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The Conservation Reserve Program, Off-Farm Work, and Farm Household Technical Efficiencies

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Abstract

Using data from a national survey of farm households in the United States, this paper examines the effects of farm households' decisions to participate in the Conservation Reserve Program (CRP) and to work off the farm on the technical efficiency of farm household production. After controlling for the self selection bias in estimating the multiple output-oriented distance functions, results show that operators' decisions to work off the farm (both separately and combined with participation in CRP) lead to higher technical efficiencies for farm household production— implying improvements in the resource allocation between farm and other productive activities by farm households. The technical efficiencies of household production of those farm households participating only in the CRP are lower.

Key Words: Conservation Reserve Program, off-farm work, household technical efficiency.

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Introduction

Due to the diverse nature of farms and the increasing interconnection between the farm business and farm household, the context within which agricultural policy is formulated is increasingly complex (Offutt 2002). Improvements in the well being of farm households have been due to the interaction of technological adoption that released labor from farms and economic growth that pulled labor off the farms. The dependence of farm families on income from off-farm work has increased steadily in many OEDC countries, narrowing, or reversing, the gap between incomes of farm and non-farm households (e.g., Gardner 2000; OECD 2003, p. 7). According to data from the U.S. Department of Agriculture, these effects in the United States have been particularly dramatic; off-farm income as a share of total U.S. farm household income rose from about 50 percent in 1960 to more than 80 percent in recent years. (USDA 2007a).

For developed countries on both sides of the Atlantic, these changes in the composition of farm household income occurred largely against the backdrop of a traditional commodity-oriented farm policy until environmental goals were elevated along side commodity policy objectives beginning in the mid-1980 (OECD 2001, p. 47). These environmental objectives were promoted through the conservation compliance provision of U.S. farm policy legislation and a variety of measures introduced in other OECD countries that focused on inappropriate farm management practices incompatible with environmental objectives. The implementation of measures to improve the environmental performance of agriculture has often been accompanied by payments for changes in land use for adopting low-input or organic farming systems. In the United States, the Conservation Reserve Program (CRP), introduced during that period as well, has become the largest Federal program targeting land use, and it now pays farmers about $2 billion per year to remove 39 million acres from crop production (USDA 2007b).

Although CRP payments are small compared with off-farm income, each may constitute a significant source of reliable income to farm households not directly related to the agricultural production, a characteristic that may gain added significance as farmers are exposed to greater market price risk. For this reason, it would seem reasonable to hypothesize that these decisions are interrelated. Moreover, since both CRP participation and off-farm work remove substantial resources from agricultural production, these decisions are likely to have important implications for the efficiency of farm production, but for the efficiency of farm household production as well. The recent study by Phimister and Roberts (2006) of the effects of off-farm work on the intensity of agricultural input use in England and Wales is evidence that there is broad interest in related issues, as is a recent study that relates farm efficiency to off-farm work by farm operators by Goodwin and Mishra (2004).

The primary purpose of this paper is to investigate the effects of the decisions to participate in CRP and to work off the farm by farm operators in the United States on the technical efficiency of farm household production. Because CRP participation and off-farm work affect the level of resources available for farm production, it is important to quantify the effects of these decisions on the technical efficiency of household production, including farm and non-farm activities. Therefore, to measure technical efficiency, we account explicitly and separately for both the resources committed to CRP and off-farm work and the returns from the commitment of the resources within the context of the broader farm household production activities. Our measures of technical efficiency are derived from estimated stochastic multi-product, output-oriented distance functions for farm households. Separate functions are estimated for each of four groups of farms, those that: participate in both CRP and off-farm work; participate only in CRP; participate only in off-farm work; and participate in neither. In addition to the sales of farm outputs and consistent with other studies of farm household efficiency both in the United States and elsewhere (e.g. Paul and Nehring 2005; Nehring, *et al.* 2005; Chavas, *et al.* 2005 and Gonzalez and Lopez 2007), earnings from off-farm work are included as a separate output of the farm household for households in the appropriate groups. Because of our specific interest in the effect of CRP participation on the efficiency of farm household production, payments for land enrolled in CRP are also included as a separate output of the farm household for those households in the appropriate groups. To account for input use appropriately, household labor committed to off-farm work and land committed to CRP are included in the multiple output distance functions for the households.

Several other features distinguish our analysis from recent studies on household efficiency at the farm household level. First, we estimate multiple output distance functions that control for the potential self selection bias due to both CRP participation and off-farm work.[1] To account for this simultaneity, perhaps in part due to some unobserved heterogeneity, we test for the selection bias in order to justify statistically our corrections for these two decisions in farm household production. In so doing, we must then decompose the random and the technical inefficiency components of the composite errors in the distance functions using a method-of-moments procedure.[2] Finally, to examine the extent to which CRP participation and off-farm

[1] The rationale of correcting for self selection in estimating these frontier functions is in the same spirit as that of Goodwin and Mishra (2004, p. 726). They argue that off-farm labor supply is likely to be endogenous to farming efficiency, since efficiency is a factor in determining the implicit wage for on-farm labor. Phimister and Roberts (2005, p. 495) also argue that "unless this potential simultaneity [between off-farm work and on agricultural production] is taken into account, estimates derived from the econometric models may be biased." A similar argument suggests that farming efficiency would affect the implicit value of land in production and, in turn, affect the supply of land for CRP.

[2] As is seen below, the terms incorporated into the distance functions to correct for self selection are derived from a bivariate choice model of participation in CRP and off-farm work. Furthermore, the distinct exogenous factors that explain participation in off-farm work and CRP also characterize the environment in which farm and household production take place. Thus, in the same spirit as that suggested by Coelli *et al*. (2005, pp. 281-282), our specification accounts for the effects of these non-stochastic "environmental" variables on technical efficiency, only in our case, the effect is an indirect one operating through the terms that correct for self selection. Unfortunately,

work may affect the distributions of the household efficiency, we compare these four distributions of technical efficiency among the four mutually exclusive participation groups by stochastic dominance criteria, and we test for differences in the distributions using methods by Davidson and Duclos (2000).

By way of a brief summary, our results suggest that farm operators' decisions to work off the farm (both separately and combined with participation in CRP) have increased technical efficiency—implying improvements in the resource allocation by farm households. In contract, participation in the CRP appears to be accompanied by lower measures of technical efficiency for the combined household activities. Furthermore, while the central focus of our analysis is on the efficiency of farm household production, the results from the estimated choice model offer support for the hypothesis that decisions to participate in the CRP and in off-farm work are indeed correlated. Through an examination of these results, we also develop a better understanding of how these decisions depend on the human capital and risk attitudes of farm operators, as well as land quality, farm size, and participation in other government programs.

We begin the remainder of the paper by formulating the discrete choice model. We then go on to introduce the methods by which technical efficiency for farm household production is estimated. We next describe the data, and the discussion of empirical results is followed by some concluding comments and a discussion of policy implications.

Modeling the Choices—A Bivariate Probit Model

As is commonly seen in the discrete choice literature, each of these two decisions is determined by a comparison between benefits from participation with those from non-participation. The CRP participation decision can be thought of as being determined by a

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because of the need to decompose the error structure in the distance functions, these separate indirect effects cannot be isolated.

comparison of the government's potential payment for land in CRP with the reservation per acre return to retain land in production. Similarly, the decision to work off the farm is determined by a comparison of the potential off-farm wage with the shadow value of time in farming. The participation equations that capture these comparisons can be specified as (Greene 2003):

(1) $I_1{*} = H_1{'}X_1 + e_1$

$I_2{*} = H_2{'}X_2 + e_2$

$I_i = 1$ *iff* $I_i{*} \geq 0$; and $I_i = 0$ *iff* $I_i{*} \leq 0$ i =1, 2

where X_1, X_2 are the two vectors of distinct exogenous factors that are associated with the participation in CRP and the decision to work off the farm, respectively. H_1 and H_2 are vectors of the parameters, and e_1, e_2 are the random disturbance terms. The latent choice variables (I_1*, I_2*) represent the propensities of each decision. The actual binary decision indicator for each decision is observed as 1 (0) only if the latent variable is greater (less) than zero.[3] Suppose the joint distribution of (e_1, e_2) follows a bivariate normal distribution, where the correlation coefficient (ρ) captures the joint nature of these two decisions. The consistent estimators can be obtained by using the maximum likelihood method on the log likelihood function (Greene 2003):

(2) $$\log L = \sum_{i=1}^{n} \log\Phi\{[(2I_1 - 1)(H_1{'}X_1)],[(2I_2 - 1)(H_2{'}X_2)],[((2I_1 - 1))(2I_2 - 1)\rho]\}$$

The bivariate probit model is an extension of the binary choice case that allows for a correlation between pairs of binary choices. Therefore, a likelihood ratio test can be conducted to test if these two decisions are independent (i.e. $H_0 : \rho = 0$).

