One challenge to estimating the parameters of a technology adoption model is that technology is selected jointly with land allocation. The article estimates a nested logit model of technology and crop choices that accounts for unobserved correlation among decisions. Estimation is conducted with a data set of adoptions, in contrast to the more common approach of using cross-section observations of existing technologies. Estimation results support the choice of a nesting structure as opposed to a more standard multinomial logit model. Adoption of precision irrigation technology is shown to be more sensitive to financial incentives affecting input price and technology cost than suggested by previous studies.

Key words: land allocation, nested logit, resource conservation, technology.

Beginning with the seminal work of Grilliches (1957, 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 can vary with the choice of output. Accordingly, farmers' land allocation decisions may have a significant influence on the pattern of technology diffusion.

One common approach to capturing the influence of land allocation on technology adoption is to treat crop choice as an exogenous variable in a cross-section estimation of the technology choice problem. A typical approach is to estimate a single-equation, discrete choice model of technology adoption such as multinomial logit with crop choice as a right-hand-side variable. Alternatively, some articles estimate the technology choice model conditional on crop choice.

In contrast to previous work, we estimate the parameters of a nested logit model of the joint probability of technology adoption and land allocation. Relative to a standard multinomial logit, the nested logit approach relaxes the assumption of Independence of Irrelevant Alternatives and allows us to capture the dissimilarities among different crop-technology choices. For example, adoption of a particular crop-technology pair may require a technology-specific set of skills or capital, and we expect that substitution among crops produced with one technology would differ from substitution patterns among crops produced with different technologies.

Another important methodological difference between our article and past work on technology adoption is that we estimate model parameters based on a data set of adoptions rather than a cross-section sampling of current technology and crop choices. The problem with the latter approach is that if technology or crop is a durable good, then some choices could have been made years in the past. The estimates of adoption behavior resulting from cross-section data on existing technology use may be misleading if underlying conditions have changed. The end result of our estimation choices is a more precise understanding of the economics of input use efficiency, and the ability to design more efficient and effective conservation policies.
Understanding the factors that influence adoption of conservation technology is important for policy design. Water conservation provides a good example. 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, for example, drip, microsprinkler, and other technologies. Reductions in agricultural water use have large, positive external benefits by making water available for urban consumption and to enhance instream flows. Through more accurate modeling of the diffusion process of precision technologies, it is possible to design more appropriate and effective interventions that can improve environmental quality at lower economic cost.

Previous Research

We consider the question of technology choice and land allocation with reference to the problem of irrigation technology adoption. The empirical literature on irrigation technology choice has identified the price of water as an important incentive for adoption of water-saving irrigation systems (see, e.g., 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. Numerous papers, such as Caswell and Zilberman (1986), Negri and Brooks, Shrestha and Gopalakrishnan (1993), and Green et al., find 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). Caswell and Zilberman (1986) explain this result within the context of a conceptual model of technology selection. Because of the importance of environmental conditions on the crop-technology choice, we use field-level observations of technology adoptions.

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. Various articles 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).

Lichtenberg acknowledged that technology and crop can be chosen simultaneously. Using a panel of county-level choices, he estimated a multinomial logit model of land allocation and irrigation decisions among major crops in Nebraska. For six crop-technology pairs, Lichtenberg regressed the log of the ratio of harvested acreage relative to dry farmed hay acreage on a quadratic function of own price, expected hay price, technology cost, and average land quality in the county. Computational difficulties prevented the use of simultaneous equations or maximum likelihood methods. The modeling of crop and technology choice in the present article is more detailed than in Lichtenberg, who only considers adoption of a single technology (center pivot irrigation) versus dry farming. This article also employs farm-level data on adoptions and more detailed descriptions of environmental conditions. Further, the nested logit model allows us to relax the IIA assumption implicit in the multinomial logit model, and permits a more realistic modeling of actual crop-technology choices in a more complicated environment than the one considered by Lichtenberg.

