IRRIGATION WATER DEMAND: PRICE ELASTICITIES AND CLIMATIC DETERMINANTS IN THE GREAT LAKES REGION

By

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ABSTRACT

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Even in a water abundant context, the spatial and temporal concentration of irrigation withdrawals can create water scarcity. Many studies have explored irrigation management behavior in the western U.S. Comparatively, the determinants of irrigation behavior in a water abundant context have not been extensively studied. This paper explores the environmental and market determinants of irrigation management in a five-state Great Lakes region. I find evidence that corn, soybean, and potato irrigators respond to the cost of water at the intensive margin. Evidence of a water-price effect at the extensive margin is mixed. Additionally, this study is unique in its consideration of the water-use effects from extreme heat and precipitation variability. I find important effects of long-run average temperature on crop acreage allocation decisions and short-run extreme heat events on water application rates. Though I do not find evidence of a water-use response to intra-seasonal precipitation variability, I present a number of precipitation variability and drought measures that might be considered in future research.

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CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

A relative abundance of research explores water management decisions within regions that suffer from particularly thorny resource challenges, for example, the activities of western irrigation districts or the mining of the Ogallala Aquifer. Little is known, however, about the factors that drive the decisions of supplemental irrigators operating in the eastern U.S., a region characterized by relative water abundance. Yet, even these water-abundant regions are not free from water resource concerns. In water-abundant regions, irrigation water withdrawals can lead to surface water scarcity, especially when they are seasonally and spatially concentrated (Mubako, Ruddell, and Mayer 2013). The transferability of results from western studies to a water-abundant context is limited by the structural differences in management behavior between regions (Moore, Gollehon, and Carey 1994).

A recent study noted that "even in relatively water-rich regions, withdrawal and consumption of water has the potential to create instream freshwater ecosystem water scarcity, especially at seasonal and local scales" (Mubako, Ruddell, and Mayer 2013, 671). This study explored the irrigation management behavior of firms in the Western Great Lakes Basin – Illinois, Indiana, Michigan, Minnesota, and Wisconsin.

Aquifers in the Great Lakes region tend to be shallow and connected to surface water resources, leading to sensitivity of surface water systems to groundwater withdrawals

(Wallander 2017). Importantly, Mubako et al. found that in the Kalamazoo River watershed in Southwest Michigan, “most instream water scarcity is caused by localized consumptive uses of water in late summer months at small spatial scales of less than 300 km^2” (2013, 678). The most extreme examples of scarcity occurred where there were heightened concentrations of irrigation withdrawals located specifically within a small-scale upland watershed. These intense localized withdrawals caused scarcity impacts that reverberated through downstream segments including the main river stem. Mubako et al. noted that irrigation withdrawals are particularly important drivers of scarcity because they typically occur at sensitive times and locations. Irrigation withdrawals are most heavily concentrated during low-flow summer months, and, unlike other consumptive withdrawals, they are most often located in “smaller-scale upland agricultural watersheds, where stream baseflows are relatively small and more vulnerable to seasonal changes.”

Mubako et al. selected the Kalamazoo River watershed as their study location using a set of criteria for generalizability. The Kalamazoo watershed possesses environmental and water-use characteristics that are typical of and thus reasonably generalizable to other midsize watersheds in water-rich regions. The Mubako et al. study, among others (Luukkonen et al. 2004; Zorn, Seelbach, and Rutherford 2012; Watson, Mayer, and Reeves 2014), suggests that adaptive management of water scarcity in water-rich regions like the

Great Lakes Region must address the sensitivity of aquatic ecosystems within localized scales of space and time.

1.2 Climate Context

A significant body of research explores the effects of climate change on agricultural yields. Deschénes and Greenstone (2007) found that climate change is likely to have a net positive effect on agricultural output and profit. In a conflicting result, Schlenker and Roberts (2009) found that yields are likely to diminish significantly before the end of the century due to the damaging effects of extreme heat events. The exploration of potential nonlinear effects of climate and weather conditions has not spilled over into the irrigation water demand literature.

The typical approach in the irrigation literature includes the estimation of linear temperature and precipitation effects. This approach excludes any important nonlinear temperature effects such as those identified by Schlenker and Roberts. Olen, Wu, and Langpap (2016) included an indicator for counties that are historically drought prone in their model of irrigation application rates. The literature has not addressed the effect of extreme heat or precipitation variability on water application rates. This thesis introduces measures of extreme heat and precipitation variability to the literature on irrigation demand.

1.3 Water Management Institutions in the States

Michigan, like most states in the relatively water abundant eastern United States, applies riparian doctrine to guide surface water allocation, an institution derived from the common law tradition (Lautenberger and Norris 2016). The three key provisions of riparian doctrine are as follows: “only riparians are legally entitled to make use of surface water; these water rights are not quantitatively fixed; each riparian’s water use must be ‘reasonable’ in relation to the water use of other riparians in the basin” (Griffin 2006, 121). Under the principle of reasonable use, a landowner has the right to use water that is adjacent to his property as long as his use does not unreasonably harm the water use of other riparians.

The application of the reasonable use principle to groundwater users emerged in Michigan common law to resolve conflicts between groundwater and surface water users (Lautenberger and Norris 2016). The right to use groundwater is vested in those who own the overlying land. When conflict occurs between two or more riparian users, two or more groundwater users, or between riparians and groundwater users, the courts must apply the principle of reasonable use. Water law rooted in riparian doctrine and the principle of reasonable use typically lacks a predictable system for prioritizing uses (Griffin 2006). This uncertainty leads to costly, unpredictable litigation for each unique case of conflict. The challenging nature of conflict resolution under Michigan’s legal institutions is generalizable to all Great Lakes States because the water use institutions in all Great Lakes States are rooted in the riparian tradition (Dellapenna 2005).

1.4 The Great Lakes Compact

The Great Lakes – St. Lawrence River Basin Water Resources Compact calls upon the Parties – Illinois, Indiana, Michigan, Minnesota, New York, Ohio, Pennsylvania, and Wisconsin −to "develop and maintain a water resources inventory for the collection, interpretation, storage, retrieval, exchange, and dissemination of information concerning the water resources of the party" (*Great Lakes—St. Lawrence River Basin Water Resources Compact* 2005). The Parties are also obligated to manage water withdrawals and consumptive uses:

> *Each Party shall create a program for the management and regulation of New or Increased Withdrawals and Consumptive Uses by adopting and implementing Measures consistent with the Decision-Making Standard. Each Party, through a considered process, shall set and may modify threshold levels for the regulation of New or Increased Withdrawals in order to assure an effective and efficient Water management program that will ensure that uses overall are reasonable, that Withdrawals overall will not result in significant impacts to the Waters and Water Dependent Natural Resources of the Basin, determined on the basis of significant impacts to the physical, chemical, and biological integrity of Source Watersheds…* (Great Lakes—St. Lawrence River Basin Water Resources Compact 2005, sec. 4.10.1)

The Compact outlines five criteria that collectively comprise the Decision-Making Standard for new withdrawals. In brief: withdrawn water must return to the source watershed less an allowance for consumptive use; withdrawals must be implemented to insure no significant individual or cumulative adverse resource impact; the withdrawal must incorporate environmentally sound and economically feasible water conservation measures; the withdrawal must be in compliance with all relevant law; and the withdrawal must be reasonable, taking into consideration the hydrological interconnection of water sources and the balance between water-use benefits – economic development, social development, and environmental protection. In accordance with the Compact, the States have implemented differing regulatory regimes for water withdrawal management.

In 2008 Michigan implemented a series of new laws to comply with the compact. This statutory development, along with a preceding 2005 Michigan Court of Appeals decision, expanded Michigan's legal structure to address the interaction between groundwater and surface water. These developments further changed the relations between water users and the public.

> *"Michigan's recent water use statutes have established a new legal relation that assigns to large quantity water users a duty to limit water use in order to protect the right of the public to benefit from the state's water resources. This new legal relation has no effect on the existing legal relations among water users, but it does decrease the amount of water available for withdrawal."*

"The new legal relation between the public and water users, administered through a cap on total withdrawals, increases the likelihood that conflicts will occur among water users." (Lautenberger and Norris 2016, 916)

Importantly, Michigan's new water use regime "limits the amount of available water, but it makes no effort to prioritize how available water should be used" (Lautenberger and Norris 2016, 916).

1.5 Study Objective

Consider the importance of cropland irrigators, who cumulatively compose the largest consumptive water use sector in Michigan (Seedang and Norris 2011, 6). Water resources are particularly sensitive to irrigation withdrawals because they tend to be temporally and spatially concentrated. Additionally, water use for agricultural irrigation has varied significantly in recent years, but, most notably in Michigan, there is an upward trend in agricultural water use in recent years. Due to limits in state reported water use data, the size and direction of a trend is less clear in the other states (see figure 1.1). Thus, an improved understanding of the conditions that drive irrigation decisions will make water-use conflicts more predictable and may serve as a guide for estimating the marginal product of irrigation water use in a supplemental irrigation context.

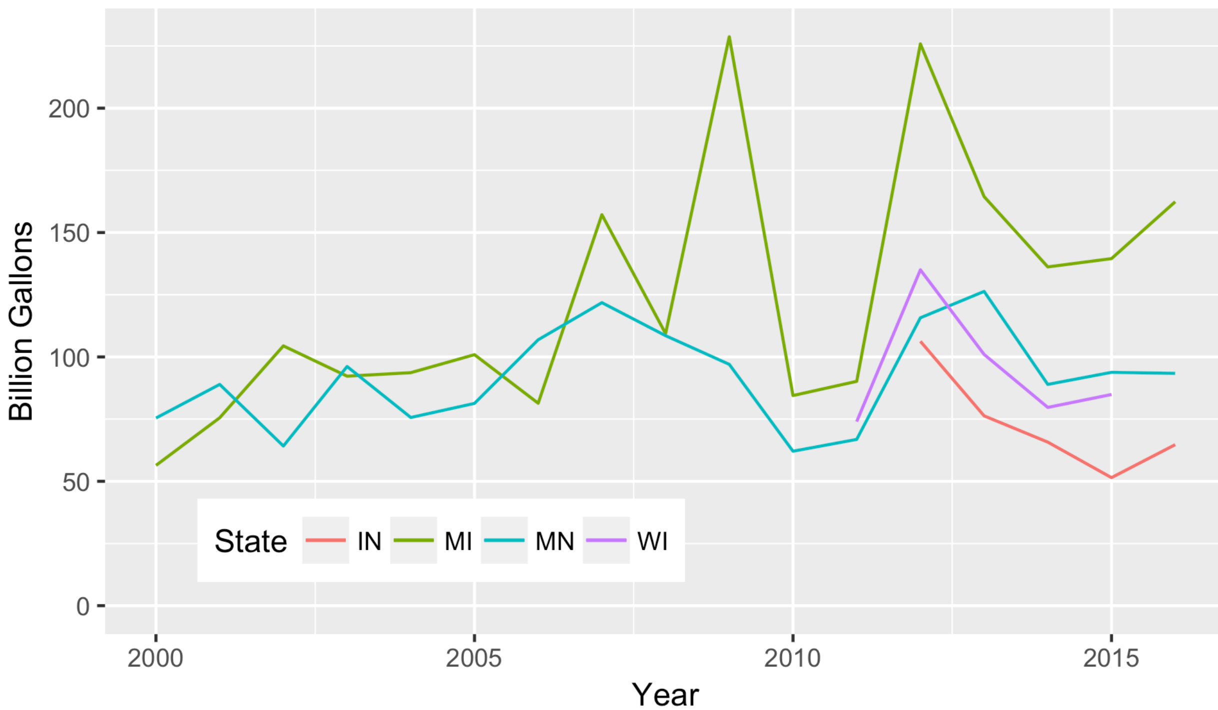

Figure 1.1 Agricultural irrigation water use by state
Source: State water use reporting documents (multiple)
IN: http://www.in.gov/dnr/water/4841.htm
MI: http://www.michigan.gov/deq/0,4561,7-135-3313_3684_45331-370128--,00.html
MN: https://www.dnr.state.mn.us/waters/watermgmt_section/appropriations/wateruse.html
WI: https://dnr.wi.gov/topic/WaterUse/WithdrawalSummary.html

The specific objective of this study is to estimate the water-use response of irrigators in water abundant regions to various climatological, environmental, and price conditions. Secondary data sources, including the Farm and Ranch Irrigation Survey conducted every five years, were used for this study, which is focused on the response of irrigators across water application, crop acreage, and technology adoption decisions. The intensive margin estimation addresses the annual irrigation water application rate per acre. The extensive margin estimation includes an acreage allocation decision and an irrigation investment decision. The crop acreage and water application results are related to provide an estimate of the long run elasticity of water use.

