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"The Relationship between Priority and Value of Irrigation Water Used with Prior Appropriation Water Rights" by Gi-Eu Lee, Kimberly Rollins, and Loretta Singletary

Appendix

A.1. Water Rights with a Common Owner and/or Shared Headgate

Table A.1 below shows the numbers of water rights clustered by common owners and by shared headgates. To account for potential correlations in error terms generated by these clusters, we define a "common-owner *o*" cluster as contiguous lands with a single owner, and a "headgate *g"* cluster for lands sharing the same river headgate and point of diversion. Assuming only one cluster level, Equation [1] can be re-written as [2] and [3] below, in which *g* represents the g^{th} headgate cluster and *o* is the o^{th} cluster of contiguous lands with a single owner. Equation [4] allows for both types of clusters.

$$Priority_{i,g} = \alpha + \boldsymbol{\gamma Z_{i,o}} + \boldsymbol{\beta\, X_{i,o}} + T_i(\boldsymbol{\gamma_p Z_{i,o}} + \boldsymbol{\beta_p X_{i,o}}) + \delta T_i + u_{i,o} \quad [2]$$

$$Priority_{i,o} = \alpha + \boldsymbol{\gamma Z_{i,o}} + \boldsymbol{\beta\, X_{i,o}} + T_i(\boldsymbol{\gamma_p Z_{i,o}} + \boldsymbol{\beta_p X_{i,o}}) + \delta T_i + u_{i,g} \quad [3]$$

$$Priority_{i,og} = \alpha + \boldsymbol{\gamma Z_{i,og}} + \boldsymbol{\beta\, X_{i,og}} + T_i(\boldsymbol{\gamma_p Z_{i,og}} + \boldsymbol{\beta_p X_{i,og}}) + \delta T_i + u_{i,og} \quad [4]$$

The subscripts index non-repeated observation *i* in cluster *o* or *g*. In Equation [2] and [3], $u_{i,o} = c_o + \varepsilon_{i,o}$ and $u_{i,g} = c_g + \varepsilon_{i,g}$, where c denotes the unobserved within-cluster correlation. In Equation [4], common-owner and headgate clusters are considered together and $u_{i,og} = v_o + c_{og} + \varepsilon_{i,og}$, as v_o denotes unobserved constant correlation of cluster o, and c_{og} denotes the correlation of cluster *g*. The nested structure of clusters is represented by the order of subscripts. Thus, Equation [4] assumes the headgate cluster is nested within a common-owner cluster. An alternative assumption is common-owner clusters are nested within headgate clusters thereby switching the order of subscripts. We may also assume that the two sets of clusters are crossed rather than nested. In this case, $u_{i,og} = v_o + c_g + \varepsilon_{i,og}$ and the order of cluster subscripts has no meaning. Table 3 reports findings for Equation [3] and Equation [4]. We also estimate the model using alternative cluster structures and find the results are robust. Cameron and Miller (2015) describe how to apply these methods using cross-sectional data.

Table A.1. Numbers of Water Rights per Headgate and Common-Owner Clusters

Number of Water Rights per Headgate Cluster	Frequency	Number of Water Rights per Common-Owner Cluster	Frequency
66	1	22	1
15	1	16	1
14	1	13	1
12	2	9	4
11	2	8	2
10	1	7	4
9	1	6	2
8	2	5	8
7	4	4	9
6	7	3	13
5	6	2	19
4	11	1	117
3	10		
2	15		
1	33		

A.2. Effective Number of Clusters

A rule of thumb threshold of 50 clusters generally is used for cluster-robust inference. In our data, the number of observations in each cluster is unequal and so the asymptotic property may no longer hold (Carter, Schnepel, and Steigerwald 2017). Under this circumstance, Carter, Schnepel, and Steigerwald (2017) suggest the effective number of clusters as an alternative measurement. When the effective number of clusters is less than 50, Cameron, Gelbach, and Miller (2008), MacKinnon and Webb (2017), as well as Lee and Steigerwald (2018) suggest using wild bootstrapping to estimate the variance.

