Agricultural Mechanization and Non-Farm Labor Supply of Farm Households: Evidence from Bangladesh

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Abstract

This paper investigates the role of adoption of agricultural mechanization on the non-farm labor supply behavior of farm households using a longitudinal data set from Bangladesh. The paper uses an agricultural household model to establish the link between the labor-saving technology adoption decision and the non-farm labor supply behavior. To control for potential endogeneity between the farm mechanization and the non-farm labor supply behavior; we use bivariate probit model (BPM), endogenous switching probit model (SPM) and endogenous treatment effects (ETE) model. The results confirm that labor-saving technology adoption raises both the probability of participation in the rural non-farm sector and the labor-supply to the rural non-farm sector. The average treatment effects (ATE) on the probability of participation in the rural non-farm sector are 0.30 in the BPM and 0.21 in the SPM. The results from the ETE model also confirm that the farm households double their labor supply in the rural non-farm sector, given the adoption of labor-saving technology. (JEL: J22, Q12, Q16)

Key Words: Agricultural Mechanization, Farm Households, Non-Farm Labor Supply

I. Introduction

Economic opportunities in the rural non-farm (RNF) sector have long been recognized as an integral part of rural livelihoods in developing countries (see Lanjouw and Lanjouw, 2001; Lanjouw and Feder, 2001). The RNF sector is an important source of employment in many countries, and it has been a key driver of overall economic development in many East Asian economies (Lin and Yao, 1999; Lanjouw and Lanjouw, 2001; McCulloch et.al., 2007). It is also evident that non-farm income is critical to the welfare of rural households in developing countries (Rosenzweig, 1988). In many developing countries, a considerable portion of farm households earn income from non-farm sources, and income from the non-farm sources constitutes between 20% and 70% of total household earnings (Adams, 2002; Newman and Gertler, 1994; Reardon et al., 2000; Rizov et al., 2000). It is not required to be a skilled worker to engage in non-farm economic activities and the unskilled labor is the primary source of non-farm earnings for the poorest and subsistent African farmers, who often earn a significant share of their income from the non-farm sources (Barrett, Reardon, & Webb, 2001; Reardon, 1997).

The importance of the RNF sector as a source of employment, and as a driver of rural economic growth and poverty reduction is growing all over the developing world. For example, in Bangladesh, growth in rural non-farm income accounted for almost 40 percent of poverty reduction between 2000 and 2005, while growth in farm income contributed about 21 percent only in the same period (World Bank, 2013). In Bangladesh, the rural non-farm sector is no longer viewed as "residual" sector, and it remains a persistent employment source of half of the rural workforce since the mid-1980s (Sen, 1996; World Bank, 2016). The extremely narrow scope for expanding agricultural land, the growing and more educated labor force, and increasing demand for non-farm goods and services all imply that future economic development policies in densely populated developing countries will focus to ensure robust growth of the RNF sector.

Despite the structural changes in most developing economies, the labor force has not moved out of agriculture as rapidly as expectedly. Successful movement of surplus labor from agriculture to the advanced sector has long been considered to be an important feature of economic development. Labor migration from the rural farm sector to the advanced urban sector has been analyzed for many countries and at many points of time (see Lewis, 1954; Harris and Todaro, 1970). However, extraordinary agricultural growth following the '*green revolution'* and exciting development of physical infrastructure (e.g. roads and highway, bridges) and communication technology (e.g. cell phone, the internet, etc.) have expanded the non-farm sector significantly beyond urban areas. The clear demarcation between the urban advanced sector and the rural farm economy is disappearing fast in many developing countries. Thus, farm household members can work both in the farm sector and the non-farm sector simultaneously; and working in the non-farm sector does no longer require the farm household to move its working members in the urban areas permanently or temporarily. A farm household may relocate its labor endowment between the farm and the non-farm uses through its optimization behavior as an economic agent. Individual from a farm household may work in the non-farm sector as part-time work or full-time employment. As an agricultural economy experiences significant shocks and readjustment, relocation patterns of a farm household's labor endowment are critical characteristics of rural labor market development and this issue has drawn attention from many economists (see Sumner, 1982; Huffman, 1991).

A number of theoretical and empirical literature has investigated how a farm household may relocate its labor hours among the farm, and the off-farm uses through optimization behavior (Sumner, 1982; Huffman, 1991; Mishra and Goodwin, 1997; and Goodwin and Holt, 2002). Much of the focus in the earlier literature on the off-farm labor supply of farm household has been, however, on modeling and examining the off-farm labor supply effects of farming efficiency and farm income volatility. A similar question involves the extent to which off-farm labor supply of farm household changes may occur in response to agricultural mechanization due to the adoption of labor-saving technology. Despite its importance to the development process, the economic literature has not devoted sufficient attention to the joint analysis of farm households' labor supply decision in the non-farm sector and the technology adoption decision.

The poverty outcomes and agricultural productivity outcomes of agricultural modernization have been studied extensively in the literature on agricultural mechanization (see David & Otsuka, 1994; deJanvry & Sedoulet, 2002; Evenson & Gollin, 2003; Minten & Barrett, 2008). Despite some earlier studies focused on the effects of agricultural mechanization on employment and wage earnings of the poor and tenant farmers (Binswanger and Braun, 1991, The Nuffield Foundation, 1999, Minten & Barrett, 2008); the general labor market responses of farm households due to agricultural mechanization have been overlooked in the relevant literature. Farnandez-Cornezo et.al. (2005) finds positive off-farm income effects of herbicide-tolerant soybeans adoption by farm households. However, the technology of the herbicide-tolerant soybeans is not a labor-saving technology in the strict sense; it reduces management time. Ahituv and Kimhi (2002) finds that farm capital investment reduces the farm households' participation in the off-farm employment opportunities, implying that family labor and farm capital are complements in agricultural production.

Agriculture in most developing countries is going under significant structural transformation over the last few decades. Developing nations, except the nations in Sub-Saharan Africa, have adopted labor-saving agricultural technologies at an unprecedented level. Intensification of production system has created power bottlenecks around the land preparation, harvesting and threshing operations even in the densely populated Asian countries and this power bottlenecks are alleviated with the adoption of labor-saving agricultural technology which in turn raises agricultural productivity and reduces the per-unit cost of crop production (Pingali 2007). Tractors number in India rose from 0.19 per 1000 hectares in 1961 to 9 per 1000 hectares by 2000 (Pingali, 2007).Mandal (2002) estimates that, in Bangladesh, around 150,000 power tillers have been imported annually since liberalized import policies took place in the mid-1990s.

Mechanization has often been considered by the critics as detrimental for densely populated “labor surplus” countries as negative agricultural employment effects of mechanization in terms of displacement of labor and tenant farmers. If the argument is true, then what are the rationales of rapid mechanization of the power-intensive operations even in the Asian countries with high population densities and low wages such as India, Bangladesh and the Philippines (Herdt, 1983, Pingali and Binswanger 1987). Existing evidence indicates, however, mechanization of power-intensive operations, water lifting, tillage, milling, etc., have minimal labor displacement effects (Pingali 2007). On the other hand, Hormozi et al. find a strong positive correlation between agricultural mechanization and technical efficiency of rice producers. The productivity effects of agricultural mechanization can come from three sources: yield changes, area expansion, and labor-savings. The evidence presented in the literature indicates that, for power-intensive operations, generally no significant yield difference exists between the animal draft and the tractor tillage (Herdt, 1983 and Binswanger, 1978). If we find no yield differences between animal draft and tractor farms, we must conclude that the transition to tractor-drawn plows is rarely motivated by improvement in tillage quality. Area expansion and/or labor saving must be the driving forces for such a transition. The scope of expanding the area under cultivation in the densely populated country is extremely narrow which is clearly indicated by the tiny amount of arable land per agricultural worker (for example, 0.26 hectare per worker over 2006–2011 in Bangladesh, according to FAO).

The evidence presented in the literature indicates that, for power-intensive operations, the productivity benefits of mechanization consist mainly of labor savings. Pingali, Bigot, and Binswanger (1987) reviewed 24 studies on labor use of farm households, and twenty-two of the 24 studies reviewed reported lower total labor use per hectare of crop production for tractor farms compared to draft animal farms. Twelve studies reported reductions in labor use of 50% or more. The greatest reduction in labor use was for land preparation, and labor used for land preparation was reduced by 50% or more. These results indicate that labor savings resulting from the transition to tractors are confined mainly to land preparation. A natural question follows that what has been the use of those “saved labor” through agricultural mechanization? The answer to this issue has only been hypothesized in the relevant literature by pointing the finger towards non-farm use.

Excellent non-farm employment opportunities may induce farm households even in densely populated countries with land scarcity to mechanize farm operations. Cultivators became prevalent in Japan during the late 1950s, when agricultural wages rose sharply in response to high labor demand from post-war industrialization (Ohkawa, Shinohara, and Umemura, 1965). In recent decades, fast growing south Asian countries like Bangladesh and India have shown a similar trend and experienced significant rural labor market tightening with a pronounced increase in rural real wages (Hnatkovska and Lahiri, 2013; Hossain et al. 2013). The use of labor-saving technology (e.g. tractors, threshers, etc.) in agriculture and the rapid expansion of the non-farm sector have created a scope for farm households to release their underemployed labor time in the agricultural sector for higher productive off-farm works in the non-farm sector.

This chapter focuses on this issue and examines whether the agricultural mechanization could induce farm households to participate and to supply more labor hours in the non-farm sector. Existing literature about the farm household’s multiple job-holding has evolved mainly in the USA and in other developed countries (see Goodwin and Holt, 2002; Goodwin and Mishra, 2004). Research on multiple-job holding by farmers in low-income countries, to our knowledge, is scarce. Moreover, the off-farm labor supply effects of the labor-saving technology adoption by farm households remains less studied in the relevant literature. This chapter uses a unique longitudinal survey data set from rural Bangladesh to investigate the role of the labor-saving technology adoption in farm production on the non-farm labor supply decisions of farm households. An agricultural household model with the off-farm labor supply is used to establish the relationship between the labor-saving technology adoption and the off-farm labor supply decisions of farm households through the elasticity of substitution between labor and capital in agricultural production.