The model used in this article also contrasts to the recent work of Wu et al. on the design of soil conservation policies. They consider the land allocation and technology adoption decisions as joint and decompose the joint probability into the product of a conditional (technology | crop) and a marginal (crop) probability. However, Wu et al. estimate these two probabilities independently, making the assumption that the marginal and conditional probabilities are uncorrelated. As an alternative, the nested logit framework pursued in our article allows for correlation among different groups of technology and crops,
Moreno and Sunding Technology Adoption and Land Allocation

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Figure 1. Model of crop and technology choice
effectively capturing the realistic constraints
faced by decision makers when selecting out-
puts and inputs.3 Although specification of the
nested logit model imposes an ex ante struc-
ture on substitution patterns, often the rel-
evant structure is quite apparent, especially
when the researcher is considering adoption
of well-known technologies in a particular
setting. In the case of irrigation technology
adoption considered in this article, the nesting
structure is based on real physical constraints
faced by farmers in our study area.

Empirical Model of Technology Choice
and Land Allocation

Technology adoption is taken to be a choice
over three alternatives: (1) high-efficiency,
low-pressure irrigation technologies such as
drip and microsprinkler systems, (2) tra-
ditional gravity or furrow technology, and
(3) high-pressure sprinkler technologies. The
possible crop choices considered in this arti-
cle are citrus, deciduous, vines, truck, and
field crops, the major crop categories produced in
the study area.

The farmer chooses the crop and technology
pair that maximizes net benefit, but the substi-
tution among crops varies by technology. We
represent the set of crop-technology choices in
figure 1 as a two-level nested choice where the
farmer chooses technology and crop jointly,
but for each technology the crop choices differ.
However, by partitioning the crop-technology
choice we do not assume that the choice is
made sequentially; in figure 1, a tree structure
allows us to represent patterns of substitution
among correlated crop choices that are ob-
erved in our study area.

Let \( U_{nij} \) represent the \( n \)th farmer’s net ben-
fit from choosing technology \( i \) and crop \( j \). The
farmer will choose the \( ij \)th alternative if \( U_{nij} > U_{nkj} \) \( \forall i \neq k \) and \( j \neq l \). The researcher does not
know the farmer’s preferences, but observes
characteristics of the farmer and attributes of
the choices. Therefore, we can decompose the
farmer’s utility into an observed component
\( V_{nij} \) and an unobserved component \( \varepsilon_{nij} \), that is,

\[
U_{nij} = V_{nij} + \varepsilon_{nij}.
\]

We assume that the random errors \( \varepsilon_{nij} \) are
distributed extreme value and are uncorre-
lated across nests but not within nests. Sup-
pose that the farmer chooses among \( i = 1, \ldots, T \) technologies and \( j = 1, \ldots, C \) crops.
For each technology the farmer adopts, there
is a subset of crops he or she produces. De-
note this set of crops \( C_i \) for each technology \( i \).
We can write the probability of observing
adoption of choice \( ij \) as the joint probability

\[
P_{ij} = \frac{e^{V_{ij}}}{\sum_{i \in T} \sum_{j \in C} e^{V_{ij}}}.\]

Although technology adoption and crop
choice may be jointly determined, ultimately,
we are interested in how policy impacts the
adoption of conservation technology and wa-
ter use efficiency in agriculture. Therefore, we
isolate technology adoption behavior from the
joint probability of adopting a crop-technology
pair by decomposing the joint probability into
a conditional and marginal probability. De-
composing the joint probability in equation (2)
leads to the nested logit model and significantly
simplifies the estimation of the joint probabil-
ity (Maddala).

We specify \( V_{nij} \) as

\[
V_{ij} = \alpha'Z + \beta'X_{ij} + \gamma'W + \gamma'Y_i,
\]

where \( Z \) is a vector of observed individual
characteristics that affect the crop-technology
choice, \( X_{ij} \) is a vector of observed attributes
of the technology-crop \( ij \), \( W \) is a vector of
individual characteristics affecting tech-
nology choice, and \( Y_i \) is a vector of at-
tributes affecting technology \( i \). Thus, our model
estimates technology and crop choices by in-
corporating both individual characteristics and
choice attributes, therefore, the coefficients of

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3 The legitimacy of estimating a multinomial logit model for tech-
nology can be tested directly with the nested logit model. The multi-
nomial logit is a special case of the nested logit when the inclusive
value coefficient is equal to 1, or the correlation among choices
is 0.
individual field characteristics vary by choice, but the coefficients for choice attributes do not.