[3] Subscript 1 is for the CRP decision and subscript 2 is for off-farm work by the operator.

Estimating Technical Efficiencies for the Farm Household

To estimate technical efficiencies for farm households, we adopt methods similar to those of Paul and Nehring (2005). That is, we estimate the multi-output production technology by stochastic frontier techniques applied to output distance functions. [4] We estimate separate distance functions for the four groups: those that participate in both CRP and off-farm work; those that participate only in CRP; those that participate only in off-farm work; and those that participate in neither.[5] To account for their effects on farm and farm household outputs, we treat the decisions to work off the farm and participate in CRP as endogenous.[6]

The Multiple Output Distance Functions

Following the specification similar to that in previous studies (e.g., Shephard 1970; Grosskopf *et al.* 1995; Paul *et al.* 2000), each multi-output distance function is specified as $D(x, y) = \min\{\theta : (y / x) \in T(x)\}$, where *x, y* are input and output vectors and T (.) represents the production technology. The distance function is non-decreasing, positively linearly homogeneous and concave in y and decreasing in x.[7] To estimate this function, linear homogeneity with respect to outputs must be imposed, which can be accomplished by normalizing by one of the outputs (e.g. Coelli and Perelman 2000). The multi-output distance

[4] From a theoretical point of view, it may, as suggested by one of the reviewers, be appropriate to specify and estimate a dual indirect multiple-output, multiple-input household revenue function. However, there are no prices included within the ARMS data; it was impossible to consider this strategy in this study. Moreover, Mundlak (1996) argues for a primal modeling approach to estimate production technology because econometricians do not know the prices (or price expectations) that firms (or households in our case) use to make their production decisions.

[5] For the group that participates in both CRP and off-farm work, there are three outputs for the farm household: farm output, off-farm income and CRP payments. For the group that participates only in CRP, there are two outputs for the household: farm output and CRP payments. For the group that participates only in off-farm work, there are also two outputs for the farm household: farm output, off-farm income; and for the group that participates in neither, there is only one output of the farm household: farm output. Since there is only one output for farm households in this latter group, the output distance function reduces to a single output production function which can still be estimated using stochastic frontier techniques (e.g. Coelli and Perelman 2000).

[6] Although Paul and Nehring (2005) and Nehring *et al*. (2005) specify off-farm income as an output of the farm household, they do not account explicitly for the effects of the decision to work off the farm in estimating technical efficiency.

[7] We focus on a multiple output distance function, but our results also apply to a single output farm production function, which is merely a special case the multi-output distance function.

functions can be rewritten as: $D(x,ky)=kD(x,y)$ for any $k > 0$. The conventional way is to define the factor k as $1/y_j$, where y_j is the output for specific output j, and then obtain $D_0(x,y/y_j)=D_0(x,y^*)$, where y^* are the other output vectors normalized by output y_j. Assuming a translog functional form approximation yields:[8]

$$(3)\qquad \ln(D_i/y_{ji})=\alpha_0+\sum_{m=1}^{M-1}\alpha_{mi}\ln y^*_{mi}+\frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1}\alpha_{mn}\ln y_{mi}*\ln y_{ni}+\sum_{k=1}^{K}\beta_{ki}\ln x_{ki}$$

$$+\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kli}\ln x_{ki}*\ln x_{li}+\sum_{k=1}^{K}\sum_{m=1}^{M-1}r_{kmi}\ln x_{ki}*\ln y*_{mi}$$

$$=TL_i(x_i,y_i*,\alpha_i,\beta_i,r_i)$$

where i is the specific participant group (i = 1,…,4), m and n are outputs, l and k are inputs. For convenience, we rewrite equation (3) as:

$$(4)\qquad -\ln(y_{ji})=TL_i(x_i,y_i*,\alpha_i,\beta_i,r_i)-\ln(D_i)$$

Equation (4) is consistent with the standard stochastic production frontier framework (Aigner *et al.* 1977), since it can be further rewritten as:

$$(5)\qquad -\ln(y_{ji})=TL_i(x_i,y_i*,\alpha_i,\beta_i,r_i)+v_i-u_i\ =TL_i(x_i,y_i*,\alpha_i,\beta_i,r_i)+\varepsilon_i$$

where the random variable (v_i) is assumed to have a normal distribution, N~(0, σ^2_{vi}); the random variable (u_i) is the technical inefficiency component, and it is assumed to follow a half normal distribution, N^+~(0, σ^2_{uj}). These two components are assumed to be independent. The random variable (ε_i) is the composite error.

Correcting for Self-Selection

Since the decisions to work off the farm or to participate in CRP may be correlated to farm output or the level of farm household production due to some unobservable heterogeneity, a

[8] The translog functional form is not only flexible, but it allows us to impose the necessary homogeneity constraints. This specification is commonly utilized in other studies (e.g. Paul and Nehring 2005; Coelli and Perelman 2000).

potential problem of self-selection may exist. Although perhaps desirable, it is not possible within this model to deal with the sample selection problem by applying full information maximum likelihood methods.[9] As an alternative, we utilize a two-stage estimation method similar to those in Bradford *et al.* (2001) and Huang *et al.* (2002) who deal with a single binary choice within a stochastic frontier model. In the first stage, we estimate the multi-output distance function based on the composite error term, including as regressors of the correction terms for self selection bias estimated from the bivariate probit choice model. In contrast to Bradford *et al.* (2001) and Huang *et al.* (2002), we derive these correction terms for self selection based on a semi-parametric framework proposed by Das *et al.* (2003) and earlier by Lee (1983).[10]

The need for this semi-parametric framework can be explained in the following way. We know that conditional expected production for each group, given the joint distribution between the errors and the random error of the bivariate probit model (e_1, e_2, ε_i), is:

$$(6)\quad -E(\ln(Y_i)\,|\,I_1, I_2) = TL_i(x_i, y_i{*}, \alpha_i, \beta_i, r_i) + E(\varepsilon_i\,|\,I_1, I_2) = TL_i(x_i, y_i{*}, \alpha_i, \beta_i, r_i) + \rho_{1i}\lambda_{1i} + \rho_{2i}\lambda_{2i}$$

where λ_{1i} and λ_{2i} are correction terms for self selection bias corresponding to CRP and off-farm work decisions, respectively. However, the application of the standard Heckman type formula for ($\lambda_{1i}, \lambda_{2i}$), only valid under the trivariate normal distribution assumption among (e_1, e_2, ε_i), is not appropriate since it has been shown that the composite error (ε_i) does not follow a normal

[9] Conceptually, it is difficult to accommodate the bivariate probit choice mechanism in a one-step MLE procedure to estimate the multiple-output distance function. To gain efficiency by dealing with the sample selection problem directly, one has to specify the conditional distributions for the components, (v_i-u_i | I_1, I_2), and estimate equation (5) along with the bivariate choice equation (1) in one step with maximum likelihood methods. However, this is challenging because the random variable u is assumed to be a one-sided error, and the joint distribution is multivariate. To the best of our knowledge, no one has developed a tractable empirical method to solve this particular problem as it relates to estimating stochastic production frontiers.