CHAPTER 2: THEORETICAL FRAMEWORK

2.1 Approaches in the Literature

The literature on irrigation demand has established a number of viable methods for demand estimation. Scheierling, Loomis, and Young (2006) distinguished between three broad categories of approach: mathematical programming, field experiment, and econometric.

Many early irrigation water demand studies employed mathematical programming methods, particularly linear programming, and deductive techniques (Frank and Beattie 1979). This is partly due to the fact that, historically, irrigation data has been available in in only limited forms (Ogg and Gollehon 1989). Mathematical programming approaches allow for great flexibility in extrapolating the model to produce results under hypothetical future conditions, but the reliability and accuracy of these results will depend on the strength of the assumptions. Generally, linear programming approaches are sensitive to assumptions about economic and technological conditions (Scheierling, Loomis, and Young 2006).

A second body of irrigation demand literature uses field experiments. These studies link agronomic data with economic production functions. The value marginal product of irrigation water can be estimated with the statistical relationship between plant yield and water application. Some studies also account for fertilizer application and weather

(Scheierling, Loomis, and Young 2006). Field experiment studies are inductive, similar to econometric studies, but the results are generated from smaller collections of data. The results of field experiment studies are typically more constrained to a limited set of conditions than econometric or mathematical programming studies. In a review of irrigation water demand research, Scheierling et. al. (2006) found that the price elasticities of water demand are generally very inelastic due to a lack of modeled adjustment possibilities.

Econometric approaches encompass the third major form of irrigation study. Early applications of this approach modeled total farm demand for irrigation water using price and fixed factor quantity data (Nieswiadomy 1985; Frank and Beattie 1979). Later approaches have used models of multi-output firms to allow for crop substitution (Moore, Gollehon, and Carey 1994; Hendricks and Peterson 2012; Mullen, Yu, and Hoogenboom 2009). Econometric studies are inductive in nature, employing historical data to determine the demand for agricultural inputs within the range of observed historical conditions. This approach produces results that are not as readily extrapolated to new sets of conditions when compared with mathematical programming approaches; however, the use of observed farm production data avoids the sensitivity to programming assumptions.

2.2 Econometric Approaches in the Literature

The majority of the existing literature on irrigation demand in the U.S. is confined to water-scarce western states. A national scale 2006 meta-analysis of irrigation demand including studies dating from 1963 to 2004 did not include a single study east of the Mississippi; over a third of the studies used data from California irrigators (Scheierling, Loomis, and Young 2006). Recent notable studies have evaluated the effect of energy prices on agricultural groundwater extraction from the high plains aquifer and the effects of water scarcity and climate conditions on irrigation decisions in the Western U.S. (Olen, Wu, and Langpap 2016; Hendricks and Peterson, 2012; Pfeiffer and Lin 2014).

Only a small number of irrigation demand studies have evaluated irrigation management decisions in the relatively water abundant eastern regions of the U.S. This geographical imbalance is likely due to a number of factors: the scarcity and heightened water concern in western states, limitations in data availability, and a general assumption that the low cost of water in eastern states would lead to a near zero price elasticity for irrigation water.

With evidence from Georgia, Gonzalez-Alvarez et al. (2006) concluded that even outside of the water scarce west, the cost of irrigation water is an important factor in farm irrigation decisions. There are a number of management choices that might be influenced by the cost of irrigation water: "Irrigation efficiency can be improved, crops can be irrigated less, and farmers can pay closer attention to soil moisture and irrigation timing" (Gonzalez-Alvarez, Keeler, and Mullen 2006, 311). One of the few irrigation management studies considering firms east of the Mississippi found that irrigation water demand is "modestly affected by water price (with elasticities between -0.01 and -0.17) but more so by crop price (with elasticities between 0.5 and 0.82)" (Mullen, Yu, and Hoogenboom 2009, 1421). These studies used pump and well characteristics to estimate the marginal cost of irrigation.

In contrast to agricultural inputs purchased in competitive markets, the own-price elasticity for irrigation water demand is uniquely challenging to measure where crop irrigators receive irrigation water from unpriced sources, most often on-site groundwater wells and occasionally surface-water pumps. Efforts to circumvent the lack of an explicit unit price through the use of imputed irrigation costs suffer from bias issues (Mieno and Brozović 2016). The various approaches to measuring water cost are discussed further in Chapter 3.

2.3 Theoretical Model

This analysis focuses on firm irrigation management decisions across a decision framework that includes expansion of irrigated acreage, crop allocation, and water application decisions. The problem is rooted in a simple total profit function for a multi-output irrigating firm (equation 1).

$$\Pi(\boldsymbol{p}, b, N, \boldsymbol{x}) \tag{1}$$

Where $\boldsymbol{p}$ is a vector of crop prices, b is the cost of irrigation water, and $\boldsymbol{x}$ is a vector of other exogenous environmental variables (climate, weather, soil quality).[1] N is the land constraint.

Farms face an initial optimization problem that takes the following form:

[1] Mathematical symbols are presented in italic font. Symbols that represent vectors are also bold.

$$\Pi(\boldsymbol{p}, b, N, \boldsymbol{x}) = \max_{k}\{\Pi(\boldsymbol{p}, b, N, \boldsymbol{x}) \colon N = N_{t-1} + k\} \tag{2}$$

In this form, the optimization expresses the firm's decision to expand total irrigated acreage. N is total irrigated acreage in a given year, which is the sum of last year's irrigated acreage and any expansion (or reduction) happening in the given year, k. After each growing season, firms make irrigation expansion decisions with updated perceptions of climate-related risk and price conditions that reflect the last growing season.

To develop a theoretical framework for the crop allocation decision, the total profit function is decomposed into a set of individual irrigated crop profit functions, where i indicates a particular crop:

$$\pi_i(p_{\boldsymbol{i}}, b, n_i^*, \boldsymbol{x}) \tag{3}$$

The optimization can be restated as a choice of irrigated acreage allocation for the individual crops, constrained by the total acreage under irrigation $\boldsymbol{N_{irr}^*}$.

$$\Pi(\boldsymbol{p}, b, N, \boldsymbol{x}) = \max_{n_1 \dots n_m} \left\{ \sum_{i=1}^{m} \pi_i(p_{\boldsymbol{i}}, b, n_i^*, \boldsymbol{x}) : \sum_{i=1}^{m} n_i = N_{irr}^* \right\} \tag{4}$$

The estimable forms for the crop allocation and water application decisions are derived from the crop level model of a multioutput irrigating firm. At the intensive margin, the specific management behavior of interest is the volume of water applied to a particular crop – corn, soybeans, or potatoes – given that a firm is growing the crop on a field with irrigation infrastructure in place.

2.4 Empirical Model

Assuming a normalized quadratic profit function, the estimable empirical functions are linear in the exogenous variables (Lau 1978; Moore and Negri 1992; Moore, Gollehon, and Carey 1994). The equation for n, expansion of irrigated acreage, is presented as a function of crop prices, water cost, total cropland, and environmental conditions. Due to data limitations, a proxy was used in place of the theorized dependent variable. Expenditure on irrigation equipment for new expansion, k (measured in dollars), was used as the dependent variable in the expansion estimation rather than an acreage measure. In equations 5 and 6, j indexes the output prices for the m crops.

$$k = a + \sum_{j=1}^{m} \beta_j p_j + \delta b + \tau N + \sum_{s=1}^{t} \eta_s x_s \tag{5}$$

The empirical model for crop-acreage allocation is similar in structure, but with effects that vary by crop i.

$$n_i^* = a^i + \sum_{j=1}^{m} \beta_j^i \, p_j + \delta^i b + \tau^i N + \sum_{s=1}^{t} \eta_s^i x_s \qquad i = 1, \dots, m \tag{6}$$

This function is intended to capture the indirect water use response observed as the change in the allocation of irrigated land among the m crops, each of which has unique water requirements and favors certain environmental conditions. In the irrigation investment and crop acreage models, the environmental and price variables, $\boldsymbol{x}$ and $\boldsymbol{p}$, include weather and price conditions lagged one year with additional controls for long run climate conditions. The variables were chosen to reflect the information available to the firm in the winter of the survey year when investment and planting decisions are made.

Application of Hotelling's lemma to the individual crop profit function produces the estimable intensive margin water demand function.

$$-\frac{\delta\pi_i(p_{\boldsymbol{i}}, b, n_i^*, \boldsymbol{x})}{\delta b} = w_i(p_{\boldsymbol{i}}, b, n_i^*, \boldsymbol{x}) \qquad i = 1, \dots, m \tag{7}$$

$$w_i = \alpha^i + \boldsymbol{\beta}^i p_i + \delta^i b + \tau^i N + \sum_{s=1}^{t} \eta_s^i \ x_s \qquad i = 1, \dots, m \tag{8}$$

The general forms for the two estimations are similar although cross prices do not appear in the empirical function for *w*. The price and environmental variables that appear in the water application models are selected to reflect the information and conditions available to the firm during the irrigation season. The construction and specifications of each variable are further explored in Chapter 3.

CHAPTER 3: DATA AND HYPOTHESES

3.1 Data Overview

Individual response data from the USDA Farm and Ranch Irrigation Survey (FRIS) is the foundational data set for this analysis. It contains firm level responses on water application rates, irrigated acreage, expense for irrigation pumping, and other irrigation management topics. The sample used in this study is a subset of the national FRIS survey. The selected sample includes major irrigating states in the Great Lakes region – Illinois, Indiana, Michigan, Minnesota, and Wisconsin, and it covers three years – 2003, 2008, and 2013. The FRIS data is supplemented with environmental and price data from a number of third party sources.

Precipitation and temperature data were obtained from the PRISM Climate Group. Solar radiation, humidity, and wind speed data were obtained from the Department of Energy's National Solar Radiation Database, Physical Solar Model 3.0. Soil quality data was derived from the NRCS STATSGO database. Finally, state level crop price data was obtained using USDA Quickstats.

Due to limitations of the survey data used for this study, each firm is geographically identified at the county level. The climate and soil data characteristics were aggregated and related to the FRIS response data at the county level.

3.2 FRIS

Survey data on agricultural management decisions and firm characteristics was obtained from the USDA National Agricultural Statistics Service Farm and Ranch Irrigation Survey (FRIS). FRIS is a supplement to the Census of Agriculture (COA), a general farm management survey conducted on five-year cycles. The FRIS is collected in the years following the COA from a sample frame of firms who reported having participated in irrigation in that particular COA. For this study, FRIS responses have been selected from 2003, 2008, and 2013.

In 2013, the national FRIS sample targeted 35,000 farms and obtained responses from 34,966. The targeted farms were selected via a stratification strategy. The major irrigators in each State were assigned to a certainty stratum (i.e. probability=1). The remaining noncertainty strata (probability < 1) were sampled systematically by acreage. The boundaries of each strata were uniquely defined by State to reflect each State's distribution of farm size measured as total acres irrigated. 2,095 farms were selected from the certainty stratum, and the remaining 32,871 farms were selected from the various noncertainty strata (FRIS 2013, Appendix A-1). This sampling strategy was also used for the 2003 and 2008 FRIS. The individual response data includes weights that are used to correct for the inherent non-randomness of the sample selection strategy.

The three most recent survey cycles are a natural selection for this analysis because there were changes to certain relevant questions in the FRIS between 1998 and 2003. This sample time frame also covers a dynamic period in the implementation of the Great Lakes—St. Lawrence River Basin Water Resources Compact, to which each of the states in the study is a party. (Although only Michigan has almost all of its agricultural area within the Great Lakes Basin, Wisconsin and Minnesota treat in-basin and out-of-basin water use management the same.)

The selected sample includes corn, soybean, and potato irrigators. These crops compose the majority of the irrigated acreage in the five states. Agricultural irrigation occurred on over 2.5 million acres across the five-state region in 2012. Figure 3.1 displays these acres by the share in each crop. The relative shares of irrigated acreage for each crop are similar across the states in the region with the exception of Wisconsin, where vegetables are particularly dominant. This study does not consider vegetable irrigation because the data is limited in distinguishing between vegetable types. Additionally, there are relatively few farms growing individual vegetable types and management practices are likely to vary by type.