Following Maddala, the joint probability of adopting technology $i$ and choosing crop $j$ given in equation (2) can be written as

\[ P_{ij} = P_{ji} P_i \]

where

\[ P_{ji} = \frac{e^{\alpha_{ij} Z + \beta X_{ij}}}{\sum_{j \in C_i} e^{\alpha_{ij} Z + \beta X_{ij}}} \]

and $C_i$ is the set of crops grown with technology $i$, as shown in figure 1. The marginal probability of adopting technology $i$ is

\[ P_i = \sum_{j \in T} \frac{e^{\eta W + \gamma Y_i + \alpha_j Z + \beta X_{ij}}}{\sum_{j \in C_i} e^{\alpha_{ij} Z + \beta X_{ij}}} \]

Defining an inclusive value for each technology $i$ as

\[ I_i = \ln \left( \sum_{j \in C_i} e^{\alpha_{ij} Z + \beta X_{ij}} \right) \]

we can express equation (6) more concisely as

\[ P_i = \frac{e^{\eta W + \gamma Y_i + I_i}}{\sum_{j \in T} e^{\eta W + \gamma Y_i + I_i}} \]

where $T$ is the choice of the three technologies, drip, sprinkler, and gravity. The inclusive value $I_i$ explicitly links the technology choice to the crop choice. The coefficient $\tau$ is a measure of independence among the choices in the nest given by the $i$th technology and the statistic $1 - \tau$ is a measure of correlation (Train 2003). When $\tau = 1$ there is complete independence among choices in the $i$th nest, therefore, the model collapses to a multinomial logit. Therefore, a test of the restriction that $\tau = 1$ tests whether the nested logit model is appropriate. The inclusive value measures the attractiveness of choosing a crop within the nest for the $i$th technology.

**Data and Estimation**

We estimate the two-level nested logit model using Limited Information Maximum Likelihood (LIML) and data from Kern County, California.\(^4\) The estimation proceeds by first estimating the bottom level of figure 1, that is, the probability of adopting crop $j$, given the choice of technology $i$. Next we calculate the inclusive values for each technology as in equation (7) and estimate the top level, technology choice, with the inclusive values as explanatory variables. The purpose of the inclusive values in correlation (8) is to explicitly account for the correlation of crop and technology choice and to test this relationship.

To estimate this model, we construct a data set from various sources. We start with field-level observations of technology adoptons in Arvin-Edison Water Storage District.\(^5\) Arvin-Edison provided data for over 2,300 fields in the district for the years 1999–2002 (total of 9,500 observations) and from these data we identify the fields where we observe new technology-crop pairs.\(^6\)

A problem we encountered in identifying technology and land use changes on a particular field was that the field can change size and shape each year, although this is relatively uncommon. Each field is a subset of land within a land parcel, and while size of the parcel is fixed, the specific crop choice within the parcel may be reallocated from season to season. Furthermore, each field is uniquely identified solely by its geographic location. Therefore, we merged the data spatially using ArcGIS to identify technology and land use changes at each location for the period 1999–2002. Using the merged data, we identified 1,845 fields on which a new technology was adopted or a new crop was planted, or both during the period 1999–2002. Land use in Arvin-Edison is mixed and the original data from the district included observations on nonagricultural land use and fallowing. Since technology choice is not relevant for either category, we excluded all nonagricultural land use and fallowed land from the study data set.

First we turn to estimation of the bottom level model, the crop choice conditional on technology. The decision to adopt a particular crop-technology combination is affected by the profitability of the crop. One measure of profitability is the value of the output produced

\[ 4 \text{ For discussion of LIML estimation of the nested logit see either Train or Greene.} \]

\[ 5 \text{ Arvin-Edison is in Kern County, which has been noted as California’s center for diffusion of precision agricultural technologies (Caswell).} \]

