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The Supply of Off-Farm Labor: A Random Coefficients Approach

Daniel A. Lass and Conrado M. Gempesaw II

A joint model of off-farm labor decisions for farm operator and spouse is presented. Attention is given to operator and spouse participation decisions as well as associated problems of multiple sample selectivity biases. Two-stage fixed and random coefficient methods, corrected for possible selectivity biases, are used to estimate supply function parameters. Results indicate that supply function parameters are random. Variation in important supply parameters is investigated. Results also illustrate the importance of spouse decisions on off-farm labor supply function structure.

Key words: farm labor, off-farm labor, random coefficients.

Studies of farm family off-farm labor supply decisions have appeared frequently in the literature. Theoretical models based on the assumption of utility maximization have focused on the family's time allocation, i.e., Huffman (1980). Empirical applications typically have focused on a single family member, ignoring possible implications of joint decisions. Mroz and Thompson have shown that results from empirical models of married women's labor supply decisions are sensitive to model specification; however, neither Mroz nor Thompson explicitly considered the importance of joint decisions. Joint decision making is of greater importance to the farm family when both husband and wife allocate their time among farm work, off-farm work, home production, and leisure. Recently, empirical models have been extended to joint estimation of farm operator/spouse or male/female participation and supply decisions (Huffman and Lange; Gould and Saupe; Tokle and Huffman). Huffman and Lange demonstrated the importance of modeling household decisions jointly, concluding that off-farm labor supply functions

vary significantly in structure depending upon the spouses' decisions.

Theoretical results from utility models of time allocation show that expected signs for many parameters are ambiguous. For example, the impact of off-farm wage on labor supply may be negative or positive. The pure substitution effect of an increase in off-farm wage results in an increase in off-farm hours worked and decrease in leisure. The income effect is a priori uncertain. If leisure is a normal good, the income effect from an increase in off-farm wage has the opposite effect of, and may outweigh, the substitution effect. In addition, an increase in off-farm wage would lead to a decrease in onfarm hours, assuming no externalities.¹ Expected effects of human capital on participation and supply decisions of farm households are also ambiguous. Additions to the stock of education, for example, may improve efficiency of farm labor, thereby increasing the shadow value of on-farm time. However, increases in education also lead to higher off-farm wages. The relative strengths of these two effects on participation and supply decisions are unknown and are left as empirical questions.

Objectives of this paper are to embody important features of theoretical models of off-farm labor supply in an empirical model for the farm family. The first important feature is the application of methods appropriate for joint farm family labor supply decisions. Given Huffman

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¹ Streeter and Saupe present evidence of positive external effects from farm work.

and Lange's results, it is important to consider impacts of the spouse's decision when estimating an individual's off-farm participation and supply decisions. The second feature of our empirical model is to recognize ambiguity of expected parameter signs. Previous empirical models of off-farm labor supply have used fixed coefficient methods. The random coefficients model (RCM) (Hildreth and Houck, Swamy 1970) allows us to estimate individual parameter vectors. Permitting random regression coefficient vectors can account for inter-individual heterogeneity that often manifests itself as aggregation bias. Tests for randomness of RCM parameters provide an indication of the validity of constant-parameter results. Considering variation in important parameter estimates also indicates likely ranges for values.

Model Specification

Farm households are assumed to maximize utility (Huffman 1980)

(1)
$$U = U(O, L_1, L_2; H, E)$$

subject to constraints

(2)
$$P_o O = P_q Q - RS + W_1 M_1 + W_2 M_2 + V$$

(3)
$$Q = f(S, F_1, F_2; H, G)$$

(4)

$$T_l = L_l + F_l + Y_l$$
; and $Y_l \ge 0$, for $l = 1, 2$.

Leisure of only two household members, the operator (l = 1) and spouse (l = 2), are considered. The household chooses levels of purchased goods (O), leisure $(L_1 \text{ and } L_2)$, farm labor $(F_1 \text{ and } F_2)$, off-farm labor $(Y_1 \text{ and } Y_2)$, and farm inputs (S). Assumed fixed are stocks of human capital (H), prices for other goods (P_{o}) , farm output price (P_q) , farm input prices (R), off-farm wages (W_1, W_2) , other income (V), and other exogenous factors (F and G) that shift the utility function and production function, respectively. Both operator and spouse are assumed to have opportunities of supplying on-farm labor (F_1 and F_2) and off-farm labor (Y_1 and Y_2). The typical budget constraint (2) is imposed on the household, with farm profits and off-farm wages contributing to household income. This problem is similar to Shishko and Rostker's analysis of multiple job holding. An important difference arises in the constraint imposed by the production function (3); given normal regularity conditions, operator and spouse's on-farm labor will face diminishing marginal returns. Finally, constraints (4) say that leisure, on-farm labor, and off-farm labor compete for total time available.

An interior solution exists if optimal allocations of time to leisure, on-farm, and off-farm work are all nonzero. Optimal levels of choice variables then can be determined by solving first order conditions (see Huffman 1980). However, corner solutions may exist for operator and spouse's off-farm work. If corner solutions exist, off-farm labor supply functions are determined by simultaneously solving Kuhn-Tucker conditions. Huffman and Lange discuss in detail the conditional nature of farm family decisions.

