employ household-specific proxy variables to control for the effects of household unobserved variables (Benjamin, 1992). We improve on Le (2009) theoretical approach to estimate the structural parameters without having to use iterative procedure that required arbitrary selection of starting values. The consistent reduced form estimates are then used to recover estimates of the structural parameters using the minimum distance estimation (Rothenberg, 1973). Estimates of shadow wages (in Table 6) shows the mean shadow wage of women is greater than the mean shadow wage of men. At the 75th percentile shadow wage of men is almost unchanged but that of women is closer to men. These differences provide evidence that female productivity should be acknowledged and supported for economic development.

We have 2 major contributions to the literature. (1) We improve the empirical model to estimate the marginal productivity of labor in agricultural households using structural model of labor supply. (2) We develop a model to understand contribution of household members in the production process and provide evidence of females are as productive or better than their male counterparts. Our results suggest a need to increase investment in female productivity to improve household welfare outcomes, which reaffirms with the suggestion made by Lundberg, Pollak, and Wales (1997).

2 Theoretical Model

The theoretical framework in this paper is based on a standard time-allocation model. A farm household maximizes a joint utility function defined over leisure (l), consumption (C) and a vector of preference shifters (A-demographic variables, m- males, f-females). Therefore, the agricultural household solves the following maximization problem:

$$\max_{C,l_m,l_f} U(C, l_m, l_f; A) \tag{1}$$

s.t. Full Income Budget Constraint (FIBC):

$$C + l_f w_f^* + l_m w_m^* = \Pi + Y + w_m M_m + w_f M_f + V(N_m, N_f; J). \tag{2}$$

where,

$$\Pi = pQ(L_m, L_f, z; F) - p_z z. \tag{3}$$

Total Time Available and Labor Supplied:

$$T_i = h_i + l_i \ \ \& \ \ h_i = L_i + M_i + N_i. \tag{4}$$

where, $U(.)$ and $Q(.)$ are quasi-concave utility and concave farm production functions. C is goods consumed either purchased in the market (c) or produced at home (v), i.e. $C = c + v$. Π is the profit from farm production; p is the price of farm output; w_m and w_f are market wages for male and female; p_z is the price of farm input z; M_m and M_f are time spent in the labor market by male and female; h_i is the total labor supplied by individual i; L_i is the labor supplied to own farm by individual 'i'; M_i is the labor supplied to the market; and N_i is the labor supplied to household production. F is quasi-fixed inputs such as land and machinery. $V(N_m, N_f; J)$ is the household production function with J being inputs such as electricity and refrigerator. Solving the utility maximization problem in equation 1 using constraints in equations 2, 3, and 4, the shadow wage is derived. The theoretical model is connected to the empirical model using shadow income and shadow wage which are derived using the semi-parametric production function in the utility maximization problem as the household members are both producers and consumers of produced agricultural products. The solution to this utility maximization problem gives us the optimal household labor supply function $h_i = h_i(w_m^*, w_f^*, y^*; A)$.

3 Empirical Model

3.1 *Estimation of Shadow wage*

Skoufias (1994) and Jacoby (1993) point out the shadow wage can be estimated even if there is an imperfection in the market as shadow wage is the marginal productivity of labor (MPL) at the optimal point on the production function. To determine the MPL, we define a semi-parametric production function, $\bar{Q} = L^{\lambda_L} f(z, F, \sigma)$, where f(.) is a non-parametric function, z includes all the inputs, F is the quasi-fixed input and σ is the stochastic component in agricultural production. This functional form is more flexible than Cobb-Douglas or translog functions, which are the most widely used forms in the literature.

In order to account for the differences in productivity between genders we modify $\bar{Q}$ and define it as:

$$\bar{Q} = L_m^{\lambda_m} L_f^{\lambda_f} z_1^{\lambda_1} f_1(z_2, F, \sigma) \tag{5}$$

where L_m, L_f are male and female labor respectively, z_1 is one variable input and z_2 is remaining variable inputs and f(.) is non-parametric function as shown above.

