DISSERTATION

THREE ESSAYS ON ENERGY INPUTS, TECHNOLOGY, AND CONSERVATION POLICY IN IRRIGATED AGRICULTURAL PRODUCTION

Submitted by

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ABSTRACT

THREE ESSAYS ON ENERGY INPUTS, TECHNOLOGY, AND CONSERVATION POLICY IN IRRIGATED AGRICULTURAL PRODUCTION

This dissertation explores the role of energy inputs, irrigation technology, and conservation policy in irrigated agricultural production. In the first chapter, I utilize empirical and simulation modeling to understand the impact of non-linear energy pricing on groundwater use decisions in the Republican River Basin of Colorado. The second chapter empirically investigates how peer effects and resource availability influence a producer's choice to adopt a resource-conserving irrigation technology using data from the Trifa Plain of Morocco. The third chapter develops a hydroeconomic model which pairs groundwater demand with a physical model of resource dynamics to quantify how a groundwater conservation policy implemented within a subsection of the Republican River Basin of Colorado creates resource and input market spillovers.

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I would like to thank my wonderful partner, Megan, and my parents, Bob and Marjorie, for supporting me throughout the journey of graduate school. Thanks for always believing in me. Thanks to every member of my doctoral committee for providing excellent mentorship and friendship throughout graduate school and patiently teaching me how to be an economist. Thanks to the many teachers and students in CSU's Department of Agricultural and Resource Economics Department. You all have been my family and seen me through the best and worst times. A special thanks to Denise Davis, Donna Sosna, and Kathy Bruce who have always been patient and wonderful administrative gurus. Also, thanks to Salah Eddine for excellent research assistance when collecting data in Morocco. Finally, thanks to the many teachers that fomented in me a love of learning.

DEDICATION

For my grandfather, Council L. Mains

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1.1 Introduction

Groundwater resources are vital for agricultural production in many arid regions of the world, providing irrigation inputs for over 38% of global irrigated land [Siebert et al., 2010]. The common pool nature of groundwater precipitates inefficient rates of extraction that may exceed recharge, leading to aquifer depletion and posing a serious threat to global food security [Rosegrant and Cline, 2003, Konikow and Kendy, 2005]. Despite the growing scarcity of aquifer resources in many regions, groundwater often remains unpriced, implying that other relevant price signals, such as food, energy, or input prices, govern groundwater use decisions [Tsur and Dinar, 1997, Johansson et al., 2002, Kemper, 2007]. The objective of this research is to understand how non-linear input price schedules potentially exacerbate common pool resource problems using groundwater extraction for irrigation as a theoretical and empirical illustration.

Groundwater utilization requires significant amounts of energy to pump water from aquifer to field and energy prices often constitute the only pricing mechanism guiding groundwater use. Many energy providers employ non-linear pricing strategies to meet cost recovery and revenue smoothing objectives [Wilson, 1993, Commission, 2008]. However, past literature examining the relationship between energy price and water use considers only constant marginal pricing regimes and relatively little is known about the impact of non-linear pricing [Hendricks and Peterson, 2012, Pfeiffer and Lin, 2014b]. This is a crucial difference as characterizing and estimating demand under non-linear pricing regimes differs from the case of constant marginal pricing. We address this gap in the literature by exploring how non-linear energy pricing affects groundwater extraction decisions.

Specifically, we empirically estimate demand responsiveness for the case in which energy pricing follows a decreasing block rate (DBR) schedule. Our empirical analysis exploits a unique dataset which pairs spatially explicit groundwater demand with evolving energy price structures. We use empirical results to simulate the implications of energy pricing on groundwater depletion and short-run producer welfare. Simulation results demonstrate that 4-7.5% of groundwater use can be attributed to the incentives created by DBR energy pricing. These are an economically significant results as they demonstrate how energy pricing potentially exacerbates the common pool resource challenges of shared aquifers while also elucidating a more general relationship between priced inputs and unpriced environmental goods and resources.

The relationship between energy and groundwater extraction is an example of a broader economic problem wherein priced inputs are complementary[1] to unpriced resources in the production of a good or service [Foster et al., 2017a, Foster et al., 2018]. The characteristics of many environmental goods and resources preclude or complicate trade within a market, implying that these goods lack an efficient pricing mechanism [Janmaat, 2004, Kroeger and Casey, 2007]. Yet many environmental goods and resources, from air quality to biodiversity, serve as vital inputs to production. Missing pricing mechanisms imply that other salient price signals, e.g., the price of complementary and substitute inputs, influence how firms and households use environmental and resource inputs. In this context, input pricing decisions generate effects that reverberate throughout vulnerable ecosystems and scarce natural resource stocks. We analyze these effects within the Republican River Basin of Colorado, a sub-basin of the High Plains Aquifer (HPA), to understand how energy pricing regimes potentially exacerbate the challenges associated with common pool resource management.

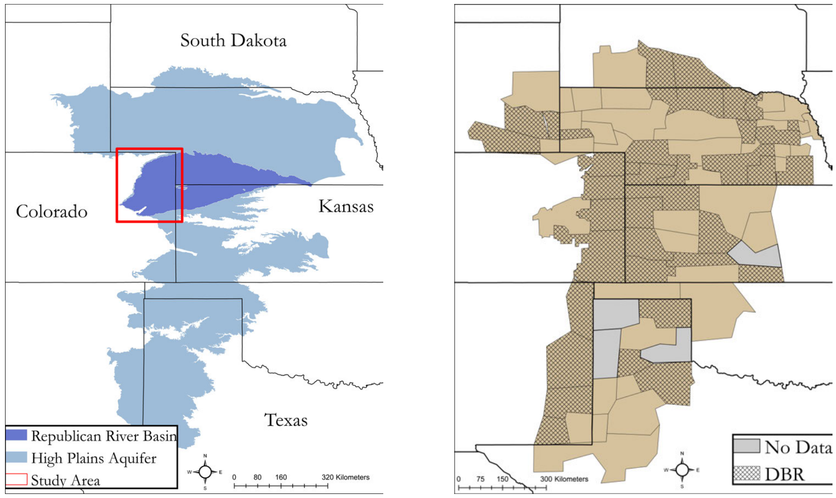
[1]Two inputs are complementary to each other if increasing the use of one input increases the marginal product of second input [Mas-Colell et al., 1995]. The relationship between energy and water is a special case of this as demand for energy is derived from demand for water and energy. While our analysis focuses on the case wherein priced goods are complementary to an unpriced environmental good or natural resource, a similar relationship exists when inputs are substitutes to the environmental good or natural resource, except in this case increased (decreased) input prices boost (diminish) natural resource demand.

This research builds on three distinct strands of literature. First, we contribute to the broader non-linear pricing literature by examining the distributional impacts of heterogeneous rate structures [Burtless and Hausman, 1978, Hausman, 1980, Olmstead et al., 2007, Olmstead, 2010, Ito, 2014]. Second, we advance the water demand research by exploring the common pool resource implications of agricultural water use subject to DBR pricing [Scheierling et al., 2006, Schoengold et al., 2006, Bar-Shira et al., 2006]. Finally, this paper enriches the literature analyzing priced inputs and unpriced environmental goods and resources by questioning how complementarity in production affects resource outcomes [Moroney and Toevs, 1977, Hannesson et al., 2010].

The paper proceeds as follows: In Sections 1.2 & 1.3, we provide background on irrigated agriculture in the HPA and Republican River Basin of Colorado and a cursory survey of the literature. In Section 1.4, we describe a simple theoretical model of water demand under DBR energy pricing given profit maximization motives while the exploring the distributional impacts of a transition to constant energy pricing. In Section 1.5, we describe an empirical model which estimates agricultural water demand. In Sections 1.6 & 1.7, we describe data sources, present empirical modeling results, and develop and present results from a counterfactual simulation model examining the impacts of a shift to constant energy pricing. Finally, Section 1.9 provides a conclusion summarizing the paper's findings and explores implications for water conservation policymaking.

1.2 Background

The HPA is the largest aquifer in the United States and supplies over 30% of the total groundwater used for irrigation in the nation [Steward et al., 2013a]. Figure 1.1a presents the extent of the HPA, the Republican River Basin (dark blue), and the study area whose data are employed in later empirical modeling (indicated by red frame). The future of the HPA, and the rural agricultural economies which it supports, is uncertain as rates of extraction exceed recharge in many regions of the aquifer. Recent research predicts that some areas of the HPA will reach the end of economically viable groundwater irrigation by 2050 [Haacker et al., 2016], inducing a shift to less productive dryland agriculture and diminishing land values across the region [Hornbeck and Keskin, 2014].



(a) High Plains Aquifer

(b) REC pricing

Figure 1.1: Electricity in the HPA [2]

Groundwater extraction in the HPA depends on access to energy. Electricity is the most important source of energy for irrigated agricultural production in the HPA, powering over 77% of irrigated farms and 70% of irrigation wells in HPA states [NASS, 2013]. Over 70 Rural Electric Cooperatives (RECs) provide electricity to residential, commercial, and irrigation customers throughout the HPA region [Brown, 1980]. Groundwater pumping comprises an important part of REC operations, representing a plurality of the electricity distributed by RECs in the HPA region [USDA, 2011]. While this energy access has facilitated rural and agricultural development [Kitchens and Fishback, 2011], it has also contributed to the depletion of the region's groundwater resources.

The utilization of DBR energy pricing structures, which over half the RECS of the HPA utilize for irrigation customers, relates to the economies of scale inherent in electricity distribution as well as cost recovery objectives [Wilson, 1993]. The cooperative nature of REC ownership requires that any excess revenues be distributed back to customers intermittently, as such, cost-recovery is a primary objective guiding REC pricing [Gardner and Young, 1984]. Figure 1.1b presents the

[2]Figure 1.1b presents the boundaries of the 73 electricity distribution cooperatives which overlay the HPA. Cross-hatched RECs utilize DBR electricity pricing from irrigation customers. Data is not available for 4 RECs who are not legally able to share details of their rate structure with non-members. Note that municipal electricity providers are excluded from the figure. REC service area boundaries are approximations of actual service area territories.

spatial distribution of REC pricing regimes in the HPA and demonstrates the prevailing use of DBR energy pricing in the region.

The Republican River Basin of Colorado (hereafter the Basin) embodies many of the characteristics which define agriculture throughout the HPA. As in many regions of the HPA, the rural economy of the Basin relies on irrigated agriculture supported almost exclusively by groundwater resources[3] powered with electricity provided by RECs [4] [Rhodes and Wheeler, 1996, Thorvaldson and Pritchett, 2007]. Similar to the rest of the HPA, irrigation customers in the Basin are an important part of REC operations[5].

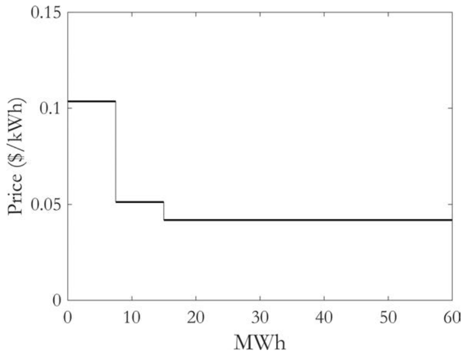
Electricity pricing in the Basin follows regional trends in that RECs utilize DBR pricing for irrigation customers wherein the thresholds of the price schedule are a function of well pump characteristics, namely horsepower (HP). Specifically, RECs in the Basin utilize thresholds defined in terms of kilowatt hours (kWh) of demand per well pump HP[6]. As such, well pumps with more HP must utilize more kilowatt hours (kWh) to move onto the next (lower) marginal price block. Figure 1.2 depicts one of the Basin's REC's (Y-W) rate structure in 2016. Well pumps constitute a significant long-term capital investment and once installed, well pump HP remains fixed [Dumler et al., 2007]. Therefore, while HP is a choice that producers make, it is a long-run decision that remains fixed over shorter time horizons. In the data used in our analysis, less than 6% of wells altered their HP between 2009 and 2017. As such, we treat well pump HP as predetermined and thus exogenous to annual water demand variation. We evaluate the robustness of our results to this

[3]Groundwater from the HPA is the primary is source of irrigation water as there are only 57 active surface water rights in the Basin, which supply less than 4% of water applied to crops [Maupin et al., 2014, CDNR, 2017].

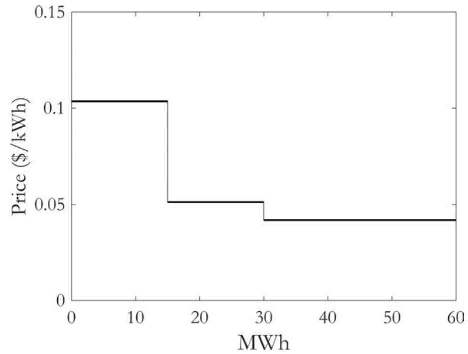
[4]Electricity provided by the Basin's RECs power over 90% of the irrigation wells in the Basin [USDA, 2013]. None of the Basin's RECs generate electricity but instead buy energy from Tri-State Generation and Transmission which is a cooperatively owned by 43 RECs throughout Colorado, New Mexico, Nebraska, and Wyoming.

[5]The importance of groundwater pumping in REC operations is directly linked to the relatively low population density of the Basin and the large quantity of electricity necessary to pump groundwater to the surface. An average well in the Basin demands 116,000 kWhs of energy annually which is roughly 12 times the total annual energy consumption of the average household in the United States [U.S. EIA, 2016].

[6]Two RECs, Y-W and Highline, provide electricity within our study area. Y-W's price thresholds are $400 \frac{kWh}{HP}$ and $1000 \frac{kWh}{HP}$ while Highline's price thresholds were $300 \frac{kWh}{HP}$ and $600 \frac{kWh}{HP}$ before 2013 and $400 \frac{kWh}{HP}$ afterwards as Highline switched from a three to two block price schedule.



(a) 50 HP Well Pump



(b) 100 HP Well Pump

Figure 1.2: Y-W irrigation customer rate structure, 2016
(1 MWh = 1,000 kWh)

assumption in Section A.2 of the Appendix where we limit our analysis to only those wells that do not change their HP.

RECs bill irrigation customers on a monthly basis but the marginal price of electricity at a given point in time depends on cumulative well-level annual demand for electricity. RECs meter irrigation customers at the well-level. Therefore, electricity pricing for a given well does not depend on the water or energy use of another well, even if both wells are owned or operated by the same producer. Monthly bills communicate price information, namely where along the rate structure the previous month's demand was located. This information is also available in real-time at the well's electricity meter which tallies cumulative annual electricity demand. Finally, RECs communicate any changes in their rate structure to constituents by mail before the beginning of the growing season, typically in January.

1.3 Literature Review

This research builds upon the methodological contributions and results of the non-linear pricing literature, research on agricultural water demand, and a broader literature on the relationship between priced inputs and unpriced resources.

1.3.1 Non-Linear Pricing

There exists an extensive literature exploring the effect of non-linear pricing in a diverse array of applications from labor supply to household electricity demand. The methodological crux of this literature lies in appropriately addressing the endogeneity that exists between price and consumer or firm decision-making. Past literature employs structural [Taylor, 1975, Nordin, 1976, Burtless and Hausman, 1978, Hausman, 1980, Hausman, 1985] and reduced-form [Terza and Welch, 1982, Agthe et al., 1986, Chicoine et al., 1986, Nieswiadomy and Molina, 1988, Nieswiadomy and Molina, 1989, Ito, 2014] empirical approaches to address potential endogeneity. We contribute to this literature by examining the distributional implications of price structures.

Structural approaches in the literature employ likelihood-based methods to model demand under non-linear pricing structures. The genesis of these structural econometric methods lies at the intersection of labor supply and consumer demand literatures [Burtless and Hausman, 1978, Hausman, 1980, Hausman, 1985]. [Hanemann, 1984] leverages the modeling insights employed in the labor supply literature to create a framework for consumer demand, commonly referred to as the discrete/continuous choice (DCC) model, which assumes that consumers jointly respond to marginal prices and thresholds when choosing demand.

The reduced-form literature instruments for price with rate structure parameters (e.g. thresholds, price levels) relying on the identifying assumption that rate structure parameters are exogenous to individual demand. [McFadden et al., 1977] present an alternative, three stage least squares approach which uses predicted demand quantities as an instrument for price. More recently, [Ito, 2014] investigates household electricity demand under varying non-linear price structures and tests whether households respond to marginal or average price. Results reveal that households respond to average rather than marginal price demonstrating how information costs determine the salient price signal determining demand. This result is important as it calls into question the DCC model's assumption that consumers are fully informed of their position within the price schedule.

We contribute to this non-linear pricing literature by analyzing the impact of rate structures on the distribution of resource use and welfare. Past literature examines heterogeneous rate structures and potential endogeneity in utility rate structure choice [Olmstead et al., 2007]. We build on these insights by leveraging within REC variation in rate structure based on well HP to evaluate the impact rate structure heterogeneity.

1.3.2 Agricultural Water Demand

This paper also advances the literature that examines how agricultural water use responds to price signals. A large swath of this literature aims to measure the price elasticity of demand for irrigation water [Howitt et al., 1980, Wheeler et al., 2008, Schoengold et al., 2006, Scheierling et al., 2006]. Broadly, this literature finds that demand for irrigation water is relatively inelastic, suggesting the high value of on-farm water use and lack of available substitutes. We build on this literature by exploring the agricultural water demand under DBR pricing.

Given that many scarce water resources remain unpriced, researchers analyze the impact of other price signals (e.g. energy inputs) to understand how producers respond to changing water prices. [Hendricks and Peterson, 2012] model water demand as a function of extensive margin choices and estimate the price responsiveness of agricultural water use via heterogeneous pumping costs. [Pfeiffer and Lin, 2014b] similarly evaluate how groundwater users respond to varying energy prices but utilize a sample selection model to incorporate cropping decisions. However, [Pfeiffer and Lin, 2014b] and [Hendricks and Peterson, 2012] both limit their analysis to constant marginal pricing regimes despite the pervasive use of non-linear energy pricing in the HPA (see Figure 1.1b). Other literature examines the impact of energy subsidies on groundwater use in developing country settings and further demonstrates the relationship between energy price and groundwater depletion [Fishman et al., 2016, Foster et al., 2017a, Foster et al., 2018].

[Mieno and Brozović, 2016] explore how measurement error in imputed irrigation costs may bias empirical estimates of the price elasticity of agricultural groundwater demand. Their results are important as much of the groundwater demand literature relies on assumptions of uniformity with respect to irrigation cost parameters and the spatial interpolation of key hydrologic characteristics (e.g. depth to water). This analysis surmounts the measurement error issues presented in [Mieno and Brozović, 2016] by utilizing novel data from well tests measuring the quantity of energy required to pump a unit of water (see Section 1.6 for further explanation), rather than imputed irrigation costs.

A relatively smaller literature evaluates the impact of non-linear energy pricing on agricultural water use. Notably, [Gardner and Young, 1984] develop a linear programming model to analyze the use of DBR electricity pricing for irrigation customers in the same region studied in this paper. Their results highlight the tension between REC revenue smoothing objectives and groundwater conservation. In a related paper, [Bar-Shira et al., 2006] analyze the use of increasing block rate (IBR) water pricing on conservation outcomes using the DCC modeling framework. Simulation results demonstrate that IBR water pricing generates groundwater conservation compared to the counterfactual scenario of constant water pricing. However, their analysis relies on the assumption that water users have perfect information regarding their position within the price schedule, an assumption questioned by results presented in [Ito, 2014]. This paper builds on the agricultural water demand literature by empirically evaluating price responsiveness under a DBR structure which to our knowledge has not been addressed in the literature.

1.3.3 Priced Inputs and Unpriced Resources

Finally, this paper builds on a literature exploring the connection between priced inputs and unpriced environmental goods and resources. This paper contributes to this literature by analyzing the case where priced inputs are complementary to unpriced resources. Previous literature examines how inputs can serve as substitutes for resources as stocks become depleted. [Moroney and Toevs, 1977] explore implications of substitutability or complementarity between natural resources and capital/labor within industries which rely on renewable and non-renewable resources. [Hannesson et al., 2010] empirically treat the substitutability between natural and human capital in fisheries and conclude that increased levels of labor productivity counteract the effects of shrinking resource stocks. In the context of water and agriculture, [Cai et al., 2008] explore how other inputs can serve as substitutes for water and ease the constraints of water scarcity.

A related literature focuses on the case of complementarity between priced inputs and resources and demonstrate how the price of complementary goods can increase adoption rates for resource conserving technologies and promote the provision of ecosystem services [Wossink and Swinton, 2007, Fabrizio and Hawn, 2013]. Within the context of water and energy, [Scott, 2013] recognizes how energy pricing influences groundwater use and calls for pricing regimes to confront resource depletion and aid adaptations to climate change. [Foster et al., 2017a, Foster et al., 2018] use modeling and experimental methods to examine how changing energy subsidy policies impact groundwater depletion. In a similar paper, [Fishman et al., 2016] further explore this connection by analyzing how a shift to volumetric, or marginal, electricity pricing can address India's pervasive groundwater depletion problems.

This literature begins to outline how the connection between priced inputs and unpriced resources applies within the context of water and energy. This paper furthers that understanding by exploring the role of input price structure in groundwater use decisions while cultivating greater knowledge of the factors which aid or hinder resource and environmental sustainability.

1.4 Theoretical Model

In this Section, we develop a theoretical model of water demand under a non-linear input pricing regime. This model is then utilized to generate hypotheses regarding the impact of a shift to a constant input pricing regime on the distribution of water use and welfare across agricultural producers.

Suppose an agricultural producer aims to maximize profits by choosing a volume of water (w) to extract which is unpriced outside of the energy inputs required for extraction. Assume that output is sold at a constant price ρ, energy inputs are priced according to a DBR structure, and each unit of water requires a fixed amount of energy inputs (Q) defined by Q = Aw. For simplicity and congruence with the empirical application, let the DBR energy schedule consist of three blocks and two thresholds. Given the known relationship between energy and water, the energy price schedule, $P(w)$, may be written in terms of water, yielding thresholds $\bar{w}^1$ and $\bar{w}^2$, where $\bar{w}^1 < \bar{w}^2$, and water prices p^1, p^2, and p^3, where $p^1 > p^2 > p^3$. Also assume there exists a function, $f(w; Z)$, representing the agricultural producer's production as it relates to water conditional on exogenous characteristics (e.g. resource constraints, soil type, weather, etc.) which are represented by the time variant parameter Z.

Let the agricultural producer's demand and inverse demand[7] for water be represented by $D(p; Z)$ and $\Gamma(w; Z)$, respectively, where p is the marginal price of water and w is water quantity. Note that extensive margin choices are not contained in Z, thus neither $D(p; Z)$ or $\Gamma(w; Z)$ are conditional on crop choices. Rather, cropping choices are implicit in demand and potentially vary with water price changes. The profit maximizing agricultural producer chooses optimal water demand such that the marginal benefit of water equals marginal price[8]. Figure 1.3 graphically represents water demand decisions for two water users whose demand differ according to exogenous characteristics defined by Z_1 and Z_2. Since time-variant Z captures the effect of weather, demand also varies across time and a given agricultural producer's optimal demand may be located on the highest or lowest marginal price block across time.

Now suppose that the energy provider shifts their pricing regime from $P(w)$ to a constant marginal price, p^c. The exact price defining the new constant marginal pricing regime depends on both the cost structure and objectives of the energy provider as well as the price elasticity of water demand. If the energy provider aims to generate the same revenue with the new constant price and initial demand is distributed across all price blocks, then the constant price must fall between p^1 and p^3. For clarity we abstract away from the energy provider's choice of a revenue-neutral constant price and assume this price equals p^2.

This new pricing regime changes the distribution of water demand across agricultural producers. For example, under constant energy pricing, lower water-using agricultural producers, $\Gamma(w; Z_1)$, increase water demand from $w_1^{P(w)}$ to $w_1^{p^c}$ as the marginal price of water determining demand decreases from p^1 to p^c. Similarly, higher water-using agricultural producers, $\Gamma(w; Z_2)$,

[7] $\Gamma(w; Z) = [D(p; Z)]^{-1}$

[8] $\frac{\partial f(w;Z)}{\partial w}\rho = p$

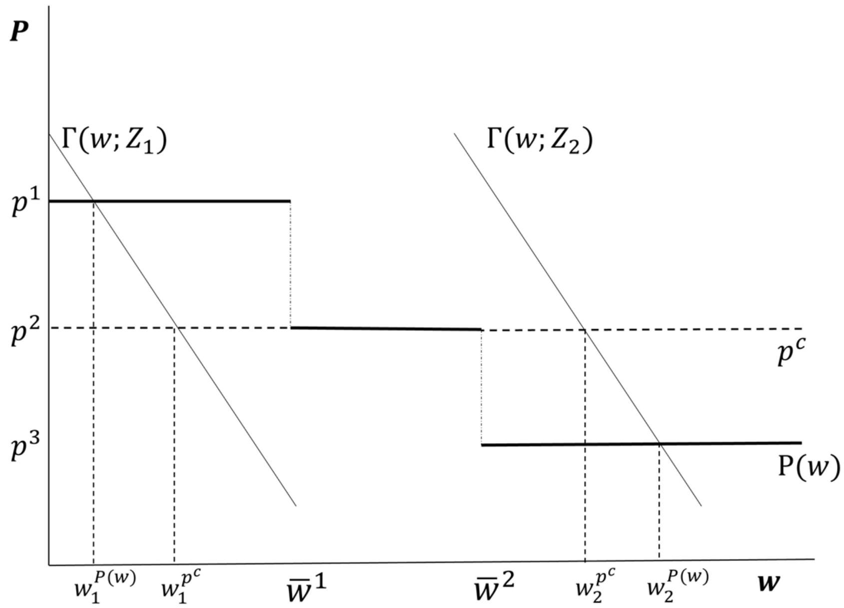


Figure 1.3: Conceptual model of agricultural water demand

decrease water demand from $w_2^{P(w)}$ to $w_2^{p^c}$ as the price signal influencing demand on the margin increases from p^3 to p^c.

A transition to constant energy pricing also generates changes in the short and long-run welfare of agricultural producers. In the short-run, constant pricing affects welfare by influencing groundwater demand and changing the price of infra-marginal units of energy and water. While in the long-run, constant pricing changes producer welfare by altering resource dynamics through time. Namely, costs and benefits accrue to producers in future time periods when constant energy and water pricing induces changes in resource availability. The theoretical and empirical analysis presented in this paper focuses on the short-run welfare impacts of constant pricing and does not incorporate how changes in current resource use affect future resource availability.