The increase of market-based rentals of agricultural technology in Bangladesh brings the benefit of modern technology within the reach of the subsistence farm households. For example, about 89 percent of farm households use tractor or power tillage for land preparation in agricultural production, while only 5 percent farm households own a tractor/power tiller. This structural shift has changed the input ratios used in farm production. Tractor/power tillage is regarded as labor-saving technology and the use of tractor/power tiller reduces the labor requirement in land preparation and thus releases extra labor hours of farm households. Thus, the joint analysis of agricultural households' decisions regarding the adoption of labor-saving technology and the off-farm labor supply will add additional knowledge to the relevant literature. The adoption of mechanized technology raises agricultural productivity which in turn increases returns to time employed in farming. Thus, an income effect could increase the farm operator's leisure time while a substitution effect could raise the time used in farm production. Due to subsistence nature of farming in developing countries and extremely low arable land per capita, the scope of raising work hours in the farm sector is somewhat limited for most farm households. Thus, the farm operator may supply labor hours in the non-farm sector as long as returns from the non-farm sector are higher than the opportunity cost of leisure time. Through this dynamics, the adoption of mechanized technology in farming could lead to a higher supply of labor hours into the non-farm sector by a farm household.

The population density in Bangladesh is the highest in the world and the challenge to agricultural livelihoods is clearly indicated by the tiny amount of arable land per agricultural worker (0.26 hectare per worker over 2006–11, according to FAO). Certainly rural farm households need to diversify their income sources and livelihood strategies, not only to manage risks but to ensure more rapid income growth. The evidence suggests that such diversification is well underway in Bangladesh (Sen, 2003 and World Bank, 2016) While absolute and functionally landless households depend on rural non-farm economy greatly for their survival, farm households are also increasingly engaging in non-farm economic activities to diversify risks of farm income volatility due to price shocks and production loss, and to smooth consumption in the lean season.

The main objective of this study is to explore the impact of agricultural mechanization on the labor supply behavior of farm households. The specific objectives are: to examine the off-farm participation effects of the adoption of labor-saving farm technology and to examine the off-farm labor supply effects of the labor-saving technology adoption. The chapter looks at the joint decisions of the off-farm labor supply and the labor-saving technology adoption of farm households using primary data obtained from a nationally representative longitudinal survey data for the years of 2000, and 2008[1].

The rest of the chapter is organized as follows. Following the introductory discussions in section 1.1, Section 1.2 outlines the conceptual and theoretical framework. While Section 1.3 describes the econometric model employed for estimation; section 1.4 presents and discusses data source, sampling strategy and summary results. Section 1.5 presents the results of econometric models and the analysis of the results. The chapter ends with the concluding remarks anddd policy implications in section 1.6.

II. Theoretical Model

The chapter uses the agricultural household model, developed by Singh et al., 1986; and modified by Sadoulet and deJanvry, 1995; to establish the relationship between the labor-saving technology adoption decision and the off-farm labor supply decision through the elasticity of substitution between labor and capital in farm production. Goodwin and Holt

[1] For detail survey results and sampling strategy, see Hossain and Bayes (2009).

(2002) and Fernandez-Cornezo et.al. (2005) modified this agricultural household model to study the off-farm labor supply decisions of farm households in Bulgaria and the USA respectively. We use the Goodwin and Holt (2002) and Fernandez-Cornezo et.al. (2005) version of the agricultural household model with the introduction of the agricultural technology adoption decision into the production techniques to identify the off-farm labor supply function of farm households. The significant deviation from the earlier works (such as Goodwin and Holt (2002); and Fernandez-Cornezo et.al. (2005)) is that we treat farm household as an economic agent instead of farm operator. Since the independence among individuals within the same households could be hardly assumed and household member's economic decisions are jointly determined. Labor supply decisions of rural farm households in developing countries, however, are governed by the household's utility maximization problem which is subject to the constraints on total time endowment, income, and farm production technology. Households' members are assumed to receive utility from a vector of members' leisure and non-economic activities at home (l), a vector of purchased goods (q), and a vector of household characteristics (z)-such as human capital, age, household size that are exogenous to household's decisions. Farm households maximize utility, U, subject to income, technology and time constraints. The agricultural household utility function can be modeled as

$$U = U(q, l; z) \tag{1}$$

Where U is assumed to have usual regularity properties of utility function such as twice differentiability, quasi-concavity and increasing in q, l, and z. Farm households generate utility from consumption of good q, from leisure l which includes home time as well, and from other household characteristics, z, such as human capital, age, household size and so on. The model assumes that marginal utility of consumption good and leisure approaches to infinity as consumption goes to zero which ensures that a positive amount of consumption good and leisure are always consumed.

The objective of the farm household is to maximize utility from the consumption of goods and leisure subject to the farm production, income and time constraint. The income, farm production technology and time constraints can be represented as

$$p_c q + rX(T) = p_f Q + wM \quad \{\text{Income constraint}\} \tag{2}$$

$$Q = Q\{X\,(T), F(T), D)\} \quad \{\text{Technology constraint}\} \tag{3}$$

$$H = M + F(T) + l \quad \{\text{Time constraint}\} \tag{4}$$

(2) is the household's income constraint where p_c is the consumer price of q, p_f is the unit price of output, w is is wage rate for non-farm works, X is vector of other inputs such as land, capital, fertilizers, etc.; and r is the column vector of prices of inputs in X. M denotes the labor time spent in the off-farm works. Unlike Goodwin and Holt (2002) and Fernandez-Cornezo et.al. (2005), we exclude income from other sources (e.g. capital gains, interest income etc) in income constraint, as income from other sources is rare among Bangladeshi farm households. Farm income depends on the price of agricultural output, p_f; on input prices, r; and on the amount of time spent on farm works, F.

Equation (3) represents household's technology constraint where F is labor time devoted to the farm and T stands for the labor-saving technology adoption decision of farm households. The adoption of labor-saving technology reduces the labor requirement in farm production. Thus, the adoption of agricultural technology should be incorporated into the production technology implicitly, not as a shifter of the production function. D is a vector of exogenous factors that shift Q. The production technology is assumed to have all the regularity conditions such as twice differentiable, increasing in inputs etc.

Equation (4) is the time constraint of the agricultural household. Each household has a fixed amount of time, H, which is allocated among farm work, off-farm work and leisure. This agricultural household model assumes that marginal productivity of farm labor approaches to infinity while on farm work is zero, implying interior solution of the model, $F > 0$. However, off-farm labor works, M, could be zero as well, $M \geq 0$.

Plugging 3 into 2, we combine the technology and the income constraint into the following constraint:

$$pq + rX(T) = p_f Q(X(T), F(T), D) + wM + A \tag{5}$$

Now we can solve the agricultural household model given the differentiable utility function and $\lambda\ and\ \mu$ as the Lagrange multipliers of the income and the time constraints respectively:

$$L = U(q,l,d) + \lambda\left[p_f Q(X(T),F(T),D) + wM + A - pq - rX(T)\right] + \mu[H - M - F(T) - l]$$

The Kuhn-Tucker first-order conditions are:

$$\frac{\partial L}{\partial q} = U_q - \lambda p = 0 \tag{6}$$

$$\frac{\partial L}{\partial l} = U_l - \mu = 0, \tag{7}$$

$$\frac{\partial L}{\partial T} = \lambda\left[p_f\ \left\{\left(\frac{\partial Q}{\partial X}\right) * \left(\frac{\partial X}{\partial T}\right) + \left(\frac{\partial Q}{\partial F}\right) * \left(\frac{\partial F}{\partial T}\right)\right\}\right] - r\left(\frac{\partial X}{\partial T}\right) - \mu\left(\frac{\partial F}{\partial T}\right) = 0 \tag{8}$$

$$\frac{\partial L}{\partial X} = \lambda[\ p_f \frac{\partial Q}{\partial X} - r] = 0 \tag{9}$$

$$\frac{\partial L}{\partial F} = \lambda\, p_f\ \frac{\partial Q}{\partial F} - \mu = 0 \tag{10}$$

$$\frac{\partial L}{\partial M} = \lambda w - \mu \leq 0, \quad M\ (\lambda w - \mu) = 0 \tag{11}$$

$$\frac{\partial L}{\partial \lambda} = p_f Q(X(T),F(T),D) - wM + A - pq - rX = 0 \tag{12}$$

$$\frac{\partial L}{\partial \mu} = H - M - F(T) - l = 0 \tag{13}$$

Given the positive amount of labor supply to off-farm works, an interior solution occurs and equation (10) and (11) hold with equalities. From equation (10) and (11), we can reach to a familiar condition

$$p_f\ \frac{\partial Q}{\partial F} = w \tag{14}$$

The marginal value of the farm labor must be equal to the off-farm wage rate. Solving equation (6) (7) and (11) would give us another familiar condition

$$\frac{U_q}{U_l} = \frac{p}{w} \tag{15}$$

The condition in (15) implies that the marginal rate of substitution between consumption and leisure should be equal to the ratio between the price of consumption good and the wage rate.

When interior solution occurs, and equations (9) and (10) can be solved independently to obtain farm labor demand as optimal consumption and production decisions can be separated because the value of the household's time is determined by the off-farm wage rate ($w = \frac{\mu}{\lambda}$) (Huffman, 1991).

Solving the model, we could find following on-farm labor demand functions and input demand functions:

$$F^*=F(r, w, p_f, T, D) \tag{16}$$

$$X^*=X(r, w, p_f, T, D) \tag{17}$$

Substituting these optimal input demand functions into the technology constraint (3) would give us optimal output as following:

$$Q^*=Q(r, w, p_f, T, D) \tag{18}$$

Solving jointly equations (6) (7) (12) and (18), household's optimal amount of leisure demand and consumption good can be derived as followings:

$$l^*= l(r, w, p_c, p_f, T, D) \tag{19}$$

$$q^*=q(r, w, p_c, p_f, T, D) \tag{20}$$

Plugging optimal leisure hours and on farm labor demand into the time constraint, the derived supply of off-farm labor (Huffman, 1991) is following:

$$M^* = H - F^* - l^*$$

$$=M(r, w, p,\ p_f, T, D,\ z) \tag{21}$$

Given the total amount of labor endowment of a farm, the adoption of labor-saving technology in agricultural production is expected to raise the supply of labor into the RNF sector.

To estimate both the participation and the labor supply effects of the labor-saving technology adoption, we estimate two simplified reduced from participation and labor supply equations rather than estimating a structural model of labor supply[2]. The theory suggests that all exogenous variables affecting the marginal value of time in any activity should be included in these equations.

