Intrafirm Effects on Water Conservation in Agriculture

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Abstract

Conservation technology adoption behavior is frequently analyzed at the smallest unit of production to capture important heterogeneity among adopters. Conclusions about firm-level decisions are drawn from these microunit outcomes. However, there may be significant intrafirm interactions that create a dependence among the microunits. This paper tests and quantifies these effects. Using a unique dataset of agricultural water use in California, this paper finds significant differences in water price elasticities of conservation technology adoption between the standard model and models that accounts for the intrafirm interactions.

Keywords: conservation, technology adoption, agriculture, water resources, irrigation intrafirm behavior (JEL:Q16 Q25 Q28 Q55 L23)

1 Introduction

Because water resources are usually not allocated through markets, policy makers must decide how to manage these resources. Conservation is an important part of water management policy and can be achieved through adoption of water-conserving technologies. Although profitable technologies are available, slow or incomplete adoption of these technologies is often observed. One explanation for this gap in agriculture is that adopters are heterogeneous and face specific adoption constraints. To capture this heterogeneity and better understand adoption, the literature models adoption at the microunit, the smallest unit of production such as field or parcel on a farm. However, when adoption decisions are made over many microunits, there may be important interactions among the microunit-level decisions. In particular, decisions about technology adoption on one field may be influenced by decisions made on all fields within a farm. This paper explores whether and to what extent such intrafirm interactions impact of the adoption decision at the microunit and how these interactions affect water conservation policy in agriculture.

Failing to account for interactions may bias estimates of the effect of policy incentives. For example, suppose that a farmer has many fields and has an expertise in the water-conserving technology. This expertise lowers the farm's cost of adoption on the next field. This farm may be more likely to adopt a water-conserving technology independent of policy incentives, such as an increase in the cost of water or an adoption subsidy. Ignoring these interactions may overstate the policy's effect on conservation incentives because the observed effect is confounded by microunit interactions.

The importance of social interactions in technology adoption has been widely documented in the literature, particularly the effect of geographic neighbors on technology adoption. However, the literature on conservation technology adoption has largely ignored intrafirm interactions in adoption and often interprets microunit decisions as farm-level decisions.

Whereas the more general literature on technology adoption has found significant intrafirm interactions. Significant intrafirm effects may suggest economies of scale in conservation technology adoption across fields, thus aggregating microunit response to changes in policy incentives may mislead policy evaluation.

Intrafirm interaction in technology adoption has largely been ignored by the literature because data linking microunits to firms is difficult to obtain. The dataset for this study includes limited information about landowners and parcel-level land use. Interactions among microunits are multidimensional, giving these interactions a spatial characteristic. By applying the tools of spatial econometrics, this paper is able to test and measure the effect intrafirm interactions with limited information on land ownership across agricultural parcels.

Unlike much of the previous work, the dataset used in this paper identifies new technology adoptions rather than technology utilization and links farms to microunits. Preliminary estimates show that spatial interactions are significant and price elasticity of adoption is 0.94 in the standard model and only 0.67 in the spatial interactions model.

In the next section we review the literature on technology adoption in agriculture and spatial and economic interactions. Section 3 decribes the study dataset and estimates spatial autocorrelation models of technology adoption. Section 4 concludes to paper.

2 Literature Review

The importance of geography in technology adoption has a long history the social sciences literature.(Sunding and Zilberman 2001) As geographic data has become more accessible, geographic characteristics continue to be important factors in understanding adoption. However, interactions in technology adoption may also occur through more generally defined economic proximity. (Hussler 2004; Moretti 2004)

Case 1992 develops a model that allows for spatial effects in farm technology adoption, specifically the sickle for harvesting rice. Using data from Indonesian farm households, neighbors are specified as other farm households within the same district, thus defining related units in terms of geographic proximity.[1] She finds that neighbors, defined as geographically contiguous units, have an important influence on farmer's decisions to adopt new technologies and notes that ignoring this influence can bias the estimated influence of policy instruments adoption behavior.

Foster and Rosenzweig 1995 explore the influence of neighbors on learning of a new technology, high-yielding variety rice and wheat seeds. While the theoretical model presented in Foster and Rosenzweig does not limit "neighbor" to geographic neighbors, in the empirical application, neighbor effects are given by village experience, a geographic measure of proximity. They find evidence of learning spillovers among neighbors, where more experienced neighbors increase a farmer's profitability. They also find that farmer's tend to free-ride off neighbor's experimentation and learning.