Figure 1.4 characterizes the short-run welfare implications of constant pricing for higher water-using agricultural producers with inverse demand, $\Gamma(w; Z_2)$. For example, in Figure 1.4 the welfare losses associated with a reduction in demand from $w_2^{P(w)}$ to $w_2^{p^c}$ are given by $\int_{w_2^{p^c}}^{w_2^{P(w)}} [\Gamma(w; Z_2) - p^3]dw$. However, this does not fully account for total welfare changes as the infra-marginal price

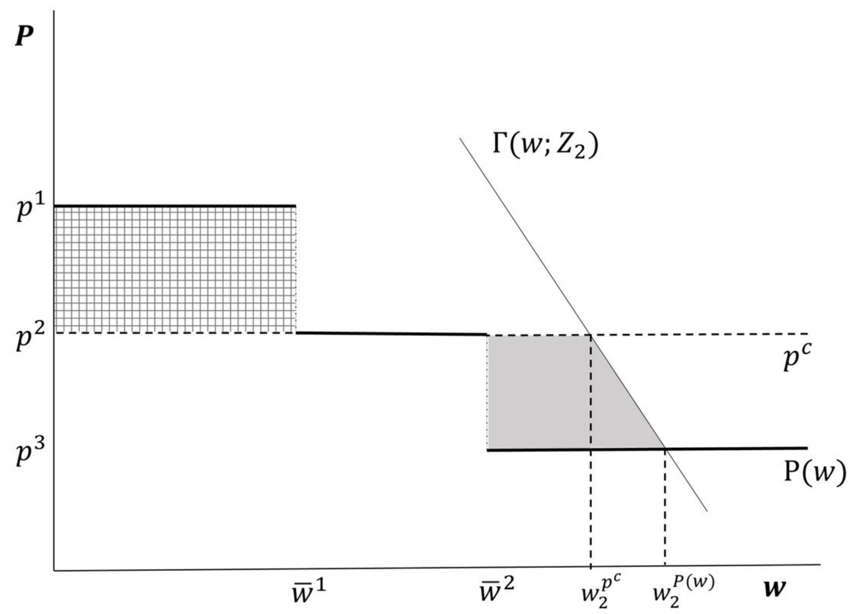


Figure 1.4: Welfare impacts of constant water pricing[9]

increases on the interval $[\bar{w}_2, w_2^{p^c}]$ while decreasing on the interval $[0, \bar{w}_1]$ when pricing is constant. As such, short-run changes in welfare are a function of both the change in demand, or demand effects, and the difference between infra-marginal prices and the constant price, or infra-marginal effects.

To formalize our characterization of short-run welfare changes, suppose that an agricultural producer demands $w^{P(w)}$ units of water under the DBR price schedule $P(w)$ and w^{p^c} units of water under constant pricing, p^c. Welfare changes arising from a shift to constant pricing are then given by

$$\Delta\, Welfare = \int_{max(w^{p^c}, w^{P(w)})}^{min(w^{p^c}, w^{P(w)})} \Big[\Gamma(w; Z) - min(P(w^{P(w)}), p^c)\Big] dw + \int_{0}^{min(w^{p^c}, w^{P(w)})} \Big[P(w) - p^c\Big] dw \tag{1.1}$$

[9]The shaded area in Figure 1.4 represents welfare losses and the cross-hatched area represents welfare gains arising from a transition to constant energy pricing, p^c.

where $P(w^{P(w)})$ represents the marginal price of water when $w^{P(w)}$ units are demanded and $P(w)$ gives marginal price at an arbitrary w when water pricing is DBR.

The first term in equation (**??**) depicts welfare gains and losses attributable to a change in demand from $w^{P(w)}$ to w^{p^c}, or demand effects. The interval of the definite integral signs welfare changes as the agricultural producer's indirect utility function is increasing in water implying negative demand effects when $w^{p^c} < w^{P(w)}$ and positive demand effects otherwise. The second term of equation **??** characterizes gains and losses in welfare arising from infra-marginal price differences, or infra-marginal effects.

Assuming that p^c falls somewhere between the first and last price blocks of $P(w)$[10], welfare gains accrue to agricultural producers demanding water along the first price block as both terms in equation **??** are positive. Welfare impacts for producers demanding water along later price blocks are less straightforward as they depend on both water demand effects and infra-marginal price changes. For example, consider the producer whose demand is given by $\Gamma(w; Z_2)$ in Figure 1.4, the net outcome of a shift to constant pricing depends on the relative magnitude of water demand effects and infra-marginal price differences. The producer's welfare losses arising from infra-marginal effects increase as demand in the final block increases because the producer must pay a higher marginal price for more units of water that were less expensive when pricing followed a DBR structure. Pairing this theoretical prediction with the likelihood of negative demand effects for higher water-using producers, we hypothesize that negative welfare impacts concentrate among those producers that demand the most groundwater. Short-run welfare gains are guaranteed for producer's demanding water along the first block of the rate schedule $P(w)$ as they face a lower marginal price and increase their demand. However, the welfare implications for producers demanding along later price blocks remains unclear as it depends on the producer's price elasticity of demand for water and the parameters of $P(w)$ relative to p^c. We address this theoretical uncertainty in our empirical and simulation modeling to measure the magnitude of these effects and their implications for short-run welfare changes under constant pricing.

[10]This assumption holds for a revenue-neutral shift to constant pricing.

Our theoretical model illustrates the distributional impacts of a shift from DBR to constant pricing. We hypothesize that decreases in water demand concentrate among high water-using producers as they face higher marginal prices under constant pricing. Similarly, low water-using agricultural producers increase their water use when pricing is constant as they face a lower marginal price. As such, the impact of a transition to constant pricing on aggregate energy and water demand depends on the initial distribution of demand among the rate structure's blocks. For example, if the majority of producers demand within the rate structure's first block, then a transition to constant pricing potentially increases aggregate water demand as the majority of users experience a decrease in price. If most producers demand in later blocks of the price structure, then it is more likely that the constant pricing regime will result in diminished energy and water demand. The precise impact of constant pricing depends crucially on producer's responsiveness to changes in price, which we address empirically in our later modeling to uncover the impact of constant pricing on aggregate demand.

1.5 Empirical Model

In this Section, we develop an empirical model of water demand as a function of energy prices (P) and exogenous factors (Z) aiming to test the hypotheses generated in Section 1.4. The model estimates how input prices and other exogenous factors determine water demand for agricultural producers and allows us to resolve theoretical ambiguity about impacts of a change from DBR pricing to a constant price regime.

To facilitate comparison with previous treatments of water demand in the literature, we assume constant elasticity and estimate the water demand function in log-log form [Hewitt and Hanemann, 1995, Olmstead, 2010]. Let water demand by the i^{th} well[11] in time t be given by

$$log(w_{it}) = \alpha_i + \delta_t + \gamma log(P_{it}) + \beta Z_{it} + \varepsilon_{it} \tag{1.2}$$

[11] Available water demand data is reported at the well-level (see Section 1.6 for further description). We estimate water demand at the well-level which allows our model to better capture time variant and invariant differences across wells. To account for potential unobservables at the well-owner level, we cluster standard errors at the owner level in all modeling specifications.

where factors influencing water demand are captured by a well-level fixed effect, α_i, time fixed effects, δ_t, and the vector of covariates[12], Z_{it}, with associated parameter vector β. P_{it} is the marginal energy price and, as the model is estimated in logs, the parameter γ represents the price elasticity of demand for water. We also introduce an idiosyncratic error term, ε_{it}. Finally, note that this formulation of agricultural water demand does not include cropping choices as covariates, rather we employ a flexible formulation of demand which implicitly accounts for adjustments along the extensive margin.

We follow standard economic theory and estimate the effect of marginal price, rather than average price, on water demand. Recent literature suggests that consumers may respond to average price rather than marginal price signals when information costs associated with knowing where demand falls on the rate structure are significant and total expenditures on the good are a small proportion of their budget [Ito, 2014]. However, in the context of agricultural water demand in the Basin, energy costs constitute a significant proportion[13] of farm expenses and most producers' well pump technology readily supplies information on cumulative water use [CSU, 2013].

Identification Strategy

There exist several sources of potential endogeneity concerning our estimation of groundwater demand. First, the utilization of non-linear price schedules for electricity in the study area introduces reverse causality between price and demand as a producer's pumping decision influences their marginal price. Second, given that electricity rate structures vary as a function of well pump characteristics, specifically well HP (see Sections 1.2 and 1.6), producers potentially have the ability to affect their rate structure by endogenously choosing their well's HP. Finally, well location decisions and the structure of REC governance present additional sources of endogeneity as these avenue potentially allow producers to influence their energy price schedule.

[12]e.g. resource availability, weather, market conditions, soil type, well pump characteristics

[13]Energy costs related to pumping groundwater constitute 15% of pre-harvest expenses for irrigated producers in the Basin [CSU, 2013].

To address this potential for endogeneity, we employ a fixed effect, instrumental variable (FE-IV) identification strategy common in the non-linear pricing literature as our preferred model specification [Terza and Welch, 1982, Agthe et al., 1986, Nieswiadomy and Molina, 1989, Olmstead, 2010, Ito, 2014]. Our FE approach controls for time-invariant unobservables like management capacity and soil attributes which potentially affect groundwater demand. We utilize parameters of the DBR rate structure as instruments for a well's marginal energy price. Instrumenting for marginal price addresses the first source of endogeneity attributable to non-linear energy pricing by breaking the reverse causality between price and demand using exogenous rate structure parameters.

We instrument for endogenous marginal energy price with the difference between the first and last price of the well's rate structure ($p^1 - p^3$) and the REC-year-HP average volume of water required to reach the final price block, excluding wells with the same HP as the observation. For example, we determine the REC-year-HP average water threshold value for a given well with 100 HP by grouping all water threshold observations within the same REC and year that have HP not equal to 100 and finding the average water threshold. Our water threshold instrument addresses the second potential source of endogeneity introduced by energy price structures which vary according to a well's HP. By instrumenting with average water threshold values that exclude the cohort of wells with the same HP our instrument removes bias related to producers endogenously determining their well pump's HP. We further test the robustness of our results to this potential source of bias by restricting our sample to those wells which do not report a change in HP during our study period. These results are reported in Section A.2 of the Appendix.

Endogenous well location decisions and REC governance structures also present potential concerns for obtaining unbiased coefficient estimates. Well location decisions that depend on differences between REC rate structures threaten the validity of our instrumental variable approach as inter-REC variation in rate structure parameters is no longer exogenous to individual groundwater demand but instead depends on the cohort of wells choosing each REC as their energy supplier. However, this potential source of endogeneity is unlikely given that well locations are fixed once installed and well location decisions were taken long before any recent differences in REC pricing or management were revealed to producers[14]. This suggests that other factors like land quality, distance to markets, and groundwater availability, for which there is significant heterogeneity across the Basin, were more relevant in the initial well location decisions rather than differences between REC's in their energy pricing.

The governance structure of RECs also presents an additional source of endogeneity that potentially threatens our identification strategy. RECs in the Basin are governed by elected boards comprised of REC constituents. As such, there is the possibility that producers in the Basin could use REC boards to influence REC rate structure decisions to benefit agricultural operations. This is unlikely for several reasons. First, the composition of REC boards reflects the breadth of customer classes (e.g. residential, commercial, irrigation, municipal) served by the REC. As such, irrigation customer representation does not constitute a majority in REC governing boards and any changes to irrigation rate structures would require the support of representatives from other customer classes. Second, REC cost recovery objectives constrain board members from significantly changing rate structures for their benefit as the REC must still generate sufficient revenue to cover the fixed and variable costs of distribution. Third, there exists significant heterogeneity in resource availability and well pump technology across agricultural producers in the Basin. As such, changes in the rate structure that would benefit a particular producer is unlikely to benefit all producers which undermines the probability that producers act collectively to influence electricity rate structures. Finally, we observe only one change in block threshold values among the two RECs in Basin between 2011-2017 providing further evidence that political capture by irrigation customer representatives does not significantly influence variation in rate structures.

Finally, we explore the robustness of our results to choice of instrument in Section A.1 of the Appendix. We also scrutinize the stability of our results to our preferred model specification, FE-IV, by estimating a pooled OLS, instrumental variable (POLS-IV) model which is also com-

[14]Drilling a new groundwater well in a new location involves significant fixed costs and most wells in the Basin were initially installed between 1960 and 1980.

mon in the water demand literature [Hendricks and Peterson, 2012, Mieno and Brozović, 2016]. These robustness checks reveal that our results remain qualitatively similar across differing price instruments and restricted samples.

1.6 Data

We utilize a novel panel data set of groundwater and electricity demand for 1,392 irrigation wells in the Republican River Basin of Colorado from 2011 to 2017 to estimate the empirical model of water demand presented in Section 1.5. The data set includes electricity price, weather, and aquifer related variables to account for factors that influence demand for electricity and groundwater. In this Section, we describe these data, their sources, and the necessary data transformations required for our empirical modeling.

Estimation of the econometric model outlined in Section 1.5 requires knowledge of the marginal price of electricity that each well faces annually. However, electricity demand data is not directly available given privacy concerns among RECs in the Basin, rather we impute total demand by leveraging data on well pump characteristics and efficiency collected in well capacity tests required by the State of Colorado[15]. Figure 1.5 presents a diagram outlining the process and data used to impute marginal electricity prices.

The process of imputing marginal prices begins with data on well-level annual groundwater extraction collected by the State of Colorado [CDNR, 2017]. Groundwater pumping data is then paired with a well-level Power Conversion Coefficient (PCC) which is collected in well capacity tests and measures the number of kilowatt hours (kWh) required to pump one acre foot of water which is largely a function of the vertical distance between the aquifer and the surface [CDNR, 2018]. Figure 1.6 presents the distribution of PCC across wells in 2017 demonstrating the extent of pumping cost heterogeneity. The pairing of well-level groundwater demand and PCC measurements yields imputed annual electricity demand. Next, we utilize data on well locations and REC

[15]Rule 12 of State Administrative Rule 2 CCR 402-2, which was implemented in 2009, requires that every high capacity groundwater well in the Republican River Basin test their well yield, i.e. capacity, every two years.

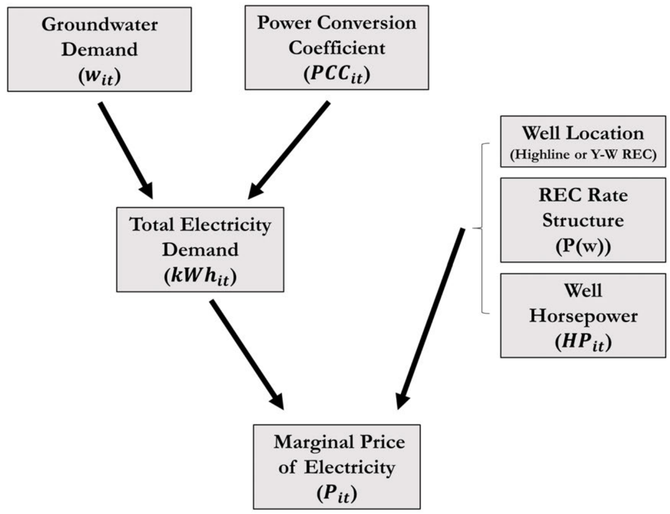


Figure 1.5: Flowchart of marginal price data generation

boundaries to associate each well in the Basin with its electricity provider and that provider's rate structure for irrigation customers [CDNR, 2015, Y-W, 2017, Highline, 2017]. Figure 1.7 displays irrigation customer rate structure price levels through time for Highline and Y-W RECs. Finally, we integrate annual electricity demand with annual REC rate structures and well HP which is reported in well capacity tests and influences rate structure thresholds (see Section 1.2) to impute the marginal price of electricity for each well-year observation.

We further utilize well test data to account for changes in groundwater availability across time via well capacity[16] [CDNR, 2018]. Recent research suggests that well capacity is an important determinant of groundwater use decisions along the intensive and extensive margins [Foster et al., 2014]. Annual weather data consists of spatially explicit[17] estimates of monthly precipitation and daily maximum temperature mapped to each well location [Oregon State University, 2018]. Monthly precipitation quantities are aggregated across the growing season[18] and daily maximum temperatures are combined to a count of growing season days with maximum temperature above

[16]Well capacity is sometimes referred to as well yield.

[17]4 km resolution.

[18]We assume the growing season is May 1^{st} through August 31^{st}.

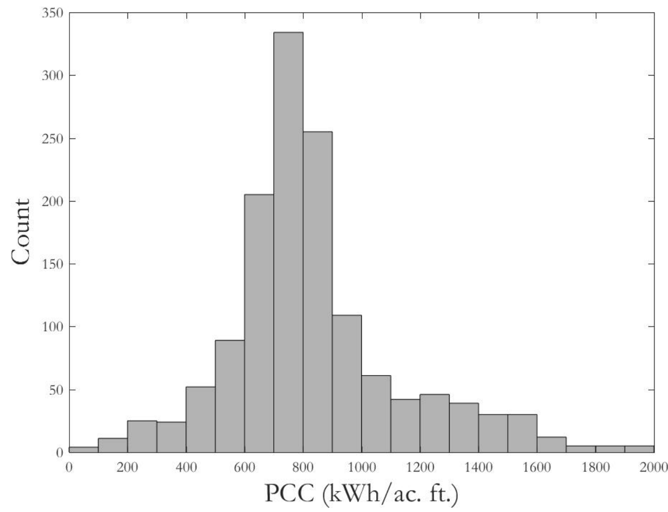
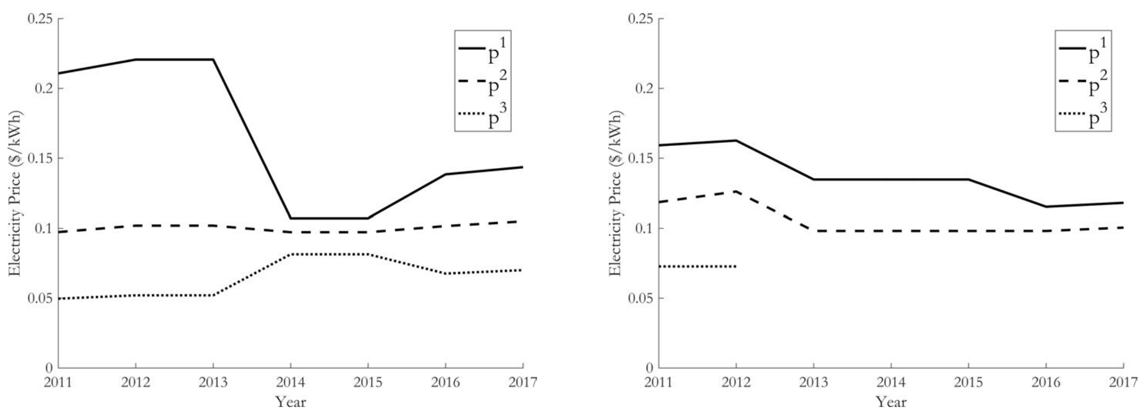


Figure 1.6: Distribution of PCC, 2017



(a) Y-W

(b) Highline

Figure 1.7: REC electricity prices, 2011-2017[19]

35° Celsius. SSURGO irrigation capability class data is matched to irrigated parcels to account for cross-sectional variation in soil quality which we utilize in our non-FE model specifications [Soil Survey Staff, 2018]. Irrigation capability class data classifies soil types according to their suitability for irrigation (1 = most suitable, 8 = least suitable).

[19]In 2012 Highline transitioned from a three to two block price schedule.

Table 1.1 presents summary statistics on groundwater and electricity demand, and well characteristics[20]. Table 1.1 demonstrates the importance of farm energy costs related to water demand, which account for up to 15% of total pre-harvest costs in the Basin, confirming how agricultural water demand differs significantly from household demand as the typical household spends only 0.4% of its monthly income on water [Mayer et al., 1999, CSU, 2013]. Well capacity and HP data and their standard deviations also illustrate the degree of heterogeneity in groundwater availability and well pump technology exhibited across wells within the Basin.

1.7 Empirical Results

In this Section, we present results from the econometric model developed in Section 1.5 with data described in Section 1.6. Model results are presented in Table 1.2.

Our preferred model specification is FE-IV, which addresses the endogeneity of price and controls for unobserved time-invariant well characteristics. Results of the FE-IV model are presented in column (4) of Table 1.2 where the estimated price elasticity of demand exhibits the sign expected by economic theory and is statistically significant. Furthermore, our preferred specification's estimated price elasticity falls within the range of elasticities reported in the groundwater demand literature [Scheierling et al., 2006, Schoengold et al., 2006]. This result is qualitatively robust across differing modeling specifications presented in columns (1)-(3). Model results presented in columns (1) and (3), which do not instrument for price, reveal the upward bias of price elasticity estimates when price endogeneity is not addressed. Finally, we assume our panel dataset of 1,392 yearly observations across 7 years is sufficiently long in the time dimension to accurately identify well-level fixed effects used for estimation of the inverse demand curve parameters [Arellano, 2003].

Coefficient estimates of other covariates included in the model follow intuition in their sign and significance. Across all model specifications well capacity coefficient estimates are consis-

[20]PCC, HP, and discharge pressure are fixed in the short run but may vary in the medium run as agricultural producers may invest in new well pumps or irrigation systems. We test the robustness of results to potential endogenous changes in irrigation system discharge pressure and pump HP in Section A.2 of the Appendix.

Table 1.1: Summary statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Panel Data				
Groundwater Demand (acre feet/year)	229.32	103.18	0	1046.83
Electricity Demand (mWh/year)	116.16	52.11	0	630.40
Electricity Cost ($)	13488.24	6281.95	0	65556.87
Well Capacity (gallons/minute)	793.10	314.89	7.76	2852.28
Precipitation (inches/growing season)	11.75	3.78	3.73	21.72
Temperature (# days w/ temp $> 35°C$)	18.99	14.16	0	55
Irrigation Capability Class (factor variable)	2.026	0.8451	1	6
Well Pump Characteristics				
Power Conversion Coefficient (PCC) (kWh/acre foot)	511.23	127.34	126.60	1863.94
Horsepower (HP) (work/time)	112.36	42.67	10	700
Discharge Pressure (kPa)	44.11	25.57	5.00	567.00

Table 1.2: Empirical modeling results, groundwater demand

	Dependent variable:			
	Log(Pumping)			
	POLS	POLS-IV	FE	FE-IV
	(1)	(2)	(3)	(4)
Log(Price)	-0.8345^{***}	-0.4531^{***}	-0.7953^{***}	-0.2519^{***}
	(0.0654)	(0.0676)	(0.0661)	(0.0634)
Well Capacity	0.0009^{***}	0.0009^{***}	0.0003^{***}	0.0003^{***}
	(0.00003)	(0.00003)	(0.00003)	(0.0001)
Precipitation	-0.0008^{***}	-0.0007^{***}	-0.0008^{***}	-0.0007^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Temperature	-0.0020^{*}	0.0026^{*}	-0.0013	0.0051^{***}
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Irrigation Class	0.0277^{**}	0.0331^{***}		
	(0.0087)	(0.0088)		
Constant	2.7307^{***}	3.5367^{***}		
	(0.1590)	(0.1588)		
Observations	9,400	9,400	9,400	9,400
R^2	0.4570	0.4360	0.2886	0.2361
Adjusted R^2	0.4567	0.4357	0.1646	0.1030
F Statistic	$1{,}581.0860^{***}$	$1{,}441.0520^{***}$	811.8179^{***}	605.6612^{***}

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Standard errors clustered at the well owner
Models also include a year fixed effect whose output is omitted

tently positive and statistically significant pointing to the importance of resource constraints in groundwater demand. We also find that growing season precipitation negatively affects groundwater demand while the number of days with a maximum temperature above 35° Celsius increases groundwater demand. This follows intuition as precipitation and groundwater pumped for irrigation are roughly substitutes in agricultural production and higher temperatures increase demand for groundwater as increasing rates of evapotranspiration necessitate additional irrigation to maintain plant health [Hargreaves and Samani, 1985]. Coefficient estimates for the factor variable irrigation class points to increasing demand for groundwater as soil quality diminishes (e.g. higher sand content). Finally, we test the robustness of our results to potential endogeneity in rate structures by restricting the sample to wells which do not report a change in either well HP or irrigation system discharge pressure[21]. These results are presented in Section A.2 on the Appendix and qualitatively align with modeling results generated using the full sample.

1.8 Counterfactual Simulation

In this Section, we leverage the results from our preferred empirical modeling specification, FE-IV, to simulate the counterfactual scenario of constant electricity pricing and test the theoretical predictions delineated in Section 1.4. Specifically, we simulate the counterfactual scenario wherein RECs in the Basin transition to a constant electricity pricing regime in 2017. We begin by outlining the methods used to determine REC-specific constant prices and then utilize these methods to explore how constant electricity pricing affects groundwater demand and welfare across agricultural producers in the Basin.

We assume that RECs choose pricing structures that allow the recovery of their distribution and procurement costs[22]. Therefore, we calculate the REC-specific, 2017 constant price that achieves

[21] Agricultural producers can also decrease the energy requirements of their irrigation system by adopting lower discharge pressure application valves [Fipps, 1995]. In the context of this paper, a decrease in irrigation system discharge pressure decreases a well's PCC but does not influence the thresholds or marginal prices of their rate structure.

[22] Neither Y-W or Highline generate electricity. Both RECs buy electricity from Tri-State Generation and Transmission Association, Inc. via long term contracts.

the same level of expected revenue as DBR pricing generated between 2011 and 2016. More specifically, for the k^{th} REC, whose wells are indexed by j ($j = 1 \ldots J$), we determine the 2017 constant pricing regime, p^c_k, which minimizes the difference between predicted average REC revenue under DBR pricing, $\bar{TR}_k^{P(w)}$, and predicted average REC revenue under constant pricing, $\bar{TR}_k^{p^c}$, between 2011 and 2016. We multiply preferred model specification demand predictions[23], $\hat{w}_{it}^{P(w)}$, with PCC_{it} to yield predicted annual well-level electricity demand. To calculate REC revenue under DBR pricing, we match each well's predicted annual electricity demand to their REC's rate structure in time t, $P_{kt}(w)$, to produce total annual well-level electricity expenditures. Finally, predicted expenditures are aggregated across J wells and T years ($T = 6$), and averaged across T to give $\bar{TR}_k^{P(w)}$. More formally, we calculate average REC revenue using the following equation

$$\bar{TR}_k^{P(w)} = \frac{\left[\sum_{t=1}^{T}\sum_{j=1}^{J}\hat{w}_{it}^{P(w)} * PCC_{it} * P_{kt}(w)\right]}{T} \tag{1.3}$$

REC-specific annual and average revenues are reported in Section A.3 of the Appendix.

