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Producer Preferences for Alternative Irrigation Practices in the Arkansas Delta

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Producer Preferences for Alternative Irrigation Practices in the Arkansas Delta

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ABSTRACT

We use a bivariate sample selection model to address peer network effects on participation in and/or intensity of use of land being irrigated by alternative irrigation practices in the state of Arkansas. As groundwater in the state becomes more limited, the use of scientific scheduling, flowmeters, and more efficient row crop water application systems will allow producers to better manage water resources. We find relatively large, positive relationships between belonging to a peer network of the same irrigation practice and participation in that practice. Intensity of use of alternative irrigation techniques is mostly influenced by which crop type the practice is associated with and income.

DEDICATION

I would like to thank my parents and sister for their unwavering support throughout my academic career. Each of them has inspired me to put my best foot forward and never settle for the easy route. My family is truly my inspiration.

I would also like to express my gratitude to my advisor, Dr. Kent Kovacs, as well as Dr. Bruce Dixon for their support and guidance through this thesis.

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INTRODUCTION

Diminishing groundwater resources are threatening the security of nearly half of the world's drinking water supply and 43% of the world's irrigation water supply (van der Gun 2012). One common solution policymakers have relied on to reduce groundwater use is to improve irrigation efficiency. The foundation for improving irrigation efficiency is measuring how much of the water applied to the field eventually reaches the plant (Bryant, et al., 2017). Additionally, how the water is applied is vitally important. However, several recent empirical studies have shown that using more efficient irrigation technologies may increase total farm-level water use and groundwater (e.g., Pfeiffer and Lin, 2014). Finding ways to increase efficiency and reduce groundwater use are especially important in the state of Arkansas and other irrigation intensive states (West, et al., 2016). This paper examines which factors, specifically peer networks, influence Arkansas producers' use and share, or intensity, of alternative irrigation techniques for irrigation efficiency.

In our study, a producer is considered to be in a peer network if he or she knows a family member, friend, or neighbor who uses a certain irrigation practice. Belonging to a peer network does not necessarily mean that producer also uses the practice, but as the study shows, the two are positively related and highly significant. Our goal is to determine how peer networks might play a role in the continued use of these irrigation practices and share of acres of land which are being irrigated or measured by them. We expect to find large, positive relationships between belonging to a peer network of the irrigation practice in question. When the dependent variable is a type of irrigation practice, then we hypothesize belonging to a peer network of that same irrigation practice would have a large, positive relationship relative to other variables. This relationship could come about in two ways: 1) the relationship formed before the irrigation practice was adopted or 2) the relationship exists because the producer adopted that irrigation practice. With the data available to us, the causality of the relationship cannot be determined; however, it helps establish a building block which further studies can expand upon.

In addition, we expect belonging to peer network groups of practices connected to the same type of crops to positively influence the relationship with the irrigation practice in question. For example, we believe a producer using a row crop water application system would be more likely to be associated with other row crop water application system peer networks such as surge irrigation, center pivots, or precision leveling. These examples showcase the continued use of the water application system, but not the share of acres of land affected by it. For that set of relationships, we expect similar results to their binary usage counterparts.

As of 2012, Arkansas ranked third in farm acres irrigated, totaling 4.8 million acres. Between 2007 and 2012, the state's irrigated base expanded by 343,220 acres, a 7.7% increase. Only Mississippi had a higher percentage increase with 20.7%; however, the total acreage increase for Mississippi was less than Arkansas at 283,317 acres (USDA, 2013). The top two states in irrigated acres, Nebraska and California, decreased irrigated acreage by 3.1% and 1.9%, respectively. In fact, of the top ten irrigated states, only Arkansas, Idaho, Kansas, and Mississippi increased their acreage (USDA, 2013). For more perspective, of the 55.8 million acres of farmland under irrigation in the United States in 2012, about 8.6% of it was in Arkansas, and about three out of five cropland acres in Arkansas are being irrigated (West, et al., 2016).

In terms of total volume of water applied for irrigation, Arkansas also ranks third in the United States as of 2013 with 6.45 million acre-feet of water applied, while California substantially leads in this category with 23.49 million acre-feet of water applied (West, et al., 2016). The average amount of irrigation water applied per acre in Arkansas in 2013 is 16 inches. This is the same rate of application as fifth-ranked Texas, but less than the 37 inches in California and more than the 12 inches in second-ranked Nebraska (West, et al., 2016).

Arkansas producers draw groundwater from the Mississippi Alluvial Aquifer. While groundwater levels remain relatively high closer to the Mississippi River, central and southern Arkansas producers face diminishing groundwater levels (West, et al., 2016). The Arkansas Natural Resources Commission (ANRC) publishes a yearly groundwater report for the state which identifies ‘critical groundwater areas’ determined to have “significant groundwater depletion or degradation” (ANRC, 2018). The critical groundwater areas are concentrated in the Grand Prairie region (central Arkansas), the Cache region (east Arkansas, west of Crowley’s Ridge), and the South Arkansas region (ANRC, 2018). These areas have depths to groundwater of 66 feet to 150 feet, compared to non-critical areas which have depths to groundwater under 50 feet – although this is not the sole metric in determining critical status (ANRC, 2018).

Nationwide, at least half of irrigated cropland acreage uses less efficient, traditional irrigation application systems such as pressure sprinkler systems (Schaible and Aillery, pg. iv, 2012). Alternative practices may include soil moisture sensors, commercial irrigation scheduling services, and computer-based crop growth simulation models that help producers decide when and how much to irrigate (Schaible and Aillery, pg. 12, 2012). These practices contrast to the traditional practices which include physically looking or touching the plants, gravity systems without enhancements, or regularly scheduled irrigation times.

Schaible and Aillery (2012) point out that traditional water application systems will become even less efficient as application losses increase due to higher evaporation rates caused by rising temperatures from greenhouse gas effects. In Arkansas, reliance on the irrigation water from the Mississippi alluvial aquifer prompted the 2014 Arkansas water plan to recommend irrigation enhancements (ANRC, 2014). Such practices include Mississippi State University's Row-crop Irrigation Science and Extension Research (RISER) program for soybean and corn production and zero-grade leveling for rice production (Krutz, et al., 2014). In 2013, roughly 36% of farms and 45% of irrigated acres in Arkansas use at least one efficient irrigation practice (USDA, 2013). The most common practice is precision leveling or zero-grade leveling with 22% of all irrigated acres followed by tailwater recovery systems, diking, time limits or alternative row crop irrigation with 18% of all irrigated acres (USDA, 2013). Our study examines three categories of efficient irrigation technologies: scientific irrigation scheduling, flowmeters, and row crop water application systems.

