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Simultaneity of Technology Adoption and Productivity

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A simultaneous equation generalized probit model is estimated to determine factors affecting technology adoption by California dairy farmers. Since productivity and technology choice are jointly determined, a single-equation approach to determine whether productivity affects technology adoption is subject to simultaneity bias. Since the system of equations contains both continuous and discrete endogenous variables, generalized probit is used. The findings indicate that the biased single-equation estimates tend to exaggerate relationships with explanatory variables, and in some cases, lead to different implications. This emphasizes the need to use the consistent and asymptotically more efficient generalized probit results to account for simultaneity.

Key words: California, dairy, generalized probit, simultaneous equations, technology adoption.

Introduction

Since Cochrane developed his treadmill model of technology adoption, many economists have examined how technological change has affected the structure of farming. The hypothesis that early adopters are more likely to survive than late adopters stresses the need to identify the factors influencing adoption at the farm level. Sociologists and economists have looked at the adoption process in an attempt to understand which farmers might adopt a new technology and which ones might be late adopters, and thus are more likely to go out of business. Models have been developed to test hypotheses on factors influencing technology adoption. Sociologists (Rogers; Rogers and Stanfield) have found that the adoption of a new technology is positively influenced by the current level of productivity of the farmer. Feder and Slade used a regional measure of productivity of their *ex post* adoption model and found it was significant in explaining the adoption of technology by rice farmers in northwest India. However, economic theory tells us that technology affects productivity. Thus, technology and productivity appear to be jointly determined. Therefore, estimating a single-equation *ex post* technology adoption model with productivity as an explanatory variable is subject to simultaneous equation bias. This raises the question about the validity of previous work on technology adoption in agriculture.

To test the effect of productivity on *ex post* adoption of technologies, productivity and technology adoption decisions must be estimated as a system of equations. In the following section, such a model is developed, consisting of a mixed system of observed continuous and discrete endogenous variables. The model is applied to a sample of California dairy farmers. It is estimated using a generalized probit (GP) method, yielding consistent pa-

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rameter estimates with desirable asymptotic properties. The results are compared to biased single-equation estimates. The model is used to examine how productivity affects producers' decision making and technology adoption.

The Model

A technology adoption model is constructed following McFadden, and Domencich and McFadden, relying on Thurstone's random utility formulation. The ith individual's preferences are assumed to be given by the expected utility of the present value of profit. Profit in turn depends on both technology choices (denoted by the vector Y_{1i} for the ith individual) and productivity (denoted by Y_{2i} for the ith individual). That is, the expected utility of profit is a function of the technology chosen, as well as productivity, which are both treated as choice variables. This implies that for an expected utility-maximizing decision maker, technology choice and productivity are jointly determined. In general, technology choice is a function of the attributes of each technology, including its price, and the attributes of the individual, X_{1i}.[1] Productivity is also a function of the attributes of the ith individual and other explanatory variables, X_{2i}. In the absence of a priori information on functional form, a linear functional form is used.

Some of the technology variables Y_{1i} are discrete choices. Each discrete choice is assumed to be equal to one if the ith individual chooses the technology, and zero otherwise. It can be shown, following Maddala, that the probability of the ith individual choosing a particular technology can be represented by a probit model. Since productivity and technology choice are jointly determined, a simultaneous system of equations is appropriate. This simultaneity is examined by specifying a structural model with selected dependent variables as "right-hand-side" variables. Productivity is a continuous variable, while many technology decisions are a discrete choice. Since they are both observable endogenous variables, it is not a latent variable model like that of Nelson and Olson. In the absence of latent variables, the model can be consistently estimated using Heckman's 2SLS method. However, Lee (1981) shows that Amemiya's GP estimator is asymptotically more efficient than Heckman's estimator for observed endogenous variables as well as latent variables.

Divide the jointly determined variables into two groups, $g = 1, \ldots, G$ discrete choices and $h = 1, \ldots, H$ continuous variables, such that G plus H equals K ($k = 1, \ldots, K$), the total number of endogenous variables in the system. For the ith individual, the structural form of the model can be written as follows:

$$Y_{ig} = \begin{cases} 1 & \text{if } X_{ig}\beta_g + Y^*_{ig}\gamma_g + \epsilon_{ig} > 0, \\ 0 & \text{otherwise;} \end{cases} \tag{1}$$

$$Y_{ih} = X_{ih}\beta_h + Y^*_{ih}\gamma_h + \epsilon_{ih}, \tag{2}$$

where Y_{ig} and Y_{ih} are endogenous variables. Y_{ig} is the ith individual's actual choice of the gth technology, where $g = 1, \ldots, G$ discrete observable variables. Y_{ih} is the hth continuous dependent variable, which includes productivity, $h = 1$, and the continuous technology choices, $h = 2, \ldots, H$. The Xs are exogenous variables pertaining to each equation. Y^*_{ig} and Y^*_{ih} are the right-hand-side dependent variables in the gth and hth equations, excluding Y_{ig} and Y_{ih}, respectively. The betas and gammas are coefficients of the model. Assume ϵ_i is an error term that is independently, identically, and normally distributed with mean zero.