We follow a similar approach to calculate $\bar{TR}_k^{p^c}$ but utilize model parameter estimates to simulate well-level groundwater demand as a function of constant price, p^c_k. Specifically, well-level simulations of groundwater demand under constant electricity pricing are given by the following equation

$$log(\hat{w}_{it}^{p^c}) = \hat{\alpha}_i + \hat{\delta}_t + \hat{\gamma}log(p^c_k) + \hat{\beta}Z_{it} \tag{1.4}$$

where $\hat{w}_{it}^{p^c}$ represents the simulated demand under constant marginal price, p^c_k, and $\hat{\alpha}_i$, $\hat{\delta}_t$, $\hat{\gamma}$, and $\hat{\beta}$ depict parameter estimates from the preferred FE-IV model specification. We then calculate REC average total revenue under a given constant energy price, p^c_k, using the following equation

$$\bar{TR}_k^{p^c} = \frac{\left[\sum_{t=1}^{T}\sum_{j=1}^{J}\hat{w}_{it}^{p^c} * PCC_{it} * p^c_k\right]}{T} \tag{1.5}$$

[23]We exponentiate model predictions, i.e. $\hat{w}_{it}^{P(w)} = \exp(\widehat{log(w_{it})}) = exp(\hat{\alpha}_i + \hat{\delta}_t + \hat{\gamma}log(P) + \hat{\beta}Z_{it})$.

Finally, for the k^{th} REC we determine the 2017 constant price which minimizes the difference between average annual revenue between 2011 and 2016 under DBR and constant pricing according to the following optimization problem

$$\underset{p_k^c}{\text{minimize}} \quad \Lambda = [\bar{TR}_k^{P(w)} - \bar{TR}_k^{p^c}]^2 \tag{1.6}$$

which, for the k^{th} REC, finds the value of p_k^c that minimizes the difference between average total REC revenue under DBR and constant pricing regimes between 2011 and 2016. Predicted constant prices for Highline and Y-W RECs are 0.1074 and 0.1179, respectively. The relative difference[24] between average REC revenues generated using p_k^c versus $P_{kt}(w)$ is less than 0.02%.

1.8.1 Counterfactual Simulation: Groundwater Demand

We evaluate groundwater demand under the counterfactual by utilizing the 2017 constant prices derived by the optimization problem in equation 1.6 to simulate well-level demand using equation 1.4. We then sum these simulated demand quantities across wells to determine aggregate demand under constant pricing and compare to aggregate demand under DBR pricing. Results reveal that a transition to constant electricity pricing in 2017 decreases aggregate groundwater pumping by approximately 5% compared to the alternative scenario of DBR pricing in 2017.

Figure 1.8 plots well-level changes in 2017 pumping against well capacity while differentiating between wells based on which price block defined their observed 2017 pumping. Only wells which demand water on the first, highest marginal price block in 2017 increased groundwater demand as a result of the transition to constant pricing. Under constant pricing these wells experience a decrease in the price signal determining their demand as the derived revenue-neutral constant prices are less than both REC's first block's marginal price. Wells that demand water on the third marginal price block[25] experience the largest decreases in groundwater demand under constant pricing in 2017.

[24] Relative Difference $= \frac{\left|\bar{TR}_k^{p^c} - \bar{TR}_k^{P(w)}\right|}{\left|max(\bar{TR}_k^{p^c}, \bar{TR}_k^{P(w)})\right|}$

[25] Only Y-W utilizes a three block rate structure in 2017.

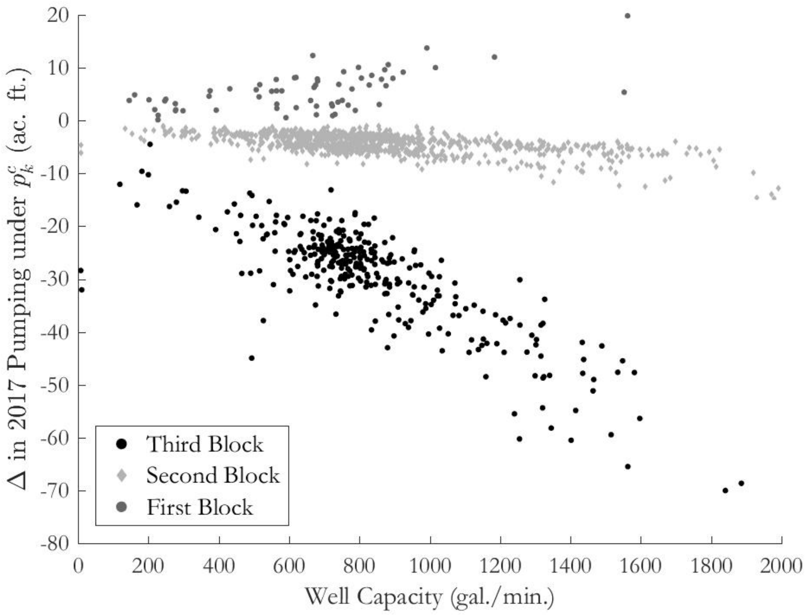


Figure 1.8: Change in 2017 Pumping vs. Well Capacity

These large reductions in demand derive from a relatively large increase in marginal price when electricity pricing is constant. Furthermore, these reductions in demand increase with well capacity suggesting that REC rate structures and resource availability jointly determine the distribution of water use impacts across wells. Finally, wells which demand on the second price block[26] experience relatively minimal reductions in demand that also increase with higher well capacity. These minimal decreases in demand are related to the relatively small increase in marginal price experienced by these wells under constant pricing as both REC's second block's marginal prices are only slightly larger than the derived constant prices (see Figure 1.7).

We also explore how the implementation of a constant pricing regime influences aggregate demand in years previous to 2017. To generate the appropriate comparison, we determine what each well's demand under DBR pricing would be between 2011 and 2016 if their REC priced electricity according to the rate structure used in 2017 and aggregate demand across wells within a given year. We then compare these annual, aggregate pumping decisions under the 2017 DBR rate

[26]These include Y-W wells that demand on the second block of their rate structure and Highline wells which demand on the second, final price block of their rate structure. As mentioned in in Section 1.2, Highline utilized a two block rate structure after 2013.

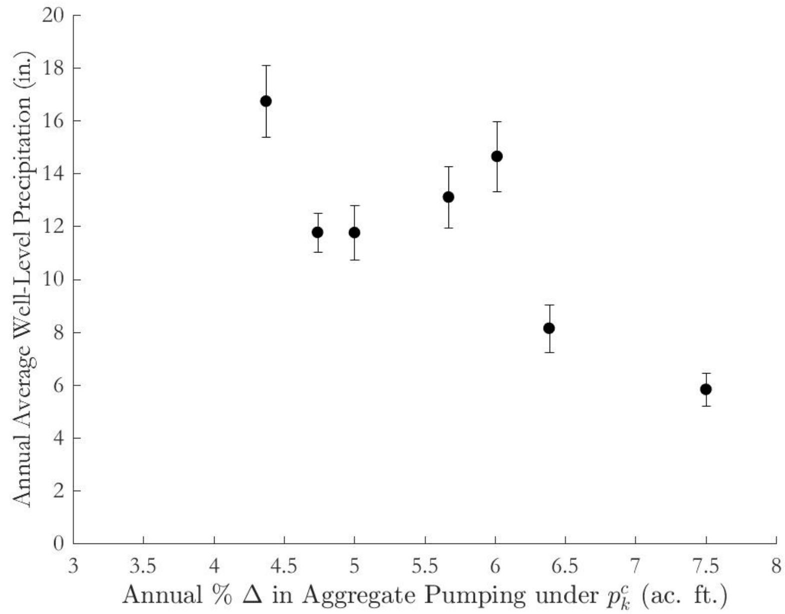


Figure 1.9: Change in Annual Pumping vs. Average Precipitation

structure to annual simulated aggregate pumping when electricity pricing is constant throughout the 2011 to 2017 time period and equal to the constant prices derived previously. This approach allows us to identify the impact of constant pricing separate from variation in REC rate structures across time.

Our simulation results reveal that a transition to constant electricity pricing reduces annual aggregate groundwater demand by between 4 and 7.5% depending on the year. Figure 1.9 plots annual percent decreases in aggregate pumping against annual averages[27] of well-level precipitation demonstrating how exogenous growing season weather affects the conservation potential of constant electricity pricing. Generally, years with less than average well-level precipitation experience greater reductions in aggregate pumping when electricity pricing is constant. This result is related to the fact that wells demand more groundwater in years with less precipitation, thus increasing the impact of the constant pricing regime as more wells demand on the final block of the DBR price structure and experience a larger increase in price under the constant pricing regime.

[27]Vertical bars plot the 25^{th} and 75^{th} quartiles of well-level annual precipitation.

Results on the impact of constant pricing presented should be interpreted as the sum of both intensive and extensive margin adjustments. However, past research finds that extensive margin adjustments are relatively small compared to the total effect of energy prices on groundwater demand [Pfeiffer and Lin, 2014b].

1.8.2 Counterfactual Simulation: Costs of Reduced Groundwater Demand

A transition from DBR to constant electricity pricing in 2017 also yields short-run changes in welfare. Section 1.4 provides a theoretical treatment of welfare changes, positing that welfare gains are guaranteed for lower water-using agricultural producers[28]. Welfare impacts of constant pricing are less clear for higher water-using producers as their welfare depends on both water demand effects and infra-marginal price differences (see equation **??**). In this Section, we address this theoretical ambiguity by simulating welfare changes arising from a transition to constant pricing in 2017, revealing how the relative magnitude of demand and infra-marginal effects influence welfare outcomes.

To calculate short-run welfare changes for agricultural producers, we solve equation 1.2 for marginal price, yielding an expression of the producer's inverse water demand function

$$\Gamma(w; \hat{\alpha}_i, \hat{\delta}_t, \hat{\beta}, Z_{it}, \hat{\gamma}) = \exp\left[\frac{log(w)}{\hat{\gamma}} - \frac{\hat{\alpha}_i}{\hat{\gamma}} - \frac{\hat{\delta}_t}{\hat{\gamma}} - \frac{\hat{\beta} Z_{it}}{\hat{\gamma}}\right] \tag{1.7}$$

where price is a function of water demand, covariates, and model parameters. The change in short-run welfare for the i^{th} well in 2017 is given by

[28]Specifically, welfare gains are guaranteed for producers whose demand under DBR pricing is located along the first block of the price schedule and when RECs pursue a revenue-neutral transition to constant pricing.

$$\Delta\, Welfare_{i,2017} = \underbrace{\int_{min(\hat{w}_{i,2017}^{P(w)}, \hat{w}_{i,2017}^{p_k^c})}^{max(\hat{w}_{i,2017}^{P(w)}, \hat{w}_{i,2017}^{p_k^c})} \Big[\Gamma(w; \hat{\alpha}_i, \hat{\delta}_t, \hat{\beta}, Z_{i,2017}, \hat{\gamma}) - \min(P_{i,2017}, p_{ik}^c)\Big] dw +}_{Demand\ Effects_{i,2017}}$$

$$\underbrace{\int_{0}^{min(\hat{w}_{i,2017}^{p_k^c}, \hat{w}_{i,2017}^{P(w)})} \Big[P_{k,2017}(w) - p_{ik}^c\Big] dw}_{Infra-marginal\ Effects_{i,2017}} \tag{1.8}$$

where p_{ik}^c is the constant price faced by the i^{th} well served by the k^{th} REC, $P_{i,2017}$ is marginal price under DBR in 2017, and $P_{k,2017}(w)$ is a function that outputs 2017 marginal price of the k^{th} REC for an arbitrary w. As outlined in Section 1.4, the first term in equation 1.8 depicts the welfare changes associated with altered water demand, or demand effects, while the second term accounts for changes in welfare arising from differences between the infra-marginal prices of $P_{k,2017}(w)$ and p_{ik}^c, or infra-marginal effects.

We utilize equation 1.8 to calculate short-run welfare changes for each well in our sample. Results reveal that on average a transition from DBR to constant electricity pricing in 2017 reduces welfare by nearly \$700 per well, or 5.5% of average electricity expenditures under DBR pricing (see Table 1.1 in Section 1.6). Aggregating across wells, the transition results in a loss in short-run producer welfare of approximately \$1 million. While the transition to constant electricity pricing leads to average and aggregate losses in producer welfare, the distribution of welfare impacts across wells demonstrates that some wells benefit from constant electricity pricing. Figure 1.10 depicts the distribution of $\Delta\, Welfare_{i,2017}$, revealing that while average welfare impacts are relatively small and negative some wells experience large losses and gains in welfare in the counterfactual scenario. These short-run results do not account for long-run welfare changes as our model does not account for the future benefits attributable to diminished short-run resource use.

Equation 1.8 describes how well-level changes in welfare are a function of demand and infra-marginal effects. Section 1.4 explores these effects and posits that their relative magnitudes jointly determine welfare costs and benefits. Specifically, demand effects increase welfare only for those

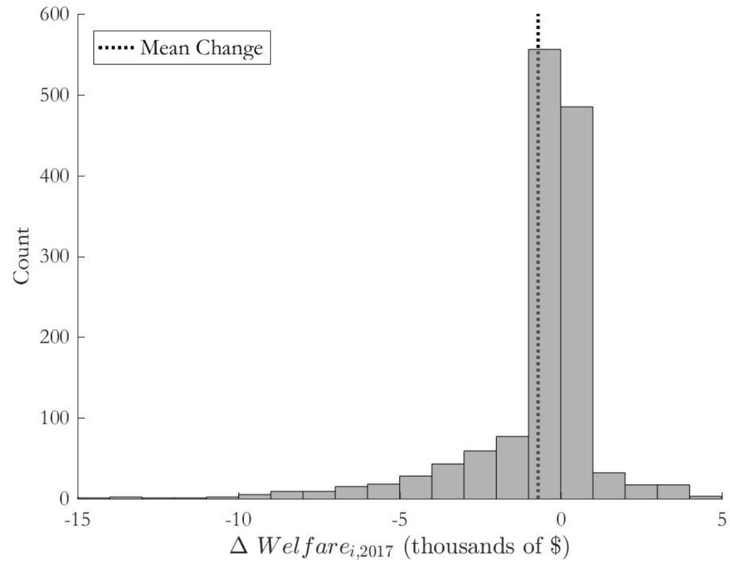


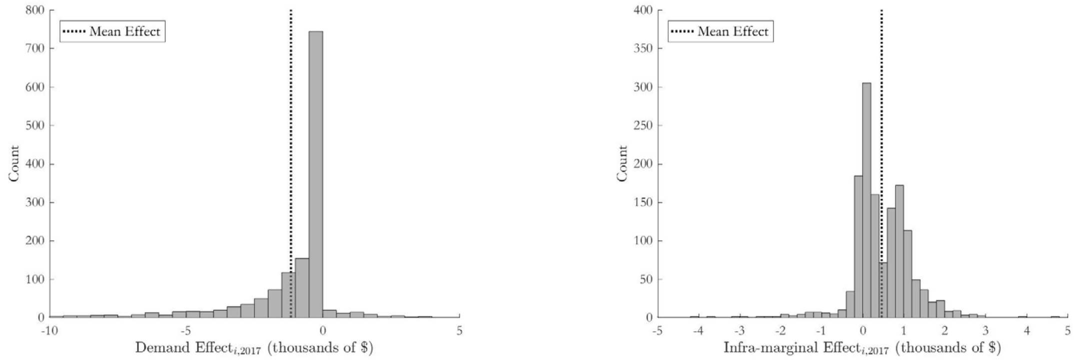
Figure 1.10: Distribution of Δ $Welfare_{it}$

wells that increase their demand under constant pricing which is relatively uncommon given the changes in well-level demand predicted (see Figure 1.8). The magnitude and sign of infra-marginal effects are less clear as they depend on $P_{i,2017}$ and the difference between infra-marginal prices and the constant price. Differentiating between demand and infra-marginal effects aids an understanding of who accrues the welfare benefits and costs displayed in Figure 1.10. Namely, welfare benefits accrue to wells when positive infra-marginal effects[29] outweigh negative demand effects[30] while welfare costs occur when negative demand and infra-marginal effects outweigh positive infra-marginal effects.

We explore how these disparate effects determine welfare outcomes in Figures 1.11a and 1.11b which plot the distribution of demand and infra-marginal effects, respectively. Demand effects are largely negative given the paucity of wells which increase their water use in the counterfactual and

[29]Positive infra-marginal effects occur when producers pay less for infra-marginal units of electricity in the constant pricing counterfactual while negative infra-marginal effects occur when producers pay more for infra-marginal units of electricity. It is possible and likely that producers experience both positive and negative infra-marginal effects on different units of water demand within a given year.

[30]Demand effects may also be positive but this occurs rarely in our simulation as 95% of wells demand at levels exceeding the first block of the price schedule and thus see an increase in marginal price implying their demand effect is negative.



(a) Demand effects **(b)** Infra-marginal effects

Figure 1.11: Demand and infra-marginal welfare effects

the abundance of wells which experience a higher marginal price under constant pricing. Infra-marginal effects presented in Figure 1.11b demonstrate how differences between infra-marginal prices and the constant price generate average benefits for producers. Finally, comparing Figures 1.11a and 1.11b with Figure 1.10 reveals how the magnitude of welfare gains from infra-marginal effects can exceed the welfare costs of demand effects. Comparing welfare changes attributable to demand effects to total welfare impacts suggests that in some cases infra-marginal effects outweigh demand effects and producers using less water under the constant pricing regime experience increases in their total welfare in 2017.

We analyze the spatial distribution of welfare impacts of constant electricity pricing in Figure 1.12 which maps well-level results, saturated thickness[31], and REC boundaries in the Basin. For visual simplicity, we classify each well as either experiencing a welfare gain or loss as a result of the transition to constant pricing in 2017. The distribution of welfare impacts presented in Figure 1.12 provides some visual evidence of the importance of spatially variable resource stocks, measured by saturated thickness, in determining welfare outcomes. Specifically, wells that expe-

[31]Saturated thickness quantifies groundwater availability by measuring the vertical distance between the bottom (impermeable layer) and top (water table) of the aquifer which approximates the groundwater stock influencing pumping decisions.

rience short-run welfare losses have, on average, 6 feet more saturated thickness and 50 gal./min. more well capacity[32] than wells that gain under constant pricing.

The relationship between resource availability and changes in welfare and groundwater demand (see Figure 1.8) point to a potential inefficiency introduced by constant pricing. Namely, the constant pricing regime does not consider heterogeneity in the social costs of pumping across space. Previous research finds that the long-run gains from reduced groundwater pumping depend on initial aquifer conditions wherein producers with minimal initial groundwater stocks accrue more gains from diminished pumping [Foster et al., 2017b]. This result demonstrates that in a dynamic setting, the social costs of pumping costs are likely higher for wells with relatively lower capacity. Constant electricity can introduce inefficiencies by increasing water use in regions where external pumping costs are highest (i.e. low water users). While decreased water use concentrates in areas with higher well capacity and abundant groundwater availability where external costs are likely lower.

1.9 Conclusion

This paper theoretically and empirically describes how resource users respond to non-linear (DBR) input pricing regimes. We utilize empirical modeling results generated using groundwater and electricity data from eastern Colorado to simulate the counterfactual scenario of constant input pricing. Simulation results reveal how DBR input pricing increases resource use when the input and resource are complements in production, demonstrating how input pricing decisions reverberate through natural resource stocks. This is a particularly important result in the context of groundwater-fed irrigated agriculture in the Basin and throughout the HPA given growing common-pool resource depletion concerns and interest in groundwater conservation. The prevalence of DBR electricity pricing (see Figure 1.1) works against conservation efforts as rate struc-

[32]Well capacity is determined by the saturated thickness, hydraulic conductivity, and specific yield of the aquifer at the well's location. Hydraulic conductivity measures the speed at which groundwater moves horizontally in the aquifer and specific yield describes how the aquifer's geologic composition affects the total volume of water available at a given level of saturated thickness.

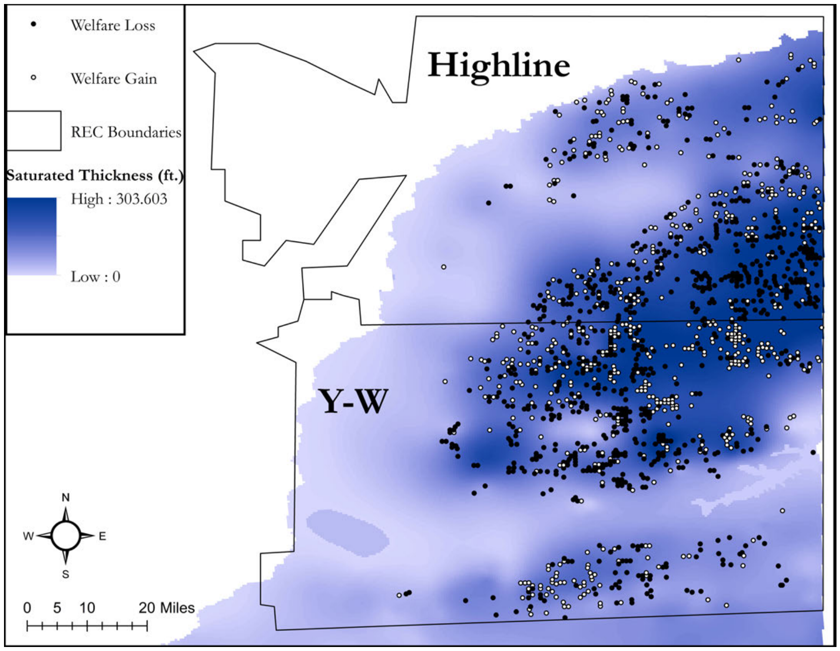


Figure 1.12: Spatial Distribution of Average Welfare Effects

ture price signals encourage increased levels of extraction compared to constant pricing regimes. These results inform groundwater conservation policy in the HPA by highlighting how REC electricity pricing influences well-level and aggregate extraction decisions. More research is needed exploring the use of input price signals, for example, increasing block rate electricity pricing, as an instrument to alleviate resource depletion.

Counterfactual simulation results also uncover that a transition to constant input pricing imposes short-run welfare costs on resource users. However, on average these welfare cost are minimal, only constituting approximately 6% of average annual well-level energy expenditures. Welfare costs are minimal because infra-marginal price effects diminish the welfare effects associated with reduced groundwater withdrawals. Differentiating between demand and infra-marginal effects uncovers that in some cases producers who demand less groundwater under constant pricing experience an increase in their short-run welfare as less expensive infra-marginal water prices compensate producers induced to conserve water. This result has significant policy relevance as it demonstrates how lump-sum transfers, potentially generated using revenues from price-based management policies, can mitigate the welfare impacts of resource conservation efforts.

Finally, our modeling approach does not account for the potential long-run benefits that may accrue to resource users induced to decrease their resource demand. These long run benefits of conservation may be significant, particularly for resources like groundwater where the benefits of diminished extraction manifest primarily in the long and medium run. As such, our short-run welfare analysis results do not measure the full welfare effects of a transition to constant electricity pricing. Future research should integrate economic and hydrologic modeling to examine the long and medium run impacts of resource conservation and how these impacts influence the welfare effects of conservation. Also, our model does not explicitly differentiate between intensive and extensive margin adjustments induced by the constant pricing regime. While previous research finds extensive margin impacts are relatively small compared to the total effect of energy prices, the literature has not evaluated how non-linear energy pricing influences extensive margin choices [Pfeiffer and Lin, 2014b]. Future research in this area should disentangle the intensive and extensive margin to analyze how non-linear energy pricing impacts cropping patterns.

Chapter 2

Peer Effects, Resource Availability, and Conservation Technology Adoption: Evidence from the Trifa Plain of Morocco

2.1 Introduction

A growing world population and changing climate place increasing pressure on agricultural production and scarce water resources [Vörösmarty et al., 2000]. Promoting the adoption of efficient irrigation technologies is a favored policy option to conserve water resources and sustainably intensify agricultural production to confront food security concerns [Evans and Sadler, 2008]. Despite these efforts, global adoption of efficient irrigation technology remains low while interest in investigating the determinants of adoption have surged in both policy and research communities [Koundouri et al., 2006]. This paper contributes to this literature by exploring how peer effects and resource availability jointly influence the adoption of an irrigation technology that conserves natural resources.

A growing literature recognizes how social interactions are important in determining technology diffusion patterns [Foster and Rosenzweig, 1995, Conley and Udry, 2010, Genius et al., 2014, Sampson and Perry, 2018]. This literature posits that individual technology adoption decisions depend on peer group adoption rates which allow individuals to learn about the potential returns of the technology. A similar literature argues that economic, demographic, and environmental or resource characteristics determine technology adoption choices within the context of irrigation [Foltz, 2003, Dridi and Khanna, 2005, Koundouri et al., 2006, Garb and Friedlander, 2014]. In many scenarios, individual adoption decisions generate outside impacts, particularly when adoption influences conservation behavior among individuals utilizing a common pool resource (CPR). This paper contributes to the technology adoption literature by recognizing these outside impacts and investigating how peer effects and resource availability affect adoption and conservation behavior. Specifically, we investigate the adoption of drip irrigation systems which potentially alter how individuals utilize common pool water resources.

Drip irrigation increases the application efficiency of irrigated agricultural production by directly applying water to the plant's root zone thereby minimizing application losses [Camp, 1998]. A large body of agronomic literature finds that drip irrigation adoption increases crop yields and potentially reduces variable input costs [Tiwari et al., 2003, Sezen et al., 2006, Yahyaoui et al., 2017]. Furthermore, the adoption of drip irrigation generates benefits for other resource users if efficiency gains translate into conservation[33] when water resources are scarce and common pool. As such, drip irrigation adoption potentially constitutes a change in individual conservation behavior. This paper evaluates how peer effects and resource availability influence drip irrigation adoption decisions and alter conservation behavior using data from the Trifa Plain of northeastern Morocco.

The characteristics of agriculture in the Trifa Plain provide an ideal setting to explore the relationship between resource availability (e.g. groundwater) and peer effects. First, the region has a long history of furrow, flood-irrigated agriculture dating back to French colonization [Daoud and Engler, 1981]. Recently, the Trifa Plain has seen an increase in drip irrigation system adoption which research suggests increases water use efficiency and agricultural productivity [Kang et al., 2004, Ibragimov et al., 2007]. Second, Moroccan agricultural policy extends generous subsidies to cover the cost of drip irrigation systems, suggesting that capital constraints are less binding in adoption. Third, while surface water availability is ubiquitous throughout the Trifa Plain, the distribution of groundwater is heterogeneous [El Idrysy and De Smedt, 2006]. Finally, agricultural production in the Trifa Plain's climate requires irrigation for most high-value crops [Feltz and Vanclooster, 2013]. We exploit these characteristics to measure how groundwater availability and peer effects jointly determine the rate of drip irrigation adoption.