Under scientific scheduling, we consider all forms of scientific scheduling, and then two specific groups: 1) soil moisture sensors and 2) ET/atmometer along with Woodruff Charts (ETCW). Soil moisture sensors are used in conjunction with timed water application systems to inhibit or allow a scheduled irrigation based on variations in the moisture of the soil (Qualls, et al., 2001). Although shown to increase efficiency in water application, producers have shown reluctance to adopt them due to the uncertainty about eventual savings outweighing the relatively high initial cost of purchase, installation, and operation (Blonquist, Jr., et al., 2006). Atmometers are used to monitor evapotranspiration (ET) of crops by simulating the water use of a well-watered reference crop (Andales, et al., 2007). This way producers can determine whether or not to irrigate based on the amount of water the crop is losing or retaining. Typically, the reference crop for atmometers is alfalfa (Andales, et al., 2007). Woodruff (1975) developed a chart to aid Missouri corn producers to schedule water applications based on amount of rainfall – this is not to be confused with the Arkansas Irrigation Scheduler. Modern versions of Woodruff charts became publicly available as a computer software program in June 2001 and have grown in popularity with producers in states adjacent to Missouri (Henggeler, 2009).

Our second category, flowmeters, includes all types, and then is broken down into mounted flowmeters and portable flowmeters, as described by Louisiana State University's AgCenter Research and Extension (2008). Mounted flowmeters are the most common type and measure the velocity of water inside a pipe via a propeller. The flowmeters are mounted either directly in the pipe or on a flanged joint. Portable flowmeters are relatively new and do not require any modification to the irrigation system and are installed at the universal hydrant or propeller (Louisiana State University, 2008). Their appeal comes from their ability to be moved around, hence portable, and easy installation and removal. A downside is the relatively higher cost compared to the mounted flowmeters (Louisiana State University, 2008).

The row crop water application systems category includes three practices: 1) computerized hole selection, 2) center pivot systems, and 3) surge irrigation. Computerized hole selection uses a computer software program known as Pipe Hole and Universal Crown Evaluation Tool (PHAUCET) that determines the diameter of the hole cut into the poly-pipe based on pressure changes along the tubing, pipe diameter, row length, and elevation changes in the field (UAEX, undated). Using computerized hole selection allows water to reach the ends of varied length rows more evenly and can aid in runoff and pumping time (Bryant, et al., 2017). Bryant, et al. (2017) indicate using computerized hole selection can save producers $10 per acre for a traditionally shaped field and up to $25 per acre for an irregularly shaped field.

Center pivot systems operate by drawing water from the ground, from a well, at a central "pivot" and the extended sprinkler system rotates circularly, spraying water over the crops. These are most common in western states since they are more cost-effective when groundwater is the preferred option over obtaining water from surface bodies of water (Schaible and Aillery, 2012). In Arkansas, they are normally found in heavy cotton-producing areas. They are used instead of traditional furrow irrigation when a producer's field is impossible or impractical to irrigate in that manner, and are best suited for large square-, rectangular-, or circular-shaped fields free of obstacles (UAEX, undated). Center pivots allow areas of higher elevation in a field to be irrigated as if the field was uniformly downward-sloping.

Surge irrigation pulses water down the furrows as opposed to a continuous stream. It does this by diverting water to the left or right of the pipe via valve movement (Fipps, undated). It has the potential to increase furrow irrigation efficiency to levels usually associated with sprinkler or drip irrigation systems (Fipps, undated). Henry and Krutz (2017) state that it works on the principle that dry soil infiltrates water faster than wet soil. Once the upper part of the furrow has been sufficiently saturated, another pulse of water is pumped over the wet soil where it eventually settles into the next dry spot in timed cycles (Fipps, undated). Surge irrigation improves down furrow distribution efficiency, and, for most soil types, reduces the amount of water needed during the first few irrigations (Fipps, undated)..

Reliance on groundwater from the Mississippi alluvial aquifer calls attention to its conservation and sustainability. While eastern states like Arkansas are not as regulated as western states in regards to water use, there is a growing concern (Schaible and Aillery, 2012). Arkansas finds itself in a unique situation since it could replace groundwater demand with ample surface water sources. As depth to groundwater increases, thus increasing costs of pumping, producers will need to look for alternative ways to apply water to their irrigated acres.

The literature is in consensus that the alternatives described in this study can aid in enhanced water application to fields, but how these practices are disseminated amongst producers is not clear. Identifying factors which lead to continued use of these practices is helpful twofold: 1) it is reasonable to hypothesize a factor explaining continued use could also be used to explain initial adoption and 2) continued use is the next logical step in the technology adoption process and becomes even more critical as reliance on groundwater increases. In addition, the share of acres of land irrigated by these alternative irrigation practices should be studied in conjunction with continued use because if a producer finds one of these practices useful, he or she should be looking to expand that usage.

LITERATURE REVIEW

While noneconomic social sciences focus more on the impacts peer groups have on technology dissemination (Rogers, 1962), economists maintain their interest in more traditional measurements, like access to physical capital or human capital such as learning from extension services (Feder, Just, and Zilberman, 1985). Maertens and Barrett (2012) emphasize the underdeveloped economic literature of how social networks influence technology adoption. Since the 2012 study, more emphasis has gone toward social networks' impact on irrigation technology adoption (Genius, et al., 2014; Taylor and Zilberman, 2017).

It is important to note, however, our study does not attempt to draw conclusions about what motivates initial adoption. We examine relationships between existing use and share of land that uses alternative irrigation technologies and peer networks. This approach adds to the literature twofold: 1) newer studies have focused on adoption, but not whether producers continue to use more efficient irrigation systems, and 2) how shares of acres are affected by the efficient systems. While adoption is the first step, continuation of the practice and expanded use of it are the logical next steps in improving irrigation efficiency long term and are the focus of this study.

