Water Availability, Land Allocation,
and the Role of Irrigation Districts under Prior Appropriation Doctrine

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Title: The Economic Benefits of Irrigation Districts under Prior Appropriation Doctrine: An Econometric Analysis of Agricultural Land-allocation Decisions

Abstract: The economic literature has established that prior appropriation doctrine induces heterogeneity in risk among water users, which leads to an inefficient allocation of resources. In this study, we show that irrigation districts alleviate that risk by deviating from the strict application of prior appropriation doctrine. As a result, farmers inside irrigation districts are able to plant more water-intensive crops than farmers outside irrigation districts, which increases average profitability. We empirically examine this hypothesis by leveraging a geo-referenced dataset in Idaho's Eastern Snake River Plain spanning 2007-2014 at the spatial scale of the individual water right. Our results indicate that on average, irrigation districts allocate larger portions of their land to drought-sensitive, high-value crops such as sugarbeets and potatoes. As a result of differences in planting decisions, members of irrigation districts earn on average $16.20 per acre, or 6.0% more per year than those outside of irrigation districts. (JEL codes: Q15, Q12, C35)

Keywords: irrigation districts; land allocation; risk pooling; water rights; water scarcity

Throughout the western United States, water use is governed by the doctrine of prior appropriation, which allocates water based on the principle of "first in time, first in right." Water rights that were established later in time (junior rights) will be curtailed during a water shortage to ensure sufficient water to satisfy those established earlier in time (senior rights). In the absence of competitive water markets, this feature of prior appropriation doctrine has the potential to create heterogeneity in risk among water users and an economically inefficient allocation of resources (Burness and Quirk, 1979). Recent studies have found empirical evidence in support of the hypothesis that the seniority based structure of prior appropriation drives differences in the behavior of otherwise similar farmers. When facing water constraints, farmers often respond by adjusting their land allocation in the medium to long run, with the result that farmers with junior rights tend to plant a greater share of their land to drought-tolerant, low-value crops than otherwise similar farmers with senior rights (Hornbeck and Keskin, 2014). The economic literature suggests that these differences in planting decisions result in a 5-10% loss in land rent (Brent, 2017; Cobourn et al., 2017).

Given that prior appropriation has been slow to evolve in response to increased water scarcity, a question that arises is whether and how irrigators mitigate risk in water availability within the constraints imposed by current institutions (Libecap, 2011). Previous studies have looked at two potential means of mitigating risk in water availability. One is diversification across water source (i.e., a water portfolio), the other is access to water markets. With respect to diversification across source, Hornbeck and Keskin (2014) show that access to groundwater enables farmers switch from non-irrigated to irrigated agriculture and from drought-tolerant to water-intensive crops, generating an increase in farmland value. Mukherjee and Schwabe (2015) find that in addition to groundwater, access to supplementary water from water districts increases farmland value. With respect to access to water markets, Burness and Quirk (1979) show theoretically that competitive water markets achieve an efficient allocation of water in an appropriative system. Empirical studies demonstrate that the efficiency gains from water markets are likely to be substantial (e.g. Calatrava and Garrido, 2005; Ghosh et al., 2014; Hansen et al., 2008; Howitt, 1998; Howitt and Hansen, 2005). However, diversification across water sources and access to water markets are constrained by the current geographical and institutional environment in the US West. Access to groundwater is subject to the geographical distribution of underground aquifers and large-scale water markets remain thin (Bretsen and Hill 2006; Brewer et al. 2007).

In this paper, we investigate whether access to irrigation districts enables farmers to mitigate risk in water availability. Irrigation districts are semi-governmental farmer cooperatives that allocate water acquired under prior appropriation rights to their members (Griffin, 2006; Libecap, 2011; Rosen and Sexton, 1993).[1] They differ from individual farmers in an appropriative system in several respects. First, irrigation districts typically hold a broad set of water rights that spans different seniorities, which reduces risk in water deliveries due to curtailment. Second, water is proportionally allocated among farmers within irrigation districts (Michelsen et al., 1999). The proportional allocation of water spreads risk from individuals across all district members, analogous to the function of insurance pools. Third, water transfers between district members are subject to lower transactions costs than transfers among farmers outside of irrigation districts. As a result, irrigation districts often facilitate informal transfers, thereby offering the advantages of a small-scale water market. These features of irrigation districts all reduce the chance of a critical curtailment in water deliveries for an individual farmer inside the district, thereby reducing the risk in water availability borne by members of irrigation districts relative to irrigators outside districts.

The objective of this study is to test empirically whether there exist systematic differences in land-allocation decisions between farmers inside and outside of irrigation districts. Our empirical

[1]Irrigation districts are often state government entities. The district acts as a trustee for its members and receives and distributes irrigation water among them. Functioning as a local governing body, they are granted tax-exempted status and the ability to issue bonds.

analysis focuses on the Eastern Snake River Plain (ESRP) of Idaho, a major agricultural production region that relies heavily on irrigation. We take advantage of several detailed geo-referenced datasets to summarize annual crop choices from 2007-2014 at the scale of the individual water right. Using these data, we estimate a fractional multinomial logit (FMNL) model to explain observed land-share decisions by farmers in a multi-crop system as a function of water rights attributes (e.g., seniority), membership in an irrigation district, and a vector of spatially referenced control variables including soil characteristics, temperatures, and precipitation.

This study contributes to the economic literature in two primary ways. First, we disentangle the economic benefits provided by irrigation districts from the effect of water rights seniority. This bridges a gap in the existing literature, which focuses separately on irrigation district and seniority effects. The majority of the economic literature in this area examines questions related to prior appropriation at the scale of the irrigation district (Brent, 2017; Buck et al., 2014; Mukherjee and Schwabe, 2015). These studies either do not consider seniority (Mukherjee and Schwabe, 2015) or acknowledge the potential to underestimate the seniority effect (Brent, 2017). Cobourn et al. (2017) focus on estimating the seniority effect at the scale of the individual farmer, while controlling for membership in an irrigation district. However, their approach does not capture the interaction of the seniority and irrigation district effects, i.e., the difference in benefits between irrigation districts with a portfolio of more senior rights and those with a more junior portfolio of rights, nor does it control for differences in the characteristics of irrigation districts themselves.

Our second contribution to the economic literature is that we use a direct approach to model farmers' crop-specific land-allocation decisions, which allows us to describe how farmers adapt crop production in response to variation in natural and institutional characteristics. Previous studies examine these differences indirectly through hedonic property markets (e.g., Brent, 2017; Schlenker et al., 2007) or at an aggregate level (e.g. Deschenes and Greenstone, 2007; Hornbeck and Keskin, 2014; Moore and Negri, 1992; Moore et al., 1994). Hedonic studies can retrieve the value of water through its premium in land rent, but are not able to explain the underlying mechanism that generates the premium. In contrast, our approach enables us to explore the adaption mechanisms farmers undertake in response to water constraints. Moreover, while aggregate data on production and water use are often more readily available, aggregation across water rights obscures variations in the institutional differences in property rights that vary at the scale of the individual.

Our empirical results demonstrate that farmers in irrigation districts plant land to a more profitable set of crops than otherwise similar farmers outside of districts. On average, farmers inside irrigation districts allocate more land to sugarbeets and potatoes, which are relatively drought-sensitive, high-value crops. As a result of these differences in planting decisions, members of irrigation districts earn an average of $16.20 per acre, or 6.0% more per year, than those outside of irrigation districts. This is comparable to existing estimates in the literature, such as the effect associated with a change in water deliveries of 0.15 AF/acre in Buck et al. (2014) and the effect of an increase in seniority of two standard deviations in Brent (2017) and Cobourn et al. (2017). The estimate found herein exceeds that of access to water districts in Mukherjee and Schwabe (2015). Our results suggest the potential for substantial efficiency gains associated with access to an irrigation district, which offers a way to mitigate the risk in water availability that arises due to seniority in an appropriative system.

1 Background on Irrigation Districts

Most irrigation districts were established in the early 1900s to facilitate the construction of water infrastructure such as pipes and canals, which exhibit high fixed costs and increasing returns to scale (Michelsen et al., 1999). Irrigation districts greatly reduce bargaining and transaction costs between irrigators who share the infrastructure, and they were regarded as an institutional innovation that sped the process of settling and developing the US West (Rosen and Sexton, 1993).

Irrigation districts continue to play an important role in diverting and delivering water in the US West. Irrigation districts provide water to one-quarter of the irrigated area of the region, though the reliance is more pronounced in some states, such as California, where districts provide water to one-half of the irrigated land area (Kenny et al., 2009; Maupin et al., 2014; Smith, 1989). Like other special districts in the US, irrigation districts are defined by fixed geographical boundaries. Any farmer who resides within an irrigation district is considered to be a member of the district and is entitled to own share(s) in the district's water supply. Irrigation districts collectively hold prior appropriation water rights that are administered by the state in order to divert water, just as individual farmers do. Water delivered to the district under its water right(s) is allocated among district members in proportion to the share(s) owned by each.