[33]Recent literature calls into question the notion that investments in efficient irrigation technologies, like drip irrigation systems, necessarily result in water conservation as resource users respond to the change in technology along the extensive margin [Ward and Pulido-Velazquez, 2008, Pfeiffer and Lin, 2014a].

This paper utilizes a novel panel dataset of parcel-level drip irrigation system adoption decisions to estimate the effect of peer group adoption and groundwater availability on the probability of adoption. Empirical results provide modest evidence regarding the importance of social learning and peer effects in irrigation technology adoption [Genius et al., 2014, Sampson and Perry, 2018]. We also find evidence that resource availability decreases the likelihood of adoption which aligns with past research results and demonstrates the role of resource constraints in determining conservation behavior and adoption decisions [Caswell and Zilberman, 1983, Foltz, 2003].

This paper proceeds as follows: in the next Section, we survey relevant peer effect and conservation technology literature and situate the paper's contribution within that literature. In Section 2.3, we provide an overview of irrigated agriculture within the Trifa Plain. In Section 2.4, we develop an empirical framework to model the adoption of a resource conserving irrigation technology. In Section 2.5, we describe the data utilized to estimate our empirical model of irrigation technology adoption. Finally, in Sections 2.6 and 2.7, we present results detailing the relationship between drip irrigation adoption, peer effects, and resource availability and conclude with a discussion of the policy implications of our results.

2.2 Literature Review

This paper builds on several veins of literature exploring the determinants of technology adoption. In this Section, we survey this literature beginning with more general treatments of technology adoption and ending with applied research efforts exploring the adoption of irrigation technology. Finally, we provide an overview of the peer effects literature and discuss how this literature addresses identification challenges.

Economists and social scientist have long been concerned with individual technology adoption decisions. [Griliches, 1957] is often cited as the seminal treatment of technology adoption within the context of agriculture. Recent literature builds on [Griliches, 1957] by empirically and theoretically modeling technology adoption under differing institutional settings [Besley and Case, 1993, Acemoglu et al., 2007, Magnan et al., 2015]. A separate but related literature investigates aggregate technology adoption decisions aiming to understand why developing countries exhibit low adoption rates for productivity and profit enhancing technologies [Feder et al., 1985, Lee, 2005, Suri, 2011].

A related literature focuses on technology adoption among agricultural producers, generating results that reveal how environmental, economic, and demographic characteristics determine adoption decisions [Just and Zilberman, 1983, Sunding and Zilberman, 2001, Duflo et al., 2011]. Of particular importance for our paper are the applied research efforts examining the determinants of irrigation technology adoption [Just and Zilberman, 1983, Dinar and Yaron, 1990, Green et al., 1996, Carey and Zilberman, 2002, Genius et al., 2013]. [Caswell and Zilberman, 1985] is a seminal paper in this vein of research which develops a stylized theoretical framework to understand an agricultural producer's irrigation technology adoption decision. [Shah et al., 1995] extends this framework to the case of irrigation technology adoption with non-renewable resource extraction (e.g. groundwater). [Taylor and Zilberman, 2017] provide an exhaustive review of the drip irrigation technology adoption literature.

This literature generates several hypotheses pertinent to our analysis. Specifically, [Caswell and Zilberman, 1985] find that well-depth and its associated pumping costs are a significant determinant of irrigation technology adoption decisions. As water resources become more scarce, the benefits of adopting an efficient irrigation technology, like drip irrigation, increase. Our paper empirically tests this hypothesis by evaluating how the availability of groundwater affects drip irrigation system adoptions. Similarly, [Foltz, 2003] posits that the learning costs associated with drip irrigation technology influence adoption decisions. We test this hypothesis by incorporating the effect of peer group adoption on individual adoption decisions, leveraging the methodological advances of recent empirical literature investigating the role peer effects play in individual decision-making.

A related literature recognizes the importance of peer effects in individual adoption decisions [Bollinger and Gillingham, 2012a, Bollinger et al., 2018]. Generally, this literature posits that social learning is the primary mechanism through which peer effects influence adoption decisions [Conley and Udry, 2010,Maertens and Barrett, 2012]. This literature identifies that the spatial clustering of outcomes arises from both contextual and endogenous effects [Manski, 1993,Cohen-Cole and Fletcher, 2008]. Exogenous contextual effects generate clustering in outcomes as characteristics shared among groups or spatial units generate similar outcomes. To control for these contextual effects we follow [Sampson and Perry, 2018] who investigate the role of peer effects in the adoption of groundwater-fed irrigated agriculture in Kansas using a rich set of spatial fixed-effects and trends to control for the possibility of peer self-selection. In particular, [Sampson and Perry, 2018] utilize common correlated effects (CCE) developed by [Pesaran, 2006] to account for region-specific trends that influence groundwater adoption but are unrelated to peer effects.

Endogenous effects include those interactions wherein the decision of an individual is causally affected by the behavior of other individuals in their peer group. For example, an agricultural producer may learn about the benefits of drip irrigation from adopting members of their peer group. This relates to what [Manski, 1993] identifies as the "reflection problem" wherein an individual's decision influences group outcomes and vice-versa. However, in our context it is unlikely that individual choices affect group behavior within a given time period as an individual's choice to adopt drip irrigation likely only affects group behavior through a lag given the time needed to install a drip irrigation system. We incorporate these endogenous effects by following [Bollinger and Gillingham, 2012a] and controlling for peer group adoptions, or the installed base, in our empirical modeling. In our context, installed base refers to the lagged number of adoptions within an individual's peer group.

2.3 Study Area

The Trifa Plain is the most productive agricultural region of northeastern Morocco with over 39,000 ha of cultivated land irrigated in a semi-arid climate adjoining the Mediterranean Sea [El Idrysy and De Smedt, 2006]. Figure 2.1 situates the Trifa Plain and its principal source of water, the Moulouya River, within North Africa. The economy of the region is built around the cultivation of perennial fruit, particularly citrus, and annual crops, such as potatoes, sugar beet,

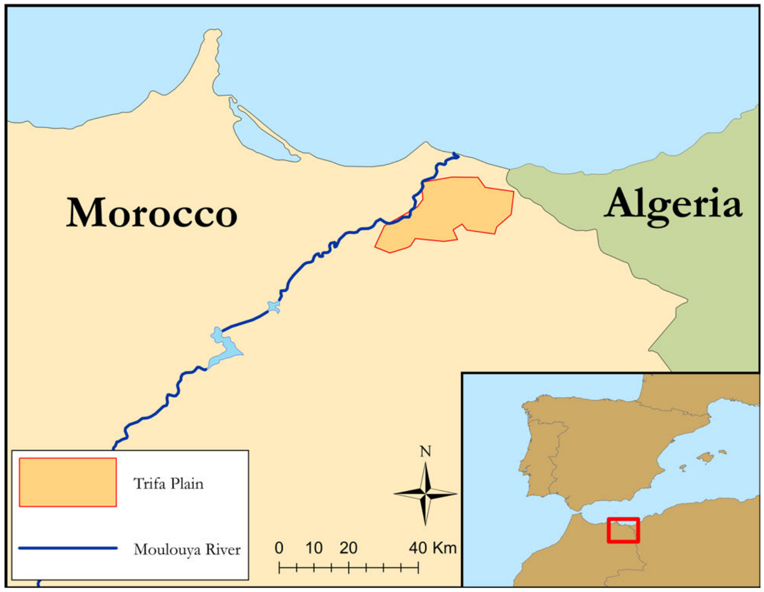


Figure 2.1: Trifa Plain of northeastern Morocco

loquat and vegetables. Over 60% of the region's cultivated land is planted in citrus [Feltz and Vanclooster, 2013]. The region's climate is characterized by cool, wet winters and hot, dry summers making irrigation a necessity for most crops with the exception of some cereals and forage.

The Trifa Plain traditionally relied on imported water[34] and groundwater wells to support the region's agricultural economy [Fetouani et al., 2008]. Figure 2.2 maps the primary[35] irrigation canal that imports water from the Moulouya river into the Trifa Plain. Figure 2.2 also maps the location of the 834 active groundwater wells in the Trifa and an approximation of the aquifer extents. Aquifer locations are an approximation as they are based upon water table data collected from existing groundwater wells, as such, we cannot preclude the existence of groundwater in other locations in the Trifa. Therefore, in our later empirical analysis, we treat the existence of an active groundwater well within a parcel as the indicator of groundwater availability.

[34] Water is imported into the Plain via a system of canals from two reservoirs located in the Moulouya river basin. Water imports are administered by the Office Régional de Mise en Valuer Agricole de Moulouya (ORMVA-Moulouya) and fluctuate according to inter-annual variation in precipitation and snowpack in the Moulouya catchment. Imported water is uniformly allocated among all agricultural producers based on the size of their farm.

[35] From the primary irrigation canal, which is lined with concrete, a system of smaller canals and ditches delivers water to individuals farms.

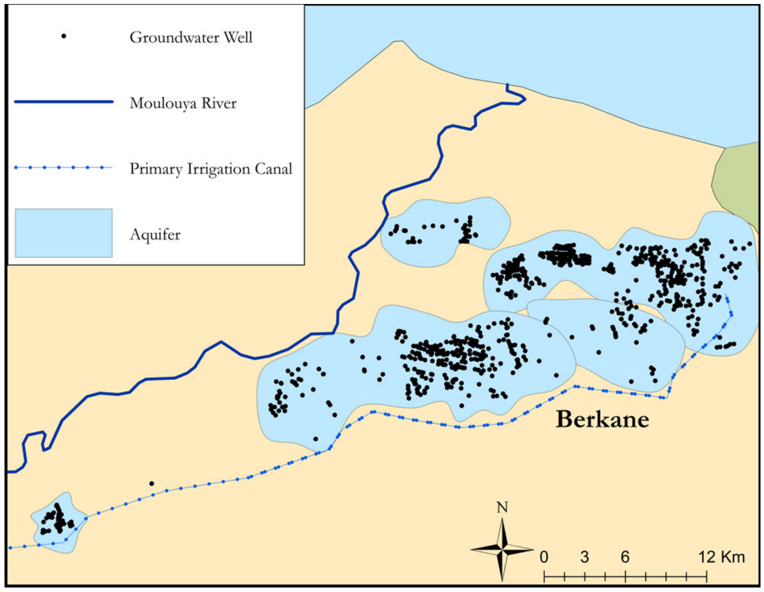


Figure 2.2: Aquifer, wells, and irrigation canals of the Trifa Plain

Growing irrigation demand and climatic variability catalyzed governmental efforts to promote water conservation and agricultural productivity through drip irrigation and water storage basin adoption [Badraoui and Dahan, 2011]. These policymaking efforts resulted in the implementation of a generous subsidy program administered by the Ministry of Agriculture to support the adoption of drip irrigation systems among Moroccan farmers which include producers in the Trifa Plain. The subsidy program covers between 60 and 100% of the costs of drip irrigation system installation, depending on the timing of adoption and farm size[36]. The subsidy program also requires and covers the installation costs of water storage basins. The necessity of water storage basins is related to water quality issues that require water to settle in a basin before application through the drip irrigation system. As such, water storage basins which increase the productivity of irrigation are synonymous with drip irrigation systems in the study area [Rost et al., 2009, Wisser et al., 2010].

Figure 2.3 presents the cumulative adoption of drip irrigation systems within the study area between 2002 and 2012 while Figure 2.4 depicts the spatial distribution of adoptions in 2002,

[36]Currently, farms of less than 5 hectares are eligible for subsidies covering 100% of the costs of installation while farms grater than 5 hectares are eligible for subsidies covering 80% of costs.

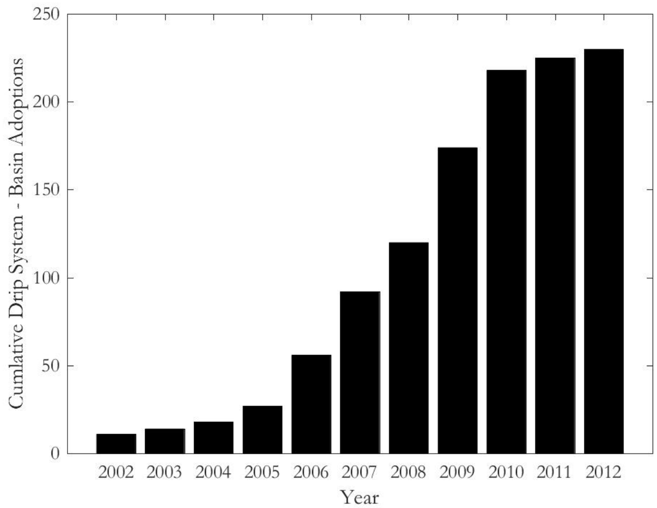
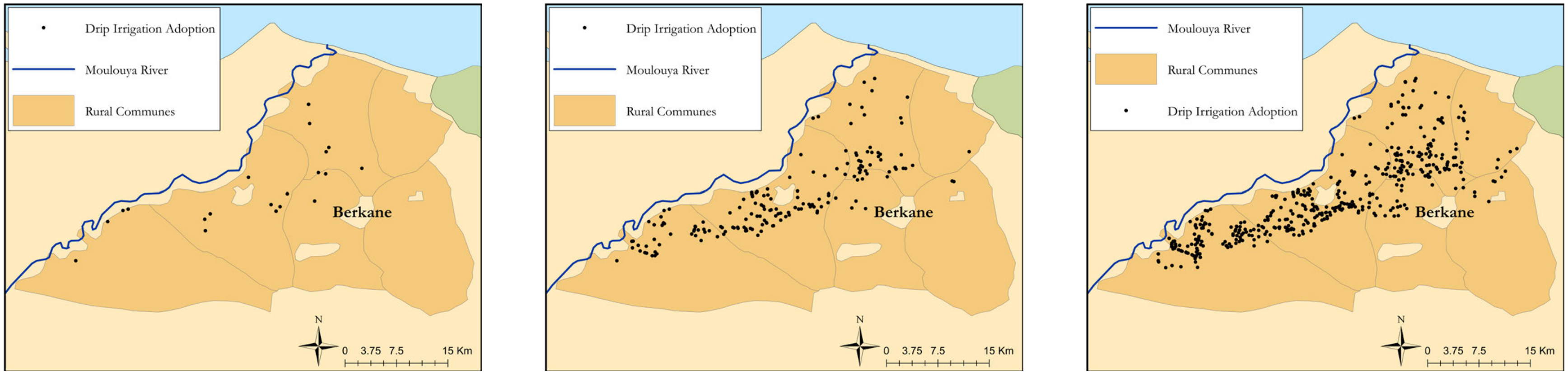


Figure 2.3: Cumulative drip irrigation system adoptions, 2002-2012

2007, and 2012 as well presenting the boundaries of the Trifa Plain's rural communes[37]. These figures demonstrate the rapid uptake of drip irrigation systems and the spatial distribution of these adoptions within the Trifa Plain. Despite these recent increases, research suggests that aggregate drip irrigation adoption rates in the Trifa Plain and Morocco remain low [Jobbins et al., 2015]. This paper aims to understand how peer effects and resource availability determine patterns of drip irrigation adoption across time.

[37]Rural communes are administrative and governmental entities similar to counties in United States. The communes of the Trifa Plain consist of Boughriba, Zegzel, Fezouane, Madagh, Chouihiya, and Laatamna



(a) 2002 **(b)** 2007 **(c)** 2012

Figure 2.4: Spatial distribution of drip irrigation system adoptions, 2002, 2007, and 2012

2.3.1 Producer Survey

To better understand agricultural production and the determinants of irrigation technology adoption decisions in the study area, an in-person survey was conducted during the Spring of 2018. The survey was implemented among 100 producers in the Trifa Plain and collected farm-level information on cropping and irrigation technology. The choice of which producers to survey was based upon a rural commune stratified random sample of farm locations collected by the Moroccan Economic Competitiveness (MEC) project which was funded by USAID and implemented by Development Alternatives INC (DAI).

The average farm size among those producers surveyed was 13.2 ha. while the average farm size of the data collected by MEC was 11.3 ha. which provides some evidence that our survey was broadly representative of the region's agricultural producers. Anecdotally, many of the producers surveyed farmed on land their family received after the end of French colonization in 1956 when the large French farms which once existed in the Trifa Plain were split up and distributed to Moroccan nationals. Furthermore, given Moroccan inheritance laws many farms are owned by multiple individuals within the same family, many of whom do not live in the Trifa Plain or work on the farm. These complex ownership structures complicate land transactions as all owners must agree to sell, providing some evidence that land tenure within the Trifa Plain is static.

Of the producers surveyed, 51 utilized a drip irrigation system on their operation and 45 had access to groundwater. All the producers utilizing drip irrigation adopted the technology after 2002 when the Moroccan Government's drip irrigation subsidy program began, and many producers noted the importance of subsidies in their choice to adopt drip irrigation. 68% of producers surveyed planted the majority of their cultivated land in perennial crops, primarily differing varieties of citrus (e.g. mandarins, navel oranges, tangerines, etc.) which aligns with regional trends regarding perennial crop cultivation [Feltz and Vanclooster, 2013]. Among the 45 producers surveyed whose operation has a groundwater irrigation well, only 6 (13%) adopted a drip irrigation system by 2018.

Many surveyed producers that adopted drip irrigation mentioned the increased management effort needed to operate their system. Specifically, producers recounted that transitioning their operation to drip irrigation demanded additional management of water quality given the potential for nutrient loading and system blockage. Few of the producers surveyed also lived on the plots they farmed, opting instead to live in nearby towns and commute to their fields. As such, the neighbors which constitute their peer group are potentially more spatially dispersed than those producers which farm parcels near their own.

2.4 Empirical Model of Adoption

In this Section, we develop an empirical model of irrigation technology adoption using [Sampson and Perry, 2018]'s notation and discuss the suite of spatial and time controls we utilize to account for common contextual effects. Suppose the i^{th} individual faces the decision of whether to adopt a drip irrigation system in each period t. Let $d_{it} = 0$ denote the decision to continue farming without drip irrigation and $d_{it} = 1$ denote the decision to adopt drip irrigation. The perceived profit associated with each decision is given by $\pi_{it}^{d_{it}}$.

The returns to adopting a drip irrigation system (π_{it}^{1}) consist of the perceived present and future value of increased irrigation application efficiency less installation costs. The returns of not adopting (π_{it}^{0}) consist of the expected profit of current irrigated farming (surface or groundwater) plus the value of the future option to adopt. The net profit of drip irrigation system adoption is then given by $\pi_{it} = \pi_{it}^{1} - \pi_{it}^{0}$ and the agricultural producer adopts when $\pi_{it} > 0$.

As in [Sampson and Perry, 2018], we conceptualize an optimal stopping model wherein an individual chooses when, if ever, to adopt a drip irrigation system. Previous literature has dealt with such models of adoption, or more broadly, when to start or end an activity through two approaches. One strand directly estimates the parameters of the individual's dynamic decision making process [Rust, 1987, Lin, 2013]. However, this approach can be computationally intensive particularly with a large sample [Sampson and Perry, 2018]. Another approach involves approximating the individual's dynamic decision making process with a reduced-form, limited dependent variable model [Pietola, 2003, Bollinger and Gillingham, 2012a, Burke and Sass, 2013, Sampson and Perry, 2018]. Past research shows that reduced-form models perform as well as structural models in terms of prediction [Provencher, 1997]. As such, we employ a reduced-form, random effect approach in estimating drip irrigation system adoptions. We utilize a random effects model to account for the likely case that unobserved heterogeneity exists within our sample.

Let the latent return function, π_{it}, expressing the i^{th} individual's adoption decision in time t, be a given by the following function:

$$\pi_{it} = \underbrace{y_{i(t-1)} + \beta' x_{it} + \theta_{it} + \mu_i}_{v_{it}} + \varepsilon_{it} \tag{2.1}$$

where $y_{i(t-1)}$ represents the installed base of adoptions in the i^{th} individual's peer group in the previous time period, x_{it} is vector of observable covariates, θ_{it} is a vector of regionally-specific time trends and common correlated effects, and μ_i is an unobserved, random individual effect where $\mu_i \hookrightarrow \mathcal{N}(0, \sigma_\mu^2)$, and ε_{it} is the model error term. Given our formulation of the latent function, π_{it}, the probability that $d_{it} = 1$ is given by the following logit expression

$$p_{it} = \frac{e^{v_{it}}}{1 + e^{v_{it}}} \tag{2.2}$$

where p_{it} represents the probability that the i^{th} individual adopts in time t. Given these probabilities, model parameters are estimated using maximum likelihood.

The installed based characterizing the endogenous effect of peer adoption on individual adoption decisions is defined as $y_{i(t-1)} = \sum_{h \in g[i]} F_{j(t-1)}$, where $F_{j(t-1)} = 1$ if the j^{th} peer within the i^{th} individual's peer group, $g[i]$, adopted drip irrigation in a time period before t. The vector of observable covariates, x_{it}, consists of variables that account for distance to surface water canals and wholesale markets as well as size of their operation and the subsidy program their operation qualifies for. We account for the possibility of other unobserved factors by including a rich set of fixed effects and regional time trends captured in the parameter θ_{it}. Specifically, we include rural commune dummy variables and interactions between those fixed effects and quadratic time trends. We also address potentially unobserved spatially-temporally varying effects by specifying common correlated effects (CCE) for each rural commune as well as the entire Trifa Plain. We follow [Sampson and Perry, 2018] and define CCE as $\frac{\sum_i d_{it}}{I_t}$ where I_t represents the number of individuals that have yet to adopt drip irrigation in time t.

We also account for unobserved heterogeneity amongst individuals in our preferred random effect model specification. Estimation of the random effect model rests on the following assumptions: 1) the random effect (RE), μ_i, and model covariates, x_{it}, are independent; 2) model covariates are strictly exogenous; 3) the random effect is normally distributed with variance, σ_μ^2; and 4) there exist no serial correlation in the dependent variable conditional on model covariates and the random effect[38] [A. Colin Cameron, 2005]. While these assumptions are stringent, the random effects model allows our empirical framework to account for further unobserved differences between individuals not captured in θ_{it}. Given the strict assumptions required for the RE specification, we also estimate pooled OLS (POLS) and linear probability specifications which rely on fewer assumptions but do not explicitly model unobserved heterogeneity among individuals.

There is potential concern regarding the assumed exogeneity between our model covariates and unobservables captured by the estimated random effect and the model's error term. If our covariates are not independent of these unobservables, then our model's ability to generate unbiased parameter estimates is suspect. Including a rich set of spatial and time controls partially address these selection on unobservables concerns in so far as these unobservables correlate at the regional level. However, the concern remains for unobservables at the individual level, for example if producers with more management capacity choose to farm larger operations with groundwater available that are also closer to markets and the primary surface water canal. To that extent, we rely on anecdotal evidence regarding the fixed nature of land tenure in Trifa Plain to address these exogeneity concerns. Namely, the historical and institutional setting of land tenure in the Trifa Plains and Morocco as a whole wherein many agricultural land parcels are owned by many individuals within the same family who received the land after the end of French colonization suggest

[38]This assumption can be relaxed, see [Wooldridge, 2010].

that what parcels producers farm is mostly a function of what family they were born into rather than attributes of the parcel of agricultural land.

Finally, there a several important features in our data that warrant discussion. Firstly, once we observe an individual adopt a drip irrigation system we do not observe if that individual stops using their system. This presents a challenge in our modeling regarding the appropriate manner to code the binary dependent variable representing adoption after the adoption decision is taken. We could potentially set $d_{it} = 1$ for all subsequent periods after adoption. However this approach assumes the drip irrigation system is utilized in each subsequent year, which may not be the case and could potentially bias model estimates. Similarly, we could follow [Rode and Weber, 2016] and code post-adoption decisions as zero but this approach assumes the individual utilizes their drip irrigation system for at most one year which seems unreasonable given the effort required to adopt. We follow [Sampson and Perry, 2018] and drop observations from the sample in subsequent time periods after their initial adoption while keeping these observations of adoption in our calculation of the installed based. [Sampson and Perry, 2018] use Monte Carlo simulations to test how their method of coding adoption decisions affects parameter estimates and conclude that dropping post initial adoption decisions generates peer effect parameter estimates below the true estimate. As such, this approach to coding adoption decisions produces conservative peer effect parameter estimates.

2.5 Data

In this Section, we describe the parcel-level drip irrigation system adoption data we utilize to estimate the econometric model of technology adoption presented in Section 2.4. We integrate open-source parcel data with spatially-referenced drip irrigation adoption decisions observed in the Trifa Plain to generate a panel dataset of 1,364 parcel-level observations across the 2002-2012 time period.

We utilize geospatial data collected in the Trifa Plain by the Morocco Economic Competitiveness (MEC) Project implemented by Development Alternatives Inc. and funded by USAID. These primary data were collected between 2011 and 2012 and include a geospatially referenced inventory of all drip irrigation system adoptions in the Trifa Plain up to 2012. These data also include information on the timing of adoption as well as a full inventory of groundwater wells.

As in many developing country contexts, the Trifa Plain lacks reliable, georeferenced land tenure data which complicates matching drip irrigation adoption to individuals and their land. To surmount this challenge, we utilize publicly available OpenStreetMap[39] (OSM) data to define agricultural parcels within the Trifa Plain. A growing literature examines the validity and quality of open source, user-generated geospatial data, concluding that such data sources are quite accurate where metrics to asses their quality exist [Haklay, 2010, Mondzech and Sester, 2011, Barron et al., 2013, Forghani and Delavar, 2014]. A smaller literature analyzes the use of OSM road network data to define land parcels in urban and rural settings and finds OSM derived parcel data a useful alternative when other parcel data sources are not available [Liu and Long, 2015, Arsanjani et al., 2015, Liu et al., 2017].

We utilize road networks and geospatial data on urban boundaries to define agricultural land parcels [Liu and Long, 2015, Arsanjani et al., 2015, Liu et al., 2017]. Specifically, we utilize OSM road network data within land classified as agricultural in the Trifa Plain to generate 1,364 land parcels. This characterization of land parcels does not account for potential patterns of land ownership that differ from parcel boundaries. For example, it is likely that some agricultural producers own or manage multiple parcels nearby each other. However, we do not observe these patterns of land tenure. In our later empirical modeling, we assume that the own effect of an individual adopting drip irrigation on one of their nearby parcels is the same as the peer effect of another producer adopting on a nearby parcel.

We match individual land parcels to the 236 drip irrigation adoption decisions observed in our data. We define the installed base for a given parcel in time t as the number of parcels within a 0.5,1,2, or 3 km buffer[40] of the parcel's centroid that adopted drip irrigation before t and also

[39] ©OpenStreetMap contributors

[40] Concentric circle.

control for the number of parcels within a given buffer to account for variation in the number of neighboring parcels or peer group size. Summary statistics regarding the average number of adopters or the installed based are provided in Table 2.1, which demonstrates the gradual increase in adoptions from 2002 to 2012.