III. Empirical Specification

To estimate the impact of the agricultural mechanization on farm households' off-farm labor supply decisions, we adopt a simple reduced form model to identify the role of agricultural technology adoption on the participation and the labor supply decisions of farm households towards the off-farm employment opportunities. To estimate the non-farm participation effects of the labor-saving agricultural technology adoption, we use following regression specification based on the theoretical background in the preceding section:

$$P_{it} = \alpha + \beta X_{it} + \delta Z_{it} + \rho_t + \varepsilon_{it} \tag{22}$$

Where P_{it} denotes the participation/labor supply of i^{th} household in the RNF sector at year, t. X_{it} is a vector that includes number of variables representing households and workers characteristics. Z_{it} attributes household's agricultural technology adoption status. Year specific effects are represented by ρ_t, while ε_{it} stands for idiosyncratic normally distributed error terms.

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[2] Mishra and Goodwin (1997) and Goodwin and Holt (2002) also estimated a simplified reduced from model rather than estimating structural model of labor supply.

Two separate versions of the model (22) need to be used to estimate the effects of the adoption of labor-saving technology adoption by the farm households on their off-farm labor supply decisions. The first version would model the participation decision while the second set would model the magnitude of labor supply to the off-farm works. An ordinary least square (OLS) estimation of linear probability model (LPM) or the maximum likelihood estimation of Probit of equation (22) can estimate the impact of the technology adoption on the non-farm participation decision. Similarly an OLS or the maximum likelihood estimation of endogenous treatment effects (ETE) of equation (22) can estimate the impact of the technology adoption on the extent of non-farm labor supply. The participation decision model of equation (22) can be presented as follows:

$$P_{it}^* = \alpha + \beta X_{it} + \delta Z_{it} + \rho_t + \varepsilon_{it} \tag{23}$$

Where $P_{it}^* \geq 0$ if $P_{it} = 1$

$P_{it}^* < 0$ if $P_{it} = 0$

Where P_{it} stands for the NFP decision (Probit). P_{it}^* is a latent variable which is unobserved if P_{it}^*<0.

The labor supply decision model of equation (22) can be presented as follows:

$$P_{it} = \alpha + \beta X_{it} + \delta Z_{it} + \rho_t + \varepsilon_{it} \tag{24}$$

Where P_{it} stands for the labor supply decision.

Estimation of the impact of the technology adoption on the participation and the labor supply behavior of farm households, however, presents some difficulties. When the unobserved households' characteristics (e.g. skill and abilities of workers) are correlated with both the off-farm work decision and the technology adoption decision may produce 'spurious' correlations and may give biased estimates of the effects of the technology adoption on the off-farm participation decision. Moreover, farm households with partially or fully involved in the non-farm sector can adopt labor-saving technology to substitute the forgone labor hours that are supplied to the non-farm sector. Thus, the OLS regression of the off-farm work decision on the technology adoption decision might be capturing the positive "effect" of ‘reverse causality’. Though the workers’ schooling may capture their capacity and skill to some extent; it is, in general, not possible to control for all such potential confounding factors in a regression specification, and thus regression results without taking care of endogeneity may be misleading. To control for the possible endogeneity between the technology adoption decision and the off-farm labor supply decision, instrumental variable (IV) approach is used to estimate the relevant models of equation (23) and (24).

For participation equation, the study follows three standard econometric methods; namely, the instrumental variable (IV) approach; the bivariate probit model (BPM) and the endogenous switching probit model (SPM). While IV approach with binary dependent variable may encounter the limitations of a linear probability model (LPM), the IV version of LPM model facilitates several tests to examine the validity of the relevant instruments, and we expect the validity tests of instruments are not to be troubled by the limitations of LPM in the IV model. However, main results regarding the non-farm participation effects of the labor-saving technology adoption are drawn from the BPM and the SPM, which are particularly designed for dealing with a binary dependent variable with endogenous dummy treatment variables. Both the BPM and the SPM rely on normality assumptions. The SPM, however, is more efficient as it relaxes the assumption of equality of coefficients of the participation equation in two regimes. We have estimated both models for two reasons. First, the BPM provides average marginal effects (hereafter, AME) of all the covariates in the participation equation along with the average treatment effects (hereafter, ATE) of the technology adoption; while retrieving marginal effects for all the covariates is a cumbersome process in the SPM. Second, the SPM provides regime specific coefficients for all the covariates which help to get an idea about regime specific role of covariates, while the BPM assumes equality of coefficients in the participation equation across the regimes. Moreover, estimating both models helps us to check the robustness of the estimates of ATE.

For labor supply equation, for the same reasons, we follow two standard econometric approaches as well; namely, the instrumental variable (IV) approach; and the endogenous treatment effects (ETE) model. Although the use of a linear IV model with an endogenous dummy regressor is inefficient, we use this model to check the validity of instruments. Given the binary nature of the endogenous regressor that represents the labor saving technology adoption decision, the ETE model is the most efficient one to estimate the labor supply effects of the technology adoption in farm production. The ETE model also allows censoring the observation for which the non-farm labor supply is not observed.

We have used pooled random correlated effects model for each specification to get the "fixed effects" estimate for variables that vary over time and across households and to avoid the problem of "incidental parameter problem". Though the use of Fixed Effect model would be ideal, fixed effects models suffer the '*incidental parameter problem'* and exclude the variables that don't vary over time. Thus, correlated random effects (CRE) estimation of the model mentioned above is a suitable option (Wooldridge, 2013). The CRE approach usually provides the Mundluck estimates .

Identification Strategy

The initial challenge to establish the causal impact of the technology adoption decision on the non-farm participation decision is the possibility of unobserved characteristics of farm households which simultaneously affect their non-farm participation decision and their technology adoption decision. For example, farm households with educated working members may participate in the non-farm sector more to diversify their earning sources and adopt modern technology in agricultural production to substitute their forgone labor hours. A simple comparison between the percentages of non-farm participation among the technology adopter farm households and the non-adopter farm households would overstate the non-farm participation effects of the labor-saving technology adoption. Alternatively, small or marginal farm holding may not be appropriate for the use of labor-saving technology and may not participate in the rural non-farm sector due to labor constraints, leading to a 'spurious' negative relationship between the non-farm participation decision and the technology adoption decision of farm households. Therefore, the direction of selectivity bias is theoretically uncertain.

We, therefore, use village level average rainfall in the previous ten years, the presence of operating land with clay loam soil, and operating land with very high level of elevation as instruments for the likelihood of a household's adoption of tractor or power tiller for land preparation in farm production. Higher rainfall makes the tillage process easier and induces farm operators to rely less on mechanized tillage (as it has cost implication) and to use family labor and cattle/bullocks. Land with clay loam soil is difficult for tilling and thus induces farm operators to use mechanized tillage. Therefore, a household with the land of clay loam soil is 3 percent more likely to use mechanized tilling compared to a household without the land of clay loam soil. Land with high elevation is close to homestead land and thus induce households not to use hired mechanized tillage, and use family labor and cattle/Bullock for tilling instead. Thus, farm households that operate land with high elevation are less likely to adopt the mechanized tillage. Thus, the use of rainfall, soil quality, and land elevation are valid candidates for the instrument of the mechanization decision.

Our identification strategy is that all these instruments, apart from their influence through the households' tractor/power tiller use, do not affect the non-farm participation decision of a farm household. Instrumental variable estimation relies on this exogeneity assumption and. Thus, the validity of the instruments is crucial for reliable estimates. One potential threat is that rainfall in a village might influence the farm productivity which in turn affects the non-farm participation decision which in turn affect the technology adoption decision. Considering this possibility, we control for the farm productivity by incorporating gross margin in farm production of each farm households. The validity of the instruments has been checked as well, and the instruments have passed all the relevant tests for weak identification and over-identification.

IV. Data and Summary Statistics

The data for this study are drawn from a unique longitudinal survey of a nationally representative sample of rural households in Bangladesh. The survey spanned about two decades (1988-2008) and was conducted to assess changes in rural poverty and livelihoods in response to technological progress, food price hike, etc. The baseline survey was administered by the Bangladesh Institute of Development Studies (BIDS) in 1988[3]. It included 1,240 rural households from 62 villages in 57 out of 64 districts in Bangladesh for the study the impact of technological progress on income distribution and poverty in Bangladesh (Hossain et al. 1994; Rahman and Hossain 1995). The households were revisited in 2000, 2004, and 2008. However, in this paper, we could access only data for 2000, and 2008 and, therefore, this study limits its analysis in 2000 and 2008. The sample size in the repeat surveys of 2000 and 2008 were 1880 and 2010, respectively. The information is collected through a semi-structured questionnaire designed to gather information on demographic details, land use, costs of cultivation, livelihoods, farm and non-farm activities, commodity prices, ownership of non-land assets, income, expenditure, and employments. In addition to these data, the dataset provides extensive details of the farms characteristics, including details on soil type, elevation, irrigation sources, and tenurial arrangements, among others.

To study the off-farm labor supply effects of agricultural technology adoption using a panel survey, I need to look at the problem of the splitting of households, as it makes it difficult to compare the households' performances over time. Splitting of households is a very common scenario in rural Bangladesh, especially after the death of household head, typically the father. Thus, the splitting of the household has serious implication for land and other non-land asset endowments. Among the original 1880 sample households that were surveyed in 2000, 1598 households (about 85 percent) remained intact throughout the period of 2000-08. Thus, the split of the households and the attrition due to migration occurred at a rate of nearly 1.9 percent per year for the period of 2000-08. Among the 1598 intact households, we use 852 sample households in our analysis as the rest of the households were not involved in farm production in either 2000 or 2008[4].

[3] The benchmark survey used a multistage random sampling method. The sample size has been adjusted in each round of survey to make the sample representative to the rural population for the survey year. In the first stage, 64 unions were selected randomly from the list of all unions. In the second stage, one village was selected from each of the unions that best represented the unions in terms of population density, land distribution and literacy rate. Two villages were later excluded for the difficulties administering survey in those villages due to their remoteness. A census of households was conducted in the selected villages to stratify the households according their land ownerships, land tenure and literacy.