Among the three models used, only the OLS regression with the CRV estimator may suffer from this issue. The RE and ME models are unlikely affected because they do not rely on the CRV estimator to address the within-cluster correlation. While the variance estimators used in RE and ME are robust to heteroscedasticity, we find that our test results and conclusions do not change when variance is obtained by the regular non-robust estimator. We report these results in Table A.2.1 below.

To address the concern associated with the OLS results, we first calculate the effective number of clusters using Lee and Steigerwald's (2018) Stata command. We find that for some variables the effective number of clusters falls below 50. However, a feature of our dataset may relieve concern regarding the number of clusters. According to Carter, Schnepel, and Steigerwald (2017), if the covariate is uncorrelated within clusters, the corresponding test statistic is minimally affected even if the effective cluster number is small. We find this is the case for our key variables of interest, the interaction terms for alfalfa and grass hay productivity.

Cameron, Gelbach, and Miller (2008), MacKinnon and Webb (2017), as well as Lee and Steigerwald (2018) suggest that wild bootstrapping can produce a more conservative test statistic when the effective number of clusters is below the threshold. We find that after implementing wild bootstrapping for the key coefficients of the OLS regression, the test results, reported in Table A.2.2, are unchanged. Thus, our conclusions remain the same.

Table A.2.1. Regression Results of Current Alpine Decree: Regular Variance Estimator

	(1) OLS	(2) RE	(3) ME
Alfalfa	2.829***	2.773***	2.442***
	(0.475)	(0.474)	(0.472)
Grass	-5.139*	-4.762*	-4.170
	(2.721)	(2.740)	(2.974)
Dist_River	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)
Sup_Source	-1.045	-1.233+	-1.023
	(0.752)	(0.787)	(0.869)
WestFork	-7.443***	-7.931***	-9.381***
	(1.609)	(1.676)	(1.861)
M_Carson	-8.438*	-8.265*	-6.983
	(4.377)	(4.423)	(4.857)
LandSize	-0.014**	-0.012**	-0.009*
	(0.005)	(0.005)	(0.005)
Transferred	20.786***	20.556***	18.773***
	(5.036)	(4.991)	(4.970)
Alfalfa_T	-3.534***	-3.558***	-3.414***
	(1.318)	(1.309)	(1.221)
Grass_T	6.295	4.399	0.932
	(7.168)	(7.132)	(7.109)
Dist_River_T	-0.006***	-0.006***	-0.005***
	(0.002)	(0.002)	(0.002)
Sup_Source_T	-11.043***	-9.607**	-7.931**
	(4.252)	(4.243)	(4.032)
WestFork_T	-19.618***	-17.282***	-12.099**
	(5.434)	(5.597)	(5.970)
M_Carson_T	-15.796**	-15.859**	-15.623*
	(7.431)	(7.487)	(8.097)
LandSize_T	0.041***	0.036***	0.027**
	(0.012)	(0.012)	(0.011)
Constant	1867.536***	1867.732***	1868.216***
	(1.440)	(1.519)	(1.683)

Standard errors in parentheses. In ME regression, headgate is nested under comingled groups.
$^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2.2 Testing Coefficients of Key Variables Using Wild Bootstrapping

Variable	Test Statistics		Significance
One Cluster	(Common-owner)		
Alfalfa	t =	5.2290	***
	Prob>|t| =	0.0000	
Alfalfa_T	t(181) =	-2.5624	*
	Prob>|t| =	0.0681	
Grass	t(181) =	-2.0460	*
	Prob>|t| =	0.0711	
Grass_T	t(181) =	1.6825	
	Prob>|t| =	0.2112	
Two Clusters	(Common-owner_Headgate)		
Alfalfa	t(96) =	4.4966	***
	Prob>|t| =	0.0020	
Alfalfa_T	t(181) =	-2.5768	*
	Prob>|t| =	0.0591	
Grass	t(96) =	-3.1673	*
	Prob>|t| =	0.0711	
Grass_T	t(181) =	1.9230	
	Prob>|t| =	0.2583	

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

A.3. Spatial Autocorrelation

As described in the Data section, potential interdependence occurs among observations of water rights within the same headgate or located contiguously under single ownership. Thus, correlation is not solely a function of distance, as is more typical of spatial autocorrelation models. To verify that our results are also robust to potential spatial autocorrelation, we estimate Equation (1) using the spatial-autoregressive model developed by Drukker, Prucha, and Raciborski (2013) and the HAC variance estimators developed by Hsiang (2010).

