Essays on the Economics of Climate Change, Water, and Agriculture

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Dissertation submitted to the Faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Forestry

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June 19, 2018
Blacksburg, Virginia

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(ABSTRACT)

In an era of global-scale climate change, agricultural production faces a unique challenge due to its reliance on stochastic natural endowments, including temperature, precipitation, and water availability for irrigation. This dissertation presents a series of essays to examine how agricultural producers react and adapt to challenges presented by climate change and scarce irrigation water allocated through the prior appropriation doctrine. The dissertation approaches the problem from three distinct perspectives: institutional differences, climate and water availability, as well as producers' expectation on future endowments.

Chapter 2 presents an institutional perspective, in which I investigate how different water allocation mechanisms within the prior appropriation doctrine result in differences in producers' crop allocation decisions. I find that water users in irrigation districts are able to plant more water-intensive crops than farmers outside irrigation districts.

Chapter 3 presents the interaction between nature and human systems, in which I examine how the physiological complementarity of temperature and water availability diffuses from crop yield (at the intensive margin) to crop allocation strategies (at the extensive margin). Using a theoretical model I show that the observed complementarity reflects a combination of two mechanisms: yield impact through physiological complementarity, and adaptation response through shifting crop allocation patterns. Using an empirical model, I find that farmers adapt to changing climate conditions by growing more profitable crop mixes when presented with more growing degree-days (GDD), precipitation and groundwater access.

Chapter 4 presents a behavioral perspective, in which I test how producers' expectation formation processes lead to short term over-adjustments to weather and water availability fluctuations. Using a fixed-effect regression on lagged weather and water realizations, I find that agricultural producers engage in a combination of cognitive biases, including the availability heuristic and the reinforcement strategy. Adopting these alternative learning mechanisms causes farmers to significantly over-react to more recent fluctuations in weather and water availability when making *ex ante* acreage and crop allocation decisions.

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(GENERAL AUDIENCE ABSTRACT)

In an era of global-scale climate change, agricultural production faces a unique challenge due to its reliance on variable natural factors, including temperature, precipitation, and water availability for irrigation. This dissertation presents a series of essays to examine how agricultural producers react and adapt to challenges presented by climate change and scarce irrigation water allocated through the prior appropriation doctrine. Chapter 2 presents an institutional perspective, in which I investigate how different water allocation regimes result in differences in producers' cropping decisions. I find that irrigation districts benefit its users by allowing them to plant more water-intensive crops than farmers outside irrigation districts. Chapter 3 presents a natural science perspective, in which I examine how temperature and water availability jointly affect agricultural production and adaptation. I find that farmers significantly adapt to changing climate conditions by growing more profitable crop mixes when presented with higher temperature, precipitation, and groundwater access. Chapter 4 presents a behavioral perspective, in which I test how agricultural decision making are affected by how producers form expectations over future climate. I find that agricultural producers engage in a combination of cognitive biases when forming expectations, and as a result over-react to more recent fluctuations in weather and water availability when making acreage and crop allocation decisions.

Dedication

To my family, for their unconditional love and support.

Acknowledgments

I owe a great deal to a number of people during the process of completing this dissertation, and along the course of my entire graduate study.

First and foremost, I would like to thank Dr. Kelly Cobourn for her constant support and insightful guidance. I would not be able to complete this dissertation without her unreserved mentoring. I also want to thank my committee members: Dr. Greg Amacher, for setting an inspiring example in both teaching and research; Dr. Klaus Moeltner, for teaching me academic rigor as well as occasional humor; and Dr. Val Thomas, for forcing me to think outside the box and communicate with the broader audience.

I am grateful to the advice, comments, and criticisms provided on my scholarly work from Oliver Browne, Steven Buck, Siân Mooney, Jesse Tack, and participants at the Health Economics Lab at Virginia Tech. I also want to thank the cooperation and support for my data request from Idaho Department of Water Resources, and David Hoekema in particular. I am grateful to Amoz Kats for his invaluable advice on how to become a better person.

Lastly, I am in debt to my wife and best friend, Weizhe Weng. She is often the first listener to my research ideas, and the first reader to my manuscript. Her wit, grit, patience, and unselfishness is a constant inspiration for me. I am extremely fortunate to have her in my life.

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Chapter 1

Introduction

In an era of global-scale climate change, agricultural production faces a unique challenge due to its reliance on stochastic natural endowments, including temperature, precipitation, and water availability for irrigation. The economic literature establishes that while mild warming may benefit agricultural production (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2007), an increase in the frequency of extreme heat events largely offsets this benefit (Schlenker and Roberts, 2009; Lobell et al., 2013; Burke and Emerick, 2016). A separate literature has shown that while increased water availability in the form of precipitation or supplemental irrigation water is beneficial to agriculture (Schlenker, Hanemann, and Fisher, 2005, 2007; Buck, Auffhammer, and Sunding, 2014; Tack, Barkley, and Hendricks, 2017), changes in the variability of water inflows are likely to be far more important in the future than changes in the mean (Urban et al., 2015; Hendricks, 2018). This dissertation combines these threads in the literature to explore how variation in both temperature and water availability are likely to influence agricultural productivity, and how agricultural producers adapt to those changes.

A majority of the economic literature on the effects of climate change on agriculture has focused on either crop yield (Schlenker and Roberts, 2009; Lobell et al., 2013) or land rents (Schlenker, Hanemann, and Fisher, 2005, 2007; Deschênes and Greenstone, 2007). An equally important, but less studied question concerns how agricultural producers adapt to changing patterns in natural endowments. The effect of changing natural endowments on agricultural production is not only determined by the physiological effect on crop yields. As climate and water patterns shift, producers will change their behavior in response. Thus, the extent to which climate change and increasing water scarcity affect agriculture are not only determined by the physiological impact of climate and water on crop yields, but also by how farmers' adaptive decisions, such as changing acreage or crop allocation, can offset or intensify the impact. These important adaptive decisions, such as the choice of acreage, crop and irrigation use, cannot be identified by land rent studies, nor are they characterized by crop yield studies.