[10] Lee (1983) proposed a flexible self-selection correction term for any given choice structure. In his case, the estimation of the sample selection model with a multinomial logit structure had been developed. Das *et al.* (2003) extend Lee's (1983) method to the fully nonparametric case. The approach proposed by Lee and Das *et al.* is semi-parametric in that it does not require specific knowledge of the joint distribution between the choice and outcome equations.

distribution.[11] Rather, these two terms that correct for selection bias can be calculated as (Das *et al.* 2003, p. 35):

(7) $$\lambda_{1i} = \frac{\phi[\Phi^{-1}(prob(I_{1i}=1))]}{prob(I_{1i}=1)}; \qquad \lambda_{2i} = \frac{\phi[\Phi^{-1}(prob(I_{2i}=1))]}{prob(I_{2i}=1)}$$

where prob(I_{1i}=1) and prob(I_{1i}=1) are the estimated marginal probabilities of CRP participation and off-farm work from the bivariate probit model; $\phi(.)$ and $\Phi^{-1}(.)$ are the density function and the inverse cumulative density function of the standard normal distribution, respectively. By including these terms that correct for self-selection bias, the application of OLS to equation (6) by group gives consistent estimators for ($\alpha_i, \beta_i, r_i, \rho_{1i}, \rho_{2i}$).

Calculating Technical Efficiencies

To calculate technical efficiency for each participant within each group, the composite error term of equation (5) is further decomposed into its random error and technical inefficiency components. To do this, we must first recognize that the expected values of the one-sided error terms (E (u_i)) are not equal zero. Equation (5) can be rewritten as:

(8) $$-\ln(\hat{Y}_i) = TL_i(x_i, y_i*, \hat{\alpha}_i, \hat{\beta}_i, \hat{r}_i) + \hat{\varepsilon}_i = Y_i^F - E(u_i) + [v_i - u_i + E(u_i)],$$

which implies that:

(9) $$TL_i(x_i, y_i*, \hat{\alpha}_i, \hat{\beta}_i, \hat{r}_i) = Y_i^F - E(u_i) \quad \text{and} \quad \hat{\varepsilon}_i = [v_i - u_i + E(u_i)] = e_{scfi} + E(u_i).$$

Using the predicted residuals ($\hat{\varepsilon}_i$) from equation (9), the parameters (σ_{vi}^2) can be calculated based on the fact that the second and third central moments of ($\hat{\varepsilon}_i$) should be equal to the second and third central moments of (v_i-u_i) since $E(u_i)$ is constant. The parameters ($\hat{\sigma}_{ui}^2, \hat{\sigma}_{vi}^2$) and the composite error can then be calculated as (see Huang *et al.* 2002):

[11] We thank a thoughtful reviewer for this observation.

(10) $\hat{\sigma}_{ui}^2 = (\frac{m_3}{\sqrt{2/\pi}(1-4/\pi)})^{2/3}$; $\hat{\sigma}_{vi}^2 = m_2 - (1-\frac{2}{\pi})\hat{\sigma}_{u_i}^2$; $\hat{e}_{scf\,i} = \hat{\varepsilon}_i - \sqrt{\frac{2}{\pi}}\hat{\sigma}_{u\,i}$.[12]

Once this equation (10) has been estimated, the calculation of the technical efficiency index requires point estimates of the random variable u_i for each farmer. Following Jondrow *et al.* (1982), the expected value of u_i given the composite error (v_i-u_i) under the assumption of a half-normal distribution is:

(11) $E(\hat{u}_{ij} \mid \hat{e}_{scfij}) = \frac{\sigma\lambda}{(1+\lambda^2)}[\frac{\phi(\frac{\hat{e}_{scfij}\lambda}{\sigma})}{1-\Phi(\frac{\hat{e}_{scfij}\lambda}{\sigma})} - \frac{\hat{e}_{scfij}\lambda}{\sigma}]$; j = 1,..,n and i = 1,..,4

where $\sigma = (\hat{\sigma}_{ui}^2 + \hat{\sigma}_{vi}^2)^{1/2}$, $\lambda = \frac{\hat{\sigma}_{u_i}}{\hat{\sigma}_{v_i}}$.

The technical efficiency index of each farmer within each group can be calculated as:

(12) $TE_{ij} = \exp\{-E(\hat{u} \mid \hat{e}_{scf_{ij}}\}$.

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[12] Equation (10) can be derived as follows: under the half-normal distribution, u_i is assumed to be $N^+(0, \sigma_{ui}^2)$. The first three moment conditions for u_i are:

$$E(u_i) = \sqrt{\frac{2}{\pi}}\sigma_{u_i}; \quad V(u_i) = \frac{\pi-2}{\pi}\sigma_{u_i}^2 \ ; \quad E(u_i{}^3) = -\sqrt{\frac{2}{\pi}}(1-\frac{4}{\pi})\sigma_{u_i}^3.$$

To solve for the parameters ($\sigma_{vi}^2, \sigma_{ui}^2$), recall the definitions of second and third moments:

$$m_2 = \sigma_{vi}^2 + V(u_i) = \sigma_{vi}^2 + \frac{\pi-2}{\pi}\sigma_{ui}^2 \quad ; \quad m_3 = E(u_i{}^3) = -\sqrt{\frac{2}{\pi}}(1-\frac{4}{\pi})\sigma_{ui}^3.$$

Solving these two equations, the consistent estimators of ($\sigma_{vi}^2, \sigma_{ui}^2$) can be shown as:

$$\hat{\sigma}_{ui}^2 = (\frac{m_3}{\sqrt{2/\pi}(1-4/\pi)})^{2/3} \quad \text{and} \quad \hat{\sigma}_{vi}^2 = m_2 - (1-\frac{2}{\pi})\hat{\sigma}_{ui}^2 \ .$$

Once the estimators of ($\sigma_{vi}^2, \sigma_{ui}^2$) have been determined, the components of the error in the stochastic frontier can be obtained as: $\hat{e}_{scf\,i} = \hat{\varepsilon}_i - \sqrt{\frac{2}{\pi}}\hat{\sigma}_{u\,i}$. Olson *et al.* (1980) have shown the consistency of the estimators based on the two-stage method of moments.

The Data

The primary farm household data for this study are drawn from the 2001 Agricultural Resource Management Survey (ARMS), an enumerative survey conducted each year by the National Agricultural Statistics Service (NASS) of USDA. The ARMS database is one of USDA's primary vehicles for collecting and disseminating data on a wide range of issues about agricultural resource use and farm financial conditions. For purposes of this study, the ARMS data on off-farm income and participation in the variety of traditional farm programs and environmentally-related programs (e.g. CRP), are particularly important. Since our primary objective is to understand how decisions to participate in CRP and work off the farm affect the technical efficiency of farm household production, we limit our attention to farms classified as crop farms.[13] There are 2,190 observations in the sample.

To underscore the interrelationships between CRP and the off-farm work by farm operators, participation rates in the sample are exhibited in Table 1. About 22% of the farm households participate in CRP, and for about 56% of these farm households, the operator also works off the farm.[14] This means that only 280 (about 12%) of the farm households participate in both activities. Furthermore, while 950 farm households (about 44%) participate only in the off-farm labor market, only 209 (about 10%) participate only in CRP.

In a study also based on the ARMS data and designed to identify the effect of CRP payments on acreage enrolled in CRP, Chang and Boisvert (2009) document the importance of

[13] We do so for two important reasons. First, based on the 2001 ARMS data, most CRP participants are crop farms; the participation rate is 22%, with an average enrollment of 163 acres. In contrast, livestock farms accounted for 52% of all farms, but only 2% of livestock farms were in CRP, with an average enrollment of 4 acres. Furthermore, given the diversity of crop farming nationwide, it is already a considerable stretch to argue that there is a single production function for CRP participants and another for non-participants. The inclusion of livestock farms would have only compounded the difficulties in specifying and estimating the multiple output distance functions.

[14] The participation rates for our study are weighted by full sample weights, since we are interested in the farm household population. Our results are compatible with those by Ahearn and Lee (1991). According to Census of Agriculture, about 30% of farm operators worked some off the farm in 1929; this increased to about 53% by 1982.

including in our choice model environmentally related characteristics of the land enrolled in CRP, as well as some indication of the level of CRP payment. Although the ARMS database contains valuable information on the farm operation and the farm household, it unfortunately lacks information on land quality on the farm, local area economic characteristics, and certain aspects of the physical terrain or the quality of the area's land base that likely affect decisions to participate in the CRP and to work off the farm. To compensate for this lack of data, we also rely on some data from additional sources. For example, by aggregating data from the individual CRP sign-up files for 2001, we were able to include county-level indexes for wind and water erosion and county averages for the maximum allowable CRP rent payments.[15] The economic characteristics of local area are also merged into our ARMS data set. These are county-level data from the Bureau of Economic Analysis income files in 2000, the Bureau of Economic Analysis employment files in 2000, the Bureau of Labor Statistics, and the Census of Population, STF-3 file.