Genius, et al. (2014) considered irrigation adoption in Greece with a focus on peer networks. Their study separated its variables into four categories: 1) economic, 2) farm organizational and demographic, 3) environment, and 4) social learning – what we are calling peer networks (Genius, et al., 2014). Categories 1 to 3 are controls in our study, while category 4 is the focus. Genius, et al. (2014) used distance between adopters, exposure to extension outlets, and distance from extension outlets as social learning variables. Greater distance between adopters increased the time before adoption of irrigation technology by 0.172 years per one unit increase in the distance (pg. 340), while exposure to extension outlets and shorter distance from extension outlets decreased the time before adoption by 0.293 years and 0.306 years, respectively (pg. 340-1). Before Genius, et al. (2014), Koundouri, et al. (2006) used peer networks across towns on the island of Crete to analyze adoption of irrigation technologies. Their independent variables were extension visits and active information gathering – defined as a producer proactively searching for information on these irrigation technologies – and she found positive relationships with adoption for both, but relatively low magnitudes compared to other variables in the study. Extension visits increased the probability of adoption by 9.52% and active information gathering increased the probability by 15.04% (pg. 666). Environmental variables, such as soil type and aridity index, had the largest, positive affects toward the probability of adoption (pg. 666). In contrast, our variables are specific to irrigation practices found in the Arkansas Delta and use knowledge of peer practices to proxy for social learning variables. These peer networks more broadly capture the social learning than general knowledge of, or exposure to, extension outlets or distance to adopters.

It is also important to understand how networks interact. The two primary interactions are frequency and directionality – how often nodes are interacting and how information is transmitted between those nodes (Maertens and Barrett, 2012). There is a rich literature on social networks or peer effects – albeit not historically in economic literature (Maertens and Barrett, 2012). The literature is in consensus that social networks are "defined by individual members (nodes) and the links between them through which information, money, goods, or services flow" (Maertens and Barrett, 2012, pg. 353). Unfortunately, it is difficult to measure the peer networks in our study by frequency and directionality since we do not have the appropriate data for such analysis. Both modes are likely represented in the peer network variables available to us.

The peer effect literature also emphasizes the difficulty in inferring causality even when the social networks are well measured. The primary concern is endogenous evolution of the peer networks through feedback (Barrett, 2005; Jackson, 2008; Stephens, 2009). There are almost certainly correlated factors amongst nodes within a social network. In addition, simultaneous interaction and behavioral changes amongst nodes create an issue where it becomes difficult to separate endogenous effects from exogenous effects (Manski, 1993).

The methodology used in social network adoption papers has evolved as well and should be similar to our approach, even though we are not exploring adoption rates. One of the most common methodological approaches has been to use conceptual models, such as threshold models (Taylor and Zilberman, 2017). In this context, threshold models work by analyzing how many nodes in a producer's social network need to adopt the technology before the producer in question also adopts (Taylor and Zilberman, 2017). When there are two choices, conceptual models can provide an insightful way to analyze when a producer may change his or her mind in regard to adopting a more efficient irrigation technology. As the literature expanded (Useche, 2003; Koundouri, et al. 2006; Kulecho and Weatherhead, 2007; Alcon, et al., 2011; Genius, et al., 2014), economists were noting the growing complexities in social networks; therefore, conceptual models could not capture the entire story. Since the mid-2000s, economists have used more econometric approaches (Koundouri, et al., 2006; Maertens and Barrett, 2012; Genius, et al., 2014; Taylor and Zilberman, 2017), believing that a broader analysis of explanatory variables is required before specifying and/or limiting a study to one or two potential choices a producer has to make (Taylor and Zilberman, 2017).

We also believe many of the control variables in our study should serve in a similar fashion to categories 1 to 3 used from Genius, et al. (2014). Other irrigation adoption papers, which do not include social network analysis, often use variables related to weather, soil types and/or permeability, crop type, cost of water, crop price, income, and field size (Green, et al., 1996; Schuck and Sunding, 2005; Koundouri, et al., 2006; Genius, et al., 2014; Schoengold, et al., 2014). If a certain explanatory variable leads to adoption, then it would be logical to hypothesize that same variable would lead to at least participation in the same alternative irrigation practice, if not the expansion of its use. Since our data are taken from a single year, producers affirming they use a certain technique must have adopted it previously and are continuing to use it.

A Schaible and Aillery (2012) report outlines some factors which affect irrigation technology investment. The report found consistencies in motivation for adopting more efficient technology, with slight variations based on where in the United States the producer was located. Producers in the western United States cite reduction in applied water and lower labor costs as key elements, while eastern producers are more interested in improving crop yield and quality (Schaible and Aillery, 2012). Lying on the edge of the east-west divide, Arkansas producers may share commonalities with both sets of producers.

The report also asserts that producers looking to expand irrigated acreage would likely need to invest in new, high-efficiency systems, while those looking to reduce irrigated acreage should first remove acres which are currently being irrigated by lower efficiency systems (Schaible and Aillery, 2012). A decision to increase or decrease irrigated acreage may also be determined by the particular crop being grown. Lower valued crops, like hay and other pasture crops, would be less likely to be included in a plan to increase irrigated acreage (Schaible and Aillery, 2012). Findings in this report influenced the selection of our control variables, such crop type, income, and current irrigation technologies being used.

While major strides have been made in including peer networks and their relationship to adoption of irrigation technologies, or at least their relationship with irrigation technology use (Maertens and Barrett, 2012; Genius, et al., 2014; Taylor and Zilberman, 2017), our search of the literature could not find any studies that analyze the share of those irrigation technologies producers use on their land. Our study aims to not only analyze the effects peer networks have on participation in irrigation technologies, but also how those effects influence usage intensity.

METHODS

To determine which factors are associated with the use of the irrigation measurement tools and techniques, and the factors that explain the acres of land that use these conditional on the use of the irrigation tools and techniques, we use a bivariate sample selection model (Heckman, 1979). The models are estimated by maximum likelihood which allows us to examine the impact of each independent variable on the dependent variables, and will increase our understanding of which variables may be influencing producer choices when it comes to degree of use of the irrigation measurement tools and techniques. Each bivariate sample selection model contains a participation equation and an outcome equation. The participation equation dependent variable is binary to indicate use of given irrigation measurement tools and techniques or not, while the outcome equation dependent variable includes the share of acres that are affected by the technique; in the case of flowmeters, it is the share of pumps which have flowmeters.

In a sample selection model, 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

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

and a resultant outcome equation that

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

This model specifies that y_2 is observed when $y_1^* > 0$, whereas y_2 has no meaningful value when $y_1^* \leq 0$. The latent variables y_1^* and y_2^* indicate that the mechanism motivating participation (y_1^*) and the share of acres for a particular irrigation technique (y_2^*) are not observed for all sample observations. The standard approach specifies a linear model with additive errors for the latent variables, so

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

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

with need for non-standard estimation methods of β_2 if ε_1 and ε_2 are correlated (Heckman, 1979).