Off-farm supply decisions are assumed to be made jointly by the farm family. The resulting off-farm labor supply function for the operator (spouse) is conditional upon the participation decision of the spouse (operator). Our model results in four off-farm work regimes: (1) both operator and spouse work ($Y_1 > 0, Y_2 >$ 0); (2) only the operator works ($Y_1 > 0, Y_2 =$ 0); (3) only the spouse works ($Y_1 = 0, Y_2 > 0$); and (4) neither operator nor spouse work offfarm ($Y_1 = 0, Y_2 = 0$). The reduced form of the operator's off-farm supply function when the spouse also works off-farm is

(5)
$$Y_1^1 = Y_1(W_1, W_2, P_o, P_q, R, H, E, V, G),$$

where the superscript denotes off-farm work regime. In this regime, operator's supply depends upon spouse's wage. Operator supply does not depend upon spouse's wage when the spouse does not work off-farm:

(6)
$$Y_1^2 = Y_1(W_1, P_o, P_q, R, H, E, V, G).$$

The spouse's supply function is defined similarly when both work (regime 1) and when only the spouse works (regime 3).

Empirical Model

The empirical model of farm family off-farm work includes supply functions for operator (Y_1) and spouse (Y_2) , and two participation decision rules. Unobserved indicators (I_i^*) are assumed to represent differences between individuals' value (W_i) of off-farm time and on-farm time at zero hours of off-farm work. If the potential market wage of an individual's off-farm time is greater than the shadow value of on-farm time, a positive number of off-farm hours will be observed. Thus participation decision rules determine observed values for Y_i :

(7)
$$Y_{li} \begin{cases} > 0 & \text{if } I_{li}^* = Z_{li}' \alpha_l + \varepsilon_{li} > 0 \\ = 0 & \text{if } I_{li}^* = Z_{li}' \alpha_l + \varepsilon_{li} \le 0; \end{cases}$$

for all households, i = 1, ..., N. The complete model is

(8)

$$Y_{1i} = x'_{1i}\beta_1 + u_{1i},$$

$$Y_{2i} = x'_{2i}\beta_2 + u_{2i},$$

$$I^*_{1i} = Z'_{1i}\alpha_1 + \varepsilon_{1i},$$

$$I^*_{2i} = Z'_{2i}\alpha_2 + \varepsilon_{2i},$$

which allows for joint participation and supply decisions. Model errors u_1 , u_2 , ε_1 , and ε_2 are assumed jointly distributed with zero means. The likelihood function for joint supply functions (8) can be specified; however, maximizing the likelihood function is difficult. An extension of Heckman's two-stage procedure to account for multiple selection rules can be applied to obtain consistent estimates of supply functions for different off-farm work regimes (see Maddala, pp. 278-83).

There are two sources of sample selection in the model: the operator works or does not and the spouse works or does not. While these two selectivity criteria, indicated by I_{1i}^* and I_{2i}^* in (8), are unobserved, we do observe binary indicators.

(9)
$$I_{li} \begin{cases} = 1 & \text{if } I_{li}^* = Z_{li}' \alpha_l + \varepsilon_{li} > 0 \\ = 0 & \text{if } I_{li}^* = Z_{li}' \alpha_l + \varepsilon_{li} \le 0. \end{cases}$$

The bivariate probit model is appropriate for firststage estimation of joint participation decisions defined by (9).

An individual's supply function structure is conditional upon participation decisions in (9). Population regression functions consistent with (5) or (6) above must consider the dependent variable's conditional nature:

(10.1)
$$E(Y_1|x^1, I_1^* > 0, I_2^* > 0)$$

= $x^{1'}\beta_1^1 + E(u_1|I_1^* > 0, I_2^* > 0);$

(10.2)
$$E(Y_2|x^1, I_1^* > 0, I_2^* > 0)$$

= $x^{1'}\beta_2^1 + E(u_2|I_1^* > 0, I_2^* > 0);$

(10.3)
$$E(Y_1|x^2, I_1^* > 0, I_2^* < 0)$$

= $x^{2'}\beta_1^2 + E(u_1|I_1^* > 0, I_2^* < 0)$

(10.4)
$$E(Y_2|x^3, I_1^* < 0, I_2^* > 0)$$

= $x^3 \beta_2^3 + E(u_2|I_1^* < 0, I_2^* > 0).$

The model results in four off-farm labor supply functions associated with the first three regimes. Supply function structures for different regimes vary in terms of variables included and values of parameters. Vectors x^1 , x^2 , and x^3 represent sets of independent variables for the regimes indicated. For example, $x^1 = \{W_1, W_2, P_o, P_q, R, H, E, V, G\}$.

Conditional expectations of u_1 and u_2 may be nonzero, resulting in selectivity bias (Heckman). First-stage bivariate probit results are used to calculate variables analogous to "Heckman's lambda" for the multiple-selection case. Operator and spouse selectivity adjustments are included in equations (10.1)–(10.4) to account for nonzero error expectations. The following set of labor supply functions can then be estimated in the second stage:

(11.1)
$$Y_{1i}^1 = X_i^{1'} B_1^1 + \mu_{1i}^1, \forall i \in n^1$$

(11.2)
$$Y_{2i}^1 = X_i^{1'} B_2^1 + \mu_{2i}^1, \forall i \in n^1,$$

(11.3)
$$Y_{1i}^2 = X_i^2 B_1^2 + \mu_{1i}^2, \forall i \in n^2$$

(11.4)
$$Y_{2i}^3 = X_i^{3'} B_2^3 + \mu_{2i}^3, \forall i \in n^3,$$

where n^1 , n^2 , and n^3 denote subsets of sample households for the regime indicated. Independent variable and parameters vectors contain necessary elements to correct for selectivity bias; for example, $X_i^1 = [x_i^1 \Lambda_{11i} \Lambda_{12i}]$ and $B_1^1 =$ $\{\beta_1^1 \zeta_{11}^1 \zeta_{12}^1]$, where x_i^1 was defined above. The Λ s are selectivity adjustment variables, and the ζ s are covariances of errors u_i and ε_i , (Maddala, pp. 278–83).² Random errors, μ s, now have the desired zero expectations.

