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Noah Hayward

University of Arkansas, Fayetteville

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The role of peer irrigators on the choice and intensity of efficient irrigation techniques

Noah Hayward¹

¹*University of Arkansas – Agribusiness Management and Marketing
Concentration*

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Abstract

We evaluate the use and the proportion of farmland that uses prominent irrigation practices in Arkansas, USA. A bi-variate sample selection model evaluates the determinants of the share of irrigated land in a farm that uses each practice. We evaluate the relationship between the irrigation practices peers use and the intensity that another farmer utilizes that same irrigation practice(s). So, if a peer of an Arkansas Delta farmer uses center pivot irrigation, for example, it increases the probability that the farmer him or herself will use acreage using center pivot by 66%. Conversely, a peer using surge irrigation only results in a farmer using surge irrigation themselves on 9% more acres. A peer that uses pivot decreases the proportion of irrigated land that uses flowmeter by .05. However, a peer using computerized hole selection increases the proportion of irrigated land on a farm using irrigation scheduling by 2.20. We interact the peer effect variables with location and farm practices of a farm to examine heterogeneity in the peer relationship. A peer using computerized hole selection increases the likelihood a farmer uses computerized hole selection by 55%, but if the farmer is in the South Delta, the likelihood of using the practice increases to 115%.

Keywords: Scale and choice in irrigation methods, Social learning, Peer networks

Introduction

Agriculture is responsible for roughly 80% of ground and surface water consumption in the United States (USDA 2019). The adoption and diffusion of modern irrigation technologies can result in many beneficial factors such as, reducing cost for farmers and preserving our natural resources. More efficient irrigation practices can reduce consumptive water use and may lower aquifer overdraft. Through modern irrigation technologies, farmers improve consumptive efficiency. However, greater consumptive efficiency lowers the return flows and recharge of aquifer levels for irrigated agricultural areas downstream (Grafton et al. 2018). The adoption of irrigation practices results in a large upfront capital expense but potentially lower operating expenses in the future. The future operating expenses are uncertain, and farmers likely rely on trusted peers for information on whether the potential gains of an irrigation practice outweigh the upfront costs. To add, we examine the notion of social learning and how prevalent it is within farming communities in the Arkansas Delta. By examining how peers impact Delta farmers' decisions to adopt a certain irrigation practice, policy makers can understand what irrigation practices to promote to increase adoption of a certain irrigation practice. We analyze how peers impact their decision to use a certain practice and how much land will be irrigated by a particular practice. Unlike previous research, we measure the intensity of use of a particular practice through the proportion of land irrigated by that practice. We hypothesize that the social interactions and relationships among farmers directly relate to how farmers choose irrigation methods and sources.

We examine a broad array of irrigation practices in use by agricultural producers in the Lower Mississippi River Basin of Arkansas (flowmeters, center pivot, Tail-water

recovery systems, etc.) to understand how social learning affects the use of an irrigation practice and the proportion of land on the farm that utilizes that irrigation practice. Our measure of social learning refers to whether a farmer's peer such as a friend or family member uses one or more of twelve specific irrigation practices. We condition this measure of social learning through interaction variables such as, where a producer lives (lived in county in Crowley's Ridge (Ridge), lived along Mississippi River (River), lived in Grand Prairie (GP), lived in North Delta (ND), lived in South Delta (SD)), what kind of financial assistance they are receiving (FIN), if a peer participated in general conservation partnership program (CPP), computer hole selection (CHS), if payment for tail-water recovery system or reservoir was through a federal program (FED), if peer participated in a conservation program (CRP). We contribute to literature examining the role peer effects have on the choice of agricultural practices through information about a range of related irrigation technologies potentially in use by a peer. Few studies also consider how intensively irrigation practice use occurs through an analysis of the proportion of land using these practices.

Social learning is one way to receive information about irrigation practices (Genius et al. 2014, Conley and Urdy 2010, Sampson and Perry 2010). Genius et al. 2014 find that social learning and extension services are synergistic ways of increasing farmers knowledge and reducing the time to adoption of drip irrigation (Genius et al. 2014). The influence of social learning and extension services were both highly statistically significant at reducing the adoption time. Conley and Urdy (2010) find that pineapple producers in Ghana make decisions on input use levels based on whether the input use of a peer in a previous year was a success or failure. Banderia and Rusal (2006) found that the decision

for Mozambique farmers to adopt sunflower based on the diffusion of farmers network (family and friends) shows relationship to be an inversely U-shaped. Thus, social learning effects are positive and significantly impact farmers decision when there are few farmers (1-10). However, when farmers' networks consist of many farmers (>10) the effect of social learning is negative and the impact is equal to having a network of zero (Banderia and Rusal 2006). Sampson and Perry (2019) contribute to the importance of social learning by examining peer effects on the adoption of a water efficient technology known as low energy precise application (LEPA). Sampson and Perry (2019) found that each additional peer adopting LEPA within 1km, increases the probability of a farmer to adopt LEPA themselves by 26%. As the distance increases between peers the marginal effect of adoption decreases greatly. Sampson and Perry (2019) were able to conclude that distance among peers plays an important part in determining whether a farmer adopts LEPA or not.

Other factors that determine irrigation practice use include farm characteristics and farmer demographics (Dridi and Khanna 2005). Economic factors (Schoengold and Sunding, 2014) (e.g. water price, cost of agriculture technology, farmers income, etc.) and farm characteristics (Genius, 2014) (e.g. farm size, soil type, location) and farmer demographics (Genius 2014) (e.g. age, education) also play part in the diffusion of modern irrigation. Sprinkler adoption increased among farms that had higher water cost, larger farmers, and farms that relied heavily on groundwater (Frisvold and Bai 2016). Frisvold and Bai (2016) conclude there is a positive monotonic correlation between farm size and sprinkler adoption. Water price also had a positive and significant effect on sprinkler adoption. As price increases, the adoption of sprinkler irrigation increases (Frisvold and Bai 2016). Type of crop also plays part in the diffusion of irrigation practices (Shuck et al.

2005). If a producer cultivates a certain crop such as corn (requiring intensive management), this increases the adoption of sprinkler systems by 0.3%. Wheeler et al. (2010) find that being a member of an irrigation district was a strong determinant in investing in new irrigation technologies. District irrigators were most likely to invest in irrigation technologies due to the need for sufficient and timely irrigation (Wheeler et al 2010). In analyzing a Colorado drought, producers adopted new irrigation practices such as gated pipe and sprinkler irrigation (Schuck et al. 2005). The main components determining adoption were land tenure, farm size, and available water supply (Schuck et al. 2005).

The Delta region is significant for Arkansas agriculture by contributing twenty billion dollars annually to the economy (Stovall, 2017). The main crops within this region include cotton, soybeans, and rice. Arkansas contributes 49% percent of all rice production in the United States (AFB, 2019). In order to maximize yields, it is important that these crops are properly irrigated at all stages of plant growth. Groundwater overdraft, as a result of intensive irrigation, threatens the long-term viability of irrigated crop production (ANRC, 2014). The lack of adequate rainfall during the growing season lead Arkansas farmers to pump groundwater at unsustainable levels. Unsustainable pumping of groundwater makes the aquifer susceptible to pollution and salt intrusion (NRC, 1997). Currently only about 60% of applied water reaches the intended crop, and policy makers recommend more efficient irrigation practices to reduce run-off and evaporation (ANRC, 2014).

Modern irrigation technologies have the potential to preserve Delta groundwater and surface water resources. Through social learning, farmers gain adequate knowledge allowing them to choose efficient irrigation practices. Knowing which irrigation practices are used by

peers influences the use of a particular irrigation practice and that can help policy makers develop a strategy to increase irrigation efficiency. For example, if peers' use of a particular practice can increase adoption by others, allowing policy makers to target educational efforts for these practices would be beneficial. If policy makers want to incentivize the use of center pivot, increasing communication with farmers already using center pivot could influence peer farmers to adopt as well. Another possibility is that farmer use of a different practice such as flow meters could motivate peer farmers to adopt center pivot. Also, policy makers can use farmers' locations, for example, to further allow them to focus resources adequately in a particular region. Policy maker's ability to understand how peers influence the use of different irrigation practices ultimately helps them to connect the appropriate farmers to increase irrigation efficiency

We separate the paper into six sections. First is a literature review that provides previous research on social learning and other variables that play a part in the adoption and diffusion of irrigation technology. Next are methods that present a bivariate sample selection model to find factors that correlate with the use of irrigation practices and the proportion of land covered by that practice. The data section follows where we explain the data collection process and the information obtained from Arkansas Delta producers. Next is the results section, and here we summarize the key findings followed by a discussion of the key results. Last, the conclusion summarizes our significant findings and suggests a research direction for future work on social learning within farming communities.

Literature review

Genius et al. (2014) examine the adoption of drip irrigation by 265 olive-producing farmers in Crete, Greece between 1994 and 2004. Farm characteristics and farmer demographics

play a role in the time until adoption of drip irrigation, but the emphasis in the analysis is on the different measures of social learning and extension services.

Genius et al. (2014) found both extension services and intra-farm communication are strong determinants of technology adoption. Effectiveness of each type of information is enhanced by the presence of the other. Exposure to extension services equals a strong positive & very significant effect on rate & reduces adoption time by months. Adopters and Extension together were very significant in reducing the time until adoption by months (Stock of adopters*extension services). Distance between extension outlets had a negative marginal effect, meaning that if a farmer was further removed from extension the shorter time of adoption. They suggest that this finding is a result of extension agents typically targeting farmers in remote areas and thereby farm from extension outlets. Along with extension services, social interactions between farmers were significant in reducing time of adoption. A farmer with a large stock of adopting peers of drip irrigation speeds up time to adopt by months. Increasing distances between peer farmers increased time of adoption by months.

Sampson and Perry (2019) examine peer effects on the adoption of a significant water efficient technology: low energy precise application (LEPA). A data set from 1990-2014 analyzes farmers behavior in the High Plains aquifer region of Kansas. Sampson found precise evidence of peer influence in the adoption of LEPA (net of environmental factors). Each additional farmer adopting LEPA within one km increases chances of adoption by roughly .03 percentage points. Importantly, each additional adoption of LEPA within 1 km, increases probability of adoption by peers by .26 percentage points. An adopter or potential adopter of LEPA within 1-2km, decreases the marginal effect by almost half compared to an adopter within 0-1km. Hence, the farther the distance between peers the less likely LEPA adoption and vice

versa. To put this in perspective, installations 5-10km away showed a statistically significant 10-fold reduction in adoption compared to a peer within 1km (Sam and Perry 2019).