This dissertation presents three essays that examine how agricultural producers react and adapt to changing natural factor endowments. In Chapter 2, I approach the problem from an institutional perspective, examining how prior appropriation doctrine drives producers' crop-allocation decisions. In Chapter 3, I take a natural science perspective, examining how the physiological complementarity of temperature and water availability affects crop yields by influencing water-use decisions at the intensive margin as well as crop-allocation strategies at the extensive margin. In Chapter 4, I take a behavioral perspective, testing how producers form expectations over natural factor availability, and how the process of forming those expectations may lead to short-term over-adjustments to recent weather and water availability signals.

For all chapters, I focus specifically on examining the effect of natural endowments on irrigated agriculture in the U.S. West, where quantifying producer adaptation has been proven more challenging than modeling agriculture in the humid U.S. East(Schlenker, Hanemann, and Fisher, 2007). A distinguishing feature of western agriculture is its heavy reliance on irrigation water, which is economically scarce and variable in supply. On top of that, water in the U.S. West is predominantly allocated not with market mechanisms, but with prior appropriation water rights, under which water is allocated based on the principle of ”first in time, first in right.” Prior appropriation creates a unique set of challenges for economists, both in terms of the economic implications of the water allocation institutions themselves (Buck, Auffhammer, and Sunding, 2014; Mukherjee and Schwabe, 2015; Brent, 2017; Cobourn et al., 2017) and in how climate change effects are filtered through water allocation institutions to affect irrigated agriculture (Manning, Goemans, and Maas, 2017). The economic literature, particularly empirical works, is scant on both of these topics because of the complexity of water rights and because of difficulties in finding high-quality data on water rights ownership and producers’ adaptive behaviors.

In Chapter 2, “The Economic Benefits of Irrigation Districts under Prior Appropriation Doctrine: An Econometric Analysis of Agricultural Land-allocation Decisions,” I explore how irrigation districts benefit their water users by deviating from strict application of the prior appropriation doctrine. The economic literature has suggested that prior appropriation creates heterogeneity in risk among water users, which leads to an inefficient allocation of resources (Burness and Quirk, 1979; Cobourn et al., 2017). In this essay, I argue that irrigation districts are able to alleviate this heterogeneity in risk through several potential channels, including proportional water allocation, risk sharing, and easier water transfers. As a result, water users in irrigation districts are able to plant more water-intensive crops than farmers outside irrigation districts, which increases average profitability.

In Chapter 3, “The Effect of Climate Change on Irrigated Agriculture: Water-Temperature Interactions and Adaptation in the Western U.S.,” I examine how water and temperature jointly drive agricultural production decisions and adaptation. Previous empirical studies have observed a positive interaction effect between temperature and water on land rents, and attribute that to a physiological increase in crop water demand under a warmer climate (Fezzi and Bateman, 2015; Hendricks, 2018). In this essay, I develop a theoretical model to show that complementarity between temperature and water availability actually reflects a combination of two effects: physiological complementarity that drives crop yield at the intensive margin, and the ability to shift crop allocation patterns, which drives adaptation at the extensive margin. I empirically test the long-term and short-term responses of farmers to non-linear temperature and different source of water supply using field-scale remote sensing data on land allocation. I find that farmers grow more profitable crop mixes when presented with higher growing degree-days (GDD), precipitation, and groundwater access. I also find that compared to long-term responses, short-term responses in land allocation are smaller in magnitude and differ in their driving factors.

In Chapter 4, "Weather Fluctuations, Expectation Formation, and Short-run Behavioral Responses to Climate Change," I investigate how past weather fluctuations influence future agricultural decision-making through the channel of expectation formation. A premise adopted in many previous studies is that farmers form expectation on future climate using long-run normals. Yet if decision makers' subjective expectations on climate variables deviate from long-run normals, then farmers will react disproportionately to more recent climate signals, incurring short-term over-adjustment costs. I find that agricultural producers engage in a combination of cognitive biases that are not consistent with Bayesian updating, including the availability heuristic and the reinforcement strategy. Adopting these alternative learning mechanisms causes farmers to significantly over-react to recent fluctuations in weather and water availability when making *ex ante* acreage and crop-allocation decisions.

The three essays presented in this dissertation are unified by a common theme: individual producers' decision-making shapes how agriculture will be affected by climate change and water scarcity. I show that adaptation measures are made by producers in response to climate signals, but that behavioral response is also driven by the types of institutions that allocate water across farms, as well as the way in which farmers form subjective expectations over future climate. As such, this dissertation adds to the growing literature on understanding how producers adapt to the challenges from global and regional environmental changes.

I also present evidence on the differences in the short and long-run adaptation to variable climate and water endowments. Chapter 2 and 3 show that surface water availability, governed by prior appropriation water rights, has an in-significant effect on crop-allocation decisions in the long run, while Chapter 3 and 4 show that changes in availability of surface water drive crop-allocation and acreage decisions in the short run. This finding coincides with previous studies, which suggest that responses to surface water availability are significant in the short-run for individuals (Buck, Auffhammer, and Sunding, 2014), but not necessarily in the long-run across individuals with different water rights (Brent, 2017; Cobourn et al., 2017).

Additionally, the three essays add to other lines of inquiry in the economic literature: Chapter 2 contributes to the literature on understanding the economic consequences of prior appropriation water rights, and more generally on the value of water to agriculture; Chapter 3 contributes to the empirical estimation of agricultural adaptation to climate change; and Chapter 4 contributes to the literature on understanding the enduring economic impacts of weather fluctuation, and on understanding agents' learning mechanisms.