Three types of the household outputs are recognized. Gross cash sales are used as the measure of agricultural output, and the two non-farm outputs are: the wages and salaries from the off-farm work and the annual payment of CRP as the income from environmental program participation. Four inputs, including hours worked on the farm, operated acres, hired labor cost,

[15] Data from the CRP signup files, which have been used elsewhere, including in a study of farmers' attitudes toward CRP bidding by Vukina *et al.* (2008), were made available to us by Robert Dubman and Shawn Bucholtz of the ERS, USDA. However, these data only relate to the enrollments in 2001. Therefore, while it is possible to use these data to assign county level indexes for these variables to our observations, it is still impossible to merge the information for any farms that might be in both this file and the ARMS data because the farmer identification numbers are different. It is also important to emphasize that this is but one issue of concern to those using the ARMS data for complex economic analysis. It relates to broader concerns regarding the feasibility of integrating ARMS with other surveys and data sources, as well as some potential for bias due to the simultaneous nature of CRP enrollment and efficiency and the lack of repeated sampling with the ARMS data. Recommendations to address the integration issue and the feasibility of obtaining panel data from ARMS are contained in a recent review of the USDA's Agricultural Resource Management Survey by the National Research Council of the National Academy of Sciences (NRC 2007).

and capital, are specified.[16] Hired labor costs include regular hired labor and contract labor. Capital use is measured by the fixed value of building and farm equipment, excluding the value of principal operator's dwelling. The hours of off-farm work are added to the hours worked on the farm for farmers with off-farm work. The aggregate input for land (LAND) is defined as the total operated land area, including land owned, plus land rented in, less land rented out. Because this variable is an input included in the multiple output distance functions, it includes any land in CRP, because land in CRP is an input that must be accounted for in household production for the two groups that participate in CRP.[17]

Empirical Results

The Bivariate Choice Results

Table 3 presents the results of the maximum likelihood estimation of the bivariate probit model.[18] The parameter *RHO* (= 0.15) is the correlation between the error terms in the two participation equations. The value of the likelihood ratio test under the null hypothesis that *RHO*

[16] Output is the same as used by Goodwin and Mishara (2004) to study the effect of off-farm work on farm production efficiency. The list of inputs is similar (but not identical) to those specified by Nehring *et al*. (2005), and we measure them differently. Any aggregate measure of materials inputs was so collinear with capital that it was eliminated—an implicit assumption is that they are in fixed proportion to capital.

[17] In contrast, the variable in Table 2 defined as CROPSIZ1 (defined as operated acreage of cropland) includes all land in the LAND variable, less land enrolled in CRP and less land in wild hay production. Our hypothesis is that while farm size (as measured by cropland) should affect participation in CRP and/or off-farm work, this measure of size should exclude land enrolled in CRP.

[18] To account for the complex stratified sample design, ERS has developed a delete-a-group jackknife procedure based on dividing the ARMS data into 15 nearly equal and mutually exclusive groups, with associated group (also called replicate) weights (Dubman 2000). While this procedure has proven reliable for estimating variances of many financial statistics (most are linear functions of the data) in large samples, much less is known about the performance in complex econometric models, particularly those involving relatively small subsamples of the ARMS data. As Goodwin and Mishra (2006) point out, it is not clear that the stratification scheme does not alter the likelihood functions beyond simple weights. They also argue that the appropriateness of applying the predefined jackknife replicate weights to several subsamples of the ARMS data, as in our case, is unclear. Since our focus is only on crop farms, the numbers of observations in the subsamples may well below the limits at which the "…jackknife estimator faces structural problems in its application" (Dubman 2000, p.11). This inability to correct for this sample design in estimating standard errors suggests that one must exercise more than a normal degree of caution in extending any statistical inferences to the general population. The full sample weights, however, are used in our analysis to reflect the appropriately the national characteristics of the crop farm households.

is equal to zero is 8.02, which is greater than the critical value (3.84) for the 5% significant level or higher. Therefore, we reject the hypothesis that these choices are independent.

Determinants of CRP Participation

Participation in CRP depends generally on some characteristics of the farm, the farm operator, land quality, and the circumstances in the local economy (Table 3). The probability of participation in CRP increases with farm size (CROPSIZ1), but is lower if the farm is primarily engaged in vegetable, fruit, and cotton, rather than other crop farms. This difference probably reflects the higher opportunity cost of removing land from production on vegetable or fruit farms.

CRP participation is also determined by environmental characteristics. Perhaps it is no surprise to see that farm households located in areas where the maximum allowance of CRP rental payments are higher are more likely to participate in CRP, *ceteris paribus*. Furthermore, it appears that participation in CRP is more likely in counties with high indexes for both wind and water erosion.

There are two variables that suggest participation in CRP is related to the life-cycle of the farm operator. The likelihood of CRP participation increases with age (OP_AGE). Thus, as farmers get older, committing some land to CRP may be one way of reducing operator labor requirements on the farm. This may also be a way of holding onto farmland assets until they are needed for the retirement years, or so that they can be passed on through an estate. The fact that there is a positive correlation between the probability of farmers working off the farm and the probability of participation in CRP (as measured by *RHO*) may also reflect a desire to reduce operator labor requirements as land is taken out of production. Finally, the likelihood of CRP participation increases as a farmer’s education (OP_ED_C) level increases; this is perhaps an indication that investments in human capital might lead to increases in CRP participation.

There are also several ways in which risk can affect the participation in CRP. As aversion to risk increases, the likelihood of participation in a program where payments are certain, such as CRP, should increase. This conclusion is supported by the negative sign on the variable "RISK" in Table 3 (e.g. high values for "RISK" are associated with farmers who prefer more risk). This result is also not inconsistent with Hennessey (1998) in that, with the decreasing absolute risk aversion (DARA), farmers are likely to be less concerned about diversifying into risk-free income opportunities as wealth increases through decoupled payments.[19] However, it is difficult to know if the attitudes toward risk are driving this result, or if it is also in part due to the fact that in order to receive decoupled payments, the land must be kept in good agricultural use (including fallow). Farmers would likely incur both fixed and variable costs to do so. Furthermore, by receiving decoupled payments rather than enrolling land in CRP, a farmer retains his program base acreage and the option of bringing land back into production or even converting it to non-agricultural uses. Finally, since commodity program related loan deficiency payments (LDP_A) reduce farm income variability, these payments also reduce risk averse farmers' likelihood of allocating farm resources to CRP.

Participation in other programs is also associated with the likelihood for CRP participation. For example, if the farmer is enrolled in a voluntary agricultural district, subject to a farmland preservation easement, or is located in an agricultural protection zone (the variable AGDIST), the farmer is less likely to participate in CRP. Many farmers participate in these types of programs (most of which are state or local programs) out of concern for maintaining their land in agricultural production in rapidly growing areas where there is competition for land for non-agricultural purposes. Therefore, these farmers would be less likely to enroll land in a program

[19] By assuming non-constant absolute risk aversion, Hennessey's (1998) framework is also consistent with our results in the sense that he shows that under these conditions, decoupled payments can affect crop production alternatives.

such as CRP that essentially takes land out of production. The fact that the likelihood of CRP participation falls as the proportion of population that is urban rises would seem to reinforce this explanation, as would the fact that there is probably a higher option value for land in these areas that would be more difficult to realize on land that cannot be converted to a non-farm use for at least the duration of a CRP contract.[20] In contrast, farmers who participate in the Environmental Quality Incentives Program (EQIP)[21] are also more likely to participate in CRP. Participation in both EQIP and CRP could reflect a farmer's stewardship for the environment by removing particularly venerable land from production, while at the same time using more environmentally friendly practices on land still in production.