We hypothesize that supply function parameters are random. By dropping subscript for operator (l = 1) and spouse (l = 2) as well as regime superscripts for expository purposes, RCM can be written as

(12)
$$Y_i = x_i' \beta_i + u_i;$$

where x_i and β_i are $K \times 1$ vectors for each observation. Each individual's parameter vector, β_i , varies from the mean vector, $\bar{\beta}$, by a vector of random errors, ε_i :

(13)
$$\beta_i = \bar{+} \varepsilon_i.$$

Using (13) we write (12) in matrix notation as

(14)
$$Y = x\beta + D\varepsilon + u;$$

where Y is a $(n \times 1)$ vector, x is a $(n \times K)$ matrix of the stacked x'_i , D is a $(n \times nK)$ diagonal matrix of the x'_i , ε is a $(nK \times 1)$ vector of $\varepsilon_i s$, and u is a $(n \times 1)$ vector. Disturbances u_i and ε_{ik} are assumed to have zero means. It is also assumed that $E(u_i \varepsilon_{ik}) = 0$ for all i and k,

² Details of calculations for the selectivity variables and parameters are available upon request.

 $E(u_i^2) = \sigma_i^2$, $E(u_i \ u_j) = 0$ for $i \neq j$, $E(\varepsilon_i \ \varepsilon'_j) = \Delta$ for i = j, and $E(\varepsilon_i \ \varepsilon'_j) = 0$ for $i \neq j$. Given these assumptions, composite disturbance vector $w = D\varepsilon + u$ will have a mean vector of zero and covariance matrix:

(15)
$$V(\theta)$$

= $\begin{bmatrix} x_1' \Delta x_1 + \sigma_1^2 & 0 & \dots & 0 \\ 0 & x_2' \Delta x_2 + \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & x_n' \Delta x_n + \sigma_n^2 \end{bmatrix}$.

The model is essentially Hildreth and Houck's and is a special case of Swamy's panel data model (1970). Parameter moments, rather than parameters themselves, are fixed. Estimation of moments can be viewed as an application of Aitken's generalized least squares. Using Swamy (1970), applying Aitken's generalized least squares to (14) results in the minimum variance estimator of $\hat{\beta}$:

(16)
$$\overline{b}(\theta) = [x'V(\theta)^{-1}x]^{-1}x'V(\theta)^{-1}y$$

with covariance matrix given by

(17)
$$V[\bar{b}(\theta)] = [x'V(\theta)^{-1}x]^{-1}.$$

Estimation of (14) using (16) requires that (17) and (15) be known. The SWAMSLEY Fortran based algorithm (Swamy and Tinsley) provides a minimum average risk linear estimator, which can be shown to be more efficient than the generalized least squares estimator for given values of β and Δ (Havenner and Swamy). Since Δ is unknown, the SWAMSLEY algorithm allows for initial data-based selection of Δ , with either zero or nonzero off-diagonal elements. After several iterations, stable values of $\bar{\beta}$ and Δ are obtained. Asymptotic *t*-ratios are calculated by dividing each estimated moment by the square root of the covariance matrix's corresponding diagonal element(17). Individual parameter estimates are derived using the mean parameter vector and estimates of individual errors $(\hat{\varepsilon}_i)$. Griffiths discusses the solution for the errors $\hat{\varepsilon}$ from estimates of the composite error vector \hat{w} .

Estimators of mean parameter vectors and individual parameter vectors are best linear unbiased (Swamy 1971, Griffiths). However, both $\bar{\beta}$ estimators and individual parameter vectors may suffer from sample selection bias. Errors u_i in equation (12) will have the same nonzero expectation as equations (10.1)–(10.4). Adjustments discussed for fixed coefficient models are applied to RCMs. For example, RCM for operator's supply function when the spouse also works is

(18)
$$Y_{1i}^1 = X_i^{1\prime} B_{1i}^1 + \mu_{1i}^1,$$

where X_i^i is defined above and $B_{1i}^1 = [\beta_{1i}^1 \zeta_{11i}^1 \zeta_{12i}^1]$.

Supply functions in (11.1)–(11.4) will be estimated by Heckman's two-stage procedure and as two-stage RCMs. For regime 1, operator and spouse supply functions will be estimated jointly to allow for cross-equation correlation of errors. (Singh and Ullah extend RCM to the seemingly unrelated case.) Supply functions for the operator when the spouse does not work (regime 2) and for the spouse when the operator does not work (regime 3) are estimated separately. Individual RCM parameters will be estimated and distributions of values considered. Of particular interest are individual labor supply responses to changes in off-farm wage rates.