Define the production function as,

$$Q = \bar{Q} e^{\epsilon} \tag{6}$$

where ϵ is a random weather shock and $E(e^{\epsilon}) = 1$. Farmers do not know Q so their MPL is based on the expectation of Q.

$$MPL_i = p\frac{\partial E(Q)}{\partial L_i} = p\frac{\partial \bar{Q}}{\partial L_i} = p\lambda_i Q e^{\epsilon}/L_i \tag{7}$$

Also, from the utility maximization, the variable input z_1 is used until its marginal product is equal to price, i.e.

$$p_z = p\frac{\partial \bar{Q}}{\partial z_1} = \lambda_1 p\frac{\bar{Q}}{z_1} \tag{8}$$

Combining equations 7 and 8,

$$MPL_i \equiv w_i^* = \frac{\lambda_i z_1 p_z}{\lambda_1 L_i} \tag{9}$$

To estimate shadow wages, it is necessary to estimate the λ parameters. Shadow income can be defined as,

$$y^* = pQ(L_m, L_f, z; F) - p_z z + w_m M_m + w_f M_f + Y + V(N_m, N_f; J) \tag{10}$$

The shadow income in equation 10 has household production $V(N_m, N_f; J) = \delta_m N_m + \delta_f N_f$ and labor supplied to the farm. δ_m and δ_f are coefficients of efficiency for male and female. $E(Q(L_m, L_f, z; F)) = E(\bar{Q})$. $\bar{Q}$ is derived from equation 8. For household production, labor can be substitutable between male and female. Defining the household production function as a general production function, and using marginal productivity of labor, we can derive $V(N_m, N_f; J) = MPL_m N_m + MPL_f N_f$. We know $MPL_i = w_i^*$, regardless of market failure. The labor supply function can be defined as $h_i = h_i(w_m^*, w_f^*, y^*; A)$. The labor supply functions for econometric estimation are as follows:

$$h_m = \alpha_{m1} w_m^* + \alpha_{m2} w_f^* + \alpha_{m3} y^* + \alpha_{m4} A_m + \omega_m \tag{11a}$$

$$h_f = \alpha_{f1} w_f^* + \alpha_{f2} w_m^* + \alpha_{f3} y^* + \alpha_{f4} A_f + \omega_f \tag{11b}$$

The shadow wage is calculated by solving equations 11a and 11b by substituting w_i^* and y^* from equations 9 and 10. Dependent variables in regression equations 11a and 11b are total labor supplied by male (h_m) and female (h_f) in a household respectively. The distribution of dependent variable is presented in Figure 3.

3.2 *Reduced Form Solution Estimation*

Plugging equations 9 and 10 into equations 11a and 11b. We get,

Male equation in reduced form:

$h_m = \alpha_{m1}(\frac{\lambda_m}{\lambda_1}\frac{P_{z1}z1}{L_m}) + \alpha_{m2}(\frac{\lambda_f}{\lambda_1}\frac{P_{z1}z1}{L_f}) + \alpha_{m3}(\frac{P_{z1}z1}{\lambda_1} - P_z Z + Y + w_m M_m + w_f M_f + (\frac{\lambda_m}{\lambda_1}\frac{P_{z1}z1}{L_m})N_m + (\frac{\lambda_f}{\lambda_1}\frac{P_{z1}z1}{L_f})N_f + \alpha_{mi}Ai$

$h_m = \underbrace{\alpha_{m1}\frac{\lambda_m}{\lambda_1}}_{\beta 1}\frac{P_{z1}z1}{Lm} + \underbrace{\alpha_{m2}\frac{\lambda_f}{\lambda_1}}_{\beta 2}\frac{P_{z1}z1}{Lf} + \underbrace{\frac{\alpha_{m3}}{\lambda_1}}_{\beta_3}P_{z1}z1 - \underbrace{\alpha_{m3}}_{\beta_4}(P_z Z + Y + w_m M_m + w_f M_f) + \underbrace{\alpha_{m3}\frac{\lambda_m}{\lambda_1}}_{\beta_5}P_{z1}z1(\frac{N_m}{L_m}) + \underbrace{\alpha_{m3}\frac{\lambda_f}{\lambda_1}}_{\beta_6}P_{z1}z1(\frac{N_f}{L_f}) + \underbrace{\alpha_{mi}}_{\beta_7}Ai$

$$h_m = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + controls \tag{12}$$

Female equation in reduced form:

$h_f = \alpha_{f1}(\frac{\lambda_f}{\lambda_1}\frac{P_{z1}z1}{L_f}) + \alpha_{f2}(\frac{\lambda_m}{\lambda_1}\frac{P_{z1}z1}{L_m}) + \alpha_{f3}(\frac{P_{z1}z1}{\lambda_1} - P_z Z + Y + w_m M_m + w_f M_f + (\frac{\lambda_m}{\lambda_1}\frac{P_{z1}z1}{L_m})N_m + (\frac{\lambda_f}{\lambda_1}\frac{P_{z1}z1}{L_f})N_f + \alpha_{fi}Ai$

$h_f = \underbrace{\alpha_{f1}\frac{\lambda_f}{\lambda_1}}_{\delta 1}\frac{P_{z1}z1}{Lf} + \underbrace{\alpha_{f2}\frac{\lambda_m}{\lambda_1}}_{\delta 2}\frac{P_{z1}z1}{Lm} + \underbrace{\frac{\alpha_{f3}}{\lambda_1}}_{\delta_3}P_{z1}z1 - \underbrace{\alpha_{f3}}_{\delta_4}(P_z Z + Y + w_m M_m + w_f M_f) + \underbrace{\alpha_{f3}\frac{\lambda_f}{\lambda_1}}_{\delta_5}P_{z1}z1(\frac{N_f}{L_f}) + \underbrace{\alpha_{f3}\frac{\lambda_m}{\lambda_1}}_{\delta_6}P_{z1}z1(\frac{N_m}{L_m}) + \underbrace{\alpha_{fi}}_{\delta_7}Ai$

$$h_f = \delta_1 X_1 + \delta_2 X_2 + \delta_3 X_3 + \delta_4 X_4 + \delta_5 X_5 + \delta_6 X_6 + controls \tag{13}$$

3.3 *Structural Parameter Estimation*

The estimating equations are highly nonlinear in the structural parameters. A previous study (Le, 2009) proposes the nonlinear generalized method of moments estimation. However, the nonlinearities are so severe that it is difficult to achieve convergence of the nonlinear estimator. Le (2009) recognizes this convergence problem and implements an iterative estimation procedure that takes advantage of the reduced form equation, which is linear in its parameters, but the iterative procedure requires an arbitrary selection of starting values on each iteration.

Alternatively, estimating structural parameters is ideal for minimum distance estimation proposed by Rothenberg (1973). We adopt this estimation strategy that requires consistent estimation of the reduced form equation, followed by estimating of the structural parameters by minimizing the Euclidean distance between the unknown structural parameters and the estimated reduced form parameters. Derivation of structural parameters θ in our paper is depicted in Table 1.

The first challenge to identification is the consistent estimate of the reduced form parameters. The reduced form variables are complicated nonlinear functions of the data. Those functions almost certainly contain variables that are correlated with unobserved variables at the regional and household levels. Following Benjamin (1992), we control for unobserved regional variables by controlling for ward-level fixed effects. The ward is the smallest observed geographical identifier of the geographic region that households live in. The sampling scheme sampled multiple households in each ward.

In the absence of natural experiments or instruments satisfying exclusion to correct for household level unobserved variables, we employ imperfect proxy variables to mitigate the confounding effects of household level unobserved variables. Proxy variables must exhibit two properties, they must be correlated with unobserved variables, a property that cannot be verified. Second, they must be redundant in the estimation equation. That is, if we include proxy variables, a, in an estimation equation $E(y|x)$, then we must have:

$$E(y|x, u) = E(y|x, u, a)$$

That is the proxy variables must have no explanatory power after the control variables, x, and unobserved variables, u, are accounted for. Their only significance in the estimating equation is due to their correlation with the unobserved variables. The response variable in the reduced form equations is labor supply. The control variables include wage and income variables that are standard explanatory variables for labor supply. We control for demographic shifters such as number of adult males in the household, number of adult females in the household, number of children in the household. Age of the individual, age square, educational dummy variables are used as proxy variables to capture unobserved level effects such as ability, experience. We argue that these variables should satisfy the redundancy requirement of proxy variables. In the context of households in Nepal, after controlling for wages, income and demographic shifters the proxy variables should not have any independent effect on labor supply.