Genius et al. (2014) found that both extension services and social learning are similar in terms of results by which they reduce time of adoption. However, social learning can be impacted by geographical proximities and distance between peer farmers. Overall, extension services and social learning statistically significantly reduced adoption time and the two information sources complemented each other. A farmer's choice of Modern Irrigation Technologies (MIT) is heavily dependent on farm characteristic and farm demographics. This being, peer influence and extension services enhance a farmer's knowledge on MIT, which ultimately reduces the time until adoption.

Sampson and Perry (2018) explain how it was quite troublesome distinguishing the difference in effects of both endogenous and contextual effects. A related issue known as the "reflection problem" (Manski 1993), shows that within a certain time frame, the decision of an individual influences the decision of his group and vice versa. However, recent information found the influence on farmers adoption of ground water irrigation may be dependent on the "installed base" of farmers' peers (Bollinger and Gillingham 2012). Installed base refers to the cumulative number of adoptions within the previous calendar year. Sampson and Perry (2018) emphasized the importance to control for the contextual factors such as energy costs, farm characteristics, etc. to avoid biased peer effect results. Sampson and Perry (2018) include a data set of covariates that could potentially impact the return to irrigation (farm characteristics) and a data set of county subdivision fixed effects, specific quadratic trends, and statewide and within-Groundwater Management District common correlated effects (Pesaran 2006). Accounting for

these potential effects, Sampson and Perry (2018) are able to control for region-specific fluctuations not related to peer interactions.

Sampson and Perry (2018) define peers using two definitions: (1) the 13 nearest neighbors and (2) the 25 nearest neighbors. The difference in groups allows for them to test for sensitivity of peer effects between specification of group size and whether a peer's impact is decreased with increasing distances between farmers. Taking a first look at the impact of peer influence over the years, they estimate the cumulative adoption curve (with and without peer effects).

Analyzing the predicted adoption curve with peer effect, shows it to be very comparable to the true adoption curve. As shown, the counterfactual adoption curve falls short of the true adoption curve during all years as predicted. Converting results to a quantity measure, Sampson and Perry (2018) estimated the distribution of water use for a time period of 1990 to 2014 from WIMAS data. The simulation expected that water rights appropriations resulting from peer effects would have accumulated for roughly 10.8 million acre-feet of ground water extraction to date. This is significant because 10.8 acre-feet would supply roughly 3 years of annual extraction from the Kansas High Plains aquifer.

Bandiera and Rasul (2006) examine northern Mozambique farmers' decision processes related to adopting a new crop (sunflower) and how it relates to the diffusion choices within farmers's networks of family and friends. Bandiera and Rasul (2006) discovered the relationship to be an inverse-U shape. Thus, social effects are a positive and impact farmers decision when there are only few adopters in network. Conversely, the social effect is negative when there are many adopters within the farmers network. They also find that farmers with better information on the new crop are less sensitive to peer

adopting decisions. Last, farmers adoption decisions are most correlated within family and friends more so than religion-based networks.

Baseline regression results examines the adoption decision of individual farmers on the number of adopters among his family or friends. Both family and friends were positive and significantly related. An increase in one stand deviation in the number of adopters (family and friends) in network increases propensity to consume by 0.134.

Farmers with a network between 1–5 peers that currently grow sunflowers increase the propensity to cultivate sunflower by 0.27. Farmers with a network between 6-10 peers that currently grow sunflowers, increases the propensity to cultivate 0.58. Farmers are most likely to cultivate than not if he/she has between 6-10 peer adopters among family and friends; however, farmers with network (current sunflower cultivators) of greater than 10 increases propensity to cultivate by 0.30, similarly to having zero adopters in social network. Bandiera and Rasul (2006) conclude from the spline regression that the relationship between number of adopters among peers (family and friends) is inverse-U shaped. Bandiera and Rasul (2006) also find, roughly 70% of Mozambique farmers have at least one adopter of sunflower cultivation among close peers, while non-adopters are significantly more likely to have zero adopters within peers. Overall, Banderia and Rasul (2006) best illustrate their results by showing the relationship between farmer and network of family and friends to be shaped as an inverse-U. Thus, Mozambique farmers are much more likely to cultivate sunflower when some (1-10) peers within network also adopt and less likely when many (>10) adopt.

Conley and Udry (2010) investigates the impact of social learning in the adoption and diffusion of new agriculture technologies in Ghana. Conley and Udry (2010) gathered majority of their data from a two-year survey (1996-1998) of 180 households within three

villages in southern Ghana. These villages in southern Ghana have many pineapple producers, allowing Conley and Urdy to better understand the diffusion of agriculture technologies for pineapple cultivators. Conley and Urdy (2010) found evidence that farmers often base technology adoption decisions on the success/failure of the farmers peer previous season.

Conley and Urdy (2010) find that a farmer is more inclined to change fertilizer after knowledge of his peer farmer using comparable amounts of fertilizer and achieving lower than expected profits. Next, farmer increases (decreases) amount of fertilizer after peer farmer achieves high profits when using more (less) fertilizer than original farmer. Also, farmers engagement to new information regarding productivity of fertilizer within peers is much higher if farmer is new to cultivating pineapple. Last, farmer has a higher response rate to news of productivity of fertilizer from pineapple cultivators who are veteran farmers and similar wealth status as himself. Conley and Urdy (2010) found that over 20 percent of veteran farms have reached out to peers for advice on pineapple farming.

To put into context, “good news” refers to an increase in profits from a farmer’s peer previous period with a given input level (fertilizer). “Bad news” refers to a decrease in profit from a farmer’s peer previous period within a given input level (fertilizer). Conley and Urdy (2010) found famers observations of peers ‘bad news’ of previous input level strongly increase farmers to change input levels himself. A one-standard-deviation increase (0.12) in a farmer’s observation of ‘bad news’ from a peer’s previous fertilizer use, results to an increase of probable change by 15 percentage points. A one-standard-deviation increase in a farmer’s observation of ‘bad news’ from a peer’s alternative fertilizer levels, results in a decrease in the probability of changing fertilizer themselves by

9 percentage points. The effect of ‘good news’ on a farmer’s probability to change is positive at alternative levels of fertilizer and negative at ‘good news’ of previous levels. Overall, the impact of ‘bad news’ a farmer receives from peers is much greater in terms of being statistically significant than ‘good news’. This is likely because a farmer’s probability of changing input levels is much higher when a peer has bad crop season rather than a good one. A good crop season would result in the farmer not making as much change to the input levels previously used.

Weather also plays a major role in the decisions of how and when to irrigate. In 2002, Colorado faced the worst drought in state history (Shuck, 2005). As a result of the drought, producers were forced to adopt new irrigation practices such as gated pipe and sprinkler irrigation. The main factors in determining the adoption included land tenure, farm size, and available water supply (Shuck, 2005). Schuck et al. (2005) analyze farmer’s choice of irrigation systems using a survey following the 2002 drought. Drought conditions X years prior the survey significantly increased the number of farms using more efficient sprinkler systems rather than gravity systems. Adoption of the sprinkler technology also depends on land tenure, cropland acreage, and level of education.

Frisvold and Bai (2016) examine how climate and other factors influence a farmer’s choice between sprinkler versus gravity-flow irrigation across 17 western states. Frisvold and Bai (2016) use data from USDA Farm and Ranch irrigation survey in determining the impact of outside factors with a focus on climate change. Their results suggest sprinkler systems are more prevalent in areas that are cooler and experience higher precipitation levels. Vice versa, sprinkler adoption is less prevalent in areas that experience warmer and drier climates. However,

Frisvold and Bai (2016) found that sprinkler adoption increased among farms that had high water costs, larger farms, and farms that relied more on groundwater.

Green et al. (2001) evaluate the results from a micro parameter approach based on field-level data, which is used to assess the effect of economic variables, environmental characteristics, and institutional variables on irrigation technology choices. Green et al. (2001) found that water price is not the most significant factor in irrigation technology adoption. Instead, physical and agronomic characteristics show to be more significant over water price.

Genius et al. (2014) found larger tree density is statistically significant at reducing the time until adoption of drip irrigation. One more tree per acre shortens time until adoption by 3.5 months. Farm size is not statistically significant among the results on the adoption of drip irrigation; however, an acre larger farm may reduce the time until adoption by roughly 1.4 months. Farm altitude significantly increases the time until adoption, for every hundred feet greater altitude the adoption is a month (1.09) later. Installation cost increase of an additional dollar per acre for drip irrigation increases the time until adoption by 2.89 months, but this is not statistically significant.

Schuck et al. (2005) find that owners who are non-operators are less likely to adopt sprinkler technology than owners who are operators. This is due to the diminishing benefits to owners who are not operators on the long-term investments that would be shared with a tenant. The amount of cropland acreage has the opposite effect on sprinkler adoption. When irrigated acreage increases on a farm, there is also an increase in the adoption of sprinkler systems on the farm. Cultivation of corn requiring intensive management increases the adoption of sprinkler systems by 0.003 acres.

Frisvold and Bai (2016) found that very large farms had a higher percentage of acreage under sprinkler systems compared to small, medium, and large farms. As such, coefficients become increasingly more negative as farm size is decreases and vice versa. Knowing this, Frisvold and Bai (2016) conclude there's a positive, monotonic correlation between farm size and sprinkler adoption. Water cost also had a positive and significant effect on sprinkler adoption, as water price increases adoption of sprinkler technology also increases.

Schoengold and Sunding (2014) analyze the impact on a farmers decision to adopt precision technology (PT) when input prices are stochastic. Schoengold and Sunding conduct an empirical model from California irrigation district from 1999-2002, which focuses on water price and irrigation technology adoption. The outcome is significant in determining whether programs/contract that decreases input price unpredictability may lower the adoption of conservation practices. However, examining a model of technology adoption, Schoengold and Sunding found that net effect of input price risk is unprecise and depend on many variables. Schoengold and Sunding determined that stable input prices increases the adoption of precision technology. However, the significance of the impact relies on crop choice and land characteristics.