Single-equation estimation of equations (1) and (2) via probit and OLS, respectively, results in inconsistent coefficient estimates due to the simultaneous equation bias. Amemiya's GP estimator is consistent and asymptotically more efficient than Heckman's estimator (Lee 1981). The first stage of GP estimation is to derive instruments from the reduced form estimation of the model (Amemiya; Lee 1981; Maddala). This reduced form can be written as:

(3) $$Y_{ig} = \begin{cases} 1 & \text{if } X_i\pi_g + u_{ig} > 0, \\ 0 & \text{otherwise;} \end{cases}$$

(4) $$Y_{ih} = X_i\pi_h + u_{ih},$$

where X_i is a matrix of all the explanatory variables, containing X_{ig} and X_{ih}, the πs are reduced form coefficients, and the us are error terms. The Y_{ig} equations are consistently estimated via probit, and the Y_{ih} equations are estimated with ordinary least squares. The coefficient estimates, $\hat{\pi}$ or pi-hat, which are consistent parameter estimates of the parameters in (3) and (4), are used as "instruments" in GP to estimate the structural form parameters across all i individuals (see Amemiya for the derivation):

(5) $$\hat{\pi}_k = J_k\beta_k + \hat{\pi}_k^*\gamma_k + \eta_k,$$

where $k = 1, \ldots, K$ endogenous variables, and g and h are discrete and continuous endogenous variables, respectively, in k, such that $G + H = K$; $\hat{\pi}_k$ acts as an instrument for Y_k, while the $\hat{\pi}_k^*$ act as instruments for the jointly-dependent endogenous variables in the kth structural form equation. The $\hat{\pi}$s are estimated from (3) and (4) and used to construct $\hat{\pi}_k^*$. The J_k are matrices of zeros and ones, such that $XJ_k = X_k$, the exogenous variables in the kth structural form equation; the betas and gammas are the structural form coefficients from equations (1) and (2). The η_k are the error terms in the kth structural form equation.

Constructing the following matrices: $\hat{H}_k = [J_k \mid \hat{\pi}_k^*]$ and $\hat{\alpha}_k' = [\hat{\beta}_k' \mid \hat{\gamma}_k']$, the generalized probit ordinary least squares (GP OLS) estimates are:

(6) $$\hat{\alpha}_k = (\hat{H}_k'\hat{H}_k)^{-1}\hat{H}_k'\hat{\pi}_k,$$

where (6) generates consistent estimates of the structural form parameters. GP generalized least squares (GP GLS) estimates of (5) also are consistent, but asymptotically more efficient than both Amemiya's GP OLS[2] and Heckman's 2SLS estimates[3] (Lee 1981). To implement the GLS approach, one needs to estimate the appropriate covariance matrix. Since $\eta_k = \hat{\pi}_k - J_k\beta_k - \hat{\pi}_k^*\gamma_k$, the covariance matrix needed for Amemiya's GP GLS estimates is:

(7) $$\mathrm{Cov}(\eta_k) = \Omega_k = \mathrm{Cov}(\hat{\pi}_k) + \sum_{k^*} \gamma_k^2\mathrm{Cov}(\hat{\pi}_k^*) - \sum_{k^*} 2(X'X)^{-1}s_{k^*}\gamma_k,$$

where k denotes the kth structural form equation, and k^* refers to the jointly-dependent variables on the right-hand side of the kth structural form equation. The gammas are the parameters estimated via OLS in equations (5) and (6); the s_{k^*} are the covariances of u_k, the kth reduced form error term from (3) and (4), and u_{k^*}, the reduced form error terms pertaining to the jointly-dependent variables on the right-hand side of the kth equation. Amemiya [equation (3.9)] showed that the last term in (7) is asymptotically equivalent to $-2\mathrm{Cov}(\hat{\pi}_k, \hat{\pi}_k^*\gamma_k)$.