When irrigation districts face curtailment of one or more of their water right(s), the reduction in water availability is spread across irrigators in proportion to their share(s) in the district. As shown in Burness and Quirk (1979), this proportional allocation results in an efficient allocation of water when farmers use homogeneous production technologies.[2] This system of proportional allocation smooths the risk of water availability across irrigators within the district. Given that irrigation districts typically hold numerous and diverse water rights, the probability is small that an irrigation district will be critically or completely curtailed during a growing season (Cobourn et al., 2017).

Some irrigation districts also facilitate water transfers between members. These are often

[2]This result requires the assumption that land exhibits constant return to scale, which is implicit in Burness and Quirk (1979), as well as in land-allocation models such as Cobourn et al. (2017); Moore and Negri (1992); Moore et al. (1994).

accomplished informally with advertisements of potential sales and purchases posted in the district office. These transfers involve lower transactions costs than transfers outside of irrigation districts for two primary reasons. The first is that the infrastructure required to move water between farms is already established. The second is that these transfers are not subject to administrative review by the state water agency due to the potential for third-party effects (externalities) to arise when water deliveries are moved from one point in space to another (Gisser, 1983, 2011; Johansson et al., 2002). Third-party effects are most likely to arise when a transfer alters return flows to a waterway. This issue is less likely to arise in an irrigation district because existing conveyance infrastructure ensures that any unconsumed water returns to the same waterway. Outside of irrigation districts, the presence of water markets is limited in the current political and legal environment (e.g., Bretsen and Hill 2006; Brewer et al. 2007).

2 Empirical Model

In this study, we are interested in explaining how farmers allocate a fixed land base across multiple crops as a function of water availability. Specifically, we are interested in whether prior appropriation water rights constrain farmers' land-allocation decisions and whether access to an irrigation district may alleviate that constraint and any corresponding inefficiency arising from prior appropriation. The economic literature to date has taken two general approaches to examining similar problems. The first is to develop a theoretical model of multi-output irrigated production that forms the basis for a structural system of estimable equations explaining crop supply and input allocation decisions (Moore and Negri, 1992; Fezzi and Bateman, 2011; Lansink and Peerlings, 1996). Though this approach has the advantage of theoretical consistency, it comes at the cost of empirical flexibility and tractability (Carpentier and Letort, 2014) . A second approach taken in the literature is a reduced-form empirical modeling approach to explain land allocation (share) decisions. Prominent examples in this literature include Wu and Segerson (1995) and Miller and Plantinga (1999). Although the reduced-form approach is theoretically consistent with a multi-crop production model only under certain functional form assumptions, it offers the advantage of empirical tractability (Carpentier and Letort 2014).

A common reduced-form approach is to adopt the conditional logit framework (Fiszbein, 2017; McFadden, 1974). This approach assumes that the underlying profit of farmer *i* growing crop *j* on a unit of land can be expressed as a linear function of a vector of explanatory variables plus a random error term, i.e.,

$$\Pi_j = \mathbf{X}_i\boldsymbol{\beta}_j + \varepsilon_{ij} \tag{1}$$

It can be shown that if the random error term ε_{ij} follows an i.i.d. type-I extreme value distribution, then the probability that farmer *i* chooses crop *j*, $\bar{y}_{ij}$, has the form:

$$\bar{y}_{ij} = \frac{exp(\mathbf{X}_i\boldsymbol{\beta}_j)}{\sum_{k=1}^{J} exp(\mathbf{X}_i\boldsymbol{\beta}_k)} \tag{2}$$

If we interpret $\bar{y}_{ij}$ instead as the share of crop *j* in the land allocation (rather than the probability of choosing alternative *j* in a traditional conditional logit framework), then equation 2 gives rise to the fractional multinomial logit (FMNL) model.

In this analysis, we take a reduced-form approach to modeling land shares in a multi-crop system using the FMNL model. The FMNL model is a multivariate extension to the bivariate fractional logit model proposed by Papke and Wooldridge (1996). Empirically, the FMNL model has been widely used in agricultural land-allocation modeling (Cobourn et al. 2017; Fiszbein 2017; Kala et al. 2012). Underlying this model is the assumption that decision makers allocate shares of a fixed amount of land and water to a set of land-allocation choices. These shares must sum to one and are bounded by zero and one. There are several empirical advantages associated with an FMNL approach. First, if the true data generating mechanism is fractional, then a traditional linear estimator fails to acknowledge the bounded nature of the data. This may provide inconsistent estimates as well as a poor fit. The linear model is particularly problematic if the dependent variables takes the boundary values 0 or 1 with non-trivial probability (Mullahy, 2015; Papke and Wooldridge, 1996). This is problematic when examining land-allocation decisions at the scale of the individual farm because most farmers choose to produce a subset of a region's crops, which implies that zeros are likely to be prevalent in the dataset. The FMNL model accommodates these probability masses, avoiding the need to either exclude boundary observations or assign an arbitrarily small or large value to them. Secondly, the FMNL model captures potential heterogeneity in partial effects, whereas the partial effects in a linear model are assumed to be homogeneous. In our application, it is of particular interest to determine whether the effects of access to irrigation districts are heterogeneous for farmers who are exposed to different levels of risk in water supply due to water rights ownership.

The dependent variable in our FMNL model is y_{ijt}, defined as the share of land allocated to crop *j* in growing season *t* as a proportion of all allocable land owned by farmer *i*. The share of land allocated to each crop depends on the farmer's expected water availability, $\mathbf{W}_{it}$, a vector of site-specific control variables, e.g., soil and climate characteristics, $\mathbf{Z}_{it}$, a vector of input and output prices, $\mathbf{P}_t$, and unobservables ε_{ijt}:

$$y_{ijt} = f(\mathbf{W}_{it}, \mathbf{Z}_{it}, \mathbf{P_t}) + \varepsilon_{ijt} \tag{3}$$

The water available to farmer *i* for irrigation, $\mathbf{W}_{it}$, depends on the quantity of water acquired under the farmer's water rights, W_{it}^a, precipitation, W_{it}^p, access to an irrigation district, W_i^{ID}, and other factors that affect water availability, e.g., extreme heat, W_{it}^o. We can rewrite total available water as a function of these variables:

$$\mathbf{W}_{it} = f(W_{it}^a, W_{it}^p, W_i^{ID}, W_{it}^o) \tag{4}$$

The amount of water acquired under prior appropriation water rights, W_{it}^a, is in turn a function of three variables: total surface water available for allocation across all farmers, α_t, the seniority of the farmer's right(s), μ_i, and access to a portfolio of water rights, described by the parameter σ_i. An increase in α_t implies that all irrigators face a lower probability of curtailment. An increase in μ_i corresponds to an increase in seniority. More senior rights are less likely to be curtailed than junior rights, holding constant water availability. A water right portfolio may diversify across the seniority of surface water rights σ_i^s(Cobourn et al., 2017) and/or across sources including access to both surface and groundwater σ_i^g (Mukherjee and Schwabe, 2015). The more diverse the portfolio, the less likely a farm will be curtailed. Taking into account how appropriative rights depend on these parameters, we can rewrite equation (4) as:

$$\mathbf{W}_{it} = f\Big(W_{it}^a\big(\alpha_t, \mu_i, \sigma(\sigma_i^s, \sigma_i^g)\big), W_{it}^p, W_i^{ID}, W_{it}^o\Big) \tag{5}$$

In Equation 5 we partition a farmer's water supply into different components. In our empirical model, the effect of regional water availability, α_t, will be captured by an annual fixed effect. Our main FMNL model specification is thus given by:

$$G^{-1}(y_{ijt}) = \tau_j + \beta_j W_i^{ID} + \gamma_j \mu_i + \delta_{1j}\sigma_i^g + \delta_{2j}\sigma_i^s + \zeta_j \mathbf{X}_{it} + \theta T_t + \varepsilon_{ijt} \tag{6}$$

where $G^{-1}(.)$ is the inverse of the multinomial logit function defined in equation (2); W_i^{ID} is a dummy variable for whether farmer *i* has access to an irrigation district; μ_i is the seniority of a farmer's water right(s); σ_i^g is a dummy variable for whether the farm owns groundwater rights in addition to surface water rights; σ_i^s is a measurement of the diversity in priority dates when a farmer owns multiple surface water rights; $\mathbf{X}$ is a matrix of control variables, including soil, weather, and price expectations; τ is the intercept; and ε is the idiosyncratic error term. Time dummies T_t are added to control for time-related heterogeneity, e.g., unobserved surface water supply effect.[3]

Papke and Wooldridge (1996) propose a quasi-maximum likelihood (QMLE) estimator for the FMNL model, along with the correction needed to achieve consistent standard errors following Gourieroux et al. (1984a,b). Papke and Wooldridge (2008) extend the univariate fractional logit model to a panel setting. They follow Chamberlain (1980)'s method by removing individual heterogeneity by augmenting the regression equation with time averages for each individual. The resulting model may be estimated using weighted non-linear least squares, QMLE, or a generalized estimating equation approach. Mullahy (2015) extend the analyses of Papke and Wooldridge (1996, 2008) to a multivariate setting and demonstrate that the QMLE remains consistent when there exist multiple categories for the dependent variable.[4] Mullahy (2015) also show that the Papke and Wooldridge (1996) standard error correction provides consistent standard error estimates for the FMNL model. The model can be consistently estimated with the QMLE proposed by Papke and Wooldridge (1996) by maximizing the Bernoulli log-likelihood function :

$$\sum_{i=1}^{N} ln(L_i) = \sum_{i=1}^{N}\sum_{j=1}^{J} y_{ij} ln(G(X_i \beta_j)) \tag{7}$$

for which L_i is the likelihood for observation *i*, y_{ij} is as defined in equation (3), X_i is the vector of of explanatory variables for observation *i*, which includes variables identified in equations (3)-(5), and β_j is a vector of coefficients specific to each land-allocation choice.