Age and education of the farmer also play part in the adoption of new irrigation practices. Genius et al. (2014) found that farmer age is statistically significant, and a farmer tens year older reduces the time to adopt drip irrigation by .12 of a month. Farmers education of 8.1yrs or greater was not significant but helped reduce time until adoption by .37 of a month (roughly 12 days). Water price was significant in reduction time until adoption, for every addition dollar per acre-foot, farmers adopted drip irrigation roughly a year and a half sooner.

Shuck et al. (2005) conclude that since sprinkler system require technical skills to operate, education levels increase the adoption of sprinkler irrigation systems. On a scale from one to five, one being high school and five being graduate degree, increases in education increase the proportion of land irrigated by sprinkler irrigation by 0.22. This result is likely due to the technical skill required in the operation of sprinkler systems.

Wheeler et al. (2010) examines farmers adoption of “hard technology” (such as irrigation infrastructure technologies) and “soft technology” (water management or irrigation area changes) in regards to irrigations technologies, production changes, and water management changes in Albert, Canada. Wheeler et al. (2010) found substantial significance in modelling adoption of hard technology rather than soft technology. Important factors in the adoption of hard technologies included farm size, irrigation technology, off-farm income and membership of an irrigation district.

Wheeler et al. (2010) found that irrigators had a high adoption rate of new irrigation technologies (NIT) if: 1) had lower percent of off-farm income as a source of total farm income; 2) higher proportion of land irrigated by electricity; and 3) the farmer is a member of an irrigation district. Farmers with less dryland acres, higher percent of land for specialty crops, and higher proportion of land irrigated by wheel move or pressure pivot using electricity had an incentive to adopt NIT.

Wheeler et al. (2010) concluded from the results that adoption of sustainable management practices requires far more detail into the influential factors farmers face when deciding irrigation technologies. However, one consistent significant factor within the results shows adoption of NIT was determined based on whether the irrigator was private or a member of an irrigation district. Famers being private irrigators showed to

invest less in hard water technologies, likely because farmers rely less on high value crops to generate revenue. Larger portions of dryland on farm results in irrigators less likely to adopt hard water technologies. Wheeler et al. (2010) suggest the returns to different water investment are somewhat deterrent on the size of the farm.

Also, farmers with previous investments in irrigations technologies such as pressure pivot, were more likely to adopt NIT as well. This is likely due to farmers looking for further technology to become more conservative and sustainable. Irrigators with a high proportion of land irrigated by electricity were more influenced to adopt hard water technologies.

Overall, Wheeler et al. (2010) found importantly the largest impact on adoption was a farm's dependence on irrigation. District irrigators were most likely to adopt hard water technologies because of the need for sufficient and timely irrigation for specialty crops. Oppositely, private irrigators with large portions of dryland farming are the least likely to adopt due to them being least dependent on water irrigation. Last, socio-economic variables had no statistically significant effect on farmers' choices to adopt hard or soft water technologies.

Methods

A bivariate sample selection model is used to find the factors correlated between the use of irrigation sources and explain the proportion of land where each source is used. This allows the maximum likelihood of each independent variable having an impact on the dependent variables. It also better explains the influence that producers' choices have on the use and intensity of irrigation water source. Each bivariate sample selection model is composed of a participation and

an outcome equation. The participation equation's dependent variables are binary to specify the use of an irrigation source, and the outcome equation's dependent variables are the percentage of irrigated land from each source if that water source is in use.

The dependent variable in the participation equation, y_1 , is an incompletely observed value of a latent dependent variable y_1^* , where the observation rule is

$$y_1 = \begin{cases} 1 & \text{if } y_1^* > 0, \\ 0 & \text{if } y_1^* \leq 0 \end{cases}$$

and a resultant outcome equation such that

$$y_2 = \begin{cases} y_2^* & \text{if } y_1^* > 0 \\ - & \text{if } y_1^* \leq 0. \end{cases}$$

This model indicates that y_2 is observed when $y_1^* > 0$, and y_2 does not take on a value when $y_1^* \leq 0$. The latent variables y_1^* and y_2^* specify that the use and percentage of irrigation water from each source are not observed for the population as a whole. This then specifies a linear model with additive errors for the latent variables, so

$$y_1^* = x_1' \beta_1 + \varepsilon_1,$$

$$y_2^* = x_2' \beta_2 + \varepsilon_2.$$

Problems from this would arise in estimating β_2 if ε_1 and ε_2 are correlated.

We estimate using maximum likelihood, which is asymptotically efficient and uses the additional assumption that the correlated errors are joint normally distributed and homoscedastic with

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim \mathfrak{N} \left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \right].$$

The bivariate sample selection model uses the likelihood function

$$L = \prod_{i=1}^n \{Pr[y_{1i}^* \leq 0]\}^{1-y_{1i}} \{f(y_{2i} | y_{1i}^* > 0) \times Pr[y_{1i}^* > 0]\}^{y_{1i}}$$

where the first term is the participation equation when $y_{1i}^* \leq 0$, and the second term is thus the outcome equation when $y_{1i}^* > 0$.

The marginal effects in the participation equation show the change in the probability of participation in response to a one unit increase in the explanatory variables. The marginal effects in the outcome equation are the expected change in y_2 for a change in an explanatory variable, dependent on participation in use of the irrigation water source. If an independent variable appears only in the outcome equation, its marginal effect is equal to its coefficient. If the independent variable appears only in the participation equation, a change in the explanatory variable in the participation equation affects the expected value of the error term in the participation equation which, through correlation of error terms in both equations, leads to an expected change in y_2 . If the independent variable appears in both the participation and outcome equations, there is an expected change in y_2 from the direct effect from the explanatory variable in the outcome equation and an indirect effect from the explanatory variable in the participation equation because of the correlation of the error terms in both equations. The maximum likelihood estimation occurs through models available in Stata® version 13.1.

Data

Mississippi State University Social Science Research Center administered the survey via phone interviews. Prospective survey respondents were from the water user database being managed by the Arkansas Natural Resource Commission (ANRC) and all commercial crop growers identified by Dun & Bradstreet records for the state of Arkansas. Of the 3712 attempted contacts, 842 were disabled numbers, leading to a net sample size of 2870. Of the remaining contacts, 1321 were not answered when called, had a busy signal or went to voice mail. Another 925 contacts were ineligible due to illness, language barrier, or identified as non-farmer.

Overall, 624 accessible contacts were eligible to complete the survey. Of that number, 255 contacts declined to participate, 7 did not complete the survey although they scheduled callbacks, and 171 discontinued the survey. Eventually 199 producers completed the survey in full. The response rate for this survey was between 6.87% of the net sample size and 32.25% of accessible contacts. The questionnaire has about 150 questions and took respondents on average 30 to 40 minutes to finish via phone.

The dependent variables used in the participation and outcome equations are described in Tables 1A and 1B. Table 1A gives the variables used in the participation equation. These are binary variables that equal to 1 if used and 0 otherwise. Groundwater (GW) is by far the most common water source for irrigation with 93% of respondents indicating that they use ground water for irrigation. 15% of respondents use withdrawal from immediate surface water (SW), and another 15% use surface water and a reservoir storage system (RES). Those who use surface water with a reservoir and a tail water recovery system (RES_TWR) form 23% of the data set, and 18% of respondents use recycled water with no outside source (TWR_NO).

The dependent variables for the outcome equation are described in Table 1B. These are continuous variables that indicate the percentage of water used from a source. 76% of irrigation water comes from ground water (PCT_GW). Withdrawal and immediate surface use (PCT_SW) accounts for 12% of irrigation water, while surface water use and reservoir storage (PCT_RES), surface water use with reservoir and tail water recovery system (PCT_RES_TWR), and surface water use with no outside source (PCT_TWR_NO) account for 4%, 5.5% and 3% respectively.

Explanatory variables in this study were divided into three categories in Table 2: Land use and Irrigation Characteristics, Socioeconomic Characteristics, and Social Learning.

Land use and Irrigation Characteristics include binary variables that indicate the kind of crop grown by a farmer. 59% of the farmers grow rice (Rice), 81% have irrigated soybeans (IrrSoy), 40% have irrigated corn (IrrCorn), 10% grow irrigated cotton (IrrCotton), and 7% grow irrigated sorghum (IrrSorghum). The other binary variables included in this category describe the type of irrigation practices used on the farms. 81% of framers use soil moisture to schedule irrigation on farm (SoilSensor), and 34% own any flow meters (FlowMeter). While 81% use an electric pump on farm (ElectricPump), only 26% use a diesel pump on farm (DieselPump). 44% of farmers use a tail-water recovery system of some sort. The third set of binary variables in this category are for whether the producer believed the depth-to-water increased (DepthIncrease) (groundwater going down) or decreased (DepthDecrease) (ground water rising) on his or her farm. 13% of farmers believed the depth-to-water increased while 26% believed the depth to water decreased.

A fourth set of binary variables relates to the county of the respondent. The Delta was broken into five categories to group the farms in similar locations. 32% of respondents lived in a county in Crowley's Ridge (Ridge), 23% lived in a county along the Mississippi River (River), 19% lived in a county in the Grand Prairie (GP), 12% lived in a county in the North Delta and not in the previous described areas (ND), and 7% lived in a county in the South Delta and not in the previous described areas (SD). The next set of binary variables include financial capital considerations. 6% of farmers said their primary reason for a tail-water recovery system or reservoir was financial assistance (ReasonFin), 19% said it was to reduce irrigation costs or groundwater was no longer available (ReasonCost), and 7% said it was to reduce the risk of regulation or water shortage (ReasonRisk). 20% of farmers who use a tail-water recovery system or reservoir paid for it with cash (CashStorage), 22% paid through a federal program

(FedStorage), 4% paid with a bank loan (LoanStorage), 3% paid through a state tax credit system (TaxCredStorage), and 2% paid by other means (OtherStorage). The final set of binary variables relate to a farmer's participation in conservation programs. The percentage of farmers participating in a conservation reserve program (PartCRP), environmental quality incentives program (PartEQIP) or other conservation program (PartOther) is 43%, 45%, and 24%, respectively.