[4] The inclusion of the ''split households'' creates difficulties in estimating changes in the asset base of the household crucial to the application of the livelihood framework attempted in this paper. Given the focus of the

The main advantage of the 62-village panel survey over repeated cross-section (such as HIES or LFS) is to track the employment status of the same household over time. Looking at the multiple cross-section surveys (for example HIES, LFS), little movements of rural labor forces between the farm sector and the non-farm sector are observed. Between 2000 and 2010, the share of the RNF sector in total rural employment has been increased by only one percent, from 44.5% in 2000 to 45.5% in 2010 (BBS, 2013). This number based on the repeated cross-section surveys shows that the net movement of the rural workforce between the farm and the non-farm activities and often fails to capture the ultimate employment dynamics in rural Bangladesh. Analysis of labor supply decision of farm households based on longitudinal data is thus not just about capturing employment trends; it enables us to look beyond mere statistical aggregates and shed light on causalities of long-run employment patterns. The panel waves capture the decision-making moments of the same households over time. This leads to better understanding of the possible policy support necessary to further support the movement of rural workforce towards better the non-farm opportunities.

The panel nature of the data allows us to identify several ‘‘dynamic employment’’ groups on the basis of their diverse movements in and out of the non-farm sector. For the purpose of analyzing employment dynamics, we have generated two group of households based on their work status. Sample farm households that remain exclusively in farming (all the working members of a household are involved in agricultural activities only) are categorized as ‘*farm only'*; while the farm households that engage in non-farm activities (if any of working members of the household are involved in any kind of non-farm activities)[5] are considered as ‘*non-farm participant'*. Patterns of participation in the non-farm sector and its transformation over time are presented in Table 1.

Table 1 reveals a strong mobility between the farm sector and the non-farm sector throughout the period of 2000-08. A significant portion of sample households moves back and forth between the ‘*farm only'* status and the ‘*non-farm participant'* status throughout the period

present paper on understanding the ‘‘drivers of change’’ with respect to those who participated in non-farm sector and those who didn’t participated, the exclusion of the split households would not make a critical difference.

[5] Farm activities include farming, fishing, poultry and livestock rearing, forestry and agricultural wage labor. Non-Farm activities include transportation, services and entrepreneurships.

of 2000-08. During the period 2000 to 2008, there are 338 households, 39.7 percent of the total sample of 852 households, who remained in '*farm only'* status throughout the period. On the other hand, there are 212 households, 24.9 percent of the total sample, remained as '*non-farm participant'* throughout the period (Table 1). The other two categories indicate the changing employment patterns, one group participated in the non-farm activities, while the other pulled themselves out of the non-farm activities and backed to the '*farm only'* status. While 133 households, 15.6 percent of 852 households, joined in the non-farm economic activities; 169 households, 19.8 percent of the total sample, moved out of the non-farm activities in the same period.

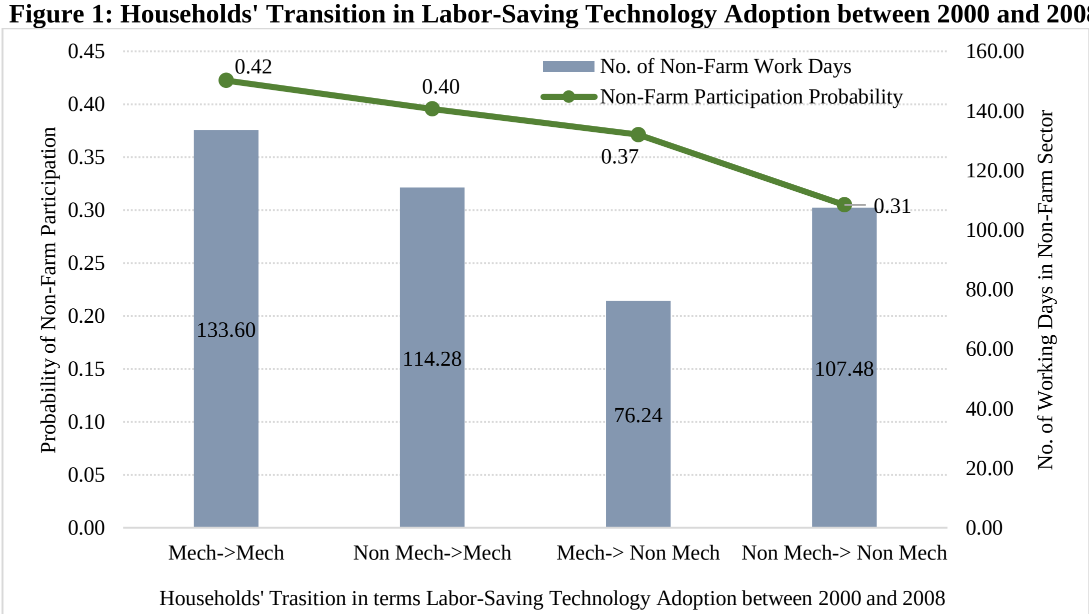
Two immediate observations follow from the above discussion. First, gross movements of the rural workforce between the farm and the non-farm activities are much larger than the net changes in the sectoral employment trends over time. Second, it is important to study the drivers of change underlying the movements of rural households between the farm and the non-farm activities to understand better the causes of movements of rural workforce towards the non-farm economic opportunities, respectively. Studying these movements provides deeper insights into the mechanisms that boost the participation of rural households to the non-farm sector, and avenues for attacking the underemployment of family labor in farm production in developing countries, than merely studying the characteristics of the non-farm participants over time.

Table 1: Transition between work statuses

			Work status in 2008		
			Work only on-farm	**Worked off-farm**	**Total**
	Work only on-farm	N	338	133	471
		Percent	39.67	15.61	55.28
Work status in 2000	Worked off-farm	N	169	212	381
		Percent	19.84	24.88	44.72
	Total	N	507	345	852
		Percent	59.51	40.49	100

Figure 1 relates the labor-saving technology adoption decision with the non-farm participation decision of farm households. The probability of participating in the rural non-farm sector is the highest (0.42) for households that remained adopter of the agricultural technology throughout the period between 2000 and 2008; while the probability is lowest (0.31) for households that remained non-adopter of agricultural technology throughout the same period. The likelihood of the non-farm participation is also higher for households that changed their status from the non-adopter of agricultural technology in 2000 to the adopter in 2008 compared to that of the non-adopter in 2008. The bar chart also shows that households that adopt the labor-saving agricultural technology work more in the non-farm sector compared to households that do not adopt the labor-saving agricultural technology. Farm households that remained adopter of agricultural technology between 2000 and 2008 worked on average 133 days in the rural non-farm sector; while households that didn't adopt the labor-saving technology in land preparation in the same period worked on average 107 days in the rural non-farm sector. Households those moved from the non-adopter status to the adopter status regarding agricultural technology adoption in land preparation between 2000 and 2008 work on average 114 days in the rural non-farm sector. On the other hand, households that were the adopter in 2000 and the non-adopter in 2008 work the lowest (only 76 days) in the rural non-farm sector.

Figure 1: Households' Transition in Labor-Saving Technology Adoption between 2000 and 2008



Source: Author's Calculation

Summary statistics of the key variables are provided in Table 2. It is evident from the Table 2 that age of household head is increasing over time regardless of the sector of employment. Households with more working members, higher family size, and greater female labor force participation are more inclined to participate in the rural non-farm sector. This statistics imply that households with more working members are likely to diversify their employments out of agriculture. As expected, schooling helps rural households to move out of farming and to get in the non-farm sector opportunities. While average schooling years was around four years through the period between 2000 and 2008 for households working only in on-farm; the matched figure was around five years for the same period for households that participated the non-farm sector.

The likelihood of non-farm participation of rural farm households is found to be sensitive to the initial asset position, e.g. the amount of land owned (Table 2). For the period, 2000 to 2008, the proportion of households that participated in the non-farm sector remained almost stagnant for the marginal/small and large landowner category, declined for the medium landowner category, and increased for the absolutely/functionally landless households. The propensity of NGO membership was higher among the non-farm participant households compared to the farm only households. The difference was about 10 percent throughout the period between 2000 and 2008. The returns from agricultural land and family labor (proxied by gross margin of farm production) were slightly lower in 2000 for households with the non-farm participation than the households with farm only status. However, the gross margin of agricultural production for the non-farm participant households were 30 percent higher in 2008 compared to that of the farm only households. Land fragmentation often is to blame as a source of inefficiency in farming as high land fragmentation requires more labor time as it is time-consuming to travel between plots. Here we find that land fragmentation was higher among the farms households that remained exclusively in farming in both years.

Table 2 also presents summary statistics for the instruments used in the estimation. The rainfall was usually lower for households that participated in the RNF sector. The proportion of farm households with clay loam land was higher among the participant households compared to the non-participant households. The propensity of land with high elevation was greater among the farm only status farm households compared to the non-farm participant households in 2000, and the propensity got reversed in 2008.

Age of farm household head may represent a general experience that increases the marginal value of time in each activity, and younger household heads are expected to participate in the non-farm sector more and thus the sign of the age variable is expected to be negative. Having more than one working member in the family may have a positive effect while larger household size may have either positive or adverse effects on the off-farm labor supply decisions. Female labor force participation is also expected to have the positive effect of the non-farm labor supply decision. Educational qualification of farm operators may affect positively to work in the off-farm sector. Land ownership may be negatively related to the off-farm labor supply decision of households. Having less land may require less labor in farming which in turn induce the farmer to work in the off-farm sector. Both the land fragmentation and the gross margin from farming are expected to have adverse effects on the non-farm participation of farm households.

The propensity of participation in the RNF sector is also found to be associated with households' technology adoption, as the propensity of technology adoption is higher among the non-farm participant households. The adoption rates are 63 percent and 88 percent among the households with '*farm only'* status in 2000 and 2008 respectively; while the matched figure are 69 % and 91 % among the non-farm participant households in 2000 and 2008 respectively.