The first term in (7) is the covariance of the kth set of instruments estimated in equations (3) and (4). For the G continuous endogenous variables, $k = g$:

(8) $$\mathrm{Cov}(\hat{\pi}_g) = s_g^2(X'X)^{-1},$$

where s_g^2 is the variance of the gth reduced form equation (3). For the H dichotomous variables, $k = h$:

(9) $$\mathrm{Cov}(\hat{\pi}_h) = (X'A_hX)^{-1},$$

where A_h is a diagonal matrix whose tth element is $f_t^2F_t^{-1}(1 - F_t)^{-1}$, where f_t is the standard normal density function evaluated at $X_t\hat{\pi}_h$, and F_t is the standard normal distribution function evaluated at $X_t\hat{\pi}_h$ (Amemiya, p. 1196).

Equations (8) and (9), the GP OLS parameter estimates from (6), and the variance estimates from equations (3) and (4) are used to estimate the k covariance matrices given by (7), the covariance matrices for Amemiya's GP GLS estimation method. Amemiya's GP GLS estimates for the kth structural form equation are:

$$\hat{\alpha}_k = (\hat{H}'_k\hat{\Omega}_k^{-1}\hat{H}_k)^{-1}(\hat{H}'_k\hat{\Omega}_k^{-1}\hat{\pi}_k). \quad (10)$$

Factors Affecting Technology Adoption

Choice of the explanatory variable in the structural form equations is guided by economic theory, especially human capital theory, sociological work on technology adoption, and empirical findings in technology adoption studies. Feder, Just, and Zilberman surveyed economic studies of technology adoption and found that farm size, risk and uncertainty, human capital, labor availability, credit, land tenure, and complementary input availability were the major factors affecting the adoption of agricultural technologies. While the empirical findings in their survey focused on developing countries, the theoretical and much of the empirical findings are relevant to technology adoption in developed countries.

Farm size reflects the scale effects of fixed technologies, technologies which are complements to fixed technologies, or technologies that require fixed quantities of human capital. Feder, Just, and Zilberman suggested that farm size may be a proxy for access to credit and other inputs, access to information (human capital), and ability to bear risks.

Uncertainty and risk aversion decrease the propensity for individuals to adopt technologies. While measuring an individual's risk perceptions and risk aversion is difficult, economic theory tells us that their perceptions are influenced by information and human capital. Thus, human capital (the ability to acquire and process information) variables may be used as proxies for risk. Education and experience are two common measures of human capital. Research by Nelson and Phelps, and by Wozniak has shown that education is a measure of human capital which reflects the ability to implement new technology. While education is expected to increase technology adoption, experience eventually may have a decreasing effect on adoption. Experienced farmers may be better able to assess new technologies, but as experience increases, the planning horizon of the decision maker becomes shorter, until eventually the returns to adopting a new technology are not equal to the costs.

Labor, credit, and other inputs are all complements to the adoption of a technology. To the extent that any of these are limiting, they will act as limiting factors to the adoption of a new technology. Conflicting theories and empirical findings about the effect of land tenure are discussed in Feder, Just, and Zilberman. However, because the current study pertains to California milk producers, virtually all of whom are also the proprietors, land tenure does not play a role in this study.

Feder, Just, and Zilberman's survey is consistent with sociological research. Sociologists, especially Rogers, performed much of the seminal work on which economists based their technology adoption studies. Rogers and Stanfield found that the current level of productivity affects adoption of technologies, farm size, farmer experience, education, and industry involvement associated with innovation. From an economist's standpoint, these are human capital measurements, with productivity representing the farmers' management ability, education and experience representing their ability to assess information and risk, and industry involvement being an indicator of how receptive and well informed a manager is.

Data

Data were collected in a telephone survey between 10 August and 23 October 1987 from 153 randomly selected California Grade-A milk producers. The sample represents 7% of the producer population in California. California is a suitable state for analysis of technology adoption because it is one of the nation's largest and most productive dairy regions. It is second in total milk production, and third in productivity per cow [U.S. Department of Agriculture (USDA)]. Producers were asked structured questions about technology use, and characteristics of themselves and their farms. The response rate was 86%. For comparison, the sample average production of milk per cow per year is 17,813 pounds, compared to the state average of 17,966 pounds per cow per year.