The most obvious non-geographic source of interaction among microunits is belonging to a common farming operation or firm. The literature on technology adoption has found that firm-level effects have a strong influence on adoption of technology. A farmer's decisions on a particular field may be correlated with decision across the entire farming operation. In making technology adoption and utilization decisions, human capital or specialized skills available to the entire farm may affect the productivity of a particular production choice. For example, McWilliams and Zilberman 1996 show that firm size and education are significant factors in timing of technology adoption.

Other factors in the adoption and technology utilization decision, include how firms handle uncertainty (Just and Zilberman 1983) or competition (Audretsch and Feldman 1996). Costs of adoption and economies of scale across the entire operation may also affect the

[1] It may be argued that geographic proximity in the rural districts of Indonesia are also likely to exhibit economic proximity. Case does not rule this out, she notes, "If information were available about the amount of influence each household wields, this could be incorporated into the W [spatial weights] matrix."

choice of production technologies. Furthermore, the farmer's personal characteristics may be correlated across microunits owned by a particular farmer, and thus affect conservation choices (Ise and Sunding 1998) If farm-level factors create significant correlation across micro-units, care must be taken when interpreting outcomes from micro-level analysis.

3 Empirical Analysis

Following the literature on technology adoption in agriculture, I control for four types of variables in our estimations of technology adoption: Profitability of adoption (P), capacity for conservation (C), location quality (L), and owner characteristics (O).

I begin with the base model (Model 1) of technology adoption at the microunit-level, ignoring owner and spatial interactions. The base model is

$$Y = X_P\beta + X_C\beta + X_L\beta + \epsilon \tag{1}$$

where the subscripts P, C, L indicate the matrix of independent variables in each of the four categories given above. The errors in ϵ are random, homoscedastic, normally distributed errors with $E(\epsilon) = 0$, $Var(\epsilon) = \sigma_\epsilon^2$, and $E(X'\epsilon) = 0$. The dependent variable, Y is measured as the percent of acreage in a parcel that has a new water conserving technology.

To control for owner-level characteristics that may produce interactions among microunits, I add owner characteristics to Model 1 and estimate Model 2:

$$Y = X_P\beta + X_C\beta + X_L\beta + X_0\beta + \epsilon. \tag{2}$$

To allow for spatial correlations, I follow Case 1991 and specify the following spatial autoregressive model:

$$\begin{aligned} Y &= \rho WY + X\beta + u \\ &= (I - \rho W)^{-1}XB + (I - \rho W)^{-1})u \end{aligned} \tag{3}$$

where W is the spatial weights matrix and ρ represents the extent of influence neighbors have on one another. The errors u are given by

$$\begin{aligned} u &= \lambda Wu + \psi + \epsilon \\ &= (I - \lambda W)^{-1}\psi + (I - \lambda W)^{-1})\epsilon, \end{aligned} \tag{4}$$

where λ is the extent of unobserved spatial correlation. The term ψ are farm-specific errors, which I assume to be random.

The spatial weights matrix, W, is a formal representation of the spatial relationship of all units to all other units. Each element in the spatial weights matrix (henceforth SWM) is given by w_{ij}, where i and j indicate the microunits. Tests of spatial relationships compare outcomes at each unit and relate these to every other unit according to the relationship specified in the spatial weights matrix.

I test for interactions among the microunits by specifying three specification for W: intrafirm interaction through common ownership, interaction from geographic proximity and a combination of intrafirm and geographic proximity. In the first case, I construct a binary, contiguity matrix based on ownership. In this spatial weights matrix, which I denote as W_1, w_{ij} is equal to 1 if microunits i and j have the same land owner, 0 otherwise. In the distance spatial weights matrix (W_2), w_{ij} is the inverse of the distance, measured in miles, between each microunit i and j. I use inverse distance between the pair of microunits to reflect that the influence between microunits declines as they become further apart. Finally the elements of the owner-geography spatial weights matrix are equal to the inverse distance between i and j if they have the same owner, 0 otherwise. Similarly as in W_2, I use inverse distance in W_3 to capture that the influence between commonly owned parcels may decline as the geographic distance grows. In all three cases, I assume that $w_{ij} = 0$ if $i = j$.

