Simultaneous Estimation of Technology Adoption and Land Allocation

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Abstract

The paper considers the econometric modeling of technology adoption when crop choice is simultaneous. Bivariate probit is used to estimate a model of irrigation technology choice and land allocation using a unique field-level data set from California's Central Valley. Special attention is paid to the proper calculation of marginal effects in the bivariate probit model, which are often useful for policy purposes. Estimation results confirm that the choices of irrigation technology and land allocation are simultaneous. With regard to the influence of price incentives on agricultural water use, estimation results from the bivariate probit model indicate that the influence of water price on the adoption of precision irrigation technology is much larger than previously realized. A univariate model of technology choice that treats land allocation as exogenous underestimates the effect of water price on the adoption of precision technology by over 40 percent.

JEL Classifications: Q15, Q25, C35

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Beginning with the seminal work of Griliches (1957 and 1958), economists have attempted to explain the process of technology diffusion in agriculture. Some farming technologies of interest are embedded in specific crops, for example specialized seeds; others such as mechanical implements can be used to produce a variety of crops. In the latter case, it has been observed that the marginal productivity of investment in various agricultural technologies varies widely by crop (see the recent survey article by Sunding and Zilberman). Accordingly, farmers' land allocation decisions may have a significant influence on the pattern of technology diffusion.

While this much is clear conceptually, there are nonetheless obstacles to overcome when estimating the parameters of the technology choice problem. If land allocation is itself influenced by the same factors that explain technology choice (factors such as soil quality, microclimate, and relative prices), then there is an important simultaneity problem that must be addressed when estimating the parameters of the technology adoption problem. In this paper, we pursue the question of modeling technology diffusion while accounting for the potential simultaneity of land allocation.

We consider this question with reference to the problem of farmers' choice of irrigation technologies. Agriculture is a major user of water in the western United States and is under pressure from urban and environmental interests to reduce water use. Water-use efficiency can be achieved through investment in capital goods, such as precision irrigation technology (e.g., drip, microsprinkler and other technologies). Because reductions in agricultural water use have large, positive external benefits by making water available for urban consumption and to enhance instream flows, there has been much interest in understanding adoption behavior with respect precision technologies in agriculture. In particular, there is a large literature that explores the adoption of water-saving irrigation technologies. With few exceptions, the empirical literature on irrigation technology adoption treats crop choice as an exogenous factor in the technology adoption decision, or estimates equations for technology choice contingent on a prior decision to grow a particular crop.

This paper models irrigation technology adoption and crop choice as a system of simultaneous equations. Estimation is based on field-level data from California's San Joaquin Valley. The estimation results provide strong evidence that the technology adoption and land allocation decisions are in fact simultaneous. We compare the bivariate probit results to those resulting from a univariate probit estimation of the technology adoption problem alone (as is typical of the literature). The total effects of changes in the right-hand side variables are compared between the two equations; additionally we decompose marginal effects in the bivariate model into direct and indirect effects that are missing in the univariate model.

Beyond their general interest to agricultural economists concerned with technology adoption and diffusion, the results of this paper deepen our understanding of how farmers respond to changes in water pricing and delivery policies. For example, the results clarify how the changes in the price of water affect farm-level irrigation decisions. If crop and technology choices are indeed simultaneous, then basing water pricing and other policy decisions on the biased estimates of single-equation models may lead to ineffective choices.

The Role of Land Allocation in Technology Adoption

The empirical literature on irrigation technology adoption has identified the price of water as an important incentive for adoption of water-saving irrigation systems (Caswell and Zilberman (1985), Negri and Brooks, Green et al.). The logic is compelling: substituting capital for water is more likely to occur when the relative price of water, and hence the marginal value of conservation, is high.

An interesting outcome of many econometric studies of irrigation technology adoption, however, is the important, even dominant, role of environmental conditions. The role of land quality, for example, has been explored extensively in the literature. Caswell and Zilberman (1985) finds that various dimensions of land quality including slope and soil permeability are important factors influencing the adoption of precision irrigation technology (since it is land-quality augmenting), and Caswell and Zilberman (1986) explains this result within the context of a conceptual model of technology selection. Using a national cross-section of farms, Negri and Brooks also find that physical characteristics of farms are important determinants of technology adoption. In a field-level study of irrigation technology adoption in Hawaiian sugar cane production, Shrestha and Gopalakrishnan find that soil characteristics are important factors in technology adoption. Green et al. also find that soil conditions influence the choice of irrigation technology, indeed to a much larger degree than price in their sample.