\[ 6 \text{ We include changes in crop as an adoption because the grower has the opportunity to adopt a new technology when he or she grows a new crop.} \]
Table 1. Descriptive Statistics for Variables in Estimation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Top-Level Choice: Technology Choice Attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost of Adoption ($/acre)</td>
<td>652.04</td>
<td>320.48</td>
<td>250.00</td>
<td>1,470.00</td>
</tr>
<tr>
<td>Water Use (Acre-fee/acre)</td>
<td>1.57</td>
<td>3.15</td>
<td>0.21</td>
<td>54.49</td>
</tr>
<tr>
<td><strong>Individual Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field Slope (Gradient%)</td>
<td>1.24</td>
<td>0.97</td>
<td>0.50</td>
<td>8.95</td>
</tr>
<tr>
<td>Soil Permeability (in/hr)</td>
<td>2.87</td>
<td>2.37</td>
<td>0.13</td>
<td>13.00</td>
</tr>
<tr>
<td><strong>Bottom-Level Choice: Crop Choice Attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop Value per Acre ($)</td>
<td>4,862.38</td>
<td>1,993.30</td>
<td>517.66</td>
<td>7,738.98</td>
</tr>
<tr>
<td><strong>Individual Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price of Water ($/acre-foot)</td>
<td>130.33</td>
<td>69.91</td>
<td>58.00</td>
<td>219.70</td>
</tr>
<tr>
<td>Field Size (acres)</td>
<td>47.70</td>
<td>33.23</td>
<td>0.00</td>
<td>201.00</td>
</tr>
<tr>
<td>Frost-free Days</td>
<td>272.77</td>
<td>6.19</td>
<td>198.50</td>
<td>275.56</td>
</tr>
<tr>
<td>Value of Owner’s Land</td>
<td>432,280</td>
<td>602.040</td>
<td>0</td>
<td>3,930,000</td>
</tr>
<tr>
<td>Surface Water (0/1)</td>
<td>0.47</td>
<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Percent of Owner’s Land in Crop</td>
<td>0.16</td>
<td>0.25</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

on a field. We measure crop value as the annual acreage-weighted average of the output value per acre for specific crops in each crop category.\(^7\) For example, the crop value for citrus includes values for oranges, lemons, and grapefruit weighted by the acreage produced in Arvin-Edison. We constructed the crop values from data reported in Kern County Commissioner’s Reports for the years 1999–2002. Descriptive statistics for crop value are reported in table 1.

We also expect that adopting a crop-technology pair will be affected by the long-term reliability of water supply. To test for the effect of water supply reliability on technology adoption, we take advantage of the fact that the district has two service areas with different levels of water supply reliability. The district’s endowment of a high-quality ground water aquifer has allowed it to successfully implement conjunctive water management practices. 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.

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. However, the price of ground water is determined by both the price of fuel, that is, 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 factor that may affect the profitability of a crop is the cost of water. Table 2

---

\(^7\) This measurement of crop value implicitly assumes farmers have naïve expectations of output prices; a similar assumption is made in our use of current water prices. In reality, a more complete approach would involve modeling expectations for prices and costs over the life of the capital investments and possibly the risks associated with prices and costs. As pointed out by a referee, all of this would require much more careful attention to the dynamics of the adoption decisions.
Table 2. Production and Irrigation Costs for a Selection of Crops and Technologies

<table>
<thead>
<tr>
<th>Crop-Technology</th>
<th>Total Production Costs ($/acre)</th>
<th>Irrigation Costs (%)</th>
<th>Irrigation Costs as a Share of Total Production Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citrus Drip</td>
<td>6164</td>
<td>5%</td>
<td>5%</td>
</tr>
<tr>
<td>Deciduous</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gravity (a)</td>
<td>3244</td>
<td>22%</td>
<td>22%</td>
</tr>
<tr>
<td>Drip (b)</td>
<td>3097</td>
<td>22%</td>
<td>22%</td>
</tr>
<tr>
<td>Vines Drip</td>
<td>2581</td>
<td>8%</td>
<td>8%</td>
</tr>
<tr>
<td>Gravity (c)</td>
<td>2120</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>Truck Flood</td>
<td>5422</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Field Flood</td>
<td>648</td>
<td>29%</td>
<td>29%</td>
</tr>
</tbody>
</table>

Note: All prices are adjusted for inflation and are represented in 2003 dollars; PPI-Farm Products. Total production costs per acre are after accounting for capital recovery.

8 The cost of water can be as high as 20% of per acre production costs. Therefore, we expect water cost to be an important factor in the crop choice conditioned on technology. We compute the cost of water for surface water users as the unit charge plus the fixed fee per acre-foot of water using water rates from Arvin-Edison. For ground water users, we compute the cost of water 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 reported in table 1.