We estimate by maximum likelihood, which yields consistent and asymptotically efficient parameter estimates, and uses the additional assumption that the error terms are jointly normally distributed and homeskedastic, with

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

A crucial aspect of the model is whether σ_{12} is nonzero (Cameron and Trivedi, 2010). If $\sigma_{12} \neq 0$, then estimation of the outcome equation is non-standard. The participation equation can be consistently estimated in isolation from the outcome equation, but the outcome equation must include consideration of σ_{12} if $\sigma_{12} \neq 0$.

The bivariate sample selection model implies the likelihood function

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

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

While the interpretation of parameter estimates of the outcome equation are standard, the parameter estimates in the participation equation are difficult to interpret. As a result, a variety of marginal coefficients are computed to interpret results.

One group of marginal effects is how changes in the independent variables in the participation equation affect the probability of participating. These marginal effects show the change in the probability of participation in response to a one unit increase in a given explanatory variable. Marginal effects for the outcome equation are interpreted as the expected change in y_2 for a change in an explanatory variable, conditional on participation in use of the irrigation practice. 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 ($\sigma_{12} \neq 0$), 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 direct effect from the explanatory variable in the outcome equation and an indirect effect from the explanatory variable in the participation if the error terms are correlated ($\sigma_{12} \neq 0$).

The bivariate sample selection model is identified because there are variables in the participation equation which are not in the outcome equation. Some models do not find σ_{12} to be significant, but we use a bivariate sample selection model for all models for uniformity, and to capture any potentially undetected correlation in the error terms. For each equation, variables with t-values of less than 1 were dropped from the final specification. The maximum likelihood estimation for bivariate sample selection model used Stata® version 13.1.

DATA

The sample data comes from a survey completed in October 2016 that were collected via telephone interviews administered by the Mississippi State University Social Science Research Center[1]. Potential survey respondents came from the water user database managed by the ANRC and commercial crop growers identified by Dun & Bradstreet records for the state of Arkansas. Of 3,712 attempted contacts, 842 resulted in calls to disabled numbers, resulting in a net sample size of 2,870. Of the remaining contacts, 1,321 led to no answer, busy signal, or voicemail. Another 925 contacts were ineligible due to illness or language barrier or identified as a non-farmer. In total, 624 contacts reached were eligible to complete the survey. Among the eligible contacts, 255 contacts declined to participate, seven scheduled callbacks but did not complete the survey, and 171 contacts discontinued the survey. The final sample size is 199 producers that completed the survey in its entirety for a response rate of 32.25%.

The dependent variables (Table 1.1) are split into two types: binary and share, which is on a scale between 1 and 0. The binary variables have 174 observations, while the share variables have an observation when there is participation. .

The scientific scheduling variables (Table 1.1) have the lowest participation and share of any other dependent variables. 13% of respondents use scientific scheduling, 8 % use soil moisture sensors, and 6% use one or more of the atmometers, computerized scheduling, and Woodruff Charts. Given participation in the scheduling practice, the share of use for the scheduling techniques range from 5% of irrigated acres to 2%.

[1] The survey was part of an effort to understand irrigation practices over four states in the Mississippi Delta region, namely Arkansas, Missouri, Mississippi, and Louisiana.

The use of flowmeters (Table 1.1) has the second highest percentage of use at 36%, with mounted flowmeter and portable flowmeter use being 27% and 16%, respectively. Share for flowmeter variables is based on the number of pumps which have a flowmeter, as opposed to irrigated acres. Producers who use portable flowmeters have a much larger share of pumps with them, 17%, relative to all types of flowmeters and mounted flowmeters, which is 9% and 7%, respectively. Producers who choose to use portable flowmeters have a higher proportion of flowmeters on their pumps although the portable flowmeters are more expensive than mounted flowmeters. .

Surge irrigation (Table 1.1) has the lowest usage of the row crop water application systems, 18%, and shares the lowest share percentage with soil moisture sensors at 2%. Computerized hole selection and center pivot use is similar, 34% and 38%, respectively. Their shares are similar as well with computerized hole selection users deploying it on 11% of their irrigated acres, while center pivot users irrigate 9% of their irrigated acres with the system.

Peer networks are the explanatory variables of primary interest in this study (Table 1.2). In the survey, respondents were asked to answer "yes" if "close family members, friends, or neighbor producers has used [irrigation practice or tool] in the past 10 years." The only peer network variables with less than fifty percent of respondents answering in the affirmative were alternate wetting and drying (35%) and surge irrigation (37%). Most peer network variables ranged between 55% and 75%, with precision leveling having the most affirmative answers at 90%.

We compare our sample to the 2012 Census of Agriculture using several variables collected in both surveys. This comparison indicates our sample is comparable to that of the census. The observations for farm operations with less than 300 acres are dropped because these operators are unlikely to have commercial operations. In total, 25 observations were dropped. The shares of irrigated land in rice (share_irr_rice)[A][2] are similar between the Census of Agriculture and our sample (29.0% versus 27.5%). The shares are also similar for soybean (share_irr_soy)[B][3]. The share is slightly higher in our sample (55.0%) than in the census (49.2%). In our sample, the years of farming experience (exper) (Table 1.3) range from 1 to 60 years with an average of 32.8 years. This is higher than the average in the Census of Agriculture (24.5 years). Most likely, this is due to the census reporting years of experience as operators rather than total years of farming experience, as in our survey.

In addition to the variables described above, several other variables are included in our analysis to control for crop choice. The shares of irrigated land of cotton (share_irr_cotton)[A] and sorghum (share_irr_sorghum)[B] in acres are included, as well as dummy variables for growing corn (d_corn)[A], cotton (d_cotton)[B], rice (d_rice)[A], sorghum (d_sorghum)[A], and soybean (d_soy)[A]. Most producers grew soybeans (96%), sorghum (75%), and rice (72%); while the least occurring crop was cotton (13%). Shares of soybean were also the highest (55%). Although sorghum was grown by 75% of farmers, it only made up an average of 1% of their acreage.

Variables were also created to control for irrigation practices and other farm management characteristics (Table 1.3). These include shares of end blocking (share_eb), total reservoirs (tot_res), and whether a producer had switched from center pivot to furrow irrigation (d_piv_fur). The final variables in this category include the use of cover crops (d_covercrops), share of acres deep tilled (share_deeptill), share of acres fertilized by gypsum (share_gypusm), and the use of electric or diesel pumps (d_electric, d_diesel).

[2] Variables with "[A]" are found in the Summary Statistics table in the Appendix.
[3] Variables with "[B]" are found in Table 1.3.