We propose to fit a pooled FMNL model using the QMLE proposed by Papke and Wooldridge (1996). Although we possess a dataset with a panel structure, we do not control for individual-

[3] Adding dummy variables for basins poses a challenge for model convergence.

[4] See, e.g., Sivakumar and Bhat (2002) for the development of the FMNL model in the transportation literature.

specific heterogeneity using panel data methods for several reasons. First, the econometrics literature has not yet developed a viable method to estimate the panel FMNL model. Papke and Wooldridge (2008) propose to estimate panel fractional probit models via the Chamberlain (1980) method. However, there are two obstacles in applying their method to this study. First, the likelihood function for a multimonial probit model can only be meaningfully constructed on binary variables, not on share variables. This prohibits the extension of the panel fractional probit model to a multivariate setting. Another complication for Papke and Wooldridge's estimator is that it requires augmenting the regression model with time averages, which would eliminate all time-invariant variables. Because our primary variables of interest, those related to water rights, are time invariant, running a model like Papke and Wooldridge (2008) is not feasible.

Using a pooled cross-sectional model is sufficient in this analysis to examine the effect of irrigation institutions on land-allocation decisions. Our purpose is to draw inference mainly from between rather than within variation in land-allocation decisions. The institutional factors of water availability, namely water rights seniority and irrigation district access, are fixed over time but vary across individuals. As a result, between variation captures systematic differences in land allocation due to institutional factors, whereas within variation will reflect non-institutional factors such as crop rotation patterns and expectations for weather conditions. Thus, using land allocation variations from a cross-sectional or short panel dataset are sufficient to identify the causal impact from water institutions if we control for other determinants of water availability properly. Furthermore, irrigation institutions are exogenous in the sense that land allocation can affect water rights or access to an irrigation district due to institutional constraints. Also, we are not worried about endogeneity emerging from sample selection or spatial sorting, which most hedonic models suffer from (Klaiber and Smith, 2013). Agricultural land sales in Idaho are usually accompanied by the sale of the water right(s) associated with that land. Thus, although the ownership of a farm may change, the associated water right(s) or the claims to irrigation district water likely will not.

To minimize the impact of omitted variable bias, we control for factors modeled in the literature, including those that reflect water availability, soil quality, and the weather conditions that impact agricultural production and yield. There are factors that we are unable to control for due to data limitations, such as water storage capacity and irrigation technology. However, our approach incorporates differences in inputs or technology that are related to water availability. In the long run, those differences likely arise due to the endogenous choices farmers make when facing different water availability scenarios. For example, farmers inside an irrigation district have a more secure water supply, and thus less incentive to invest in water-saving irrigation technologies such as drop nozzles. This may result in systematic differences in irrigation technology between irrigation districts and individual farmers. However, because the difference is actually caused by the benefits that irrigation districts brings to their members, it should be included as part of the irrigation district effect.

The parameter estimates obtained by maximizing equation (7) represent the logit-transformed odds ratio for each specific choice relative to a baseline choice. The marginal effects for continuous explanatory variables are given by:

$$ME_{jk} = \frac{\partial \hat{\mathbf{y}}_j}{\partial \mathbf{x}_k} = \hat{\mathbf{y}}_j(\beta_{jk} - \bar{\boldsymbol{\beta}}_k) \tag{8}$$

where $\hat{\mathbf{y}}_j$ is an 1*N vector of predicted probabilities for choice j, and $\bar{\boldsymbol{\beta}} = \sum_{m=1}^{J} \beta_{mk}\mathbf{y}_m$ is the an 1*N vector of probability weighted average of $\boldsymbol{\beta}_k$. The discrete effect for a zero-one dummy variable is given by:

$$DE_{jk} = Pr(y = j|\mathbf{x}_{x_k=1}) - Pr(y = j|\mathbf{x}_{x_k=0}) \tag{9}$$

which is the change in the predicted land share when the dummy variable x_k increases from zero to one. Both the marginal and discrete effects in equations (8) and (9) differ with the levels of the explanatory variables, and thus between different farmers. In order to obtain marginal or discrete effects, we aggregate partial effects for different individuals to obtain average partial effects (APE). There are two ways to obtain APE from the individual heterogeneous partial effects. The partial effects at the mean approach (PEM) involves calculating partial effects by setting all covariates at their sample mean, and using the partial effect at that point. The partial effects on average approach (PEA) involves calculating partial effects for each observation and taking the average. There is no agreement in the literature as to which method is preferred (Greene, 2008). In this paper we use the PEM method to calculate APE.

We also calculate the average partial effects on profits (APEP). APEP is analogous to the concept of the traditional parameter estimates and standard errors in a linear model. We do this by aggregating crop shares with respect to their profits per acre, as well as their respective variances, i.e.,

$$E(APEP_k) = \sum_{j=1}^{J} APE_{j,k} * profit_j$$

and

$$V(APEP_k) = \sum_{j=1}^{J} V(APE_{j,k}) * profit_j^2$$

where $APEP_k$ is the average partial effect on profits for explanatory variable k, and $APE_{j,k}$ is the average partial effect of crop shares for crop *j*, explanatory variable *k*. Here we assume that the standard errors of each crop-specific APE are independent of each other, and thus the variance of APEP is the sum of the variances of all crop-specific APEs times the square of their respective profits.

3 Data

Our empirical analysis focuses on the East Snake River Plain (ESRP) in southeastern Idaho (Figure 1). The ESRP is a major agricultural production region and water user in the Intermountain West. Agricultural production in the region relies heavily on irrigation water: 74.7% of farmlands are irrigated (NASS, 2012), and irrigated agriculture accounts for 85.6% of water withdrawals in the ESRP (Kenny et al., 2009). The primary crops produced in the region are alfalfa, barley, corn, potatoes, sugarbeets, and wheat. The main water source for the region is the Snake River and its tributaries. Surface water flows and groundwater recharge depend highly on winter precipitation and snowmelt. About 60% of the irrigated croplands are irrigated with surface water. The other 40% are irrigated with groundwater (NASS, 2014).

[Insert Figure 1 here.]

One advantage to focusing on the ESRP as study region is that Idaho maintains a spatially referenced water rights database administered by the Idaho Department of Water Resources (IDWR).[5] From this database, we are able to identify the spatial boundaries of water rights. The individual water right forms our cross-section in the dataset. The boundaries of water rights are not the same as the boundaries of the farm. Unfortunately, we do not have data to describe the latter, but the water right is appropriate as an individual unit of observation because water right boundaries delineate the land base over which water is a quasi-fixed input to production (Moore and Negri, 1992). Additionally, we acquire water right titles, source of water, and priority dates associated with the farm. This allows us to conduct analysis at the individual water rights level. And, more importantly, knowing the spatial boundaries of the farm entities allows us to match it with other spatially referenced dataset such as land use, soil and weather. We plan to fit a cross-section

[5] Available from https://research.idwr.idaho.gov

FMNL model by pooling over time periods. As explained in the previous section, econometric challenges prohibit us from adopting panel data methods.

There are a total of 6429 unique water rights for irrigation within the ESRP. Among those, 1679 farms hold at least one surface water right, and 15 are irrigation districts. Figure 2 shows the geographical locations of irrigation districts within the ESRP. We exclude those districts who hold only groundwater titles from the analysis because groundwater users do not usually face curtailment risks from the appropriation system, which makes their water supply more reliable than surface water.[6] This means that groundwater users are likely to behave systematically different with respect to land and water allocation than surface water users. Because our goal in this analysis is to find a valid counterfactual for farms residing inside surface water irrigation districts, groundwater users are not included in the sample. We also exclude all observations that have fewer than five pixels in the cropland data layer that are identified as growing the region's major crops or idled.[7]

For irrigation districts, we are able to identify the water rights boundaries for each district based on the IDWR data. These boundaries usually coincide with the administrative boundaries of the districts. We are not able to distinguish property boundaries for individual farms inside irrigation districts. This means that the land-allocation decisions for irrigation districts are observed in aggregate. This is a limitation of our dataset, and we provide robustness checks to show that this caveat does not undermine our main result. We assume that farmland inside the boundary of an irrigation district uses district water unless the parcel has access to other water sources. This assumption is used in the previous literature when intra-district water delivery data is not available (Buck et al., 2014; Schlenker et al., 2007).