An important control variable in the crop choice estimate is the number of frost-free days. Some crops, such as citrus, are sensitive to frost conditions. Locations prone to frost may not be suitable for certain crops, thus limiting the grower’s crop choice. We include frost-free days and the square of frost-free days in the bottom level equations. We expect frost-free days to have a positive effect on most crops, but for this effect to vary among crops. We obtained data on frost-free days from the Natural Resource Conservation Service.

We address owner-level decision-making on each field by including information about the landowner for each field in our sample. Using landowner data from the Kern County Tax Assessor, we identified fields owned by the same landowner. For each landowner, we compute the percent of the entire farm’s acreage in a particular crop in the previous year. In computing this variable, we include all fields owned by a landowner, including fields without adoptions. On average, landowners own 5–7 fields and these fields are often not geographically contiguous. This variable is included in the crop equations to control for the fact that farmers may have specialized skills in production of a particular crop. As a measure of wealth, we also include the assessed value of all land parcels owned by a landowner.

To test for economies of scale in production on a particular field, we also include field size.

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8 Total production costs were available for a small sample of crops and years, as shown in table 2.
(in acres) as an explanatory variable. Descriptive statistics for landowner variables are included in table 1.

Now we turn to a description of the dependent variable in the top-level equations, the technology choice. In estimating the technology equation we expect that the cost of adopting a new technology has a strong influence on the decision to adopt. We measure the cost of adoption as the investment cost per acre for each technology (University of California Cooperative Extension). See table 1 for descriptive statistics on the cost of adoption.

We also consider factors that affect the technology’s productivity, including technology-specific water use, land quality and the field’s location. Based on parameters reported in Schoengold, Sunding, and Moreno, we compute water use for each technology. An interesting outcome of many econometric studies of irrigation technology adoption is the important, even dominant, role of environmental conditions. Therefore, we control for field slope and soil permeability using data from the Kern County office of the Natural Resource Conservation Service. In addition, to control for unobserved spatial differences in technology choice we also include a dummy variable for one of six geographic regions in the water district.

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, we expect slope to have a positive effect on the probability of adopting drip technology, and a negative effect on gravity 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. This observation is consistent with the notion that high-efficiency irrigation technologies are land-quality augmenting.

### Estimation Results

Parameter estimates for the bottom-level equations are given in table 3. Table 4 contains the estimates for the top-level equation of technology choice. Before discussing the

<table>
<thead>
<tr>
<th>Table 3. Probability of Crop Adoption Given Technology Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conditional Probability Coefficient Estimates</strong></td>
</tr>
<tr>
<td>**Crop</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>(0.3152)</td>
</tr>
<tr>
<td>Price of Water</td>
</tr>
<tr>
<td>(0.0232)</td>
</tr>
<tr>
<td>Surface Water</td>
</tr>
<tr>
<td>(3.2979)</td>
</tr>
<tr>
<td>Value of Owner’s Land</td>
</tr>
<tr>
<td>Percent of Owner’s Land in Crop</td>
</tr>
<tr>
<td>(0.8787)</td>
</tr>
<tr>
<td>Field Size</td>
</tr>
<tr>
<td>(0.0061)</td>
</tr>
<tr>
<td>Frost-Free Days</td>
</tr>
<tr>
<td>(0.0225)</td>
</tr>
<tr>
<td>Frost-Free Days Squared</td>
</tr>
<tr>
<td>(0.0001)</td>
</tr>
<tr>
<td>Crop Value</td>
</tr>
<tr>
<td>(0.0003)</td>
</tr>
<tr>
<td>Log Likelihood</td>
</tr>
<tr>
<td>McFadden $R^2$</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses. * significant at 10%; ** significant at 5%, *** significant at 1%.
estimated probabilities of adoption, we return to the threshold question of correlation among the choices. In table 5 we report tests of the hypothesis that the coefficients on the inclusive values are equal to 1. We can reject the null at least at the 1% level for gravity and drip, but fail to reject the null for sprinkler. All three inclusive values are jointly significantly different from 1. An inclusive value coefficient significantly different from 1 suggests dissimilarity among the alternatives. Thus, these estimation results support our choice of a nesting structure at least for drip and gravity technologies.