Determinants of the Off-Farm Work Decision

As expected, the decision of the farm operator to engage in off-farm work also depends on characteristics of the farm, the farm operator, and the circumstances in the local economy (Table 3). As in much of the existing literature (e.g. Sumner 1982; Benjamin and Guyomard 1994; Abdulai and Delgado 1999), our results continue to confirm the fact that older farmers are more likely to work off the farm. However, the effect is nonlinear. Although the operator's education (OP_ED_C) has a positive effect on the probability of participation in off-farm labor market, the years of experience on the farm (OP_EXP) has a negative effect that increases at an increasing rate. Farm operators raised on farms (RAISE_OP) are also less likely to work off the farm. Since returns to off-farm labor are likely to be less variable than farm returns, the

[20] Duke (2004) also found that the likelihood of participation in CRP is lower in urban areas.
[21] The Environmental Quality Incentives Program (EQIP) is a voluntary conservation program for farmers and ranchers who promote agricultural production and environmental quality as compatible goals. It offers financial and technical help to assist eligible participants implement management practices on eligible agricultural land. Because EQIP was enacted in 1996, the rate of participation in EQIP reflected in the 2001 ARMS data is extremely modest (less than one percent, Table 2). Consequently, while the conclusion that those participating in EQIP are also more likely to participate in CRP has intuitive appeal, it is difficult to have much confidence in this empirical result. However, in a very different context, Goodwin and Smith (2003) offer additional evidence that participation in other farm programs can affect CRP participation.

indication that the likelihood of off-farm participation is lower for farm operators willing to accept more risk (a negative coefficient on "RISK" in Table 3, a variable that increases as a farmer is willing to accept more risk) is consistent with the theory of risk averse behavior, but the effect is not statistically significant.

The likelihood of working off the farm decreases with family size (H_SIZE), but increases if the spouse is primarily a homemaker (SP_HMAK). This latter result may not square with the fact that the operator's likelihood of working off the farm increases with the spouse working off the farm.[22] The likelihood of participation in off-farm work declines with farm size (CROPSIZ1) and farm tenancy (TENANCY), and is lower for vegetable operations (VEGE) and cotton farms (COTTON). The negative effects on the likelihood of participation of both net worth (NETWORT1) and participation in government programs (e.g. AMTA_A) other than CRP may reflect wealth or scale effects on off-farm labor supply (Goodwin and Mishra 2004). The negative effect of tenancy (as measured by the proportion of acreage owned) on the likelihood for off-farm job participation reflects a greater commitment to agricultural production (*ceteris paribus*) from operators who own their own land. Finally, there is some indication that the strength of the local economy, as measured by the proportion of jobs that are manufacturing (MANUF), increases the likelihood of participation in off-farm work. The relative extent to which the local economy depends on jobs in the trade (TRADE) sectors reduces the likelihood to work off the farm.

[22] To disentangle these results, we might well have to specify the characteristics of household size in greater detail and also deal with the fact that the decision of the spouse to work off the farm may be endogenous. It would be empirically challenging in estimating the distance functions needed for the efficiency analysis discussed below.

Technical Efficiencies of Farm Households

The estimated multi-output distance functions are presented in Table 4. These functions fit the data quite well, and many of the coefficients are statistically significant. [23] For all models, the estimated input production elasticities are positive at the sample means but differ across groups.[24] For example, the estimated production elasticities for land inputs are 0.45 and 0.13 for the group of farms participating in CRP and working off-farm, and for the group of farms participating in neither activity, respectively.

The results of the Wald tests under the null hypothesis that the two terms included in the estimated distance functions to correct of self-selection bias are jointly equal to zero are all greater than the critical values for these four groups of farmers (the bottom of Table 4). These results indicate that household production and the participation in CRP and working off the farm are correlated due to some unobserved factors, and they support our corrections for the self-selection bias.

Comparing Distributions of Estimated Technical Efficiencies Among Groups

Based on the estimates in Table 4, the composite error terms are then decomposed into their respective random error and technical inefficiency components according to equations (8) through (11), and estimates of the technical efficiencies for each farm household in the sample are calculated according to equation (12).

To discuss the differences in technical efficiencies of household production across the four participant groups, it is important to emphasize, as we do in footnote 2, that these differences are affected directly by the terms accounting for self-section, but also indirectly

[23] The standard errors of the estimators of these coefficients are based on the bootstrap method with 500 replications.
[24] Using the coefficients of the multi-output distance functions, we calculate these input production elasticities at the sample means of the data for each group. We then calculate the standard errors of these input elasticities based on the delta method. Thus, these standard errors can be regarded as the first-order approximations to the asymptotic standard errors of the input elasticities (Greene 2003).

through the distinct exogenous factors that explain participation in off-farm work and CRP and also characterize the environment in which farm and household production take place, although it is impossible to isolate these separate indirect effects. To discuss these differences in the technical efficiencies, we also report sample statistics in Table 5 and depict the cumulative distributions by group in Figure 1. To better understand the extent to which these distributions of technical efficiencies may differ by group, they are ranked by stochastic dominance criteria. Since it is well known that stochastic dominance criteria are not terribly robust in identifying differences in distributions (e.g. Pope and Ziemer 1984), we also test the null hypotheses that distributions of each pair of groups are the same by applying the test procedure developed by Davidson and Duclos (2000). The numbers in parentheses in Table 5 are the minimum values of the test statistics (distributed asymptotically normal) for tests under the null hypothesis.

It is evident from Table 5 that, on average, the technical efficiency of household production is the highest for the subgroup participating in both off-farm work and CRP (e.g. subgroup (1,1)). Moreover, the distribution of farm household production for this subgroup statistically dominates other distributions either by first-degree or second-order stochastic dominance. These results provide important evidence in support of the hypothesis that since both the CRP and off-farm work remove substantial resources from agricultural production, doing so would improve the technical efficiency of the productive activities of the entire farm household. This is also true for those farms where the operator works off the farm, but where there is no land committed to CRP (e.g. subgroup (0,1)). In this case, the technical efficiency for the household is higher on average than that for farm production by those farmers participating in neither CRP nor off-farm work (0.72 vs. 0.43), and the former distribution also dominates the latter by first-degree stochastic dominance (Table 5).

In contrast, for those farms where land is taken out of production and enrolled in the CRP, but the operator does not work off the farm, average household technical efficiency is 0.34. This suggests that while removing both land and labor from agricultural production improves the technical efficiency of farm household production, removing labor alone through off-farm work still improves resource allocation, but this is not true when only land is taken out of production through CRP participation.

Finally, by examining the shape of these distributions of technical efficiency, we are also able to examine the effects on efficiency of off-farm work in somewhat greater detail than found in previous studies (e.g. Goodwin and Mishra 2004). The distribution of household efficiency of the farmers with off-farm work (te3_h) is dominated by the distribution of farm household participation in CRP and working of the farm (te1_h) at the second degree. Since the distributions cross, it is also important to compare those farms in the lower tails of the two distributions. In particular, the CDF for those with operators working off the farm lies to the left of those for the group that participating in both CRP and off-farm work. This evidence shows that the technical efficiency for the group (0,1) is lower than the technical efficiency of group (1,1) for a rather large proportion of the farm households. Thus, for the relatively inefficient farms, reallocating some labor to off-farm jobs and land in CRP seems to improve the efficiency for these farms. However, the story is different for farmers with relative higher technical efficiencies in that the CDF for those with operators only working off the farm lies to the right of those for the group that participating in both activities. It is in this part of the distribution that one might well have expected lower technical efficiencies for this group relative to the group involved in both activities, but it is not the case.

Concluding Remarks and Policy Implications

To better understand the interaction between the farm business and the farm household, this paper focuses on several issues related to decisions by the farm household regarding participation in the Conservation Reserve Program (CRP) and off-farm work. Our discussion is followed by the development of formal econometric specifications for the important components of the empirical analysis. By estimating these econometric models, we identify those factors that explain participation in these two major non-production related sources of income for farm households. For the appropriate subgroups of farm households, and accounting explicitly for the self-selection bias in estimating multi-output distance functions, we compare differences in technical efficiencies of the household production across subgroups of farms.