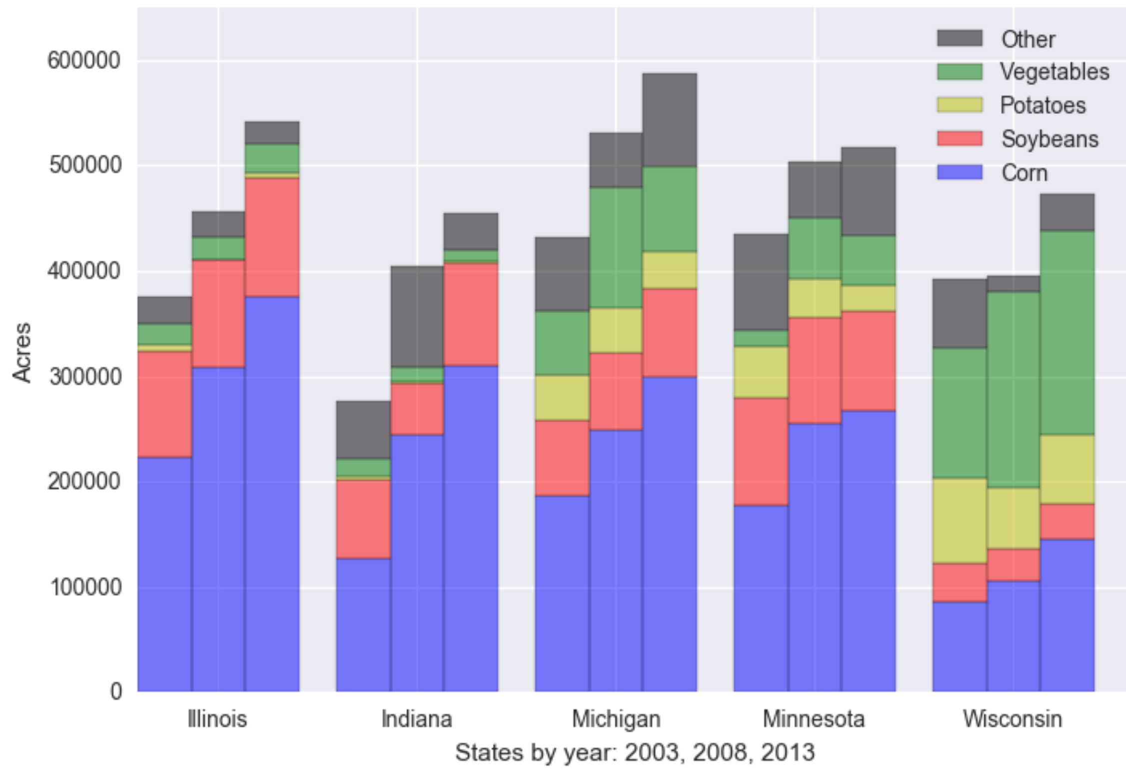

Figure 3.1 Sample frame: irrigated acres by state and year
Source: FRIS summary reports 2003, 2008, 2013

Potato irrigation occurs on a very small percentage of irrigated acreage in the southern part of the region (i.e. Illinois and Indiana). Potato irrigation occurs on a larger share of acreage in the northern part of the region and is an important crop to evaluate because it generally requires greater irrigation volume than the other crops addressed in this study.

Figure 3.2 displays the spatial distribution of irrigated acres as reported in the COA 2012. The figure highlights the presence of several key irrigation areas within the sample region. Most notably, the largest concentrations of irrigating farms are in Southwest Lower Michigan/Northern Indiana and Central Minnesota.

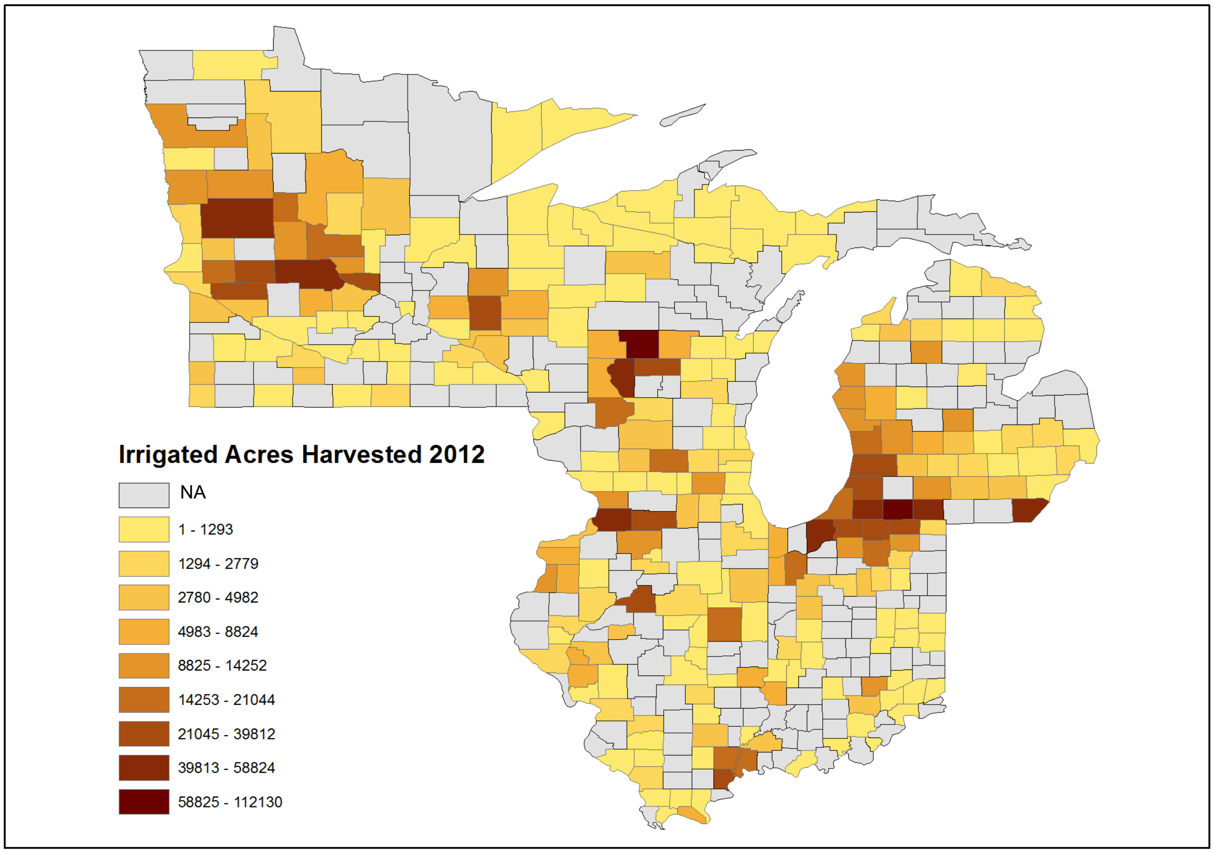

Figure 3.2 Spatial distribution of irrigated acres, 2012

Note: NA indicates counties where data was suppressed in published USDA COA summary tables to protect survey respondent confidentiality.

Table 3.1 contains the number farms by year, state, and crop as they appear in the final study sample. The 4,750 farms are relatively evenly distributed over the three sample years and five sample states. Summing the number of firms over the three crops in a given state and year will not sum to the reported total number of firms because many firms irrigate more than one of the studied crops.

Table 3.1 Number of farms in study sample, by year, state, and crop

		STATE					
		IL	IN	MI	MN	WI	Total
2003	All Crops	392	292	233	335	271	1,523
	Corn	372	270	207	302	205	1,356
	Soybean	301	207	138	228	131	1,005
	Potato	10	8	39	40	91	188
2008	All Crops	336	309	288	362	228	1,523
	Corn	324	288	269	328	182	1,391
	Soybean	200	207	163	231	98	899
	Potato	3	3	36	33	60	135
2013	All Crops	420	361	292	355	276	1,704
	Corn	392	343	263	324	238	1,560
	Soybean	255	227	177	204	111	974
	Potato	8	8	38	23	67	144
Total	All Crops	1,148	962	813	1,052	775	4,750
	Corn	1,088	901	739	954	625	4,307
	Soybean	756	641	478	663	340	2,878
	Potato	21	19	113	96	218	467

Some firms in the sample can be matched across the several years using a unique firm identifier. In the selected sample, approximately ten percent of unique firms appear in all three survey years, comprising twenty percent of the observations in the sample. Approximately eighteen percent of unique firms appear in two years of the survey, comprising twenty five percent of the observations.

Table 3.2 contains the total irrigated acreage of firms observed in the sample by year, state, and crop. In 2013, the sample includes firms covering approximately 1,060,000 irrigated acres of corn, soybeans or potatoes. This represents approximately 40% of the total irrigated acreage in the region in 2012 (all crops). That is to say, the sample includes a large portion of the total irrigation activity in the region.

Table 3.2 Total irrigated acres in study sample by state, year, and crop

		STATE					
		IL	IN	MI	MN	WI	Total
2003	Corn	134.2	77.9	94.2	91.9	56.9	455.1
	Soybean	63.7	38.4	34.9	48.6	26.0	211.7
	Potato	2.0	0.8	31.7	41.1	59.6	135.3
2008	Corn	157.4	105.9	162.2	115.5	62.7	603.7
	Soybean	50.1	44.8	44.1	45.6	19.9	204.4
	Potato*	(S)	(S)	25.6	28.4	45.3	102.2
2013	Corn	206.9	163.5	158.4	126.4	89.1	744.3
	Soybean	61.9	49.4	42.9	40.6	21.8	216.6
	Potato*	(S)	(S)	26.5	14.3	54.3	100.6
Total	Corn	498.5	347.3	414.9	333.8	208.7	1803.1
	Soybean	175.7	132.6	121.9	134.8	67.6	632.6
	Potato	9.7	1.7	83.8	83.8	159.1	338.1

Note: All values reported in thousands

*S indicates values suppressed to protect response confidentiality in accordance with USDA publication standards.

3.3 Dependent Variables

The FRIS questionnaire asks firms to report annual water applications to each irrigated crop as an annual per-acre value. These reported values were used directly as the dependent variable in the water application estimation. The following tables – 3.3, 3.4, and 3.5 –present descriptive statistics for water applications by crop. Across all states and years, firms in the sample applied an average of 7.0 acre-inches of irrigation water to corn and 6.4 acre-inches to soybeans.

Table 3.3 Farm level descriptive statistics: water applied to corn (in/acre)

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	7.7	5.5	6.2	7.4	7.6	6.9
	sd	4.1	3.1	2.6	2.9	3.7	3.5
2008	*mean*	6.2	6.4	6.5	7.6	7.7	6.8
	sd	3.8	3.1	2.4	2.6	3.5	3.2
2013	*mean*	7.9	6.5	6.5	7.3	7.7	7.2
	sd	5.1	3.2	3.3	2.7	3.6	3.8
Total	*mean*	7.3	6.2	6.4	7.4	7.7	7
	sd	4.5	3.2	2.8	2.7	3.6	3.5

Table 3.4 Farm level descriptive statistics: water applied to soybeans (in/acre)

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	7.6	4.8	5.3	7.2	6.7	6.5
	sd	4.2	2.9	2.3	2.8	3.1	3.4
2008	*mean*	6.1	6.3	5.8	6.9	6.7	6.3
	sd	3.8	7.6	2	2.4	3.6	4.5
2013	*mean*	7.5	5.6	5.2	6.6	7	6.4
	sd	5.1	2.5	2.6	3.7	4.3	3.9
Total	*mean*	7.1	5.6	5.4	6.9	6.8	6.4
	sd	4.5	4.9	2.3	3	3.6	4

Table 3.5 Farm level descriptive statistics: water applied to potatoes (in/acre)

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	10.3	7.1	9.8	9.7	10.4	10
	sd	7.2	3.9	4.2	2.6	4.4	4.3
2008	*mean*	6.4	6.8	9.3	9.5	10.6	9.8
	sd	1.8	1.4	3.5	2.6	6.9	5.2
2013	*mean*	5.6	9.8	8.3	8.1	9.7	8.9
	sd	3.9	3.5	6.2	4	4.7	5
Total	*mean*	7.9	8.1	9.1	9.3	10.2	9.6
	sd	5.9	3.6	4.8	3	5.3	4.8

Potatoes are the most water intensive of the three crops, receiving an average of 9.6 inches per acre. The difference in water intensity provides the basis for the hypothesized effects of water cost in the crop allocation model. In response to higher water prices, firms are expected to substitute away from potatoes and toward corn and soybeans.

The dependent variables in the crop allocation models are the FRIS reported values for irrigated acreage of the specific crop. Descriptive statistics for each crop are presented in tables 3.6, 3.7, and 3.8. For example, the average firm growing irrigated corn in Illinois in 2003 allocated 361 acres of irrigated land to corn.