Thus, a consistent estimation of the reduced form parameters is accomplished with a combination of regional fixed effects and household-level proxy variables. The consistent reduced form parameters, $\hat{\beta}$, are used to recover structural parameters θ through the minimum distance estimation which can be considered a special case of nonlinear generalized method of moments. The minimum distance estimation requires that there be at least as many reduced form parameters as structural parameters, otherwise the structural parameters are not uniquely identified. In our model, the number of structural parameters equals the number of reduced form parameters, so we have exact identification. Given the mapping $f(\theta) = \hat{\beta}$ from structural to reduced form parameters, minimum distance estimation estimates structural parameters, θ by minimizing:

$$\left(f(\theta) - \hat{\beta}\right)' \hat{V}^{-1} \left(f(\theta) - \hat{\beta}\right)$$

where $\hat{V}$ is the variance-covariance matrix of the reduced form parameters.

4 Data

The data in this study come from the 2010 Nepal Living Standard Survey Phase III (NLSS III) which follows the Living Standards Measurement Survey (LSMS) methodology developed and promoted by the World Bank. The NLSS III contains a survey of 5,988 households from about 500 primary sampling units throughout the country. The survey covers both rural and urban areas of Nepal. We define a household as an agricultural household if (a) the household has non-zero revenue from crops or livestock, and (b) the household head's main occupation is agriculture even though the head can have multiple jobs.

The sample in the analysis consists of 9,844 individuals in 2,022 households after dropping households that do not match the definition of agricultural household above. In addition, households with missing fertilizer costs are dropped. Individuals with no own farm labor are also dropped from the analysis to reach the sample size used in our analysis. All the individuals in a household below the age of 14 are characterized as children. Table 2 depicts mean and standard deviation of variables used in the analysis.

5 Result

The reduced form estimates are obtained from equations 12 and 13 separately. The equations are estimated separately to satisfy the identification condition for minimum distance estimation. Joint estimation of equations will not satisfy this crucial condition for the minimum distance approach. The first columns of Table 3 and Table 4 are ordinary least squares (OLS) estimates of reduced form coefficients. The second column of Table 3 and Table 4 are fixed effect estimates with household proxies. The proxy variables strip out the marginal effects from unobserved attributes in significant ways. The reduced form estimates cannot be interpreted. The reduced form estimates are used to recover the structural parameters using minimum distance estimation. In Table 5, we show the structural parameters recovered from the reduced form model. These structural parameters are used to calculate shadow wage as shown in equation 9.

Estimates of shadow wage of male and female using λ values and the mean of the data are 267 and 331 rupees per hour respectively after controlling for ward-level fixed effects.[2] Table 6 shows the shadow wage by gender at each quantile of own farm labor distribution. Figure 4 presents the kernel density of shadow wage by gender showing close overlap in marginal productivity of male and female.

The shadow wage is calculated using equation 9 for male and female. We use λ_m and λ_1 from equation 11a to estimate the shadow wage for male in equation 9. Similarly, λ_f and λ_1 from equation 11b are used to estimate the shadow wage for female in 9. α_{m1} is the coefficient of male shadow wage in the male labor supply equation 11a while, α_{m2} is the coefficient of female shadow wage in the male labor supply equation 11a. The result from male labor supply equation 11a shows a reduction of 0.447 male hours per year with an increase in shadow wage by 1 rupee per hour. The coefficient of shadow income α_{m3} implies an increase of 0.0002 male hours per year. The change in the coefficient of female shadow wage in the male equation is not statistically significant. For the female labor supply equation 11b, the change in shadow wage of male α_{f2} is not statistically significant. The female α_{f1} shows a reduction of 0.795 female hours per year with an increase of 1 rupee per hour. The coefficient for shadow income α_{f3}, also positive, shows the increase of 0.0001 female hours per year. The similarity in marginal productivity of labor of male and female as depicted in Figure **??** implies that there can be significant increase in household productivity and labor market productivity by supporting investments to encourage female role in production process.