Dairies in California are large, with an average of 400 milking cows. Typically, the cows are grouped by production level (strings) in corrals. The corrals may have 100 or more cows. Given the number of cows, managers need accurate information about an individual cow's productivity in order to make culling, breeding, and other management decisions. The most widely used record keeping system is a service provided by the Dairy Herd Improvement Association (DHIA). The DHIA service provides data on milk production, milk composition, breeding, etc. for individual cows and for the herd. Over 65% of the surveyed farmers used DHIA for production record keeping. Although a few of the remaining farmers used other private services for record keeping, most of them used no formal record keeping system.

The primary factor thought to influence the producer's decision to use DHIA is the productivity of his/her herd, measured by milk production per cow per year (*PRO*). The higher the productivity, the greater is the value of the information. Productivity is also a measure of the producer's management ability and reflects adoption of other technologies. Experience and education are two human capital measurements that reflect the producer's ability to assess new technologies. Education is expected to have a positive effect on the adoption of DHIA. Experience is expected to have an increasing, then decreasing effect; experience is thought to improve the producer's ability to assess the use of DHIA until either a point when the planning horizon becomes too short for the producer to expect a positive return from DHIA, or the producer's experience supplants the information generated from DHIA. Farm size was thought to influence the decision to use DHIA; however, it was too collinear with the other variables to be included.

While productivity affects the decision to use DHIA, it is also affected by it; thus, productivity is an endogenous variable (*PRO*). Feed inputs also would obviously affect milk production per cow. This is measured by the pounds of concentrate feed fed to the high string per day (*FEED*). Frequency of milking also affects milk production. Twice-a-day milking is standard practice, but some dairies utilize three-times-a-day milking (3*X*) for some or all of their herd. There are at least two reasons why three-times-a-day milking could increase production: the udder places a volume limit on the amount of milk produced, especially for high producing cows; and frequent milking stimulates milk production, simulating the effect of the increasing demand for milk by a growing calf.

In addition, region or climate plays a role in productivity. There are three major dairying regions in California: Southern California, consisting mainly of the hills surrounding Los Angeles; the Southern San Joaquin Valley, or the South Valley, centered around Tulare County; and Northern California, with dairies located primarily around San Francisco and Sacramento. Dairies in both Southern and Northern California tend to have older facilities and equipment. As one would expect, given land values, Southern California dairies are very intensive, with several hundred cows in confinement on a few acres. Virtually all feeds are purchased. Northern California dairies tend to have more land, have some pasture, and grow forage. South Valley dairies generally have "state-of-the-art" facilities, are large relative to the rest of the state, have no pasture, but grow forage and perhaps some grain for feed. Given the intensity of operations in Southern California (SC), it is expected that they would have the highest productivity, followed by the South Valley. Northern California's (NC) dairies are expected to have the least productive cows, not only because of less intensive management, but also due to more limited access to feed by-products, many of which are produced in the San Joaquin Valley.

Three of the explanatory variables for productivity are endogenous. DHIA has already been discussed. However, the amount of feed and the frequency of milking are also endogenous decisions determined simultaneously with adoption of DHIA and level of productivity. Milk producers use productivity (*PRO*) as a guide to the amount of feed they give their herd. Some employ nutritionists or utilize feed ration programs to determine how much energy the cows require. Therefore, record keeping on productivity (*DHIA*) would likely be relevant in determining the amount of concentrate fed. Both would be expected to have a positive effect on *FEED*. In addition, a human capital measure, education (*EDU*) could capture the producer's ability to use the productivity information for his/her herd. Frequency of milking might also affect how much is fed. Correcting for the increase in production, frequency of milking would be expected to reduce the amount fed by decreasing the inefficient reabsorption of milk that remains in the udder too long. Industry involvement reflects the extent to which a producer is seeking out information (*INDUS*). Since education and industry involvement indicate the ability to process and seek out information, one would expect them to imply greater efficiency in feed use, and hence their signs would be negative.

The primary motivation of milking three times a day (3*X*) is to increase productivity; hence, it is expected to be positively correlated with productivity (*PRO*). Given that most dairies are milking for several hours two times a day, milking three times a day could require milking around the clock. This could imply a night crew and night manager. It is expected that larger dairies would have an easier time of moving to this type of operation. However, some larger dairies may already be milking 24 hours a day in order to accommodate two milkings a day. Hence, three-times-a-day milking may not be feasible without expanding facilities. Therefore, it is expected that three-times-a-day milking would have a quadratic relationship with herd size. Human capital, measured by education (*EDU*), is expected to be associated with 3*X*, since 3*X* would require greater management skills and knowledge.