Our findings support the hypothesis that decisions by the farm household to participate in CRP and to work off the farm are interrelated. Participation in CRP depends generally on farm characteristics, the farm operator (including age, experience, and attitudes to risk), environmental characteristics of the land, and the circumstances in the local economy. As one would expect, decisions to work off the farm are related to many of these same factors, although the direction and magnitude of some of the effects are quite different. It is also true that both decisions are affected by participation in other farm programs. In particular, the probability of participation in CRP increases with farm size, but perhaps due to the higher opportunity cost of land removed from production, the probability of participation is less if the farm is primarily engaged in vegetable or fruit production.

To shed additional light on the effects of these two decisions on the farm household production efficiency, we estimate multi-output distance functions for farm households engaged in CRP and/or off-farm work. Our results indicate that the operators' decisions to work off the farm (including those that also participate in CRP) have led to significant improvements technical efficiency, perhaps in part due to better allocation of resources. It is difficult to know why the reverse is true for those participating in CRP, but not working off the farm. One possible explanation is that the efficiency of household production is reduced by taking land out of production without making comparable reductions in labor used on the farm. Regardless of the reasons for these differences, the technical efficiency of the entire household is influenced by differential local and regional opportunities for off-farm work and to enroll land in CRP. These considerations could be increasingly important in future farm-level decisions, and in changes in the policy incentives to encourage participation in environmentally related programs such as the CRP. These considerations could be particularly important in certain areas of the country where the opportunity costs of enrolling land in CRP to promote environmental objectives have increased recently due to increased demand for corn and oil crops in the production of bio-fuels.

References

Abdulai, A., and C. Delgado. 1999. "Determinants of Nonfarm Earnings-Based Husbands and Wives in North Ghana." *American Journal of Agricultural Economics* 81: 117-130.

Ahearn. M., and J. Lee. 1991. "Multiple Job-Holding Among Farm Operator Households in the United States". In *Multiple-Job Holding Among Farm Families*, edited by M. Hallberg., J. Findeis., and D. Lass. Iowa State University Press, Ames, IA.

Aigner, D., C. A. Lovell, and P. Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6: 21-37.

Benjamin, C., and H. Guyomard. 1994. "Off-Farm Work Decisions of French Agricultural Households." In R. Caillavet, H. Guyomard., and R. Lifran (eds). *Agricultural Household Modelling and Family Economics*: 65-85. Amsterdam. New York. Elsevier.

Bradford, W., A. Kleit., M. Krousel-Wood., and R. Re. 2001. "Stochastic Frontier Estimation of Cost Models within the Hospital." *Review of Economics and Statistics* 83: 302-309.

Chang, H. H., and R. N. Boisvert. 2009. "Distinguishing between Whole-Farm vs. Partial-Farm Participation in the Conservation Reserve Program." *Land Economics* 85: 144-161.

Chavas, J. P., R. Petrie, and M. Roth. 2005. "Farm Household Production Efficiency: Evidence from the Gambia." *American Journal of Agricultural Economics* 87: 160-179.

Coelli, T., and S. Perelman. 2000. "Technical Efficiency of European Railways: A Distance Function Approach." *Applied Economics* 32: 1967-1976.

Coelli, T., D. Prasada Rao, C. O'Donnell, and G. Battese. 2005. An Introduction to Efficiency and Productivity Analysis, 2nd edition. New York, NY: Springer Science+Business Media, Inc.

Das, M., W. Newly, and F. Vella. 2003. "Nonparametric Estimation of Sample Selection Models." *Review of Economic Studies* 70: 33-58.

Davidson, R., and J. Duclos. 2000. "Statistical Inference for Stochastic Dominance and for the Measurement of Poverty and Inequality." *Econometrica* 68: 1435-1464.

Dubman, R.W. 2000. "Variance Estimation with USDA's Farm Costs and Returns Surveys and Agricultural Resource management Study Surveys." Working Paper No. AGES 00-01, Economic Research Service, United State Department of Agriculture, Washington, D.C.

Duke, J. 2004. "Participation in Agricultural Land Preservation Programs: Parcel Quality and a Complex Policy Environment." *Agricultural and Resource Economics Review* 33: 34-49.

Gardner, B. 2000. "Economic Growth and Low Incomes in Agriculture." *American Journal of Agricultural Economics* 82: 1059-1074.

Goodwin, B., and V. H. Smith. "An Ex Post Evaluation of the Conservation Reserve, Federal Crop Insurance, and Other Government Programs: Program Participation and Soil Erosion." *Journal of Agricultural and Resource Economics* 28: 201-216.

Goodwin, B., and A. Mishra. 2004. "Farming Efficiency and the Determinants of Multiple Job Holding by Farm Operators." *American Journal of Agricultural Economics* 86: 722-729.

Goodwin, B., and A. K. Mishra. 2006. "Are Decoupled Farm Program Payments Really Decoupled? An Empirical Evaluation." *American Journal of Agricultural Economics* 88: 73-89.

Gonzalez, M., and R. Lopez. 2007. "Political Violence and Farm Household Efficiency in Columbia." *Economic Development and Cultural Change* 55: 367-392.

Greene, W. H. 2003. *Econometric Analysis*. Englewood Cliffs, NJ: Prentice Hall, Inc.

Grosskopf, S., K. Hayes., and J. Hirschberg. 1995. “Fiscal Stress and the Production of Public Safety: A Distance Function Approach.” *Journal of Public Economics* 57: 277-296.

Heckman, J. 1979. “Sample Selection Bias as a Specification Error.” *Econometrica* 47:153-161.

Hennessy, D. 1998. “The Production Effects of Agricultural Income Support Policies Under Uncertainty.” *American Journal of Agricultural Economics* 80: 46-57.

Huang, M., C. Huang, and T. Fu. 2002. “Cultivation Arrangement and the Cost Efficiency of Rice Farming in Taiwan.” *Journal of Productivity Analysis* 18: 223-239.

Isik, M., and W. Yang. 2004. “An Analysis of the Effects of Uncertainty and Irreversibility on Farmer Participation in the Conservation Reserve Program.” *Journal of Agricultural and Resource Economics* 29: 242-59.

Jondrow, J., C. A. K. Lovell, I. S. Materov, and P. Schmidt. 1982. “On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model.” *Journal of Econometrics* 19: 233-238.

Lass, D., J. Findeis, and M. Hallberg. 1991. “Factors Affecting the Supply of Off-farm Labor: A Review of Empirical Evidence.” In Hallberg, M.C., Findeis, J.L., and D.A. Lass (eds). *Multiple Job-Holding among Farm Families*. Iowa State University Press. Ames. Iowa.

Lee, L. 1983. “Generalized Econometrics Models with Selectivity.” *Econometrica* 51: 507-512.

Mundlak, Y. 1996. Production Function Estimation, Reviving the Primal. *Econometrica* 64: 431–438.

Nehring, R., J. Fernandez-Cornejo, and D. Banker. 2005. “Off-farm Labour and the Structure of U.S. Agriculture: the Case of Corn Soybean Farms”, *Applied Economics* 37: 633-649.

NRC. 2007. *Understanding American Agriculture: Challenges for the Agricultural Resource Management Survey*, National Research Council, National Academy of Sciences, Washington, D. C.

OECD. 2001. *Environmental Indicators for Agriculture: Volume 3 Methods and Results*, Agriculture and Food, Organization for Economic Co-operation and Development. France: Paris.

OECD. 2003. *Farm Household Income: Issues and Policy Responses*, Organization for Economic Co-operation and Development. France: Paris.

Offutt, S. 2002. "The Future of Farm Policy Analysis: A Household Perspective." *American Journal of Agricultural Economics* 84: 1189-1200.

Olson, J., P. Schmidt, and D. Waldman. 1980. "A Monte Carlo Study of Estimators of Stochastic Frontier Models." *Journal of Productivity Analysis* 10:103-117.

Parks, P., and J. Schorr. 1997. "Sustaining Open Space Benefits in the Northeast: An Evaluation of the Conservation Reserve Program." *Journal of Environmental Economics and Management* 32: 85-94.

Paul, C. J. M., and W. Johnson., and G. Frengley. 2000. "Efficiency in New Zealand Sheep and Beef Farming: The Impacts of Regulatory Reform." *Review of Economics and Statistics* 82: 325-337.