Three income variables (Table 1.3) are used to control for income ranges. High-income level (d_income_high) includes producers with a total income above $200,000, constitutes 14% of respondents. Producers with a middle-income level (d_income_mid) had a total income between $75,000 and $200,000. This represented the largest share of income at 42%. 24% of producers chose not to report income (d_income_na). Producers with a total income of less than $75,000 are the intercept.

RESULTS AND DISCUSSION

Scientific Scheduling Results

The role of peer networks is evident in the use and share of scientific scheduling overall (Table 2.1). Belonging to a peer network of scientific scheduling users has a positive relationship with its use, as well as having a formal education in agriculture. Indeed, belonging to a peer network for a dependent variable in question typically has a positive relationship with use since most users of an irrigation practice have close peers who also use the practice. In addition, belonging to a peer network of computerized hole selection, a newer technology like scientific scheduling, and a center pivot peer network has a positive effect on the share of acres that use scientific scheduling, while belonging to peer networks of older practices like end blocking, zero grade leveling, and flowmeters have negative effects on the share of scientific scheduling use. Belonging to a multiple inlet peer network group has a positive relationship with the use of scientific scheduling and, more specifically, soil moisture sensors. This may be due to multiple inlet irrigation being relatively common practice to increase irrigation efficiency, so most users of scientific scheduling would know someone who uses the technique.

Center pivots are an efficiency enhancing irrigation practice (Schaible and Aillery, 2012, pg. 26) and producers with peers who use this practice would thus also be more interested in scientific scheduling. Also, producers who switched from center pivot to furrow irrigation are more likely to have larger shares of land using scientific scheduling and soil moisture sensors. This is a reasonable relationship since those who made the switch would be looking to cut down on the high costs of center pivots but still have an interest in irrigating efficiently. Growing cotton has a negative relationship in the share of scientific scheduling a producer uses, and this suggests that non-cotton producers using center pivots are more likely adopting scientific scheduling.

There is a relatively high, positive impact that the share of irrigated sorghum has on the share of soil moisture sensors. Sorghum is a less water intensive crop that could be grown when water is scarce, and those who cultivate this crop may keep a closer eye on water use with larger shares of acres that use soil moisture sensors. However, operations with a larger share of sorghum have a lower share of acres using ETCW.

Producers who use cover crops also use scientific scheduling, and more specifically, ETCW. The producers who use cover crops likely have a concern for soil conservation and moisture levels. This could explain an interest in water conservation through ETCW. The share of irrigated soybean acres is positive with soil moisture sensor use. Soybeans are often the highest farmland share of any irrigated crop, so producers that cultivate more soybeans invest more heavily in irrigation.

Producers with a high-income level have a positive relationship with scientific scheduling. Additionally, having a high-income level results in a positive relationship in regard to the intensity of use of all three variables in this category. Having a high-income level allows producers to invest in these scheduling practices, as well as use more of it once adopted.

Experience plays a seemingly suggestive role in the use of scientific scheduling at large and soil moisture sensors, but an unexpected one regarding scientific scheduling intensity. Having more experience leads to lower percent chance of using these techniques, but a higher share of irrigated acres affected given adoption. It seems that more experienced producers may be reluctant at first, but once adoption occurs, they will increase the amount of acres which are using scheduling to be irrigated.

Flowmeter Results

Belonging to a peer network of flowmeter users (Table 2.2) has a highly significant, positive relationship with using flowmeters and, more specifically, mounted flowmeters. However, growing rice itself – where more well pumping occurs – does not have a significant impact on flowmeter use. Perhaps the use of flowmeters has more ties to specific regions of water shortage than the cultivation of a particular crop. Support for this view comes from the positive and significant relationship between the number of reservoirs and flowmeter use. On-farm reservoir construction typically only occurs in places where there is serious concern about water shortage. More evidence of the connection between water shortage and flowmeter use comes from the negative relationship belonging to a center pivot peer network has with the share of flowmeters per pump, and the positive relationship between the use of flowmeters and mounted flowmeters with producers who switched from center pivots to furrow irrigation and those with higher shares of end blocking. The use of center pivots is primarily used in crop production close to the Mississippi River. This region has more groundwater available, so producers would be less keen about tracking their water use. Instead, they are adjusting to uneven fields. Those switching to furrow irrigation want to lower the maintenance costs of operating center pivot systems but are still aware of limited water resources and would perhaps be more interested in tracking their water use.

Furthermore, peer networks of precision leveling and surge irrigation, row crop water application systems, have negative relationships with the use of all flowmeters and mounted ones, and the share of portable flowmeters, respectively. Since row crops use less irrigation water than conventionally grown rice, belonging to a peer network of irrigation practices for row crops relates to less concern about tracking water use. The peer network groups associated with rice, zero-grade leveling and on-farm reservoir, have a positive relationship with the share of portable flowmeters. So while growing rice itself is not significant for explaining flowmeter use, those with knowledge of certain rice irrigation practices are more apt to use portable flowmeters.

Income seems to play a role in the share of portable flowmeters on a farm. All income variables are positive and significant in the outcome equation. Since low income is the intercept, this shows that a higher level of income is potentially a threshold, allowing producers to purchase more portable flowmeters.

Producers with more experience have a larger share of pumps using flowmeters. It seems that producers with more experience have built up a larger collection of flowmeters over time. Additionally, producers with a middle-income level are more likely to use mounted flowmeters. However, producers with a high-income level do not have a significant change in use. The middle-income level could be a threshold for producers to use mounted flowmeters, but a higher income level does not provide any more incentive than a middle-income level does.

Row Crop Water Application Systems Results

Only a few variables were significant with the use and share of computerized hole selection (Table 2.3). As expected, belonging to a peer network of computerized hole selection users has a positive relationship with its use. Since computerized hole selection is a newer practice, it makes sense that its users come from a more isolated grouping. The share of gypsum has a positive relationship with the share of computerized hole selection. Producers use gypsum to dilute the salinity and replenish these soils. Too much water applied to the furrows without computerized hole selection can increases the salinity of the soils. Gypsum and increasing intensity of use of computerized hole selection are then both ways to address saline soils, and this explains why a larger share of gypsum use is positively correlated with computerized hole selection. The share of irrigated sorghum has a negative relationship with the share of computerized hole selection. Sorghum is a less water intensive crop and brings lower values, so producers irrigate their sorghum less frequently.