The continuous variables in this category relate to the acreage devoted to each crop and the expected yield (in tens of bushels) from the crops. Total average acreage under irrigation (IrrAcres) is 2,325. The average acreage of irrigated land of corn (IrrCornAcres) is 319 acres, that in cotton (IrrCottonAcres) is 116 acres, and sorghum (IrrSorghumAcres) is 35 acres. There are on average 121 acres in soybeans (IrrSoyAcres), 645 acres in rice production (RiceAcres), and 305 acres in grain production (IrrGrainAcres). Other continuous variables describe the characteristics of the tail-water recovery systems and storage reservoirs. The average number of irrigated acres using a tail-water recovery system (TwrAcres) is 300.7 acres, while the average age of the tail-water recovery systems (TwrAge) is 16.68 years. The average total number of reservoirs on a farm (TotRes) is 0.76 reservoirs, and the number of irrigated acres using reservoir water (ResAcres) is 39.02 acres. The average age of reservoirs found on farms (ResAge) is 24.30 years.

In the *Socioeconomic Characteristics* category, the highest education attained by producers in our sample vary considerably. 57% report having an agricultural education background (AgEdu), 23% reported earning an associate's or vocational degree (College), 42% reported earning a bachelor's degree (Bach), and 9% reported earning higher than a bachelor's degree (AdvEdu). 39% of respondents have a household income between \$75K and \$200K

(IncMid), 15% have an income greater than \$200K (IncHigh), and 23% did not report any income (IncNA). The final variable in the category was the number of years farming (Exper). Respondents had on average 32.70 years of farming experience.

The *Social Learning* category is primarily on peer networks and information sharing. Binary variables are used to solicit response from this question: “Please tell me if one or more of your close family members, friends or neighbor producers has used this practice in the past 10 years?” 88% of respondents know someone who has used precision leveling (PeerPLevel), 66% know someone who has a tailwater recovery system (PeerTWR), 68% know someone who uses a center pivot (PeerPivot), 72% know someone who uses zero grade leveling (PeerZeroGrade), 60% know someone who has a reservoir storage (PeerRes), 35% know someone who uses surge irrigation (PeerSurge), 53% know someone who uses computerized hole selection (PeerCHS), 63% know someone who owns and uses flowmeters (PeerFlowMeter), 50% know someone who uses end blocking, cutback irrigation, or furrow diking in irrigation (PeerEndBlock), and 32% know someone who use the alternate wetting and drying for rice irrigation (PeerAltWetDry). These responses do not imply respondents use any of these afore mentioned practices, but rather sought to determine if there is contact with extension offices he or she has, and ultimately how belonging to these different peer networks affect adoption of irrigation measurement tools.

The final set of social learning variables are interaction variables to examine the relationship between participating in a conservation program, using practices promoted by extension personnel, or geographic location with a farmer’s peer network. 6% of farmers lived in the South Delta and know someone using tail-water recovery (PeerTWR*SD). 33% of farmers participate in a conservation reserves program and know someone using tail-water recovery (PeerTWR*CRP). 10% of farmers live in the North Delta and know someone using center pivot

(PeerCP*ND). 9% of farmers participate in a regional conservation program and know someone using center pivot (PeerCP*RegCons). 9% of farmers also live in the North Delta and know someone using zero grade leveling (PeerZG*ND). 36% of farmers participate in an environmental quality incentives program and know someone using zero grade leveling (PeerZG*EQIP). 16% live in the Grand Prairie and know someone using a reservoir (PeerRes*GP).

Knowing someone using surge irrigation showed a lot of interactions as well. 5% live in the Grand Prairie and know someone using surge irrigation (PeerSurge*GP). 4% live in the South Delta and know someone using surge (PeerSurge*SD). 3% installed a tail-water recovery system or reservoir because of financial assistance and also knew someone using surge irrigation (PeerSurge*Fin). 8% of farmers know a peer using surge and also paid for the surface water infrastructure through a federal program (PeerSurge*Fed). Knowing someone using surge irrigation and using computerized hole selection (PeerSurge*CHS) or participating in an environmental quality incentives program (PeerSurge*EQIP) occurs with 14% and 20% of farmers.

Reason to install either a tail-water recovery system or reservoir of financial assistance and knowing someone using computerized hole selection (PeerCHS*Fin), flow meters (PeerFlowMeter*Fin), or alternate wetting and drying (PeerAltWetDry*Fin) happens 5%, 5%, and 3% of the time, respectively. 5% of farmers participate in a regional conservation program and know someone using alternate wet and dry (PeerAltWetDry*RegCons). 6% live in the South Delta and know someone using precision leveling (PeerPLevel*SD). 5% adopted surface water infrastructure because of financial assistance and knew someone using precision leveling (PeerPLevel*Fin). Knowing someone using precision leveling and paying for tail-water recovery

or reservoirs through a federal program (PeerPLevel*Fed) occurs 20% of the time. Finally, 23% of farmers participate in another conservation program and know someone using precision leveling (PeerPLevel*Other).

Results

Explaining the use of the irrigation practices

Marginal effects for explaining the use of irrigation practices appear in Tables 3 and 4. The marginal effects in Table 3, are for the explanatory variables that relate to farmer's peer network of fellow irrigators. Having a peer that uses an irrigation technique increases the likelihood the farmer will adopt these practices as well. If a peer uses flowmeter for irrigation, the likelihood of using a flowmeter by the farmer increases by 64%. If peer uses flowmeter irrigation in the ridge area, the likelihood of using flowmeter only increases by 19% ($.64 - .45 = .19$). If peer uses flowmeter irrigation and the producer is in the North Delta, the likelihood of using flowmeter increases by 27% ($.64 - .37 = .27$). A peer using flowmeter irrigation and the producer is in the River area, the likelihood of using flowmeter increases by 34% ($.64 - .3 = .34$). If peer uses both flowmeter and computerized hole selection, the likelihood of the producer using flowmeter increases by 88% ($.64 + .24 = .88$).

If a peer uses pivots for irrigation, the likelihood of a farmer using pivot irrigation increases by 66%. Having a peer that uses pivot only increases the likelihood of a producer using pivots by 13% ($.66 - .53 = .13$), when the producer received financial assistance for a tail-water recovery system or reservoir. If a peer uses irrigation scheduling, the likelihood of using pivots for irrigation decreases by 27%. However, if a peer uses irrigation scheduling and the producer received financial assistance for a tail-water recovery system or reservoir, the likelihood of using pivot increases by 18% ($-.27 + 0.45 = .18$).

If a peer uses computerized hole selection for irrigation, the likelihood of a farmer using computerized hole selection increases by 55%. If a peer uses computerized hole selection in the Grand Prairie, the likelihood of using CHS increases by 22% ($.55 - .33 = .22$). However, a peer using computerized hole selection in the South Delta, the likelihood of using CHS increases by 115% ($0.55 + 0.6 = 1.15$). Having a peer that uses computerized hole selection and primary reason for adoption was financial assistance for tail-water recovery system or reservoir, increases the likelihood of a producer using CHS by 137% ($.55 + .82$), when the producer received financial assistance for tail-water recovery system or reservoir as well. If a peer uses computerized hole selection and participated in other conservation programs, the likelihood of using CHS increases by 75% ($0.55 + 0.2 = 0.75$).

If peer uses surge irrigation, the likelihood of a farmer using surge increases by 9%. If a peer uses surge irrigation in the Grand Prairie, the likelihood of using surge increases by 56% ($.09 + .47$). If a peer uses surge irrigation in the Ridge Area, the likelihood of using surge increases by 33% ($.09 + .24$). If a peer uses Zero Grade for irrigation, the likelihood of a farmer using Surge decreases by 15%.

Table 4 shows the marginal effect for the farm, irrigation, and socioeconomics variables to explain the use of an irrigation practice. Having a producer that cultivates cotton is 24% less likely to use flowmeter. For a producer that transitioned from pivot to furrow, they're 26% more likely to use flowmeter. Having a producer that cultivates sorghum is 45% more likely to use pivot. A producer that cultivates cotton is 80% more likely to use pivot. A producer that uses a tail water recovery system is 31% less likely to use pivot. Having a producer that uses a diesel

pump is 50% more likely to use computerized hole selection. A producer using deep till is 32% more likely to use computerized hole selection.

Explaining the share of land that use the irrigation practices

Marginal effects for explaining the proportion of irrigated land that uses an irrigation practice appear in Tables 5 and 6. The marginal effects in Table 5 are the peer network variables that explain the proportion of irrigated land that uses an irrigation practice. Having a peer that uses pivot increases the proportion of irrigated land that uses scheduling by 1.09. A peer that uses zero grade decreases the proportion of irrigated land that uses scheduling by 0.77. A peer that uses computerized hole selection increases the proportion of irrigated land that uses scheduling by 2.20. Having a peer that uses end blocking, cutback irrigation, or furrow diking in irrigation, increases the proportion of irrigated land that uses scheduling by .62. Having a peer that uses zero grade and the producer is in the ridge area means the proportion of irrigated land that uses scheduling decreases by .47 (-.77 +.3). Having a peer that uses end blocking and the producer uses computerized hole selection correlates in the proportion of irrigated land that uses scheduling actually decreases by .44 (.62 – 1.06) .

A peer using precision leveling decreases the proportion of irrigated land that uses flowmeter by .18. A peer that uses pivot decreases the proportion of irrigated land that uses flowmeter by .05. Having a peer that uses surge irrigation decreases the proportion of irrigated land that uses flowmeter by .13. A peer that uses flowmeter increases the proportion of irrigated land that uses flowmeter by .33. Having a peer that uses pivot and the producer is in the South Delta means the proportion of irrigated land that uses flowmeter actually increases by .21 (-.05 +.26). Having a peer that uses pivot and the producer uses computerized hole selection means

that the proportion of irrigated land that uses flowmeter decreases by .24 (-.05 + -.19). Having a peer that uses pivot and the producer participates in the regional conservation partnership program means the proportion of irrigated land that uses flowmeter increases by .17 (-0.05+.22). Having a peer that uses pivot and the producer participated in other conservation programs means the proportion of irrigated land that uses flowmeters actually increases by .14 (-.05+.19). Having a peer that uses flowmeter and the producer is in the ridge area means the proportion of irrigated land that uses flowmeter only increases by .04 (.33-29). Having a peer that uses flowmeter and the producer is in the North Delta means the proportion of irrigated land that uses flowmeter increases by .10 (.33-.23) Having a peer that uses flowmeter and the producer is in the river area means the proportion of irrigated land that uses flowmeter increases by .19 (.33 - .14). Having a peer that uses flowmeter and the producer uses computerized hole selection means the proportion of irrigated land that uses flowmeter increases by .43 (.33+.10).