Bruesch and Pagan have noted that RCM fits into the class of heteroskedastic error models and have proposed a test which becomes a test of RCM. However, the sample selection problem results in heteroskedastic errors and confounds the Bruesch-Pagan RCM test. In this study, we used a test proposed by Swamy (1971). If supply function parameters are random, then matrix Δ will contain nonzero elements. Thus the appropriate hypothesis test for RCM is H_o: $\Delta = 0$ and H_a: $\Delta \neq 0$. Swamy (1971) develops likelihood functions for his panel data model. The test statistic used here is straightforward application for two equation (regime 1) and single equation (regimes 2 and 3) cases.

Data

A survey of Pennsylvania farm households provided data used in this analysis. A random sample of farms, stratified by county, was drawn from Agricultural Stabilization and Conservation Service (ASCS) tape.³ Data for 1985 were collected by telephone interview from November 1986 through April 1987. Questionnaires from 989 Pennsylvania farm households were complete, a response rate of about 30%. To identify factors affecting choices by primary farm decision makers, data were collected for the farm

³ The ASCS list of farms may not accurately represent the true farm population. Comparison of the survey and the 1982 Census of Agriculture in terms of the distribution of farms by cash sales indicated our data were representative. See Hallberg, Findeis, and Lass (1987) for a complete description of the data.

operator and spouse.⁴ Theory suggests that prices and other exogenous factors are arguments of off-farm participation and supply models, but with the exception of wages all households in the sample were assumed to face similar price levels. Analysis will focus on impacts of wages and other exogenous factors, on off-farm participation, and supply decisions. The data set contains off-farm employment information for each individual, characteristics of each individual and the farm family, farm characteristics, financial indicators, and location measures. Only farm households with both operator and spouse present were used. After deleting respondents with missing values, data for 610 farm households were available for empirical analysis.⁵

Off-farm employment was measured by total hours worked in 1985. Wages were measured in dollars per hour worked. Forty-six percent of these households reported no off-farm employment. In 18% of households, both operator and spouse worked off-farm. Only the operator worked off-farm in 26% of the households. In the remaining 10%, the spouse was the sole offfarm participant. Pennsylvania farm operators and spouses had substantial off-farm employment hours. When both work off-farm, the operator worked nearly full-time on average (39 hours per week), and the spouse worked an average of 32 hours a week. When the spouse did not work off-farm, the operator averaged about 37 hours per week. The spouse worked about 28 hours per week when the operator did not work off-farm.

Wage rates are assumed to represent exogenous evaluation of individuals' human capital stock. Wage functions often are modeled and used in supply functions as predicted endogenous variables (Huffman and Lange, Sumner). But this eliminates important variation. In this study, actual wages were used to estimate supply functions. Wages are only arguments of supply functions. Theoretically, the difference between off-farm wage and shadow value of farm labor determines the dependent variable in participation models. Hours supplied off-farm typically have been found to have a positive relationship to off-farm wages (see Hallberg, Findeis, and Lass for reviews).

Individual characteristics include age, education, off-farm experience, and years farming. Age was measured in years, as were education (high school graduate = 12 years), off-farm experience, and farm experience. Including age in quadratic form allows estimation of life cycle effects. Where life-cycle effects are observed, participation and hours supplied typically peak between ages 45 and 55. However, evidence of life cycle effects is conflicting (e.g., Rosenfeld). Off-farm experience was measured by the number of years the individual had off-farm work, including current job and previous jobs. Off-farm experience data were available only for individuals who worked off-farm. Previous empirical evidence has found farm experience to be negatively related to participation probability. Education and off-farm experience generally have positive effects on participation and supply.

Number of children in the family less than five years of age and those children aged five to eighteen were included to indicate number of dependents, a factor which has been found to be an important explanatory variable for farm women in off-farm participation and supply functions (Rosenfeld; Thompson; Tokle and Huffman). Since most spouses in this study are female, it is anticipated that number of children is more important to the spouse's decision. Also included in the data set was a measure of other income (non-wage income) available to the family. Other income was measured as a percentage of total family income. If leisure is a normal good, higher levels of other income would result in fewer hours of off-farm employment. Previous empirical results generally support this hypothesis although estimates have been inelastic (Sumner, Thompson).

Categorical and binary variables were included as farm characteristics. Ideally, the guasirent or production function would be estimated, with predicted values included in participation and supply models (Huffman 1980, Streeter and Saupe); however, necessary survey data were not available. A single categorical variable for farm sales, ranging from one (<\$10,000) to five (>\$500,000), was used as an alternative. We expect lower participation and fewer hours supplied for operators of larger farms. Binary variables for farm type were also included, using livestock (beef, hogs, and sheep) as basis for comparison. Participation and supply depend upon time requirements for different farm types. Dairy farm operators, for example, would be expected to have lower participation rates and fewer hours supplied.

⁴ Ninety-six percent of all farm operators were male (table 2), 99% of operators in regime 1 were male, and all spouses in regime 3 were female. It is likely that the models will capture most structural differences due to gender.

⁵ Several additional observations for supply functions were lost from each regime as a result of missing off-farm wage rates.

Several variables were used to capture location relative to centers of population or employment. Distance to nearest town was used in participation models to capture access to employment possibilities. Individuals who worked off-farm were asked how far they drive one way to work. Actual commuting distance to current job was used to measure location relative to employment centers for off-farm workers. Commuting distance also indicates costs associated with participation and labor supply. Cogan has shown that effects of such costs are ambiguous.