Finally, it should be noted that industry involvement (*INDUS*) is itself an endogenous decision. Since DHIA sponsors educational and social meetings as well as record keeping services, it would be expected that producers who subscribe to DHIA would be more likely to be involved in the dairy industry. It is also expected that there is a quadratic relationship between involvement and herd size (*COW* and *COWSQ*); involvement increases with herd size until herds are so large that the producers are better able to seek out information by themselves (e.g., by hiring consultants). Education (*EDU*) is expected to be somewhat of a substitute for industry involvement, with the educated individual seeking out and assessing information directly, rather than through a group. Since three-times-a-day milking is uncommon (less than 8% of the producers utilize it), it is expected that 3*X* will be an indicator of innovators, and hence will be negatively associated with those (followers) that seek out information from industry groups.

Given these relationships, the following simultaneous system is estimated with two continuous and three discrete endogenous variables: production per cow per year in 1,000 pounds (*PRO*), the pounds of concentrate fed to the producer's high producing cows per day (*FEED*), adoption of a record keeping system by the milk producer (*DHIA*), whether the producer milks twice or three times a day (3*X*), and industrial involvement measured by belonging to more than one producer group (*INDUS*).[4] The simultaneous system of structural form equations with continuous [equation (2)] and discrete [equation (1)] endogenous variables is:

$$PRO = f(\text{Constant}, SC, NC, \boldsymbol{FEED}, \boldsymbol{DHIA}, \mathbf{3}\boldsymbol{X}); \tag{11}$$

$$FEED = f(\text{Constant}, EDU, \boldsymbol{PRO}, \boldsymbol{DHIA}, \mathbf{3}\boldsymbol{X}, \boldsymbol{INDUS}); \tag{12}$$

$$DHIA = f(\text{Constant}, YO, YOSQ, EDU, \boldsymbol{PRO}); \tag{13}$$

$$3X = f(\text{Constant}, EDU, COW, COWSQ, \boldsymbol{PRO}); \tag{14}$$

and

$$INDUS = f(\text{Constant}, EDU, COW, COWSQ, \boldsymbol{DHIA}, \mathbf{3}\boldsymbol{X}). \tag{15}$$

The endogenous right-hand-side variables are in bold. Equations (11) and (12) are continuous variables (subscript *h*), while equations (13), (14), and (15) are dichotomous choices (subscript *g*). Choices of explanatory variables are explained above. *SC* and *NC* are dummy variables for Southern California and Northern California, as discussed above.

Education (*EDU*) is measured by the operator's years of formal education. Experience is measured by the decades a producer has operated a dairy farm (*YO*) and the decades squared (*YOSQ*).[5] Herd size is measured in 100s of milking cows (*COW*) and the term squared (*COWSQ*).[6]

Empirical Results

The software package LIMDEP 6.0 was used to estimate the reduced form coefficients in equations (3) and (4) to derive instruments for Amemiya's GP. The coefficients are estimated by probit analysis and ordinary least squares, respectively. Estimation of the coefficients for Amemiya's GP OLS in equation (6) and Amemiya's GP GLS in equation (10), as well as the covariance matrices (7), (8), and (9), were calculated using Gauss 3.1 software. Estimates of the structural form coefficients for GP GLS are presented in table 1.

For contrast, biased single-equation estimates are included in table 2. Note the improvement in fit by using GP GLS over single-equation estimates. Note also the differences in the size, significance, and in some cases the sign of the coefficients between the two models. In general, the single-equation models appear to have more significant coefficients; however, since the variables are jointly determined, the single-equation estimates are biased, inconsistent, and asymptotically less efficient. Hence, the *t*-statistics may be misleading.

Record keeping (*DHIA*) does significantly affect productivity [equation (11)], adding 783 pounds of milk per cow per year. The intercept is 17,182 pounds per cow per year (the mean production per cow of the sample is 17,813 pounds). The other variables have the expected signs, but are not significant. Their magnitudes are as expected, however: production increases by 342 pounds per cow per year in Southern California and decreases by 670 pounds in Northern California over the South Valley, each pound of concentrate fed per day increases milk production by 47 pounds per cow per year, and three-times-a-day milking increases production by 269 pounds per cow per year.[7] Biased single-equation estimates would indicate a larger, significant relationship between feed and three-times-a-day milking and productivity.