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Chapter 2

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

Reprinted from Canadian Journal of Agricultural Economics, Xinde Ji and Kelly M. Cobourn, The Economic Benefits of Irrigation Districts under Prior Appropriation Doctrine: An Econometric Analysis of Agricultural Land-allocation Decisions, forthcoming, doi:10.111/cjag.12165

2.1 Introduction

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

Given that prior appropriation has been slow to evolve in response to increased water scarcity, a question that arises is whether and how irrigators mitigate risk in water availability within the constraints imposed by current institutions (Libecap, 2011). Previous studies have looked at two potential means of mitigating risk in water availability: diversification across water source and access to water markets. Diversification across source may include a combination of surface water and groundwater resources or access to different surface water resources. For example,Hornbeck and Keskin (2014) show that access to groundwater enables farmers to switch from non-irrigated to irrigated agriculture and from drought-tolerant to water-intensive crops, generating an increase in farmland value. Mukherjee and Schwabe (2015) document a benefit from diversification across surface water and groundwater, but also demonstrate that access to supplementary surface water from water districts increases farmland value. Competitive water markets can theoretically achieve an efficient allocation of water in an appropriative system, as demonstrated by Burness and Quirk (1979) . A number of studies demonstrate that the efficiency gains from water markets are likely to be substantial in practice (e.g. Calatrava and Garrido, 2005; Ghosh, Cobourn, and Elbakidze, 2014; Hansen, Howitt, and Williams, 2008; Howitt, 1998; Howitt and Hansen, 2005). Despite their promise as mechanisms to achieve an efficient allocation of resources, diversification across water sources and access to water markets are constrained by the current geographical and institutional environment in the US West. Access to groundwater is subject to the geographical distribution of underground aquifers, access to diverse surface water resources is constrained by existing conveyance and storage infrastructure, and large-scale water markets remain thin (Bretsen and Hill 2006; Brewer et al. 2007).

In this paper, we investigate whether access to irrigation districts enables farmers to mitigate risk in water availability. Irrigation districts are semi-governmental farmer cooperatives that allocate water acquired under prior appropriation rights to their members (Ghimire and Griffin, 2014; Griffin, 2006; Libecap, 2011; Rosen and Sexton, 1993).[1] They differ from individual farmers in an appropriative system in several respects. First, irrigation districts typically hold a diverse set of water rights, which reduces risk in water deliveries due to curtailment. Second, water is proportionally allocated among farmers within irrigation districts (Michelsen et al., 1999). The proportional allocation of water spreads risk from individuals across all district members, analogous to the function of insurance pools. Third, water transfers between district members are subject to lower transactions costs than transfers among farmers outside of irrigation districts. As a result, irrigation districts often facilitate informal transfers, thereby offering the advantages of a small-scale water market. These features of irrigation districts reduce the chance of a critical curtailment in water deliveries for an individual farmer inside the district. Thus, they reduce risk in water availability for members of irrigation districts relative to irrigators outside districts.

Our objective in this study is to test empirically whether there exist systematic differences in land-allocation decisions between farmers inside and outside of irrigation districts. Our empirical analysis focuses on the Eastern Snake River Plain (ESRP) of Idaho, a region that relies heavily on irrigation for agricultural production. We take advantage of several detailed geo-referenced datasets to summarize annual crop choices at the scale of the individual water right. Using these data, we estimate a fractional multinomial logit (FMNL) model

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

to explain observed land-share decisions by farmers in a multi-crop system as a function of water rights, membership in an irrigation district, and a vector of spatially referenced control variables including soil characteristics, temperatures, and precipitation.

This study contributes to the economic literature by empirically distentagling the economic benefits provided by irrigation districts from the effect of water rights seniority, which renders some water rights more secure. The majority of the economic literature on this topic examines questions related to prior appropriation at the scale of the irrigation district, but does not examine the benefits derived from membership in an irrigation district (Brent, 2017; Buck, Auffhammer, and Sunding, 2014; Mukherjee and Schwabe, 2015). Moreover, the existing literature often does not consider seniority (Mukherjee and Schwabe, 2015) or acknowledges the potential to underestimate the seniority effect (Brent, 2017). An exception is Cobourn et al. (2017), who also focus on the effect of water rights seniority on the land-allocation decisions of farmers in the ESRP. We broaden our focus by comparing land-allocation decisions between farmers in irrigation districts (with group-owned rights) and those outside of irrigation districts (with privately owned rights). As a result, we are able to address three new research questions: we evaluate differences in land-allocation decisions between lands allocated under private and group water rights while controlling for seniority; we examine the interaction between these two effects, i.e. whether farmers that are part of groups with more senior water rights plant different crops than those that are part of groups with less senior water rights; and we evaluate the effects of access to multiple water sources on land-allocation decisions.

A second contribution to the economic literature is that we use a direct approach to model farmers' crop-specific land-allocation decisions, which allows us to describe how farmers adapt crop production in response to variation in natural and institutional characteristics.

Previous studies examine these differences indirectly through hedonic property markets (e.g., Brent, 2017; Schlenker, Hanemann, and Fisher, 2007) or at an aggregate level (e.g. Deschênes and Greenstone, 2007; Hornbeck and Keskin, 2014; Moore and Negri, 1992; Moore, Gollehon, and Carey, 1994). Hedonic studies can retrieve the value of water through its premium in land rent, but are not able to explain the underlying mechanism that generates the premium. In contrast, our approach enables us to explore the adaption mechanisms farmers undertake in response to water constraints. Moreover, while aggregate data on production and water use are often more readily available, aggregation across water rights obscures variations in the institutional differences in property rights that vary at the scale of the individual.