Having a peer that uses pivot increases the proportion of irrigated land that uses pivot by .18. Having a peer that uses end blocking, cutback irrigation or furrow diking in irrigation decreases the proportion of irrigated land that uses pivot by .22. A peer that uses wetting and drying for rice irrigation decreases the proportion of irrigated land that uses pivot by 0.23. A peer that uses wetting and drying for rice irrigation and the producer is in the ridge area means the proportion of irrigated land that uses pivot only decreases by .01 (-.23+.22). Having a peer that uses end blocking and the producer participates in the conservation reserve program means the proportion of irrigated land that uses pivot only decreases by .06 (-.22+.16).

A peer that uses computerized hole selection increases the proportion of irrigated land that uses computerized hole selection by .17. A peer that uses tail-water recovery increases the proportion of irrigated land that uses surge by .05, although this is not statistically significant at

the 10% level. A peer that uses tail-water recovery and the producer is in the Grand Prairie means the proportion of irrigated land that uses surge actually decreases by .19 (.05 - .24).

Having a peer that uses tail-water recovery and the producer's primary reason for the adoption of tail-water recovery and reservoirs is financial assistance means the proportion of irrigated land that uses surge decreases by .12 (.05-.17). Having a peer that uses tail-water recovery and the producer participates in the regional conservation partnership program means the proportion of irrigated land that uses surge increase by .18 (.05 + 0.13).

Table 6 shows the marginal effects for the farm, irrigation, and socioeconomic variables to explain the proportion of irrigated land that uses an irrigation practice. A producer that grows irrigated cotton has a 1.40 lower proportion of irrigated land that uses scheduling. A producer that uses irrigated cover crops has a 1.00 higher proportion of irrigated land that uses scheduling. A producer that grows irrigated sorghum acres has a 6.13 lower proportion of irrigated land that uses scheduling. A producer that has formal education related to agriculture has a 1.15 higher proportion of irrigated land that uses scheduling. A producer that has a household income between \$75,000 and \$200,000 has a .95 higher proportion of irrigated land that uses scheduling than a producer with a household income less than \$75,000. A producer that has a household income greater than \$200,000 has a further .86 higher proportion of land that uses scheduling. A producer that did not report their income available (IncNA) has a 2.4 higher proportion of land that uses scheduling than a producer with a household income less than \$75,000. For each additional year of farming experience, a producer has a 0.016 higher proportion of land that uses scheduling.

A producer that uses irrigated cotton has a 0.19 lower proportion of land that uses flowmeter. A producer that transitioned from pivot to furrow has a 0.16 higher proportion of

land that uses flowmeter. For each additional year of farming experience, a producer has a 0.004 higher proportion of land that uses flowmeter. A producer that grows irrigated sorghum has a 0.12 higher proportion of land that uses pivot. A producer that grows irrigated cotton has a 0.23 higher proportion of land that uses pivot. A producer that uses a diesel pump on farm has a 0.59 lower proportion of land that uses pivot. A producer that has formal education related to agriculture has a 0.18 higher proportion of land that uses pivot.

A producer that grows irrigated sorghum has a 1.46 lower proportion of land that uses computerized hole selection. A producer that uses gypsum has a 0.80 higher proportion of land that uses computerized hole selection. A producer that did not make their income available (IncNA) has a 0.26 higher proportion of land that uses computerized hole selection than a producer with a household income less than \$75,000. A producer that has a diesel pump on farm has a 0.56 lower proportion of irrigated land that uses surge. For each additional year of farming experience, a producer has a 0.006 lower proportion of land that uses surge.

Discussion

The Table 3 results indicate that the influence of peers on an agricultural producer's irrigation practices differs across Arkansas region. For a producer who has a peer using a flowmeter, this increases the producer's likelihood of using flowmeter by 64%. However, the region where the producer lives modifies how much having a peer with a flowmeter influences the likelihood that the producer uses a flowmeter. For example, a producer in the Crowley's ridge area with a peer that uses a flowmeter only has a greater likelihood of flowmeter use of 19% rather than 64%. Likewise, a producer that lives in the North Delta or close to the Mississippi River only has a higher likelihood of flowmeter use of 27% and 34%, respectively. For a producer who has a peer using computerized hole selection, the producer's likelihood of

computerized hole selection use increases by 55%. This likelihood increases a further 60% if the producer lives in the South Delta. However, a producer who lives in the Grand Prairie only has a 22% greater likelihood rather than 55%. For a producer who has a peer using surge irrigation, the producer's likelihood of surge irrigation use only increases by 9%. The likelihood increases a further 24% if the producer lives in the Crowley's ridge area, and the likelihood increases by a substantial 47% if a producer lives in the Grand Prairie region.

There appears to be substitution among irrigation practices through the peer effects. A producer who has a peer using an older practice such as end blocking is less likely to use a newer practice such as scientific scheduling. Likewise, a producer who has a peer using scheduling is 27% less likely to use an older practice such as a center pivot. Having a peer that uses precision leveling and center pivot, both older practices, make a producer more likely to use an older practice such as a flowmeter. Having a peer using computerized hole selection, a relatively new practice, increases the likelihood of a producer using a newer practice such as scientific scheduling. A producer that has a peer using surge irrigation, a relatively new practice, is less likely to use a decades old practice such as a flowmeter. Cover crops are a newer practice for resource stewardship, and the use of cover crops correlates with having a peer using a recent irrigation practice such as scientific scheduling.

There also appears to be substitution among irrigation practices according to the types of crops a producer is growing. Having a peer was that use an irrigation practice for rice make a producer less likely to use an irrigation practice for row crops. For example, having a peer using zero grading or alternate wetting and drying, which increase irrigation efficiency for rice, make a producer less likely to use row crop irrigation practices such as computerized hole selection and tail-water recovery. Producers that grow cotton are less likely to use scheduling and flowmeters,

and their peers often use center pivot. Producers that grow sorghum, a less irrigation intensive crop, are more likely to use center pivot and are much less likely to use computerized hole selection.

Producers with a formal agriculture education irrigate a higher proportion of their land with scientific scheduling and center pivot. Both the pivot and scheduling practices involve the use of sophisticated equipment, and a formal education in agriculture could help producers to understand such equipment. Producers with more years of farming experience had a higher proportion of irrigated land using scientific scheduling and flowmeter, but a lower proportion of irrigated land using surge irrigation. Greater farming experience could make producers have an appreciation for timely irrigation through better scheduling and for knowing the amount of water crops receive by using flowmeters. However, farming experience has less influence on the proportion of land that uses surge irrigation, which is a less popular technique in the region. Producers with greater income irrigate a larger proportion of cropland with scientific scheduling since economies of scale matter for achieving a good return on investment in scheduling.

Conclusion

We determine the significance of social learning through knowledge of irrigation practices by friends and family, and the impact this has on Arkansas delta farmers to adopt a particular irrigation practice. In addition to examining if a farmer's social learning led to the adoption of a certain irrigation practice, we also examine the proportion of land irrigated by that particular practice as well. We found a peer's use of center pivot had the greatest impact on a farmer using center pivot themselves. We see that having a peer that uses CHS and also receives financial assistance for tail-water recovery systems or reservoir has the highest impact

on a farmer using CHS themselves. We see that a peer use of a particular practice had a significant impact on farmers to use themselves, with wide range of influence in-between.

The use of a particular irrigation practice by a peer is a strong determinant on whether a farmer uses that same practice themselves. We conclude that if a farmer has a peer within his network using center pivot, the probability of the farmer adopting center pivot themselves increases by 66%. Likewise, a farmer's peer using flowmeter for irrigation increases the likelihood a farmer adopts flowmeter himself by 64%. A peer uses computerized hole selection for irrigation, the likelihood of a farmer using computerized hole selection increases by 55%. Lastly, a peer uses surge irrigation, the likelihood of a farmer using surge increases by 9%. To sum, a peer using center pivot has the greatest impact on a farmer to adopt it themselves at 66%. Conversely, a peer using surge has the least impact on a farmer to adopt it themselves at 9%. We can see how farmer's use of a particular irrigation practice depends on the entire suite of irrigation practices of his fellow peers. For example, if a peer uses irrigation scheduling the likelihood of a farming using pivot decreases by 27%. If a peer uses Zero Grade for irrigation, the probability the farmer uses surge decreases by 15%. These suggest there is a substitution between scheduling and pivot and a substitution between zero grade to surge.

Furthermore, when examining peer variables associated with interaction for location and farm characteristics, we find statistical significance where there is none for the peer variable without an interaction term. The impact of a peer using CHS alone (55%) has far greater impact when taking into account of interaction terms. For example, when a peer uses CHS in the South Delta, the probability a farmer using CHS increases to 115%. Having a peer that uses CHS and also receives financial assistance for tail-water recovery systems or reservoir, increases

a farmer's probability of CHS use to 137%. The additional interaction variables indicate the many differences across farm operations and how heterogeneous a peer effect can be.

Examining the proportion of land being used under these practices shows, a peer that uses computerized hole selection increases the proportion of irrigated land that uses scheduling by 2.20. A peer using flowmeter increases the farmers proportion of land to use flowmeter by .33. A peer using wetting and drying for rice irrigation, decreases proportion of irrigated land using pivot by .23. A peer using CHS resulted in a farmer increasing the proportion of land using CHS by .17. Lastly, a peer using TWR increases the proportion of land using Surge by .05. There is some correlation in the proportion of land that uses a practice , and the probability in the use of that same practice. Both the proportion of land in CHS and the probability farmers use CHS increase when knowing a peer that uses the CHS practice. Likewise, a peer's use of flowmeter increases both the farmer's use and proportion of farmland that uses a flowmeter.

Examining the marginal effects for other variables (non-peer related) we find some that resulted in being statically significance as well. Among the non-peer related variables, IrrSorghum (producer cultivating sorghum) and IrrCotton (producer cultivating cotton) are of most significance. Meaning a farmer producing sorghum is 45% more likely to use center pivot. Furthermore, a producer cultivating cotton increases the likely to use center pivot by 80%. Other than crop type for instance, a producer using a diesel pump on farm, is 50% more likely to adopt computerized hole selection.