Productivity is significant in explaining the amount of concentrate fed [equation (12)]. This indicates that cows are "fed to production"; that is, the amount of feed is determined by the calories needed to produce their current milk production. The constant is also significant. However, the other explanatory variables are not. The signs and magnitudes are plausible: each year of education reduces feed by 1.4 pounds per day, record keeping increases feed by 8.8 pounds per day, three-times-a-day milking reduces feed by 3.2 pounds per day, and industry involvement decreases feed by .1 pound per day. Record keeping was expected to have a positive effect, since without it, one does not have accurate information in order to feed to production. Education and industry involvement were expected to decrease amount fed as the producer used this information to feed more efficiently, while more frequent milking was expected to reduce amount fed by reducing the amount of milk reabsorbed by the cow. The magnitude and the signs are quite different for the single-equation results: record keeping is significant, but has only one-fourth the effect; $3X$ has a large and significant positive effect, indicating frequency of milking would increase the amount fed *apart* from the increase in production, which implies that it would reduce feed efficiency; industry involvement, while not significant, is positive for the single-equation model, implying information gained from industry functions would increase *FEED*.

The significant constant in equation (13) indicates a somewhat uniform propensity for participation in DHIA across the survey observations.[8] The relationships between experience (*YO* and *YOSQ*) and record keeping are insignificant but of the expected signs, indicating a quadratic relationship.[9] This implies that records are more useful as one gains experience, but that very experienced farmers do not use or possibly do not need records. Education does have a significant effect on the decision to participate in DHIA record

Table 1. Generalized Probit GLS Structural Form Coefficient Estimates of Productivity and Technology Adoption [equations (11)-(15)]

	Coefficient	Standard Error	t-Statistic
PRO: $R^2 = .99$			
Constant*	1.718	.371	4.634
SC	.034	.067	.510
NC	−.067	.077	−.875
FEED	.005	.012	.400
*DHIA***	.078	.054	1.460
3*X*	.027	.036	.744
FEED: $R^2 = .97$			
Constant**	−53.050	39.806	−1.333
EDU	−1.390	1.089	−1.277
*PRO**	46.781	21.004	2.227
DHIA	8.837	9.149	.966
3*X*	−3.184	3.481	−.915
INDUS	−.104	5.315	−.020
DHIA: $R^2 = .89$			
Constant*	−4.929	2.662	−1.851
YO	.050	.406	.123
YOSQ	−.031	.082	−.382
*EDU**	.099	.044	2.244
*PRO***	2.405	1.570	1.532
3*X*: $R^2 = .92$			
Constant**	−12.300	8.880	−1.385
EDU	−.008	.119	−.065
COW	.416	.557	.747
COWSQ	−.026	.035	−.763
PRO	5.275	5.960	.885
INDUS: $R^2 = .86$			
Constant	.041	2.116	.019
EDU	−.172	.378	−.454
COW	.267	.450	.592
COWSQ	−.023	.032	−.728
DHIA	1.411	3.228	.437
3*X*	−.480	1.112	−.432

Note: Single and double asterisks (*) indicate significance at the 5% level and 10% level, respectively, with 109 or 110 degrees of freedom.

keeping, presumably because more educated producers can more effectively use the information. Production also significantly affects the decision to use record keeping services, presumably because there is a higher payback to the information as production per cow increases. Given the nonlinear nature of discrete choice models, the magnitudes of the coefficients cannot be evaluated directly. When evaluated at the mean value of the explanatory variables: the marginal effect of each year of experience is to decrease the probability of using DHIA by 2.8%, the marginal effect of each year of education is to increase the probability of using DHIA by 3.5%, and the marginal effect of each 1,000 pound increase in productivity per cow is to increase the probability of using DHIA by about 8.5%. The single-equation estimates indicate the same signs and significance; however, the magnitude of the effect of productivity on *DHIA* is smaller and the influence of education on *DHIA* is larger.

Multicollinearity appears to plague equation (14) for three-times-a-day milking (3*X*), since only the constant is significant. While not significant, the signs for herd size and productivity are as expected; herd size is quadratically related to adoption of 3*X*, and productivity is positively related to 3*X*. One would expect three-times-a-day milking to

Table 2. Biased and Inconsistent Single-Equation Structural Form Coefficient Estimates of Productivity and Technology Adoption [equations (11)-(15)]