Our empirical results demonstrate that farmers in irrigation districts plant land to a more profitable set of crops than otherwise similar farmers outside of districts. On average, farmers inside irrigation districts allocate more land to sugarbeets and potatoes, which are relatively drought-sensitive, high-value crops. As a result of these differences in planting decisions, members of irrigation districts earn an average of \$16.20 per acre, or 6.0% more per year, than those outside of irrigation districts. We also find that the benefit of access to an irrigation district is greatest for farmers with more junior rights than those with relatively secure senior rights. Our results suggest the potential for substantial efficiency gains associated with access to an irrigation district, which offsets inefficiency introduced by seniority in an appropriative system.

2.2 Background on Irrigation Districts

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

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

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

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

curtailed during a growing season (Cobourn et al., 2017).

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

2.3 Empirical Model

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

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

$$\Pi_j = \mathbf{X}_i \boldsymbol{\beta}_j + \varepsilon_{ij} \tag{2.1}$$

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

$$\bar{y}_{ij} = \frac{exp(\mathbf{X}_i \boldsymbol{\beta}_j)}{\sum_{k=1}^{J} exp(\mathbf{X}_i \boldsymbol{\beta}_k)} \tag{2.2}$$

If we interpret $\bar{y}_{ij}$ as the share of crop j in the land allocation (rather than the probability of choosing alternative j in a traditional conditional logit framework), then equation 2.2 gives rise to the fractional multinomial logit (FMNL) model.

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

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

$$y_{ijt} = f(\mathbf{W}_{it}, \mathbf{Z}_{it}, \mathbf{P_t}) \tag{2.3}$$

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

$$\mathbf{W}_{it} = f(W^a_{it}, W^p_{it}, W^{ID}_i, W^o_{it}) \tag{2.4}$$

The amount of water acquired under prior appropriation water rights, W^a_{it}, is in turn a function of three variables: total surface water available for allocation across all farmers, α_t, the seniority of the farmer's right(s), μ_i, and access to a diverse set of water rights, described by the parameter σ_i. An increase in α_t implies that all irrigators face a lower probability of curtailment. An increase in μ_i corresponds to an increase in seniority, where more senior rights are less likely to be curtailed than junior rights, holding constant water availability. Access to diverse water rights may include diversity across water right seniority σ^s_i (Cobourn et al., 2017) and/or across water sources σ^g_i (Mukherjee and Schwabe, 2015). Taking into account how appropriative rights depend on these parameters, we can rewrite equation 2.4 as:

$$\mathbf{W}_{it} = f\Big(W^a_{it}\big(\alpha_t, \mu_i, \sigma(\sigma^s_i, \sigma^g_i)\big), W^p_{it}, W^{ID}_i, W^o_{it}\Big) \tag{2.5}$$

In Equation 2.5 we partition a farmer's water supply into different components. In our empirical model, the effect of regional water availability, α_t, will be captured by an annual fixed effect. Our main FMNL model specification is thus given by:

$$G^{-1}(y_{ijt}) = \tau_j + \beta_j W_i^{ID} + \gamma_j \mu_i + \delta_{1j}\sigma_i^g + \delta_{2j}\sigma_i^s + \zeta_j \mathbf{X}_{it} + \theta T_t + \varepsilon_{ijt} \tag{2.6}$$

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

Our empirical strategy is to compare differences in the average land allocation decisions between farmers inside and outside of irrigation districts via a pooled FMNL model. Our strategy relies on two assumptions: 1) irrigation districts membership is exogenously determined, and 2) irrigation district membership is not correlated with unobserved natural endowments in the error term.

We argue that the first assumption holds for three reasons. First, irrigation districts were formed to solve an infrastructure-coordination problem, not a water-allocation problem (Bretsen and Hill, 2006; Libecap, 2011; Rosen and Sexton, 1993). The economic benefits derived from irrigation district membership in the present are an unintended consequence of infrastructure development during the Progressive Era (1890-1920). Second, irrigation district service areas have remained unchanged for nearly a century. Membership in irrigation districts is determined by geographical location, rather than by self-selection into or out of

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

the district. Thus, selection bias in irrigation district membership is not problematic in our analysis. Third, evidence suggests that patterns of land settlement and water appropriation in the region are at most weakly correlated with natural endowments such as weather, climate, and soil (Lee, Rollins, and Singletary, 2017; Leonard and Libecap, 2016). Even if a correlation exists, controlling for soil and weather conditions should safeguard our main explanatory variable of interest. Summary statistics suggest that in fact irrigation districts have less favorable natural endowments than farmers outside of irrigation districts on average. This means that natural endowments cannot explain the estimated benefits associated with irrigation district membership.

Although we possess a dataset with a panel structure, we do not control for individual-specific heterogeneity using panel data methods. The econometric literature has not yet developed a viable method to estimate the panel FMNL model. Papke and Wooldridge (2008) propose to estimate panel fractional probit models via the Chamberlain (1980) method. However, there are two obstacles in applying their method to this study. The likelihood function for a multinomial probit model can only be meaningfully constructed on binary rather than multimodal variables, which prohibits the extension of the panel fractional probit model to a multivariate setting. Further, Papke and Wooldridge's estimator requires augmenting the regression model with time averages, which would eliminate all time-invariant variables. Because water rights attributes are time invariant, estimating a model based on Papke and Wooldridge (2008) is not suitable for this analysis.

Using a pooled cross-sectional model is a reasonable alternative if we can control for omitted variables. Our purpose is to draw inference mainly from between rather than within variation in land-allocation decisions. Our variables of primary interest, water rights seniority and irrigation district access, are fixed over time but vary across individuals. As a result, between variation captures systematic differences in land-allocation decisions due to institutional factors, whereas within variation will reflect non-institutional factors such as crop rotation patterns and expectations for weather conditions. Thus, using land-allocation variability from a cross-sectional or short panel dataset is sufficient to identify the effect from water institutions if we are able to control for other determinants of water availability.