Conley and Urdy (2010) find that farmers modify fertilizer inputs to correspond to peers that had previously successful yields. We do not distinguish between good vs bad in terms of peer information transmission but whether a peer uses a particular practice. The variability we observe in the influence knowing a peer has on a farmer's use of different practices could be

because of unobserved information about the “good” vs “bad” of each practice. Genius et al. (2014) find both extension services and intra-farm communication are strong determinants of technology adoption. Likewise, we find peer networks and technical assistance have a strong correlation with the use of technology. For example, a farmer with a peer that use center pivot and participated in the Regional Conservation Partnership Program (RCPP) had a greater share of land using flowmeter by .22 than a farmer with a peer that uses center pivot but does not participate in the RCPP. The peer networking was a result of a farmer's peer using a particular practice as well as how much land was being used. We find significant results in terms of how irrigation use of a peer impacts the farmer themselves as well as the proportion of land irrigated by the practice.

Sampson and Perry (2019) and Bandiera and Rasul (2006) measure proximity to recent technology adopters and the stock of adopters and how this correlates with technology adoption. Sampson and Perry (2019) measure proximity between adopters and find that each additional adoption of LEPA within 1 km, increases probability of adoption by peers by .26 percentage points. Sampson and Perry (2019) conclude that adopters outside of 1 km decreases chances to adopt by nearly half. Bandiera and Rusul (2006) measure stock of adopters and conclude that if there are 10 adopters this increases the chance to cultivate sunflower by roughly 60%. However, greater than 10 adopters result in the same as a farmer having zero networking.

We do not know the exact distance between peers or the number of adopters, and this could be another reason that the influence of knowing a peer that uses a practice differs in magnitude across practices. Peer influences may become less dependent among stock of adopters and distance due to the increasing use of the internet.

There is more to learn on how social learning influences to farmer's choices of irrigation practice. Some limitation we had was the unknown number of peers and how far away these peers were from the Arkansas delta farmers within our survey. Other limitations include the lack of micro level data such as, information on field characteristics of physical features (soil/slope) or farm management features (type of ownership/production practices) which also play part in adoption of new irrigation. An alternative approach is to mitigate groundwater overdraft is the conversion to the use of surface water. Surface water can come from on-farm reservoirs, tail-water recovery systems, or directly from lagoons. Farmers use of social learning has potential to make the adoption to surface water more efficient by gaining knowledge from fellow producers. The diffusion of new practices has the potential to conserve our waters sources for sustainable irrigation by Arkansas farmers.

References

- Arkansas Natural Resources Commission (ANRC). 2014. Arkansas Water Plan Update 2014.
- Banderia, O., and I. Rasul. 2006. Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal* 116 (514): 869-902.
- Bouldin, J.L., N.A. Bickford, H.B. Stroud, and G.S. Guha. 2004. Tailwater Recovery Systems for Irrigation: Benefit/Cost Analysis and Water Resource Conservation Technique in Northeast Arkansas. *Journal of the Arkansas Academy of Science*, 58, 23-31.
- Conley, T.G., and C.R. Urdy. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100: 35-69.
- Czarnecki, J.M., A. Omer, and J. Dyer. 2017. Quantifying Capture and Use of Tailwater Recovery Systems. *Journal of Irrigation and Drainage Engineering*, 143(1).
- Foster A, Rosenzweig M. 1995. Learning by doing and learning from others: human capital and technical change in agriculture. *Journal of Political Economy*, 103(6), 1176–209.
- Frizvold, G. and Bai, T. 2016. Irrigation Technology Choice as Adaption to Climate Change in the Western United States. *Journal of Contermpary Water Research & Education*. P. 62-77
- Genius, M., P. Koundouri, C. Nauges, and V. Tzouvelekas. 2014. Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects. *American Journal of Agricultural Economics*, 96(1), 382-344.
- McCarty, J. (2019, June). Sustainability in water systems. Lecture Conducted from the University of Arkansas, United States.
- Popp, J., E. Wailes, K. Young, J. Smartt, and W. Intarapapong. 2003. Use of On-farm Reservoirs in Rice Production: Results from the MARORA Model. *Journal of Agricultural and Applied Economics*, 35(2), 371-379.
- Rogers, E.M. 1995. *Diffusion of Innovation*, 4th Edition. New York: Free Press.
- Sampson, G.S., and E.D. Perry. 2019. The Role of Peer Effects in Natural Resource Appropriations: The Case of Groundwater. 101 (1): 154-171.
- Schuck, E., W. Frasier, R. Webb, L. Ellingson, and W. Umberger. 2005. Water Resource Development: Adoption of More Technically Efficient Irrigation Systems as a Drought Response. No. 4, 651-662
- Stovall, B. (2017, January) Rise of The Arkansas Delta. JoStovall, B., & *, N. (2020, July 22). Rise of the Arkansas Delta. Retrieved from <https://www.farmflavor.com/arkansas/arkansas-crop-livestock/rise-arkansas-delta/#:-:text=Varying and productive soils helped, farming following three decades later.>
- United States Department of Agriculutre (USDA). 2019. Irrigation & Water use 2019.

Table 1A. Dependent variables for participation equation

Variable	Definition	Percentage
SciSched	=1 if use scientific scheduling	0.123
SoilSens	=1 if soil moisture sensors	0.082
ETcompwood	=1 if ET Comp wood	0.058
FlowMeter	=1 if use flow meter	0.352
MountFM	=1 if use mounted flow meter	0.264
PortableFM	=1 if use portable flow meter	0.164
CHS	=1 if use computer hole selection	0.347
CP	=1 if use center pivot	0.376
Surge	=1 if use surge	0.188

Table 1B. Dependent variables for outcome equation

Variable	Definition	Mean	Std. Dev	10 th Percentile	90 th Percentile
Share_SciSched	Share of land that uses scientific scheduling	0.044	0.17	0	0.05
Share_SoilSens	Share of land that uses soil moisture	0.023	0.13	0	0
Share_ETcompwood	Share of land that uses ET Comp Wood	0.020	0.11	0	0
Share_FM	Share of land that uses Flow meter	0.089	0.20	0	0.31
Share_Mount_FM	Share of land that uses Mounted Flow meter	0.072	0.18	0	0.27
Share_Port_FM	Share of land that uses portable Flow meter	0.017	0.062	0	0.04
Share_CHS	Share of Land that uses Computerized hole selection	0.107	0.22	0	0.45
Share_CP	Share of land that uses Center Pivot	0.085	0.21	0	0.30
Share_Surge	Share of land that uses Surge irrigation	0.021	0.097	0	0.04

Table 2. Explanatory variables for irrigation water source modeling

Variable	Definition	Percentage
<i>Peer Network</i>		
PeerPLevel	=1 if peers used precision leveling	0.90
PeerTWR	=1 if peers used tail-water recovery system	0.71
PeerPivot	=1 if peers used center pivot	0.65
PeerZeroGrade	=1 if peers used zero grade leveling	0.75
PeerSurge	=1 if peers used surge irrigation	0.36
PeerCHS	=1 peers used Computerized hole selection	0.56
PeerFlowMeter	=1 if peers used flowmeters on the wells	0.65
PeerEndBlock	=1 if peers used alternate used end blocking, cutback irrigation, or furrow diking in irrigation	0.55
PeerSched	= 1 if peers used scheduling	0.53
PeerAltWetDry	=1 if peers used wetting and drying for rice irrigation	0.35
PeerTWR*GP	=1 if peers used tail-water recovery systems in the Grand Prairie region	0.19
PeerTWR*Fin	=1 if peers used tail-water recovery system and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.06
PeerTWR*RegCons	= 1 if peers used tail-water recovery system and participated in regional conservation partnership program	0.11
PeerPivot*RegCons	=1 if peers used center pivot and participated in regional conservation partnership program	0.09
PeerSurge*GP	=1 if peers used surge irrigation and located in the Grand Prairie	0.05
PeerSurge*Ridge	=1 if peers used Surge irrigation and located in Ridge area	0.14

PeerCHS*Fin	=1 if peers used computerized hole selection and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.05
PeerZG*Ridge	=1 if peers used Zero Grade and located in Ridge	0.24
PeerEnd*CHS	=1 if peer used End blocking and computerized hole selection	0.21
PeerSched*Fed	=1 if peer used scheduling and fed storage	0.13
PeerPivot*SD	=1 if peers used center pivot in the south delta region	0.03
PeerPivot*CHS	=1 if peer used center pivot and computerized hole selection	0.30
PeerPivot*RegCons	=1 if peer used center pivot and participated in regional conservation partnership program	0.10
PeerPivot*Other	=1 if peer used center pivot and participated in other conservation program	0.21
PeerPivot*Fin	=1 if peers used center pivot and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.04
PeerFM*Ridge	=1 if peers used flow meter and located in ridge	0.20
PeerFM*ND	=1 if peers used flow meter and located in North Delta	0.04
PeerFM*River	=1 if peers used flow meter and located in the river region	0.16
PeerFM*CHS	=1 if peers used flow meter and computerized hole selection	0.26
PeerCHS*GP	=1 if peers used computerized hole selection in the Grand Prairie	0.11
PeerCHS*SD	=1 if peers used computerized hole selection in the South Delta	0.03
PeerCHS*Fin	=1 if peers used computerized hole selection and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.05
PeerCHS*Other	=1 if peer used computerized hole selection and participated in other conservation program	0.19

PeerEND*CHS	=1 if peers used end blocking and computerized hole selection	0.21
PeerEB*CRP	= 1 if peers used End Blocking and participated in conservation reserves program	0.28
PeerAltWetDry*Ridge	=1 if peers used wetting and drying irrigation located in the ridge	0.10

Peers include family members, friends or neighbors using technology within the past 10 years