Paul, C. J. M., and R. Nehring. 2005. "Product Diversification, Production Systems, and Economic Performance in U.S. Agricultural Production." *Journal of Econometrics* 126: 525-548.

Phimister, E., and D. Roberts. 2006. "The Effect of Off-farm Work on the Intensity of Agricultural Production." *Environmental and Resource Economics* 34: 493-515.

Pope, R., and R. Ziemer. 1984. “Stochastic Efficiency, Normality, and Sampling Errors in Agricultural Analysis.” *American Journal of Agricultural Economics* 66: 31-40.

Shephard, R. 1970. *Theory of Cost and Production Functions*. Princeton, NJ: Princeton University Press.

Sumner, D. 1982. “The Labor Supply of Farmers.” *American Journal of Agricultural Economics* 64: 449-509.

U.S. Department of Agriculture. 2007a. *Amber Waves* 5(1). Economic Research Service, U.S. Department of Agriculture. Washington, D.C.

U.S. Department of Agriculture. 2007b. Conservation Reserve Program Enrollment Statistics and Program Information 2004 Fiscal Year. Washington, D.C.: Farm Service Agency Report, 2004.

Vukina, T., X. Zheng., M. Marra., and A. Levy. 2008. “Do Farmers Value the Environment? Evidence from a Conservation Reserve Program Auction.” *International Journal of Industrial Organization* 26: 1323-1332.

Table 1: Sample Distribution of Participants in CRP and Off-farm Work

	CRP Program		
Off-farm Work	0	1	Total
0	751	209	960
%	*(34)*	*(10)*	*(44)*
1	950	280	1,230
%	*(44)*	*(12)*	*(56)*
Total	1,701	489	2,190
%	*(78)*	*(22)*	

** Weighted with full sample weights.

Table 2: Summary Statistics

Variable	Variable Definitions	Mean	Std. Dev.
Program Participation			
CRP	If household enrolled in CRP or CREP (=1); otherwise (=0)	0.22	0.42
OP	If the operator worked off the farm (=1); otherwise (=0)	0.56	0.50
Characteristics of the Operator and Spouse			
OP_AGE	Age of the operator	54.64	13.79
OP_ED_C	Education level of the operator (years)	13.03	2.44
OP_EXP	Years of the operator working on farm job	25.61	63.27
RISK	Risk preference of the operator; = 0 if risk averse, 10 if risk loving	4.47	2.42
RAISE_OP	If the operator was raised on the farm (= 1); otherwise (= 0)	0.79	0.41
SP_HMAK	If the spouse is a home maker (= 1); otherwise (= 0)	0.25	0.44
H_SIZE	Number of household members	2.74	1.27
Farm Household Characteristics of the Farm			
CROPSIZ1	Operated acreage of cropland divided by 1,000	0.32	0.68
TENANCY	Owned acreage divided by total acreage	0.95	2.09
GRAIN	If cash grain farm (= 1), otherwise (=0)	0.42	0.49
VEGE	If vegetable farm (= 1), otherwise (= 0)	0.05	0.23
FRUIT	If fruit farm (=1), otherwise (= 0)	0.10	0.30
COTTON	If cotton farm (= 1), otherwise (= 0)	0.02	0.15
AMTA_A	Per acre AMTA (Agricultural Market Transition Act) payment	5.54	12.69
LDP_A	Per acre LDP (Loan Deficiency Payment) payment	8.34	18.24
NETWORT1	Household net worth ($100,000)	4.60	15.72
AGDIST	If farm is in local agricultural preservation program (=1); otherwise (= 0)	0.05	0.22
Environmental Characteristics			
MAXPAY	Maximum CRP payment allowance (county level)	60.88	23.50
WATER	Index of water erosion (county level)	11.82	8.05
WIND	Index of wind erosion (county level)	2.65	3.59
EQIP	If participate in EQIP (=1), otherwise(= 0)	0.00	0.05
Location and Local Economic Conditions			
URBAN	Percent of labor market area's population in urban areas, (1990 census)	56.48	21.77
MANUF	LMA’s employment in manufacturing (%), lagged one year	13.97	6.87
TRADE	LMA’s employment in wholesale and retail trade (%), lagged one year	20.32	2.34
REGN1	If ERS region 1(Heartland) (=1); otherwise (=0)	0.29	0.45
REGN3	If ERS region 3 (Northern Great Plains) (=1); otherwise (=0)	0.07	0.26

Table 2: Summary Statistics (cont.)

Variable	Variable Definitions	Mean	Std. Dev.
REGN567	If ERS region 5 (E. Uplands) ,6 (S. Seaboard), 7 (Fruitful Rim) (=1)	0.29	0.46
REGN9	If ERS region 9 (Mississippi Portal) (=1); otherwise (= 0)	0.05	0.22
Production Performance			
OUTPUT	Agricultural sales ($1,000)	58.39	209.92
CRPOUT	CRP Annual Payment ($1,000)	1.43	5.21
OFFOUT	Income from off-farm work ($1,000)	9.18	46.41
HOUR_OFF	Hours worked off the farm by operator and spouse	1,978	1,646
ACRE_CRP	Acres enrolled in CRP	38.11	161.99
HOUR	Hours worked on the farm by the operator and spouse	1,692	1,399
LC_C	Operating cost, including livestock, crop, and energy expenses	36,258	98,352
LAND	Operated acres	405	923
CAPITAL	Value of total non-current assets minus the operator dwelling ($1,000)	466	1598
LABOR	Hired labor cost	9,822	61,906

* Note: all variables are weighted with full sampling weights.

Table 3: Estimations of the Bivariate Probit Model

Variable	Coefficient	t-value
	CRP Decision	
Constant	-2.02	-5.33
OP_AGE	0.03	8.87
OP_ED_C	0.05	3.28
EQIP	0.93	1.91
AGDIST	-0.93	-3.12
MAXPAY	0.01	3.56
WIND	0.01	0.44
WATER	0.02	2.14
AMTA_A	-0.02	-3.16
LDP_A	0.00	-1.52
RISK	-0.04	-2.20
CROPSIZ1	0.38	12.11
REGN1	0.13	1.02
REGN567	-0.89	-6.90
REGN9	0.69	3.17
URBAN	-0.01	-7.62
GRAIN	-0.66	-6.47
VEGE	-1.96	-4.06
FRUIT	-1.81	-5.09
COTTON	-0.99	-3.83
	Off-farm Work Decision	
Constant	0.72	0.64
OP_AGE	0.10	4.08
OP_AGESQ	-1.51	-9.38
OP_ED_C	-0.05	-0.77
OPAE	0.00	1.55
OP_EXP	-0.02	-4.25
OP_EXPSQ	0.00	4.26
H_SIZE	-0.10	-3.34
CROPSIZ1	-0.55	-16.12
RAISE_OP	-0.19	-1.99
MANUF	0.02	3.48

Table 3: Estimations of the Bivariate Probit Model (cont.)

Variable	Coefficient	t-value
TRADE	-0.04	-2.51
AMTA_A	-0.01	-2.85
LDP_A	0.00	-2.16
RISK	-0.02	-1.46
NETWORT1	-0.01	-1.88
SP_HMAK	0.15	1.93
REGN3	0.28	2.02
REGN567	-0.23	-2.70
TENANCY	-0.04	-2.05
GRAIN	0.17	1.85
VEGE	-1.47	-9.68
FRUIT	0.02	0.15
COTTON	-0.60	-2.77
RHO	0.15	2.96
Log-likelihood	-1,839	
LR test*	8.02	

Variables are defined in Table 2.

RHO is the correlation coefficient.