We also utilize additional geospatial data to control for groundwater availability, parcel size, drip irrigation adoption subsidies, and market and surface water access. We define parcel-level resource/groundwater availability as a dummy variable which equals one if a groundwater well is observed within a given parcel at any point in time between 2002 and 2012, and zero otherwise. In total, we observe 437 parcels with groundwater availability. We assume that groundwater availability is exogenous given anecdotal evidence that producers farm on land initially distributed to their families after the end of French colonization, over 70 year ago and before the advent of large-scale groundwater-fed irrigation in Trifa Plain.

We control for variation in drip irrigation adoption subsidies by including a dummy variable which indicates whether a parcel is less than 5 hectares, which is the threshold to qualify for the 100% drip irrigation adotion subsidy. Parcels larger than 5 ha. also qualify for subsidies but these cover a smaller proportion of adoption expenses. Finally, we control for parcel-level surface water and market access by calculating distance to the largest wholesale market in the Trifa Plain, which is located in Berkane, and the distance to the nearest large surface water canal for each parcel in the sample. These variables capture differences in transportation costs and conveyance losses in surface water delivery. Table 2.2 presents summary statistics for these time-invariant covariates.

2.6 Results

Tables 2.3 and 2.4 present random effect (RE) model specification results for the econometric framework developed in Section 2.4. Specifically, Tables 2.3 and 2.4 show model results when the peer group is defined by the number of neighbors adopting within 1 km and 3 km, respectively, of an individual's parcel. The columns in Tables 2.3 and 2.4 present model results with increasing levels of spatial and time controls wherein column 1 uses no additional spatial or time controls while

Table 2.1: Summary statistics on peer group drip irrigation adoptions

	# Neighboring Adopters Within			
Year	$1/2$ km	1 km	2 km	3 km
2002	0.05	0.16	0.37	0.60
2003	0.07	0.20	0.47	0.77
2004	0.09	0.26	0.62	1.01
2005	0.14	0.38	0.94	1.48
2006	0.26	0.72	1.86	2.72
2007	0.43	1.15	3.11	4.56
2008	0.56	1.50	4.08	6.07
2009	0.79	2.15	5.93	8.83
2010	1.00	2.73	7.46	11.15
2011	1.03	2.78	7.65	11.51
2012	1/04	2.79	7.63	11.52

Table 2.2: Summary statistics on parcel characteristics,

Variable	Mean	Std. Dev.	Min.	Max
GW Available	0.18	0.39	0	1
Parcel Size (Ha)	20.10	30.38	0.604	194.19
Parcels $<$ 5 Ha.	0.14	0.34	0	1
Distance to Berkane (km)	11.99	5.40	1.26	23.44
Distance to Irrigation Canal (km)	5.13	4.06	0	19.07

Table 2.3: Drip irrigation adoption model with peer group defined as parcels within 1 km

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 1 km	0.295***	0.180***	0.166***	0.130*
	(0.0484)	(0.0347)	(0.0438)	(0.0548)
GW Available	-0.219	-0.435	-0.460	-0.705+
	(0.382)	(0.278)	(0.302)	(0.428)
# of Peers Adopting X GW	-0.0910	-0.0689	-0.0750	-0.0878
	(0.104)	(0.0836)	(0.0897)	(0.118)
Parcel Size	-0.0346***	0.0173*	0.0189*	0.0286*
	(0.0101)	(0.00832)	(0.00908)	(0.0128)
Parcel Size^2	0.000209**	-0.000123+	-0.000132+	-0.000194*
	(0.0000689)	(0.0000626)	(0.0000678)	(0.0000950)
Less than 5 Ha.	-0.996**	0.104	0.119	0.262
	(0.366)	(0.271)	(0.294)	(0.404)
Distance to Canal	-0.261***	-0.0527	-0.0667+	-0.129*
	(0.0369)	(0.0345)	(0.0382)	(0.0527)
Distance to Market	-0.128***	-0.0447+	-0.0477+	-0.0701+
	(0.0208)	(0.0255)	(0.0280)	(0.0389)
# of Parcels W/I 1 km	-0.0962***	-0.00649	-0.00545	-0.000638
	(0.00957)	(0.00854)	(0.00933)	(0.0129)
σ^2_μ	1.785***	0.560*	0.949**	2.330***
	(0.232)	(0.270)	(0.323)	(0.140)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend
$^+ p < 0.1$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table 2.4: Drip irrigation adoption model with peer group defined as parcels within 3 km

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 3 km	0.148***	0.0960***	0.150***	0.0591^{+}
	(0.0203)	(0.0187)	(0.0292)	(0.0320)
GW Available	-0.464	-0.776*	-0.751*	-1.052*
	(0.550)	(0.373)	(0.383)	(0.504)
# of Peers Adopting X GW	0.0160	0.0190	0.0135	0.0269
	(0.0402)	(0.0321)	(0.0332)	(0.0429)
Parcel Size	-0.0476***	0.0201*	0.0206*	0.0277*
	(0.0112)	(0.00922)	(0.00951)	(0.0121)
Parcel Size^2	0.000276***	-0.000136*	-0.000138*	-0.000184*
	(0.0000756)	(0.0000683)	(0.0000702)	(0.0000892)
Less than 5 Ha.	-1.268**	0.0937	0.104	0.213
	(0.406)	(0.300)	(0.308)	(0.386)
Distance to Canal	-0.291***	-0.0768*	-0.0787^{+}	-0.128*
	(0.0397)	(0.0385)	(0.0404)	(0.0502)
Distance to Market	-0.140***	-0.0503^{+}	-0.0513^{+}	-0.0631^{+}
	(0.0216)	(0.0285)	(0.0294)	(0.0370)
# of Parcels W/I 3 km	-0.0324***	-0.00207	-0.00337	-0.000213
	(0.00329)	(0.00283)	(0.00297)	(0.00381)
σ^2_μ	2.443***	1.045**	1.135**	2.059***
	(0.150)	(0.320)	(0.364)	(0.177)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

column 4 uses the full suite of controls. Our preferred model specification results are contained in column 4 of Tables 2.3 and 2.4 which control for commune-specific effects, commune-specific quadratic trends, and study area and commune-specific common correlated effects (CCE).

Our empirical model finds modest evidence regarding the positive impact of peer effects on drip irrigation adoption. Namely, in both model specifications as increasing levels of spatial and time controls are included the impact of neighboring adoptions, or peer effects, remains positive and statistically significant, at at least the 10% level. The significance of peer effects diminishes as additional spatial and time controls are added to the model specification. Specifically, the inclusion of CCEs which control for time variant regional trends significantly reduces the statistical significance of peer group adoption rates on individual adoption decisions. This result demonstrates how the inclusion of a rich set of spatial and time controls reduces residual variation necessary to identify peer effects, particularly when dealing with smaller sample sizes.

We also evaluate the average marginal effect of peer group adoption and find that a producer is 0.23% more likely to adopt when one additional peer within 1 km adopts while a producer is 0.10% more likely to adopt when one additional peer with 3 km adopts, these average marginal effects are statistically significant at the 5% and 10% levels, respectively. These results follow intuition regarding the diminished marginal effect of peer adoption as the peer group increases in size. Furthermore, these estimated marginal effects align with marginal peer effect estimates in past literature, in both developed and developing country contexts, which finds that an additional peer adopting increases the likelihood of individual adoption between 0.1% and 0.76% [den Broeck and Dercon, 2011, Maertens and Barrett, 2012, Krishnan and Patnam, 2013, Bollinger et al., 2018, Sampson and Perry, 2018].

Modeling results also reveal a consistent negative and statistically significant, at at least the 10% level, relationship between the availability of groundwater and the likelihood of adoption. This result speaks to the importance of resource constraints and availability in determining adoption decisions and aligns with past empirical and theoretical research investigating the relationship between technology adoption and resource constraints and price [Caswell and Zilberman, 1985, Foltz, 2003]. In our context, agricultural producers with groundwater are less resource constrained than their counterparts who rely solely on stochastically available surface water supplies. As such, the expected parcel-level returns of drip irrigation adoption are less when groundwater is available on the parcel than when groundwater is not available.

We also estimate marginal peer effects for both producers with and without groundwater available on their operation. These results reveal that average marginal peer effects are consistently greater for producers without access to groundwater on their operation. Specifically, for the model with peer groups defined by a 1 km buffer, the average marginal peer effects are 0.17% and 0.24% for producers with and without groundwater, respectively, which are both significant at the 5% level. For the model with peer groups defined by a 3 km buffer, average marginal peer effects are 0.06% and 0.11% for producers with and without groundwater, respectively. However, only the marginal peer effect for producers without groundwater is statistically significant at the 10% level. These results suggest that peer effects are potentially more salient among producers without access to groundwater.

Results also reveal a positive and statistically significant relationship between the probability of adoption and parcel size when the full set of spatial and time controls are included. Furthermore, the positive coefficient on parcel size squared implies that the magnitude of this positive effect is decreasing as parcel size increases. We also find that the 5 ha indicator variable is not statistically significant in any of the specifications which include spatial or time controls. This result suggests that differences in drip irrigation subsidies are not a significant factor driving adoption decisions.

Finally, our results indicate a negative relationship between the probability of drip irrigation adoption and distance to market, implying that access to markets and the government services in Berkane are a significant determinant of adoption decisions. Our results also reveal a relatively consistent and statistically significant relationship between distance to surface water canal and the probability of adoption which is somewhat counterintuitive given we would expect that parcels further from a canal would be more resource constrained given water conveyance losses and thus experience increased returns from adoption. Rather, it is likely that this variable is capturing a separate effect, particularly if the location of surface water canals was determined by land quality attributes which are otherwise not controlled for in our model.

We also estimate our empirical model of drip irrigation adoption using the percentage of peers adopting within the peer group. These results are presented in Section B.3 of the Appendix and demonstrate that the impact of peer adoption is less robust when the peer effect variable enters the model as percentage rather than a level. This result provides evidence that there may be differing mechanisms based on percentage rather than level of peer group adoption through which peer effects influence adoption decisions.

We test the robustness of our empirical results in Sections B.1 and B.2 of the Appendix which presents model results for differing spatial buffers defining peer groups, model specifications, and formulations of the peer effect variable. Results in Section B.1 wherein peer groups are defined by 1/2 and 2 km buffers are similar to those presented here, providing evidence that our results are not particularly sensitive to the distance defining a parcel's peer group. Section B.2 displays empirical model results using a pooled OLS model specification which qualitatively align with the random effects specification results presented above.

2.7 Conclusion

This paper investigates agricultural producers' decision to adopt an efficient irrigation technology and how peer effects and resource constraints determine this choice. We utilize parcel-level data on drip irrigation adoption decisions from the Trifa Plain of northeastern Morocco to empirically estimate this relationship. Our results reveal that peer effects, based on spatial proximity, have a limited impact on drip irrigation adoption decisions when spatial and time controls are included in our empirical modeling. We also find that groundwater availability negatively influences drip irrigation adoption.

Our results regarding the impact of peer effects on drip irrigation adoption provide modest evidence supporting the notion that peer group adoption rates influence individual adoption decisions. Specifically, we find that an additional peer adopting increases the likelihood of individual adoption between 0.10% and 0.23%, depending the spatial buffer defining the peer group. This result aligns with past technology adoption literature which finds peer group adoption a significant determinant of adoption decisions [Conley and Udry, 2010, Bollinger and Gillingham, 2012b, Sampson and Perry, 2018]. We describe our results as modest given the diminished level of statistical significance of peer effects as increasing levels of spatial and time controls are included. However, this result may be related to our relatively small sample size and the minimal residual variation left to identify peer effects after controlling for unobservables with the full suite of controls common in the literature (e.g. regional time trends, CCEs). Future research should explore peer effect identification issues within the context of small sample sizes common in data poor regions.

Our results also reveal that resource availability decreases the probability of drip irrigation adoption which aligns with past conclusions in the literature [Caswell and Zilberman, 1983, Foltz, 2003]. The availability of alternate water supplies measured by access to groundwater diminishes resource constraints and reduces the returns to drip irrigation adoption. We also find that marginal peer effects are diminished for producers with access to groundwater compared to those without access, implying that peer effects are potentially more salient for more resource constrained producers. These results demonstrate the potential impact of conservation policies that incentivize individuals to account for resource scarcity via pricing or other resource management policies on the adoption of efficiency-enhancing technologies. More specifically, our results suggest that drip irrigation subsidy rates that vary according to resource availability could potentially increase drip irrigation adoption rates among the least resource constrained individuals. Future research should investigate how the source of water available to producers influences the likelihood of engaging in pro-conservation behavior and adopting an efficiency enhancing irrigation technology.

A weakness of our analysis lies in our characterization of land parcels based upon road boundaries. It is likely that actual patterns of land tenure and management do not strictly align with road-based land parcels. This potentially introduces some biases in our modeling if other avenues (e.g. land ownership) outside peer effects influence how adoption decisions in a given parcel affect neighboring parcels. Future research should evaluate the impact of using road-based parcels rather than observed land ownership patterns in models of technology adoption and land-use.

Chapter 3

Endogenous Input Markets and Pro-Conservation Behavior: The Spillovers of Groundwater Management

3.1 Introduction

The management of common pool resources (CPR) is a major policy concern which attracts significant attention in the natural resource and environmental economics literature. Much of this literature focuses on identifying optimal policy regimes that align private resource use decisions with socially efficient objectives [Gardner et al., 1990, Fisher et al., 2010, Madani and Dinar, 2012]. In practice, institutional and physical constraints often preclude the implementation of efficient (first-best) management policies across the entirety of a resource. Rather, political and jurisdictional boundaries often fracture CPR management efforts, creating a regulatory patchwork within the resource's extent. This occurs in fisheries, large aquifers, watersheds, and atmospheric CO_2, which often cross national and other political borders [Heikkila, 2003, Schnier and Anderson, 2006, Just and Netanyahu, 2012].

The patchy implementation of CPR management policies creates spillovers which reverberate through physical systems and markets [Jacobson, 2014]. An extensive literature exists analyzing policy spillover and leakage in the context of air quality [Chen, 2009, Fell and Maniloff, 2018], forestry [Gan and McCarl, 2007, Warman and Nelson, 2016], and fishery regulation [Halpern et al., 2009, Gaines et al., 2010, Cunningham et al., 2016]. [Pfaff and Robalino, 2017] classify the channels through which conservation policy spillovers and leakage occur. We build on this literature by investigating how input markets interact with resource dynamics to determine the net effect of conservation policy spillovers. Specifically, we analyze the economic spillovers arising from patchy CPR management in the context of groundwater where energy input markets[41] and natural resource dynamics connect CPR users.

Groundwater is an ideal resource to explore the impacts of patchy CPR management as many of the world's most productive aquifers cross state and national political boundaries[42]. As such, groundwater management and conservation within many shared aquifers takes place under a range of institutional and legal settings. The High Plains Aquifer (HPA) overlies 8 states[43] in the central United States and supports millions of acres of irrigated cropland exemplifies the patchwork of jurisdictions determining CPR management [Scanlon et al., 2012]. The HPA is hydrologically connected across jurisdictions, suggesting that conservation efforts in one jurisdiction affect resource availability in neighboring jurisdictions [Voss, 2014]. Furthermore, groundwater users in the HPA are also connected by common input markets (e.g. energy, fertilizer, pesticides and herbicides) serving the irrigated agricultural economy. This paper develops a hydroeconomic model of irrigated agricultural production in the Republican River Basin of Colorado, a sub-basin of the HPA, to evaluate how the patchy implementation of groundwater conservation policies generates positive and negative spillovers for neighboring groundwater users when prices for complementary and/or substitute inputs are endogenous.

This paper contributes to the broader integrated modeling literature that aims to align rigorous economic models with accurate portrayals of physical systems by recognizing how policy-induced changes in resource dynamics generate impacts in non-resource markets [Muller and Mendelsohn, 2007, Garnache et al., 2017]. We also contribute to the more context-specific hydroeconomic modeling literature by developing a framework that captures how groundwater conservation policies affect common input markets. Hydroeconomic models integrate economic models of resource

[41]Energy inputs are complementary to groundwater inputs in irrigated agricultural production as energy inputs increase the productivity of groundwater by allowing groundwater pumping and application on crops.

[42]e.g. High Plains, Wajid, Nubian, Guarani, and Upper Rhine Aquifers. The High Plains aquifer underlies several U.S. States, the Wajid aquifer underlies both Yemen and Saudi Arabia, the Nubian aquifer underlies parts of Chad, Sudan, Egypt, and Libya, the Guarani aquifer underlies areas of Argentina, Brazil, Paraguay, and Uruguay, and Upper Rhine aquifer underlies areas of France and Germany.

[43]Texas, New Mexico, Oklahoma, Kansas, Nebraska, Colorado, Wyoming, and South Dakota

use with physical models depicting resource dynamics across time to provide policy-relevant insights and better understand the costs and benefits of groundwater management [Harou et al., 2009, Koundouri, 2004]. Specifically, we model how energy distribution firms adjust their pricing regimes in response to groundwater conservation policy implementation. This approach recognizes the unique one-to-one relationship between energy and groundwater demand and how groundwater conservation policies potentially induce energy input firms to change prices and spread the fixed costs of maintaining distribution networks across fewer units of energy [Pfeiffer and Lin, 2014a]. The relationship between groundwater conservation and the prices charged by energy distribution firms constitutes a special case of the broader connection between input markets and environmental goods or natural resources. For most inputs we would expect that a decrease in demand would decrease price, however this is not the case for energy distribution firms given they must recover the fixed costs of maintaining their distribution network.

We also contribute to the hydroeconomic modeling literature by employing a novel empirical approach in estimating individual groundwater demand as a function of resource availability and energy prices. Past hydroeconomic models utilize parameters from the literature to estimate groundwater demand functions [Gisser and Sánchez, 1980, Provencher and Burt, 1993, Guilfoos et al., 2013, Guilfoos et al., 2016] or develop structural models of groundwater demand based on agronomic characteristics and economic theory [Hrozencik et al., 2017]. However, these approaches do not account for unobserved agricultural producer and well characteristics[44] which potentially influence demand. We improve upon this approach by leveraging well-level data on groundwater demand in the Republican River Basin of Colorado to empirically estimate reduced-form groundwater demand functions that reflect the characteristics of irrigated agricultural production in the study area.

We utilize our hydroeconomic model to analyze conservation policy spillovers by simulating both baseline (no-policy) and policy scenarios and comparing their outcomes across time. Our results reveal how input market and resource effects jointly determine the spillovers associated

[44] e.g. management ability, irrigation technology and efficiency, land tenure, and conservation preferences.

with patchy CPR management policies. Specifically, we find that resource users neighboring the policy area accrue benefits in the form of increased levels of resource availability. However, these gains largely dissipate when resource users share a common input market for electricity with users subject to the policy regime due to higher input prices. The policy implications of this result are significant as it demonstrates how input price endogeneity generates costs for resource users not subject to CPR management policies.

This paper proceeds as follows: in Section 3.2, we review the pertinent economic literature and situate this paper's contribution within that literature. In Section 3.3, we develop a theoretical model which depicts how both common input markets and resource dynamics distribute the costs and benefits of groundwater management policies. In Section 3.4, we describe the physical and institutional attributes of groundwater-fed irrigated agriculture in the Republican River Basin of Colorado. In Section 3.5, we present the hydroeconomic model which consists of empirically derived groundwater demand equations, common energy input markets, and aquifer dynamics. Results are presented in Section 3.6 and their significance discussed in Section 3.7.

3.2 Literature Review

In this Section, we review the pertinent economic literature and place the three primary contributions of this paper within that literature. First, this paper contributes to the broader environmental economics literature by analyzing the spillovers, or externalities, arising from patchy CPR management in a novel context, groundwater. Second,the paper builds on past research examining the relationship between economic inputs and natural resources by recognizing and modeling how input markets serve as conduits for CPR management impacts. Finally, this papers advances the hydroeconomic and integrated modeling literature by linking empirically estimated groundwater demand functions with a physical model of an aquifer to estimate management policy impacts and economic value.

A large body of applied research in environmental and natural resource economics examines the spillovers arising from environmental regulation related to land conservation programs [Jacobson, 2014, Pfaff and Robalino, 2017], air quality [Chen, 2009, Fell and Maniloff, 2018], fisheries [Halpern et al., 2009, Gaines et al., 2010, Cunningham et al., 2016]), and forests [Gan and McCarl, 2007, Warman and Nelson, 2016]. Broadly, this literature finds that the magnitude of the benefits and costs imposed by patchy CPR management depends on the characteristics of the physical system and the policies managing that system. For example, the creation of marine reserves creates significant positive spillovers for neighboring fisheries while land conservation programs potentially generate negative spillovers for landowners impacted by the policy given potential adjustments along the extensive margin [Jacobson, 2014].

[Pfaff and Robalino, 2017] review how the implementation of conservation programs generate impacts beyond program borders. Specifically, [Pfaff and Robalino, 2017] identify input reallocation, market prices, learning, non-pecuniary motivations, and ecological-physical links as the primary channels through which conservation policy spillovers and leakages occur and note that in many cases multiple channels determine aggregate spillover effects. We build on the insights presented by [Pfaff and Robalino, 2017] and focus our analysis of the spillovers arising from patchy groundwater management policies on market prices, specifically input market prices, and ecological-physical channels. We utilize a novel hydroeconomic modeling approach to separate the effects of these disparate channels.

A developing literature investigates spillovers that occur between water and energy, finding that behavioral interventions and policy in one sector affect the other sector and vice versa [Zhou et al., 2016, Jessoe et al., 2017]. However, the literature has not explored spillovers within the context of water conservation despite evidence that water users respond to water use restrictions and the spatial externalities imposed by neighboring use decisions [Pfeiffer and Lin, 2012, Drysdale and Hendricks, 2018]. Furthermore, the common pool nature of groundwater and the patchwork of jurisdictions regulating many of the world's most productive aquifers suggest that economically significant spillovers may occur within a shared groundwater resource when its management is non-uniform across space.

Another growing body of literature examines the relationship between energy and groundwater use. Broadly, this literature finds that changes in energy pricing and subsidies influence water demand [Pfeiffer and Lin, 2014a, Foster et al., 2017a, Foster et al., 2018]. Other literature has suggested utilizing energy policy as a tool to address groundwater depletion concerns [Scott and Shah, 2004, Scott, 2013, Fishman et al., 2016]. However, a relative paucity of literature has investigated how changes in water demand affect energy markets despite the evidence linking water and energy demand. These effects are likely significant when energy demanded for water use constitutes a large portion of the total market, as is the case for electricity distribution firms in the HPA. We address this gap in the literature by quantifying how the spatial externalities of reduced groundwater withdrawals induced by conservation policy generate positive spillovers for neighboring, unregulated resource users. We also build on this literature by acknowledging the multiple channels which distribute policy spillovers and modeling the input market effects of groundwater conservation policies.

This paper also contributes to a vein of literature that recognizes the role that input markets play in determining the use of environmental goods and natural resources. This literature focuses on the complementarity and substitutability of natural and man-made inputs to production and explores how this relationship influences natural resource stocks and environmental quality [Moroney and Toevs, 1977, Cai et al., 2008, Hannesson et al., 2010, Manning et al., 2013]. However, this literature has not explored how the relationship between inputs and natural resources affects the distribution of CPR management policy impacts across resource users or space. We address this gap in the literature by analyzing how input markets serve as conduits for policy impacts in the context of groundwater where energy inputs are required for natural resource extraction.

Finally, this paper makes a methodological contribution of the hydroeconomic modeling literature by taking a reduced-form empirical approach in estimating groundwater demand functions. Early hydroeconomic economic literature utilized stylized models of groundwater demand and resource dynamics to assess the costs and benefits of groundwater management [Gisser and Sánchez, 1980, Provencher and Burt, 1993, Brill and Burness, 1994]. More recent literature integrates calibrated hydrologic models of groundwater flow recognizing the importance of accurately depicting natural resource dynamics and spatial externalities [Brozović et al., 2010, Mulligan et al., 2014, Guilfoos et al., 2013, Guilfoos et al., 2016, Hrozencik et al., 2017]. This paper follows these recent advances in the literature and utilizes a hydrologic model of the Republican River Basin to measure how pumping decisions influence spatially-explicit future groundwater availability.

Despite these advances in accurately modeling groundwater resource dynamics, most hydroeconomic modeling research utilizes parameters from the literature, applied uniformly across wells, to estimate individual demand functions wherein differences in pumping depth and the marginal cost of extraction provide the only source of variation across wells [Mulligan et al., 2014, Guilfoos et al., 2013]. They often fail to capture the significant heterogeneity in resource access conditions faced by producers [Foster et al., 2014]. A notable exception is [Hrozencik et al., 2017] who integrate economic and agronomic models to estimate groundwater demand functions that reflect observed heterogeneity. This paper builds on these past treatments of groundwater demand in the literature by utilizing a reduced-form modeling approach to estimate heterogeneous demand functions. Our method permits estimating demand functions that reflect the unique characteristics of the study area and unobserved differences between producers. More broadly, our methods demonstrate how to leverage empirical tools to estimate individual behavior and integrate these insights into physically-based models of resource dynamics.

3.3 Theoretical Model

In this Section, we develop a theoretical model that characterizes the resource and input market spillovers associated with groundwater conservation policies. Suppose the functions $w_1(p^Q, \tau_1, \psi_1)$ and $w_2(p^Q, \tau_2, \psi_2)$ represent groundwater demand for two agricultural producers that utilize a common pool aquifer. Their demand for groundwater is a function of the marginal price of energy[45],

[45] All groundwater sources with the exception of artisan springs require some form of energy to utilize in agricultural production.

p^Q, price-based groundwater management policies, τ_1 and τ_2, and resource availability at the well location, ψ.

The two agricultural producers share a common energy input market defined by p^Q wherein changes in demand by one producer influences the price faced by both producers. Specifically, diminished demand by one producer increases the energy price faced by both producers[46] which reflects how many cooperatively owned or regulated monopoly energy distribution firms adjust their pricing according to changes in aggregate demand as the fixed costs of their distribution network are distributed over fewer units of energy. Since groundwater management policies change demand, it follows that marginal energy price, p^Q, is a function[47] of τ_1 and τ_2. The changes in demand induced by management policies also influence aquifer dynamics. As such, resource availability for both agricultural producers is a function[48] of τ_1 and τ_2.