[2] 2011 Exchange rate: 1 USD = Rs (70 to 85) Central Bank of Nepal

6 Conclusion and Discussion

The shadow wage of males is lower than the shadow wage of females in agricultural households in Nepal, on average. However, the distribution shows the range in productivity is similar (Figure 4). The marginal increase in female labor to wage increase is significantly larger than the male marginal increase on the average and middle of the shadow wage distribution. Shadow wages have been measured with a semi-parametric household production function. One potential limitation of the estimates is the cross-sectional data. There may be time-varying unobserved heterogeneity that we cannot account for. We control for unobserved regional variables by performing fixed effects estimation at the ward level. There exists heterogeneity based on the labor supplied to own farm production among households. For the estimation of shadow wage, labor supplied in own farm plays a very important role in this framework. The result from this study suggests that females have a higher marginal productivity of labor in household production compared to the market wage received by them. The average market wage is higher for males than females but shadow wage shows that females have higher productivity than males. This finding suggests that females are underpaid in the labor market compared to their marginal productivity, calling for investment to encourage female production and to increase compensation for their work.

The method used in the paper can be applied to various outcomes where we cannot directly observe wage. This method can be used in studies to better understand the non-monetary labor contribution of members of the household. It can also be used to understand the productivity in informal labor markets. The estimates of shadow wage obtained can be used to determine household labor allocation in agricultural households as we cannot observe the market wages for families that work on their own farms. This paper provides a new method with much weaker functional form assumptions to estimate the shadow wage.

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Appendix

The maximization problem shown in equation 1 subject to 2, 3 and 4 are as follows:
$\max U(C, Tm - hm, Tf - hf; A)$ subject to

$$C = pQ(Lm, Lf, z; F) - p_z z + w_m M_m + w_f M_f + Y + V(N_m, N_f; K)$$

FOC: $\frac{\partial U_c}{\partial C} = \lambda$

$\frac{\partial U_{L_i}}{\partial L_i} = \lambda p \frac{\partial Q}{\partial L_i}$

$MPL \equiv \frac{\frac{\partial U_{L_i}}{\partial L_i}}{\frac{\partial U_c}{\partial C}} = p\frac{\partial Q}{\partial L_i} \equiv w_i^*$

Table 1: Structural parameters derived from reduced form parameters

θ	β
θ_1	$\frac{\beta_1\beta_4}{\beta_5}$
θ_2	$\frac{\beta_5}{\beta_3}$
θ_3	$\frac{\beta_3}{\beta_4}$
θ_4	$\frac{\beta_2\beta_4}{\beta_6}$
θ_5	$\frac{\beta_6}{\beta_3}$
θ_6	β_4

Table 2: Summary statistics

Variable	**Mean**	**Std. Dev.**
Male own farm work (Hrs/year)	2003.241	1923.01
Female own farm work (Hrs/year)	1911.345	1606.941
Male market work (Hrs/year)	844.303	1256.563
Female market work (Hrs/year)	247.667	635.087
Male household work (Hrs/year)	1938.552	1524.197
Female household work (Hrs/year)	4580.667	2541.809
Total labor supplied male (Hrs/year)	4786.096	2910.461
Total labor supplied female (Hrs/year)	6739.679	3407.724
Wage male (Rs/Hr)	189.816	562.612
Wage female (Rs/Hr)	45.861	106.12
Total input cost (Rs/year)	13971.459	23487.582
Cost of fertilizer (Rs/year)	3933.172	7697.805
Exogenous income (Rs)	6734.148	52965.297
Age	30.371	19.715
Household size	6.402	2.806
Adult male in HH	1.861	1.012
Adult female in HH	2.18	1.091
Number of children	2.36	1.807
Formal School (0= No,1 = Yes)	0.736	0.441
Primary School (0 = No, 1 = Yes)	0.215	0.411
Secondary School (0 = No, 1 = Yes	0.031	0.173
High School or More (0= No, 1 = Yes)	0.013	0.114
N	9884	

Table 3: Reduced form estimates for male equation

	(OLS) Hm	(Cluster) Hm
x1	-77.94***	-35.34***
	(13.82)	(7.810)
x2	-53.03***	-26.72***
	(7.031)	(4.577)
x3	34.57***	11.07***
	(2.941)	(1.753)
x4	0.192***	0.0907***
	(0.0248)	(0.0130)
x5	4.739**	7.172***
	(1.685)	(0.925)
x6	4.272***	0.519
	(0.693)	(0.481)
No. of Male		1655.3***
		(26.15)
No. of Female		5.272
		(24.45)
No. of Children		283.8***
		(14.86)
Age		5.414
		(3.946)
Age sq		-0.0439
		(0.0507)
Formal Education		-301.2
		(284.1)
Primary Education		-114.1
		(285.4)
Secondary Education		-146.0
		(302.6)
High School or more		-297.0
		(328.3)
Constant	4433.3***	1062.2***
	(40.98)	(300.5)
N	9884	9884
Fixed effect	No	Yes