The next subsection describes the data I use to estimate Models 1 and 2 and test these models for spatial interactions. The subsequent subsections, I show that there are significant spatial interactions in conservation technology adoption in our study area. I then estimate the models and test the coefficients ρ and λ for significance. If ρ is significantly different from zero, our model exhibits lagged spatial effects. If λ is significantly different from zero, our model exhibits spatial error correlation. The model may also exhibit both types of interactions. I estimate the appropriate models to allow for either lag effects, spatial errors or both.

3.1 Data

The primary source of data on technology use come from annual land use surveys conducted by the Arvin-Edison Water Storage District (Arvin-Edison) in Kern County, California. These data provide observations of technology use on fields in the district. The observations are taken and recorded by district technicians on an annual basis. The district provided the data as ArcMap shapefiles for 1999-2002, thus facilitating computation of geographic distances. I limit the data set to owners with at least two parcels. Our data set includes 531 observations in 2000, 2001 and 2002.

Although the data are collected at the field level, using the field as a unit of observation is problematic in defining adoptions. Fields within parcels are often reconfigured and crop and technology use shifted around the parcel, without behavioral changes in technology use. To work around this problem, I aggregate technology use to the tax parcel. The size and shape of the parcel is fixed.

Adoption of a conservation technology is an increase in the percent of land in a parcel that utilizes high-efficiency technology. I define water use efficiency as the percentage of applied water that is effectively utilized by the crop. Irrigation technology is generally categorized as drip, sprinkler and gravity. Drip includes all low-pressure irrigation technologies, including drip and micro-sprinkler, sprinkler includes all high-pressure sprinkler technologies, and gravity includes furrow and flood irrigation technologies. For most applications drip and sprinkler technologies are generally considered water-conserving technologies.

This paper considers several measures of the profitability of the technology: the price of water, the reliability of water supplies, crop revenue, and the cost of adoption. Arvin-Edison also provided data on water price. The district's endowment of a high-quality ground water aquifer has allowed it to successfully implement conjunctive water management practices and divides customers into a surface water service area and a ground water service area. 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 ground water service area receive 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 ground water 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. The cost of water for surface water users is the unit charge plus the fixed fee per acre-foot of water using water rates from Arvin-Edison. For ground water users, the cost of water is based on the depth-to-ground water from annual ground water maps also provided by Arvin-Edison. Descriptive statistics for service area and cost of water are also reported in Table 1.

By design, the price of water for fields in the surface water areas is relatively stable. However, the price of ground water is determined by both the price of fuel (i.e., electricity and diesel) and the depth from which the water must be pumped. The changing ground water table and fuel prices introduce variability in the price of water for ground water users, whereas the district stabilizes surface water prices. Interestingly, the water district sets rates so that the expected cost of water is the same for surface and ground water users. Because the marginal cost of ground water is the product of 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.

Another important factor in conservation technology adoption is long-term reliability of water supply (Moreno and Sunding). To test for the effect of water supply reliability on technology adoption, I compute the percent of acres that are in the surface water area. I take advantage of the fact that the district has two service areas with different levels of water supply reliability.

Crop revenue is the annual acreage-weighted average of the output value per acre. I obtained data on the crop values from Kern County Commissioner's Reports for the years 1999-2002. The cost of adoption is taken from the UC Extension Crop Production Studies for the relevant technologies and crops on each parcel. Descriptive statistics for crop revenue and adoption costs are reported in Table 1.

Each parcel's capacity for absorbing conservation technology may also have large effect on adoption (Hollenstein 2002). In particular, new technology adoptions are often associated with a new crop production. Crop data are included in the crop surveys provided by Arvin-Edison, described above. The crop surveys categorized crop production at a disaggregated level. However, I aggregate the crop categories to the five major crop groups produced in the study area: citrus, deciduous, vines, truck and field crops. I identify a microunit switching to a new crop if that crop was not produced on the field in the previous year.