Another consistent finding in the irrigation technology literature is that the type of crop grown is important in determining the technology selected. Conceptually, it is not surprising that land allocation should have an impact on the choice of irrigation technology. Water requirements vary by crop, and thus the marginal value of water conservation varies by crop. Further, alternative irrigation systems usually perform differently on different crops for agronomic reasons. For example, sprinkler irrigation is useful on citrus because it provides frost protection; drip irrigation does not have this benefit. Various papers in the literature have dealt with the role of crop choice as it influences the choice of irrigation technology. For example, Green et al. include four crop types as exogenous explanatory variables in their micro-level estimation of technology adoption. Other studies estimate technology choice equations conditional on the type of crop produced (Shrestha and Gopalakrishnan, Green and Sunding).

The approach taken in these papers to the influence of crop choice is not satisfying for the reason that the factors affecting technology choice also affect crop choice, with the result that land allocation is best treated as an endogenous variable. For example, land characteristics such as soil permeability and field slope can have a strong influence on the choice of crop as well as irrigation technology. This observation suggests that technology and crop choice should be modeled as a simultaneous system.

A notable exception to the treatment of crop as an exogenous variable in irrigation technology adoption is Lichtenberg. His paper suggests that technology choice and crop choice are simultaneous decisions and finds that irrigation technology adoption augments land quality and thus affects crop choice. However, Lichtenberg uses county-level data to control for land quality variation. While he suggests that the technology and crop choices are simultaneous, computational difficulties prevent him from applying simultaneous equation estimation techniques.

The purpose of our paper is twofold. The first is to obtain unbiased estimates of the technology adoption decision by correcting for the simultaneity of the crop choice in the technology decision. If crop and technology choice are simultaneous, ignoring the correlation between the choices results in biased estimates of the technology adoption equation. To avoid this problem, we estimate a field-level model of technology adoption and crop choice using bivariate probit in place of the more common univariate probit specification. The estimation results confirm our choice of specification in that the estimated correlation coefficient between the two equations is strongly significant.

The second main goal of the paper is to decompose the effects of the explanatory variables, particularly the effect of water price, on technology adoption into direct effects from the technology and the indirect effects on technology from the endogenous crop production decision. This decomposition deepens our understanding of a particularly important problem in western agriculture: how farmers respond to changes in water price and availability.

Empirical Model of Technology Choice and Land Allocation

The econometric model rests on the assumption that farmers simultaneously choose irrigation technology and crop to maximize net returns. Technology choice is taken to be a choice between traditional gravity and high-pressure sprinkler technologies, and newer, low-pressure irrigation technologies such as drip and microsprinkler systems. In particular, the farmer chooses to adopt a high-efficiency technology, $T = 1$, when returns of this technology exceed returns from low-efficiency technologies, $T = 0$.

We are also interested in the farmer's decision to invest in production of permanent crops. Let C represent the crop choice, where C = 1 if the farm produces a permanent crop on a particular field and C = 0 otherwise. The distinction between permanent and annual crops is important for several reasons. Because acreage in permanent crops is not easily changed once the production decision is made, choosing to produce a permanent crop is a long-term investment decision. Furthermore, permanent crops are generally less water-intensive than annual crops, thus producers can respond to changes in water price by investing in permanent crops as well as through investment in water-saving technologies.

The econometric model of technology and crop choice is given by the following two-equation system:

(1) $T^* = a'_1 x_T + a'_2 C + e$, where T = 1 if T* > 0

(2) $C^* = b'_1 x_C + m$, where C = 1 if C* > 0

Equation (1) represents the technology adoption decision and is equivalent to the model estimated by Green et al (and consistent with most of the empirical literature on technology adoption). Equation (2) represents the crop choice decision. T^* and C^* are the latent net benefits from adopting a water-saving irrigation technology and producing a permanent crop. T^* and C^* are observed as the binary variables T and C, as defined above. The covariates in x_T and x_C include crop choice, water price, field characteristics and microclimate variables. The error terms e and m represent the unobservable variables that affect technology and crop choice. The correlation coefficient between the errors measures the extent of correlation between the technology and crop decisions, if any.

The model of technology and crop choice is recursive, in that crop appears in the technology equation, and simultaneous in that unobserved variables that affect technology choice may also affect crop choice. Furthermore, technology and crop are observed as binary variables. The bivariate probit technique provides a consistent, fully efficient estimate of the model and is computationally straightforward (Greene). Estimating the system using a univariate probit model would produce biased estimates in the presence of correlation between the equations. Two-step procedures for systems with a binary endogenous variable and a continuous endogenous variable, such as the model suggested in Rivers and Vuong, give inefficient estimates in a model with binary endogenous variables, even when the Rivers-Voung type models are adapted to a model with binary endogenous variables. Two-step methods do not account for correlation across the equations.