[6] Currently, groundwater usage is not systematically monitored or diversion limits enforced in the ESRP. On some occasions, the water rights of groundwater users may be called by surface water user groups when the two resources are connected. In these cases, groundwater rights may be curtailed because they are for the most part junior to surface water rights. However these water calls affect only a small portion of groundwater users.

[7] Five pixels translates to approximately 1.1 acres of cropland.

In Equation (6) we set up the main FMNL regression model for our study. Here we explain in detail how the independent and dependent variables are constructed. The effect of seniority, μ, is captured using the average of water right quantile, which will be explained below. The effect of surface water portfolio effect σ^s is portrayed by the standard deviation of the water right quantile.[8] Effect of groundwater sources σ^g is captured as a dummy variable of whether a farm holds any additional groundwater rights. We also include a series of soil characteristics, weather normals of the past three years, and prices received for all crops. Table 1 provides the description of variables included in our model, and Table 2 provides the summary statistics for them.

To better capture the marginal effect of seniority (priority date) on water availability, we perform a standardized rank transformation on water rights priority dates. Specifically, all surface water rights are ranked by their priority dates from the earliest to the latest, and are standardized continuously to a zero-one range, and each right is assigned a rank based on the "quantile" of the right in the hierarchy of rights. Quantile is a continuous variable between 0 and 1 that is calculated as the rank of the water right divided by the total number of observations. For example, the first water right (with the earliest priority date) in the system has a quantile value of 0, the median water right has a quantile value of 0.5, and the last right (with the lastest priority date) has a quantile value of 1. The rationale for this transformation is that the distribution of priority dates is not uniform in time. As shown in Figure 3, most surface water rights were filed during the progressive era (1890-1920); fewer rights were filed after 1930. This means that a one-year increase in seniority during the progressive era will represent a much larger increase in the rank of priority than a one-year increase in seniority in the 1950s. If we put priority dates directly into our empirical model, the marginal effect of a one-year seniority change will be heterogeneous across time. A rank transformation, in contrast, guarantees that the quantile of each right is uniformly distributed in the appropriation system and that the marginal effect on a one-percentage quantile

[8]Specifically, define the standard deviation of a single water right to be zero, which can be viewed as a portfolio with no diversification at all.

change becomes more homogeneous.

[Insert Figure 2 here.]

[Insert Figure 3 here.]

We also acknowledge that the quantile rank for each water right is not equivalent to the probability of curtailment. The link between water rights quantile and the probability of being curtailed is nonlinear. To capture that nonlinear relationship one needs to know, at a minimum, the distribution of water flows in the river system as well as the amount of water that may be appropriated under each water right. This information usually requires use of a regional hydrological-statistical model, which is unavailable to us. The rank transformation serves as a second-best alternative, and is an improvement over the use of priority dates or date range dummies (Brent, 2017; Cobourn et al., 2017).

We obtain land-allocation data from National Agricultural Statistics Service (NASS)'s Cropland Data Layer (CDL). CDL is a crop-specific land cover dataset for the continental US based on satellite imagery and calibrated classification algorithms (National Agricultural Statistics Service, 2007-2014). The dataset is available for the ESRP for the year 2005, and from year 2007 to present. For each water right in our cross section, we use the CDL to identify the percentage of land allocated to the six major crops in the region: alfalfa, barley, corn, potato, sugarbeet and wheat, as well as land idlement.

We obtain soil data from the SSURGO database, a soil database developed by USDA-NRCS. The SSURGO dataset contains a crop-specific yield estimate for each soil type, from which we construct an average irrigated crop yield map for wheat and corn. This allows us to capture the possibility that a parcel of land is especially suitable for certain crops but not for others, which may explain some of the observed crop choices. We also include common soil quality indicators in our model, such as irrigated and non-irrigated soil capability class, percent clay, percent slope, and the k-factor [9].

We obtain weather data from the PRISM climate dataset developed by Oregon State University, which provides downscaled, spatial projects of climate variables. We include in the model three weather variables that are important in determining crop productivity and water availability: growing degree-days(GDD), extreme weather conditions, and cumulative precipitation over the course of the growing season.

Growing degree-days is a non-linear transformation of temperature, which assumes that plant growth is linear only between moderate temperature ranges from 8°Cto 32°C(Ritchie and NeSmith, 1991). The use of growing degree-days is common in estimating agroeconomic models (e.g. Schlenker et al., 2007; Deschenes and Greenstone, 2007) and is suggested by the economic and agronomic literature as a preferred method over the use of average monthly temperatures (Schlenker et al., 2007). Extreme heat conditions are detrimental to crop growth and significantly reduce crop yields (Burke and Emerick, 2016).[10] Extreme heat conditions contribute to increased rates of plant evapotransporation, which cause increased water demands for crops. Cumulative precipitation over the growing season measures the supplemental water supply provided by precipitation, which offsets the demands for irrigation water.[11]

[Insert Table 1 here.]

[Insert Table 2 here.]

[9] The k-factor is a quantitative description of the erodibility of a soil.

[10] For the purposes of this analysis, we define extreme heat as daily maximum temperatures in excess of 35°C.

[11] Cumulative precipitation over the growing season is calculated between June 1 and September 30.

4 Results

Our main specification is described in equation 6 . Estimation results are shown in Table 3 and the average partial effects (APE) are shown in Table 4. Robust standard errors, calculated as in Papke and Wooldridge (1996), are reported in Table 3 and are used to generate standard errors for the APEs via Krinsky-Robb simulations.

[Insert Table 3 here.]

[Insert Table 4 here.]

Average partial effects on profits (APEP) are shown in the first column of Table 5. The average crop-specific profit statistics for APEP is calculated by subtracting the average cost from the average revenue between 2005 and 2013, which is shown in Figure 4. Revenue for a crop in a given year is calculated by multiplying the price received with the average yield of that crop in the state of Idaho, which is provided by USDA-NASS (National Agricultural Statistics Service, 2012). Crop-specific cost of production statistics are compiled from different sources, including USDA ERS data and the University of Idaho's crop costs and returns series (Patterson, 2009, 2013, 2014; USDA Economic Research Service, 2006-2013).

[Insert Table 5 here.]

[Insert Figure 4 here.]

Our results indicate that irrigation districts allocate a significantly larger share of land to potatoes, sugarbeets, and wheat and less land to alfalfa and corn, relative to individual farms. This is consistent with our hypothesis that irrigation districts generally plant more water-intensive crops and less drought-tolerant crops, with the exception of wheat and corn. A farmer residing in an irrigation district has an average edge of $16.20 per acre, or 6.0% in profits, compared to a similar farmer outside of an irrigation district. Holding additional groundwater rights is also beneficial. Compared with those farmers who have access to surface water only, farmers who hold both groundwater and surface water rights on average allocate a larger share of land to corn, potatoes, sugarbeets, and fallow, and less land to alfalfa and barley. These systematic differences lead to a $31.23 per acre, or 11.5% profit premium associated with owning groundwater rights.

Both seniority variables in our model, the mean and the dispersion of water rights quantiles, have insignificant APEs. This result differs from other studies in the region, such as Xu et al. (2014b) and Cobourn et al. (2017). However, this result is most likely a reflection of the low statistical power that our model exhibits, and should not be interpreted as a nullification of the Burness and Quirk (1979) hypothesis. Other factors that have significant impacts on farm profit, including growing degree-days, precipitation, soil yield capacities for wheat and corn, and the k-factor. The sign of all of these variables are as expected: farms with warmer weather and more precipitation, as well as more productive soils tend to choose a more profitable mix of crops.

Heterogeneity in Partial Effects

One of the advantages of using the FMNL model is that it captures the heterogeneity in partial effects among different observations. As Papke and Wooldridge (2008) point out, the difference between linear and non-linear models is not important with regard to the estimation of APEs, but is important in determining whether and to what extent the partial effects differ across the distribution of the variable of interest. We calculate APEs for the irrigation district dummy for different quantiles of water rights seniorities. Figure 5 shows the discrete effect of irrigation districts along the distribution of water rights seniority quantiles, holding all other variables at their average values. Result shows that the largest benefit of residing in an irrigation district is for the most junior water right holders, at 17.94$/acre with a standard error of 6.08$/acre, while the lowest benefit happens for the most senior water rights holders, at 14.37$/acre with a standard error of 5.95$/acre. This suggests that the benefit of access to an irrigation district is greatest for farmers with more junior rights than those with relatively secure senior rights.

[Insert Table 5 here.]