Location quality includes soil quality as well as proximity to markets. An interesting outcome of many econometric studies of irrigation technology adoption is the important,

Table 1: Summary Statistics for Regression Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Average Cost of Water ($/AF)	231.83	39.58	168.00	394.53
Percent of Parcel in SWSA	0.48	0.49	0.00	1.00
Field Slope (gradient)	1.28	0.93	0.50	8.75
Soil Permeability	2.51	2.40	0.13	13.00
Value per Acre ($1,000s)	3.67	2.12	0.00	11.61
Percent Farm in Drip	0.18	0.23	0.00	1.00
Farm Crop Diversity	1.00	0.25	0.40	1.97
Percent Farm in Citrus	0.08	0.15	0.00	1.00
Percent Farm in Deciduous	0.06	0.15	0.00	0.99
Percent Farm in Vines	0.14	0.25	0.00	1.00
Percent Farm in Truck	0.39	0.28	0.00	1.00
Percent Farm in Field	0.23	0.24	0.00	1.00

N = 531

even dominant, role of environmental conditions (Green and Sunding 1997). Therefore, I control for field slope and soil permeability using data from the Kern County office of the Natural Resource Conservation Service. Field slope is defined as the gradient of the field, measured as a percentage. Drip technologies may be more suitable on steep slopes than gravity or sprinkler technologies because they allow gradual distribution of irrigation water and reduce runoff. Accordingly, I expect slope to have a positive effect on the probability of adopting drip technology. Soil permeability measures the rate at 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 crops grown on sandy, highly permeable soils.

Data used in the literature on irrigation technology adoption frequently do not include sufficient information to associate microunit outcomes with specific farming operations, making it difficult to control for firm-level effects. However, I take advantage of parcel-level data and link land owner information from the Kern County property tax roll data to the adoption data. Using this link, I construct the owner contiguity matrix and associate farm characteristics to microunit outcomes.

While a landowner is not necessarily the same entity as a farming operation, I assume that landowner characteristics closely reflect farming operation characteristics. This assumption is reasonable for the farms in our study area. First, landowners in the study area, even if leasing their land, are "hands-on" managers of the land and are known take an active role in the farming community in Arvin-Edison.[2] Second, I expect profit-maximizing land owners to provide the incentive to the farmer or land manager to optimize the value of the land, thus landowner behavior should reflect farmer behavior, assuming perfect information between the farmer and the landowner.

To control for the source of spatial interactions, I also collect data for farm-level characteristics of each microunit. Since firm experience has been found to be a dominant factor in technology adoption, I include two measures of experience: I measure experience with the conservation technology as the rate of utilization of that particular technology on the landowner's all other parcels. I also include experience in production of each of the five crop categories, also measured as a percent of the owner's all other land in a particular crop. Finally, to assess the effect of the farm's diversification, I include a measure of farm-level diversification, which is the number of different crops grown by the landowner divided by the average number of crops produced by landowners in the district.

3.2 Tests for Spatial Interactions

I explore two types of global spatial relationships in adoption of conservation technology among microunits. In particular I are interested in how adoption of conservation technology co-varies among microunits that are close, either through common ownership or geographi-

[2]Personal communication with Steve Lewis, engineer at Arvin-Edison, November 2005.

cally. To test global covariation, I compute Moran's I statistic, which is given by

$$I = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} Y_i Y_j}{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \sum_{i}^{N} Y_i^2} \tag{5}$$

where w_{ij} are the individual cells in the spatial weight matrix W. Each w_{ij} represents the relationship between microunit i and j, as described above. Let X_i be the adoption rate at microunit i. To test covariation of adoption rates between microunits, I specify $Y_i = (X_i - \mu)$ and $Y_j = (X_j - \mu)$, where μ is the mean of the outcome variable X. N is the number of observations.

Under the null hypothesis of no systematic spatial interactions among the microunits, the expected value of I is given by

$$E(I) = -\frac{1}{N-1}. \tag{6}$$

If the observed I is larger than the expected value, the global distribution of the outcome X is characterized by positive spatial autocorrelation, that is, high levels of adoption by microunit i are associated with high levels of adoption of close by microunits. If the observed I is lower than $E(I)$, then X is characterized by negative spatial autocorrelation, that is high levels of adoption at i are associated with low levels of adoption among units close to it.