Admittedly, our main specification does not guard against unobserved factors in the error term that may be correlated with irrigation district status. To minimize the impact of omitted variable bias, we control for factors typically modeled in the literature, including those that reflect water availability, soil quality, and the weather conditions that impact agricultural production and yield. Additionally, we offer a linear panel random effect (RE) model as a robustness check, which relies on the weaker assumption that irrigation district status is uncorrelated with individual, time-invariant heterogeneity.

Following Mullahy (2015) and Papke and Wooldridge (1996), we estimate our empirical model by maximizing the Bernoulli log-likelihood function :

$$\sum_{i=1}^{N} ln(L_i) = \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ij} ln(G(X_i \beta_j)) \tag{2.7}$$

for which L_i is the likelihood for observation i, y_{ij} is as defined in equation (3), X_i is the vector of of explanatory variables for observation i, which includes variables identified in equation 2.6, and β_j is a vector of coefficients specific to each land-allocation choice.

The parameter estimates obtained by maximizing equation (2.7) represent the logit-transformed odds ratio for each specific choice relative to a baseline choice. The marginal effect for a continuous explanatory variables is:

$$ME_{jk} = \frac{\partial \hat{\mathbf{y}}_j}{\partial \mathbf{x}_k} = \hat{\mathbf{y}}_j(\beta_{jk} - \bar{\boldsymbol{\beta}}_k) \tag{2.8}$$

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

$$DE_{jk} = Pr(y = j|\mathbf{x}_{x_k=1}) - Pr(y = j|\mathbf{x}_{x_k=0}) \tag{2.9}$$

which is the change in the predicted land share when the dummy variable x_k increases from zero to one. Both the marginal and discrete effects in equations (2.8) and (2.9) differ with the levels of the explanatory variables, and thus between different water rights. In order to obtain marginal or discrete effects, we aggregate partial effects for different individuals to obtain the average partial effects (APE). We also calculate the average partial effects on profits (APEP), which is analogous to the concept of the traditional parameter estimates and standard errors in an univariate linear model. We do this by aggregating crop shares with respect to their profits per acre, as well as their respective variances, i.e.,

$$\begin{aligned} E(APEP_k) &= \sum_{j=1}^{J} APE_{j,k} * profit_j \\ V(APEP_k) &= \sum_{j=1}^{J} V(APE_{j,k}) * profit_j^2 \end{aligned} \tag{2.10}$$

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

2.4 Data

Our empirical analysis focuses on the East Snake River Plain (ESRP) in southeastern Idaho (Figure 2.1). The ESRP is an agricultural production region that relies heavily on irrigation water: 74.7% of farmlands are irrigated (National Agricultural Statistics Service, 2012) and irrigated agriculture accounts for 85.6% of water withdrawals in the ESRP (Kenny et al., 2009). The primary crops produced in the region are alfalfa, barley, corn, potatoes, sugarbeets, and wheat. The main water source for the region is the Snake River and its tributaries. Surface water flows and groundwater recharge depend highly on winter precipitation and snowmelt. About 60% of the irrigated croplands are irrigated with surface water. The other 40% are irrigated with groundwater (National Agricultural Statistics Service, 2007-2016).

[Insert Figure 2.1 here.]

One advantage to the ESRP as a study region is that Idaho maintains a spatially referenced water rights database administered by the Idaho Department of Water Resources (IDWR).[4] From this database, we are able to identify the spatial boundaries of water rights, which forms the cross-section in our dataset. The boundaries of water rights are not the same as the boundaries of the farm, but we unfortunately do not have data to describe the latter. We choose to treat the water right as an individual unit of observation because water right boundaries delineate the land base over which water rights are enforced and water is a quasi-fixed input to production (Moore and Negri, 1992). Additionally, we acquire data on water right titles, water source, and seniority (priority date) associated with each water right. These detailed data on individual water rights attributes allow us to conduct an empirical analysis at the scale of the individual water right. And, more importantly, knowing the

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

spatial boundaries of the water right allows us to match water rights attributes with other spatially referenced datasets that describe land-allocation decisions, soil, and weather.

There are a total of 6,429 unique water rights for irrigation within the ESRP. Among those, 1,679 hold at least one surface water right, and 15 are irrigation districts. We exclude from our analysis rights only for groundwater because groundwater users do not usually face curtailment risks as part of the prior appropriation system. As a result, the water available to groundwater users is more stable and reliable than that available for surface water users.[5] We also exclude all observations with fewer than five pixels in the cropland data layer in a given year.[6] Our final sample is an unbalanced panel spanning 8 years (2007-2014), with 965 individual water rights and 15 irrigation districts.[7]

For irrigation districts, we are able to identify the water rights boundaries for each district, which usually coincide with the administrative boundaries of the districts. We assume that farmland inside the boundary of an irrigation district uses district water unless the parcel has access to other water sources. This assumption is used in the previous literature when intra-district water delivery data are not available (Buck, Auffhammer, and Sunding, 2014; Schlenker, Hanemann, and Fisher, 2007).

We do not have data on the geospatial boundaries of farms, only of water rights. As a result, we are not able to distinguish the property boundaries of individual farms

[5] Currently, groundwater usage is not systematically monitored or diversion limits enforced in the ESRP. In rare occasions, the water rights of groundwater users have been curtailed to protect surface water flows when the two resources are connected. However these water calls affect only a small proportion of groundwater users in the region.

[6] Five pixels translates to approximately 3.8 acres of cropland from 2007 to 2009, and 1.1 acres from 2010 to 2014.