Table 2: Descriptive Statistics of the covariates

Variables	Households with farm only workers 2000	2008	Households with both farm and non-farm workers 2000	2008
Mean age of household head	45.14	48.61	46.38	50.67
Mean household size	5.54	5.06	6.27	5.95
No of adult working member (% of households)				
One working member	64.10	64.89	49.87	39.13
Two working member	21.66	23.47	25.98	31.88
Three or more working member	14.23	11.64	24.15	28.99
Female worker in household (% of households)	2.55	6.71	5.25	13.62
Land ownership (% of households)				
Abs/functionally landless (<0.4 ha)	47.77	52.86	50.39	52.46
Marginal/small landowner (>=0.4 ha & <1.0 ha)	28.03	29.59	23.10	23.19
Medium landowner (>=0.1 ha & <2.0 ha)	16.99	13.02	16.80	14.49
Large landowner (>=2.0 ha)	7.22	4.54	9.71	9.86
Average schooling years of workers	4.03	3.91	4.64	5.80
Mean gross margin per hectare (in thousand Tk. In 2008 prices)	32.83	69.92	31.91	89.98
Mean of land fragmentation index	0.58	0.54	0.56	0.50
Proportion of NGO member households	0.21	0.32	0.31	0.42
Proportion of households that adopt tractor in land preparation	0.63	0.88	0.69	0.91
Mean annual rainfall (in mm) in the last ten years	1530	1532	1512	1522
Proportion of households with clay loam land	0.25	0.30	0.29	0.33
Proportion of household with high land	0.54	0.32	0.47	0.34

V. Results and Discussions

5.1. Participation Equation

This section presents the results from the estimation of the participation equation. First, an instrumental variable (IV) model is used, despite its limitation with the use of binary outcome variable, to examine the validity of the relevant instruments. The estimates from both stages of IV, first and second, along with many other test statistics are reported in Table 3. The endogeneity of the technology adoption decision needs to be checked, and both the Durbin's score statistics and the Wu-Hausman test reject the hypothesis that the technology adoption decision of a farm household is exogenous to the off-farm participation decision of that household. For validity of instruments for an endogenous regressor, instruments need to pass the orthogonality condition that instruments are orthogonal to the outcome variable. All three instruments pass the Sargan's orthogonality test as the test statistics fail to reject the null hypothesis of orthogonality of instruments to the non-farm participation decision. Besides being orthogonal to the outcome variable, instruments also need to be correlated with the endogenous regressor. The null hypothesis of an instrument's redundancy has been rejected for each instrument in LR IV redundancy tests for instruments. The instruments pass all the necessary tests (e.g. under identification test, weak identification test, and over-identification test) for being validity instruments of endogenous regressor.

Although the explanatory variables from the outcome equation are mostly statistically insignificant in the first stage regression of determining the technology adoption decision, all the instruments are statistically significant. A 1 percent more rainfall reduces the probability of the technology adoption by 0.3. All the relevant tests (Hausman, Wu-Hausman, Durbin (Score) confirm the presence endogeneity between the non-farm participation decision and the technology adoption decision of farm households. The F-stat at the first-stage regression also passes the 'more than 10' rule of thumb implying that the excluded instruments are valid and significantly relevant. We have implemented the Montiel-Pflueger robust weak instrument test as the large values of effective F statistic in the Montiel-Pflueger test corresponds to small values of the approximate asymptotic bias (Pflueger and Wang, 2014).

All instruments pass the test as the effective F statistic at 5% confidence level, 18.33, is well above the generalized two-stage least square (TSLS) critical value at 5 % worst case bias, 13.42. Thus, the use of rainfall, soil quality, and land elevation as instruments for the adoption of tractor/power tiller in land preparation does not suffer the usual weak instrument problems.

The results in the second stage indicate that the adoption of labor-saving tillage system raises the probability of non-farm participation by 0.45. Thus, the impact of technology adoption on the non-farm participation of farm households is quite high. As we are aware of the limitations of LPM, we should use these results with caution. Despite all predicted probabilities remained within the band of unity, the disturbances were not homoscedastic. Thus, the coefficients are presented in Table 3 are unbiased but not consistent. To overcome this consistency problem, we use probit model with robust standard errors.

Table 3: IV estimates and the results of the tests of validity of the instruments

	Instrumental variable (IV) 2SLS model			
	Non-farm participation equation		Mechanization equation	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Mechanized (yes=1)	0.457***	(0.175)		
Age of household head	-0.001	(0.002)	-0.001	(0.002)
Household size	0.019**	(0.008)	0.009	(0.006)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.096**	(0.037)	-0.048	(0.031)
Three adult workers	0.148**	(0.063)	-0.052	(0.050)
Female participation in labor force (yes=1)	0.089*	(0.053)	0.017	(0.036)
Log (total schooling years of workers)	0.012*	(0.007)	-0.006	(0.006)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.017	(0.039)	0.019	(0.030)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.020	(0.049)	0.003	(0.040)
Large landowner (>=2.0 Ha)	0.105	(0.068)	0.063	(0.053)
NGO membership (yes=1)	0.119***	(0.025)	-0.019	(0.022)
Log (gross margin of farming in 2008 Tk.)	0.009	(0.014)	-0.004	(0.011)
Fragmentation Index	-0.124	(0.079)	0.118	(0.067)
Year dummy (2008=1)	-0.172***	(0.054)	0.245***	(0.023)
Correlated effects	Yes		Yes	
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.302***	(0.052)
Any cultivated land with clay loam soil? (yes=1)			0.037***	(0.021)
Any cultivated land with very high elevation? (yes=1)			-0.056***	(0.021)
Constant	0.399***	(0.130)	2.718***	(0.388)
Wald chi2(21)	209.17***			
F(23, 1667)			10.63***	
R-squared	0.0214		0.1244	
Observations	1691			

Under identification tests (Ho: Model is under identified)
Anderson canon. corr. likelihood ratio stat Chi-sq(3) =54.87 (p=0.000)
Weak identification statistics: (Ho: Instruments are weak)
Cragg-Donald (N-L)*minEval/L2 F-stat = 18.33 (p=0.00)
Partial R-squared of excluded instruments: 0.0319
Test of excluded instruments: F(3, 1667) = 18.33 (p=0.000)
Tests of over-identifying restrictions
Sargan (score) chi2(2) = 1.60299 (p = 0.4487)
Basmann chi2(2) = 1.58838 (p = 0.4519)
Tests of endogeneity: (H0: mechanization is exogenous)
Durbin (score) chi2(1) = 5.24525 (p = 0.0220)
Wu-Hausman F(1,1668) = 5.19001 (p = 0.0228)
C statistic (exogeneity/orthogonality of suspect endogenous variable) Chi-sq(1)= 5.245 (p=0.022)
LR IV redundancy tests for instruments: (Ho: Instrument is redundant)
Rainfall: Chi-sq(1) =37.66***; Soil Quality: Chi-sq(1) =2.85*; and Land elevation: Chi-sq(1) =7.56**
Sargan's Orthogonality tests for instruments: (Ho: Instrument is orthogonal to the outcome variable)
Rainfall: Chi-sq(1) =1.20; Soil Quality: Chi-sq(1) =0.241; and Land elevation: Chi-sq(1) =0.802
IV heteroskedasticity test(s) using levels of Its only: (Ho: Disturbance is homoscedastic)
Pagan-Hall general test statistic : Chi-so(23)=36.026 (p=0.041)

Note: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As the IV estimation of Probit model is not a valid approach with a endogenous dummy covariate, the BPM and the SPM are used to estimate the off-farm labor supply effects of the technology adoption decision. The bivariate Probit helps to get the average marginal effects of each covariate along with the average treatment effects (ATE). On the other hand, endogenous switching probit allows estimating regime-specific coefficients of covariates in the participation equation. Results from the BPM are presented in Table 4; while Table 5 presents the results from the SPM.

Average marginal effect of the technology adoption on the non-farm participation has been decreased to 0.31 in the BPM from 0.45 in the IV approach. In the BPM, endogeneity issue between the technology adoption decision and the non-farm participation decision has been controlled through instrumenting the technology adoption decision. The goodness-of-fit test prefers the BPM over the separate Probit equations as the Wald test for $\rho = 0$ has been rejected at the 10 percent significance level, where ρ stands for the correlation coefficient between the residuals in the equations and ρ equals zero implies that the model is consist of two independent probit equations which can be estimated separately. The significant ρ implies that the exogeneity assumption cannot be met. The second goodness-of-fit test is Murphy's score test[6] which embeds bivariate normal distribution within a wide family of distributions by adding more parameters to the model and tests whether the additional parameters are all zeros using the score for the additional parameters at the BPM estimates. Despite the over rejection tendency of the Murphy's score test, we fail to reject the Murphy's score test at a 5% significance level using asymptotic chi-square critical values[7] which indicates that the BPM model fit well to the data. Specifically, the score test result indicates that the assumption of bivariate normal distribution of the error terms, which underlies the bivariate probit model, holds.

[6] For detail about this test, see Chiburis et.al. (2011).
[7] Despite Murphy (2007) suggested bootstrapping the critical values, Chiburis et.al. (2011) finds that the asymptotic critical values work well enough even for small sample.

The results from the technology adoption decision have been discussed first, and the discussion on the results of the participation equation follows. The instrument variables for the technology adoption decision of farm households have come out strongly significant. The probability of adoption of labor-saving technology decreases by 0.28 for a 1 percent increase in the average rainfall of last ten years. Having a plot with clay loam soil enhances the likelihood of mechanization by 5 percent; while the ownership of plot with high elevation reduces the probability of technology adoption by 4 percent. Among other explanatory variables from the outcome equation, only fragmentation index has come out weakly statistically significant with positive coefficient in the adoption equation.

Most marginal effects in the participation equation appear statistically significant with the expected signs. The average marginal effect of mechanization on the probability of non-farm participation of a household is 0.32 implying that households that adopt labor-saving technology in farm production are 32 percent more likely to participate in the non-farm sector. The average treatment effect (ATE) is 0.30 and the average treatment effect on the treated (ATT) is 0.29. Both the ATE and the ATT appear statistically significant with positive signs. Bootstrapped standard errors with replications of 500 and clustered household IDs are used to determine the significance of the treatment effects. The results confirm that the labor-saving technology adoption raises the probability of participation in the non-farm sector.

Among other covariates, demographic variables, human capital assets (average years of schooling of adult workers in the family) and NGO membership matter for non-farm participation mostly. Physical assets endowment (e.g. land ownership) weakly matters for the non-farm participation of farm households as only the large farmers are more likely to participate in the non-farm sector. Age of household head appears with a negative sign implying that the younger household heads are more likely to participate, but the magnitude was not statistically significant. After controlling for the number of adult workers in the family, the household size captures the impact of dependency ratios on the participation status of farm households. We find that increased household size also pushes households to participate in the non-farm sector significantly. Farm households with two adult workers and with three plus adult workers are more likely to take part in the non-farm sector by 8 percent and 12 percent respectively. Extra working member in a farm household creates scope for that household to diversify income sources out of agriculture. Table 2 shows that the number of working members has been increased for rural farm households for the period between 2000 and 2008, and households with a higher number of working members are more engaged in the non-farm sector compared to their counterparts. Having female workers in the family is also positively associated with households' likelihood to participate in the non-farm sector. The presence of an active female worker in a family can raise the probability of participation to the non-farm opportunities by 8 percent. Thus, bringing half of total adult population (women) into the workforce could boost the labor supply for the non-farm sector.