I are also interested in the extent of global heterogeneity in adoption rates among the microunits and compute Geary's c statistic to measure heterogeneity. Geary's c tests for differences in outcomes among microunits. Define $Y = (X_i - X_j)$. Geary's c is given by

$$c = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (Y_i - Y_j)^2}{2N \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \sum_{i}^{N} Y_i^2}. \tag{7}$$

Under the null hypothesis of no spatial autocorrelation, the expected value of c is 1. If the observed c is greater than the expected value, X is characterized as having negative spatial

Table 2: Tests of Spatial Autocorrelation, W_1

Variables	I	E(I)	sd(I)	z	p-value
Moran's I					
New Drip	0.284	-0.002	0.029	10.008	0.000
New Sprinkler	0.287	-0.002	0.029	10.059	0.000
Geary's c					
New Drip	0.714	1.000	0.029	-10.008	0.000
New Sprinkler	0.712	1.000	0.029	-10.059	0.000

Table 3: Tests of Spatial Autocorrelation, W_2

Variables	I	E(I)	sd(I)	z	p-value
Moran's I					
New Drip	0.112	-0.002	0.005	22.910	0.000
New Sprinkler	0.080	-0.002	0.005	16.374	0.000
Geary's c					
New Drip	0.872	1.000	0.007	-18.347	0.000
New Sprinkler	0.918	1.000	0.005	-16.071	0.000

autocorrelation. If it is less than the expected value, it is characterized has having positive autocorrelation.

Tables 2-4 report Moran's I and Geary's c statistics for drip and sprinkler adoption for each of the three specification of the spatial weights matrices. In each of these tables I report the observed value of I and c, the expected value and standard deviation. The fourth column in the tables reports the z-statistics for a test that I (the test statistic) is greater than expected for Moran's I and smaller than expected for Geary's c.

Table 4: Tests of Spatial Autocorrelation, W_3

Variables	I	E(I)	sd(I)	z	p-value
Moran's I					
New Drip	0.409	-0.002	0.033	12.472	0.000
New Sprinkler	0.417	-0.002	0.033	12.664	0.000
Geary's c					
New Drip	0.584	1.000	0.035	-11.998	0.000
New Sprinkler	0.582	1.000	0.033	-12.625	0.000

In all cases, the null hypotheses that there are no systematic spatial interactions in adoption is rejected at least at the 1 percent level. Both Moran's I and Geary's c indicate that the distribution of adoption exhibit positive global spatial autocorrelation. This suggests that over the district, adoption of water conserving technology on a parcel is influenced by adoptions on nearby parcels, either near in terms of common ownership or in terms of miles. These results are not surprising since the literature has shown that adopters in close geographic proximity tend to influence each other. It is also not surprising that the impact of common ownership has a systematic influence on adoption. One thing to note is that the z-statistics associated with the distance spatial weights matrix, W_2, in Table 3 are quite large relative to the z-statistics for the two other specifications of the spatial weights matrix. This reiterates the relevance of geographic neighbors' in adoption decisions.

I have shown that there are significant spatial interactions. There may be important factors contributing to the systematic interactions of adoption of water-conserving technology. In the next section I explore these spatial interactions using spatial error and spatial lag regressions and control for observable factors that may contribute to interactions among the microunits.

3.3 Estimation Results

Table 5 reports the linear regression estimates for Model 1 (equation 1) and Model 2 (equation 2). Both models produce similar results. Cost of water is not significant in either model. However, having a larger percentage of the parcel in the surface water service area increases the percent of land in converted to a water conserving technology. This supports previous theoretical and empirical findings that more reliable water supplies increase the incentive to adopt a drip technology. Having switched to a new permanent crop (citrus, grapes or deciduous) significantly increases the intensity of use of conservation technology. In Model 2, the farm's experience with the conservation technology is large and statistically significant. This suggests that intrafarm experience with the technology has a strong influence on microunit adoption of the technology.[3]

Following Anselin et al. 1996, I compute a robust Lagrange multiplier test of spatial lag and spatial error in Models 1 and 2. The results of this test are reported in Table 6 for each of the three spatial weights matrix specifications. The table reports the LM test statistic and its p-value in parenthesis. In the test for spatial errors, I reject the null hypothesis of no spatial error for Model 1. However, including the farm/owner variables in the estimation, I cannot reject the null. This suggests that including farm-level variables may address the source of spatial correlations. For the spatial weights matrix, W_1 and W_3, there is no evidence of a spatial lag for Model 1. However, the test for Model 2 indicates that for the spatial weights matrix that include distance, the null hypothesis of no spatial lag cannot be rejected at the 1 percent level for W_2 and at the 5 percent level for W_3. Moulton 1990 shows that including aggregated owner variables to the regression creates to correlations across within the microunit groups. This may explain the results of the spatial lag tests.