Results

Both fixed coefficient models and RCMs of supply functions required two-stage "Heckman" estimation procedures. In the first stage, operator and spouse participation decisions were estimated by maximum likelihood probit methods. Probit results were used to calculate variables for supply function's sample selectivity adjustments. Supply functions were then estimated by fixed coefficient and RCM methods. Probit results are presented first, followed by supply function results.

Participation Models

Operator and spouse participation decisions were estimated jointly, using the bivariate probit model, an appropriate model if univariate probit equations are correlated. Estimated cross-equation correlation was positive, 0.15, but not significantly different from zero (calculated t-statistic was 1.50). The correlation coefficient's lack of significance is consistent with other joint participation decision studies (Huffman and Lange; Lass, Findeis, and Hallberg 1989). Given that the hypothesis of zero cross-equation correlation was not rejected, operator and spouse univariate probit estimates are presented in table 1; they were used to calculate selectivity adjustment variables. Parameter estimates from univariate probit models were consistent with the bivariate probit results in sign and magnitude. Amemiya's pseudo R^2 , an indication of "goodness of fit," was 0.41 for the operator model and 0.18 for the spouse model. These models correctly predicted participation decisions for 82% of the operators and 76% of the spouses.

Probability of farm operator participation was affected significantly by operator's age, spouse's age, spouse's education, farm sales, and other

Table	1.	Univariat	te Probi	it Esti	mates	for
Pennsy	vlvan	ia Farm	Operato	rs and	Spous	ses

Variable	Operator	Spouse
Operator characteristics:		
Age (years)	0.3054*	-0.0441
ige (jeus)	(3.29)	(0.54)
(Age) ²	-0.0035*	0.0001
(rige)	(3.64)	(0.10)
Education (years)	0.0347	0.0003
Education (Jeans)	(1.10)	(0.01)
Sex (male $= 1$)	0.2366	(0.01)
Sex (mare = 1)	(0.77)	
	(0.77)	
Spouse characteristics:		
Age (years)	-0.1684*	0.0782
	(2.04)	(1.02)
(Age) ²	0.0016*	-0.0011
(8-)	(1.93)	(1.36)
Education (years)	0.0810*	0.1647*
20000000 (jouo)	(2.17)	(4.56)
Sex (male $= 1$)	(2.17)	0.0049
		(0.02)
Family characteristics:		(0.02)
Children ages < 5 (number)	-0.1841	-0.4383*
	(1.30)	(2.96)
Children ages 5-18 (number)	-0.0261	-0.3028*
children uges 5 16 (number)	(0.40)	(4.61)
Farm characteristics:	(0.40)	(4.01)
Years farming (years)	-0.0046	-0.0085
rous running (jours)	(0.77)	(1.38)
Farm sales (categorical)	-0.6648*	-0.1747*
Turni suies (eurogorieur)	(9.12)	(2.74)
Dairy (yes $= 1$)	-0.8384*	-0.1090
Dully (jes 1)	(4.58)	(0.62)
Field crops (yes $= 1$)	-0.0177	-0.0323
Tield crops (jes T)	(0.10)	(0.20)
Veg. and flowers (yes $= 1$)	0.1874	0.1964
(jes 1)	(0.82)	(0.87)
Nursery and forestry (yes $= 1$)	-0.2104	0.3779
iterisery and foresuly (jes 1)	(0.53)	(0.97)
Fruit (yes $= 1$)	0.2745	-0.3402
Truit (yes = 1)	(0.45)	(0.58)
Financial characteristics:	(0.45)	(0.50)
Other income (% of total inc.)	-0.0140*	-0.0028
	(3.00)	(0.64)
Location:	(3.00)	(0.04)
Distance to town	-0.0169	-0.0160
Listunee to town	(1.14)	(1.09)
Pseudo R^2	0.4054	0.1845
χ^2	339.78	134.20
<u>A</u>	337.10	134.20

Note: Numbers in parentheses are absolute values of asymptotic *t*-statistics.

*-Statistically different from zero at the 5% level of significance.

income. In addition, probability of a dairy farm operator working off-farm was significantly lower than the mean. Results support the life cycle hypothesis: maximum probability of operator's offfarm work occurred at age 43. Spouse characteristics were important to operator's decision; significant effects were found for spouse's age and education. Estimated "U-shaped" response to spouse's age may be related to spouse's life cycle. Minimum probability for the operator is at spouse's age 53, just after spouse's maximum probability of off-farm employment. Effects of education on operator's participation were found to be positive, albeit insignificant. Spouse's level of education had a significant positive effect on operator's probability of working off-farm, which is consistent with Sumner's findings. Higher levels of farm and family financial indicators reduced the probability of operator's working offfarm. Both higher farm sales and greater levels of nonwage income lessen the likelihood of operator's off-farm work.

Farm spouse responses correlated strongly to family characteristics. Significant negative effects on spouse's participation were found for households with children less than five years of age as well as for children between 5 and 18. Increased farm sales also reduced spouse's participation. Higher levels of spouse's education significantly increased participation. It is notable that operator characteristics had no effect on spouse participation decisions. If the farm sales variable captures the farm's viability, then spouse's participation depends primarily on farm operation success and the presence of children.