Suppose that groundwater management within the shared aquifer is non-uniform or patchy in that $\tau_1 > 0$ and $\tau_2 = 0$. We analyze how τ_1 influences demand by the first producer and second producer by virtue of their shared groundwater resource and common input market. The effect of τ_1 on demand by the first agricultural producer is given by the following expression

$$\frac{dw_1}{d\tau_1} = \underbrace{\frac{\partial w_1}{\partial \tau_1}}_{Direct\ Effect} + \underbrace{\frac{\partial w_1}{\partial \psi_1}\frac{\partial \psi_1}{\partial \tau_1}}_{Resource\ Effect} + \underbrace{\frac{\partial w_1}{\partial p^Q}\frac{\partial p^Q}{\partial \tau_1}}_{Input\ Market\ Effect} \tag{3.1}$$

where the terms of the total derivative represent the price effect, the direct resource effect, and indirect input market effect of the policy. Price effects are negative as increased policy levels diminish demand[49]. Direct resource effects are positive when enhanced resource availability increases demand ($\frac{\partial w_1}{\partial \psi_1} > 0$) and the policy regime expands resource availability ($\frac{\partial \psi_1}{\partial \tau_1} > 0$). The net effect of

[46]More formally, $\frac{\partial p^Q}{\partial w_1} < 0$ and $\frac{\partial p^Q}{\partial w_2} < 0$.

[47]$p^Q(\tau_1, \tau_2)$

[48]$\psi_2(\tau_1, \tau_2)$ and $\psi_2(\tau_1, \tau_2)$

[49]Assuming that water is a normal good.

τ_1 on demand by the first producer depends on the relative magnitude of price and indirect input market effects versus direct resource effects.

The implementation of τ_1 also generates impacts for the second producer which are given by

$$\frac{dw_2}{d\tau_1} = \underbrace{\frac{\partial w_2}{\partial \psi_2}\frac{\partial \psi_2}{\partial \tau_1}}_{Resource\ Effect} + \underbrace{\frac{\partial w_2}{\partial p^Q}\frac{\partial p^Q}{\partial \tau_1}}_{Input\ Market\ Effect} \tag{3.2}$$

where both resource and input market effects distribute the spillovers of τ_1 to demand by the second producer. The producers' common pool aquifer serves as a conduit for transferring policy benefits when τ_1 increases resource availability for the second producer ($\frac{\partial \psi_2}{\partial \tau_1} > 0$). While the producers' common input market transmits the costs of τ_1 as diminished aggregate demand increases energy price. The net effect of τ_1 on demand by the second producer depends on the relative magnitude of direct resource versus indirect input market effects. Specifically, the second producer increases their water user under τ_1 when the gains accrued due to resource flows induced by τ_1 outweigh the costs introduced by their common input market.

The magnitude of the potential changes in water use for agricultural producers under τ_1 depends crucially on the physical system dictating resource dynamics which determine $\frac{\partial \psi_2}{\partial \tau_1}$ and $\frac{\partial \psi_1}{\partial \tau_1}$. In the context of groundwater, resource dynamics depend on recharge rate, initial stock or saturated thickness[50], and the degree to which the aquifer is hydrologically connected or hydraulic connectivity. We incorporate these characteristics into our hydroeconomic model by utilizing a physical model (MODFLOW) calibrated for the study area that simulates groundwater flows subject to spatially and temporally-explicit pumping rates yielding a producer's future resource availability as a function of past pumping by the producer and their neighbors.

The water use impacts of τ_1 also depend on the characteristics of the producers' common energy input market which determine $\frac{\partial p^Q}{\partial \tau_1}$. We incorporate these indirect input market effects in our hydroeconomic framework by developing a model of the energy input distribution firm's

[50]Saturated thickness is the vertical distance from the confining hydrogeologic unit defining the bottom of an aquifer to the water table, or top of the aquifer [Lohman et al., 1972]

pricing decision as function of aggregate groundwater demand. We parameterize the model using data on the energy distribution firms in the study area. This model allows our hydroeconomic framework to capture how changes in demand induced by groundwater management affect energy pricing decisions throughout the common input market.

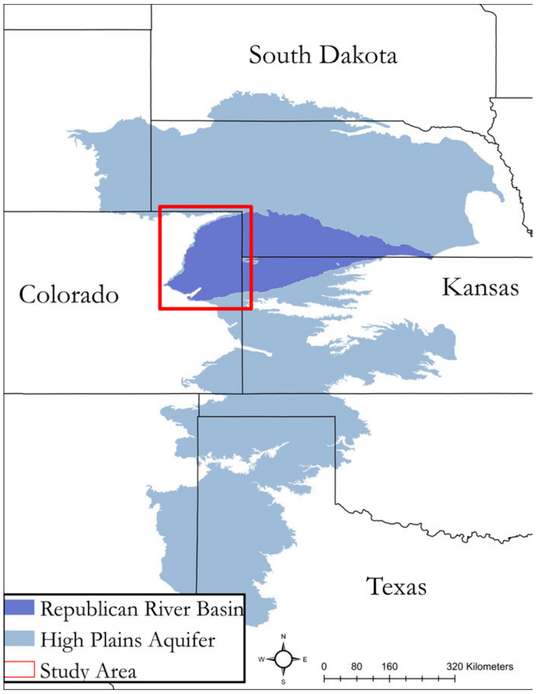
3.4 Study Area and Background

The HPA is the largest aquifer in the United States, providing over 30% of the total groundwater used for irrigation in the United States [Steward et al., 2013b]. Figure 3.1a presents the extent of the HPA and the Republican River Basin, which is a hydrologically connected sub-basin of the HPA. The red frame in Figure 3.1a indicates the study area, the Republican River Basin of Colorado (hereafter the Basin) where we focus our modeling efforts. Irrigated agriculture supported by the HPA is vital to the rural economy of the Basin [Thorvaldson and Pritchett, 2007, Maupin et al., 2014]. Groundwater depletion is a major concern in the HPA region and the Basin. Recent research predicts that some areas of the aquifer will reach the end of economically viable groundwater irrigation by 2050 [Haacker et al., 2016].

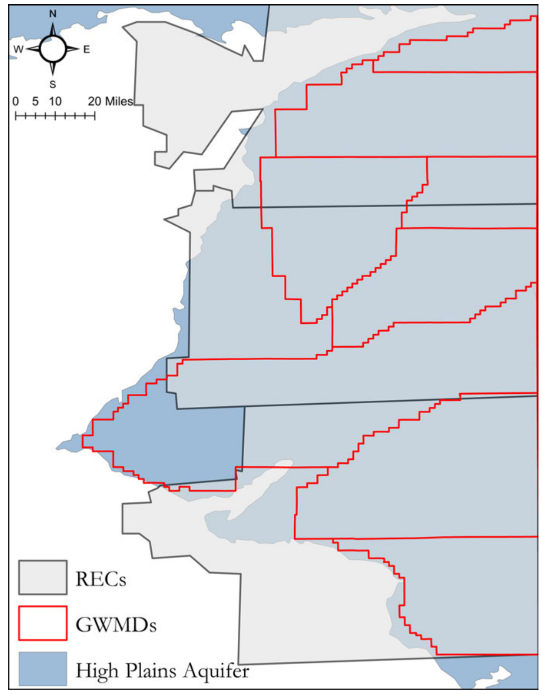
The management of the Basin's groundwater resources rests with eight[51] independent Groundwater Management Districts (GWMD) which possess legal authority to regulate groundwater use within their district. Figure 3.1b present the boundaries of the Basin's GWMD in red. There exists significant heterogeneity in groundwater availability across GWMDs, with some districts already experiencing the effects of groundwater depletion. As such, there is growing interest among GWMDs affected by depletion to enact policies to conserve their shared groundwater resource[52]. Recent research finds that initial groundwater stock is a significant determinant of the gains associated with management [Foster et al., 2017a]. This insight paired with the independence of

[51] Arikaree,East Cheyenne, Central Yuma, Frenchman, Plains, Sand Hills, Marks Butte, and W-Y.

[52] There are currently no restrictions on groundwater use in the Basin outside of the irrigated acreage and pumping limits set by the State of Colorado when each well was permitted. However, these permit restrictions are not binding as very few wells pump volumes approaching their permitted allowance. Finally, a fee of $14.50 is levied on each irrigated acre in the Basin to finance compact compliance initiatives on the Republican River.



(a) High Plains Aquifer



(b) GWMDs and RECs of the Republican River Basin of Colorado

Figure 3.1: The HPA and GWMDs and RECs of Republican River Basin

GWMDs suggests that the implementation of groundwater conservation policies is most likely to occur at the GWMD level and vary in timing according to differences in groundwater availability.

Irrigated agricultural production in the Basin requires energy inputs to pump water from the HPA and apply to crops. Electricity provided by three Rural Electric Cooperatives[53] (REC) powers over 90% of the approximately 3,000 irrigation wells located in the Basin [USDA, 2013]. Figure 3.1b presents the service area boundaries of the Basin's three RECs in black. The cooperative ownership structure of RECs relates to their creation under the Rural Electrification Act of 1936 and requires that any excess REC revenues be distributed back to constituents [Brown, 1980, Rhodes and Wheeler, 1996]. In case of REC revenue shortfalls, the US Department of Agricultural's Rural Utilities Service administers a loan program for electricity distributors in rural locations [Cowan, 2010]. The RECs of the Basin do not generate energy, instead RECs buy energy from Tri-State Generation and Transmission, whose generation portfolio includes coal, natural gas,

[53] Y-W, Highline, and K.C.

and renewable energy sources [Inc., 2017]. Irrigation customers are an important aspect of REC operations as their demand for electricity constitutes, on average, 45% of the electricity distributed by RECs in the Basin [USDA, 2011]. As such, variation in groundwater demand impacts REC operations as the fixed costs of maintaining distribution networks must be distributed across fewer units of electricity. Finally, note that several of the RECs in the Basin utilize decreasing block rate (DBR) price schedules for irrigation customers wherein the marginal price of electricity (and water) decreases as demand increases.

3.5 Hydroeconomic Model

In this Section, we describe the hydroeconomic model used to characterize the spillover effects described in the theoretical model. We begin by outlining an empirical model of groundwater demand, describe the data used to estimate the model, and present empirical model results which we use to parameterize well-level groundwater demand functions. We then develop a model of the energy input market wherein electricity prices are endogenous to demand and describe the hydrologic model of the Basin which simulates spatially-explicit changes in groundwater availability as a function of pumping decisions. Next, we detail how we integrate these components to develop the hydroeconomic model. Finally, we introduce the conservation policy scenario motivating our analysis.

3.5.1 Groundwater Demand

Let groundwater demand by the k^{th} well[54] in time t be given by

$$log(w_{kt}) = \alpha_k + \delta_t + \beta_1 log(p^w_{kt}) + \beta_2 \psi_{kt} + B\Theta_{kt} + \varepsilon_{kt} \tag{3.3}$$

[54] Available water demand data is reported at the well-level (see Section 3.5.2 for further description). We also estimate water demand at the well-level because it allows our model to better capture time variant and invariant differences across wells. To account for potential unobservables at the well-owner level we cluster standard errors at the owner level in all modeling specifications.

where factors influencing demand are captured by a well-level fixed effect, α_k, time fixed effects, δ_t, the marginal price of water, p^w_{kt}, groundwater availability, ψ_{kt}, and a vector of weather variables, Θ_{kt}. ε_{it} is an idiosyncratic error term. To facilitate comparison with previous treatments of water demand in the literature, we assume constant elasticity and estimate the water demand function in log-log form [Hewitt and Hanemann, 1995, Olmstead, 2010]. As such, the parameter β_1 can be interpreted as the price elasticity of groundwater demand wherein the water price signal, p^w_{kt} incorporates both the energy costs associated with extracting a unit of groundwater and price-based conservation policies. Finally, note that this formulation of agricultural water demand does not include cropping choices as covariates, rather we employ a flexible formulation of demand which implicitly accounts for adjustments along the extensive margin.

When electricity is priced according to a non-linear, DBR schedule the price signal to which agricultural producers respond is endogenous to their demand as increased levels of groundwater demand are associated with decreased electricity prices. To address this potential for endogeneity and generate unbiased parameter estimates we follow a fixed effect, instrumental variable (FE-IV) approach common in the non-linear pricing literature [Terza and Welch, 1982, Nieswiadomy and Molina, 1989, Olmstead, 2010, Ito, 2014]. We utilize the parameters of the DBR rate structure (i.e. difference between price levels, thresholds) as instruments for marginal electricity price. Specifically, we use the difference between the first and last price of the rate structure and the volume of water required to reach the final price block as instruments for marginal price.

3.5.2 Data for Demand Parameter Estimation

We utilize a novel panel data set of groundwater and electricity demand for 2,937 irrigation wells in the Republican River Basin of Colorado from 2011 to 2017 to estimate the empirical model of groundwater demand presented in Section 3.5.1. The dataset includes imputed marginal price of water as well as weather and aquifer related variables to account for factors that influence demand for electricity and groundwater. In this Section, we describe these data as well as their sources.

Estimation of the econometric model outlined in Section 3.5.1 requires knowledge of the marginal price of electricity and well-level energy requirements for pumping to determine the marginal price of groundwater. However, electricity use data is not publicly available, instead we calculate electricity demand by utilizing data on well pump characteristics collected in well capacity tests required by state law[55]. The process of determining marginal prices begins with data collected by the Colorado Division of Natural Resources on well-level annual groundwater extraction [CDNR, 2017]. Groundwater pumping data is then paired with a well-level Power Conversion Coefficient (PCC) which is collected in well capacity tests and measures the number of kilowatt hours (kWh) required to pump one acre foot of water yielding annual electricity demand [CDNR, 2018]. PCC describes energy requirements for pumping which are largely[56] a function of groundwater availability and the height of the aquifer. Finally, we associate each well in the Basin with its electricity provider and that provider's rate structure to calculate the marginal price of groundwater.

We also utilize well capacity test data to account for changes in resource availability across time via well capacity [CDNR, 2018]. Recent research suggests that well capacity is an important determinant of groundwater use decisions along the intensive and extensive margins [Foster et al., 2014]. Annual weather data consists of spatially explicit[57] estimates of monthly precipitation and daily maximum temperature mapped to the location of each well in the Basin [Oregon State University, 2018]. We aggregate monthly precipitation across the growing season[58] and daily maximum temperatures are combined to a count of growing season days with maximum temperature above 95° Fahrenheit.

[55]Rule 12 of State Administrative Rule 2 CCR 402-2, which was implemented in 2009, requires that every high capacity groundwater well in the Republican River Basin test their well yield, i.e. capacity, every two years.

[56]Energy requirements of pumping a unit of groundwater are a function of resource availability, the vertical distance from the aquifer to the well, and the efficiency of the well pump. PCC accounts for all these characteristics in determining energy requirements and in our simulation modeling we assume that well pump efficiency remains fixed through time while resource availability, i.e. well capacity, and the depth to groundwater vary according to resource dynamic predicted by the RRCA MODFLOW model.

[57]4 km resolution.

[58]We assume the growing season is May 1^{st} through August 31^{st}.

Table 3.1 presents summary statistics for the data we use to estimate the empirical model of groundwater demand as a function of water price, resource availability, and weather presented in Section 3.5.1. Table 3.1 demonstrates the importance of the energy costs related to water demand, which account for up to 15% of total pre-harvest costs in the Basin [CSU, 2013]. Well capacity data and its standard deviation also illustrate the degree of heterogeneity in resource availability exhibited across wells within the Basin.

Table 3.1: Summary statistics, 2011-2017

Variable	Mean	Std. Dev.	Minimum	Maximum
Panel Data				
Groundwater Use (acre feet/year)	213.9	113.2	9.7	1404.1
Marginal Water Price ($/acre foot)	67.9	101.2	2.1	1245.8
Annual Electricity Demand (mWh/year)	113.4	63.8	2.3	841.14
Annual Electricity Cost ($/year)	15101.4	15312.6	343.1	89471.7
Well Capacity (gallons/minute)	741.8	356.8	56.2	2887.1
Precipitation (in/growing season)	11.7	3.8	3.8	21.7
Temperature (# days w/ max temp $> 95°F$)	18.76	13.5	0	56.0
Well Pump Characteristics				
Power Conversion Coefficient (PCC) (kWh/acre foot)	545.7	161.2	18.85	1911.8
Horsepower (HP) (work/time)	104.9	39.1	10.0	700.0

N = 20,559 with observations of 2,937 wells across the 2011-2017 time period.

Finally, to account for the effect of growing season weather in groundwater demand functions we utilize modeled well-level data on precipitation and temperature to generate well-level weather realizations that capture dry, normal, and wet weather conditions [Oregon State University, 2018]. Specifically, we use modeled data on weather to create well-level distributions of precipitation and

Table 3.2: Empirical modeling results

	Dependent variable:			
	Log(Pumping)			
	FE	FE-IV	FE-Restricted	FE-IV-Restricted
	(1)	(2)	(3)	(4)
Log(Water Price)	-0.2450^{**}	-0.0643^{***}	-0.1248^{***}	-0.1765^{*}
	(0.0230)	(0.0210)	(0.0131)	(0.1032)
Well Capacity	0.0004	0.0004^{***}	0.0003^{***}	0.0015^{***}
	(0.0001)	(0.0001)	(0.00003)	(0.0002)
Precipitation	-0.0012^{***}	-0.0012^{***}	-0.0008^{***}	-0.0008^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Temperature	0.0005^{***}	0.0038^{***}	0.0051^{***}	-0.0003
	(0.0010)	(0.0008)	(0.0004)	(0.0037)
Observations	20,556	20,556	15,787	4,769
R^2	0.1016	0.0817	0.2550	0.0521
Adjusted R^2	-0.0483	-0.0715	0.0914	-0.3856
F Statistic	498.0977^{***}	387.6858^{***}	$1{,}107.4730^{***}$	33.4676^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors clustered at the well owner			

temperature. The median of these well-level distributions represents normal weather conditions, Θ_{kt}^{normal}. We characterize dry weather conditions, Θ_{kt}^{dry}, using the second lowest value of well-level precipitation and the second highest value of temperature observed. Wet weather conditions, Θ_{kt}^{wet}, are the second highest value of well-level precipitation and second lowest value of temperature observed.

3.5.3 Groundwater Demand Functions and Producer Welfare

Table 3.2 displays empirical modeling results relating groundwater demand to water price, well capacity, and weather variables. Note that in all model specifications we cluster standard errors at the well-owner level. Columns (1) and (2) in Table 3.2 present empirical results estimating equation 3.3 using the full sample of data. Column (1) estimates the model without accounting for the potential endogeneity of water price given non-linear electricity pricing. Column(2) addresses this potential endogeneity by instrumenting for water price with parameters of the electricity rate structure, specifically the difference between the first and last marginal prices and the amount of water required to reach the final price block.

We test the robustness of these results by restricting the sample used to estimate our empirical model. These results are presented in Columns (3) and (4) of Table 3.2. Column (3) displays FE model results when the sample is restricted to those wells which are observed to demand a quantity on the final block of their RECs price structure in every year of our sample. We assume that endogeneity is not a concern among these wells given that marginal price on the final price block always determines their demand on the margin and thus do not instrument for price. Column (4) presents FE-IV model results when the sample is restricted to those wells which are observed to demand within their RECs interior[59] price blocks. Endogeneity between demand and price is a concern for these wells as increased levels of demand may decrease their marginal price.

Broadly, the parameters estimates presented in Table 3.2 are relatively consistent in sign and significance across specifications. Water price, p^w_{kt} negatively impacts demand as theory would suggest and is statistically significant in all specifications. Water price coefficient estimates also align with previous agricultural water price elasticities reported in the literature [Schoengold et al., 2006, Scheierling et al., 2006]. Well capacity, a measure of ground availability, increases demand implying that resource constraints influence pumping decisions. Finally, coefficient estimates for weather variables, precipitation and temperature, follow intuition. Specifically, increased precipitation diminishes demand as groundwater and natural rainfall are roughly substitutes, and more days with max temperature above $95°$ Fahrenheit increases demand.

Our preferred model specification is FE-IV estimated with the full sample of data which addresses the potential endogeneity between marginal water price and groundwater demand. These parameter estimates are presented in column (2) of Table 3.2. We use these FE-IV modeling results to generate well-level groundwater demand functions

[59] e.g. demand within the RECs first or second price block.

$$w^*_{kt} = \exp(\hat{\alpha_k} + \hat{\beta}_1 log(p^w_{kt}) + \hat{\beta}_2 \psi_{kt} + \hat{B}\Theta_{kt}) \tag{3.4}$$

where $\hat{\alpha}_k$ represents estimated well-level fixed effect and $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{B}$ are model coefficient estimates. $\hat{B}$ consists of precipitation and temperature model coefficients. The water price influencing groundwater demand is a function of electricity price, PCC, and GWMD conservation policies. This formulation of water price facilitates estimating how both resource availability and conservation policies affect water price and groundwater demand.

Note that estimated time fixed effects, δ_t, are not included in our formulation of well-level groundwater demand functions. In our empirical model these time effects control for inter-annual variation in commodity and input prices, reflecting market trends for the differing years of data utilized in our empirical modeling. Given that our demand functions aim to predict extraction in future time periods without knowledge of future input or commodity market trends, we condition our well-level demand functions on the base year, 2011, which all other time fixed effects are relative to and assume the market conditions of 2011 remain constant over our simulation period. To account for the role of weather when predicting groundwater demand, we assume the parameter Θ_{kt} reflects growing season weather conditions, more formally $\Theta_{kt} \in [\Theta_k^{wet}, \Theta_k^{normal}, \Theta_k^{dry}]$. We derive Θ_k^{wet}, Θ_k^{normal}, and Θ_k^{dry} using well-level modeled data on precipitation and number of days with maximum temperature above 95° Fahrenheit [Oregon State University, 2018]. Specifically, for each well in our data set we arrange these weather data as two vectors in ascending order. Θ_k^{normal} consists of the median of both the precipitation and temperature data, or the fourth elements of the aforementioned vectors. Θ_k^{wet} consists of the second element of the temperature vector and the sixth element of the precipitation vector. Θ_k^{dry} consists of the sixth element of the temperature vector and the second element of the precipitation vector. This characterization of weather variability aligns with our hydrologic modeling wherein we iterate between differing simulation years in the RRCA MODFLOW model to capture differences in inter-annual aquifer recharge.

We also calculate estimates of producer welfare by transforming well-level demand functions described above into well-level inverse demand functions, $\Gamma_{kt}(p)$, by solving equation 3.4 for water price which yields

$$\Gamma_{kt}(p) = \frac{log(w) - \hat{\alpha}_k - \hat{\beta}_2\psi_{kt} - \hat{B}\Theta_{kt}}{\hat{\beta}_1} \tag{3.5}$$

which expresses water price as a function of water demand and estimated parameters $\hat{\alpha}_k$, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{B}$. Using this well-level expression of inverse demand, we then calculate annual producer welfare[60] for the k^{th} producer in time t whose predicted demand equals $\hat{w}_{kt}$ with the following expression

$$\Lambda_{kt} = \int_{\epsilon}^{\hat{w}_{kt}} \left[\Gamma_{kt}(p) - p^w_{kt}\right] dw \tag{3.6}$$

where p^w_{kt} is the price of water. Note that interval of integration in equation 3.6 is between an arbitrarily small ϵ and predicted demand. This relates to our assumption of constant elasticity demand functions which exhibit a vertical asymptote at zero. As such, integrating between 0 and predicted demand would yield welfare estimates approaching infinity given that our price elasticity estimate is less than one in absolute value. To surmount this challenge and numerically estimate producer welfare, we integrate between ϵ = 0.01 and predicted demand quantities, thus avoiding the vertical asymptote of $\Gamma_{kt}(p)$ at zero. In Section 3.6.3, we utilize this framework for estimating producer demand to calculate the changes in welfare attributable to the implementation of a groundwater conservation policies.

3.5.4 Electricity Pricing Model

Our theoretical presentation of the spillovers arising from patchy groundwater conservation policy implementation delineates how endogenously determined energy input prices potentially serve as a conduit to distribute policy impacts. In this Section, we develop a model of electricity input pricing as a function of aggregate groundwater demand to characterize how evolving patterns of groundwater demand influence electricity prices and vice-versa. We parameterize this model to fit the institutional setting of our study area wherein electricity inputs are provided to agricultural producers by a cooperatively-owned electricity distribution firm. Our model and its parameteri-

[60]Our ability to use derived demand to estimate quasi-rents or producer surplus rests on the assumption that water is an essential input to production in the study area.

zation describe how RECs in the study area adjust their pricing regimes to changes in aggregate groundwater demand induced by conservation policies and resource depletion.

Consider a cooperatively-owned energy distribution firm that provides energy inputs, Q, to K agricultural producers. The firm chooses the marginal price of energy, p^Q, to charge agricultural producers subject to expected groundwater demand, $\mathbb{E}[w^*_{kt}]$. For simplicity, we assume that the firm's pricing and operational choices for agricultural producers do not vary according to energy demand by other customer classes, e.g. residential, commercial. Let the firm's annual fixed costs associated with maintaining and administering their distribution network for agricultural producers be given by the constant F. Firm variable costs associated with providing agricultural producers with energy are a function of aggregate electricity demand and market price of energy, p^{mkt}. Expected total annual costs and revenues are then given by

$$\mathbb{E}[Total\ Cost] = F + \sum_{k=1}^{K} \mathbb{E}\left[w^*_{kt}\right] * PCC_{kt} * p^{mkt} \tag{3.7}$$

$$\mathbb{E}[Total\ Revenue] = \sum_{k=1}^{K} \mathbb{E}\left[w^*_{kt}\right] * PCC_{kt} * p^{Q} \tag{3.8}$$

This formulation of firm revenue abstracts away from the possibility of using facilities charges or hook-up fees to generate revenue. Given the cooperative nature of the firm's ownership, we assume that the firm chooses p^Q such that the expected difference between total costs and revenues is minimized. More formally, the energy distribution firm solves the following optimization problem to determine marginal energy price.

$$\underset{p^Q}{\text{minimize}} \quad \Big[\mathbb{E}[Total\ Cost] - \mathbb{E}[Total\ Revenue]\Big]^2 \tag{3.9}$$

We parameterize the electricity distribution firm's pricing model using data on the RECs which provide electricity to the Basin's groundwater irrigators. Specifically, we utilize publicly available data from 2011[61] on the quantity of electricity distributed across customer classes and REC fixed and variable costs. These data are presented in Table 3.3, demonstrating the importance of irrigation customer electricity demand for REC operations[62]. REC attributes introduced in Table 3.3 illustrate how the characteristics of the REC's distribution network and service area determine fixed costs.