Based on the results presented in Table 6, I estimate a spatial error model for Model 1 for each of the three specifications of the spatial weights matrix. These estimates are reported in Table 7. I estimate a spatial lag model of Model 2 for the distance spatial weights matrix (W_2) and the owner-distance spatial weights matrix (W_3). I present these estimates in Table 8.

First I compare Model 1 estimates from Table 5 to the estimates of the spatial error models in Table 7. Variables that are positive and significant in the uncorrected model, have smaller coefficients in the corrected model for all specifications of the spatial weights matrix. This may indicate that without this correction, I may over-estimate the positive influence of such as water supply reliability (SWSA), slope and crop switch variables, on adoption.

[3]I estimate the Model 2 with farm-level shares in the five crop categories to control for farm-level production, not of these variables are significant and coefficient estimates are excluded from the table.

Table 5: OLS Estimates of Models 1 and 2

	Model 1	Model 2
Cost of Water ($/AF)	0.0006	0.0004
	(0.0004)	(0.0003)
SWSA (%)	0.1102***	0.0908**
	(0.0312)	(0.0293)
Slope (%)	0.0810***	0.0403
	(0.0144)	(0.0253)
Soil Permeability	0.0059	0.0056
	(0.0054)	(0.0051)
Crop Revenue/AC	0.0000***	0.0000***
	(0.0000)	(0.0000)
New Citrus (0/1)	0.6104***	0.5314***
	(0.0617)	(0.1195)
New Grapes (0/1)	0.2878***	0.3968***
	(0.0475)	(0.0938)
New Deciduous (0/1)	0.2820***	0.3243**
	(0.0654)	(0.1166)
New Truck (0/1)	-0.0597*	-0.0681
	(0.0294)	(0.0498)
New Field (0/1)	-0.0148	0.0161
	(0.0344)	(0.0419)
Farm Drip(%)		0.4930***
		(0.1285)
Farm Crop Diversity (%)		-0.1082
		(0.0635)
Year = 2001	0.0665*	0.0475
	(0.0290)	(0.0274)
Year = 2002	0.0366	0.0123
	(0.0383)	(0.0350)
Constant	-0.3291**	-0.3282*
	(0.1110)	(0.1546)
R-squared	0.4363	0.4490
N	531	531

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Coefficients reported; standard errors in parenthesis.

Table 6: Robust LaGrange Multiplier Test

	Spatial Error $H_0 : \lambda = 0$		Spatial Lag $H_0 : \rho = 0$	
SWM	Model 1	Model 2	Model 1	Model 2
W_1	14.857	2.540	0.005	0.038
	(0.000)	(0.111)	(0.945)	(0.846)
W_2	8.65	0.356	13.151	11.057
	(0.003)	(0.551)	(0.000)	(0.001)
W_3	6.858	0.149	1.054	3.058
	(0.009)	(0.699)	(0.305)	(0.080)

Also note that the estimate of the spatial error coefficient is positive and significant under all three specifications of W, providing additional evidence of positive spatially correlated errors. The estimate of λ assuming W_2 is significantly larger than the estimates of λ under the owner-based specifications. This again suggests that geographic relationships among the adopters produces significant unobserved correlations, raising concern about the extent of bias in the estimated standard errors and the reliability of inference based on these correlated standard errors.

Now I turn to comparing the spacial lag estimates of Model 2 with the uncorrected estimates in Table 5. Estimates of the effect of water supply reliability and slope are smaller in the lag models, however the differences are not as large as in the case for Model 1. This may be due to the farm-level variables accounting for some of the interaction among the microunits. Under both specifications of the spatial weights matrix, the estimated ρ is positive and significant. This suggests that adoption by a neighbor, geographic or economic, has a direct and positive influence on adoption of a water conserving technology. As in the case for Model 1, ρ is significantly larger when I assume the interaction is due to geographic interactions.