The bivariate probit model assumes that the error terms, e and m, are jointly normally distributed with zero means, standard deviations of one, and the correlation coefficient is r. The vectors x_T and x_C contain the exogenous variables, and may be the same vectors. In our estimated model, x_T and x_C overlap but are not identical. The bivariate probit model is estimated by maximum likelihood where the probability cells are given by

$$\begin{aligned}
\Pr[T=1, C=1] &= BVN(a_1' x_T + a_2' C,\ b_1 x_C,\ r)\\
\Pr[T=0, C=1] &= BVN(-a_1' x_T - a_2' C, b_1 x_C, -r)\\
\Pr[T=1, C=0] &= BVN(a_1' x_T, b_1 x_C, -r)\\
\Pr[T=0, C=0] &= BVN(-a_1' x_T, -b_1 x_C,\ r)
\end{aligned}$$

and *BVN* is the c.d.f. of the bivariate normal distribution. The log likelihood function for the bivariate probit is

$$\ln L = \sum_i \ln \Pr\left[T_i, C_i\right], \quad \text{where } i = 0,1.$$

Data and Estimation Results

The system of equations (1) and (2) is estimated using field-level data from Arvin-Edison Water Storage District located in California's San Joaquin Valley. The sample includes 1,717 field-level observations, which accounts for approximately 76% of the district's irrigable acreage. The sample is a cross-section observed in 1993.

Arvin-Edison is in Kern County, which has been noted as the center for diffusion of precision agricultural technologies (Caswell). The district's endowment of a high-quality ground water aquifer has allowed it to successfully implement conjunctive water management practices. There are two service areas within the District. In the surface water service area, growers receive surface water provided by the District from a combination of federal supplies and District-operated wells. Rates in the surface water service area are a combination of a relatively low per-acre assessment and a volumetric charge. Growers in the groundwater service area receive groundwater recharge from the District's provision of surface water to growers in the other service area, but pump from their own wells exclusively. Growers in the groundwater service area of Arvin-Edison pay a flat per-acre fee to the District and their marginal costs of water are determined by the cost of pumping.

Turning to a description of variables used in the estimation, we begin with the endogenous variables. The binary variable *Technology* is equal to 1 if a high-efficiency (i.e., low-pressure) technology is observed on the field and 0 otherwise. We are also interested in the decision to invest in production of a permanent crop. The variable *Crop* is equal to 1 if the field is devoted to a permanent crop and 0 if it is planted in an annual crop. Table 1 describes the distribution of irrigation technologies by crop type and service area. Low-efficiency and high-efficiency technologies are evenly distributed among permanent crops in the sample. High-efficiency technologies dominate the annual crop category in our sample. Technology is evenly divided between the service areas.

The economic or policy variables of interest in this analysis are water price and service area, a measure of price variability. Water price is measured as the marginal price of irrigation water per acre-foot of water delivered to each field. Because the value of investment in more expensive high-efficiency technologies increases with the price of water, we expect that water price will have a positive influence on the decision to adopt more efficient irrigation methods.

Service area is a binary variable that denotes whether or not the observed field is located in the service area supplied with surface water (1) or ground water (0). By design, the price of water for fields in the surface water areas is relatively stable. The price of ground water is determined by both the price of electricity and the depth from which the water must be pumped. The changing ground water table and electricity prices introduce variability in the price of water for ground water users, whereas the district stabilizes surface water prices. Interestingly, the District sets rates so that the expected cost of water is the same for surface and ground water users. Because the marginal cost of groundwater is the product two random variables (pumping depth and energy cost), the price of water in the ground water service area can be considered as a mean-preserving spread of the price in the surface water service area where prices do not change much over time. Thus, the service area variable helps to gauge the influence of water price risk on crop and technology choice.

As discussed earlier, the theoretical and empirical literature has identified land quality as an important determinant of irrigation technology adoption. To control for land quality in the adoption decision, we include measures of field slope and soil permeability in both the technology and crop equations. Field slope is defined as the gradient of the field, measured as a percentage. High-efficiency technologies may be more suitable to steep slopes because they allow gradual distribution of irrigation water and reduce runoff. Accordingly, we expect slope to have a positive effect on the probability of adopting a high-efficiency technology. Perennial crops are amenable to steep slopes and therefore we expect the slope coefficient in the crop equation to be positive as well.