Those in scientific scheduling peer networks are less likely to use center pivots. If producers who use center pivots are often in groundwater abundant areas, then this explains the negative relationship with the scientific scheduling networks. Cultivation of sorghum positively relates to center pivot use. This may be simply because the farming of sorghum and cotton occurs together, and much of the cotton production occurs close the Mississippi river where groundwater is abundant and center pivots are more common. Belonging to end blocking and tailwater recovery peer networks have negative relationships with the share of center pivots. End blocking is a conservation practice for furrow irrigation, so producers would not be mixing the two, and tailwater recovery systems are common in areas with less groundwater available. Support for this claim is that the relationship between tail-water recovery system use and center pivot use is negative. Like we observed with mounted flowmeters, middle income level increases the percent chance of use, but high income is not significant, so does not seem to provide extra incentive to adopt.

Use of surge irrigation has a positive relationship with belonging to a peer network of its users, but the magnitude (1.46) is lower than the coefficient magnitude for the computerized hole selection (1.80) or the center pivot (1.69). Perhaps for rarer irrigation techniques, the role of the peer network is weaker, but high income leads to a greater intensity of surge irrigation once adopted. More experienced producers are using a lower share of surge irrigation given that they use it to begin with. This is different from what we observe with other variables, but surge irrigation is not as popular, so perhaps younger producers are the ones buying into the benefits of it. Surge irrigation use has a positive relationship with the use of electric motors on pumps, and the use of diesel pumps creates a negative relationship with the share of surge irrigation. There is a negative relationship with the share of deep tillage on the farm. Producers do not mix these practices. They will either use surge irrigation or deep tillage, since deep tillage is already a practice used to improve water infiltration.

CONCLUSION

A common observation throughout the study was the relatively large, positive relationships between belonging to the dependent variable's peer network and the use of that irrigation practice, but not with the intensity of the practice in question. This applies to scientific scheduling, flowmeters, mounted flowmeters, and all three row crop water application systems. However, none of the dependent variables from the outcome equations shared this relationship with their own peer networks. It seems that belonging to a peer network of the irrigation practice is affecting participation, but other factors more strongly affect the intensity of that use. Similar to Genius, et al. (2014) peer network variables play a larger role in the use of alternative irrigation practices and tools than other control variables. The magnitudes of the peer networks regarding participation were larger than the magnitudes of the control variables.

Income levels above $75,000 also play a role in both continued use and intensity of use. Scientific scheduling use increases with a high-income level, while mounted flowmeter use and center pivot use increase with a middle-income level. Seeing only middle-income level as significant seems to show that these techniques have thresholds between $75,000 and $200,000, but having more income than $200,000 does not provide any extra incentive for producers who were not already using to employ these techniques.

Shares of acres of land scheduled to be irrigated by scientific scheduling increased as producer income rose to middle income and then also to a high-income level. This was also the case for portable flowmeters in terms of the number of pumps that have flowmeters. Intensity of use of surge irrigation rises if the producer income level is a high. Scientific scheduling, portable flowmeters, and surge irrigation are relatively uncommon practices. It seems that higher income levels are allowing producers to amplify intensity of use of these rarer techniques.

Peer networks may be more associated with shared groundwater scarcity as opposed to being crop-specific. We would expect the use of flowmeter to positively relate with rice production; however, this is not the case. Instead, we observe the use of flowmeters as having a positive relationship with rice-specific irrigation techniques, like on-farm reservoirs and zero-grade leveling. Both those techniques are usually in areas where a lack of groundwater is a major concern.

Share of scientific scheduling was positively impacted by the producer belonging to row crop peer networks like computerized hole selection, center pivot, and surge irrigation – belonging to an end-blocking peer network was the lone row crop technique which negatively affects scientific scheduling. Peer networks groups associated with rice, like flowmeters and zero-grade leveling, had negative impacts on the share of scientific scheduling. It makes sense that rice producers would not invest in row crop scheduling practices. It is curious still that crop type does not affect either the use of or intensity of use of scientific scheduling variables.

Flowmeters shares positively relate to belonging to a peer network of on-farm reservoir users and zero-grade leveling users. In addition, the flow meter shares negatively relate to belonging to peer networks of row crop practices such as center pivots and surge irrigation. However, crop type does not significantly influence flowmeter shares. We observe the lack of a relationship between crop type and the use of flowmeters as well. Perhaps rice producers outside of water scarce regions are not concerned with tracking water use even though they are cultivating an irrigation-intensive crop. A reason we do not see a negative relationship between flowmeter share and less irrigation intensive row crop cultivation is that these crops can be in water scarce areas..

Producers using center pivots, a row crop technique, are less likely to have more acres irrigated by center pivots if the producers belong to a peer network of alternate wetting and drying or end blocking techniques. Alternative wetting and drying is a rice cultivation practice and a sprinkler irrigation through center pivots is not for rice. End blocking is a conservation technique for furrow irrigation, so producers would not use center pivot sprinkler irrigation in conjunction with furrow irrigation. .

The only control variables from prior studies that directly overlap with this study are income levels, education, and experience, although other studies did not specify whether the education related to agriculture. The role of income in our study and previous studies is the same. This is reasonable as more income would allow a producer to adopt sooner, continue using the practice, and even expand use. Having a formal education in agricultural is significant for the use of scientific scheduling and the intensity of use of center pivots. This relationship makes sense for scientific scheduling and center pivot since we expect those with an agricultural education to effectively use more technically demanding techniques.

In previous studies, experience increased time to adoption and our experience variable, when significant, showed a decrease in use of the irrigation practice. This was the case for scientific scheduling and soil moisture sensors. However, for both of these, more experience actually led to increases in the amount of acres scheduled to be irrigated by these techniques. Two possible explanations for this observation are 1) more experienced producers use their wealth of knowledge to execute these techniques more effectively, or 2) the adoption of a new technique indicates an internal preference for embracing new technologies. Koundouri, et al. (2006) and Genius, et al. (2014) did not include intensity of use in their studies, so it would be interesting to see how experience would affect those variables if they had them.

Our data do not allow us to say what the direction of the relationship is between peer networks and use or intensity of uses. The producer may use the technique because his or her peers do, or the producer may have joined the peer network group after implementing the technique on his or her farm. In future work, having panel data over many years as opposed to cross-sectional data could be helpful since we could know when adoption occurred and when the producers' relationship with their particular peer networks began. In addition, we can analyze the evolution of peer networks over time: how size of the network changes, or how directionality of information dissemination occurs. Control variables present in other studies which could aid our analysis include farm level cost of water, weather or climate change considerations, and soil type. Regardless of causality, it is clear peer networks are influential in Arkansas producers' use of alternative irrigation techniques and the share of land using those techniques. Determining causality of these relationships may prove essential as reliance on the Mississippi alluvial aquifer grows and the depth to groundwater increases.