Standard errors in parentheses

Table 4: Reduced form estimates for female equation

	(1)	(2)
	Hf	Hf
X1	-161.8***	-70.05***
	(13.55)	(6.399)
X2	-20.73**	-12.94*
	(7.643)	(5.085)
X3	29.79***	3.995*
	(3.061)	(1.975)
X4	0.0729***	0.0530***
	(0.0134)	(0.00795)
X5	11.87***	4.666***
	(1.052)	(0.490)
X6	-2.004	1.561
	(2.113)	(1.014)
No. of Male		-50.14
		(27.10)
No. of Female		1749.7***
		(27.68)
No. of Children		519.1***
		(16.18)
Age		6.964
		(4.470)
Age sq		-0.0649
		(0.0583)
Formal Education		-255.2
		(293.2)
Primary Education		-187.2
		(294.7)
Secondary Education		-126.7
		(309.5)
High School or more		-436.0
		(348.7)
Constant	6523.9***	1886.4***
	(41.92)	(309.4)
N	9884	9884
Fixed effect	No	Yes

Standard errors in parentheses

Table 5: Structural estimates for male and female equations using cluster estimation

	(Male equation 11a)	(Female equation 11b)
α_{i1}	-0.447***	-0.795***
	(0.096)	(0.130)
λ_i	0.648***	1.168
	(0.142)	(0.633)
λ_1	0.008***	0.013
	(0.002)	(0.007)
α_{i2}	-4.666	-0.439
	(3.765)	(0.283)
λ_{-i}	0.047	0.39
	(0.048)	(0.377)
α_{i3}	0.0002***	0.0001***
	(0.00004)	(0.00002)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

i - male or female -*i* female or male

Table 6: Shadow wage of male and female by quantile (Rs)

	Shadow Wage Male	**Shadow Wage Female**
mean	267.5835	331.7491
25th percentile	12.11489	10.7432
50th percentile	82.0831	86.66847
75th percentile	265.1669	281.9684
max	20959.62	18426.38