Table 3.3: REC costs, energy distribution, and attributes

	Highline	K.C.	Y-W
REC Distribution and Costs			
Total Electricity Distributed (MWH)	484,478	203,091	349,902
Total Variable Electricity Costs ($)	36,588,889	14,876,845	26,954,637
Total Fixed Costs ($)	9,485,064	5,035,131	8,314,039
p^{mkt} ($/kWh)	0.0703	0.0676	0.0711
Irrigation Electricity Distributed (MWH)	198,859	94,867	174,701
Irrigation Variable Electricity Costs ($)	15,018,287	6,949,208	13,458,060
Irrigation Fixed Costs ($)	3,893,242	2,351,989	4,151,079
REC Attributes			
Total # of Customers	10,359	6,241	8,954
# of Irrigation Customers	3,156	719	1,696
# of Full Time Employees	53	27	47
# of Customers per Mile of Distribution	2.03	2.18	2.23

We utilize these data to estimate electricity pricing regimes that reflect changing groundwater demand through time and REC cost structures. Specifically, we use REC irrigation customer fixed

[61] Ideally, our electricity distribution firm pricing model would be parameterized using data from multiple years. However, these data are not publicly available and we take a second best approach and parameterize the model using data from 2011.

[62] Data presented in Table 3.3 come from United States Department of Agriculture, Rural Borrowers 2011 Statistical Report [USDA, 2011]. Irrigation variable and fixed costs are estimated based on the percentage of total MWH distributed attributable to irrigation customers. p^{mkt} or the price that RECs pay for electricity is estimated by dividing total variable electricity costs by the quantity of kWhs purchased by the REC which is not reported in the table.

costs, F, and imputed marginal price paid by the REC, p^{mkt}, reported in Table 3.3. In determining the price that RECs pay per unit of electricity, we abstract away from the possibility of peak load or demand based pricing by the electricity generation firm and assume that RECs pay a constant marginal price, p^{mkt}, per kWh of electricity[63] which remains constant throughout the simulation period.

We leverage our empirical characterization of groundwater demand functions to estimate REC-level expected demand as a function of electricity price, p^Q, resource availability, ψ_{kt}, and weather, Θ_{kt}. We assume that RECs observe well-level resource availability but are uncertain of growing season weather when determining optimal marginal electricity prices, as such expected electricity demand is based on REC expectations regarding weather realizations and their effect on aggregate demand. We characterize this relationship by assuming that normal, wet, and dry weather conditions, Θ_k^{dry}, Θ_k^{normal}, and Θ_k^{wet} occur with probabilities Pr^1, Pr^2, and Pr^3, respectively ($Pr^1 = 0.2$, $Pr^2 = 0.6$, and $Pr^3 = 0.2$). Each REC then chooses the optimal marginal electricity price to charge irrigation customers subject to expected groundwater and energy demand within their service area, their fixed costs, and the price they pay for electricity on the wholesale market, p^{mkt}.

Finally, as noted in Section 3.4, several of the RECs in the Basin utilize DBR price structures for irrigation customers. Our energy pricing model incorporates the use of these pricing structures and assumes that RECs do not alter the thresholds of their price structure. Rather, RECs respond to evolving aggregate demand by adjusting all the marginal prices of their structure proportionally to find the suite of prices that minimize the difference between expected revenues and costs as outlined in equation 3.9.

[63]Our assumption that RECs face a constant marginal price, p^{mkt}, when purchasing electricity focuses the pricing model on REC response to changes in aggregate demand rather than exogenous changes in electricity price induced by the dynamics of the energy generation market.

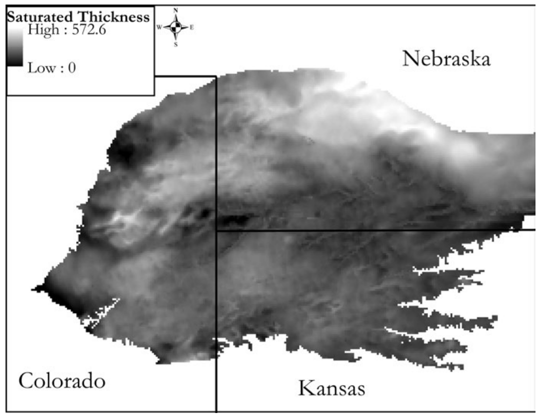


Figure 3.2: Example RRCA MODFLOW output

3.5.5 Hydrologic Model

To establish how the quantity of groundwater demanded in period t affects resource availability in $t+1$, we utilize the Republican River Basin Compact Agreement (RRCA) MODFLOW model which simulates spatially explicit groundwater levels for the 1918-2005 time period [Kuwayama and Brozović, 2013,Mulligan et al., 2014,Hrozencik et al., 2017]. The model represents the aquifer as one layer which varies in thickness and distance from the surface with a horizontal discretization of 1 mile by 1 mile [Harbaugh et al., 2000]. The model incorporates groundwater pumping, recharge from rainfall, evapotranspiration, groundwater and surface water irrigation, and canal and stream seepage. Recharge into the aquifer depends on both return flows from irrigation[64] and precipitation. The model solves a system of partial differential equations characterizing groundwater flows across grid cells on monthly stress periods with two time steps for each period and observed groundwater levels across time were utilized to test and calibrate the model. An example of MODFLOW output is presented in Figure 3.2 which maps simulated, spatially-explicit levels of saturated thickness after one year in the baseline, no-policy scenario.

The RRCA model requires data on spatially-explicit recharge and evapotranspiration. However, these modeling inputs are only publicly available for 1997-2005. We follow [Hrozencik et al., 2017] and assume that 2003, 2004, and 2005 represent dry, normal, and wet growing sea-

[64]We assume that 17% of total recharge is attributable to return flows from irrigation which is recharge parameter utilized in the original RRCA calibrated MODFLOW model.

son weather conditions where realized weather is Θ_k^{dry}, Θ_k^{normal}, or Θ_k^{wet}. Differences in realized weather allow our formulation of groundwater demand to more accurately reflect how variation in growing season weather influence pumping decisions and aquifer recharge. Dry, wet, and normal weather conditions are assumed to occur with probabilities Pr^1, Pr^2, and Pr^3. We specify a 5 year weather cycle based on the assumed frequency of normal, dry, and wet growing seasons and repeat that cycle throughout the model simulation period (normal, wet, normal, dry, and normal) which we assume to be 25 years. Finally, note that we utilize a novel methodology introduced in [Hrozencik et al., 2017] which translates changes in saturated thickness to updated well capacity which previous research suggests is an important determinant of groundwater demand [Foster et al., 2014].

3.5.6 Dynamic Model Integration

The hydroeconomic model developed in this paper integrates empirically derived, well-level demand functions, energy input markets, and aquifer dynamics to capture the spillovers associated with patchy groundwater management policies. In this Section, we briefly describe how model components are dynamically linked to one another through time. In $t = 1$ initial expected well-level groundwater demand is determined using parameters estimated in equation 3.3 with FE-IV specification, well-level resource availability observed in 2017, and parameters representing dry, normal, and wet weather conditions and their probabilities. Each REC in the Basin chooses marginal electricity price based on aggregate expected demand within their service area, fixed costs, and p^{mkt}. Finally, a realization of weather occurs and agricultural producers choose groundwater demand quantities in $t = 1$ subject to marginal electricity price determined by RECs.

Groundwater demand quantities in $t = 1$ serve as input for the RRCA MODFLOW model which then simulates groundwater flows subject to pumping decisions to output well-level groundwater availability[65] in $t = 2$. Well-level resource availability in $t = 2$ then updates REC expectations regarding groundwater demand, which in turn choose new marginal electricity prices that

[65]Both well capacity and depth to groundwater.

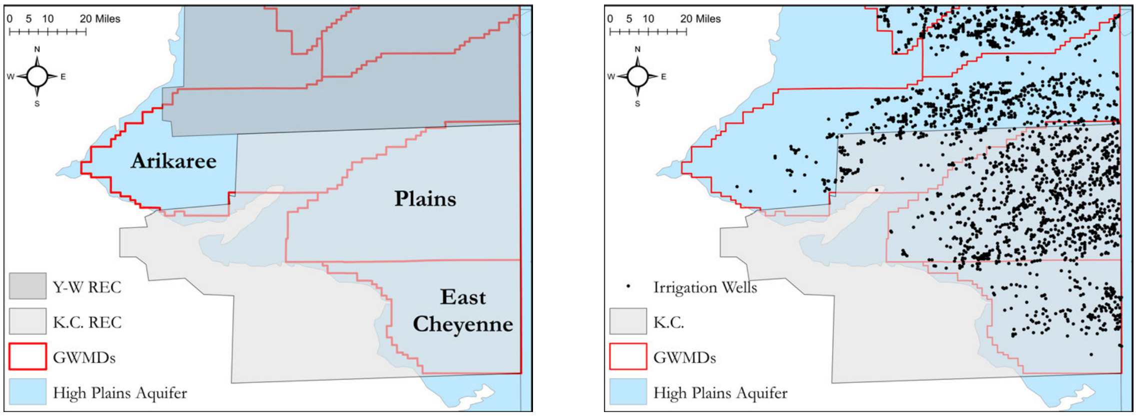
reflect changes in expected aggregate demand. Finally, another weather realization occurs and agricultural producers choose groundwater demand quantities in $t = 2$ which provides input for the next iteration of the RRCA MODFLOW model to predict resource availability in $t = 3$. In this fashion, the hydroeconomic model iterates between the RRCA MODFLOW model and our static models of groundwater demand and REC pricing using output from one model as input for the other.

3.5.7 Baseline and Conservation Policy Simulations

We utilize our hydroeconomic model to simulate two scenarios: 1) a no-policy scenario, and 2) the scenario where one GWMD in the Basin, Plains, implements a water pricing policy aiming to decrease expected aggregate district demand by 25% in $t = 1$. Our simulation model reveals that a policy of $315 per acre foot results in a 25% reduction Plains aggregate pumping in $t = 1$. We focus our simulation exercise on the Plains GWMD as it is the only GWMD in the Basin that is currently considering implementing a conservation policy. Furthermore, both Plains, Arikaree, and East Cheyenne[66] are located within the service area of K.C. REC. Figure 3.3a presents the boundaries of these GWMDs and K.C. REC while Figure 3.3b depicts the spatial distribution of irrigation wells within this area. Figures 3.3a and 3.3b demonstrate how groundwater conservation in Plains potentially generates direct resource effects for nearby resource users both within and outside of K.C.'s service area while also creating indirect input market effects for resource users within K.C.'s service area.

We simulate a price-based policy by including the policy level in the water price determining an individual producer's groundwater use. Note that the GWMD does observe electricity prices when determining policy levels but does not observe growing season weather or anticipate how the conservation policy affects electricity prices. We assume that once the policy is implemented it remains in place until the end of the simulation period and any revenues generated by the policy

[66]East Cheyenne is not located within the Republican River Basin and irrigation wells in the GWMD are not required to submit pumping records or conduct well capacity tests by the State of Colorado. Nor are the wells or aquifer in East Cheyenne part of the RRCA MODFLOW model. As such, we are not able to evaluate spillover effects arising in East Cheyenne.



(a) GWMDs and K.C. REC

(b) Spatial distribution of irrigation wells

Figure 3.3: Maps of GWMDs, RECs, and irrigation wells in study area

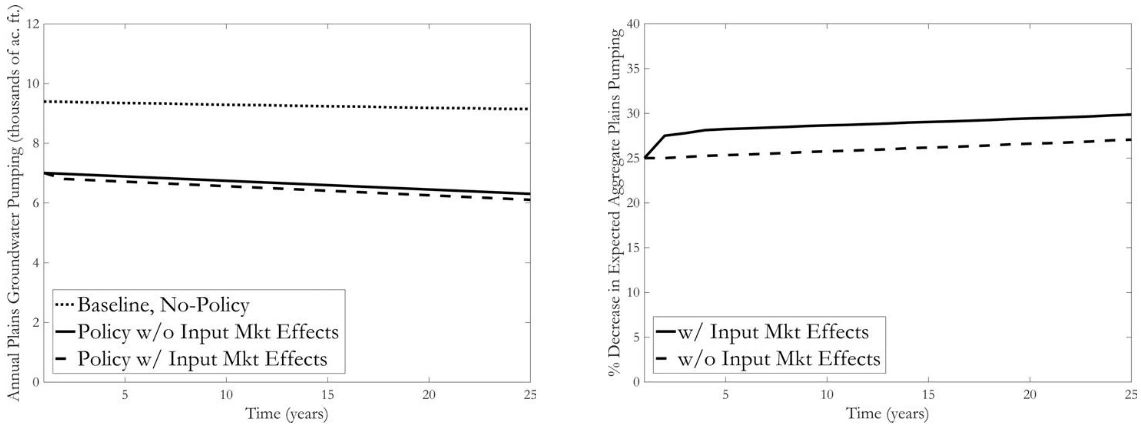
are uniformly redistributed to GWMD constituents via a lump sum transfer (with no impact on groundwater demand). Comparing outcomes in our two modeling scenarios facilitates quantifying how patchy conservation policy implementation creates positive resource spillovers for neighboring producers while simultaneously imposing costs through input markets.

3.6 Results

In this Section, we discuss our modeling results quantifying direct resource effects and indirect input market effects associated with the conservation policy simulation. Our results compare the baseline and conservation policy scenarios across time to quantify the impact of groundwater management in Plains and neighboring groundwater users with respect to water use, resource availability, and producer welfare.

3.6.1 Water Use

We now report the results of the hydroeconomic model for the policy and no-policy scenarios described in Section 3.5.7 which demonstrate how indirect input market effects influence groundwater use decisions both inside and outside the policy area. Specifically, our results quantify how the implementation of a groundwater conservation policy in Plains GWMD generates both costs and benefits for nearby groundwater users in Arikaree GWMD (see Figures 3.3a and 3.3b). Our re-



(a) Groundwater pumping in Plains GWMD in baseline and policy scenarios

(b) Groundwater conservation in Plains GWMD relative to baseline, no-policy scenario

Figure 3.4: Baseline and policy scenarios in Plains GWMD

sults also highlight how indirect input market effects alter aggregate conservation policy outcomes illustrating how non-resource channels partially determine the conservation potential of a policy.

Figure 3.4 presents the change in expected[67] aggregate Plains pumping in absolute and percentage terms over the simulation period given the implementation of a price-based conservation policy. Figure 3.4a shows simulated groundwater pumping outcomes with and without the indirect input market effects associated with a reduction in aggregate electricity demand within the K.C. REC. Figure 3.4a also demonstrates that water use is decreasing over time in both the baseline, no-policy scenario and the policy scenario. This diminished demand through time is related to reductions in groundwater availability and further compounded by increases in endogenously determined electricity prices. The conservation impact of the policy is increasing across time both with and without indirect input effects. We attribute increasing conservation impacts through time to resource dynamics within Plains. Under the conservation policy groundwater availability, both well capacity and saturated thickness, decrease throughout the simulation period as the magnitude of the policy is not sufficient to fully arrest groundwater depletion. Decreasing well capacity and saturated thickness causes the policy's impact to increase through time as resource users' marginal productivity diminishes.

[67]For visual clarity we present changes in expected Plains pumping using the probabilities of wet, dry, and normal weather conditions introduced in Section 3.5.7.

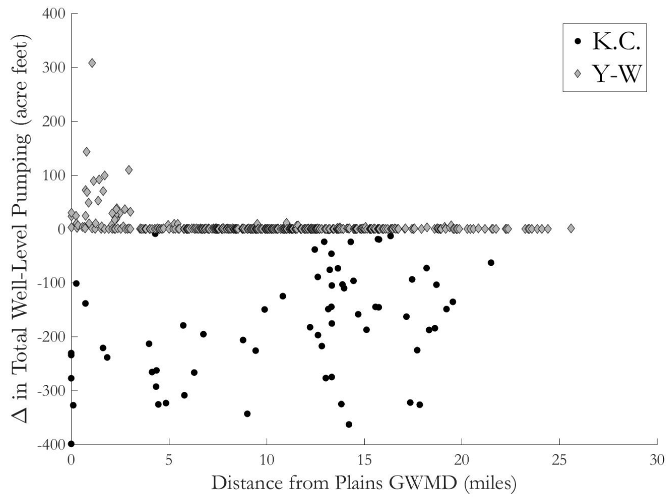


Figure 3.5: Water use spillovers in Arikaree GWMD over 25 years of policy implementation in Plains GWMD

Analyzing the impact of including indirect input market effects on conservation policy impacts in Figures 3.4a and 3.4b reveals how incorporating policy induced changes in electricity prices increases groundwater conservation outcomes. Specifically, after K.C. REC observes the change in expected electricity demand created by Plains' policy our model predicts a 27% increase in K.C.'s marginal electricity price which in turn increases groundwater conservation by approximately 3% per year. Our results demonstrate how indirect input market effects potentially increase the conservation outcome of a policy as input firms respond to evolving demand by altering their pricing regime.

The patchy implementation of groundwater conservation policies also generate impacts for nearby resource users not subject to the policy. On average, Arikaree wells in K.C.'s service area decrease their total groundwater demand by 204 acre feet over 25 years while those wells served by Y-W increase their demand by 3 acre feet over 25 years. These changes in demand constitute approximately 4% and 0.01% of the district's total water use across the simulation period, respectively. However, these results belie how a well's location relative to Plains GWMD influences the water use spillovers induced by the conservation policy.

Table 3.4 and Figure 3.5 demonstrate how proximity to Plains and input markets affect water use spillover effects. Figure 3.5 plots well-level, time-aggregated[68] changes in groundwater demand for wells in Arikaree GWMD under the policy scenario in Plains against the distance of the well from Plains GWMD. Figure 3.5 highlights how increases in groundwater pumping induced by Plains' policy cluster among wells near Plains which are served by Y-W as these wells benefit from reduced pumping in Plains and do not experience indirect input market effects.

Table 3.4 presents average changes in water use for K.C. and Y-W wells in Arikaree by distance from Plains' border. As evident in Figure 3.5, increases in water use dissipate as distance from Plains' increases for wells in Y-W's service area. Arikaree wells served by K.C. experience relatively significant changes in water use confirming the importance of indirect input effects in determining resource use outside the policy area. Proximity to Plains does not significantly alter mean changes in total groundwater demand among K.C. wells, implying that direct resource effects outweigh indirect input market effects in determining aggregate changes in water use.

Table 3.4: Average changes in total, well-level water use in Arikaree GWMD

Distance from Plains GWMD	REC	
	Y-W	K.C.
$\leq$ 1 mile	56.43	-279.98
$>$ 1 mile & $\leq$ 5 miles	9.87	-320.72
$>$ 5 miles	0.96	-167.37

Changes in well-level water use are reported in acre feet.

[68]For each well in Arikaree we calculate total groundwater demand across the simulation period for the policy and no policy scenario in Plains. We then compare time-aggregated demand to measure changes in demand attributable to the implementation of the policy regime in Plains.

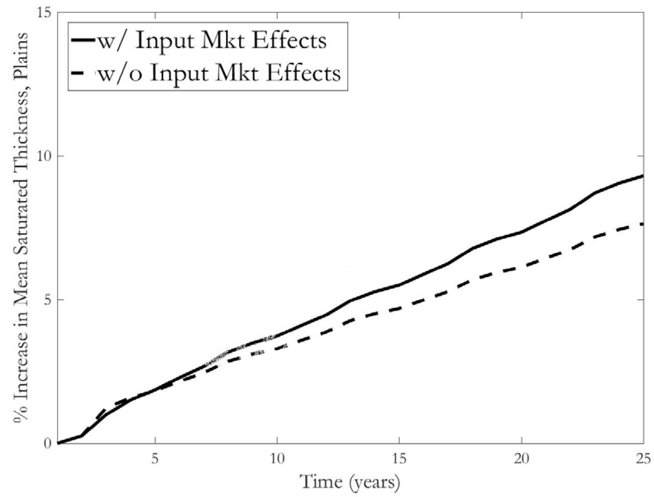
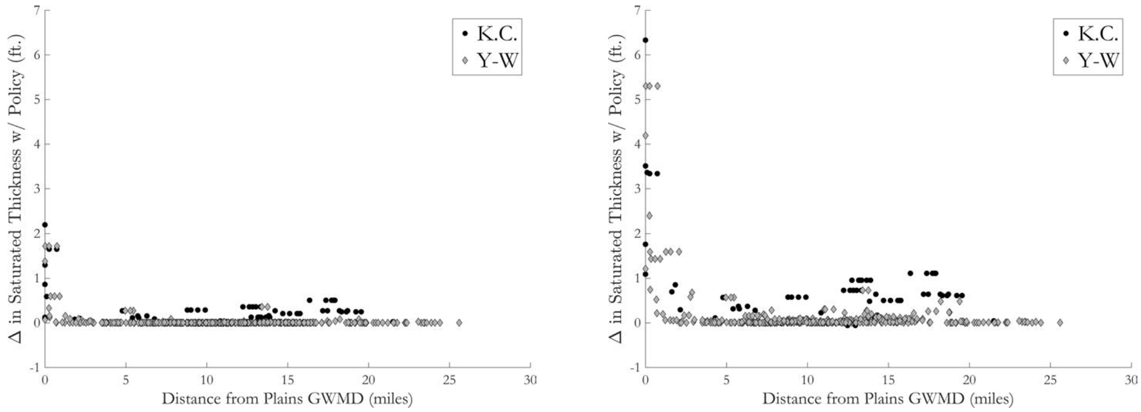


Figure 3.6: Increase in mean saturated thickness w/ policy relative to baseline, no-policy scenario in Plains GWMD

3.6.2 Resource Availability

Policy-induced changes in groundwater demand in Plains GWMD and neighboring wells also generate impacts on resource availability through time. In this Section, we present results from our hydroeconomic model quantifying how groundwater conservation policies in Plains affect resource availability both within and outside of the district. Our results demonstrate how resource dynamics influence the impact of conservation policies through time within Plains while creating positive resource spillovers for nearby wells.

Objectives to maintain resource availability through time motivate many resource conservation policies. Figure 3.6 presents the changes in resource availability through time attributable to Plains's conservation policy. Specifically, we compare the difference in mean saturated thickness through time in Plains under policy and no policy scenarios to calculate how the policy influences groundwater stocks. We find that the conservation policy increases average saturated thickness by nearly 10 feet, or 8% of the Plains' average saturated thickness, in the final simulation period compared to the no-policy scenario. We also find that not accounting for indirect input market effects diminishes the policy's impact on resource availability. Specifically, we find that not accounting for indirect effects diminishes the predicted increases in resource availability induced by the pol-



(a) Resource availability spillovers in Arikaree GWMD, 10 years

(b) Resource availability spillovers in Arikaree GWMD, 25 years

Figure 3.7: Resource availability spillovers

icy by approximately 2 percentage points in the final simulation period. This result indicates that approximately 25% of the total change in resource availability in Plains is attributable to indirect input market effect.

We also explore the resource availability impacts created by Plains' policy for neighboring wells in Arikaree GWMD. On average, Plains' policy increased Arikaree saturated thickness by 0.22 feet after 25 years of policy implementation in Plains, which is less than 0.1% of average saturated thickness in Arikaree. However, changes in resource availability vary significantly across time and the well's proximity to Plains. Figures 3.7a and 3.7b plot well-level changes in saturated thickness after 10 and 25 years of policy implementation in Plains, respectively, against the well's distance from the border of Plains GWMD, differentiating between wells served by K.C. and Y-W RECs. These Figures demonstrate how both time and proximity to Plains determine the magnitude of resource effects. Specifically, comparing Figures 3.7a and 3.7b illustrates how resource effects accumulate to wells near Plains incrementally over time according to aquifer dynamics as the impact of reduced pumping in Plains spreads outside the policy area.

Our results indicate that resource effects dissipate as distance to Plains increases which holds for both K.C. and Y-W wells. Interestingly, many of the Y-W wells nearby Plains that increased their groundwater demand under Plains' policy still experience an increase in resource availability, suggesting that resource flows from Plains' outweigh the impact of increased rates of well-level pumping in Arikaree attributable to Plains' policy. Finally, note that many wells served by K.C. and relatively distant from Plains' (10 - 20 miles) experience increases in resource availability after both 10 and 25 years of policy implementation in Plains. We attribute this increase to input market effects which induce lower rates of groundwater demand among K.C. wells that are both nearby and distant from Plains (see Figure 3.5 and Table 3.4) as these reductions in demand generate increases in resource availability through time. This result underscores how indirect input market effects interact with resource dynamics to extend direct resource effects potentially far beyond the policy area depending on input market connectedness.

3.6.3 Producer Welfare

W utilize output from the hydroeconomic model to quantify how conservation policies influence producer welfare or quasi-rent both inside and outside policy areas. Our results highlight how indirect input market effects channel conservation policy costs while direct resource effects convey policy benefits to wells in neighboring GWMDs. We also find that Plains' implementation of conservation policy results in an aggregate loss of producer welfare and that a well's initial saturated thickness influences the welfare impacts.

We utilize equation 3.6 to numerically estimate annual well-level producer welfare under both the baseline, no-policy and conservation policy scenarios using predicted groundwater demand, resource availability, and energy input prices generated by the hydroeconomic model. We then compare producer welfare under the policy and no-policy scenarios to determine annual well-level changes in welfare attributable to the implementation of the conservation policy in Plains. We assume a 5% discount rate and aggregate each well's changes in producer welfare across the simulation period to obtain a net present value (NPV). We also assess the robustness of our results to the choice of ϵ used to numerically estimate producer welfare (see Section 3.5.7). To do so, we vary the choice of ϵ and calculate discounted changes in cumulative producer welfare under these scenarios. Specifically, we calculate changes in welfare when ϵ equals 0.1 and 0.001. Both scenarios result in significantly different absolute measurements of producer welfare compared to

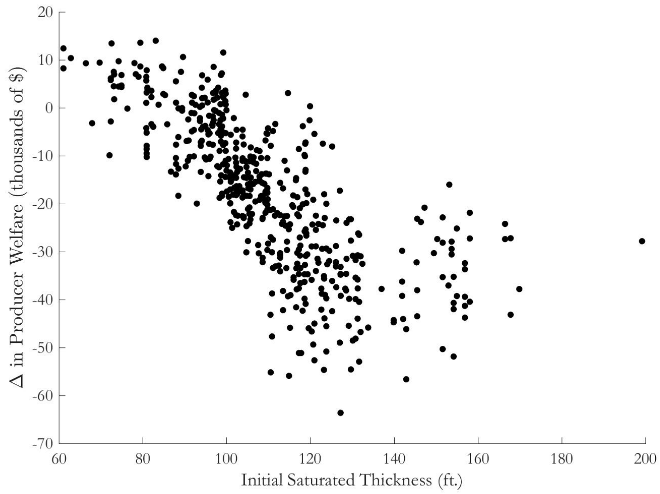
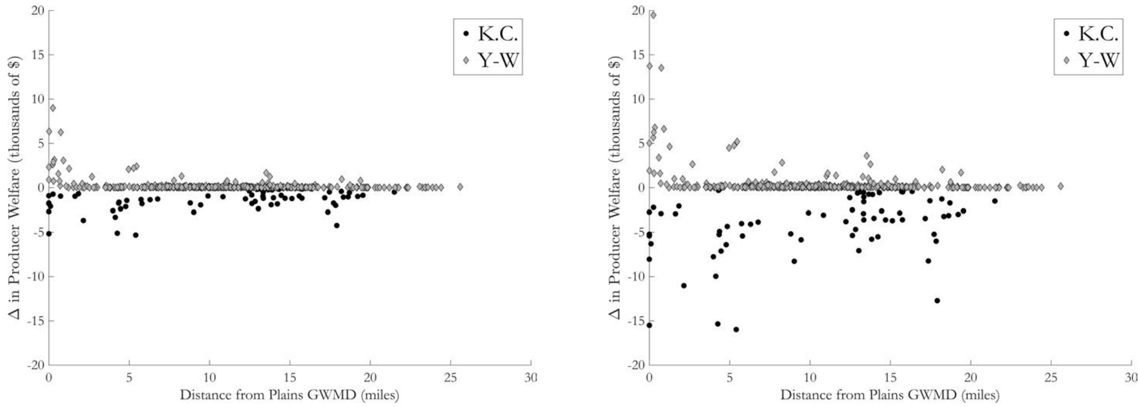


Figure 3.8: NPV of cumulative change in producer welfare in Plains GWMD after 25 years of policy implementation

our assumed value of $\epsilon = 0.01$, but relatively small alterations ($\leq 0.5\%$) in the estimated change in producer welfare attributable to the policy's implementation.