Turning to the bottom level estimates in table 3, we see that cost of water has the expected signs and are significantly different from zero for vines in the drip and gravity equations as well for field crops given sprinkler is chosen. The probability of adopting gravity and vines, again relative to citrus, is decreasing with the cost of water. The estimated coefficients for surface water are also significant for vines-drip and for truck-gravity and field-sprinkler. A negative surface water coefficient in the vine-drip equation suggests that having the more reliable surface water supply, growers switch toward citrus-drip and away from vines-drip. The percent of owner’s land in a crop is significantly different from zero at least at the 1% level and has a large impact on the crop-technology choice, suggesting that human capital factors such as experience or specialization in growing a particular crop can have a significant impact on the crop-technology choice.

Turning to the technology adoption estimation, we see that soil permeability and slope are significant for both sprinkler and drip technologies. Further, the signs are consistent with the literature (e.g., see Green et al. and Green and Sunding) and confirm again that environmental conditions play an important role in patterns of technology diffusion. Another interesting finding is that field gradient has a larger impact on adoption of drip than on sprinkler relative to gravity. This result is consistent with the notion that drip technologies are land-quality augmenting (Caswell and Zilberman (1986)) and improve the efficiency of water application on steep land.

In table 6, we explore the policy significance of our results. In particular, we report the change in the probability of adopting drip, gravity, and sprinkler when the cost of adopting each technology changes, and when the price of water changes. From a policy perspective, of course, these variables are of the most interest since they can be changed by public intervention through tax and subsidy programs. The price of water can also be affected by the introduction of water marketing opportunities.
Table 6. Marginal Effects and Elasticities

<table>
<thead>
<tr>
<th></th>
<th>Marginal Effects</th>
<th>Elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Drip</td>
<td>Gravity</td>
</tr>
<tr>
<td>Predicted Probabilities</td>
<td>0.1481</td>
<td>0.1131</td>
</tr>
<tr>
<td>Increase in Cost of Adoption of</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drip</td>
<td>−0.0006</td>
<td></td>
</tr>
<tr>
<td>Gravity</td>
<td>0.0001</td>
<td>−0.0005</td>
</tr>
<tr>
<td>Sprinkler</td>
<td>0.0005</td>
<td>0.0004</td>
</tr>
<tr>
<td>Increase in Average Cost of Water</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drip</td>
<td>0.0013</td>
<td></td>
</tr>
<tr>
<td>Gravity</td>
<td></td>
<td>−0.0004</td>
</tr>
<tr>
<td>Sprinkler</td>
<td></td>
<td>0.0000</td>
</tr>
</tbody>
</table>

that give farmers a chance to sell to willing buyers; water trading can also lower costs by allowing farmers the opportunity to buy from willing sellers.

The marginal effects in table 6 for the cost of adoption are computed as the derivative of the marginal probability of adopting technology \( i \), equation (6), with respect to the cost of adoption. Denote the cost of adoption for technology \( i \) as \( y_i \) and the coefficient on \( y_i \) as \( \gamma_y \). The marginal effect of the probability of adopting technology \( i \) due to a change in the own cost of adoption is

\[
\frac{\partial P_i}{\partial y_i} = \gamma_y P_i (1 - P_i)
\]

and the cross-price elasticities by

\[
\varepsilon_{ijy} = \frac{\partial P_i}{\partial y_j} \frac{y_j}{P_i} = -\gamma_y P_i P_j.
\]

Similarly, we obtain marginal effects on the probability of adopting technology \( i \) due to changes in water price, which appears in the bottom-level equations, by differentiating (6) with respect to water price. Denoting water price as \( z \), we can express the marginal effect as

\[
\frac{\partial P_i}{\partial z} = \frac{\partial P_i}{\partial I_i} \frac{\partial I_i}{\partial z} = [\tau P_i (1 - P_i)] \left( \sum_{j \in C_i} \alpha_{ij} P_{j|i} \right).
\]

The first term in the equation (9) follows from equation (8). To show the result for the second term, we take the derivative of the inclusive value formula in equation (7) with respect to the individual-specific variable \( z \), that is,

\[
\frac{\partial I_i}{\partial z} = \frac{\partial}{\partial z} \left[ \ln \left( \sum_{j \in C_i} e^{\alpha_{ij} z + \beta X_{j|i}} \right) \right] = \frac{1}{\sum_{j \in C_i} e^{\alpha_{ij} z + \beta X_{j|i}}} \times \left( \sum_{j \in C_i} \alpha_{ij} e^{\alpha_{ij} z + \beta X_{j|i}} \right) = \sum_{j \in C_i} \alpha_{zij} P_{j|i}.
\]

The last term in (10) is obtained by using the conditional probability given in equation (5). We use equations (9) and (10) to compute the marginal effects and elasticities in table 6.