Table 3.6 Farm level descriptive statistics: corn irrigated harvested acres

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	361	288	455	304	278	336
	sd	399	266	498	435	346	399
2008	*mean*	486	368	603	352	344	434
	sd	503	378	840	446	487	558
2013	*mean*	528	477	602	390	374	477
	sd	602	536	908	671	556	663
Total	*mean*	458	385	561	350	334	419
	sd	515	427	789	531	476	560

Table 3.7 Farm level descriptive statistics: soybean irrigated harvested acres

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	212	186	253	213	199	211
	sd	216	156	264	291	295	244
2008	*mean*	250	216	270	197	203	227
	sd	396	220	326	226	307	298
2013	*mean*	243	218	243	199	196	222
	sd	313	215	333	297	239	285
Total	*mean*	232	207	255	203	199	220
	sd	305	200	312	272	281	276

Table 3.8 Farm level descriptive statistics: potato irrigated harvested acres

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	201	108	813	1027	655	719
	sd	225	131	1260	1598	865	1128
2008	*mean*	(S)	(S)	711	859	754	757
	sd	(S)	(S)	1079	1800	1173	1315
2013	*mean*	(S)	(S)	698	622	810	699
	sd	(S)	(S)	1423	1470	1251	1279
Total	*mean*	462	88	742	872	730	724
	sd	709	111	1255	1633	1079	1229

The mean irrigated potato acreage is significantly larger than the respective means for corn or soybean, indicating a greater degree of firm concentration in potato production. Table 3.9 contains the number of firms in the sample by crop(s) irrigated. The vast majority of firms irrigated corn or both corn and soybeans in the observed years. This distribution is consistent with typical crop rotations where firms alternate between corn and soybeans on two or three-year rotations. Similarly, a majority of the potato irrigators in the sample are also irrigating other crops. This is expected as potatoes are also typically grown on a two or three-year rotation. Considering the nature of typical crop rotations, it is likely that nearly all, if not all, firms in the sample regularly participate in irrigation of at least two of the studied crops. Thus, substitution effects in the crop allocation parameters are expected to appear as a decision to participate or not participate in growing irrigated potatoes. Potato production decisions are likely partially constrained by production contracts, but the FRIS lacks a useable identifier for firms operating with production contracts.

Some firms in the sample may rotate through crops that are not addressed in this study. Notably, a significant share of potato producers are likely to rotate potato acreages with vegetables. Due to the relatively small number of firms and potentially varied nature of vegetable production management, vegetables have been excluded from this study.

Table 3.9 Sampled firms by crop(s) irrigated

Firm Type	Count	Percent
Corn Only	1,777	33.66
Soybean Only	239	4.53
Potato Only	270	5.11
Corn & Soybean	2,717	51.47
Corn & Potato	108	2.05
Soybean & Potato	33	0.63
All	135	2.56
Total	5,279	100

The dependent variable in the third and final model is the FRIS reported expenditure on irrigation technology for new expansion that occurred in the year of the survey. The majority of firms report zero for this variable, but the group of firms reporting non-zero values is large enough to fit an empirical model.

Table 3.10 Capital investment for new expansion among sampled firms

2003	*mean*	73,819
	sd	99,410
	N	183
2008	*mean*	121,058
	sd	154,492
	N	280
2013	*mean*	173,469
	sd	211,139
	N	330
Total	*mean*	131,967
	sd	165,353
	N	793

All values in CPI adjusted August 2013 dollars

3.4 Measuring the Cost of Water

The primary variable of interest is the cost of irrigation water which is hypothesized to have a negative effect on water application rates. Additionally, the cost of water is hypothesized to affect a substitution away from water intensive crops. There are three general approaches to measuring irrigation cost in the irrigation demand literature when water itself is unpriced. Here, they are referred to as the energy price approach, the engineering approach, and the average cost approach.

The energy price approach relies on variation in local energy prices applied as a proxy for the marginal water delivery cost. Mieno and Brozović (2016) showed that "energy price elasticity is identical to the irrigation cost elasticity of groundwater use when groundwater itself is not priced" (Mieno and Brozović 2016, 423). The energy price approach is simple in construction, but it does not account for a number of firm technology characteristics that affect the cost of water (e.g., groundwater depth, pumping pressure, total dynamic head). Additionally, this method is only suitable if price varies sufficiently across the sample. In the context of this study, the available measures of energy price do not provide sufficient variability to use the energy price approach.

Mieno and Brozović's sample included only electricity users. Adapting this approach to the context of this study would require a firm specific composite energy price index relating the market price (dollars per million btu) for electricity and diesel. The energy price index is computed as an average of the energy prices weighted by the firm's ratio of expenditures on the two energy sources. Prior studies have tested various methods for assigning fuel type when clear data is not available and found intensive margin price elasticity of water to be robust to the various energy price assignment methods (Pfeiffer and Lin 2014).

Pfeiffer and Lin (2014) applied this approach and tested three rules for assigning energy price where firm energy source is unknown. In the base specification, the natural gas price was assigned to firms in counties with natural gas production and the diesel price to firms in other counties. In an alternative specification, the natural gas price was assigned to firms in counties with natural gas production and the electricity price to firms in other counties. In a third alternative, the authors assigned the price of the predominant energy source – natural gas in their case – to all firms.

The two general alternatives to the energy price approach, the engineering and average cost approaches, leverage the additional variation between firms with unique water delivery infrastructure. The engineering approach requires data on pump characteristics to impute cost parameters using engineering relationships (Gonzalez-Alvarez, Keeler, and Mullen 2006; Moore, Gollehon, and Carey 1994; Hendricks and Peterson 2012). Common parameters used in the engineering approach include well depth, pump technology, pump system pressure, etc. A number of irrigation demand studies using FRIS data have applied the engineering approach to impute pumping costs (Moore, Gollehon, and Carey 1994;

Mullen, Yu, and Hoogenboom 2009; Hendricks and Peterson 2012). However, in a recent study, Mieno and Brozovic (2016) raised some potential problems with this approach.

Olen et al. (2016) used FRIS data and applied the average cost approach. This approach requires individually reported irrigation expenditure data and is distinct from the energy price and engineering approaches which aim to exclude any fixed costs associated with irrigation. A rational profit maximizing firm with complete information would optimize water use as a function of the marginal cost of water, but firms in the context of this study may instead respond to an average cost over the time scale of a regular billing cycle. This expectation applies particularly to farms that use primarily electricity as their energy source for pumping.

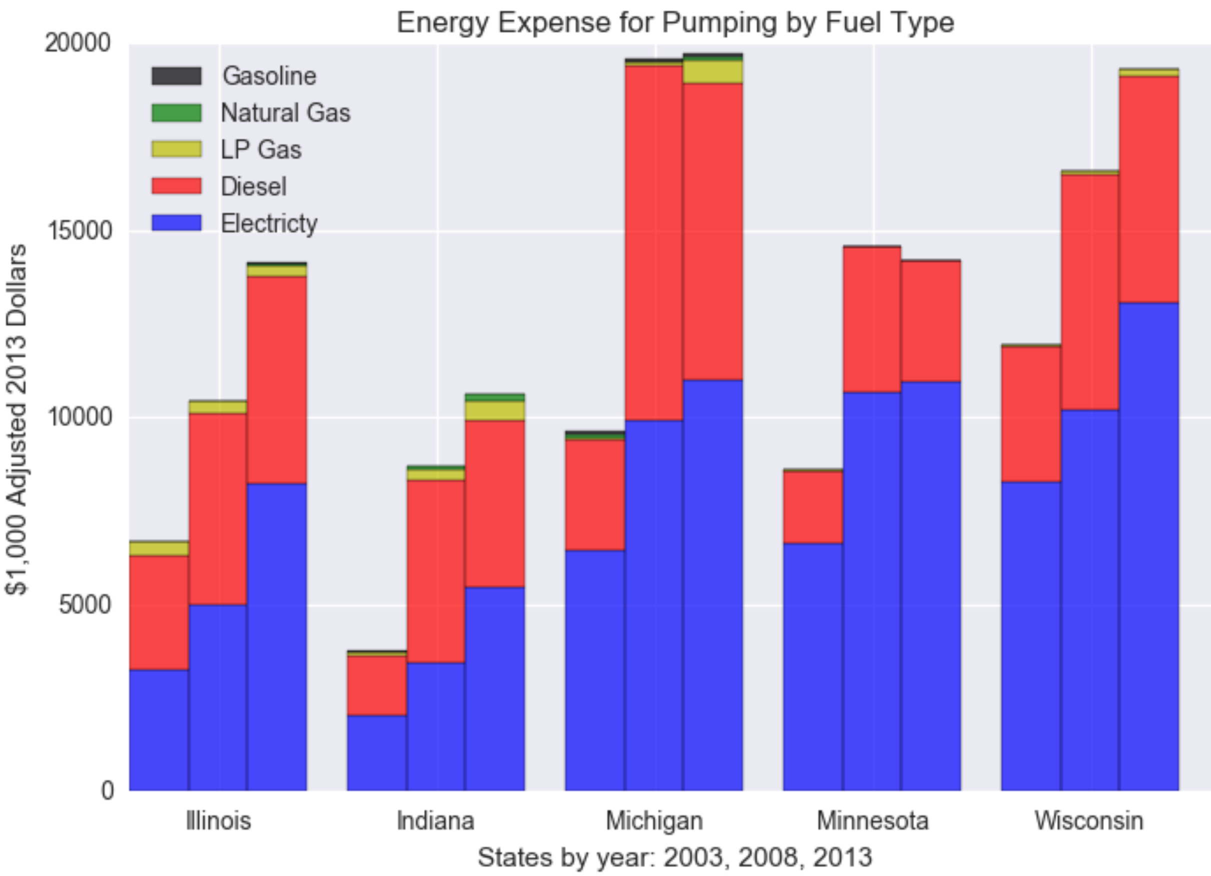

Figure 3.3 Energy expense for pumping in sample frame by fuel type

Diesel expenditures compose a large portion of the total pumping expense for irrigation, but electricity is the majority source in most state-years in the sample. Findings from Ito (2014) suggest that electricity consumers may not effectively respond to marginal prices due to complicated signals from nonlinear pricing. Many utility rate plans include pricing structures that might obscure an irrigating firm's perception of marginal cost (e.g., demand charges, block rates). Thus, the average cost of water may be more relevant than marginal cost for irrigating firms.

In this study, firm level marginal cost of irrigation water was calculated as the total annual energy expenditures for pumping, E, divided by the total number of acre inches applied by summing the crop level products of acreage allocation, n, and water application, w, for each crop i.

$$b = \frac{E}{\sum_{i=1}^{m} w_i n_i}$$

The average cost of water variable, b, may approximate the marginal cost of water when there are no significant changes in energy prices during the irrigation season and firms do not conflate fixed and marginal costs. The majority of irrigation activity occurs in a relatively short time scale (see Figure 3.4), so large variation in within-season energy price is unlikely.

The reported average cost of water might be a poor proxy for the marginal cost if irrigators were able to adjust a system's energy mix in response to within-season changes in energy price ratios. A subset of the sampled firms reports expenditures on multiple types of energy, primarily electricity and diesel. These irrigators might be potential candidates for energy switching behavior, except the nature of irrigation pump technology makes this behavior unlikely. Irrigation systems are relatively long-term investments for agricultural firms in the Great Lakes Region, and the presence of redundant pumping systems for energy switching is not a known practice (B. Russell, personal communication, February 1, 2018).

The distribution of cost estimates obtained from the sample appears in the table below. Water costs are somewhat higher in Michigan than the other states.

Table 3.11 Farm level descriptive statistics: cost of water ($/acre-in*)

		STATE					
		IL	IN	MI	MN	WI	Total
2003	*mean*	2.8	3.18	4.37	3.12	3.95	3.39
	sd	1.83	2.11	2.75	1.83	2.31	2.21
2008	*mean*	3.9	4.03	5.16	3.94	4.49	4.26
	sd	2.51	2.58	2.78	2.03	2.74	2.55
2013	*mean*	4.04	4.16	5.09	4.14	4.41	4.33
	sd	2.52	2.47	2.87	2.24	2.42	2.53
Total	*mean*	3.57	3.82	4.91	3.75	4.27	4.01
	sd	2.37	2.44	2.82	2.09	2.49	2.47

* Prices CPI adjusted to USD August 2013

The cost estimates obtained in this study sample are somewhat higher than the estimates for groundwater pumping costs in related literature. Table 3.12 contains water cost estimates from a selection of related literature.

Table 3.12 Water cost: values in the literature ($/acre inch)*

	Data Years	Region	Source	Mean
Mieno et al. 2016	2007-09, 2011-12	Nebraska	Ground	2.80
Olen et al. 2016	2008	U.S. West Coast	Surface	4.76
Hendricks et al. 2012	1992-2007	Kansas	Ground	1.09
Mullen et al. 2009	2000	Georgia	Ground	2.73
Gonzalez-Alvarez et al. 2006	1988-2003	Georgia	Ground	2.76
Schoengold et al. 2006	1994-2001	California	Surface	6.96
Moore et al. 1994	1984, 1988	Western U.S./Plains	Ground	2.99
Scheierling et al. 2006	*Mean*=1975	Various West/Plains	Various	4.35

* Prices CPI adjusted to USD 2013

The difference between the estimates found in this sample and the somewhat lower estimates in the literature may be driven by short run fixed costs of irrigation. Additionally, the difference may be partially explained by greater irrigation efficiency in regions with greater irrigation water demand (e.g., Western U.S. and Ogallala). Evidence from a t-test suggests that average water cost is higher for the sampled firms that use surface water. This difference in water cost may be caused by differences in the average pump efficiency.