[7] Small sample size for the treatment group decreases the statistical power of significance tests on the average treatment effect, increasing the probability of type II error (e.g. List, Sadoff, and Wagner, 2011). This does not undermine the validity of our empirical results since we indeed find a statistically significant result on the irrigation district treatment.

inside irrigation districts. Farms inside an irrigation district share in a common set of prior appropriation water right(s) and thus face identical water right constraints, i.e. there is no variation in water rights within a cross-sectional unit of observation. However, we observe only aggregate land-allocation decisions across multiple farms within an irrigation district.[8] This is most problematic if there is evidence of aggregation bias in land-allocation decisions for irrigation districts. We test for aggregation bias by examining whether land-allocation decisions differ systematically with the size of the water right, conditional on other explanatory factors such as climate, soil, and water supply. [9]

Equation (2.6) describes the main FMNL model estimated in our empirical analysis. Table 2.1 provides a description of the variables included in our model. Seniority, μ, is measured using a standardized rank transformation on water rights priority dates. All surface water rights are ranked by their priority dates from the earliest to the latest and are standardized continuously to a zero-one range. Each right is assigned a rank based on the "quantile" of the right in the hierarchy of rights. The rationale for this transformation is that the distribution of priority dates is not uniform in time. As shown in Figure 2.2, most surface water rights were established during the progressive era (1890-1920) and fewer rights were filed after 1930. This means that a one-year increase in seniority during the progressive era represents a much larger increase in the priority rank than a one-year increase in seniority in the 1950s. Incorporating priority date directly into the model results in a marginal effect of seniority that is heterogeneous across time. By using a rank transformation instead, we ensure that that the quantile of each right is uniformly distributed in the appropria-

[8]With geospatial data on farm boundaries, we would ideally match similar farms inside and outside of irrigation districts to compare land-allocation decisions for farms with access to shared versus individual water rights. This would change the cross-sectional unit of observation in the analysis to the farm, rather than the water right, where an individual farm may own multiple water rights with differing seniority or a single water right may be shared by multiple farms.

[9]We cannot identify the number of farmers within an irrigation district and are only able to test for aggregation bias based on the size of the water right's place of use.

tion system and that the marginal effect on a one-percentage quantile change becomes more homogeneous.[10]

[Insert Table 2.1 here.]

[Insert Figure 2.2 here.]

The empirical model also includes the two diversification variables described in Equation 6. The effect of diversification in seniority among surface water rights, σ^s, is captured by the standard deviation of the water right quantile.[11] Diversification across surface and groundwater sources, σ^g, is captured using a dummy variable for whether lands may be irrigated by a surface water right and at least one groundwater right.

Other explanatory variables in the model include soil characteristics, weather normals of the past three years, and prices received for all crops. We obtain land-allocation data from National Agricultural Statistics Service (NASS)'s Cropland Data Layer (CDL). The CDL is a crop-specific land cover dataset for the continental US based on satellite imagery and calibrated classification algorithms (National Agricultural Statistics Service, 2007-2016). The dataset is available for the ESRP for 2007-2014. For each water right in our cross-section, we use the CDL to identify the percentage of land allocated to the six major crops in the region: alfalfa, barley, corn, potato, sugarbeet and wheat, as well as land idled.

We obtain soil data from the SSURGO database, a soil database developed by USDA-

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

[11]We define the standard deviation of a single water right as zero, which represents no diversification.

NRCS. The SSURGO dataset contains a crop-specific yield estimate for each soil type, from which we construct an average irrigated crop yield map for wheat and corn. This allows us to capture the possibility that a parcel of land is especially suitable for cultivating certain crops but not others, which may explain some of the observed crop choices. We also include common soil quality indicators in our model, such as irrigated and non-irrigated soil capability class, percent clay, percent slope, and the k-factor [12].

We obtain weather data from the PRISM climate dataset, which provides downscaled, spatial projects of climate variables. We include in the model three weather variables that are important in determining crop productivity and water availability: growing degree-days(GDD), extreme weather conditions (EDD), and cumulative precipitation over the course of the growing season. We construct GDD following Schlenker and Roberts (2009)'s method with threshold temperatures at 8 and 32°C, and EDD following Lobell et al. (2013) with threshold temperature at 35°C. Growing season precipitation is measured by accumulating precipitation between June and September. Our empirical models use three-year normals of these variables to reflect farmers' expectation on these climatic variables.

Table 2.2 provides summary statistics and Table 2.3 describes the difference in sample means of the dependent and independent variables between land inside and outside of irrigation districts. The statistics in Table 2.3 indicate that irrigation districts plant a greater share of land to wheat, potatoes and sugarbeets, and a smaller share of land to corn and alfalfa, compared to individual water rights. There are also some differences in the independent variables. For example, irrigation districts are located in relatively cooler and wetter areas with slightly worse soil, on average. These factors suggest a disadvantage to irrigation district membership based solely on growing conditions.

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

[Insert Table 2.2 here.]

[Insert Table 2.3 here.]

2.5 Results

Parameter estimates for our main specification in equation 6 are shown in Table 2.4. Estimated average partial effects (APE) are shown in Table 2.5. Robust standard errors are reported in Table 2.4 and are used to generate standard errors for the APEs via Krinsky-Robb simulations.

[Insert Table 2.4 here.]

[Insert Table 2.5 here.]

Average partial effects on profits (APEP) as calculated based on equation 10 are shown in the first column of Table 2.6. The average crop-specific profit statistics for APEP are calculated by subtracting the average cost from the average revenue from 2006 to 2013, which is shown in Figure 2.3. Revenue for a crop in a given year is calculated by multiplying the price received with the average yield of that crop in the state of Idaho, based on USDA-NASS survey data (National Agricultural Statistics Service, 2012). Crop-specific cost of production statistics are compiled from different sources, including USDA ERS data and the University of Idaho's crop costs and returns series (Patterson, 2009, 2013, 2014; USDA Economic Research Service, 2006-2013).