Figure 3.8 plots discounted changes in producer welfare against initial saturated thickness for each well in Plains GWMD over the full 25 year simulation period. Our results indicate that producer welfare gains accrued to those wells with the least initial saturated thickness and policy benefits dissipate as initial saturated thickness increases. These results align with previous research in the groundwater economics literature that finds initial aquifer conditions determine gains from groundwater management [Foster et al., 2017c]. Heterogeneity in policy benefits and costs suggest that there may be gains from more spatially disaggregated conservation policies similar to Local Enhanced Management Areas (LEMA) in Kansas.

Figures 3.9a and 3.9b plot discounted changes in producer welfare after 10 and 25 years of policy implementation in Plains, respectively, against distance from Plains GWMD for wells located in Arikaree GWMD differentiating between wells served by K.C. and Y-W RECs. Comparing Figures 3.9a and 3.9b illustrates how producer welfare impacts accrue to wells near Plains incrementally through time as the impact of reduced pumping in Plains increases resource availability and producer welfare. Policy benefits accrue to wells within Y-W's service area located



(a) NPV of cumulative change in producer welfare for wells in Arikaree GWMD after 10 years of policy implementation in Plains GWMD

(b) NPV of cumulative change in producer welfare for wells in Arikaree GWMD after 25 years of policy implementation in Plains GWMD

Figure 3.9: Producer welfare spillovers

near Plains' border as these wells experience increases in groundwater availability without indirect input market effects. Policy costs concentrate among K.C. wells, even those not located in Plains GWMD, and increase through time as input market effects reduce demand and resource rents associated with groundwater extraction. Furthermore, the magnitude of these costs remains relatively uniform as distance from Plains' border increases, suggesting that indirect input market spillovers outweigh resource effect benefits even for Arikaree wells served by K.C. located nearby Plains.

3.7 Conclusion

This paper develops a hydroeconomic model of the Republican River Basin of Colorado to quantify the input market and resource spillovers associated with patchy groundwater conservation policy implementation. We utilize novel techniques in the hydroeconomic modeling literature by utilizing data on groundwater demand in our study area to empirically derive well-level demand functions. We also contribute to the hydroeconomic literature by recognizing and modeling how input markets, specifically electricity distribution firms, adjust their pricing regimes to changes in aggregate groundwater and energy demand. These methodological contributions inform future hydroeconomic modeling particularly in data rich settings where our empirical approach to estimate demand functions is feasible.

Our results compare the outcomes of no-policy and policy scenarios through time to analyze the impact of policy implementation on water use, resource availability, and producer welfare. Specifically, we find that not accounting for input market changes arising from policy implementation alters estimates of the policy's effect on demand and resource availability. We also find that input markets serve as channels distributing conservation policy costs to nearby resource users, increasing resource availability for these users while diminishing their producer welfare. Future research should further explore how conservation policy effects are distributed to resource users through non-resource channels such as land values, commodity markets, and labor.

Our results allow us to compare the magnitude of resource and input market spillovers for resource users neighboring the policy area. We find that benefits of increased resource availability attributable to the policy are largely outweighed by the costs imposed by changes in the input market. However, when input markets are not shared, economically significant benefits accrue to wells near the policy area which points to a potential free rider problem associated with patchy CPR management. These results inform future groundwater conservation policy-making by quantifying how policy costs and benefits are distributed outside the policy area according to resource dynamics and input market conditions. As such, the total impact of a patchy CPR conservation policy depends on effects both within and outside the policy area.

Hydroeconomic model results have implications for policy-making as well as future economic research related to resource management policies. Our analysis informs future resource policy-making efforts by demonstrating how non-resource channels, e.g. input markets, distribute management policy impacts across time and resource users. These non-resource channels also potentially alter the aggregate impacts of management policies and complicate policy-makers ability to design policies that meet specific resource conservation objectives. Future resource policy-making efforts should analyze how these potential non-resource channels influence both aggregate policy impacts and how those impacts are distributed across time and amongst resource users. Future economic research related to resource management should also analyze these non-resource channels in assessing the efficiency of differing management strategies. For example, recent research investigates the impact of localized efforts to manage groundwater resources in the HPA [Drysdale and Hendricks, 2018]. When assessing the impact of these localized management policies researchers should also analyze how shifts in resource demand induced by the policy potentially impact other users via non-resource channels.

Our approach to estimating the spillovers arising from patchy groundwater management policy implementation is subject to several weaknesses. First, integrating static empirical estimates of groundwater users' price responsiveness in our hydroeconomic modeling assumes that groundwater users price elasticity remains constant through time even as resource stocks become more depleted. Future research should investigate how price responsiveness evolves through time as a function of resource stock. Second, significant questions remain regarding the external validity of our results, particularly as they relate to aquifer and input market characteristics. Future research should investigate conservation policy spillovers within differing input market structures.

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Appendix A

Chapter 1: Supplemental Material

A.1 Model Robustness: Choice of Instruments

To validate the parameters utilized in our counterfactual simulation and test the robustness of empirical modeling results, we vary the choice of price instruments using the FE-IV specification of water demand. Table A.1 presents modeling results for differing instrumenting approaches. Specifically, column (1) presents empirical results using our preferred instruments, the difference between the first and last marginal price in the rate structure and the REC-Year-HP average water threshold to reach final price block wherein the average is calculated by excluding observations with that HP. The remaining columns of Table A.1 all utilize the price difference as instruments but differ in how price block threshold values are calculated. Column (2) presents results where REC-Year-HP group averages do not exclude wells with same HP i.e. averages are calculated by grouping water threshold values at the REC-Year-HP level and finding the average. Column (3) finds group averages in a similar manner to column (2) but excludes an individual well's water threshold in determining their group average. Column (4) groups water thresholds at the REC-Year level to find group averages and column (5) does the same but excludes an individual well's water threshold value when calculating the REC-Year average.

The results presented in Table A.1 demonstrate the robustness of models results to choice of price instrument. Elasticity estimates vary across instrument specifications but do not change sign or lose statistical significance.

A.2 Model Robustness: Restricted Samples

The validity of the instrumental variable approach rests on the assumption that agricultural producers do endogenously determine the rate structure they face. In this Section, we test the robustness of our results to this assumption by restricting the sample of data utilized in the estimating

Table A.1: Model robustness to choice of instruments, FE-IV models

	Dependent variable:				
	Log(Pumping)				
	(1)	(2)	(3)	(4)	(5)
Log(Price)	-0.2519^{***}	-0.2562^{***}	-0.2503^{**}	-0.2511^{***}	-0.2510^{***}
	(0.0634)	(0.0764)	(0.0761)	(0.0654)	(0.0653)
Well Capacity	0.0003^{***}	0.0003^{***}	0.0003^{***}	0.0003^{***}	0.0003^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Precipitation	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Temperature	0.0051^{***}	0.0050^{***}	0.0051^{***}	0.0051^{***}	0.0051^{***}
	(0.0010)	(0.0012)	(0.0012)	(0.0010)	(0.0010)
Observations	9,400	9,400	9,343	9,400	9,400
R^2	0.2361	0.2371	0.2354	0.2360	0.2359
Adjusted R^2	0.1030	0.1041	0.1020	0.1028	0.1028
F Statistic	605.6612^{***}	608.6956^{***}	599.3348^{***}	605.1184^{***}	605.0335^{***}

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors clustered at the well owner
Models also include a year fixed effect whose output is omitted
Differing price instruments are as follows:
Column (1): REC-Year Mean $\bar{w}^2$ for all wells with differing HP
Column (2): REC-Year-HP Mean $\bar{w}^2$
Column (3): REC-Year-HP Mean $\bar{w}^2$ exluding well's $\bar{w}^2$
Column (4): REC-Year Mean $\bar{w}^2$
Column (5): REC-Year Mean $\bar{w}^2$ exluding well's $\bar{w}^2$

Table A.2: Restricted model Results, static well pump horsepower

	Dependent variable:			
	Log(Pumping)			
	POLS	POLS-IV	FE	FE-IV
	(1)	(2)	(3)	(4)
Log(Price)	-0.8488^{***}	-0.4474^{***}	-0.8187^{***}	-0.2528^{***}
	(0.0697)	(0.0705)	(0.0704)	(0.0679)
Well Capacity	0.0009^{***}	0.0009^{***}	0.0002^{***}	0.0003^{***}
	(0.00003)	(0.00004)	(0.00003)	(0.0001)
Precipitation	-0.0008^{***}	-0.0007^{***}	-0.0008^{***}	-0.0007^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Temperature	-0.0023^{*}	0.0026^{*}	-0.0015	0.0051^{***}
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Irrigation Class	0.0280^{**}	0.0343^{***}		
	(0.0093)	(0.0093)		
Constant	2.6972^{***}	3.5429^{***}		
	(0.1680)	(0.1649)		
Observations	8,866	8,866	8,866	8,866
R^2	0.4532	0.4307	0.2862	0.2316
Adjusted R^2	0.4529	0.4304	0.1616	0.0975
F Statistic	$1{,}468.6360^{***}$	$1{,}329.9340^{***}$	756.4614^{***}	556.4170^{***}

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors clustered at the well owner
Models also include a year fixed effect whose output is omitted

the econometric model of groundwater demand to those wells which do not report any change in well HP and wells which do not report any change in irrigation system discharge pressure. Changing well pump HP influences rate structure block thresholds while and retooling irrigation systems to decrease discharge pressure results in reduced pumping costs per unit of water extracted [Fipps, 1995]. Restricted sample results are reported in Tables A.2 and A.3.

A.3 REC Revenues Through Time

Table A.3: Restricted model results, static irrigation system discharge pressure

	Dependent variable:			
	Log(Pumping)			
	POLS	POLS-IV	FE	FE-IV
	(1)	(2)	(3)	(4)
Log(Price)	-0.8266^{***}	-0.4094^{***}	-0.7681^{***}	-0.2213^{*}
	(0.0740)	(0.0790)	(0.0735)	(0.0910)
Well Capacity	0.0008^{***}	0.0009^{***}	0.0001	0.0002^{*}
	(0.0001)	(0.0001)	(0.00005)	(0.0001)
Precipitation	-0.0009^{***}	-0.0007^{***}	-0.0008^{***}	-0.0007^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Temperature	-0.0016	0.0034^{**}	-0.00001	0.0063^{***}
	(0.0010)	(0.0012)	(0.0010)	(0.0011)
Irrigation Class	0.0221	0.0303^{*}		
	(0.0133)	(0.0130)		
Constant	2.7797^{***}	3.6647^{***}		
	(0.1805)	(0.1719)		
Observations	4,708	4,708	4,708	4,708
R^2	0.4420	0.4186	0.2871	0.2363
Adjusted R^2	0.4414	0.4179	0.1601	0.1001
F Statistic	744.8387^{***}	672.3814^{***}	402.2346^{***}	304.7842^{***}
Note:	*p<0.05; **p<0.01; ***p<0.001			
	Standard errors clustered at the well owner			
	Models also include a year fixed effect whose output is omitted			

Table A.4: REC revenues, 2011-2017

Year	Y-W	Highline
2011	11,237,304	6,272,035
2012	14,438,849	8,881,095
2013	14,053,273	8,387,452
2014	7,780,864	6,290,051
2015	8,767,457	7,518,073
2016	9,715,581	6,290,051
2017	10,053,750	7,093,861
Mean	10,863,868	7,247,995
Median	10,053,750	7,093,861

Appendix B

Chapter 2: Supplemental Material

B.1 Model Robustness: Peer Group Definition

In this Section, we test the robustness of our results to the spatial buffer utilized to define peer groups. Specifically, Tables B.1 and B.2 present results when the spatial buffer defining a parcel's neighbors is 1/2 and 2 km, respectively. These alternative peer group model results qualitatively align with those presented in Section 2.6, providing evidence that our results remain consistent across differing specifications of the spatial proximity defining peer groups.

B.2 Model Robustness: Model Specification

In this Section, we present results of two alternative model specification, pooled OLS and linear probability models, to test the robustness of our results. Tables B.3 and B.4 present pooled OLS model results when a parcel's neighbors or peer group is defined by 1 and 3 km buffers, respectively. While Tables B.5 and B.6 present linear probability model results when a parcel's neighbors or peer group is defined by 1 and 3 km buffers, respectively. Both model specifications generate results that qualitatively align with the random effect model specification, which provides some evidence supporting the robustness or our results to model specification choices.

B.3 Model Robustness: Percent of Neighbors Adopting

This Section provides results of the drip irrigation adoption model when the peer effect variable is defined as a percentage of parcels adopting within a 1 and 3 km buffer. This specification differs from that presented in Section 2.6, where the peer effect variable is a count of adoptions with an additional variable controlling for the number of parcels within the buffer. Tables B.7 and B.8 present modeling results when the spatial buffer defining the percentage of peer group adoption is 1 and 3 km, respectively. Qualitatively, these results align with those presented in Section 2.6

Table B.1: Drip irrigation adoption model with peer group defined as parcels within 1/2 km

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 1/2 km	0.414***	0.240***	0.179*	0.124
	(0.0854)	(0.0636)	(0.0749)	(0.0929)
GW Available	-0.754*	-0.503+	-0.537+	-0.706+
	(0.359)	(0.262)	(0.289)	(0.385)
# of Peers Adopting X GW	-0.0713	-0.0531	-0.0688	-0.0857
	(0.216)	(0.181)	(0.196)	(0.249)
Parcel Size	-0.0420***	0.0167*	0.0187*	0.0260*
	(0.00979)	(0.00801)	(0.00890)	(0.0119)
Parcel Size^2	0.000244***	-0.000118+	-0.000131*	-0.000176*
	(0.0000675)	(0.0000606)	(0.0000666)	(0.0000876)
Less than 5 Ha.	-1.108**	0.122	0.136	0.249
	(0.359)	(0.260)	(0.287)	(0.376)
Distance to Canal	-0.262***	-0.0498	-0.0701+	-0.120*
	(0.0363)	(0.0318)	(0.0360)	(0.0478)
Distance to Market	-0.123***	-0.0434+	-0.0475+	-0.0617+
	(0.0197)	(0.0242)	(0.0271)	(0.0357)
# of Parcels W/I 1/2 km	-0.149***	0.0174	0.0178	0.0218
	(0.0166)	(0.0135)	(0.0151)	(0.0201)
σ_μ^2	1.721***	0.341	0.863**	1.916***
	(0.193)	(0.264)	(0.316)	(0.198)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2: Drip irrigation adoption model with peer group defined as parcels within 2 km

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 2 km	0.158***	0.0989***	0.114***	0.0566+
	(0.0242)	(0.0187)	(0.0262)	(0.0300)
GW Available	-0.436	-0.624*	-0.629+	-0.867+
	(0.456)	(0.318)	(0.336)	(0.444)
# of Peers Adopting X GW	0.0152	0.0103	0.00593	0.0153
	(0.0489)	(0.0386)	(0.0404)	(0.0522)
Parcel Size	-0.0417***	0.0190*	0.0201*	0.0266*
	(0.0105)	(0.00867)	(0.00922)	(0.0119)
Parcel Size^2	0.000243***	-0.000132*	-0.000138*	-0.000179*
	(0.0000707)	(0.0000651)	(0.0000687)	(0.0000877)
Less than 5 Ha.	-1.132**	0.114	0.129	0.232
	(0.382)	(0.282)	(0.298)	(0.378)
Distance to Canal	-0.272***	-0.0563	-0.0625	-0.113*
	(0.0389)	(0.0361)	(0.0389)	(0.0499)
Distance to Market	-0.144***	-0.0511+	-0.0528+	-0.0645+
	(0.0214)	(0.0271)	(0.0289)	(0.0366)
# of Parcels W/I 2 km	-0.0460***	-0.00288	-0.00318	0.000192
	(0.00487)	(0.00409)	(0.00437)	(0.00562)
σ^2_μ	2.125***	0.776**	1.008**	1.934***
	(0.183)	(0.289)	(0.339)	(0.200)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend
$^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Drip irrigation adoption model with peer group defined as parcels within 1 km, pooled OLS specification

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 1 km	0.148***	0.139***	0.122***	0.0633^{+}
	(0.0240)	(0.0251)	(0.0325)	(0.0332)
GW Available	-0.246	-0.502^{+}	-0.500^{+}	-0.505^{+}
	(0.258)	(0.258)	(0.260)	(0.271)
# of Peers Adopting X GW	-0.0308	-0.0388	-0.0401	-0.0330
	(0.0770)	(0.0702)	(0.0718)	(0.0762)
Parcel Size	-0.0179**	0.0192**	0.0197**	0.0189*
	(0.00611)	(0.00744)	(0.00747)	(0.00773)
Parcel Size^2	0.000114**	-0.000132*	-0.000134*	-0.000130*
	(0.0000412)	(0.0000587)	(0.0000591)	(0.0000612)
Less than 5 Ha.	-0.709**	0.103	0.104	0.115
	(0.224)	(0.242)	(0.242)	(0.247)
Distance to Canal	-0.142***	-0.0292	-0.0345	-0.0506^{+}
	(0.0195)	(0.0296)	(0.0296)	(0.0307)
Distance to Market	-0.0857***	-0.0312	-0.0300	-0.0299
	(0.0114)	(0.0216)	(0.0217)	(0.0223)
# of Parcels W/I 1 km	-0.0819***	-0.0103	-0.00980	-0.00516
	(0.00548)	(0.00753)	(0.00757)	(0.00783)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Drip irrigation adoption model with peer group defined as parcels within 3 km, pooled OLS specification

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 3 km	0.0431***	0.0633***	0.119***	0.0362+
	(0.00984)	(0.0107)	(0.0216)	(0.0212)
GW Available	-0.408	-0.764*	-0.730*	-0.789*
	(0.313)	(0.316)	(0.315)	(0.336)
# of Peers Adopting X GW	0.0293	0.0251	0.0212	0.0294
	(0.0272)	(0.0265)	(0.0271)	(0.0287)
Parcel Size	-0.0232***	0.0208**	0.0210**	0.0200**
	(0.00584)	(0.00725)	(0.00716)	(0.00753)
Parcel Size^2	0.000134***	-0.000138*	-0.000137*	-0.000135*
	(0.0000387)	(0.0000575)	(0.0000566)	(0.0000596)
Less than 5 Ha.	-0.742***	0.103	0.111	0.118
	(0.218)	(0.237)	(0.235)	(0.243)
Distance to Canal	-0.116***	-0.0411	-0.0395	-0.0553+
	(0.0178)	(0.0281)	(0.0283)	(0.0292)
Distance to Market	-0.0760***	-0.0306	-0.0299	-0.0293
	(0.0113)	(0.0206)	(0.0205)	(0.0216)
# of Parcels W/I 3 km	-0.0231***	-0.00390+	-0.00508*	-0.00255
	(0.00151)	(0.00217)	(0.00221)	(0.00233)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.5: Drip irrigation adoption model with peer group defined as parcels within 1 km, linear probability specification

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 1 km	0.00378***	0.00401***	0.00368***	0.00223**
	(0.000573)	(0.000600)	(0.000751)	(0.000753)
GW Available	-0.00541	-0.00603	-0.00617	-0.00674+
	(0.00381)	(0.00385)	(0.00387)	(0.00386)
# of Peers Adopting X GW	-0.00236+	-0.00235+	-0.00236+	-0.00206
	(0.00139)	(0.00139)	(0.00139)	(0.00138)
Parcel Size	0.0536***	0.0331**	0.0339**	0.0352**
	(0.0113)	(0.0125)	(0.0126)	(0.0125)
Parcel Size^2	-0.00330***	-0.00208*	-0.00212*	-0.00216*
	(0.000782)	(0.000841)	(0.000845)	(0.000842)
Less than 5 Ha.	0.00628	0.00151	0.00156	0.00180
	(0.00408)	(0.00422)	(0.00424)	(0.00422)
Distance to Canal	-0.000690*	-0.000355	-0.000404	-0.000566
	(0.000321)	(0.000520)	(0.000525)	(0.000523)
Distance to Market	0.000460*	-0.000505	-0.000494	-0.000454
	(0.000223)	(0.000405)	(0.000407)	(0.000406)
# of Parcels W/I 1 km	0.000122	-0.000210	-0.000202	-0.000157
	(0.0000895)	(0.000131)	(0.000132)	(0.000132)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.6: Drip irrigation adoption model with peer group defined as parcels within 3 km, linear probability specification

	(1)	(2)	(3)	(4)
# of Peers Adopting W/I 3 km	0.00136***	0.00144***	0.00229***	0.000790*
	(0.000192)	(0.000206)	(0.000376)	(0.000389)
GW Available	-0.00802+	-0.00855*	-0.00803+	-0.00860*
	(0.00419)	(0.00423)	(0.00424)	(0.00421)
# of Peers Adopting X GW	-0.0000144	-0.0000257	-0.000109	-0.0000458
	(0.000486)	(0.000488)	(0.000491)	(0.000487)
Parcel Size	0.0521***	0.0358**	0.0362**	0.065**
	(0.0113)	(0.0125)	(0.0126)	(0.0125)
Parcel Size^2	-0.00315***	-0.00220**	-0.00222**	-0.00223**
	(0.000787)	(0.000844)	(0.000845)	(0.000840)
Less than 5 Ha.	0.00492	0.00142	0.00137	0.00179
	(0.00412)	(0.00423)	(0.00424)	(0.00422)
Distance to Canal	-0.000805*	-0.000594	-0.000462	-0.000711
	(0.000321)	(0.000519)	(0.000522)	(0.000520)
Distance to Market	0.000471*	-0.000456	-0.000455	-0.000435
	(0.000228)	(0.000407)	(0.000407)	(0.000405)
# of Parcels W/I 3 km	0.0000223	-0.0000806*	-0.000102**	-0.0000635
	(0.0000242)	(0.0000387)	(0.0000396)	(0.0000395)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^+ p < 0.1$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

with the exception that when additional spatial and time controls are added in models presented the columns (3) and (4) the peer effect coefficient switches sign from the expected positive relationship to negative. However, this unexpected shift in the coefficient's sign is also paired with a loss in statistical significance.

Table B.7: Drip irrigation adoption model with peer group defined as parcels within 1 km

	(1)	(2)	(3)	(4)
% of Peers Adopting	4.441***	2.105*	-1.425	-0.986
	(1.280)	(0.952)	(1.616)	(2.090)
GW Available	-0.885*	-0.477^{+}	-1.190**	-1.527*
	(0.404)	(0.258)	(0.461)	(0.615)
% of Peers Adopting X GW	-0.718	-2.431	-1.077	-1.555
	(4.048)	(3.409)	(4.707)	(6.602)
Parcel Size	-0.0797***	0.0191*	-0.0931***	-0.136***
	(0.00995)	(0.00789)	(0.0119)	(0.0167)
Parcel Size^2	0.000445***	-0.000129*	0.000512***	0.000742***
	(0.0000677)	(0.0000602)	(0.0000805)	(0.000108)
Less than 5 Ha.	-1.747***	0.0920	-1.981***	-2.724***
	(0.391)	(0.257)	(0.429)	(0.576)
Distance to Canal	-0.350***	-0.0626*	-0.430***	-0.568***
	(0.0421)	(0.0308)	(0.0509)	(0.0720)
Distance to Market	-0.232***	-0.0371	-0.374***	-0.571***
	(0.0207)	(0.0234)	(0.0286)	(0.0428)
σ_μ^2	2.034***	0.263	2.828***	3.523***
	(0.175)	(0.258)	(0.128)	(0.139)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.8: Drip irrigation adoption model with peer group defined as parcels within 3 km

	(1)	(2)	(3)	(4)
% of Peers Adopting	7.462***	3.965**	-3.130	-2.565
	(2.150)	(1.371)	(2.631)	(3.430)
GW Available	-1.228*	-0.618*	-0.622+	-0.887+
	(0.493)	(0.295)	(0.320)	(0.463)
% of Peers Adopting X GW	4.315	1.222	0.385	1.178
	(4.665)	(3.723)	(3.982)	(5.780)
Parcel Size	-0.0857***	0.0194*	0.0205*	0.0289*
	(0.0111)	(0.00804)	(0.00881)	(0.0123)
Parcel Size^2	0.000481***	-0.000130*	-0.000140*	-0.000191*
	(0.0000748)	(0.0000611)	(0.0000663)	(0.0000909)
Less than 5 Ha.	-1.922***	0.0858	0.110	0.231
	(0.432)	(0.262)	(0.285)	(0.389)
Distance to Canal	-0.384***	-0.0726*	-0.0884*	-0.148**
	(0.0510)	(0.0318)	(0.0354)	(0.0486)
Distance to Market	-0.246***	-0.0377	-0.0409	-0.0561
	(0.0258)	(0.0239)	(0.0265)	(0.0367)
σ^2_μ	2.267***	0.405	0.838**	2.136***
	(0.223)	(0.271)	(0.304)	(0.158)
Commune Dummies	X	✓	✓	✓
Commune Dummies X Trend^2	X	X	✓	✓
CCE	X	X	X	✓
Observations	14059	14059	14059	14059

Standard errors in parentheses, Parcel Size^2 is parcel size squared, Trend^2 is a quadratic time trend

$^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$