Table 3.13 Cost of water: mean comparison by surface water use

Use of On-Farm Surface Water	N	*Mean*
= 0	3,748	3.87
		(0.04)
> 0	1,002	4.52
		(0.09)
Difference		-0.66
		(0.09)**

3.5 Climate and Weather Data

Precipitation and temperature data were obtained from the PRISM Climate Group. "PRISM (Parameter-elevation Regressions on Independent Slopes Model) is a climate analysis system that uses point data, a digital elevation model (DEM), and other spatial datasets to generate gridded estimates of annual, monthly and event-based climatic parameters" (Daly, Taylor, and Gibson 1997, 1). Daily precipitation and temperature records are available at a 4km grid resolution.

Current year and lagged year temperature and precipitation variables used in all models were derived using daily precipitation, maximum temperature, and minimum temperature data. Additional degree day and precipitation variability measures were produced with modifications to the daily PRISM values. PRISM also publishes 30-year normal climate variables at the same 4km raster scale. The 30-year precipitation and temperature conditions were included in the crop allocation and irrigation investment models.

The specifications for the climate variables used in this study were guided by information from agricultural irrigation extension specialists at Michigan State University. Specifically, MSU irrigation specialists indicated that May 1st -September 31st is a sufficiently wide growing season window during which environmental conditions would affect irrigation decisions, with July and August being the heaviest irrigation months (S. Miller, personal communication, September 17, 2017). Irrigation would only occur outside the growing season window under exceptional circumstances (e.g. to “water-in” a cover crop). The seasonality of irrigation water demand is also apparent in Wisconsin water use reports presented in Figure 3.5.

Temperature is hypothesized to have a positive effect and precipitation volume is hypothesized to have a negative effect on water application. Due to the relative sensitivity of potatoes, higher temperatures are hypothesized to cause a substitution away from potato production.

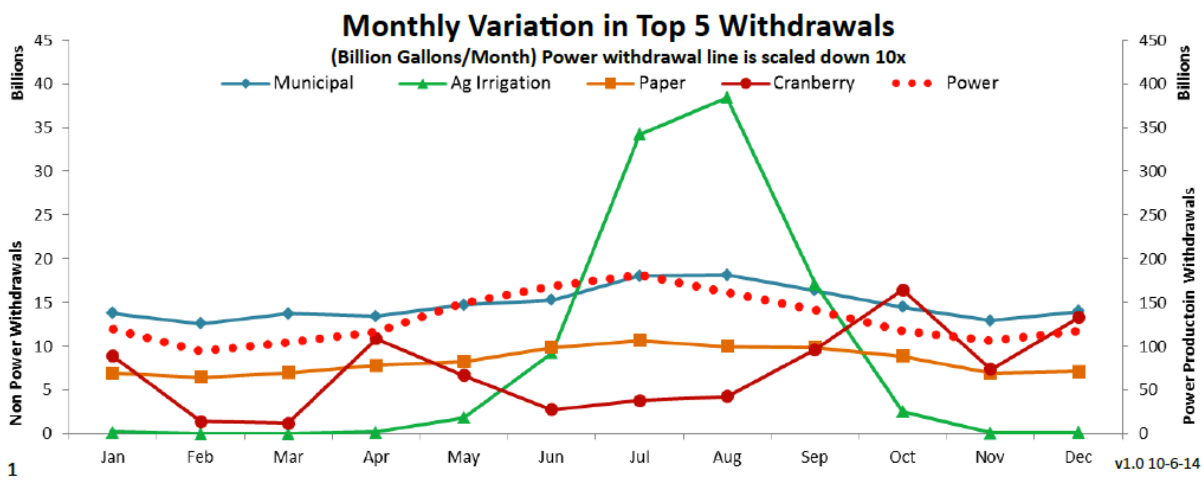

Figure 3.4 Seasonal variation in water withdrawals

Source: Wisconsin Water Use Report 2013
http://dnr.wi.gov/topic/WaterUse/documents/WithdrawalReportDetail2013.pdf

With the growing season calendar in mind, the preferred climate specification includes variables for peak irrigation season precipitation volume and average temperature. Peak irrigation season is defined as the months of July and August. These variables were generated by converting the 4km cells in the raw daily PRISM data to their central points and then taking the mean of all points that fall within the county to generate a county level aggregate. The daily, county-level precipitation data was summed to generate the cumulative values over a given time period. The mean of the daily, county-level temperature data gives the average daily max temperature over the same time period.

An additional measure was designed to account for nonlinear temperature effects. The measure, Heating Degree Days (HDD), is similar to specifications for growing degree days that are common in the crop yield literature. It was calculated as the count of degrees in excess of an extreme heat threshold (34° C), summed over days D. In the following equation, t_i is the maximum temperature on day i.

$$HDD = \sum_{i}^{D} \max\ (t_i, 34) - 34$$

The 34° C threshold has been identified as the threshold at which additional heat reduces crop yields (Deschenes and Greenstone 2007; Ritchie and NeSmith 1991). Irrigation applications are hypothesized to be increasing in HDD because irrigation is a potential strategy to mitigate heat stress.

3.6 Measures of Precipitation Variability

Literature on the effects of climate change in the Great Lakes region note that predicted changes in precipitation are somewhat less certain than expectations about temperature changes. Yet, there is some evidence that precipitation will become more variable across multiple time scales ranging from daily, to seasonal, annual, and even decadal

(Pendergrass et al. 2017; Hatfield et al. 2014). This thesis tests the hypothesis that precipitation variability increases the demand for irrigation water using measures of precipitation variability at numerous time-scales.

The predominant precipitation measures in the existing econometric irrigation demand literature include seasonal and annual precipitation volume. These broad measures do not account for the important factor of precipitation timing. Simply stated, between two locations that receive the same total precipitation over a given time period (e.g., one month), the location that receives that precipitation distributed most evenly throughout the month is expected to use less irrigation water. This expectation is a result of the limited capacity of the soil for water retention.

To test this hypothesis, three precipitation variability measures were considered. The first is the ordinary standard deviation of daily precipitation volume, calculated for all days with positive precipitation values over a given time period. This measure was applied over a growing season time-scale (May-September) and at a monthly time-scale for the peak irrigation months (July and August).

The second measure is the Shannon Index. The Shannon index is a mathematical formula used to measure how closely a given distribution approximates a uniform distribution. In this study, it was applied to daily precipitation rates during the growing season. For a given daily precipitation time series, the Shannon Index produces a single continuous value between 0 and 1 (inclusive) indicating the relative uniformity of a distribution, where 1 is perfectly uniform. The Index was developed and has been used extensively in biology literature to measure species diversity within ecosystems (Bronikowski and Webb 1996; Ramezani 2012). This thesis appears to be the first time that the Shannon Index has been applied to an analysis of water resource management.

The Shannon index value, *S,* for a time period with total number of days, *D,* is calculated as a function of p_i, the percentage of total time period precipitation that falls on day *i.*

$$S = \frac{-\sum_{i=1}^{D} p_i \ln\left(p_i\right)}{\ln\left(D\right)}$$

In this study, the Shannon Index was calculated using a May-September time period.

The third measure of precipitation variability is a count of drought events during the growing season. For this variable specification, a drought event was defined as a window of days, *d*, in which cumulative rainfall did not exceed five millimeters. The variable was considerable for two identifications for *d*, ten days and twenty days.

3.7 NRCS Soils Data

The soils data used in this paper is drawn from the USDA STATSGO database. The STATSGO "level of mapping is designed for broad planning and management uses covering state, regional, and multi-state areas."[2] Variables for this analysis were generated from the Soil Capability Class layer, which groups soils "according to their limitations for field crops, the risk of damage if they are used for crops, and the way they respond to management."

> ***Class 1*** *soils have few limitations that restrict their use.*
> ***Class 2*** *soils have moderate limitations that reduce the choice of plants or that require moderate conservation practices.*
> ***Class 3*** *soils have severe limitations that reduce the choice of plants or that require special conservation practices, or both.*
> ***Class 4*** *soils have very severe limitations that reduce the choice of plants or that require very careful management, or both.*
> ***Class 5*** *soils are subject to little or no erosion but have other limitations, impractical to remove, that restrict their use mainly to pasture, rangeland, forestland, or wildlife habitat.*
> ***Class 6*** *soils have severe limitations that make them generally unsuitable for cultivation and that restrict their use mainly to pasture, rangeland, forestland, or wildlife habitat.*
> ***Class 7*** *soils have very severe limitations that make them unsuitable for cultivation and that restrict their use mainly to grazing, forestland, or wildlife habitat.*
> ***Class 8*** *soils and miscellaneous areas have limitations that preclude commercial plant production and that restrict their use to recreational purposes, wildlife habitat, watershed, or esthetic purposes.*[3]

For this analysis, the soil capability class data was converted to create a county level soil quality variable. Soil quality is measured as the percentage of land that falls into either class 1 or class 2 in each county. This specification is similar to the approach used by Olen

[2] Source: https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629

[3] Source: https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629

et al. (2016). The expected effect of soil quality on water use at the intensive margin is negative. Higher quality soils that better retain moisture would reduce the need for irrigation. At the extensive margin, soil quality is hypothesized to have a positive effect on acreage allocations of water intensive crops (i.e. potatoes) and a negative effect on acreage allocations of less water-intensive crops (i.e. soybeans). The direction of this effect may be confounded by differences in soil types that are not captured by the capability class soil quality measure. Potato growers are generally expected to prefer sandy soils (or other soils with good drainage) because potatoes require careful control of soil moisture and can be easily damaged in overly wet or overly dry soils. Given this sensitivity, land with few impediments (as measured with the capability class data) may be a necessary, but not sufficient, condition for a typical firm to participate in potato production.

3.8 Crop Price Data

The USDA National Agricultural Statistics Service publishes monthly state level values for price received by crop. Price variables selected from this data were included in the water application, crop allocation, and irrigation investment models. In the water application estimation, a variable indicating same-year, July price received was used to measure firm expectations at the time irrigation decisions are made. Lagged marketing-year prices were included in the crop allocation and investment models to capture price expectations at the time planting and investment decisions are made.

Importantly, spatial variation in the state-level price data is limited, so the estimation of price effects relies on variation between years. Corn and soybean prices are highly correlated in the sample, so their effects cannot be distinguished in the crop allocation models.

Table 3.14 Crop price correlation matrix

	Corn Price	Soybean Price	Potato Price
Corn Price	1		
Soybean Price	0.971	1	
Potato Price	0.787	0.781	1

To address the correlation between corn and soybean prices, a composite price was calculated as the average of the corn and soybean prices faced by each firm. This composite variable is used in the crop allocation and capital investment models in place of separate corn and soybean prices.

3.9 Addressing Measurement Error

The distribution of marginal energy cost is skewed with a number of extreme values. The outliers with unexpectedly large average water cost values may be attributable to errors in the FRIS responses or data entry errors for either total energy expense or irrigation volume.

Measurement error in the dependent variable of the water application function, w_i, would be especially problematic because that term also appears in the denominator of the formula for constructing the water cost variable.

$$b = \frac{E}{\sum_{i=1}^{m} w_i n_i}$$

E is the total energy expenditure for pumping. The water cost variable, b, is a primary covariate of interest in the both the intensive and extensive margin estimations. Measurement error in w_i would introduce amplification bias in the estimated parameter on b, whereas measurement error in the numerator term E would introduce attenuation bias.

The FRIS response data allows two possible methods for measuring total volume of irrigation water applied. The first method involves summing over responses on the volume applied by water source – ground water, on-farm surface water, or off-farm water. The second approach involves aggregating the responses for acre-inches applied by crop, multiplied by the irrigated acres of each crop. The second approach was used to produce the preferred total water use measure because the crop level questions are more narrowly focused. The targeted nature of these questions reduces the likelihood of recollection error and other sources of survey response error (e.g., lack of clarity in reported units). As expected, the variance of the cost of water variable under the second approach is significantly smaller. By comparing the preferred values (summed by crop applications) to the second source (summed by water source), the sample can be restricted to the subset of observations that report consistent total water quantity values (difference between the two values < 5%).

If measurement error is driving amplification bias in the full sample, the parameter of interest estimated with the reduced sample would be expected to be smaller in magnitude. However, when the general model was estimated with the limited sample, the estimated parameter on b was slightly larger in magnitude. This suggests the results are unlikely to be significantly biased by measurement error in w_i. The model estimated with the restricted sample appears in the second column of Table 3.15.