Soil permeability measures the speed with which water percolates into the soil. This variable is measured in inches per minute. High-efficiency technologies distribute water more evenly and more gradually than low-efficiency technologies and are thus more suitable for sandy, highly permeable soils. This observation is consistent with the notion of high-efficiency irrigation technologies as land quality-augmenting, and we expect the permeability coefficient to be positive in the technology equation. Permeability has a less obvious relation to crop choice.

To control for potential economies of scale in both the technology choice and the crop choice, we included the field size (in acres) in both equations. Table 2 provides summary statistics for the continuous variables.

Estimation results for the bivariate probit model are given in Table 3. For comparison, the estimation results for the single equation probit models of the technology and crop choices are also presented in Table 3. The estimated correlation coefficient in the bivariate probit model is 0.61 and strongly significant. This finding provides evidence that there is correlation between the technology choice and crop choice equations and that the simultaneous equation approach is appropriate. A positive value of r suggests that the unobservable factors associated with a higher probability of adoption of high-efficiency technology are also associated with a higher probability of adopting a permanent crop. For example, we do not observe the farm operator's experience which may make him more likely to adopt a modern technology as well as more likely to invest in production of a permanent crop that requires more human and financial capital to produce.

In the estimated technology choice equation, the coefficient on water price is positive and statistically significant. The coefficient on perennial crop choice is also positive and significant, indicating that conditional on planting a permanent crop, farmers are more likely to adopt high-efficiency technologies.

Marginal Effects

The estimated coefficients in Table 3 are difficult to interpret directly. We compute the marginal effects of the explanatory variables on the probability of adopting high-efficiency irrigation technology and the probability of producing a permanent crop. Since the technology and crop choice decisions are jointly determined, the marginal effects in the technology equation can be decomposed into direct effects from the explanatory variables in the technology equation and indirect effects, or cross-effects, from the explanatory variables in the crop equation.

In this model, the marginal effects can be computed from the joint distribution of technology and crop choice, the marginal distributions, or the conditional distributions. Table 4 presents the average estimated event probabilities. Since our primary interest is the effect of the explanatory variables on irrigation technology adoption, we focus on the marginal effects of the marginal probability of adopting a high-efficiency technology, which is given by

$$\begin{aligned} \Pr(T=1) &= \Pr(T=1, C=1) + \Pr(T=1, C=0) \\ &= \Pr(T=1 \mid C=1)\Pr(T=1) + \Pr(T=1 \mid C=0)\Pr(C=0) \end{aligned} \tag{3}$$

conditional on the observations of x_T, x_C and C. For the bivariate probit, (3) can be written as

$$\Pr(T=1) = \Phi_{T_1|C_1}\Phi_{T_1} + \Phi_{T_1|C_0}\Phi_{C_0} \tag{4}$$

where

$$\begin{aligned} \Phi_{T_1|C_1} &= \Phi\left(\frac{a'x_T - rb'x_C}{\sqrt{1-r^2}}\right), \\ \Phi_{T_1} &= \Phi(a'x_T), \\ \Phi_{T_1|C_0} &= \Phi\left(\frac{a'x_T + rb'x_C}{\sqrt{1-r^2}}\right), \\ \Phi_{C_0} &= \Phi(-B'x_C), \end{aligned}$$

and Φ is the normal c.d.f.

Following Christofides, Hardin and Thanais (2000), the marginal effects of the continuous variables are obtained by differentiating equation (3), the marginal probability of adopting a high-efficiency technology, with respect to an explanatory variable, x_k is a variable in x_T or x_C or both, that is,

$$\text{(5)} \qquad \frac{\partial \Pr(T=1)}{\partial x_k} = a_k f_{T_1} \Phi_{C_0|T_1} + a_k f_{T_1} \Phi_{C_1|T_1} + b_k f_{C_1} \Phi_{C_1|T_1} - b_k f_{C_0} \Phi_{C_0|T_1},$$

where a_k, b_k are the coefficients corresponding to the technology equation and crop equation, respectively.