Farm and irrigation characteristics

		Percentage
IrrSorghum	=1 if grows irrigated sorghum	0.07
IrrCotton	=1 if grows irrigated cotton	0.14
Covercrops	=1 if grows covercrops	0.29
Piv_Fur	=1 if transitioned from Pivot to furrow	0.18
DieselPump	=1 if use diesel pump on farm	0.91
Ridge	=1 if county is in Crowley's Ridge	0.32
River	=1 if county is along Mississippi River	0.23
GP	=1 if county is in the Grand Prairie	0.19
ND	=1 if county is in the North Delta and not others	0.12
SD	=1 if county is in the South Delta and not others	0.07
TWR	=1 if use tail-water recovery system on farm	0.49
ReasonFin	=1 if primary reason for tail-water recovery system or reservoir was financial assistance	0.06
ReasonCost	=1 if primary reason for tail-water recovery system or reservoir was reduced irrigation cost or groundwater not available	0.19
ReasonRisk	=1 if primary reason for tail-water recovery system or reservoir was reduce risk of regulation or water shortage	0.07

CashStorage	=1 if payment for tail-water recovery system or reservoir was cash	0.20	
FedStorage	=1 if payment for tail-water recovery system or reservoir was through federal program	0.22	
LoanStorage	=1 if payment for tail-water recovery system or reservoir was bank loan	0.04	
TaxCredStorage	=1 if payment for tail-water recovery system or reservoir was state tax credit program	0.03	
OtherStorage	=1 if payment for tail-water recovery system or reservoir was by other means	0.02	
PartCRP	=1 if participate in conservation reserve program	0.43	
PartEQIP	=1 if participate in environmental quality incentives program	0.45	
PartOther	=1 if participate in other conservation program	0.24	
		Mean	Std Dev
Share_Irr_Sorghum	Share of irrigated land in sorghum	0.01	0.07
Share_DeepTill	Share of irrigated land using deep till	0.19	0.33

Socioeconomic characteristics

		Percentage	
AgEdu	=1 if formal education related to agriculture	0.59	
IncMid	=1 if household income between \$75K and \$200K	0.42	
IncHigh	=1 if household income greater than \$200K	0.13	
IncNA	=1 if household income not available	0.23	
		Mean	Std Dev
Exper	Years of farming experience	32.75	15.05

Table 3. Marginal effects for the peer network variables to explain the use of an irrigation method

Variable	Sched	FM	Pivot	CHS	Surge
PeerPivot			.66 (0.0)		
PeerZeroGrade					-0.15 (0.037)
PeerCHS				0.55 (0.00)	
PeerFlowmeter		0.64 (0.00)			
PeerSched			-0.27 (0.01)		
PeerPivot*Fin			-0.53 (0.05)		
PeerSurge					0.09 (0.46)
PeerSurge*GP					0.47 (0.01)
PeerSurge*Ridge					0.24 (0.06)
PeerCHS*GP				-0.33 (0.02)	
PeerCHS*SD				0.6 (0.05)	
PeerCHS*Fin				0.82 (0.02)	
PeerCHS*Other				0.2 (0.04)	
PeerFM*Ridge		-0.45 (0.048)			
PeerFM*ND		-0.37 (0.063)			
PeerFM*River		-0.3 (0.025)			
PeerFM*CHS		0.24 (0.018)			
PeerSched*Fed			.45 (.005)		
Pseudo R ²	0.21	0.28	0.42	0.42	0.53
Number of observations	222	222	222	222	222

a – 1%, b – 5%, C–10% Significance. P-values from the probit model estimates in parentheses.

Table 4. Marginal effects for the farm, irrigation, and socioeconomics variables to explain the use of an irrigation method

Variable	Sched	FM	Pivot	CHS	Surge
IrrSorghum			0.45 (0.009)		
IrrCotton		-0.24 (0.087)	0.8 (0.0)		
Piv_Fur		.26 (0.028)			
DieselPump				0.5 (0.015)	
TailWater			-0.31 (0.003)		
Share_Deeptill				0.32 (0.02)	
Pseudo R ²	0.21	0.28	0.42	0.42	0.53
Number of observations	222	222	222	222	222

a – 1%, b – 5%, C–10% Significance. P-values from the probit model estimates in parentheses.

Table 5: Marginal effects for the peer network variables to explain the share of land that uses and irrigation method

Variable	Sched	FM	Pivot	CHS	Surge
PeerPLevel		-0.18 (0.06)			
PeerTWR					.05 (0.70)
PeerPivot	1.09 (0.00)	-0.05 (0.66)	.18 (0.05)		
PeerZeroGrade	-0.77 (0.00)				
PeerSurge		-0.130 (0.02)			
PeerCHS	2.2 (0.015)			0.17 (0.06)	
PeerFlowMeter		0.33 (0.00)			
PeerEND	0.62 (0.084)		-0.22 (0.014)		
PeerAltWetDry			-0.23 (0.006)		
PeerTWR*GP					-0.24 (0.09)
PeerTWR*Fin					-0.17 (0.05)
PeerTWR*RegCons					0.13 (0.04)
PeerPivot*SD		0.26 (0.05)			

PeerPivot*CHS		-0.19 (0.02)			
PeerPivot*RegCons		0.22 (0.06)			
PeerPivot*Other		0.19 (0.007)			
PeerZeroGrade*Ridge	0.3 (0.034)				
PeerFM*Ridge		-0.29 (0.026)			
PeerFM*ND		-0.23 (0.04)			
PeerFM*River		-0.14 (0.05)			
PeerFM*CHS		0.10 (0.042)			
PeerAltWetDry*Ridge			.22 (0.074)		
PeerEND*CHS	-1.06 (0.025)				
PeerEND*CRP			0.16 (0.047)		
Pseudo R ²	0.76	0.10	0.14	0.09	0.09
LR test of independent equations: Chi squared statistics χ^2	16.12 ^a	63.49 ^a	1.15	9.49 ^a	1.85
Number of observations	59	81	30	40	52

a – 1%, b – 5%, C–10% Significance. Z statistics from the bivariate sample selection model estimates in parentheses.

Table 6: Marginal effects for the farm, irrigation, and socioeconomics variables to explain the share of land that uses and irrigation method

Variable	Sched	FM	Pivot	CHS	Surge
IrrSorghum			.12 (0.085)	-1.46 (0.025)	
IrrCotton	-1.4 (0.00)	-0.19 (0.04)	0.23 (0.065)		
IrrCoverCrops	1.00 (0.00)				
Gypsum				0.80 (0.022)	
PivFur		0.16 (0.02)			
DieselPump			-0.59 (0.00)		-0.56 (0.00)
IrrSorgumAcres	-6.13 (0.019)				
AgEdu	1.15 (0.01)		0.18 (0.005)		
IncMid	.95 (0.002)				
IncHigh	0.86 (0.00)				
IncNA	2.4 (0.002)			0.26 (0.016)	
Exper	0.016 (0.00)	0.004 (0.026)			-0.006 (0.00)
Pseudo R ²	0.76	0.10	0.14	0.09	0.09
LR test of independent equations: Chi squared statistics χ^2	16.12 ^a	63.49 ^a	1.15	9.49 ^a	1.85
Number of observations	59	81	30	40	52

a – 1%, b – 5%, C–10% Significance. Z statistics from the bivariate sample selection model estimates in parentheses.

Appendix A – Explanatory variables for irrigation water source modeling

		Percentage
PeerRes (older, rice production areas)	=1 if peers used reservoir storage	0.60
PeerMI 90's	=1 if used multiple inlet for rice irrigation	0.70
PeerTWR*SD	=1 if peers used tail-water recovery system and located in the South Delta	0.06
PeerTWR*Ridge	=1 if peers used tail-water recovery system in the Ridge area	0.23
PeerTWR*ND	= 1 if peers used tail-water recovery system and located in the North Delta	0.09
PeerTWR*River	=1 if peers used tail-water recovery system and located in the River area	0.11
PeerTWR*CRP	=1 if peers used tail-water recovery system and participated in conservation reserves program	0.37
PeerTWR*EQIP	= 1 if peers used tail-water recovery system and participated in environmental quality incentives program	0.40
PeerPivot*ND	=1 if peers used center pivot and located in the North Delta	0.10
PeerZG*ND	=1 if peers used zero grade leveling and located in the North Delta	0.09

PeerZG*EQIP	=1 if peers used zero grade leveling and participated in environmental quality incentives program	0.36
PeerZG*CHS	=1 if peers used zero grade and Computerized hole selection	0.28
PeerZG*Other	=1 if peer used Zero Grade and participated in other conservation program	0.25
PeerRes*GP	=1 if peers used reservoir storage and located in the Grand Prairie	0.16
PeerSurge*SD	=1 if peers used surge irrigation and located in the South Delta	0.04
PeerSurge*ND	=1 if peers used Surge irrigation and located in the North Delta	0.04
PeerSurge*River	=1 if peers used surge irrigation and located in the river area	0.07
PeerSurge*Fin	=1 if peers used surge irrigation and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.03
PeerSurge*Fed	=1 if peers used surge irrigation and payment was through federal program	0.08
PeerSurge*CHS	=1 if peers used surge irrigation and computerized hole selection	0.14

PeerSurge*EQIP	=1 if peers used surge irrigation and participated in environmental quality incentives program	0.20
PeerFlowMeter*Fin	=1 if peers used flowmeter and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.05
PeerAltWetDry*Fin	=1 if peers used wetting and drying for rice irrigation and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.03
PeerAltWetDry*RegCons	=1 if peers used wetting and drying for rice irrigation and participated in regional conservation partnership program	0.05
PeerPLevel*SD	=1 if peers used precision leveling and located in the South Delta	0.06
PeerPLevel*Fin	=1 if peers used precision leveling and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.05
PeerPLevel*Fed	=1 if peers used precision leveling and payment was through federal program	0.20
PeerPLevel*Other	=1 if peers used precision leveling and participated in other conservation program	0.23

PeerSched*SD	=1 if peer used Scheduling and located in south Delta	0.041
PeerSched*EQIP	=1 if peers used Scheduling irrigation and participated in environmental quality incentives program	0.335
PeerSched*Other	=1 if peers used scheduling irrigation and participated in other conservation program	0.19
PeerMI*CHS	=1 if peer used mitigation irrigation and computerized hole selection	0.26
PeerPivot*GP	=1 if peers used Center pivot in the Grand Prairie Region	0.07
PeerPivot*River	=1 if peer used center pivot in the River region	0.20
PeerPivot*EQIP	=1 if peer used center pivot and participated in environmental quality incentives program	0.37
PeerFM*EQIP	=1 if peers used flow meter and participated in environmental quality incentive programs	0.41
PeerLevel*Ridge	=1 if peers used flow meter and located in ridge	0.29
PeerCHS*ND	=1 if peers used computerized hole selection in the North Delta	0.06
PeerCHS*RegCons	=1 if peers used computerized hole selection and participated in regional conservation partnership program	0.09