Human capital assets, which are proxied by the average years of schooling of working members in the family, expectedly raise the likelihood of households' participation in the non-farm sector. A 1 percent increase in human capital assets could enhance the probability of participation of a household by 1.1 percent. Thus, overall improvement of educational attainment of the rural workforce could lead to a higher level of non-farm participation of the rural workers. Farm households' land ownership does not matter much as a driver of non-farm participation. Only the large farm households are 10 percent more likely to participate in the non-farm sector compared to the marginal farm households, though the magnitude is weakly significant. Gross margins, a proxy of the returns to land and family labor in agricultural production, and the land fragmentation index also appear statistically insignificant; though the land fragmentation index appears with expected negative sign.

The NGO membership of a household raises the probability of non-farm participation of that household by 11 percent. This result confirms that participation in microfinance programs raises the likelihood of involvement in the non-farm sector which is a major goal of microfinance institutions in Bangladesh.

Table 4: Bivariate probit model (BPM) marginal effects estimates

	Bivariate probit model			
	Non-farm participation equation		Mechanization equation	
	Marr. Eff.	Std. Err.	Marr. Eff.	Std. Err.
Mechanized (yes=1)	0.316***	(0.112)		
Age of household head	-0.001	(0.002)	-0.001	(0.002)
Household size	0.019**	(0.008)	0.008	(0.006)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.081**	(0.033)	-0.047	(0.030)
Three adult workers	0.122**	(0.055)	-0.046	(0.048)
Female participation in labor force (yes=1)	0.082*	(0.046)	0.029	(0.039)
Log (total schooling years of workers)	0.011*	(0.006)	-0.006	(0.006)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.011	(0.034)	0.022	(0.030)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.019	(0.044)	0.012	(0.038)
Large landowner (>=2.0 Ha)	0.104*	(0.062)	0.077	(0.055)
NGO membership (yes=1)	0.109***	(0.025)	-0.016	(0.021)
Log (gross margin of farming in 2008 Tk.)	0.007	(0.012)	0.002	(0.011)
Fragmentation Index	-0.103	(0.068)	0.105*	(0.063)
Year dummy (2008=1)	-0.134***	(0.036)	0.234***	(0.021)
Correlated effects	Yes		Yes	
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.281***	(0.046)
Any cultivated land with clay loam soil? (yes=1)			0.051**	(0.022)
Any cultivated land with very high elevation? (yes=1)			-0.041**	(0.020)
Constant				
/athrho	-0.428*	(0.264)		
rho	-0.404	(0.222)		
Wald test of rho=0: chi2(1)		2.615*		
Murphy's score test for biprobit chi2(9) =		9.6 (p-val=0.383)		
Average treatment effects (ATE)	0.298**	(0.119)		
Average treatment effects on the treated (ATT)	0.285***	(0.109)		
Observations		1691		

Both the BPM and the SPM rely on normality assumptions. The SPM, however, has many advantages over the BPM: it relaxes the assumption of equality of coefficients of the non-farm participation equations in two regimes and thus it is more efficient than the BPM. Due to regime-specific coefficients, we can observe the relative role of explanatory variables in two different regimes. The differences between the coefficients of two regimes are noteworthy. Most covariates appear statistically insignificant in explaining the participation of households in the non-farm sector. Only higher dependency ratio, represented by the household size, could induce households that do not adopt the labor-saving technology to participate in the non-farm sector.

The SPM is implemented using the *Stata*'s switch_probit module developed by Lokshin and Sajaia (2011) and the results from the SPM is reported in Table 5. The Wald test for independent equations has been weakly rejected, and the joint maximum likelihood estimation of participation equation and technology adoption equation is valid. The significant negative value of rho1 implies that the unobservable that affects households' technology adoption decision are negatively associated with the unobservable that affects households' participation in the non-farm sector. Therefore, estimating a simple probit model to estimate the non-farm participation effects of technology adoption would lead us to a bias and inconsistent results, and thus the use of SPM is a valid approach.

The instruments to be appeared statistically significant in the selection equation. While the rainfall and the land elevation reduce the probability of the adoption of power tiller or tractor in land preparation, the land with clay loam soil induces the likelihood of technology adoption of farm households in agricultural production. Land fragmentation increases the probability of the adoption of labor-saving technology as scattered land holdings require more family labor time for land preparation and, thus, it might induce farm households to use rented power tiller or tractor in land preparation. In the relevant literature, it is often argued that farm operators' education helps in quick agricultural technology adoption, but the results indicate that the schooling of working members is not an important driver for the technology adoption of the rural farm households. The size of the landholding also appears statistically insignificant as a driver of the technology adoption, though it is often argued that large farm households are more inclined to adopting the modern agricultural technology.

Overall the non-farm participation effects of households' observable characteristics, particularly the land endowment, the human capital endowment and the connectivity status; varies significantly across the regimes. Having a large family boosts the non-farm participation more for households that do not adopt mechanized land preparation than that of the households' that have mechanized its land preparation for farm production. On the other hand, having an extra worker in the family leads technology adopting households more to participate in the non-farm sector compared to that of farm households that do not adopt mechanized land preparation in farming. Female participation in the labor force induces the non-mechanized households more to participate in the non-farm sector than the mechanized households, though it appears statistically insignificant in both regimes. Both the schooling and the NGO membership matter for the non-farm participation of farm households with technology adoption. A 1 percent increase in human capital assets of agricultural households increases the probability of involvement in the non-farm sector by 3.3 percent; while the NGO membership of farm households increases the likelihood by 34 percent. The land fragmentation also behaves differently in the non-farm participation decision based on the households' adoption status of the labor-saving technology. For the adopting farm households, doubling land fragmentation index reduces the likelihood of non-farm participation by 39 percent. It is evident that small, medium and large land owner households participate in the non-farm sector equally with the marginal landowner households irrespective of their adoption status of power tiller/ tractor.

Overall, the average treatment effect (ATE) has been decreased to 0.21 in the SPM from 0.30 in the BPM. The ATEs from both the SPM and the BPM differs much with the ATE from IVREG which is expected as the linear probability instrumental variable regression, when applied to estimation of the binary choice models with binary endogenous covariate, perform poorly in cases of extreme probabilities of participation in the selection groups; in the analysis here, the proportion of households with the non-farm participation is 0.49, and the proportion of households with the mechanization is 0.88 (Altonji, Elder, and Taber, 2005).

Table 5: Endogenous Switching Probit Estimates

	Endogenous Switching Probit Model					
	Mechanized households		**Non-mechanized households**		**Mechanization equation**	
	Coeff.	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Age of household head	0.003	(0.006)	-0.019	(0.012)	-0.002	(0.006)
Household size	0.032	(0.023)	0.161***	(0.059)	0.028	(0.025)
Labor endowment dummies (ref: single working member)						
Two adult workers	0.248**	(0.107)	0.154	(0.221)	-0.179	(0.114)
Three adult workers	0.413**	(0.172)	-0.083	(0.365)	-0.166	(0.187)
Female participation in labor force (yes=1)	0.160	(0.149)	0.668	(0.504)	0.087	(0.164)
Log (total schooling years of workers)	0.033*	(0.020)	0.045	(0.043)	-0.023	(0.021)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))						
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.026	(0.109)	-0.096	(0.217)	0.087	(0.114)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.045	(0.148)	-0.008	(0.272)	0.044	(0.146)
Large landowner (>=2.0 Ha)	0.272	(0.216)	0.447	(0.437)	0.284	(0.216)
NGO membership (yes=1)	0.343***	(0.089)	0.187	(0.157)	-0.052	(0.091)
Log (gross margin of farming in 2008 Tk.)	0.009	(0.034)	-0.012	(0.081)	0.006	(0.038)
Fragmentation Index	-0.389*	(0.217)	-0.057	(0.429)	0.396*	(0.237)
Year dummy (2008=1)	-0.459***	(0.126)	-0.328	(0.316)	0.881***	(0.082)
Correlated effects variables (group means of the variables)			Yes			
Instrument variables						
Log (mean rainfall in mm in last ten years)					-1.07***	(0.214)
Any cultivated land with clay loam soil? (yes=1)					0.181*	(0.097)
Any cultivated land with very high elevation? (yes=1)					-0.168**	(0.085)
Constant	0.804**	(0.372)	0.584	(0.662)	7.735***	(1.592)
/athrho1	-0.716	0.465				
/athrho0	-0.245	0.413				
rho1	-0.615	0.289				
rho0	-0.239	0.389				
Wald test if indep. eqns. (rho1=rho2=0) Chi2			4.20 (p-val=0.12)			
Observations			1691			
Average treatment effects (ATE)			0.214			
Average treatment effects on the treated (ATT)			0.27			
Wald chi2(23)			199.65***			
Observations			1691			

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2. Labor Supply Equations

This subsection presents results for the labor supply equations. Table 6 presents results from the IV estimation; while the results from the endogenous treatment effects (ETE) model are shown in Table 7. Despite the use of IV approach is inappropriate in the case of endogenous dummy regressor, as previously discussed, IV regression has been estimated to get the tests statistics that examine the validity of the instruments extensively. Like the participation equation, the endogeneity of the technology adoption decision needs to be checked, and both the Durbin's score statistics and the Wu-Hausman tests reject the null hypothesis that technology adoption decision of farm households is exogenous to their non-farm labor supply decisions. All three instruments pass Sargan's orthogonality tests; the test statistics fail to reject the null hypothesis of orthogonality of instruments to the non-farm labor supply decision. Besides orthogonal to the outcome variable, the instruments are well correlated with the endogenous regressor, as the null hypothesis of instrument's redundancy for each instrument in LR IV has been rejected. The model also passes all the necessary tests (e.g. under identification, weak identification, over-identification) for the validity of the instruments. All the relevant tests (Hausman, Wu-Hausman, Durbin's Score) for endogeneity confirm the presence of endogeneity between the non-farm participation decision and the technology adoption decision of a farm household. The F-stat at the first-stage regression also passes the 'more than 10' rule indicating that the excluded instruments are valid and significantly relevant. The instruments also pass the Montiel-Pflueger robust weak instrument test as the effective F statistic at 5% confidence level, 18.33, is well above the generalized TSLS critical value at 5 % worst case bias, 13.42. Thus, the use of rainfall, soil quality, and land elevation as instruments for the adoption of power tiller or tractor in land preparation does not suffer from the usual weak instrument problems. Both the Wald test and the Smith-Blundell test for exogeneity reject the null hypothesis of exogeneity of the technology adoption decision.