Measurement error in the responses for expenditures by energy source is also possible. These responses are summed to produce E, total energy expenditures for pumping. Firms may misreport energy expenditures for a variety of reasons, including but not limited to a blurred differentiation between irrigation-related expenditures and other energy-related expenditures. Consider two illustrative examples. First, a firm using primarily electricity for irrigation may receive a single bill for irrigation-related and non-irrigation-related energy use. A second firm using primarily diesel fuel for irrigation may buy diesel fuel in bulk for numerous uses. When later asked to report total energy expenditures by energy source, firms may fail to accurately distinguish between these competing uses.

Table 3.15 Water application model: check for measurement error

	Full	Restrict on Water	Restrict on Cost
Water Cost	-0.211	-0.271	-0.531
	(0.037)**	(0.044)**	(0.026)**
Precipitation	-0.224	-0.204	-0.239
	(0.039)**	(0.048)**	(0.036)**
Temperature	0.264	0.163	0.232
	(0.092)**	(0.129)	(0.092)*
Soil Quality	-0.010	-0.016	-0.014
	(0.003)**	(0.004)**	(0.003)**
2008	0.289	0.272	0.588
	(0.196)	(0.275)	(0.192)**
2013	0.365	1.153	0.586
	(0.235)	(0.332)**	(0.230)*
IN	-0.345	-0.555	-0.388
	(0.215)	(0.245)*	(0.211)
MI	-0.472	-0.731	-0.306
	(0.264)	(0.352)*	(0.262)
MN	-0.002	0.023	0.011
	(0.247)	(0.327)	(0.241)
WI	0.019	-0.168	-0.086
	(0.291)	(0.407)	(0.286)
Constant	2.167	5.651	4.523
	(2.808)	(3.868)	(2.812)
R^2	0.15	0.22	0.19
N	4,729	2,571	4,307

* p<0.05; ** p<0.01

Measurement error in the numerator term of the equation for b would lead to attenuation bias of the estimated parameter on b. The distribution of the variable b, measured in \$/acre-inch and displayed in Figure 3.5, has some extreme values in the tails (<0.7 and >12.5). Unfortunately, the survey questionnaire lacks any second set of questions that might be used to check for consistency in reported expenditure levels.

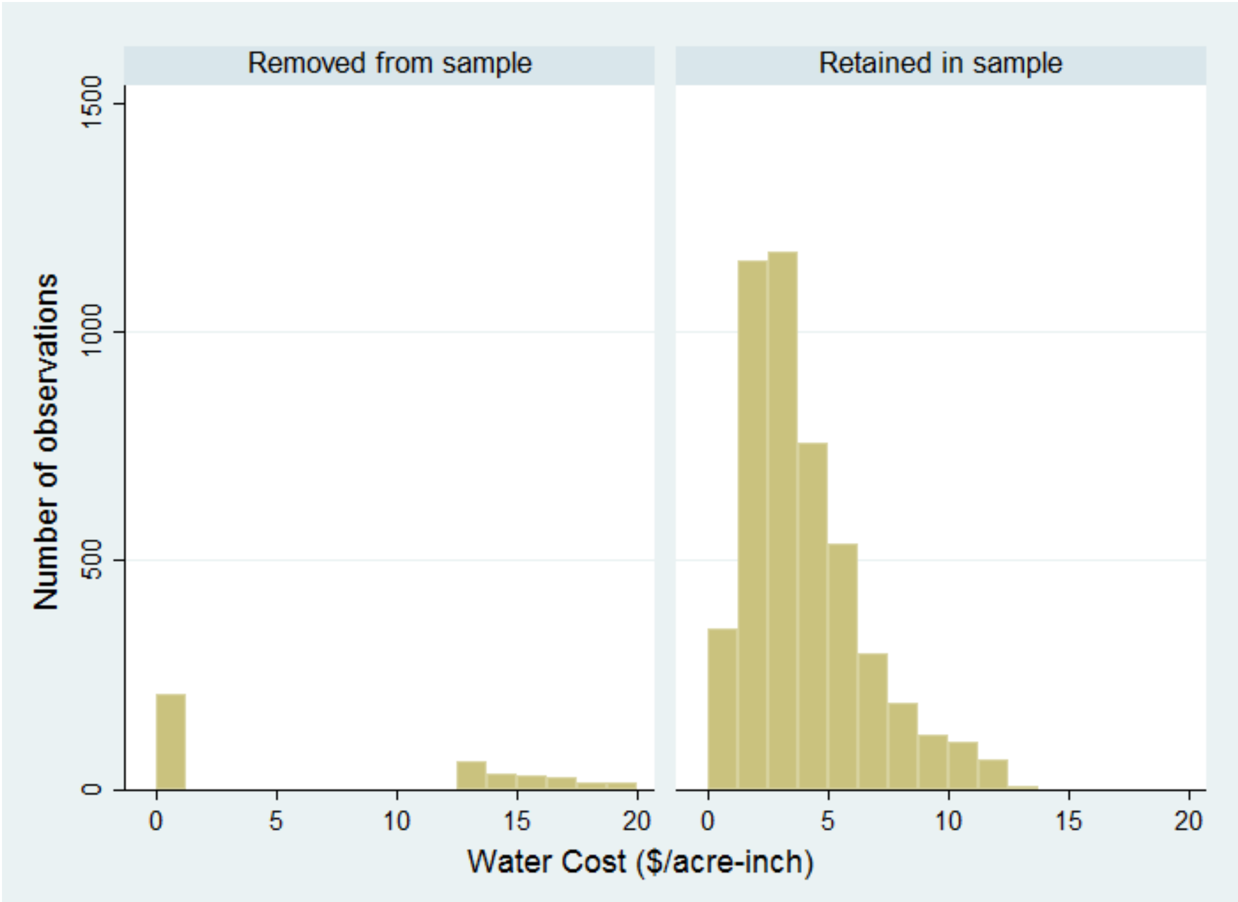

Figure 3.5 Distribution of water cost by sample exclusion rule

Note: The left panel is truncated at cost = 20. Additional outlying observations appear between 20 and 200.

To address the measurement error in the numerator of the equation for *b,* firms reporting extreme values were removed from the sample. The firms above the 95th percentile and below the 5th percentile for average cost of water, *b*, were removed from the sample for all subsequent analysis. The third column in Table 3.15 reports parameter estimates for a basic model after this exclusion. As expected, the estimated coefficient on *b* has increased due to the reduction of attenuation bias from measurement error.

3.10 Regression Weights

All regressions are reported using the USDA-provided sample weights to correct for the non-randomness in the sampling method. The probability weights denote the inverse of the probability that a farm in the sample frame has been included in the sample. In a simple sense, probability weights can be interpreted as the number of unobserved firms of a similar size that are represented by a single firm in the sample. In this context, the farms selected into the certainty strata would take a weight of 1. The farms from the non-certainty strata receive weights greater than 1. All models throughout the paper are estimated using the provided weights interpreted in Stata as probability weights.

The distribution of the sample weights within the group of observations culled from the sample closely mirrors the distribution of weights in the kept sample. Figure 3.6 displays these distributions. The figure is presented as evidence that the original sample weights have not been meaningfully biased by the data filtering rule.

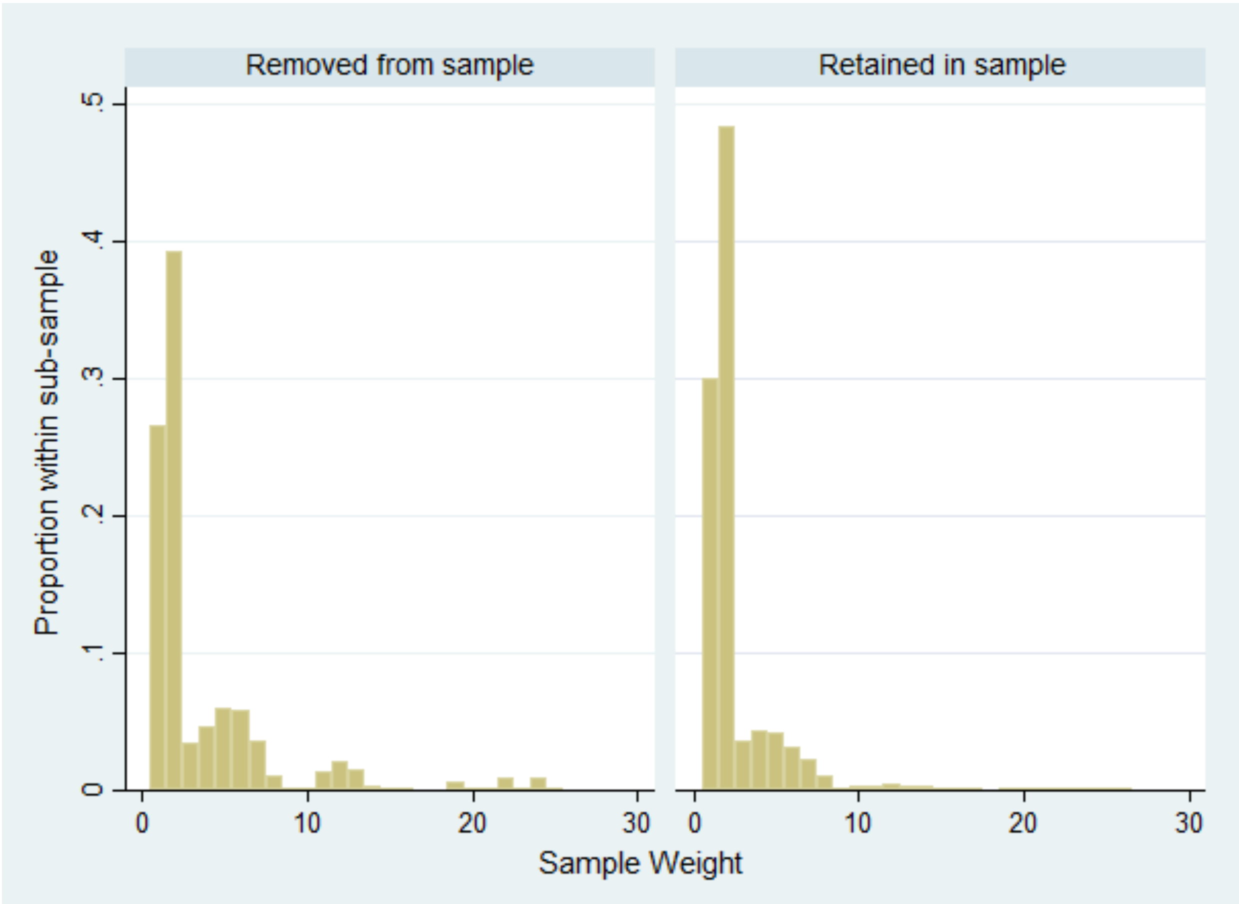

Figure 3.6 Distribution of sample weights by sample exclusion rule

CHAPTER 4: RESULTS

4.1 Water Application Estimation

Table 4.1 contains definitions and hypothesized effects of the variables that appear in the water application models. Table 4.2 contains the mean and standard deviation for each variable in the sample conditioned by participation in irrigated production of the particular crop. At the intensive margin, cross prices for the alternative crops are expected to have no effect. They were excluded from the crop specific models.

Table 4.1 Summary of variables: water application models

Variable	Variable Definition (units)	Mean (sd)	Expected Effect
Dependent			
Corn irrigation	Inches applied per acre	7.0 (3.5)	
Soybean irrigation	Inches applied per acre	6.4 (4.0)	
Potato irrigation	Inches applied per acre	9.6 (4.8)	
Cost / Price			
Cost of Water	Dollar/Acre Inch	4.01 (2.47)	−
Corn Price	July price received ($/bu)	5.13	+
Soybean Price	July price received ($/bu)	12.58	+
Potato Price	July price received ($/cwt)	9.26	+
Environmental			
Precipitation	July-August accumulation (inches)	5.82 (2.26)	−
Temperature	July-August mean daily maximum (°C)	27.84 (1.13)	+
Humidity	July-August mean relative Humidity (%)	76.24 (7.35)	−
HDD	Extreme Heat Degree Days	1.81 (3.15)	+
Soil Quality	Percent of county area in soil capability class 1 or 2	61.23 (28.48)	−

Table 4.2 Water application variables: conditional means and (standard deviations)

Variable	**Full Sample**	**Corn**	**Soybean**	**Potato**
Dependent				
Irrigation	NA	7.0 (3.5)	6.4 (4.0)	9.6 (4.8)
Cost/Price				
Cost of Water	4.01 (2.47)	3.97 (2.44)	3.89 (2.40)	4.53 (2.70)
Crop Price	NA	5.13	12.58	9.26
Environment				
Precipitation	5.82 (2.26)	5.82 (2.26	5.94 (2.32)	5.46 (1.60)
Temperature	27.84 (1.13)	27.88 (1.11)	27.99 (1.14)	27.15 (1.05)
Humidity	76.24 (7.35)	76.23 (7.35)	75.81 (7.45)	76.48 (6.62)
HDD	1.81 (3.15)	1.86 (3.19)	2.02 (3.33)	0.60 (1.45)
Percent 1&2	61.23 (28.48)	62.41 (27.84)	63.54 (26.28)	32.99 (27.71)
N	4,750	4,307	2,878	467

Table 4.3 contains results for the intensive margin specification where crop specific water application rate (inches/acre) was regressed as a linear function of price and environmental conditions. In this and all subsequent models, standard errors are clustered at the individual firm level. As hypothesized, the relationship between water cost and water application rate is significant and negative across all three crops.