The risk-sharing and water transfer benefits provided by irrigation districts suggest that access to irrigation districts should be most beneficial for those farms with the least secure (junior) rights. Owners of senior water right(s) may benefit less from membership in an irrigation district because their water right(s) are relatively secure enough against supply volatility.

APE in Linear vs. Logit Models

As discussed earlier, a panel FMNL model is not available for the purpose of this study. To check for whether individual heterogeneities may potentially bias our estimates, we estimate two linear models, the pooled ordinary least square (OLS) and the panel random effect (RE) models. In doing so, we assume that all regressors are exogenous from the random unobserved individual effects as well as the idiosyncratic error term. This assumption cannot be formally tested using a Hausman-type test against the fixed effect (FE) model since our main variables of interest (the water rights variables) are time-invariant. However, this assumption can be justified on the basis that the variables used in our model are exogenously determined. Any cropping choice made by the farmer will not alter water rights or irrigation district membership, both of which are historically determined and institutionally constrained.

Columns 2 and 3 of Table 5 present the results from OLS and RE estimation. Although a Hausman test rejects the hypothesis that OLS and RE are equivalent, the point estimates for the two models are close, especially for our main variables of interest. Other than *QMeanSurf*, which is statistically insignificant, the difference in point estimates between OLS and RE for water rights and irrigation district variables are less than 2%. This suggests that inference for our main variables of interest should not be affected by ignoring individual-specific heterogeneity.

Furthermore, point estimates for the two variables that are significant in the FMNL model, *IrrDist* and *GrndSurf*, are close to that in the two linear models. The effect of access to an irrigation district is 16.2 $/acre in the FMNL model, 15.62 $/acre in OLS, and 15.68$/acre in RE. The effect of holding additional groundwater rights is 31.2$/acre in the FMNL model, 34.91 in OLS, and 33.94 in RE. This result is similar to that found by Papke and Wooldridge (2008); in their case, the fractional probit APEs are close to those estimated in linear models. This gives additional assurance that our point estimate on the effect of access to an irrigation district is robust against different functional form specifications.

Aggregation of Irrigation Districts

In our empirical analysis, farms inside an irrigation district are measured at the aggregate level, whereas farms outside districts are measured at the individual level. This means that the observed land allocation made by irrigation districts is essentially a weighted mean of the individual farmers residing inside the district. This is acceptable as long as the land allocation with respect to farm size is homogeneous, i.e.,

$$E(\mathbf{y}|\mathbf{X}, A) = E(\mathbf{y}|\mathbf{X})$$

where A is the size of the farm, $\mathbf{y}$ is the land-allocation vector, and $\mathbf{X}$ includes all explanatory variables other than farm size. In this case, the expectation of the aggregate land allocation is the same as if it is the mean of each farm, i.e.,

$$E_D(\mathbf{y}|\mathbf{X}, A_D) = \frac{\sum_{d=1}^{D} A_d E_d(\mathbf{y}|\mathbf{X}, A_d)}{\sum_{d=1}^{D} A_d} = E(\mathbf{y}|\mathbf{X})$$

where D is the aggregate observed land allocation and $d \in [1, D]$ is the farms that are aggregated within a district.

We empirically test this area-homogeneity assumption by running an augmented regression model to see whether the size of the farm influences land allocation. To do so, we use a subsample that includes only farmers outside of irrigation districts. Using this subsample, we estimate two FMNL models: one including the size (area) of the farm, the other including the natural log of farm size.

[Insert Table 6 here.]

The APE and APEP on the farm size variables are shown in Table 6. The model that includes *log(Area)* shows that an increase in log area is associated with a decrease in the land share allocated to alfalfa, and an increase in all crops other than barley. When aggregating these land-allocation changes out, the marginal profit change due to *log(Area)* is statistically insignificant at the 5% level. The model with *Area* depicts a similar picture, with a negative APE on alfalfa, and positive APE on all crops other than barley and fallow. The marginal profit change is significant at the 5% level, indicating that controlling for all other factors, an increase of one acre in farm size leads to an increase in profit of about $0.008 per acre. To put that in perspective, if the estimated effect of access to an irrigation districts were actually due to differences in size, then the average observed farm size inside an irrigation district would have to be 2090 acres larger than the average size of an individual farm. Few farms in our sample, only 3% , are large enough to meet this criteria. If the distribution of farm sizes is similar inside and outside irrigation districts, then it is highly unlikely that farm size is the factor driving the estimated premium associated with access to an irrigation district.

Furthermore, aggregating farms inside irrigation districts results in an over-representation of dryland crops because of the nature of our definition of farms. For individual farmers, we observe the spatial boundary of the water right(s). It is likely that water rights boundaries are smaller than actual farm boundaries. Lands that are owned by a farm, but not covered by a water source, will practice dryland agriculture through all years (private communication with IDWR). These lands will be excluded from our sample as a result. In contrast, the boundaries of water rights for irrigation districts coincide with their administrative boundaries. Thus, all lands inside an irrigation district will be aggregated, including those on which dryland agriculture is practiced. Thus, the spatial boundaries of irrigation districts will over-represent dryland agriculture, resulting in an underestimation of the premium associated with access to irrigation districts.

5 Conclusion

The doctrine of prior appropriation doctrine may generate an inefficient allocation of resources by generating heterogeneous levels of risk for different water users. In this analysis, we find that irrigation districts offset any such inefficiency by deviating from the application of prior appropriation doctrine within the district. We hypothesize that through proportional allocation and internal water transfers, members of irrigation districts can ensure a more secure water supply despite holding more junior water rights. This hypothesis is confirmed by our empirical results, which suggest that irrigation districts are able to plant a more favorable set of crops than farmers outside irrigation districts. The estimated profit premium for access to an irrigation district is 6% annually.

The profit premium associated with access to an irrigation district is comparable to the advantage associated with holding senior water rights (Brent, 2017; Cobourn et al., 2017; Xu et al., 2014a), having more water (Buck et al., 2014), and having access to water portfolios (Mukherjee and Schwabe, 2015). Our results are similar to the findings of Cobourn et al. (2017) and Mukherjee and Schwabe (2015), which suggest that having partial access to irrigation district water provides economic benefits to farmers. A subtle difference between those studies and ours is that, in both Cobourn et al. (2017) and Mukherjee and Schwabe (2015), district water is likely to be used as a supplemental water source, whereas in this analysis we account for the fact that irrigation district water is the primary water source for members. This is likely the reason why we find a larger premium for irrigation districts than those studies.

Our results also contribute to the literature estimating the value of prior appropriation water rights. Previous estimates of the value of water rights have focused on either individual water rights (Cobourn et al., 2017) or irrigation districts (Brent, 2017; Buck et al., 2014). Our results suggest that there is a gap between the value of water rights owned by individual farms and water rights owned by irrigation districts. In states with individual-district hybrid appropriation systems such as Idaho and Montana, using estimates for individual farms only will overstate the inefficiency arising from heterogeneity in the risk of water availability. In states dominated by irrigation districts such as Oregon and California, heterogeneity in the risk of water availability has already been mitigated by irrigation districts. Applying these results to states dominated by hybrid or individual water rights will lead to underestimation of the true level of heterogeneity in risk and any associated inefficiency.