Several variables carried expected signs but were insignificant. Parameter estimates for the spouse support the life cycle hypothesis, with the maximum participation probability occurring at age 36; however, results were not statistically significant. Other income had a negative effect on the spouse as well as the operator, suggesting leisure (or home time) is a normal good. Finally, the greater the distance to the nearest town, the lower were probabilities of off-farm employment.

Supply Functions

To correct for sample selection bias, both fixed coefficient and RCM supply functions were estimated by two-stage methods. The *SWAMSLEY* algorithm was modified to account explicitly for heteroskedasticity created by sample selection adjustment. Univariate probit estimates were used to calculate selectivity variables included in supply functions. Data were separated into off-farm work regimes and supply functions were estimated by regime. RCM supply functions for operator and spouse in the first regime (both work) were estimated as seemingly unrelated regressions. Different conclusions were reached about the importance of selectivity variables for fixed versus RCMs. Both operator and spouse selectivity variables were significant in operator supply RCMs.⁶ Neither selectivity variable was significant in fixed coefficient models of operator supply. Only the own-selectivity variable was significant in the spouse supply function for regime 3.

Tables 2 and 3 present estimated supply functions for operator and spouse, respectively. Both fixed coefficient results and RCM mean parameters are presented for comparison. Using a likelihood ratio test (Swamy 1971), the null hypothesis, H_0 : $\Delta = 0$, was rejected at the 1% level for each regime. Calculated chi-square statistics were 323.62 for the joint model of the first regime, 118.36 for the second regime, and 102.65 for the third regime. Parameters for all regime supply functions appear to be random. The following discussion will focus on interpretation of RCM mean parameters. Mean parameter estimates for RCMs were generally consistent in sign and more efficient than fixed coefficient estimates.⁷

Consistent with Huffman and Lange's findings, structures of individual supply functions changed depending upon spouse's participation. Off-farm wages had limited importance in supply decisions of both operators and spouses. Ownwage effects on operator hours supplied were negative for both regimes, but estimated parameters were not significantly different from zero. When both operator and spouse worked off-farm, spouse's own-wage effect was positive, although insignificant. When only the spouse worked off-farm, own-wage effect was negative and significant. Operator supply response to spouse's wage was negative also, suggesting spouse off-farm labor is a substitute for the operator's. Opposite cross-wage effect was observed for the spouse, suggesting that operator off-farm supply complements spouse's off-farm supply. However, neither cross-wage effect was significantly different from zero.

Individual characteristics had significant effects on supply functions. Own-age effect for the operator was inversely related to number of hours supplied when the spouse did not work off-farm. When both operator and spouse worked off-farm, age of spouse also was inversely re-

⁶ Calculated *t*-statistics presented are conditional on the estimated selectivity terms included.

 $^{^{7}}$ Havenner and Swamy discuss the relative efficiency of the RCM estimators.

	Both work off-farm		Operator only works	
Variable	RCM Mean	2-Stage	RCM Mean	2-Stage
Operator's wage	-7.97	-14.13	-5.47	-4.88
1 0	(0.98)	(0.98)	(1.32)	(1.47)
Spouse's wage	-21.16	-27.00	N.A.	N.A.
1 0	(1.30)	(0.96)		
Operator characteristics:				
Age	21.84	28.43	-12.57*	-15.52
6	(1.47)	(1.12)	(2.13)	(1.23)
Education	-49.91*	-25.91	49.74*	37.01
	(1.76)	(0.52)	(3.24)	(1.30)
Off-farm exp.	14.60*	12.67	10.27*	11.29*
	(2.15)	(1.09)	(3.04)	(1.83)
Spouse characteristics:		()	(2.2.7)	()
Age	-49.41*	-53.89*		
8-	(3.00)	(1.70)		
Education	118.39*	92.05		
Buuvunon	(2.49)	(1.10)		
Off-farm exp.	15.46*	13.93	N.A.	N.A.
	(2.38)	(1.31)	14.7 1.	
Family characteristics:	(2.50)	(1.51)		
Children ages < 5	409.83*	352.65	-141.26*	-69.92
children uges 4 5	(2.26)	(1.01)	(2.01)	(0.45)
Children ages 5–18	-152.42*	-146.33	-28.38	-13.88
Children uges 5 16	(1.81)	(0.92)	(0.89)	(0.22)
Farm characteristics:	(1.01)	(0.72)	(0.0))	(0.22)
Farm sales	68.45	-103.33	230.85*	168.97
Talm sales	(0.40)	(0.35)	(2.41)	(0.89)
Dairy	89.54	-46.94	-270.12*	-306.56
Dally	(0.31)	(0.09)	(1.81)	(1.07)
Financial characteristics:	(0.51)	(0.09)	(1.01)	(1.07)
Other income	-26.05*	-23.70^{*}	-1.59	-2.27
ould meetine	(4.78)	(2.54)	(0.42)	(0.44)
Location:	(4.70)	(2.54)	(0.42)	(0.44)
Commuting dist. (Op.)	-4.20	-0.49	-0.30	0.31
Commuting dist. (Op.)	(1.34)	(0.21)	(0.14)	(0.15)
Commuting dist. (Sp.)	-18.82*	-17.25*	N.A.	(0.15) N.A.
Commuting dist. (Sp.)	(3.58)	(1.89)	N.A.	N.A.
Lambda (Op.)	-1448.66*	(1.89) -1141.60	-719.05*	-516.29
Lamoda (Op.)	(2.94)	(1.36)		(1.13)
Lambda (Sp.)	(2.94) 1165.89*	1133.51	(3.02) 376.52*	(1.13)
Lambda (Sp.)	(2.38)			
Constant	(2.38) 1840.09*	(1.37) 2011.72*	(2.47) 2157.76*	(0.58) 2272.71*
Constant				
	(3.30)	(2.10)	(6.67)	(3.33)

Table 2. Supply Functions for Pennsylvania Farm Operators

Numbers in parentheses are absolute values of asymptotic t-statistics.