The cost of adoption has a large effect on irrigation technology choices with own-price elasticities of \(-3.2\), \(-2.5\), and \(-0.7\) for drip, gravity, and sprinkler, respectively. The on-diagonal elements of the right-hand columns of table 6 are all negative, indicating that the probability of adopting a given technology decreases as its own cost of adoption increases. The off-diagonal elements are all positive, and some are rather large: the cross-price elasticity is about 2.0 for both sprinkler-drip and sprinkler-gravity. This finding is consistent with the notion that growers perceive they have an array of viable technology choices, and can be influenced by small changes in relative cost. In such an environment, technology subsidy programs, perhaps offered by water districts or environmental agencies, may meet with considerable success.

The price of water also appears to have a significant impact on the technology adoption...
decision. An increase in the price of water appears to encourage adoption of the most efficient technology (drip) and discourage adoption of the least efficient option (gravity). Sprinkler technology is an “intermediate” option in the sense that it is an improvement over gravity, but not as efficient as drip. Accordingly, the price of water has a small, but positive net effect on adoption of sprinkler. Again, our results indicate that financial incentives can be an effective means of improving the efficiency of water application in agriculture. The elasticity of drip adoption relative to the price of water is 1.1, indicating that relatively modest changes in price can stimulate real improvements in water use efficiency, even controlling for the indirect effect of water price changes on land allocation.

The significance of our approach relative to previous estimates can be gauged quite effectively by comparing our results to those of Green et al. That study considered choices among drip, gravity, and sprinkler technologies using a cross-section data set compiled in the same water district as in our study. As discussed earlier, Green et al. use a multinomial logit framework and treat crop choice as an exogenous variable. Green et al. did not consider the influence of technology cost on adoption, but their estimates of the elasticity of adoption probabilities with respect to the price of water are informative. They report elasticities of [0.96, −0.24, −0.84] for drip, gravity, and sprinkler, respectively, in contrast to our estimated elasticities of [1.126, −0.459, 0.002]. In both cases, drip adoption is encouraged by an increase in the price of water, although our estimate of responsiveness is about 20% higher than in the previous study. Both studies also conclude that gravity adoption is discouraged by an increase in water price. Our more general approach reverses the sign on sprinkler adoption and indicates little responsiveness to price. By accounting for the influence of water price on the land allocation decision in our estimation, we control for the observation that sprinkler technology is most interlinked with the land allocation decision. It is not surprising to find that adoption of sprinkler technology is relatively unresponsive to water price.

Conclusion

The phenomenon of technology adoption is a central problem in agricultural economics. New technology can improve the efficiency of farm production and can provide some important external benefits such as resource conservation, making it of concern to those outside the sector. Irrigation technology is a good example of this principle since the diffusion of precision irrigation technology can reduce water application and ultimately help to reduce diversions from oversubscribed water resources.

This article departs from the previous literature on the adoption of conservation technology by estimating the parameters of a nested logit model. Relative to a single-stage technique like multinomial logit, the nested logit framework relaxes the assumption of Independence of Irrelevant Alternatives and allows us to model dissimilarities among different crop choices given technology choice. Our article also takes the novel approach of estimating the model based on observed adoptions rather than all observed choices at a particular point in time.

Our use of a nesting structure confirms some previous findings in the literature, and also offers some important new observations. We confirm the general importance of environmental conditions in determining who adopts conservation technology. Drip technology, in particular, is land-quality augmenting, and a high gradient and poor water retention capacity will favor its adoption. Our results indicate that financial incentives like adoption rebates or water price increases can have a powerful effect on adoption behavior—even more than suggested by previous research. By controlling for the indirect effect of relative prices on the bottom-stage land allocation equation and accounting for unobserved correlation between land allocation and technology choice, we are able to more precisely estimate the influence of these policy variables on capital investments. Wider application of the approach outlined in this article should lead to the design of more effective conservation policies in agriculture.

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References

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