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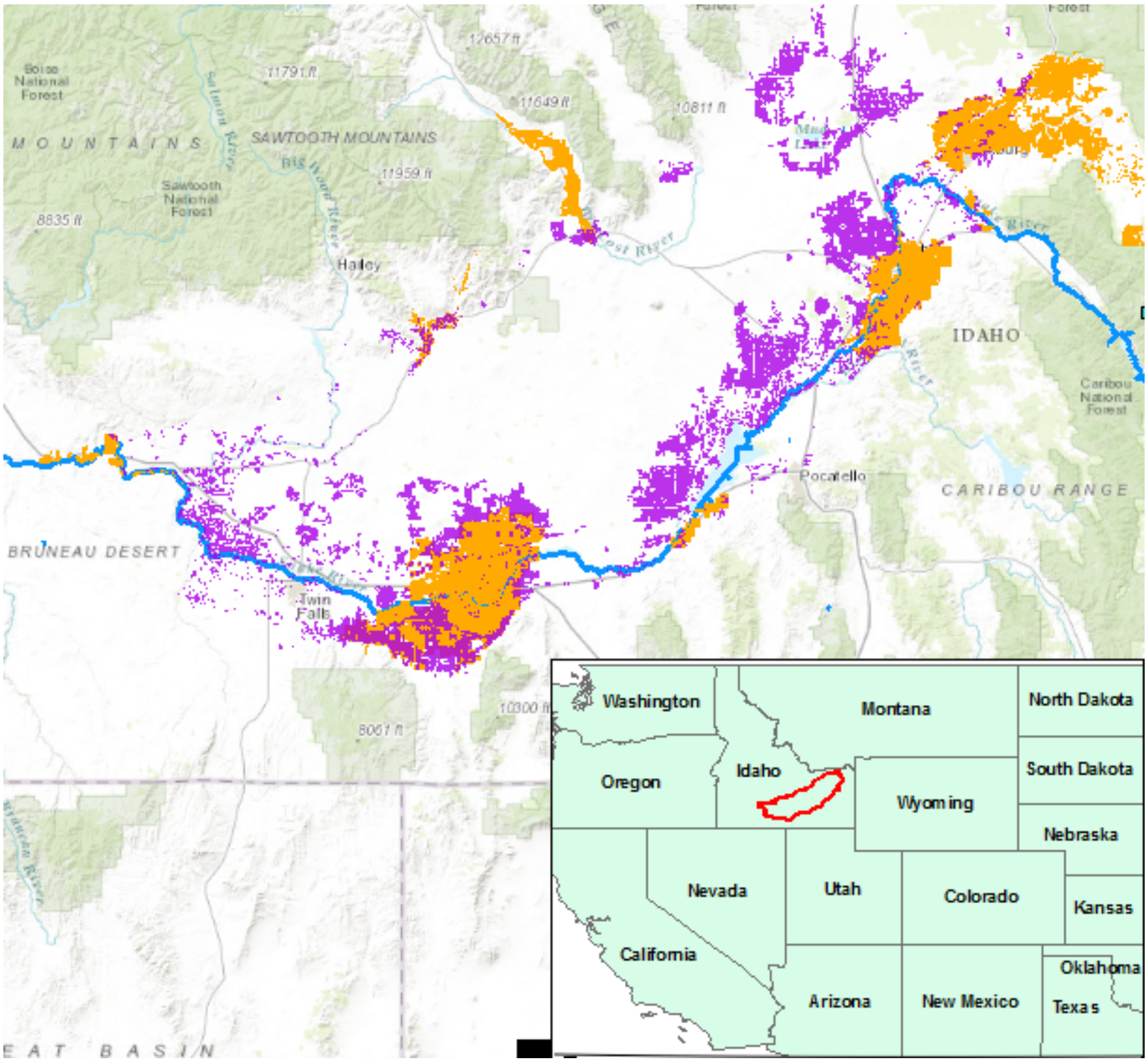

Figure 1: Map of the Eastern Snake River Plain. The dark(blue) line denotes the main stem of the Snake River. Darker(purple) areas are lands covered by individual water rights, and lighter(orange) areas are irrigation district lands. Lower-right panel denotes the relative location of the ESRP (Line polygon denotes the watershed boundary of ESRP.)

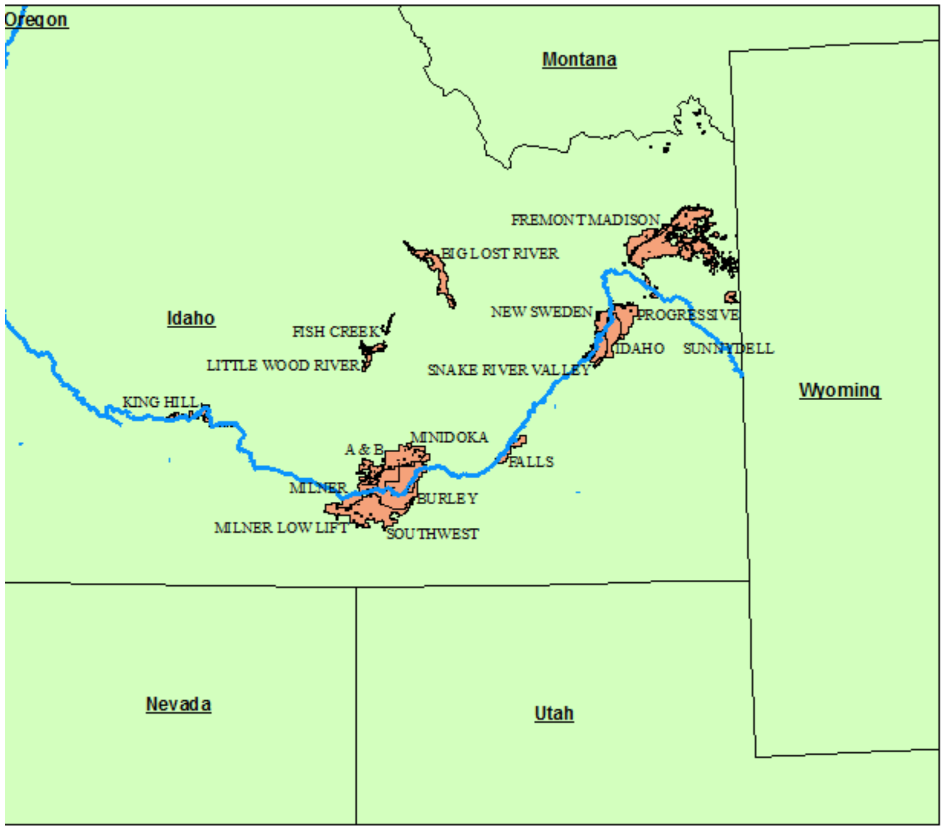

Figure 2: Irrigation Districts in the East Snake River Plain. Dark(blue) line denotes the main stem of the Snake River. Captions are the names of the respective irrigation districts.

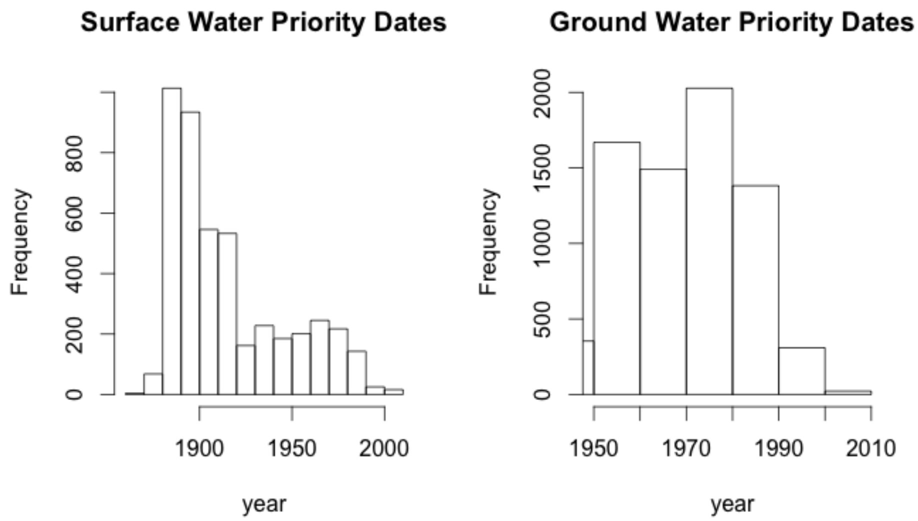

Figure 3: Water Rights Distribution Across Time. Left panel shows the appropriation date for surface water rights. Right panel shows the appropriation date for groundwater rights.