*-Statistically different from zero at the 5% level of significance.

N.A.-Not applicable.

lated to supply. A significant positive own-age effect was found for the spouse when the operator did not work. Operator's own-education had significant impacts on supply for both regimes. With higher own-education, operator hours declined when both work and increased when only the operator worked off-farm. A spouse's additional education of one year resulted in a reduction in supply by over 400 hours when the operator did not work. The number of off-farm employment years had consistently positive impacts on both operator and spouse supply functions. Own-experience effects were statistically significant in all models.

Effects of operator (spouse) characteristics on spouse's (operator's) supply decisions indicate changing structures of supply functions. When the operator or spouse did not work off-farm, their wage, off-farm experience, and commuting distance were not arguments of the supply

	Both work off-farm		Spouse only works	
Variable	RCM Mean	2-Stage	RCM Mean	2-Stage
Spouse's wage	20.51	5.63	-55.11*	-50.69*
	(0.80)	(0.20)	(3.73)	(1.70)
Operator's wage	31.13	20.72	N.A.	N.A.
	(1.21)	(1.41)		
Spouse characteristics:				
Age	-52.70*	-62.34*	67.00*	43.77
	(1.68)	(1.93)	(3.43)	(1.16)
Education	43.44	60.56	-422.31*	-282.10
	(0.55)	(0.71)	(3.98)	(1.39)
Off-farm exp.	23.44*	21.25*	45.63*	37.91*
•	(1.77)	(1.96)	(3.50)	(2.17)
Operator characteristics:			. ,	()
Age	14.53	13.56	N.A.	N.A.
	(0.46)	(0.52)		
Education	-1.38	3.19	N.A.	N.A.
	(0.02)	(0.06)		
Off-farm exp.	-14.61	-10.09	N.A.	N.A.
	(1.10)	(0.85)		
Family characteristics:	(1110)	(0.00)		
Children ages < 5	-749.12*	-800.69*	1142.19*	797.97
Chinaron ages < 5	(2.06)	(2.25)	(4.33)	(1.56)
Children ages 5-18	-344.30^{*}	-373.88*	441.37*	302.36
emilaten ages 5 16	(2.04)	(2.31)	(2.83)	(1.04)
Farm characteristics:	(2:01)	(2.51)	(2.03)	(1.04)
Farm sales	325.25	324.87	368.27*	176.28
Tam sales	(0.95)	(1.08)	(1.72)	(0.54)
Dairy	-367.25	-219.65	305.25	-4.26
Daily	(0.64)	(0.41)	(1.10)	(0.01)
Financial characteristics:	(0:04)	(0.41)	(1.10)	(0.01)
Other income	14.90	10.06	12.36	2.09
Other medine	(1.37)	(1.06)		
Location:	(1.37)	(1.00)	(1.37)	(0.16)
	10.93	8.78	11.06	0.72
Commuting dist. (Sp.)		(0.94)		9.73
Committing dist (Or)	(1.27)	· · ·	(1.35)	(1.06)
Commuting dist. (Op.)	-0.95	-6.50*	N.A.	N.A.
	(0.11)	(2.68)	2450 70*	0.400 T (*
Lambda (Sp.)	948.38	1156.15	-3458.78*	-2432.76*
	(0.58)	(1.37)	(4.70)	(1.82)
Lambda (Op.)	-568.55	-586.56	251.76	561.98
~	(1.01)	(0.68)	(0.38)	(0.57)
Constant	1425.94*	1718.42*	6047.09*	5240.00*
	(1.81)	(1.76)	(3.89)	(2.00)

Table 3. Supply Functions for Pennsylvania Farm Spouses

Numbers in parentheses are absolute values of asymptotic t-statistics.

*-Statistically different from zero at the 5% level of significance.

N.A.-Not applicable.

functions for the other. Remaining cross-individual characteristics that may affect supply decisions were age and education. Spouse's age and education were not important to the operator's supply decision. Similarly, the operator's age and education were not important to the spouse's supply decision.⁸ These results were

consistent with probit results for the spouse. When both operator and spouse worked off-farm, spouse characteristics were important to the operator's supply function, results similar to Huffman and Lange's findings for Iowa farm households.