*The critical value is $x^2(0.95,1)=3.84$

Table 4: Estimation of the Multiple Output Distance Functions

	Group (1,1)		Group (1,0)		Group (0,1)		Group (0,0)	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	13.629	1.601	12.631	3.423	14.766	2.056	1.992	1.202
LGHOUR	-0.346	-0.229	-1.569	-1.397	-3.835	-2.468	-1.277	-4.600
LGLAND	2.015	3.296	-1.184	-1.757	1.343	2.673	0.012	0.045
LGLABOR	-0.701	-1.890	-0.218	-1.445	0.060	0.277	0.551	7.333
LGCA	-5.270	-4.688	-0.729	-0.769	-0.827	-1.225	-0.297	-0.786
LGHOURSQ	-0.121	-1.579	0.076	0.664	0.244	2.815	0.108	5.797
LGLANDSQ	0.018	0.417	0.070	1.086	-0.067	-4.936	0.029	2.842
LGLABORSQ	0.003	0.655	-0.023	-3.680	-0.025	-5.841	0.047	15.744
LGCASQ	-0.073	-1.041	-0.044	-0.571	-0.013	-1.000	0.102	4.337
LGHOUR*LGLAND	-0.326	-4.531	-0.096	-0.894	-0.142	-2.388	0.051	1.604
LGHOUR*LGLABR	0.080	2.036	0.003	0.081	0.013	0.506	-0.034	-3.646
LGHOUR*LGCA	0.672	4.580	0.203	1.648	0.105	1.253	0.028	0.623
LGLAND*LGLABR	0.000	0.018	0.089	3.649	0.000	-0.002	-0.037	-6.753
LGLAND*LGCA	0.008	0.088	-0.033	-0.339	-0.004	-0.195	-0.048	-2.313
LGLABOR*LGCA	-0.020	-0.945	-0.036	-1.498	0.004	0.446	-0.065	-7.200
OUT21SQ	0.058	3.798	0.042	3.588	--	--	--	--
OUT31SQ	-0.090	-4.106	--	--	-0.072	-10.193	--	--
OUT23	0.022	0.786	--	--	--	--	--	--
OUT2**LGHOUR	0.092	3.320	0.116	3.067	--	--	--	--
OUT2*LGLAND	0.017	0.341	-0.001	-0.014	--	--	--	--
OUT2*LGLABR	0.024	2.377	-0.003	-0.341	--	--	--	--
OUT2*LGCA	-0.058	-1.075	-0.031	-0.541	--	--	--	--
OUT3*LGHOUR	0.063	1.812	--	--	0.088	9.489	--	--
OUT3*LGLAND	-0.002	-0.030	--	--	-0.101	-6.709	--	--
OUT3*LGLABR	-0.050	-3.313	--	--	-0.005	-0.973	--	--
OUT3*LGCA	-0.061	-1.131	--	--	0.004	0.244	--	--
GRAIN	0.129	1.091	-0.305	-2.428	-0.089	-1.037	0.109	1.278
FRUIT	1.948	2.010	-0.278	-0.452	0.156	1.146	0.018	0.123
COTTON	-0.107	-0.310	-0.997	-2.946	-0.208	-0.752	0.292	1.475
IMR_CRP	0.250	2.473	0.316	3.175	-0.121	-2.399	-0.241	-5.382
IMR_OP	0.199	1.964	0.081	0.947	0.188	1.753	-0.219	-4.881
Elasticities (at sample means)								
Hour	0.189	1.754	0.091	0.517	0.069	0.610	0.662	7.793
Land	0.454	2.204	0.334	2.871	0.297	7.010	0.131	3.080
Labor	0.125	0.791	0.160	1.837	0.100	5.117	0.456	17.240
Capital	0.306	1.529	0.193	3.932	0.105	2.243	0.390	7.730
Adjusted R^2	0.95		0.93		0.83		0.82	
Wald Test*	7.61		10.26		8.29		6.88	

Note: Variables are defined in Table 1.

IMR_CRP and IMR_OP are calculated Inverse Mills Ratios for CRP and OP, respectively.

* The null hypothesis is: IMR_CRP=IMR_OP are jointly equal to zero. Critical values $x^2(2,0.95)=5.99$; $x^2(2,0.90)=4.61$

Group(1,1): both in CRP and off-farm work. Group(1,0): CRP only; Group(0,1): off-farm work only; Group (0,0): neither

Standard errors of the estimators are based on the bootstrap method with 500 replications.

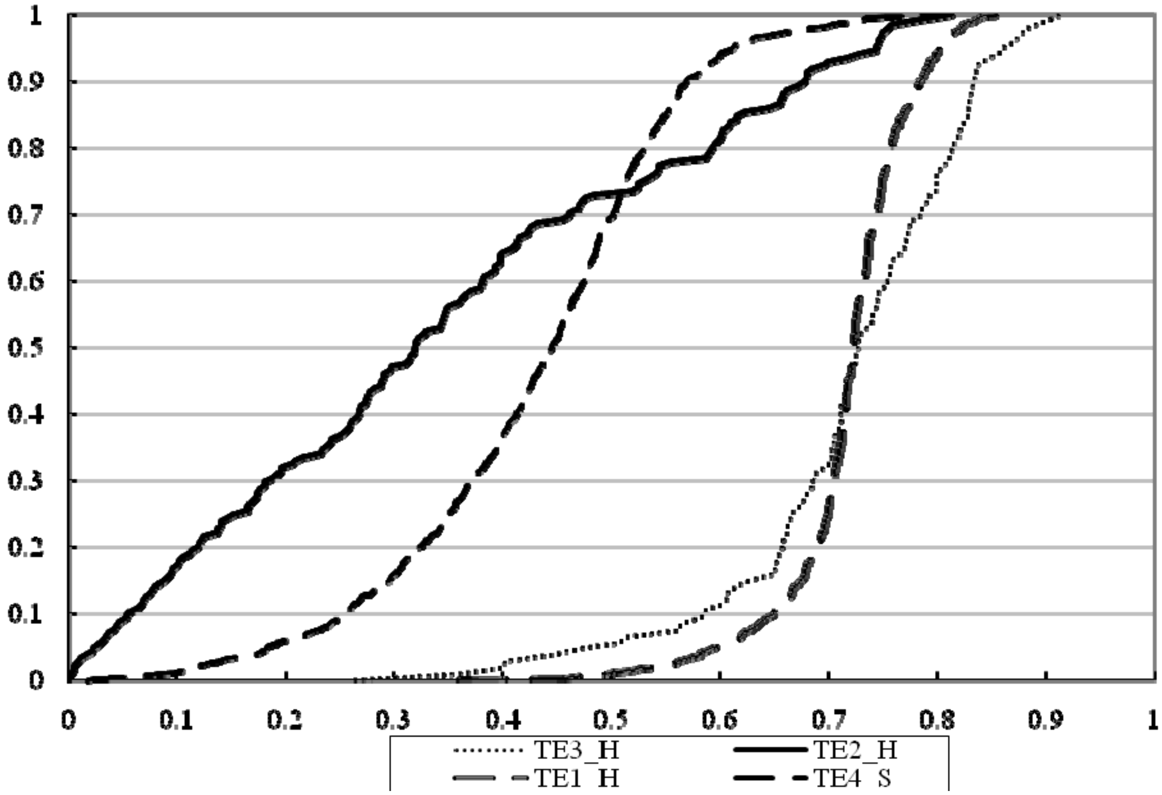
Standard errors of the elasticities are derived on the delta method.

Table 5: Sample Statistics for Household Technical Efficiencies

Group	(1,1)	(1,0)	(0,1)	(0,0)
Index	TE1_H	TE2_H	TE3_H	TE4_S
	Sample Statistics			
Mean	0.72	0.34	0.72	0.43
Std. Dev.	0.06	0.22	0.12	0.13
25 percentile	0.70	0.15	0.67	0.35
50 percentile	0.72	0.32	0.73	0.44
75 percentile	0.75	0.53	0.80	0.51
	Tests for Stochastic Dominance			
te1_h		FSD (6.65)	SSD (2.30)	FSD (7.49)
te2_h				
te3_h		FSD (3.05)		FSD (3.05)
te4_f		SSD (10.24)		

FSD and SSD represent first and second order stochastic dominance, respectively.
The minimum value of the t-statistics over the sample is reported in parentheses.
Statistics for the Stochastic Dominance tests follow Davidson and Duclos (2000).

Figure 1: Distributions of Household Technical Efficiencies



TE1_H, TE2_H, TE3_H, and TE4_S are technical efficiencies of household models of groups (1,1), (1,0), (0,1), and (0,0) respectively.
Group (1,1): For those farm households participating in CRP and working off-farm.
Group (1,0): For those farm households participating in CRP only.
Group (0,1): For those farm households working off- farm only.
Group (0,0): For those farm households participating in neither programs.

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