Rearranging terms in (5), we obtain,

$$\text{(6)} \qquad \begin{aligned} \frac{\partial \Pr(T=1)}{\partial x_k} &= a_k f_{T_1} \left(\Phi_{C_1|T_1} + \Phi_{C_0|T_1} \right) + b_k \left[f_{C_1} \Phi_{C_1|T_1} - f_{C_0} \Phi_{C_0|T_1} \right] \\ &= a_k f_{T_1} + b_k \left[f_{C_1} \Phi_{T_1|C_1} - f_{C_0} \Phi_{T_1|C_0} \right]. \end{aligned}$$

The first term in (6) is the direct marginal effect of the variable x_k on the probability of adoption a high-efficiency technology. This is analogous to the marginal effect of x_k in the single-equation probit model. The second term is the indirect effect, or cross-effect, from the crop choice in the technology equation. This term reduces to the single-equation probit marginal effect when $r = 0$.

The effect of crop choice on technology choice is given by the discrete change in the probability of adopting high-efficiency technology from switching from an annual crop to a permanent crop. This effect is given by

$$\text{(7)} \qquad \Pr(T=1|C=1) - \Pr(T=1|C=0).$$

Using equations (6) and (7), the marginal effects are computed for each observation. Table 5 presents the average marginal effect over all the observations, and also presents implied elasticities. The marginal effects measure the change in the probability of adopting a high-efficiency irrigation technology given a one-unit change in the explanatory variable. In the case of the discrete variable, crop choice, the pseudo-marginal effect reflects the change in probability of adopting a high-efficiency technology given a switch from an annual crop to a permanent crop.

From the marginal effects, it is clear that crop choice has a strong influence on the choice to adopt a high-efficiency technology. This is consistent with the literature, however the bivariate probit estimation provides efficient and unbiased estimates of the effect of crop relative to the single-equation probit. We observe a striking difference between the effect of crop choice in the bivariate probit and univariate probit models. Switching from an annual to a permanent crop increases the probability of adopting a high efficiency technology by 15 percent in the bivariate model and by 37 percent in the univariate model. This result follows from the impact of unobserved factors.

Water price has a positive marginal effect on the probability of adopting high-efficiency irrigation technologies. The total marginal effect of water price on adoption of high-efficiency technology is larger in the bivariate model that in the univariate model. The estimated elasticity of water price on the probability of adopting high-efficiency technology is 0.63. Accounting for the simultaneity of technology and crop choice, we obtain an elasticity estimate of 0.89 in the bivariate model. This finding implies that the univariate approach underestimates the elasticity of adoption with respect to water price by over 40 percent.

There are also apparent differences between the bivariate and univariate models in terms of the influence of environmental conditions. For example, field gradient has a positive effect on technology adoption in both the bivariate and univariate specifications. This variable is interesting, however, in that it shows the usefulness of calculating both direct and indirect effects. As expected, slope has a positive and significant effect on the decision to grow a perennial crop. Accordingly, this variable has positive direct and indirect effects that are entangled in the univariate model. The direct effect of percentage slope on the probability of adoption high-efficiency technology is 0.10 and the indirect effect through the crop choice decision is 0.02, for a total effect of 0.12. In the univariate model, the effect of slope is estimated to be 0.08. The implied total elasticity is estimated to be 1.01 in the bivariate model, but only 0.44 in the univariate model.

Conclusion

This paper estimates the effects of water price on technology adoption and crop choice simultaneously using a bivariate probit model. The model controls for land characteristics, in particular, soil permeability, which measures the soil's water-holding capacity, field slope, and field size. We find that field conditions are important determinants of both crop choice and technology choice. These results are consistent with the literature. However, our estimates of the effect of water price on adoption of water-saving technology is over 40 percent larger that that resulting from a specification in which crop choice is assumed to be exogenous.

The bivariate probit model permits a test of correlation across the technology and crop choice decisions. We find that the correlation coefficient between technology and crop choice is positive and strongly significant. This result suggests that there are unobserved factors and that a model that ignores the correlation is biased.

We find that the price of water has a significant effect on technology adoption as well as on crop choice. Because we model the two choices simultaneously, we can decompose the direct and indirect effects from crop choice on technology. Ignoring the correlation can be misleading because the estimates may be biased. In particular, the bivariate probit estimate of the effect of water price on technology adoption is twice as large as the effect found in the single-equation probit, which ignores the correlation between technology choice and crop choice. This bias can be critical in evaluating rate-setting policies, which are becoming increasingly important in water resource management. If the bias is ignored, we risk making poor policy decisions with respect to water pricing and adoption of precision irrigation technologies. This result is important when price incentives are used to encourage water conservation, and suggests that land allocation be considered when modeling diffusion processes for other precision farming technologies.