[Insert Table 2.6 here.]

[Insert Figure 2.3 here.]

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

Both seniority variables in our model, the mean and the dispersion of water rights quantiles, have insignificant APEs. Despite their insignificance, the signs of the estimated APEs are consistent with those found in other studies in the region, such as Xu, Lowe, and Adams (2014) and Cobourn et al. (2017). In particular, the APEs suggest that more junior water rights are more heavily fallowed than land irrigated under more senior water rights. The lack of significance for these variables here is most likely a reflection of the low statistical power that our model exhibits. Other factors that have significant impacts on farm profit include growing degree-days, precipitation, soil yield capacities for wheat and corn, and the k-factor. The sign of all of these variables are as expected: farms with warmer weather and more precipitation, as well as more productive soils tend to choose a more profitable mix of crops.

Heterogeneity in Partial Effects

One of the advantages of using the FMNL model is that it captures the heterogeneity in partial effects among different observations. As Papke and Wooldridge (2008) point out, the difference between linear and non-linear models is not important with regard to the estimation of APEs, but is important in determining whether and to what extent the partial effects differ across the distribution of the variable of interest.

We calculate APEs for the irrigation district dummy for different quantiles of water rights seniorities. Figure 2.4 shows the discrete effect of irrigation districts along the distribution of water rights seniority quantiles, holding all other variables at their average values. Our results show that the largest benefit of residing in an irrigation district is for the most junior water right holders at $17.94/acre, while the lowest benefit happens for the most senior water rights holders at $14.37/acre. This suggests that the benefit of access to an irrigation district is greatest for farmers with more junior rights than those with relatively secure senior rights. The risk-sharing and water transfer benefits provided by irrigation districts suggest that access to irrigation districts should be most beneficial for those farms with the least secure (junior) rights. Owners of senior water right(s) may benefit less from membership in an irrigation district because their water right(s) are relatively secure against fluctuations in water availability.

[Insert Table 2.4 here.]

APE in Linear vs. Logit Models

To test for whether individual heterogeneity may bias our estimates, we estimate two linear models, the pooled ordinary least square (OLS) and the panel random effect (RE) models. In doing so, we assume that all regressors are exogenous from the random unobserved individual effects as well as the idiosyncratic error term. This assumption cannot be formally tested using a Hausman-type test against the fixed effect (FE) model since our main variables of interest (the water rights variables) are time-invariant. However, this assumption can be partially justified on the basis that the variables used in our model are exogenously determined, as we have explained in the empirical strategy section.

Columns 2 and 3 of Table 2.6 present the results from OLS and RE estimation. Although a Hausman test rejects the hypothesis that OLS and RE are equivalent, the point estimates for the two models are close, especially for our main variables of interest. Other than *QMeanSurf*, which is statistically insignificant, the difference in point estimates between OLS and RE for water rights and irrigation district variables are less than 2%. This suggests that inference for our main variables of interest should not be affected by failing to control for unobserved individual-specific heterogeneity.

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

Aggregation of Irrigation Districts

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

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

where A is the size of the water right, $\mathbf{y}$ is the land-allocation vector, and $\mathbf{X}$ includes all explanatory variables other than the size of water right. We empirically test this area-homogeneity assumption by running an augmented regression model to see whether the size of water rights influences land allocation. To do so, we use a subsample that includes only farmers outside of irrigation districts. Using this subsample, we estimate two FMNL models: one including the size (area) of the water right, the other including the natural log of it.

[Insert Table 2.7 here.]

The APE and APEP on the size variables are shown in Table 2.7. The model that includes *log(Area)* shows that an increase in log area is associated with a decrease in the land share allocated to alfalfa, and an increase in all crops other than barley. When aggregating these land-allocation changes, the marginal profit change due to *log(Area)* is statistically insignificant at the 5% level. The model with *Area* depicts a similar picture, with a negative APE on alfalfa and positive APE on all crops other than barley and fallow. The marginal profit change is significant at the 5% level, indicating that controlling for all other factors, an increase of one acre in size of water right leads to an increase in profit of about \$0.008 per acre. To put that in perspective, if the estimated effect of access to an irrigation districts were actually due to differences in the size of farming operations, then the average observed farm size inside an irrigation district would have to be 2090 acres, or 10 times larger than the average size of that outside irrigation districts. Very few water rights in our sample, only 3%, are large enough to meet this criteria. If the distribution of farm sizes is similar inside and outside irrigation districts, then it is highly unlikely that farm size is the factor driving the estimated premium associated with access to an irrigation district.

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

2.6 Conclusion

The doctrine of prior appropriation may generate an inefficient allocation of resources by generating heterogeneous levels of risk for otherwise similar irrigators. Irrigation districts offer a way to mitigate this differential risk through risk pooling, ownership of water right portfolios, and informal water markets, all of which are unavailable to individual farmers outside of irrigation districts. In this analysis, we find evidence that membership in an irrigation district offsets potential inefficiencies arising due to differences in seniority under prior appropriation doctrine. In particular, irrigation district membership offers the greatest benefit to the most junior water rights, which are subject to the greatest risk of curtailment during a water shortage. With access to more secure and reliable water sources, farmers can allocate a greater share of their land to relatively drought-sensitive crops that are generally more profitable. Those farmers with access to less secure and reliable water sources hedge against that risk by planting a larger share of land to drought-resilient crops that can withstand a missed irrigation application. Our empirical results suggest that farms inside of irrigation districts are planted to a more favorable set of crops than farms outside irrigation districts, resulting in an estimated profit premium for access to an irrigation district of 6% annually.