Table 7: Spatial Error Model Estimates, Model 1

	W_1	W_2	W_3
Cost of Water ($/AF)	0.0009**	0.0004	0.0008*
	(0.0003)	(0.0003)	(0.0003)
SWSA (%)	0.0900**	0.0643	0.0911*
	(0.0324)	(0.0346)	(0.0357)
Slope (%)	0.0649**	0.0642***	0.0566*
	(0.0203)	(0.0187)	(0.0251)
Soil Permeability	0.0086	0.0065	0.0074
	(0.0056)	(0.0064)	(0.0066)
Crop Revenue/AC	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)
New Citrus (0/1)	0.5541***	0.5477***	0.5456***
	(0.0853)	(0.0821)	(0.0900)
New Grapes (0/1)	0.3599***	0.3332***	0.3494***
	(0.0804)	(0.0786)	(0.0833)
New Deciduous (0/1)	0.3189**	0.2378*	0.2780**
	(0.0986)	(0.1041)	(0.1073)
New Truck (0/1)	-0.0692*	-0.0720*	-0.0654
	(0.0334)	(0.0324)	(0.0349)
New Field (0/1)	0.0015	-0.0131	0.0059
	(0.0386)	(0.0357)	(0.0396)
Year = 2001	0.0684*	0.0537	0.0624*
	(0.0304)	(0.0291)	(0.0315)
Year = 2002	0.0379	0.0271	0.0360
	(0.0358)	(0.0345)	(0.0377)
Constant	-0.4100***	-0.1679	-0.3937***
	(0.0931)	(0.2073)	(0.0993)
λ	0.3773***	0.9338***	0.3977***
	(0.0597)	(0.0676)	(0.0993)

$*p < 0.05, **p < 0.01, ***p < 0.001$

Coefficients reported; standard errors in parenthesis.

Table 8: Spatial Lag Model Estimates, Model 2

	W_2	W_3
Cost of Water ($/AF)	0.0004	0.0004
	(0.0002)	(0.0002)
SWSA (%)	0.0708**	0.0739**
	(0.0259)	(0.0258)
Slope (%)	0.0271	0.0280
	(0.0192)	(0.0194)
Soil Permeability	0.0061	0.0073
	(0.0049)	(0.0048)
Crop Revenue/AC	0.0000***	0.0000***
	(0.0000)	(0.0000)
New Citrus (0/1)	0.5019***	0.5053***
	(0.0835)	(0.0839)
New Grapes (0/1)	0.3844***	0.3691***
	(0.0681)	(0.0674)
New Deciduous (0/1)	0.2642**	0.2851**
	(0.0972)	(0.0938)
New Truck (0/1)	-0.0681*	-0.0604
	(0.0311)	(0.0313)
New Field (0/1)	0.0079	0.0156
	(0.0356)	(0.0347)
Farm Drip(%)	0.4740***	0.3715***
	(0.0981)	(0.0988)
Farm Crop Diversity (%)	-0.0779	-0.0888
	(0.0541)	(0.0543)
Year = 2001	0.0449	0.0437
	(0.0269)	(0.0268)
Year = 2002	0.0188	0.0152
	(0.0315)	(0.0318)
Constant	-0.4474***	-0.3589**
	(0.1164)	(0.1140)
ρ	0.6635***	0.2295***
	(0.1782)	(0.0532)

$*p < 0.05, **p < 0.01, ***p < 0.001$

Coefficients reported; standard errors in parenthesis.

Table 9: Comparison of Elasticities

	Linear Model		Spatial Model	
	Water Price	Supply Reliabiltiy	Water Price	Supply Reliabiltiy
Model 1	0.94	0.24	1.16	0.26
Model 2	0.67	0.21	0.69	0.27

4 Conclusions

This paper applies basic tools of spatial statistics to show that spatial interactions among microunits are significant. Our estimates are consistent with finding in the literature that geographic neighbors can have a strong influence on adoption of new technology. We also find that intrafirm interactions are important. If these interactions are ignored, the effect of a policy to promote adoption of water-conserving technology may be estimated with bias. Furthermore, the presence of unobserved spatial correlation biases the inference about the effects of policy, such as water pricing, supply reliability, or adoption cost subsidization, may be over-optimistic.

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