Effects of children demonstrate important structural differences in supply functions for these three off-farm regimes. When both operator and spouse worked, each preschool child had a significant negative impact of nearly 750 hours an-

⁸ Variables were initially included in operator and spouse supply functions. Parameters were not statistically different from zero based on individual (t) and joint (F) tests of significance.

nually on spouse's supply. However, preschool children represented a strong incentive to supply more hours when only the spouse worked. Such an increase in hours may be influenced by fixed costs associated with establishing child care. The average spouse in this regime was younger and had a higher number of preschool children relative to other regimes, suggesting that financial pressure may have some bearing at that stage of the life cycle, but means for these variables were not statistically different. School-age children reduced spouse's supply by about 350 hours per child when both operator and spouse worked. When only the spouse worked, each school-age child increased supply by over 400 hours annually. Children also affected operator supply. School-age children had a negative impact on operator's supply. Preschool children significantly increased operator hours supplied when both operator and spouse worked, and decreased operator hours when the spouse did not work.

Farm characteristics had surprisingly little impact on supply decisions. Probit results showed that both operator and spouse reduced participation as farm sales increased. Given the decision to participate, size of farm had little impact on hours supplied when both worked off-farm. When only one worked off-farm, farm sales had a positive impact on hours supplied by both operator and spouse. Operator and spouse may be able to substitute hired labor for their own more effectively on larger farms. Farm type had little impact on participation decisions or supply functions. Only the binary variable for dairy farms was retained in final supply functions. Hours operator worked in regime 2 were significantly lower for dairy farms.

Other income had significant effects on operator's hours supplied when both worked, but did not significantly affect spouse supply functions in either regime. Commuting distance was used to capture location in the supply models. Cogan has shown that commuting time costs may increase number of hours supplied. Mean parameter estimates for the spouse were consistent with that result; however, mean parameters were not significantly different from zero. Operator's commuting distance had little impact on supply. When both worked off-farm, the operator did respond negatively to the spouse's commute.

Substantial variation was observed for individual parameters predicted from RCM supply functions. In several cases, both positive and negative values for individual parameter estimates were observed. For example, operator age

Table 4.	Individual W	Wage and Inco	ome Elas-
ticities fro	om RCM Sup	pply Function	IS

Variable	Minimum	Mean	Maximum	
	Oper	Operator elasticities		
Operator wage:				
Both work	-0.31	-0.06	-0.01	
Op. only works	-0.78	-0.05	0.04	
Spouse wage:				
Both work	-0.75	-0.11	-0.02	
Other income:				
Both work	-4.17	-0.17	0.00	
Op. only works	-0.51	-0.01	0.19	
	Spor	Spouse elasticities		
Spouse wage:	<u></u>			
Both work	0.01	0.12	0.54	
Spouse only works	-9.82	-0.72	-0.21	
Operator wage:				
Both work	0.07	0.30	2.23	
Other income:				
Both work	0.00	0.06	0.55	
Spouse only works	0.00	0.09	1.54	

had both positive and negative effects on operator supply. Individual effects of own-education on operator supply varied from the mean parameter estimate by as much as 240% when only the operator worked off-farm. Own-experience effects for the operator varied from the mean parameter estimate by over 100% when only the operator worked and by 40% when both operator and spouse worked. In spouse supply functions, own-age effects varied from the mean estimate by 35% when only the spouse worked and 21% when both worked. Own-experience varied by 22% when both worked and 42% when only the spouse worked. Individual parameters for family and farm characteristics typically varied from mean parameter estimates by less than 1%. Exceptions were individual parameter estimates for children in the model where only the operator worked off-farm.

Estimated wage and other income elasticities are presented in table 4. Operator own-wage elasticity varied from a low of -0.31 to a high of -0.01 in regime 1. However, when only the operator worked, own-wage elasticity ranged from -0.78 to 0.04. Spouse own-wage effect was statistically significant when the operator did not work off-farm. Estimated off-farm supply own-wage elasticities for the spouse ranged from -0.21 to a highly elastic -9.82. Crosswage elasticities for the spouse also varied from an inelastic 0.07 to an elastic response of 2.23. Generally other income effects were found to be statistically insignificant, with the exception of operator's off-farm labor supply when both operator and spouse worked off-farm. Estimated individual income elasticities ranged from zero to -4.17. Most income elasticities for the operator were negative, suggesting leisure (or time at the farm) is a normal good.

Conclusions

A joint model of farm families' off-farm participation and supply decisions was applied to a sample of Pennsylvania farm families. Evidence was found to support the behavioral assumption that farm operators and spouses make joint participation decisions. Operator participation decisions, for example, were dependent upon spouse's characteristics. Spouse participation decisions, however, were not dependent upon operator characteristics; family composition was more influential in spouse participation decisions. As expected, farm characteristics were important to operator participation decisions.

Off-farm supply function structures of operator and spouse were found to differ when the existence of corner solutions for both operator and spouse were explicitly acknowledged in the empirical specification. Multiple sample selection was important in estimating supply functions by random coefficient methods. When both operator and spouse work off-farm, hours supplied were affected by both individuals' characteristics. This was not the case for regimes in which only one individual worked off-farm. Thus estimating operator and spouse labor supply functions without regard for multiple selectivity issues and possible joint decisions can lead to serious biases.

The random coefficient model was used to estimate off-farm labor supply functions and appears to be an attractive tool. Hypothesis tests of parameter vector randomness supported RCM use. RCMs also provide individual parameter estimates. A number of important parameters were found to vary substantially from the mean parameter estimates. For this reason, policy simulations based on standard fixed coefficient results could provide misleading conclusions. The RCM employed here provides further information on the random nature of farm family responses, information that is necessary to establish distributional impacts of changing economic conditions on farm family welfare.

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