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Table 1: Distribution of Technology by Crop Type and Service Area

	Low Efficiency	High Efficiency	Total
Crop Type			
Annual	742	15	757
Permanent	545	415	960
Total	1287	430	1717
Service Area			
Ground	782	182	964
Surface	505	248	753
Total	1287	430	1717

Table 2: Summary Statistics for Continuous Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Field Size	53.7528	49.9160	1.0000	490.0000
Water Price	46.3968	14.6664	18.9200	87.3000
Field Gradient	1.4227	1.1611	0.5000	10.0000
Soil Permeability	2.9116	2.9902	0.1300	13.0000

Table 3: Estimated Bivariate Probit and Univariate Probit Coefficients

	Bivariate Probit		Univariate Probit	
	Coefficient	S.E.	Coefficient	S.E.
Drip Equation				
Permanent Crop (0/1)	0.6877 ***	0.2156	1.7790 ***	0.1248
Surface Water Supply (0/1)	0.7100 ***	0.1232	0.7007 ***	0.1314
Field Size	0.0002	0.0008	0.0014 **	0.0008
Gradient	0.4536 ***	0.0331	0.3740 ***	0.0335
Soil Permeability	0.0200	0.0129	0.0156	0.0137
Water Price	0.0144 ***	0.0039	0.0164 ***	0.0042
Constant	-3.0180 ***	0.3058	-3.7904 ***	0.2797
Crop Equation				
Surface Water Supply (0/1)	0.3704 ***	0.1299		
Field Size	-0.0024 ***	0.0007		
Gradient	0.3448 ***	0.0443		
Soil Permeability	0.0001	0.0121		
Water Price	0.0025	0.0044		
Township-Range 1119	-0.4154	0.3428		
Township-Range 1120	-1.6241 ***	0.3741		
Township-Range 1218	0.0146	0.6015		
Township-Range 1219	0.5141	0.3677		
Township-Range 1220	-2.4796 ***	0.4912		
Township-Range 2929	0.2189	0.4178		
Township-Range 3028	-0.3819	0.4902		
Township-Range 3029	-0.5088	0.3350		
Township-Range 3030	-0.5818 *	0.3497		
Township-Range 3129	0.0340	0.3417		
Township-Range 3130	-0.1284	0.3449		
Township-Range 3228	-0.1857	0.3658		
Township-Range 3229	-0.1934	0.3412		
Township-Range 3230	-	-		
Constant	-0.1353	0.4684		
Number of Observations	1717.0000		1717.0000	
Log Likelihood	-1582.4846		-619.7696 (Tech)	
Disturbance Correlation (ρ)	0.6142		0.0000	
Likelihood ratio test of ρ = 0	$\chi^2(1) = 21.33$, P-value = 0.00			

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level

Table 4: Estimated Event Probabilities for Technology and Crop Choice Bivariate Probit

	Predicted Probability	Observed Probability
Joint Distributions		
Pr(T = 1, C = 1)	0.1945	0.2417
Pr(T = 1, C = 0)	0.0230	0.0087
Pr(T = 0, C = 1)	0.3608	0.3174
Pr(T = 0, C = 0)	0.4218	0.4321
Marginal Distributions		
Pr (T = 1)	0.2174	0.2504
Pr (C = 1)	0.5553	0.5591
Conditional Distributions		
Pr(T = 1 | C = 1)	0.3183	0.4323
Pr(C = 1 | T = 1)	0.8588	0.9651

Table 5: Estimated Marginal Effects For Bivariate Probit and Univariate Probit Models

	Bivariate Probit				Univariate Probit		
	Marginal Effects				Marginal		Mean of
	Direct	Indirect	Total	Elasticity	Effects	Elasticity	Covariate
Technology Equation							
Permanent Crop (0/1)			0.1498	-	0.3651	-	-
Surface Water Supply (0/1)	0.1546	0.0261	0.1808	-	0.1438	-	-
Field Size	0.0000	-0.0002	-0.0001	-0.0395	0.0003	0.0621	53.7528
Gradient	0.0988	0.0243	0.1231	1.0080	0.0768	0.4394	1.4227
Soil Permeability	0.0044	0.0000	0.0044	0.0733	0.0032	0.0376	2.9116
Water Price	0.0031	0.0002	0.0033	0.8859	0.0034	0.6300	46.3968
Crop Equation							
Surface Water Supply (0/1)			0.1208	-			
Field Size			-0.0008	-0.0738			
Gradient			0.1125	0.2814			
Soil Permeability			0.0000	0.0002			
Water Price			0.0008	0.0671			