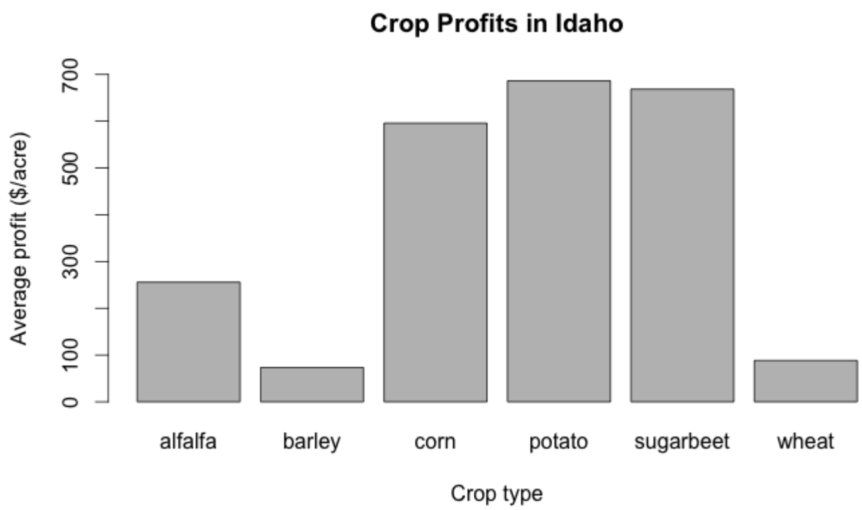

Figure 4: Average crop profits in Idaho, 2006-2013

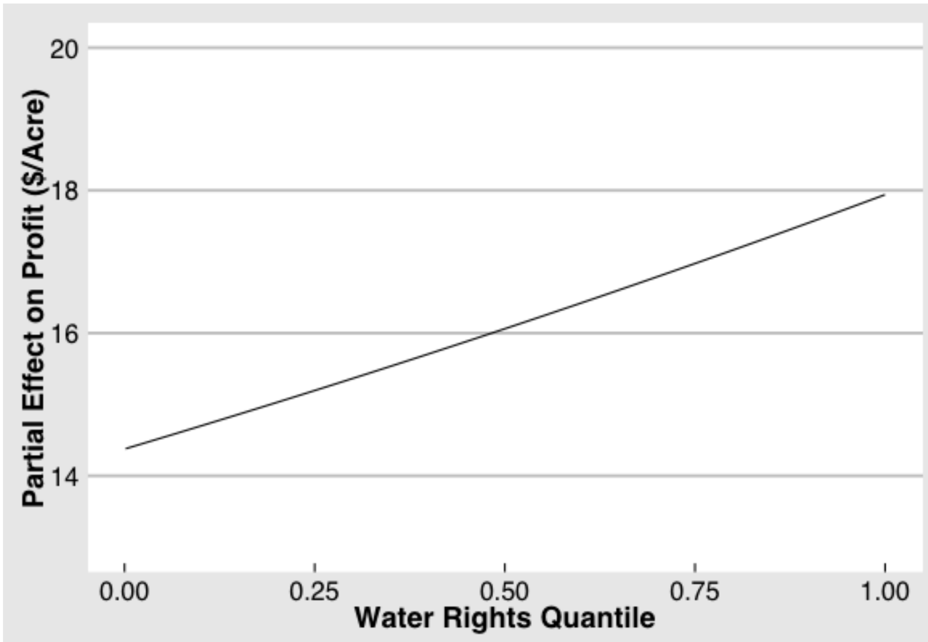

Figure 5: Partial effects of *IrrDist* at different levels of water rights quantile. The x-axis shows the distribution of water rights quantile, with 0 being the most senior, and 1 being the most junior water right. The y-axis shows the monetary value ($/acre) of the discrete effect of residing in an irrigation district.

Table 1: Description of Variable Names and Sources

Variable Name	Variable Description	Unit	Source
Area	area of individual farms	Acres	IDWR
DistArea	area of irrigation districts	Acres	
IrrDist	irrigation district dummy		
GrndSurf	groundwater dummy		
QmeanSurf	mean of water rights seniority quantile		
QsdSurf	standard deviation of water rights seniority quantile		
corn	fraction of corn planted		USDA CDL
wheat	fraction of wheat planted		
barley	fraction of barley planted		
alfalfa	fraction of alfalfa planted		
sugarbeet	fraction of sugarbeet planted		
potato	fraction of potato planted		
fallow	fraction of land fallowed		
exml3	average number of extreme heat days in last 3 years	days	PRISM
gddl3	average number of growing degree days in last 3 years	degree days	
precl3	average total summer precipitation in last 3 years	mm*100	
icclass	irrigated soil capacity class		SSURGO
nicclass	non-irrigated soil capacity class		
slope	average slope of land		
ydwheat	average yield factor for wheat	bu/hectare	
ydcorn	average yield factor for corn	bu/hectare	
claypc	percentage of clay in soil		
kfactor	soil k-factor		
pbarley	average normalized price for barley in the last year		USDA NASS
pcorn	average normalized price for cornin the last year		
pwheat	average normalized price for wheat in the last year		
psugarbeet	average normalized price for sugarbeet in the last year		
ppotato	average normalized price for potato in the last year		

Table 2: Summary Statistics of Variables. Number of observation N=7792.

Variable Name	Mean	Median	Min	Max	Std Dev
Area	206.701	94.689	2.340	6530.334	447.33
Dist_Area	37227.763	29642.514	3802.455	98166.152	28673.725
IrrDist	0.015	0	0	1	0.123
GrndSurf	0.103	0	0	1	0.304
QmeanSurf	0.54	0.546	0.001	1	0.28
QsdSurf	0.041	0	0	0.458	0.084
corn	0.144	0	0	1	0.286
wheat	0.119	0.005	0	1	0.232
barley	0.146	0.007	0	1	0.268
alfalfa	0.47	0.429	0	1	0.393
sugarbeet	0.019	0	0	1	0.105
potato	0.053	0	0	1	0.166
fallow	0.048	0	0	1	0.148
exml3	12.031	4.708	0	94.923	16.107
gddl3	1497.274	1482.925	860.119	2004.202	256.3
precl3	52.273	49.368	15.762	148.713	24.314
icclass	3.393	3.109	2	6	0.684
nicclass	5.557	6	3	6	0.938
slope	2.748	2.025	1	15.818	2.155
ydwheat	78.213	80	30	120	21.299
ydcorn	65.862	60	40	149.876	26.994
claypc	12.07	11.667	1.5	42.254	7.509
kfactor	0.271	0.254	0.02	0.57	0.13
pbarley	3.183	3.244	2.548	4.616	0.62
pcorn	3.271	3.469	2.149	4.15	0.616
pwheat	3.923	4.132	3.188	4.728	0.573
psugarbeet	30.306	29.593	20.725	45.118	8.208
ppotato	4.532	4.016	3.557	6.378	0.993

Table 3: Fractional multinomial logit parameter estimates

Variables	barley	corn	potato	sugarbeet	wheat	fallow
IrrDist	0.0499	-0.107	0.53***	1.63***	0.443***	0.167
	(0.0828)	(0.0869)	(0.0779)	(0.128)	(0.0591)	(0.136)
QmeanSurf	-0.099	-0.139	0.00372	0.271	0.143	0.325*
	(0.0964)	(0.112)	(0.146)	(0.266)	(0.1)	(0.154)
QsdSurf	0.341	-0.116	-0.049	-1.41	0.23	0.527
	(0.256)	(0.362)	(0.41)	(0.824)	(0.264)	(0.494)
GrndSurf	-0.247***	0.626***	0.356**	0.705***	-0.015	0.492***
	(0.0733)	(0.0854)	(0.111)	(0.163)	(0.0753)	(0.115)
pcorn	-0.964**	0.769	2.24***	-0.942	-0.148	-6.82***
	(0.373)	(0.449)	(0.542)	(0.991)	(0.395)	(0.784)
pbarley	0.0817	-0.347***	-0.302**	-0.213	-0.208***	-0.575***
	(0.0661)	(0.0719)	(0.102)	(0.155)	(0.0614)	(0.108)
pwheat	0.263	-0.113	-0.826*	0.325	0.896**	4.82***
	(0.266)	(0.297)	(0.374)	(0.672)	(0.279)	(0.597)
psugarbeet	0.0863**	-0.0204	-0.236***	0.113	0.00119	0.634***
	(0.0326)	(0.0392)	(0.0471)	(0.0859)	(0.0342)	(0.0685)
ppotato	-0.353	0.00678	1.14***	-0.386	-0.205	-3.78***
	(0.191)	(0.221)	(0.268)	(0.494)	(0.202)	(0.43)
exml3	-0.0248***	-0.013***	0.00759	-0.0544***	-0.00764*	0.00345
	(0.00491)	(0.00354)	(0.0048)	(0.00978)	(0.00353)	(0.0043)
gddl3	-0.00407***	0.00422***	0.000943	0.00215*	0.000528	-0.00474***
	(0.000308)	(0.000446)	(0.000534)	(0.000961)	(0.000315)	(0.00053)
precl3	-0.0218***	0.00259	0.0216***	-0.0211*	0.0159***	-0.0593***
	(0.00232)	(0.00375)	(0.00404)	(0.00877)	(0.0027)	(0.00443)
icclass	-0.268***	0.0305	-0.344***	-0.876***	-0.42***	-0.112
	(0.0554)	(0.0579)	(0.088)	(0.222)	(0.0644)	(0.0695)
nicclass	0.19***	0.593***	0.385***	1.25***	0.496***	0.766***
	(0.0338)	(0.0762)	(0.0695)	(0.164)	(0.0429)	(0.0678)
slope	0.0376	0.0371	0.0969**	0.217***	0.115***	0.154***
	(0.0202)	(0.0193)	(0.0295)	(0.0599)	(0.0229)	(0.0194)
ydwheat	0.000569	0.0187***	-0.0139***	-0.0121	-0.00646***	-0.0187***
	(0.00175)	(0.00313)	(0.00297)	(0.00638)	(0.00195)	(0.00248)
ydcorn	-0.00276	0.00633***	-0.00497	0.00645	-0.00197	-0.0144***
	(0.00178)	(0.00157)	(0.00276)	(0.00472)	(0.00205)	(0.00248)
claypc	-0.0452***	-0.0412***	-0.0689***	-0.02	-0.0225***	-0.0457***
	(0.00437)	(0.0078)	(0.00927)	(0.0141)	(0.00578)	(0.00588)
kfactor	3.78***	2.19***	5.82***	5.33***	3***	1.22***
	(0.219)	(0.371)	(0.382)	(0.651)	(0.269)	(0.301)
Number of Obs: 7792						
Log pseudo-likelihood: -10525.69						

[a] Note: Papke and Wooldridge (1996)'s robust standard error reported in parenthesis. Alfalfa is the baseline choice and thus omitted. Year dummy and constant are suppressed from the table. A triple asterisk indicates $p < 0.001$; a double asterisk indicates $p < 0.01$; a single asterisk indicates $p < 0.05$.