	Coefficient	Standard Error	t-Statistic
PRO: R^2 = .38			
Constant	1.331	.085	15.637
SC	.037	.058	.643
NC	−.012	.048	−.245
FEED	.016	.003	5.057
DHIA	.085	.042	2.021
3*X*	.124	.075	1.658
FEED: R^2 = .37			
Constant	−1.779	4.419	−.402
EDU	−.096	.165	−.582
PRO	14.276	2.464	5.795
DHIA	2.098	1.306	1.606
3*X*	4.165	2.191	1.900
INDUS	.687	1.139	.603
DHIA: McFadden R^2 = .17			
Constant	−3.993	1.289	−3.098
YO	.082	.371	.221
YOSQ	−.042	.075	−.565
EDU	.122	.039	3.164
PRO	1.724	.627	2.749
3*X*: McFadden R^2 = .42			
Constant	−15.834	4.183	−3.785
EDU	.082	.073	1.130
COW	.804	.382	2.101
COWSQ	−.053	.027	−1.914
PRO	5.698	1.847	3.085
INDUS: McFadden R^2 = .04			
Constant	−.018	.518	−.034
EDU	−.029	.036	−.813
COW	.152	.131	1.167
COWSQ	−.014	.010	−1.462
DHIA	.464	.272	1.710
3*X*	−.450	.460	−.978

be adopted by larger farms, given the additional management requirements of having a night shift to perform milking. However, larger farms may already be using milking facilities 24 hours a day to milk twice daily, so milking three times a day would require expanding or building an additional parlor. The positive coefficient on productivity indicates that $3X$ is a technology preferred by those who have already exhausted other means to increase productivity. The sign on education is unexpectedly negative, insignificant, and very small. The marginal effects evaluated at the mean values of the variables indicate that each 100 cow increase in herd size increases the probability of milking $3X$ by 1.8%, and each 1,000 pound increase per cow per year in productivity increases the probability of $3X$ by 5.6%; conversely, each year of education decreases the probability of adopting $3X$ by .08%. Single-equation coefficient estimates are similar in magnitude and sign, with the exception of education. However, single-equation estimates indicate that herd size and productivity are significantly associated with three-times-a-day milking.

Problems associated with multicollinearity are most evident in the equation for industry involvement [equation (15)]. Not a single explanatory variable is significant, although they all are of the expected sign. Education and $3X$ are negatively associated with industry involvement, indicating education is a substitute for involvement and $3X$ is indicative of innovative rather than follower behavior. Industry involvement is related quadratically to farm size; that is, involvement increases with farm size to a point at which the producer decreases his/her involvement. DHIA involvement is associated with industry involvement since DHIA sponsors educational and social meetings and DHIA membership lists are often the basis for solicitation or involvement in industry groups. The marginal effect of the variables evaluated at their means indicates that each year increase in education decreases the probability of belonging to more than one industry club by 6.4%, each 100 cow increase in herd size increases the probability of industry involvement by 1.8%, membership in DHIA increases the probability of involvement by 52.5%, and milking three times a day decreases the probability of industry involvement by 17.9%. Single-equation results are similar in sign, except for the constant; however, *DHIA* and *COWSQ* are significant.

The biased single-equation results allow one to make stronger statements about the influence of many of the explanatory variables, and in some cases, lead to different conclusions about the effect of the explanatory variables when compared to the GP GLS results. For example, in the *FEED* equation, OLS estimates imply that three-times-a-day milking has a significant positive effect on the amount fed, *apart* from the increase in productivity. This would appear to indicate that three-times-a-day milking decreased feeding efficiency.

These results emphasize the need to correct for simultaneous equation bias in the investigation of technology adoption. In particular, one may wonder how simultaneous equation bias affects the results of single-equation *ex post* adoption models. Models by Feder and Slade; Rahm and Huffman; Jansen, Walker, and Barker; Baker; Lin; Batte, Jones, and Schnitkey; and Harper et al. are examples of single-equation adoption models which may contain simultaneous equation bias. They either contain explanatory variables which are jointly determined with the adoption decisions being investigated, and/or they estimate single-equation models for two or more jointly-determined technology adoption decisions.

Of particular interest with respect to the single-equation adoption models is that they indicate significant coefficient estimates, whereas GP GLS does not. It would appear that multicollinearity becomes more of a problem within GP GLS. Indeed, the condition numbers for equations (11)–(15) are 131, 114, 129, 476, and 367, respectively, indicating a high degree of multicollinearity, especially for equations (14) and (15). Attempts to respecify these equations led to large sacrifices in each of the models' fit, and also affected the significance of coefficients in other equations through the covariance matrices. Thus, while industry involvement and three-times-a-day milking do not, on the surface, add much to the overall model, they do influence the results. From a theoretical point of view, they are jointly determined and hence should be included in the system. From an empirical perspective, their omission affects the covariance matrices used to calculate the coefficients in the other equations. Thus, even though they show little by themselves, they do add to the system.