Precipitation, temperature, and humidity variables were included at a peak irrigation season time scale (aggregated over July and August). The coefficient on precipitation is negative and significant for corn and soybean. Similarly, the effect of humidity is negative and significant across all three crops. The effect of temperature is positive and significant for soybean and potato. HDD has the expected positive effect and is significant for corn and soybean. The soil quality measure has the expected sign and is significant across all crops.

Finally, the coefficient for crop price has the expected positive sign for all crops and is significant across the corn and soybean models.

Table 4.3 Water application models: estimated coefficients

	Corn	Soybean	Potato
Water Cost	-0.527	-0.442	-0.523
	(0.026)**	(0.033)**	(0.099)**
Peak Season			
Precipitation	-0.178	-0.118	0.021
	(0.037)**	(0.058)*	(0.154)
Temperature	0.093	0.424	1.027
	(0.090)	(0.100)**	(0.298)**
Humidity	-0.035	-0.056	-0.101
	(0.011)**	(0.013)**	(0.049)*
HDD	0.106	0.111	-0.133
	(0.027)**	(0.042)**	(0.248)
Soil Quality	-0.015	-0.020	-0.050
	(0.003)**	(0.004)**	(0.011)**
Crop Price	0.198	0.133	0.339
(own-price)	(0.062)**	(0.028)**	(0.232)
Constant	9.816	0.527	-10.220
	(2.483)**	(2.777)	(9.188)
R^2	0.20	0.15	0.27
N	4,307	2,878	467

* $p<0.05$; ** $p<0.01$

The estimated elasticities are similar across the three crops (see table 4.4). These elasticities are within the range of those found in existing literature, although elasticities reported in the literature vary widely (see table 4.5). The elasticities estimated in this study are somewhat larger than elasticities estimated in a relatively water abundant context elsewhere (Mullen, Yu, and Hoogenboom 2009). It is intuitive that water demand is somewhat less price elastic for potatoes because potatoes have the greatest water sensitivity of the three crops.

Table 4.4 Water application: point elasticity estimates

		Corn	Soybean	Potato
Water Cost	*Coefficient*	-0.53	-0.44	-0.52
	Elasticity	-0.30	-0.30	-0.24
Crop Price	*Coefficient*	0.20	0.13	0.34
	Elasticity	0.15	0.26	0.35

To check for robustness, the model was estimated with state and year fixed effects to control for unobserved heterogeneity. The results are reported in Appendix A. The estimated coefficients on precipitation attenuate somewhat in the fixed effects model. Price variables that only vary at the state and year level are not significant in the fixed effects model. The water-cost effects and other weather effects are robust to the fixed effects specification.

Table 4.5 Short-run water cost elasticities in the literature

	Data Years	Region	Elasticity*
Mieno et al. 2016	2007-09, 2011-12	Nebraska	-0.53
Hendricks et al. 2012	1992-2007	Kansas	-0.10
Mullen et al. 2009	2000	Georgia	-0.095(0.07)
Schoengold et al. 2006	1994-2001	California	-0.30(0.17)
Moore et al. 1994	1984, 1988	Western U.S./Plains	0.01(0.10)
Scheierling et al. 2006	1975	Various West/Plains	-0.48(0.53)

*Where multiple elasticities are reported, values in table are mean(standard deviation)

4.2 Crop Allocation Estimation

Table 4.6 contains a summary of the variables and hypothesized effects for the crop allocation models. Crop allocation decisions are assumed to be driven by long term climate conditions with adjustments made at the margins in response to updated perceptions of environmental conditions.

Table 4.6 Summary of variables: crop allocation models

Variable	Variable Definition (units)	Mean (sd)	Expected Effect^
Dependent			
Corn Acres	Irrigated Acres	419 (560)	
Soybean Acres	Irrigated Acres	220 (276)	
Potato Acres	Irrigated Acres	724 (1229)	
Cost / Price			
Cost of Water	Dollar/Acre Inch	4.01 (2.47)	–
Composite Price*	Marketing year price received corn soybean average ($/bu)	8.12 (2.35)	–
Potato Price*	Marketing year price received ($/cwt)	8.53 (1.36)	+
Environmental			
30yr Precipitation	30-year normal growing season precipitation	19.28 (1.19)	+
30yr Temperature	30-year normal growing season average daily max temperature	25.47 (1.43)	–
Peak Temperature*	July-August mean maximum daily temperature (°C)	29.17 (1.83)	–
Peak Precipitation*	July August accumulation (inches)	7.67 (3.61)	+
HDD*	Heating Degree Days	13.87 (22.68)	–
Soil Quality	Percent of county area in soil capability class 1 or 2	61.23 (28.48)	+

*Starred variables are lagged by one year

^Expected effects indicate substitution toward greater (+) or less (–) potato production

Table 4.7 contains the means and standard deviations for the variables that appear in the crop allocation models conditioned on participation in the given crop.

Table 4.7 Crop allocation variables: conditional means and standard deviations

Variable	Corn	Soybean	Potato
Dependent			
Irrigated Acres	419 (560)	220 (276)	724 (1229)
Cost/Price			
Cost of Water	3.97 (2.44)	3.89 (2.40)	4.53 (2.70)
Composite Price	8.12 (2.35)	7.97 (2.38)	7.59 (2.36)
Potato Price	8.53 (1.36)	8.49 (1.37)	8.97 (1.19)
Environment			
30yr Temperature	25.47 (1.44)	25.60 (1.46)	24.13 (1.20)
30yr Precipitation	19.28 (1.19)	19.34 (1.16)	18.76 (1.34)
Peak Temperature	29.17 (1.83)	29.26 (1.87)	27.93 (1.46)
Peak Precipitation	7.67 (3.61)	7.74 (3.59)	7.45 (2.84)
HDD	13.87 (22.69)	14.58 (23.95)	5.97 (11.80)
Soil Quality	62.41 (27.84)	63.54 (26.28)	32.99 (27.71)
N	4,307	2,878	467

Note: Each column includes the subset of the sample that irrigates the given crop.
Standard deviations appear in parentheses.

Table 4.8 contains results for the extensive margin estimation where crop-specific irrigated land allocation (acres) was estimated as a function of price and environmental conditions. The crop specific allocation models were estimated using the tobit estimation procedure to account for the pool of observations who allocated zero irrigated acres to a particular crop.

Table 4.8 Crop acreage allocation: tobit average partial effects

	Corn	Soybean	Potato
Water Cost	-9.12	-6.77	29.65
	(1.68)**	(1.76)**	(10.80)**
Total Irrigated Acres	0.38	0.14	0.38
	(0.01)**	(0.02)**	(0.04)**
Composite Price Lag	21.17	-4.70	-42.95
	(1.78)**	(2.29)*	(13.83)**
Potato Price Lag	9.38	6.13	63.93
	(3.96)*	(4.41)	(27.18)*
Soil Quality	1.11	0.40	-4.14
	(0.17)**	(0.19)*	(1.29)**
30yr Grow-season Max	61.02	68.75	-276.96
	(8.45)**	(11.06)**	(80.31)**
30yr Grow-season Precipitation	9.18	5.37	18.36
	(4.57)*	(4.64)	(28.78)
Peak Temperature Lag	-23.59	-44.68	27.07
	(8.04)**	(10.80)**	(70.07)
Peak Precipitation Lag	3.72	-1.04	-40.20
	(1.49)*	(1.69)	(11.58)**
HDD Lag	-1.09	1.23	1.93
	(0.35)**	(0.37)**	(3.11)
N	4,750	4,750	4,750

* $p<0.05$; ** $p<0.01$

The effect of water cost is significant and negative for corn and soybeans. The effect of water cost on potato acreage is positive, significant, and larger in magnitude than for corn or soybeans. These results indicate that increasing water cost causes farms to substitute from corn and soybean production toward potato production. This is unexpected due to the water intensity of potato production. However, potatoes are a higher value crop than corn or soybeans, receiving an estimated $3,900/acre in revenue in 2017 compared to

$530 and $400 for corn and soybeans respectively.[4] Firms may optimally increase potato production in response to higher water costs because, despite the greater water intensity of potato production, water costs are a smaller percentage of per acre production costs. Relatedly, the marginal value product of irrigation water for potato production is greater than corn or soybean production.

It is possible that unobserved environmental factors that are favorable for potato production are positively correlated with water cost. Alternatively, unobserved heterogeneity in production contract participation may be affecting the result. Potato producers commonly operate under production contracts that may require a certain level of irrigation capacity. It is possible that potato-producing firms tend to have greater irrigation capacity and subsequently face higher short-run fixed costs of irrigation (e.g., greater fixed electric charges). Unfortunately, the FRIS data does not provide a viable indication of whether a firm operates under a production contract. The results of a mean comparison t-test indicate that potato producers pay higher costs for water (see table 4.9).

[4] Source: https://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=MICHIGAN

Table 4.9 Cost of water: mean comparison by potato indicator

	N	*Mean*
Potato Producer	467	4.53
		(0.13)
Other	4,283	3.95
		(0.04)
Difference		-0.58
		(0.12)**

* $p<0.05$; ** $p<0.01$

Table 4.10 contains the results of a linear regression of crop acreage, conditional on irrigating a positive acreage of the particular crops. Excluding the effects of water cost and potato price on potato acreage, the effects are similar in magnitude and direction to the tobit effects (Table 4.8). This indicates that the effects of water cost and potato price on potato production are sensitive to functional form. The remaining effects in the corn and soybean models are robust to the differing functional forms. The interpretation of the substitution effects is also limited by the difficulty in capturing potential substitutions toward crops (e.g., vegetables) or other land uses that are not addressed in this study.

Importantly, long-run average temperature has a large and statistically significant effect across both sets of models. This effect indicates that the acreage allocation to potato production is highly sensitive to average temperature. Long-run average temperature is the most important factor affecting substitution decisions between potatoes and corn/soybeans.

Coefficients for the climate, weather, and price variables generally indicate the expected effects. There is a large, positive, and significant effect of the composite price on corn acreage. The effect of the composite price on soybean acres is negative. It may be that the soybean acreage substitution effect is dominated by the corn effect. Potato price has a large positive and significant effect on potato acreage, but this effect does not persist in the linear specification.

Table 4.10 Crop acreage allocation: linear regression with crop-specific sub-samples

	Corn	Soybean	Potato
Water Cost	-4.483	-1.189	-3.224
	(1.298)**	(0.908)	(3.398)
Total Irrigated Acres	0.503	0.216	0.438
	(0.028)**	(0.018)**	(0.040)**
Composite Price Lag	12.985	-2.719	-6.879
	(1.432)**	(1.381)*	(5.807)
Potato Price Lag	10.193	1.921	-6.340
	(3.111)**	(2.528)	(18.229)
Soil Quality	1.028	0.161	0.851
	(0.143)**	(0.114)	(0.698)
30yr Grow-season Max Temperature	34.954	22.608	-53.507
	(8.415)**	(6.953)**	(24.388)*
30yr Grow-season Precipitation	7.824	-6.123	-17.151
	(2.691)**	(2.507)*	(14.507)
Peak Temperature Lag	-18.508	-13.787	1.943
	(7.353)*	(6.538)*	(21.821)
Peak Precipitation Lag	-0.233	-1.293	2.004
	(1.029)	(0.955)	(6.696)
HDD Lag	-0.474	0.526	1.538
	(0.254)	(0.230)*	(1.890)
Constant	-678.847	-2.251	1,612.758
	(90.983)**	(73.812)	(602.954)**
R^2	0.72	0.54	0.73
N	4,307	2,878	467

* p<0.05; ** p<0.01

4.3 Irrigation Investment Estimation

The irrigation investment model was estimated using the reported expenditure on irrigation capital for new expansion (as opposed to maintenance and repair or efficiency improvement) and a subset of the variables that appear in the crop allocation estimation. Table 4.11 contains a summary of variables and hypothesized effects for the investment models. Table 4.12 contains tobit marginal effects (average partial effects) for models of investment and the natural log of investment.