PeerEND*SD	=1 if peers used End Blocking in the South Delta	0.03
PeerEND*Fin	=1 if peers used end blocking and primary reason for adoption of tail-water recovery and reservoirs was financial assistance	0.05
PeerAltWetDry*River	= 1 If peers used wetting and drying irrigation located in the river area	0.07

Peers include family members, friends or neighbors using technology within the past 10 years

Farm and irrigation characteristics

		Percentage
Rice	=1 if grows rice	0.59
IrrCorn	=1 if grow irrigated corn	0.40
IrrSoy	=1 if grows irrigated soy	0.81
Part_Cons	= 1 if participated in a federal, state, or local conservation programs in the last five years other than the conservation program, environmental quality incentive program, and regional conservation partnership program	0.52
FlowMeter ?	=1 Own any flow meters	0.34
SoilSensor	=1 if use soil moisture to schedule irrigation on farm	0.81

Tot_Res	=1 if the operation has an on-farm reservoir	0.38	
ElectricPump	=1 if use electric pump on farm	0.88	
DepthIncrease	=1 if depth to groundwater increases in last 5 years	0.13	
DepthDecrease	=1 if depth to groundwater decreases in last 5 years	0.26	
		Mean	Std Dev
IrrCornAcres	Number of irrigated corn acres (in hundreds)	3.19	9.62
IrrCottonAcres	Number of irrigated cotton acres (in hundreds)	1.16	4.65
IrrSoyAcres	Number of irrigated soybean acres (in hundreds)	1.21	15.02
RiceAcres	Number of irrigated rice acres (in hundreds)	6.45	9.75
TwrAcres	Number of irrigated acres using tail-water recovery	300.70	677.95
TwrAge	Age of tail-water recovery system	16.68	15.73
TotRes	Number of reservoirs on farm	0.76	1.75
ResAcres	Number of irrigated acres using reservoir	39.02	144.23
ResAge	Age of reservoir	24.30	21.90

Share_Irr_Sorghum	Share of irrigated land in sorghum	0.01	0.07
Share_Irr_Soybean	Share of irrigated land in soybean	0.55	0.24
Share_Irr_Rice	Share of irrigated land in rice	0.29	0.24
Share_EB	Share of irrigated land using end blocking	0.13	0.26
Share_Gypsum	Share of irrigated land using gypsum	0.01	0.07
Share_DeepTill	Share of irrigated land using deep till	0.19	0.33

Socioeconomic characteristics

		Percentage	
College	=1 if some college or vocational program	0.23	
Bach	=1 if completed Bachelor's degree	0.42	
AdvEdu	=1 if completed education beyond a Bachelor's degree	0.09	
		Mean	Std Dev
Exper	Years of farming experience	32.75	15.05

Table B1 shows the marginal effects from the probit estimation that were significant between the 10th and 40th percentile after the marginal effects were applied. These values were significant as coefficients below the 10th percentile before the marginal effects were applied.

Table B1. Marginal Effects from Probit Estimation, All variables significant between 10th and 40th percentile

Variable	Sched	FM	Pivot	CHS	Surge
PeerPLevel		-0.24 (0.179)			
PeerMI	0.046 (0.17)				

PeerEND					0.073 (0.23)
PeerSched			-0.076 (0.10)		
PeerPivot*GP			-0.24 (0.15)		
PeerZeroGrade*CHS					-0.78 (0.31)
PeerZeroGrade*Other					-0.09 (0.19)
PeerSurge*ND					0.18 (0.27)
PeerSurge*river					0.15 (0.3)
PeerSurge*Fin					0.24 (0.19)
PeerCHS*ND				-0.3 (0.13)	
PeerCHS*RegCons				0.22 (0.14)	
PeerFM*EQIP		0.09 (0.37)			
PeerPLLevel*Ridge		0.18 (0.37)			
PeerSched*EQIP	0.03 (0.35)				
PeerMI*CHS	0.026 (0.26)				
Share_Irr_Soybean	0.06 (0.19)				
Share_Irr_Rice					0.12 (0.36)
Share_Deeptill					-0.13 (0.25)
PartCons	-0.04 (0.16)				
Covercrops	0.02 (0.32)				0.05 (0.40)
Piv_Fur	0.05 (0.15)				
Tot_Res		0.1 (0.27)			
ElectricPump				0.19 (0.24)	0.12 (0.19)
Inc_High	0.04 (0.25)		-0.18 (0.26)		
Inc_Mid	0.03 (0.26)		.18 (0.14)		
Exper	-0.00 (0.24)			-0.005 (0.11)	

Z statistics in parenthesis

Table B2 shows the marginal effects from the probit estimation that were not significant at the 40th percentile after the marginal effects were applied. These values were significant as coefficients below the 10th percentile before the marginal effects were applied.

Table B2. Marginal Effects from Probit Estimation, All variables not significant at 40th percentile

Variable	Sched	FM	Pivot	CHS	Surge
PeerTWR					0.05 (0.7)
PeerSched	0.013 (0.64)				
PeerSched	-0.006 (0.94)				
PeerSched*SD	0.026 (0.46)				
PeerSched*Fed	0.02 (0.41)				
PeerSched*Other	0.012 (0.425)				
PeerPLevel*Other	0.024 (0.90)				
PeerPLevel*Fed	0.059 (0.42)				
IrrCotton				0.02 (0.87)	
River		-0.092 (0.47)			
GP		0.091 (0.47)			
ND		-0.029 (0.14)			
Inc_Mid		0.7 (0.54)			
Inc_High		-0.04 (0.816)			
Inc_NA	-0.004 (0.86)	0.06 (0.65)	0.07 (0.61)		

Z statistics in parenthesis

Appendix C

Table B1 shows the marginal effects from the bivariate sample selection model estimation that were significant between the 10th and 40th percentile after the marginal effects were applied. These values were significant as coefficients below the 10th percentile before the marginal effects were applied.

Table B1: Marginal Effects from Bivariate Sample Selection, All variables significant between 10th and 40th percentile

Variable	Sched	FM	Pivot	CHS	Surge
PeerSched			-0.076 (0.10)		
PeerTWR*CRP					-0.07 (0.32)
PeerTWR*GP					
PeerTWR*Ridge					-0.15 (0.20)
PeerTWR*ND					-0.13 (0.40)
PeerTWR*River					-0.19 (0.19)
PeerTWR*EQIP					0.07 (0.32)
PeerPivot*GP			-0.07 (0.21)		
PeerPivot*River		-0.15 (0.19)			
PeerPivot*EQIP		-0.11 (0.27)			
PeerPivot*Fin			-0.15 (0.16)		
PeerCHS*GP				-0.12 (0.13)	
PeerCHS*ND				-0.085 (0.21)	
PeerCHS*SD				0.18 (0.15)	
PeerCHS*Fin				0.27 (0.11)	
PeerCHS*RegCons				0.06 (0.20)	
PeerCHS*Other				0.06 (0.15)	
PeerFM*EQIP		0.07 (0.23)			
PeerAltWetDry*River			.13 (0.31)		
PeerLevel*Ridge		0.16 (0.13)			
PeerEND*SD			-0.22 (0.25)		
PeerEND*Fin			-0.19 (0.31)		
PeerEND*CHS			-0.15 (0.11)		

PeerSched*Fed			0.13 (0.10)		
IrrCoverCrops		0.057 (0.38)			
IrrDeepTill				0.09 (0.10)	
IrrEbAcres		.16 (0.18)			
ElectricPump				0.049 (0.34)	
DieselPump				0.16 (0.11)	
TWR			-0.10 (0.11)		
IncMid		0.76 (0.18)	0.045 (0.22)	0.12 (0.2)	
IncHigh			-0.06 (0.26)		0.11 (0.21)
Exper				-0.001 (0.19)	

Z statistics in parenthesis

Table B2 shows the marginal effects from the bivariate sample selection estimation that were not significant at the 40th percentile after the marginal effects were applied. These values were significant as coefficients below the 10th percentile before the marginal effects were applied.

Table B2: Marginal Effects from Bivariate Sample Selection, All variables not significant at 40th percentile

Variable	Sched	FM	Pivot	CHS	Surge
PeerPLevel	0.294 (0.45)				1.290 (0.19)
PeerTWR					0.05 (0.7)
PeerPivot		-0.05 (0.67)			-13.203 (0.70)
PeerZeroGrade					0.005 (0.87)
PeerSurge		1.32 (0.44)			0.09 (0.46)
PeerMI	-0.12 (0.42)				
PeerEND					-0.003 (0.87)
PeerSched	-0.006 (0.94)				

PeerTWR*SD					-18.701 (0.61)
PeerPivot*ND					
PeerPivot*GP		0.02 (0.86)			
PeerPivot*RegCons					5.410 (0.59)
PeerZeroGrade*CHS					0.003 (0.87)
PeerZeroGrade*Other					0.003 (0.87)
PeerSurge*GP					-0.016 (0.87)
PeerSurge*Ridge					-0.008 (0.86)
PeerSurge*ND					-0.006 (0.86)
PeerSurge*River					-0.005 (0.87)
PeerSurge*Fin					-0.008 (0.87)
PeerPLevel*SD					22.614 (0.66)
PeerPLevel*Fed	0.059 (0.42)				
PeerPLevel*Other	0.207 (0.47)				
PeerSched*Fed	-0.045 (0.47)				
PeerSched*SD	-0.11 (0.53)				
PeerSched*EQIP	-0.08 (0.48)				
PeerSched*Other	-0.058 (0.53)				
PeerMI*CHS	-0.085 (0.5)				
Rice					-0.004 (0.87)
Irr_Cotton				-0.015 (0.73)	
IrrCoverCrops			0.036 (0.60)		-0.002 (0.87)
IrrDeepTill					0.005 (0.87)
PivFur	-0.16 (0.41)				
IrrSoyAcres	-0.2 (0.48)				
ElectricPump	0.381 (0.45)				-0.004 (0.87)
IncHigh		0.02 (0.81)		0.04 (0.73)	
IncMid					0.02 (0.7)
IncNA		.033 (0.6)	0.006 (0.87)		-0.022 (0.79)

Z statistics in parenthesis