Implications and Conclusions

An adoption model was estimated to determine the factors affecting the adoption of several technologies by California dairy farmers. Theory tells us that productivity is influenced by the adoption of technology, and some adoption models have included productivity measures to determine factors affecting technology adoption. In addition, many technological decisions are jointly determined. Therefore, single-equation estimates of an *ex post* model of technology adoption are subject to simultaneity bias. To account for this simultaneity, productivity and technology adoption decisions are estimated as a system of equations. Since many technology decisions are dichotomous choices, this implies a mixed system of continuous and qualitative endogenous variables. Lee (1981) showed that Amemiya's generalized probit (GP) GLS is consistent and asymptotically more efficient than

Heckman's 2SLS methods. However, Lee (1978) was unable to use GP GLS for his three-equation empirical study because of an ill-conditioned covariance matrix.

In this article, we have estimated a GP GLS model for productivity per cow, feed per cow, record keeping, three-times-a-day milking, and industry involvement to examine the factors which influence productivity and technology decisions. The results illustrate the joint dependence of the endogenous variables. The results indicate that record keeping does significantly affect productivity, and productivity per cow significantly affects the use of record keeping. Education also has a significant positive effect on use of DHIA record keeping, and productivity significantly affects the amount of concentrate fed per cow.

The findings are important because they suggest the need to correct for simultaneous equation bias and to strive for asymptotic efficiency. Comparing the GP GLS results to biased single-equation coefficient estimates generally leads to greater acceptance of significant relationships between variables. In addition, some signs change between the biased single-equation and GP GLS estimates. For example, three-times-a-day milking has a significant positive relationship with *FEED,* apart from any increase in productivity. Single-equation estimates would lead one to conclude that $3X$ decreases feeding efficiency. Therefore, two implications of using single-equation estimation methods to estimate *ex post* adoption of a technology are: (*a*) they may exaggerate the significance of the relationships, and (*b*) they can lead to different conclusions concerning the factors affecting technology adoption. This underscores the importance of recognizing the simultaneous equation bias and using consistent and asymptotically more efficient estimators, not just in technology adoption models, but in other applications of single-equation qualitative dependent variable models as well.

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Notes

[1] The X_is are permitted to be the same or different to allow for the most general formulation.

[2] The true variance of Amemiya's OLS GP estimates is:

$$\mathrm{Cov}(\hat{\alpha}_k^{ols}) = (\hat{H}_k'\hat{H}_k)^{-1}\hat{H}_k'\hat{\Omega}_k\hat{H}_k(\hat{H}_k'\hat{H}_k)^{-1}.$$

[3] With Heckman's method, parameter estimates of the reduced form equations (3) and (4) are used to predict the endogenous variables, $\hat{Y}_{ig}$ and $\hat{Y}_{ih}$. These are used as instruments in the structural form of the equations:

$$Y_{ig} = \begin{cases} 1 & \text{if } X_{ig}\beta_g + \hat{Y}_{ig}^*\gamma_g + e_{ig} > 0, \\ 0 & \text{otherwise;} \end{cases}$$

$$Y_{ih} = X_{ih}\beta_h + \hat{Y}_{ih}^*\gamma_h + e_{ih}.$$

[4] Virtually all the producers in the sample belonged to at least one producer organization. Therefore, the number belonging to more than one was used; 56.5% belonged to more than one dairy-related organization.

[5] Note that age had no significant impact on the probability of adoption, either with experience or as a substitute for experience. Thus, the technology to which dairy farmers are exposed at the beginning of their career may be more influential than their planning horizon in determining technology use.

[6] Notice that the units of measurement are scaled to avoid mathematical problems, but are not rounded, so information is not lost.

[7] Lack of significance may be due to few observations on three-times-a-day milking; only 7.8% of the respondents milked three times a day. However, it does correspond to anecdotes given during the survey that many farmers had tried three-times-a-day milking but reverted to twice a day because they felt there were other, less labor-intensive methods for getting the same increase in milk production.

[8] DHIA record keeping was used by 65.2% of all respondents.

[9] It should be noted that herd size, as measured by *COW* and *COWSQ,* was originally included in the model; however, due to problems of multicollinearity, none of the variables were significant. It was determined that herd size was highly collinear with the other explanatory variables and its exclusion had little effect on model fit.

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