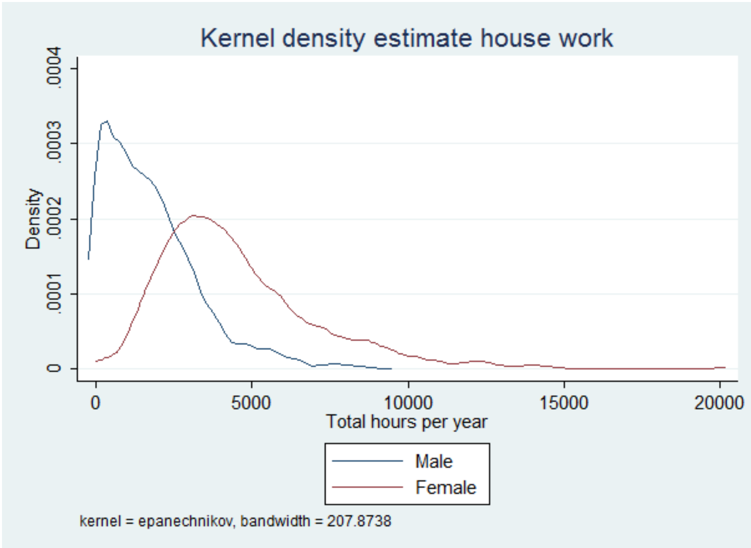

Figure 1: Hours supplied in house work by gender

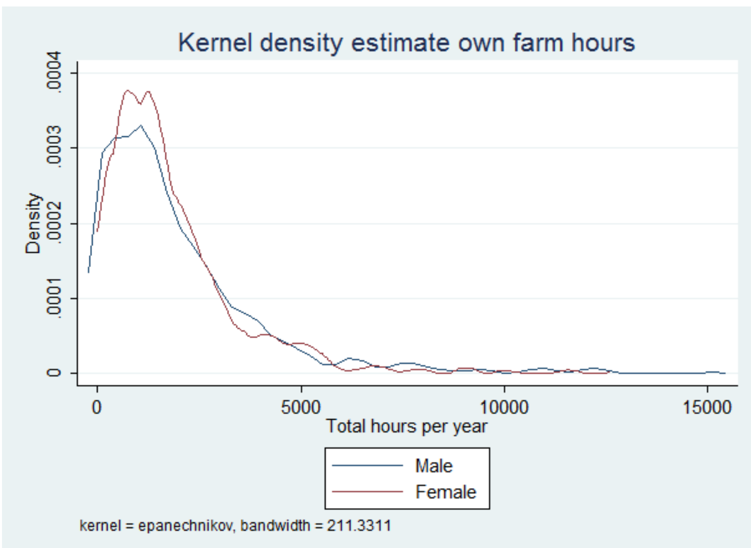

Figure 2: Hours supplied on own farm by gender

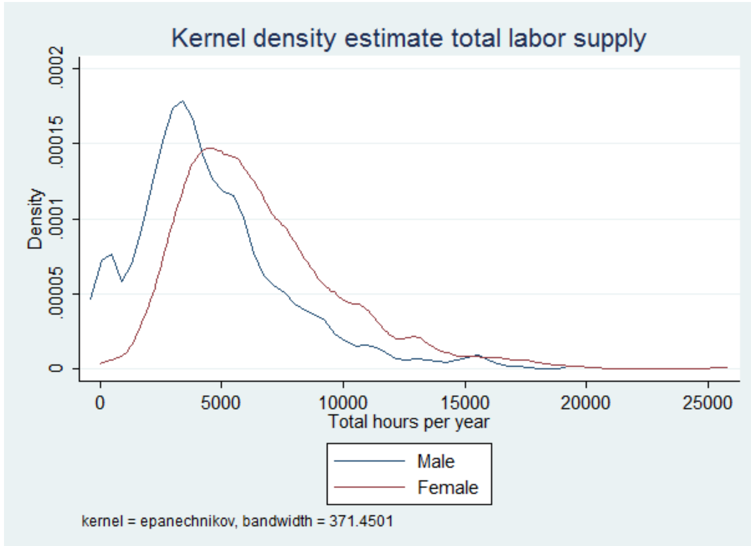

Figure 3: Household total labor supply by gender

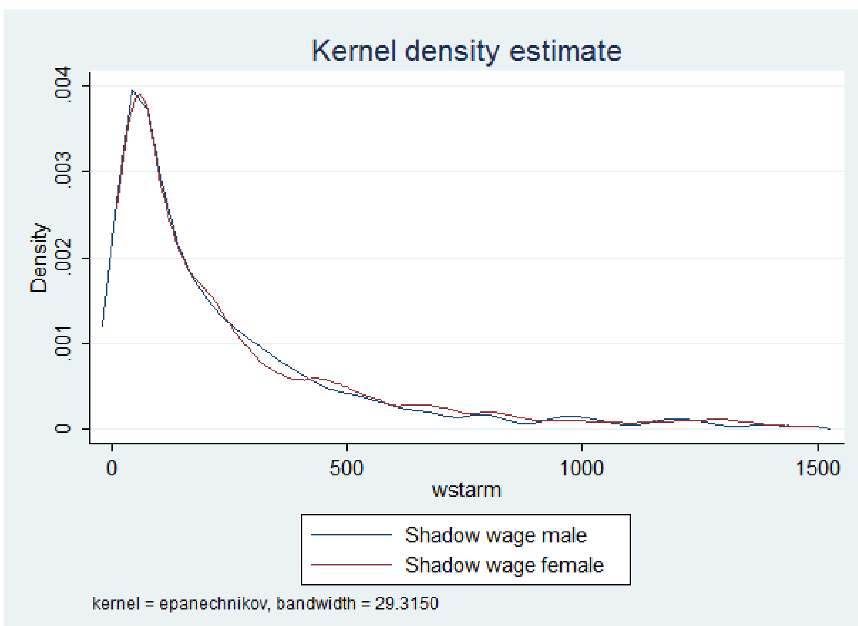

Figure 4: Kernel distribution of shadow wage by gender