Drukker, Prucha, and Raciborski's (2013) model addresses spatial autocorrelation of cross-sectional data through maximum likelihood and two-stage least square methods. Hsiang's (2010) method only corrects for the correlations in variance while the coefficients are estimated by OLS. Further, Hsiang's (2010) variance estimator is robust to both spatial correlation and serial correlation using panel data. Given our data structure, Hsiang's (2010) estimator implies the variance estimator is robust to potential cross-cluster correlation and within-cluster correlation.

Since our data are essentially cross-sectional, to apply Hsiang's (2010) method, we need to define a "time sequence" for observations within the same cluster. However, there is no real order of time causing sequential influences among the observations. Thus, we use four ways to determine a "time sequence" within each cluster: 1) "time period" is ordered from the largest to smallest land area; 2) "time period" is ordered from smallest area; 3) "time period" is ordered from most senior water right priority, and 4) "time period" is randomly assigned by a normal distribution function.

Table A.3.1 reports results using Drukker, Prucha, and Raciborski's (2013) method in column (1) and Hsiang's (2010) method in columns (2) to (5) given these four ways in which we determine time sequence. We find that the results are similar to those reported in the main text. In particular, the key variable of interest, the interaction term of alfalfa productivity, remains significant and negative. These results suggest our findings are robust to spatial autocorrelation.

Table A.3.1 Regression Results from Spatial Autocorrelation Models

	(1)	(2)	(3)	(4)	(5)
Alfalfa	2.331***	2.829***	2.829***	2.829***	2.829***
	(0.511)	(0.525)	(0.530)	(0.533)	(0.514)
Grass	-3.921	-5.139**	-5.139**	-5.139**	-5.139**
	(2.897)	(2.185)	(2.353)	(2.322)	(2.341)
Dist_River	0.006***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sup_Source	-0.568	-1.045+	-1.045+	-1.045	-1.045+
	(0.809)	(0.721)	(0.723)	(0.773)	(0.675)
WestFork	-9.321***	-7.443***	-7.443***	-7.443***	-7.443***
	(2.189)	(2.324)	(2.406)	(2.394)	(2.243)
M_Carson	-8.747*	-8.438*	-8.438*	-8.438*	-8.438*
	(4.862)	(4.679)	(4.778)	(4.686)	(4.764)
LandSize	0.001	-0.014***	-0.014***	-0.014***	-0.014***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Transferred	14.522***	20.786***	20.786***	20.786***	20.786***
	(4.748)	(6.393)	(6.382)	(6.278)	(6.353)
Alfalfa_T	-2.615**	-3.534**	-3.534**	-3.534***	-3.534***
	(1.243)	(1.379)	(1.380)	(1.344)	(1.346)
Grass_T	2.873	6.295*	6.295*	6.295*	6.295*
	(6.589)	(3.549)	(3.663)	(3.615)	(3.549)
Dist_River_T	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Sup_Source_T	-11.169***	-11.043***	-11.043***	-11.043***	-11.043***
	(3.940)	(4.012)	(4.001)	(3.496)	(3.436)
WestFork_T	-13.042**	-19.618***	-19.618***	-19.618***	-19.618***
	(5.583)	(6.725)	(6.757)	(6.768)	(6.653)
M_Carson_T	-13.894*	-15.796**	-15.796**	-15.796**	-15.796**
	(7.441)	(7.049)	(7.103)	(6.976)	(7.071)
LandSize_T	0.023**	0.041***	0.041***	0.041***	0.041***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	1872.733***	1867.536***	1867.536***	1867.536***	1867.536***
	(1.967)	(1.970)	(1.951)	(1.982)	(1.907)

Results using Drukker, Prucha, and Raciborski's (2013) method are reported in column 1 and results using Hsiang's (2010) method reported in columns (2) through (5), with the cutoffs set by maximum lags and distance in the data. "Time sequence" is ordered from largest land area in column (2), from smallest land area in column (3), from most senior priority in column (4), and randomly assigned in column (5). $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4. Influence of Supplemental Groundwater Permits