Although the explanatory variables in the outcome equation are mostly statistically insignificant in the first stage regression of determining the technology adoption decision, all the instruments appear statistically significant. A 1 percent more rainfall reduces the probability of technology adoption of a farm household by 0.3. Farm households that operate land with the clay loam soil are 3 percent more likely to adopt the mechanized tillage system compared to the farm households that do not have operating land with the clay loam soil. As before, farm households that operate land with high elevation are less likely to adopt the labor-saving technology.

Table 6: IV Model estimates of Labor Supply of Farm Households

	Instrumental variable (IV) 2SLS model			
	Non-farm labor supply equation		Mechanization equation	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Mechanized (yes=1)	2.396***	(0.909)		
Age of household head	-0.004	(0.012)	-0.001	(0.002)
Household size	0.088*	(0.047)	0.009	(0.007)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.574***	(0.208)	-0.048	(0.030)
Three adult workers	0.990***	(0.330)	-0.052	(0.048)
Female participation in labor force (yes=1)	0.475*	(0.275)	0.018	(0.041)
Log (total schooling years of workers)	0.070*	(0.038)	-0.006	(0.006)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.070	(0.205)	0.019	(0.030)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.094	(0.268)	0.003	(0.039)
Large landowner (>=2.0 Ha)	0.539	(0.367)	0.064	(0.054)
NGO membership (yes=1)	0.633***	(0.144)	-0.019	(0.021)
Log (gross margin of farming in 2008 Tk.)	0.044	(0.073)	-0.004	(0.011)
Fragmentation Index	-0.820*	(0.428)	0.116*	(0.061)
Year dummy (2008=1)	-0.812***	(0.272)	0.245***	(0.022)
Correlated effects variables (group means of the variables)		Yes		
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.30***	(0.048)
Any cultivated land with clay loam soil? (yes=1)			0.042**	(0.021)
Any cultivated land with very high elevation? (yes=1)			-0.05***	(0.020)
Constant	1.962***	(0.695)	2.710***	(0.363)
Wald chi2(21)	211.63***			
F(23, 1667)			10.30***	
R-squared	0.05		0.124	
Observations	1691			
Underidentification tests (Ho: Model is underidentified)				
Anderson canon. corr. likelihood ratio stat Chi-sq(3) =54.87 (p=0.000)				
Weak identification statistics: (Ho: Instruments are weak)				
Montiel-Pflueger robust weak instrument test: Effective F statistic: 18.326**				
Partial R-squared of excluded instruments: 0.0319				
Test of excluded instruments: F(3, 1667) = 18.33 (p=0.000)				
Sargan (score) test of overidentifying restrictions chi2(2) = 1.015 (p = 0.601)				
Tests of endogeneity: (H0: mechanization is exogenous)				
Durbin (score) chi2(1) = 4.733(p = 0.03); Wu-Hausman F(1,1668) = 4.682 (p = 0.031)				
LR IV redundancy tests for instruments: (Ho: Instrument is redundant)				
Rainfall: Chi-sq(1) =37.66***; Soil Quality: Chi-sq(1) =2.85*; and Land elevation: Chi-sq(1) =7.56**				
Sargan's Orthogonality tests for instruments: (Ho: Instrument is orthogonal to the outcome variable)				
Rainfall: Chi-sq(1) =0.982; Soil Quality: Chi-sq(1) =0.532; and Land elevation: Chi-sq(1) =0.309				
IV heteroskedasticity test(s) using levels of Ivs only: (Ho: Disturbance is homoscedastic)				
Pagan-Hall general test statistic : Chi-sq(23)=65.7 (p=0.00)				

Note: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 presents results from the ETE estimation for the level of off-farm labor supply with left censoring at 0. Similar to the participation decision, the technology adoption dummy appears statistically significant with expected sign. Adoption of labor-saving technology in land preparation makes the off-farm work days of the farm households double on average.

Besides the technology adoption decisions, as before, the estimation controls for a bunch of other household characteristics such as demography, physical assets, and human capital assets. Demographic characteristics appear as important drivers of the off-farm labor supply decisions of farm households. Both the household size and the number of adult working member increase the off-farm labor supply hours of farm households. Female participation in the workforce also induces farm households to supply more labor hours in the non-farm sector. Surprisingly, land ownership, except the large land owner households, and the gross margin (returns from cultivable landholding and family labor) appear statistically insignificant. Land fragmentation also appears statistically insignificant, though its sign is expectedly negative. The NGO membership expectedly induces farm households to supply extra labor hours in the non-farm sector and appears statistically significant with a positive sign.

The dummy for the year of 2008 appears statistically significant with negative sign implying that farm households were supplied less labor in the non-farm sector in 2008 compared to 2000. This result is not quite surprising as the return from the agricultural production has been increased significantly in 2008 due to a surge in global food prices in the late 2000s. It is evident that the growth of farm income contributed 90 percent of poverty reduction in the second half of last decade in Bangladesh (World Bank, 2013). The schooling of the worker does not have a significant effect on the off-farm labor supply of farm households, and this result is consistent with the earlier literature (see Sumner, 1982; and Mishra and Goodwin, 1997).

Table 7: Endogenous Treatment Effects Model

Log (non-farm workdays)	Endogenous Treatment Effects model Non-farm labor supply equation		Mechanization equation	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Mechanized (yes=1)	1.082***	(0.384)		
Age of household head	-0.021	(0.027)	-0.001	(0.001)
Household size	0.215**	(0.099)	0.005	(0.005)
Labor endowment dummies (ref: single working member)				
Two adult workers	1.252***	(0.448)	-0.031	(0.022)
Three adult workers	2.018***	(0.704)	-0.034	(0.035)
Female participation in labor force (yes=1)	0.997*	(0.583)	0.026	(0.032)
Log (total schooling years of workers)	0.135	(0.086)	-0.004	(0.004)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.017	(0.462)	0.031	(0.022)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.406	(0.597)	0.034	(0.029)
Large landowner (>=2.0 Ha)	1.684**	(0.803)	0.089**	(0.042)
NGO membership (yes=1)	1.510***	(0.318)	0.007	(0.016)
Log (gross margin of farming in 2008 Tk.)	0.084	(0.160)	0.004	(0.008)
Fragmentation Index	-1.308	(0.920)	0.072*	(0.044)
Year dummy (2008=1)	-0.911***	(0.338)	0.178***	(0.017)
Correlated effects variables (group means of the variables)		Yes		
Instrument variables				
Log (mean rainfall in mm in last ten years)			0.172***	(0.069)
Any cultivated land with clay loam soil? (yes=1)			0.036**	(0.017)
Any cultivated land with very high elevation? (yes=1)			-0.030*	(0.016)
Unobserved Components (Agro-ecological zone))	0.485*	(0.278)	1 (Constrained)	
Constant	2.414***	(0.568)	-1.232**	(0.515)
Log likelihood	-3582.4			
Observations	1691			
rho	0.07	(0.038)		
sigma	5.201	(0.1619)		
lambda	-0.577	(0.313)		
Wald test of indep. eqns. (rho = 0): chi2(1) =	1.76 (p-val=0.08)			

The robustness of the results has been checked through exclusion of top 10 percent of the off-farm labor supplying households in the ETE model, and the results are presented in Table A5 in the Appendix. The results show that the off-farm labor supply effect of the adoption of labor-saving technology is even higher after the exclusion of top ten percent of off-farm labor supplying households from the sample. Therefore, the labor supply effects of the technology adoption presented in Table 7 are robust and reliable.

VI. Concluding Remarks

This paper examines the role of agricultural mechanization through the adoption of the labor-saving technology, namely the use of tractor/power tiller, in the off-farm labor supply decisions of farm households using a longitudinal household survey data from Bangladesh. The study uses the Bivariate Probit model, the Endogenous Switching Probit model, and the Endogenous Treatment Effects model to identify whether the adoption of modern technology in land preparation affects the off-farm labor supply behaviors of farm households. The results confirm that the adoption of modern technology in the farm production by a farm household could raise the farm household's both the probability of participation in the non-farm sector and the number of hours worked in the non-farm sector. Also, this paper also finds that the land fragmentation could reduce both the participation in the off-farm works and the number of hours worked in the non-farm sector by a farm household; receipt of microcredit, however, induces farm households to participate in the non-farm sector and to work more in the non-farm sector.

The results have important policy implication for developing countries like Bangladesh where the farm sector is the dominant sector for productive employment. As the nonfarm employments are generally more productive and remunerative compared to farm employment. Farm mechanization could benefit the farm households by inducing them to supply more labor in the non-farm sector. Developing economies that experience high growth in the non-agriculture sector could promote agricultural mechanization through promoting private sector supply of agricultural mechanized equipments as well as private initiatives in equipment research and development. Given proper economic conditions, the private sector has been an efficient provider of equipments and mechanization services (Pingali, 2007).