Table 4.11 Summary of variables: investment models

Variable	**Mean (sd)** by investment		**Expected Effect**
	>0	=0	
Investment	132,000 (165,000)	0	
Cost of Water	4.30 (2.55)	3.95 (2.46)	–
Irrigated Acres	969 (1179)	684 (1063)	+
Composite Price*	8.52 (2.34)	8.00 (2.37)	+
Potato Price*	8.99 (1.48)	8.46 (1.31)	+
30yr Precipitation	19.25 (1.17)	19.25 (1.22)	–
30yr Temperature	25.40 (1.44)	25.40 (1.45)	+
Soil Quality	58.75 (28.41)	61.73 (28.47)	–
N	793	3,957	

*Starred variables are lagged by one year

Table 4.12 Capital Investment for new expansion: tobit average partial effects

	Investment	Log(Investment)
Water Cost	409.73	0.09
	(2,505.71)	(0.20)
Irrigated Acres	57.79	0.003
	(9.65)**	(0.0004)**
Composite Price Lag	11,403.30	0.62
	(2,984.51)**	(0.23)**
Potato Price Lag	30,638.68	2.13
	(5,800.13)**	(0.40)**
Soil Quality	-416.96	-0.04
	(272.37)	(0.02)
Temperature	12,946.93	1.09
30-year normal	(5,363.80)*	(0.41)**
Precipitation	-1,889.71	-0.17
30-year normal	(6,011.57)	(0.48)
N	4,750	4,750

* $p<0.05$; ** $p<0.01$

After controlling for firm size, measured in irrigated acres, investment is increasing in the composite (corn and soybean) and potato prices. Models exploring the effects of same year and lagged year weather conditions did not produce significant effects with the expected signs. The results of these models are reported in Appendix B

4.4 Effect of Precipitation Variability

Despite the hypothesized effect of precipitation variability on water application rates, the estimated effects are not significant. Water application rates for corn were estimated with the introduction of a number of precipitation variability measures – peak season standard deviation, Shannon index, and drought measures. The estimated effects are either statistically insignificant or, in the case of the Shannon index, have a direction that is inconsistent with theory. The estimated effects of precipitation variability measures appear in Appendix C.

CHAPTER 5: CONCLUSIONS

5.1 Price Effects

Firms respond to the cost of water by adjusting water application rates at the intensive margin. In the Great Lakes region, the intensive margin response to water cost dominates the extensive crop allocation response. This result aligns with the conclusions of Mullen et al. (2009) who found that the intra-seasonal water application effect dominates the crop allocation effect in the Southeastern U.S. This appears to be a distinction between water-abundant and water-scarce regions where crop allocation decisions appear to dominate the response to water cost (Moore, Gollehon, and Carey 1994). Firms in the sample are somewhat less responsive to crop prices than firms in the Southeastern U.S. (Mullen, Yu, and Hoogenboom 2009).

5.2 Climate and Weather Effects

Nonlinear effects of temperature and precipitation on crop yields have received some attention in the literature on climate change and agriculture (Zhang, Zhang, and Chen 2017; Schlenker and Roberts 2009; Ritchie and NeSmith 1991). These effects have been unaddressed in much of the existing irrigation water demand literature. The results of the water application models indicate that extreme heat has an important effect on irrigation water demand. The effect of extreme heat on water application rates indicates that increasing summer temperatures due to changing climate conditions would likely increase water demand throughout the region. The explored measures of precipitation variability do not significantly affect water demand in the context of this study, but future research should explore their effects on water demand in other settings.

Long-run climate conditions are significantly predictive of crop allocation decisions. Potato production is particularly sensitive to climatic temperature. This result indicates that summer temperatures may reduce the favorability for potato production in the region and may cause producers to substitute toward corn, soybeans, or other crops not addressed in this study.

The following hypothetical scenarios are illustrative examples of potential effects of climate change on irrigation demand. First, consider an increase in long-run average temperature. Hayhoe et al. (2010) concluded that average temperatures in the Great Lakes Region are likely to increase by at least 1.3°C under lower and up to 4°C under higher emissions scenarios by midcentury (2040–2069). All else equal, the projected increase in average temperature is likely to cause firms to substitute away from potato production. This effect is expected to reduce per-acre water applications by approximately 25%. The average potato producer would use 505 fewer acre-inches (42 acre-feet) farm-wide per year after switching all potato acreage to corn and soybeans. Without addressing general equilibrium effects, it is difficult to extrapolate this expectation to a regional scale.

This reduction would likely be outweighed by a second important effect. Vavrus and Van Dorn (2010) concluded that the number of extreme days (daily max temperature > 32 °C) is likely to increase from 15 days/year in the late 20th century to 36 days under low or 72 days under high emission scenarios by the end of this century. Under an additional eight days that exceed the threshold for extreme heat by one degree (measured in this study as daily maximum temperature > 34°C), firms are expected to increase water applications on Corn and Soybeans by 15%.[5] For the average firm this would amount to 293 acre inches (24.4 acre feet) farm-wide.

To understand the total combined effects of extreme heat and average temperature, consider a statistically representative firm that irrigates 245 acres of corn, 88 acres of soybeans, and 33 acres of potatoes in the current year. All else equal, this firm is expected to respond to the hypothetical mid-century temperature scenario by increasing corn and soybean water applications by the amounts discussed above. The firm is expected to convert the 33 potato acres to corn/soybeans and reduce overall water applications on those acres by 27 acre inches. For this statistically representative firm, total water application would increase from 2,483 acre inches to 2,749 acre inches. Thus, the expected total regional effect

[5] The expected effect (for eight additional 35°C days) is equivalent to the expected effect for 4 additional days where the maximum temperature reaches 36 °C.

for the given temperature scenario is a 10% increase in water application overall. The increase will be somewhat larger than 10% in counties where potatoes are not currently grown. In regions where the spatial distribution of such increases in water demand aligns with the spatial distribution of limited water availability, including areas where total withdrawals are restricted as a result of Great Lake Compact implementation, there is a heightened likelihood of conflict over water access. Other regions, where potato production is highly concentrated, may experience net reductions in water applications if the observed substitution effect persists.

In sum, agricultural activity and irrigation practices in the region are likely to be affected by changes in both long-run average climate conditions and short-run weather events. This study provides evidence that temperature is an important contributing factor of irrigation water demand both in terms of long run average conditions and short run extreme heat events. At watershed scales, the net water use effects depend on the regional production patterns.

5.3 Limitations

The results of the study should be understood in the context of the relevant limitations of the models and underlying data. Importantly, observations are spatially identified at the county level. Some firms that operate in multiple counties are identified by their primary county. This spatial proxy for firm location introduces some error in all environmental and price variables which may attenuate the resulting effects. Additionally, general equilibrium effects and developments of new adaptation strategies may confound the expected effects over longer time periods.

The FRIS questionnaire distinguishes between sweet corn, corn for silage or greenchop, and corn for grain or seed. Production for grain or seed was addressed in this study because the majority of the region's irrigated corn acreage is in this category. This grouping, however, does not allow for identification of seed vs. grain producers. There may be significant differences in management practices between these two types of producers. Seed producers commonly operate under productions contracts (tournament style or other structures), which are likely to affect firm expectations of crop price and may change irrigation management decisions. Production contracts are also unidentified for potato producers. Future research might explore the effects of tournament style or other production contract structures on the incentives to irrigate.

APPENDICES

Appendix A Robustness checks

Table A.1 Fixed effect estimates: water application

	Corn	Soybean	Potato
Water Cost	-0.526	-0.436	-0.534
	(0.026)**	(0.033)**	(0.096)**
Peak Precipitation	-0.182	-0.078	0.011
	(0.039)**	(0.068)	(0.172)
Peak Temperature	0.103	0.270	0.977
	(0.107)	(0.129)*	(0.329)**
HDD	0.130	0.103	0.227
	(0.034)**	(0.047)*	(0.304)
Soil Quality	-0.014	-0.018	-0.045
	(0.003)**	(0.004)**	(0.011)**
Peak Humidity	-0.041	-0.045	-0.092
	(0.017)*	(0.021)*	(0.080)
2008	2.057	-2.508	0.950
	(0.742)**	(2.036)	(1.793)
2013	2.221	-2.819	0.027
	(1.040)*	(2.177)	(1.922)
IN	0.051	-0.810	2.455
	(0.227)	(0.377)*	(1.364)
MI	0.057	-0.752	2.803
	(0.269)	(0.356)*	(1.794)
MN	-0.200	0.034	2.009
	(0.317)	(0.393)	(1.831)
WI	0.340	0.174	3.117
	(0.297)	(0.417)	(1.487)*
Crop Price	-0.367	0.470	0.165
(own)	(0.248)	(0.282)	(0.569)
Constant	11.284	1.490	-11.052
	(2.948)**	(3.786)	(14.023)
R^2	0.20	0.16	0.28
N	4,307	2,878	467

* $p<0.05$; ** $p<0.01$

Table A.2 Fixed effect estimates: crop acreage allocation

	Corn Acres	Soy Acres	Potato Acres
Water Cost	-9.25	-5.70	28.39
	(1.69)**	(1.75)**	(10.93)**
Total Irrigated Acres	0.38	0.15	0.37
	(0.01)**	(0.02)**	(0.04)**
Composite Price Lag	63.50	-12.78	-24.95
	(44.70)	(46.01)	(316.74)
Potato Price Lag	-2.58	16.51	-34.61
	(6.49)	(9.25)	(60.54)
Soil Quality	0.86	0.04	-3.58
	(0.17)**	(0.20)	(1.29)**
30yr Grow-season Max Temp	1.66	45.87	-234.86
	(5.69)	(6.19)**	(58.90)**
30yr Grow-season Precipitation	36.06	16.87	-27.75
	(4.88)**	(4.96)**	(37.43)
2008	-137.66	19.55	15.39
	(135.87)	(140.48)	(941.03)
2013	-292.38	13.92	167.89
	(254.15)	(259.74)	(1,790.69)
IN	-31.87	39.95	51.47
	(16.53)	(16.05)*	(190.86)
MI	34.49	20.16	190.31
	(32.55)	(37.66)	(243.20)
MN	-4.80	127.99	-181.53
	(21.79)	(21.96)**	(166.48)
WI	-138.16	-34.49	148.89
	(28.56)**	(33.07)	(226.60)
N	4,750	4,750	4,750

* $p<0.05$; ** $p<0.01$

Appendix B Investment model weather effects

Table B.1 Irrigation capital investment: lagged weather effects

	Base	Weather
Water Cost	0.09	0.04
	(0.20)	(0.20)
Total Irrigated Acres	0.00	0.00
	(0.00)**	(0.00)**
Composite Price Lag	0.62	0.78
	(0.23)**	(0.29)**
Potato Price Lag	2.13	2.56
	(0.40)**	(0.44)**
Soil Quality	-0.04	-0.04
	(0.02)	(0.02)*
30yr Grow-season Max Temp	1.09	3.63
	(0.41)**	(1.33)**
30yr Grow-season Precipitation	-0.17	0.06
	(0.48)	(0.53)
Temperature Lag		-2.70
		(1.34)*
Precipitation Lag		-0.26
		(0.21)
HDD		0.03
		(0.04)
N	4,750	4,750

* $p<0.05$; ** $p<0.01$

Appendix C Precipitation variability measures

Table C.1 Precipitation variability measures: corn water-application effects

	Peak Precip sd	Shannon	Drought 10-day	Drought 20-day
Water Cost	-0.527	-0.528	-0.527	-0.527
	(0.026)**	(0.026)**	(0.026)**	(0.026)**
Peak Precipitation	-0.189	-0.200	-0.178	-0.185
	(0.061)**	(0.039)**	(0.037)**	(0.038)**
Peak Temperature	0.091	0.138	0.093	0.114
	(0.090)	(0.095)	(0.090)	(0.090)
Peak Humidity	-0.035	-0.029	-0.035	-0.037
	(0.011)**	(0.012)*	(0.012)**	(0.011)**
HDD	0.106	0.112	0.106	0.115
	(0.028)**	(0.028)**	(0.028)**	(0.029)**
Soil Quality	-0.015	-0.015	-0.015	-0.015
	(0.003)**	(0.003)**	(0.003)**	(0.003)**
Corn Price	0.193	0.159	0.198	0.205
	(0.067)**	(0.067)*	(0.062)**	(0.062)**
Peak Precip sd	0.240			
	(1.018)			
Shannon		1.595		
		(1.044)		
Drought 10			0.002	
			(0.054)	
Drought 20				-0.136
				(0.110)
Constant	9.887	7.333	9.805	9.470
	(2.500)**	(3.046)*	(2.550)**	(2.458)**
R^2	0.20	0.20	0.20	0.20
N	4,307	4,307	4,307	4,307

* p<0.05; ** p<0.01

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