A small number of groundwater permits in the study region are used to supplement water supply shortages. The variable *Sup* indicates the number of supplemental groundwater permits to capture their influence on surface water right allocation. Since the effects of supplemental sources may also depend on other land features, we revise the model in Equation [1] to allow for supplemental groundwater permits to interact with permitted water transfers and other variables. In this setup, the triple interaction term represents the effect of a water transfer for a specific covariate, such as alfalfa productivity, given the number of supplemental groundwater permits. For robustness, we replace *Sup* with a dummy variable indexing the existence of supplemental groundwater permits (*SWG*). These regression results are reported in Table A.4.1.

Under the triple interaction model, we find the coefficients for *Alfalfa_T* are generally significant at the 90% level, which suggests our conclusions remain unchanged for observations without supplemental groundwater permits. In the top panel, the coefficients on the triple interaction term for alfalfa are negative, although not significant. This implies that with greater alfalfa productivity, a farmer who is permitted to pump supplemental groundwater when surface water flows are insufficient may be indifferent to seeking a more senior water right. The results are similar when the total number of supplemental groundwater permits is used to replace the dummy variable for supplemental groundwater permits (bottom panel). We find the coefficients of the triple interaction term for alfalfa are significant with a negative sign, implying that that one additional supplemental groundwater permit enlarges the permitted surface water transfer effect by associating more senior priority with greater alfalfa productivity. Overall, as the coefficients of the triple interaction terms with alfalfa are negative, significant or not, our main conclusions remain unchanged.

Table A.4.1 Regression Results of Triple Interaction Model: Supplemental Groundwater Permit Index (Top Panel) and Numbers of Supplemental Permits (Bottom Panel)

	(1) OLS-CRV	(2) RE	(3) ME
Alfalfa	2.217***	2.167***	1.905***
	(0.592)	(0.555)	(0.533)
Grass	-13.399***	-13.116***	-12.612***
	(3.552)	(3.503)	(3.446)
Transferred	20.892**	20.296**	18.318**
	(9.269)	(8.693)	(8.309)
Alfalfa_T	-2.932*	-2.964*	-2.860**
	(1.692)	(1.539)	(1.332)
Grass_T	11.554**	9.549*	6.838
	(5.260)	(5.042)	(4.898)
Alfalfa#SGW	1.562^{+}	1.545^{+}	1.466^{+}
	(1.052)	(1.014)	(0.971)
Grass#SGW	11.705***	12.241***	11.792***
	(4.416)	(4.431)	(4.381)
Alfalfa_T#SGW	-6.806*	-4.785	-2.353
	(4.060)	(3.448)	(2.725)
Grass_T#SGW	181.829**	136.390**	103.566^{+}
	(73.054)	(66.312)	(69.061)
Alfalfa	2.560***	2.447***	2.158***
	(0.572)	(0.528)	(0.514)
Grass	-12.706***	-12.096***	-11.764***
	(3.175)	(3.083)	(3.115)
Transferred	16.898*	16.742*	14.612*
	(9.462)	(8.760)	(8.532)
Alfalfa_T	-2.662^{+}	-2.758*	-2.535**
	(1.682)	(1.468)	(1.272)
Grass_T	15.898***	12.616***	8.088^{+}
	(5.047)	(4.847)	(5.248)
Alfalfa#Sup	0.458	0.541	0.524
	(0.494)	(0.462)	(0.416)
Grass#Sup	10.863***	10.963***	10.858***
	(3.237)	(3.193)	(3.270)
Alfalfa_T#Sup	-2.837**	-2.643***	-2.465***
	(1.133)	(0.936)	(0.730)
Grass_T#Sup	93.850***	79.885***	83.882*
	(30.836)	(30.407)	(45.317)

Note: Variables interacted with *Transferred* are indexed with *_T*. Cluster robust standard errors are reported in parentheses of the OLS column. Heteroskedasticity robust standard errors are in parentheses of the RE and ME columns. Cluster is defined by common-owner cluster in the OLS-CRV and RE estimators. In the ME model, headgate is nested under common-owner clusters. Significance levels are: $^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix References

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