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APPENDICES

Table A1: Linear Probability Model (LPM) and Probit Model (including CRE Variables)

	LPM		**Probit Model**	
	Coeff.	**Std. Err.**	**Mar. Eff.**	**Std. Err.**
Mechanized (yes=1)	0.097***	(0.028)	0.272***	(0.083)
Age of household head	-0.001	(0.002)	-0.004	(0.006)
Household size	0.022***	(0.008)	0.062***	(0.024)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.081**	(0.037)	0.215**	(0.100)
Three adult workers	0.130**	(0.061)	0.335**	(0.164)
Female participation in labor force (yes=1)	0.093*	(0.049)	0.256*	(0.131)
Log (total schooling years of workers)	0.01	(0.007)	0.028	(0.018)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.012	(0.037)	-0.023	(0.096)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.017	(0.050)	0.053	(0.127)
Large landowner (>=2.0 Ha)	0.121*	(0.064)	0.346**	(0.172)
NGO membership (yes=1)	0.119***	(0.026)	0.327***	(0.071)
Log (gross margin of farming in 2008 Tk.)	0.007	(0.013)	0.018	(0.035)
Fragmentation Index	-0.081	(0.074)	-0.226	(0.206)
Year dummy (2008=1)	-0.081***	(0.028)	-0.228***	(0.081)
Correlated effects variables (group means of the variables)				
Age of household head	-0.001	(0.002)	-0.002	(0.007)
Household size	-0.078	(0.054)	-0.225	(0.163)
Total adult workers	0.044	(0.027)	0.127*	(0.077)
Log (total schooling years of workers)	0.012	(0.008)	0.035*	(0.021)
Log (total landownership)	-0.028*	(0.015)	-0.083**	(0.042)
Log (gross margin of farming in 2008 Tk.)	-0.024	(0.018)	-0.065	(0.045)
Fragmentation Index	-0.068	(0.093)	-0.177	(0.268)
Constant	0.578***	(0.092)	0.251	(0.260)
Wald chi2(21)	209.17***			
F(23, 1667)			10.63***	
R-squared	0.094		0.1244	
Observations	1691			

Table A2: Bivariate probit marginal effects estimates (including CRE Variables)

	Bivariate Probit model			
	Non-farm participation equation		Mechanization equation	
	Marr. Eff.	**Std. Err.**	**Marr. Eff.**	**Std. Err.**
Mechanized (yes=1)	0.316***	(0.112)		
Age of household head	-0.001	(0.002)	-0.001	(0.002)
Household size	0.019**	(0.008)	0.008	(0.006)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.081**	(0.033)	-0.047	(0.030)
Three adult workers	0.122**	(0.055)	-0.046	(0.048)
Female participation in labor force (yes=1)	0.082*	(0.046)	0.029	(0.039)
Log (total schooling years of workers)	0.011*	(0.006)	-0.006	(0.006)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.011	(0.034)	0.022	(0.030)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.019	(0.044)	0.012	(0.038)
Large landowner (>=2.0 Ha)	0.104*	(0.062)	0.077	(0.055)
NGO membership (yes=1)	0.109***	(0.025)	-0.016	(0.021)
Log (gross margin of farming in 2008 Tk.)	0.007	(0.012)	0.002	(0.011)
Fragmentation Index	-0.103	(0.068)	0.105*	(0.063)
Year dummy (2008=1)	-0.134***	(0.036)	0.234***	(0.021)
Correlated effects variables (group means of the variables)				
Age of household head	-0.001	(0.002)	0.000	(0.002)
Household size	-0.080	(0.053)	0.041	(0.047)
Total adult workers	0.047*	(0.026)	-0.011	(0.023)
Log (total schooling years of workers)	0.010	(0.007)	0.003	(0.006)
Log (total landownership)	-0.030**	(0.014)	0.007	(0.012)
Log (gross margin of farming in 2008 Tk.)	-0.027*	(0.016)	0.016	(0.013)
Fragmentation Index	-0.032	(0.086)	-0.134*	(0.076)
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.281***	(0.046)
Any cultivated land with clay loam soil? (yes=1)			0.051**	(0.022)
Any cultivated land with very high elevation? (yes=1)			-0.041**	(0.020)
Constant				
/athrho	-0.428*	(0.264)		
rho	-0.404	(0.222)		
Wald test of rho=0: chi2(1)		2.615*		
Murphy's score test for biprobit chi2(9) =		9.6 (p-val=0.383)		
Avergae treatment effects (ATE)	0.298**	(0.119)		
Avergae treatment effects on the treated (ATT)	0.285***	(0.109)		
Observations		1691		

Table A3: Endogenous Switching Probit Estimates (including CRE Variables)

	Endogenous Switching Probit Model					
	Mechanized households		Non-mechanized households		Mechanization equation	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Age of household head	0.003	(0.006)	-0.019	(0.012)	-0.002	(0.006)
Household size	0.032	(0.023)	0.161***	(0.059)	0.028	(0.025)
Labor endowment dummies (ref: single working member)						
Two adult workers	0.248**	(0.107)	0.154	(0.221)	-0.179	(0.114)
Three adult workers	0.413**	(0.172)	-0.083	(0.365)	-0.166	(0.187)
Female participation in labor force (yes=1)	0.160	(0.149)	0.668	(0.504)	0.087	(0.164)
Log (total schooling years of workers)	0.033*	(0.020)	0.045	(0.043)	-0.023	(0.021)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))						
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.026	(0.109)	-0.096	(0.217)	0.087	(0.114)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.045	(0.148)	-0.008	(0.272)	0.044	(0.146)
Large landowner (>=2.0 Ha)	0.272	(0.216)	0.447	(0.437)	0.284	(0.216)
NGO membership (yes=1)	0.343***	(0.089)	0.187	(0.157)	-0.052	(0.091)
Log (gross margin of farming in 2008 Tk.)	0.009	(0.034)	-0.012	(0.081)	0.006	(0.038)
Fragmentation Index	-0.389*	(0.217)	-0.057	(0.429)	0.396*	(0.237)
Year dummy (2008=1)	-0.459***	(0.126)	-0.328	(0.316)	0.881***	(0.082)
Correlated effects variables (group means of the variables)						
Age of household head	-0.002	(0.007)	-0.005	(0.014)	0.000	(0.007)
Household size	-0.143	(0.168)	-0.683*	(0.359)	0.171	(0.188)
Total adult workers	0.083	(0.087)	0.432**	(0.178)	-0.045	(0.086)
Log (total schooling years of workers)	0.032	(0.024)	-0.001	(0.049)	0.014	(0.024)
Log (total landownership)	-0.099**	(0.049)	-0.032	(0.081)	0.022	(0.051)
Log (gross margin of farming in 2008 Tk.)	-0.061	(0.048)	-0.089	(0.118)	0.062	(0.050)
Fragmentation Index	-0.024	(0.291)	-0.239	(0.529)	-0.499	(0.318)
Instrument variables						
Log (mean rainfall in mm in last ten years)					-1.07***	(0.214)
Any cultivated land with clay loam soil? (yes=1)					0.181*	(0.097)
Any cultivated land with very high elevation? (yes=1)					-0.168**	(0.085)
Constant	0.804**	(0.372)	0.584	(0.662)	7.735***	(1.592)
/athrho1	-0.716	0.465				
/athrho0	-0.245	0.413				
rho1	-0.615	0.289				
rho0	-0.239	0.389				
Wald test if indep. eqns. (rho1=rho2=0) Chi2			4.20 (p-val=0.12)			
Observations			1691			
Average treatment effects (ATE)			0.214			
Average treatment effects on the treated (ATT)			0.27			
Wald chi2(23)			199.65***			
Observations			1691			

Note: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Linear Regression Model of Labor Supply (including CRE Variables)

	Non-farm labor supply equation	
	Coeff.	**Std. Err.**
Mechanized (yes=1)	0.527***	(0.152)
Age of household head	-0.006	(0.012)
Household size	0.105**	(0.041)
Labor endowment dummies (ref: single working member)		
Two adult workers	0.495**	(0.196)
Three adult workers	0.899***	(0.324)
Female participation in labor force (yes=1)	0.500*	(0.272)
Log (total schooling years of workers)	0.058	(0.036)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))		
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.044	(0.196)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.080	(0.257)
Large landowner (>=2.0 Ha)	0.619*	(0.356)
NGO membership (yes=1)	0.633***	(0.141)
Log (gross margin of farming in 2008 Tk.)	0.037	(0.071)
Fragmentation Index	-0.598	(0.398)
Year dummy (2008=1)	-0.340**	(0.146)
Correlated effects variables (group means of the variables)		
Age of household head	-0.001	(0.014)
Household size	-0.339	(0.292)
Total adult workers	0.233	(0.150)
Log (total schooling years of workers)	0.081**	(0.041)
Log (total landownership)	-0.141*	(0.079)
Log (gross margin of farming in 2008 Tk.)	-0.108	(0.094)
Fragmentation Index	-0.461	(0.496)
Constant	2.891***	(0.497)
F(21, 1669)	13.26 (p-val=0.000)	
R-squared	0.12	
Observations	1691	

Table A5: Endogenous Treatment Effects Model (Robustness Check excluding top 10 percent)

Log (non-farm workdays)	Endogenous Treatment Effects model Non-farm labor supply equation		Mechanization equation	
	Coeff.	**Std. Err.**	**Coeff.**	**Std. Err.**
Mechanized (yes=1)	1.285***	(0.457)		
Age of household head	-0.029	(0.032)	-0.001	(0.001)
Household size	0.193	(0.118)	0.007	(0.005)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.939*	(0.542)	-0.009	(0.022)
Three adult workers	1.143	(0.869)	-0.029	(0.035)
Female participation in labor force (yes=1)	1.502**	(0.706)	0.033	(0.033)
Log (total schooling years of workers)	0.145	(0.099)	-0.005	(0.004)
Land Endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (>=0.4 Ha & <1.0 Ha)	-0.199	(0.548)	0.023	(0.022)
Medium landowner (>=1.0 Ha & <2.0 Ha)	0.657	(0.702)	0.035	(0.029)
Large landowner (>=2.0 Ha)	2.050**	(0.955)	0.072*	(0.041)
NGO membership (yes=1)	1.718***	(0.376)	0.001	(0.016)
Log (gross margin of farming in 2008 Tk.)	0.175	(0.188)	0.002	(0.008)
Fragmentation Index	-0.397	(1.090)	0.069	(0.044)
Year dummy (2008=1)	-1.084***	(0.399)	0.165***	(0.017)
Correlated effects variables (group means of the variables)		Yes		
Age of household head	-0.000	(0.037)	0.000	(0.002)
Household size	-0.928	(0.868)	0.006	(0.036)
Total adult workers	0.522	(0.407)	-0.021	(0.017)
Log (total schooling years of workers)	0.140	(0.113)	0.004	(0.005)
Log (total landownership)	-0.502**	(0.220)	-0.004	(0.009)
Log (gross margin of farming in 2008 Tk.)	-0.459*	(0.244)	0.014	(0.011)
Fragmentation Index	-1.132	(1.356)	-0.077	(0.055)
Instrument variables				
Log (mean rainfall in mm in last ten years)			0.160**	(0.069)
Any cultivated land with clay loam soil? (yes=1)			0.035**	(0.017)
Any cultivated land with very high elevation? (yes=1)			-0.024	(0.016)
Unobserved Components (Agro-ecological zone))	0.357	(0.312)	(Constrained)	
Constant	1.913	(1.424)	-1.108**	(0.507)
Log likelihood	-2953.47			
Observation	1691			
rho	0.05	(0.039)		
sigma	5.613	(0.202)		
Wald test of indep. eqns. (rho = 0): chi2(1) =	1.15 (p-val=0.25)			