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APPENDIX

Table 1.1. Summary Statistics of Dependent Variables

Variables	Definition	Mean	Std. Dev.
share_sci_sche_ac	share of scientifically scheduled acres on total irrigated acres	0.05	0.20
d_sci_sche_ac	= 1 uses a scientific scheduling technique	0.13	
share_sms	share of soil moisture sensors on total irrigated acres	0.02	0.13
d_sms	= 1 uses soil moisture sensors	0.08	
share_etcw	share of ET/atmometers, computerized scheduling, and/or woodruff charts on total irrigated acres	0.03	0.15
d_etcw	= 1 uses ET/atmometers, computerized scheduling, and/or woodruff charts	0.06	
share_fm	share of flowmeters on total pumps	0.09	0.21
d_fm	= 1 uses flowmeters	0.36	
share_mount_fm	share of mounted flowmeters on total pumps	0.07	0.18
d_mount_fm	= 1 uses mounted flowmeters	0.27	
share_port_fm	share of portable flowmeters on total pumps	0.17	0.06
d_port_fm	= 1 uses portable flowmeters	0.16	
share_surge	share of surge irrigation on total irrigated acres	0.02	0.10
d_surge	= 1 uses surge irrigation	0.18	
share_chs	share of computerized hole selection on total irrigated acres	0.11	0.23
d_chs	= 1 used computerized hole selection	0.34	
share_cp	share of center pivots on total irrigated acres	0.09	0.22
d_cp	= 1 used center pivots	0.38	

Standard deviation for binary variables is left blank because this is a redundant transformation of the mean.

174 observations for binary variables.

Observations for share variables:

share_sci_sche_ac (23), share_sms (14), share_etcw (11), share_fm (63), share_mount_fm (47), share_port_fm (28), share surge (31.32), share_chs (19), share_cp (66.12)

Table 1.2. Summary Statistics of Peer Network Variables

Variables	Definition	Mean
d_pnet_alt	=1 close family members, friends, or neighbor producers (peer network) has used alternate wetting and drying for rice irrigation in the past 10 years	0.35
d_pnet _chs	=1 close family members, friends, or neighbor producers (peer network) has used computerized hole selection on in the past 10 years	0.56
d_pnet _cp	=1 close family members, friends, or neighbor producers (peer network) has used center pivot in the past 10 years	0.67
d_pnet _end	=1 close family members, friends, or neighbor producers (peer network) has used end-blocking in the past 10 years	0.55
d_pnet _fm	=1 close family members, friends, or neighbor producers (peer network) has used flowmeters in the past 10 years	0.66
d_pnet _mi	=1 close family members, friends, or neighbor producers (peer network) has used multiple-inlet rice irrigation in the past 10 years	0.70
d_pnet _precision	=1 close family members, friends, or neighbor producers (peer network) has used precision leveling in the past 10 years	0.90
d_pnet _res	=1 close family members, friends, or neighbor producers (peer network) has used a storage reservoir in the past 10 years	0.65
d_pnet _sched	=1 close family members, friends, or neighbor producers (peer network) has used scientific scheduling in the past 10 years	0.53
d_pnet _surge	=1 close family members, friends, or neighbor producers (peer network) has used surge irrigation in the past 10 years	0.37
d_pnet _twr	=1 close family members, friends, or neighbor producers (peer network) has used a tail-water recovery system in the past 10 years	0.71
d_pnet _zg	=1 close family members, friends, or neighbor producers (peer network) has used zero grade leveling in the past 10 years	0.75

Standard deviation for binary variables is left blank because this is a redundant transformation of the mean.

174 observations for peer network variables

Table 1.3. Summary Statistics of Select Control Variables

Variables	Definition	Mean	Std. Dev.
d_diesel	= 1 uses diesel motor for pumps	0.91	
d_electric	= 1 uses electric motor for pumps	0.88	
d_cotton	= 1 grows cotton	0.13	
d_sorghum	= 1 grows sorghum	0.75	
share_irr_sorghum	share of irrigated sorghum on total irrigated acres	0.01	0.06
share_deeptill	share of deeptill use on total irrigated acres	0.20	0.34
share_gypsum	share of gypsum use on total irrigated acres	0.01	0.07
tot_res	number of reservoirs on the farm	0.38	0.49
d_twr	=1 has a tailwater recovery system	0.49	
d_piv_fur	=1 switched any acreage from pivot irrigation to furrow irrigation	0.18	
d_income_high	=1 2014 household income from all sources before taxes is > $200,000	0.14	
d_income_mid	=1 2014 household income from all sources before taxes is > $75,000 and < $200,000	0.42	
d_income_na	=1 unreported 2014 household income from all sources before taxes	0.24	

Standard deviation for binary variables is left blank because this is a redundant transformation of the mean.

174 observations for all variables

Table 2.1. Results of Variables within Scientific Scheduling Models

Participation Equation	Scientific Scheduling	Soil Moisture Sensors	ET/atmometer, Computeriz Scheduling, Woodruff charts
d_pnet_mi	1.36[b] (0.021)	1.19[b] (0.084)	0.705 (0.140)
d_pnet_sched	1.06[b] (0.020)	--	--
d_piv_fur	1.05[b] (0.005)	1.35[b] (0.004)	--
d_covercrops	0.635[a] (0.055)	--	0.792[b] (0.031)
d_income_high	1.08[b] (0.040)	--	--
exper	-0.024[b] (0.038)	-0.045[b] (0.004)	--
share_irr_soy		2.40[b] (0.036)	
Outcome Equation			
d_pnet_chs	0.401 (0.253)	--	--
d_pnet_cp	0.706[c] (0.000)	--	--
d_pnet_end	-0.211[b] (0.043)	--	--
d_pnet_fm	-0.652[b] (0.001)	--	--
d_pnet_surge	--	--	0.345[b] (0.007)
d_pnet_zg	-0.787[c] (0.000)	-0.606[c] (0.000)	--
d_ag_edu	0.494[c] (0.000)	--	--
d_cotton	-0.644[c] (0.000)	--	--
d_covercrops	0.283[a] (0.065)	--	--
d_income_high	0.729[c] (0.000)	--	--
d_income_mid	0.393[c] (0.010)	--	--
d_income_na	1.02[c] (0.001)	--	--
exper	0.012[b] (0.019)	--	--
share_irr_sorghum	-1.71 (1.179)	8.58[a] (0.084)	-3.61[b] (0.005)

Note: a, b, c represents significance at 10%, 5%, and 1% levels.