Table 4: Average partial effects of fractional multinomial logit estimates

Variable	alfalfa	barley	corn	potato	sugarbeet	wheat	fallow
IrrDist	-0.0792***	-0.0126	-0.0161**	0.0233***	0.0406***	0.0433***	0.000669
	(0.0149)	(0.00962)	(0.0058)	(0.00379)	(0.00164)	(0.00692)	(0.00532)
GrndSurf	-0.0438***	-0.0379***	0.0483***	0.0156*	0.01***	-0.0117	0.0193**
	(0.0127)	(0.0111)	(0.00778)	(0.00771)	(0.00289)	(0.0112)	(0.00614)
QmeanSurf	-0.00672	-0.0146	-0.0107	-0.000413	0.0032	0.0168	0.0124
	(0.0169)	(0.0143)	(0.0104)	(0.00961)	(0.004)	(0.0134)	(0.00683)
QsdSurf	-0.0382	0.0361	-0.013	-0.0059	-0.0182	0.0208	0.0182
	(0.0528)	(0.0302)	(0.0248)	(0.0205)	(0.0111)	(0.0298)	(0.0192)
pcorn	0.147***	-0.0929***	0.0726***	0.127***	-0.00842***	0.0144***	-0.26
	(2.64e-09)	(1.71e-08)	(5.02e-11)	(5.68e-13)	(7.19e-07)	(1.07e-09)	(0.486)
pbarley	0.046***	0.0215***	-0.0188***	-0.0112***	-0.00163***	-0.0162***	-0.0196***
	(0.00157)	(0.000503)	(0.00121)	(0.00105)	(0.000291)	(0.00121)	(0.00191)
pwheat	-0.167***	-0.00423***	-0.0287***	-0.0568***	0.000378	0.077***	0.179
	(2.12e-08)	(9.64e-07)	(6.51e-07)	(1.36e-07)	(0.000875)	(1.51e-05)	(0.447)
psugarbeet	-0.014***	0.00813***	-0.00318***	-0.0132***	0.00109	-0.003***	0.0242
	(2.08e-09)	(5.05e-07)	(5.6e-08)	(2.73e-10)	(0.000742)	(3.75e-08)	(0.0567)
ppotato	0.0957***	-0.0242***	0.0124***	0.0666***	-0.00268***	-0.00469***	-0.143
	(1.29e-07)	(1.31e-07)	(1.69e-08)	(1.09e-10)	(2.9e-07)	(6.84e-08)	(0.233)
exml3	0.00302***	-0.00257***	-0.000544	0.000655**	-0.000605*	-0.000296	0.000348
	(0.000566)	(0.000744)	(0.000297)	(0.000244)	(0.000262)	(0.000473)	(0.000181)
gddl3	0.000161***	-0.000499***	0.000318***	6.23e-05***	3e-05***	0.000104***	-0.000177
	(1.39e-06)	(8.98e-05)	(3.11e-10)	(4.35e-08)	(5.26e-09)	(1.09e-07)	(0.000115)
precl3	0.00123***	-0.00259***	0.000336***	0.00121***	-0.000233***	0.00231***	-0.00226***
	(0.000153)	(9.61e-05)	(2.18e-05)	(6.07e-06)	(2.97e-05)	(1.42e-05)	(0.000313)
icclass	0.0678***	-0.0195*	0.0106***	-0.0114	-0.00933	-0.0384**	3e-04
	(0.0097)	(0.00887)	(0.00277)	(0.00908)	(0.0334)	(0.0126)	(0.00311)
nicclass	-0.111***	-0.00073	0.028	0.00958	0.013***	0.0385*	0.0226*
	(0.000215)	(0.00453)	(0.0327)	(0.03)	(0.00149)	(0.0167)	(0.0115)
slope	-0.0204***	0.000209	7.84e-05	0.00309	0.00224**	0.0101**	0.00468***
	(0.00273)	(0.00353)	(0.00208)	(0.00214)	(0.000857)	(0.00344)	(0.000974)
ydwheat	0.000583***	0.000211***	0.00139***	-0.000652***	-0.000137***	-0.000696***	-0.000701***
	(8.38e-05)	(1.52e-05)	(3.25e-06)	(3.27e-05)	(1.92e-05)	(2.84e-05)	(2.93e-05)
ydcorn	0.000518**	-0.000244***	0.000511***	-0.000206***	9.09e-05***	-0.000135***	-0.000536***
	(0.000191)	(2.69e-05)	(6.19e-06)	(1.75e-05)	(5.54e-06)	(2.93e-05)	(2.08e-05)
claypc	0.00981***	-0.00367***	-0.00169***	-0.00262***	-3.36e-05	-0.000671	-0.00113***
	(0.000936)	(0.000352)	(0.000343)	(0.000387)	(9.32e-05)	(0.000376)	(0.00015)
kfactor	-0.82***	0.307***	0.0524**	0.222***	0.0479***	0.199***	-0.00883
	(0.0521)	(0.0148)	(0.0192)	(0.00583)	(0.0027)	(0.0209)	(0.0112)

[a] Note: Robust standard error reported in parenthesis, calculated via the Krinsky-Robb method. Discrete effects are reported for binary variables *IrrDist* and *GrndSurf*. Marginal effects are reported for all other variables. Year dummies and constant are suppressed from reporting. A triple asterisk indicates $p < 0.001$; a double asterisk indicates $p < 0.01$; a single asterisk indicates $p < 0.05$.

Table 5: Model estimates of average partial effect on profits ($/acre)

	Models		
	(1)	(2)	(3)
Variables	FMNL	OLS	RE
IrrDist	16.2(5.98)**	15.62***(4.373)	15.68*(9.082)
GrndSurf	31.2(8.06)***	34.91***(5.439)	33.94***(10.47)
QmeanSurf	-5.8(10.4)	-2.095(6.373)	-5.492(10.52)
QsdSurf	-29.2(25.5)	-47.15***(17.43)	-48.79(30.76)
pcorn	157(0.000444)***	81.46***(12.09)	80.87***(10.13)
pbarley	-8.07(1.12)***	-5.971*(3.147)	-5.466*(2.805)
pwheat	-92.1(0.786)***	-67.59***(9.737)	-71.13***(8.184)
psugarbeet	-13.5(0.52)***	-6.719***(1.270)	-6.278***(1.050)
ppotato	73.6(0.000349)***	42.44***(8.114)	44.13***(6.625)
exml3	0.278(0.34)	0.167(0.216)	0.629**(0.261)
gddl3	0.266(0.00666)***	0.235***(0.0207)	0.159***(0.0292)
precl3	1.2(0.0459)***	0.922***(0.148)	0.251*(0.151)
icclass	4.78(23)	7.819**(3.337)	8.935(5.943)
nicclass	6.92(28.9)	-3.344(2.245)	-1.401(3.727)
slope	-0.646(2.18)	-0.796(1.233)	-0.890(1.989)
ydwheat	0.394(0.0344)***	0.787***(0.136)	0.920***(0.220)
ydcorn	0.327(0.05)***	0.630***(0.114)	0.415**(0.162)
claypc	-0.641(0.421)	-1.345***(0.332)	-1.766***(0.536)
kfactor	46.1(18.3)*	76.25***(18.23)	84.61***(28.60)

[a] Note: Column 1 shows the average partial effect on profits derived from the fractional multinomial logit (FML) model. Column 2 and 3 show linear estimates of farm profits using pooled ordinary least square (OLS) and panel random effect (RE) models. Robust standard errors reported in parenthesis. A triple asterisk indicates p < 0.001; a double asterisk indicates p < 0.01; a single asterisk indicates p < 0.05.

Table 6: Fractional multinomial logit model estimates on farm area variables

APE: Crop Type(%)	(1) logArea	(2) Area
alfalfa	-0.0522(0.00267)***	-8.1e-05(9.91e-06)***
barley	0.00162(0.00526)	6.74e-06(5.02e-06)
corn	0.0137(0.00254)***	1.73e-05(2.53e-06)***
potato	0.00909(0.00232)***	1.58e-05(1.36e-06)***
sugarbeet	0.00266(0.000881)**	5.04e-06(5.95e-07)***
wheat	0.0192(0.00419)***	3.93e-05(3.45e-06)***
fallow	0.00601(0.00229)**	-3.14e-06(2.78e-06)
APEP: profit ($/acre)		
profit	4.604(2.464)	0.00772(0.00315)*

[a] Note: Model (1) includes the natural log of farm area (in acres) as an explanatory variable, and model (2) includes the level of farm area. All other control variables except the irrigation district dummy are included. Robust standard errors reported in parenthesis. A triple asterisk indicates $p < 0.001$; a double asterisk indicates $p < 0.01$; a single asterisk indicates $p < 0.05$.