Table 2.2. Results of Variables within Flowmeter Models

Participation Equation	Flowmeters	Mounted Flowmeters	Portable Flowmeters
d_pnet_fm	1.54^{c} (0.000)	1.86^{c} (0.00)	1.13^{c} (0.001)
d_pnet_precision	-0.781^{a} (0.063)	-1.63^{c} (0.001)	--
d_piv_fur	0.679^{b} (0.032)	0.784^{b} (0.03469)	--
d_income_mid	--	0.582^{a} (0.085)	--
share_eb	--	1.06^{b} (0.028)	--
tot_res	0.524^{b} (0.023)	0.952^{c} (0.000)	--
Outcome Equation			
d_pnet_cp	-0.149^{b} (0.046)	--	--
d_pnet_res	--	--	0.066 (0.142)
d_pnet_surge	--	--	-0.107^{c} (0.002)
d_pnet_zg	--	--	0.096^{b} (0.019)
d_income_high	--	--	0.156^{b} (0.032)
d_income_mid	--	--	0.137^{c} (0.004)
d_income_na	--	--	0.128^{b} (0.016)
exper	0.004^{a} (0.092)	--	--

Note: a, b, c represents significance at 10%, 5%, and 1% levels.

Table 2.3. Results of Variables within Row Crop Water Application Systems Models

Participation Equation	Computerized Hole Selection	Center Pivot	Surge Irrigation
d_pnet_chs	1.80^{c} (0.000)	--	--
d_pnet_cp	--	1.69^{c} (0.000)	--
d_pnet_end	--	--	0.476 (0.107)
d_pnet_sched	--	-0.440^{a} (0.083)	--
d_pnet_surge	--	--	1.46^{c} (0.000)
d_pnet_zg	--	--	-0.916^{c} (0.008)
d_cotton	--	2.02^{c} (0.000)	--
d_electric	0.499 (0.214)	--	0.834^{a} (0.075)
d_income_mid	--	0.545^{a} (0.094)	--
d_sorghum	--	1.01^{b} (0.027)	--
d_twr	--	-0.736^{c} (0.004)	--
share_deeptill	0.498 (0.149)	--	-0.974^{a} (0.073)
Outcome Equation			
d_pnet_alt	--	-0.131^{b} (0.047)	--
d_pnet_end	--	-0.279^{c} (0.000)	--
d_ag_edu	--	0.184^{c} (0.006)	
d_twr	--	-0.026 (0.533)	--
d_diesel	--	-0.433^{c} (0.003)	-0.560^{c} (0.000)
d_income_high	--	--	0.169^{b} (0.051)
exper	--	--	-0.007^{c} (0.000)
share_gypsum	0.813^{b} (0.020)	--	--
share_irr_sorghum	-1.36^{b} (0.038)	--	--

Note: a, b, c represents significance at 10%, 5%, and 1% levels.

Table 3.1 Summary Statistics of Control Variables only found in Appendix

Variables	Definition	Mean	Std. Dev.
d_corn	= 1 grows corn	0.45	
d_rice	=1 grows rice	0.72	
d_soy	= 1 grows soybeans	0.96	
share_irr_cotton	share of irrigated cotton on total irrigated acres	0.04	0.13
share_irr_rice	share of irrigated rice on total irrigated acres	0.29	0.24
d_part_cons	=1 belongs, or has belonged, to a conservation organization	0.53	
d_use_tax	=1 used state tax credits program for conversion to surface water or land leveling	0.20	
d_aware_tax	=1 aware of state tax credits program for conversion to surface water or land leveling	0.48	

Standard deviation for binary variables is left blank because this is a redundant transformation of the mean.

174 observations for all variables.

Table 4.1 Results of Control Variables within Scientific Scheduling Models

Participation Equation	Scientific Scheduling	Soil Moisture Sensors	ET/atmometer, Computerized Scheduling, Woodruff charts
d_corn	--	--	0.582 (0.385)
d_diesel	--	--	-0.718 (0.529)
d_income_high	--	0.934 (0.708)	0.670 (0.542)
d_income_mid	0.558 (0.444)	0.702 (0.578)	0.509 (0.484)
d_income_na	-0.130 (0.558)	0.315 (0.693)	-0.074 (0.615)
d_part_cons	-0.725[b] (0.344)	-0.812[b] (0.411)	-0.734[a] (0.382)
d_sorghum	--	2.60 (1.76)	--
d_twr	--	0.727 (0.483)	--
d_use_tax	--	0.844[a] (0.434)	--
exper	-0.024[b] (0.012)	-0.045[b] (0.015)	--
share_irr_sorghum	--	-22.76 (17.78)	--
share_irr_soy	0.944 (0.772)	--	--
Outcome Equation			
N/A	N/A	N/A	N/A

Table 4.2 Results of Control Variables within Flowmeter Models

Participation Equation	Flowmeters	Mounted Flowmeters	Portable Flowmeters
d_aware_tax	--	0.342 (0.238)	--
d_cotton	-0.578 (0.382)	-0.751 (0.459)	--
d_diesel	--	--	0.824 (0.525)
d_income_high	0.112 (0.391)	0.559 (0.444)	--
d_income_mid	0.276 (0.290)	--	--
d_income_na	0.434 (0.346)	0.605 (0.411)	--
share_gypsum	--	--	3.45 (3.07)
Outcome Equation			
d_covercrops	0.079 (0.071)	--	--
exper	--	0.003 (0.002)	--
share_eb	0.138 (0.118)	--	--

Table 4.3 Results of Control Variables within Row Crop Water Application Systems Models

Participation Equation	Computerized Hole Selection	Center Pivot	Surge Irrigation
d_corn	--	0.270 (0.257)	--
d_cotton	0.368 (0.344)	--	--
d_covercrops	--	--	0.300 (0.288)
d_diesel	0.737 (0.484)	--	--
d_income_high	--	-0.593 (0.448)	--
d_income_na	--	0.233 (0.379)	--
exper	-0.009 (0.008)	--	--
share_irr_rice	--	--	0.948 (0.633)
Outcome Equation			
d_covercrops	--	0.104 (0.068)	--
d_income_high	0.002 (0.118)	--	--
d_income_mid	0.105 (0.094)	--	0.035 (0.076)
d_income_na	0.238[b] (0.110)	--	-0.013 (0.083)