The profit premium associated with access to an irrigation district is comparable to the advantage associated with holding senior water rights (Brent, 2017; Cobourn et al., 2017; Xu, Lowe, and Adams, 2014), having access to more water (Buck, Auffhammer, and Sunding, 2014), and having access to water portfolios(Mukherjee and Schwabe, 2015). Our results are similar to the findings of Cobourn et al. (2017) and Mukherjee and Schwabe (2015), which suggest that having partial access to irrigation district water provides an economic benefit to farmers. We find a larger profit premium for irrigation districts than either of those studies. This is likely because both Cobourn et al. (2017) and Mukherjee and Schwabe (2015) consider cases in which irrigation district water is used as a supplemental water source, whereas in this analysis we account for cases in which irrigation district water is the primary water source.

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

Studying the differences between irrigation districts and private farmers provides us with suggestive insight into how group ownership and proporational sharing in water shortages affect land-allocation decisions, relative to the case in which prior appropriation and seniority are applied to each irrigator. The economic literature has established the prospective benefits of water markets, yet these markets remain slow to develop and historical property rights institutions persist. An outstanding question is whether the inefficiencies arising from existing institutions are substantial. Our study suggests that the answer to this question depends on the prevalence of group membership and water right sharing systems. In areas where these arrangements are prevalent, the losses arising from prior appropriation are likely minimal and competitive water markets may yield relatively lower benefits among agricultural irrigators.

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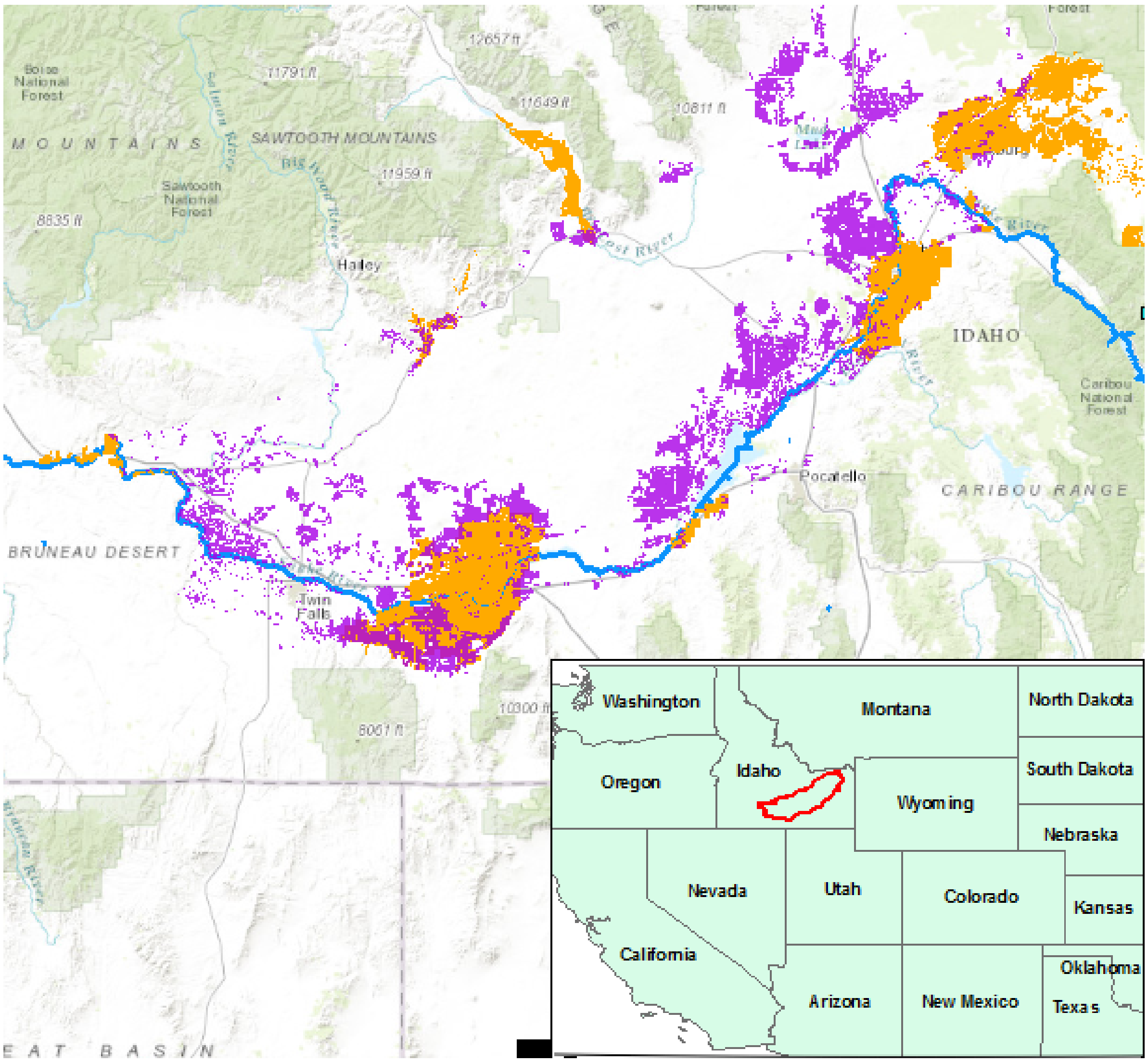

Figure 2.1: Map of the Eastern Snake River Plain. The dark line denotes the main stem of the Snake River. Darker areas are lands covered by individual water rights, and lighter areas are irrigation district lands. Lower-right panel denotes the relative location of the ESRP (Line polygon denotes the watershed boundary of ESRP.)

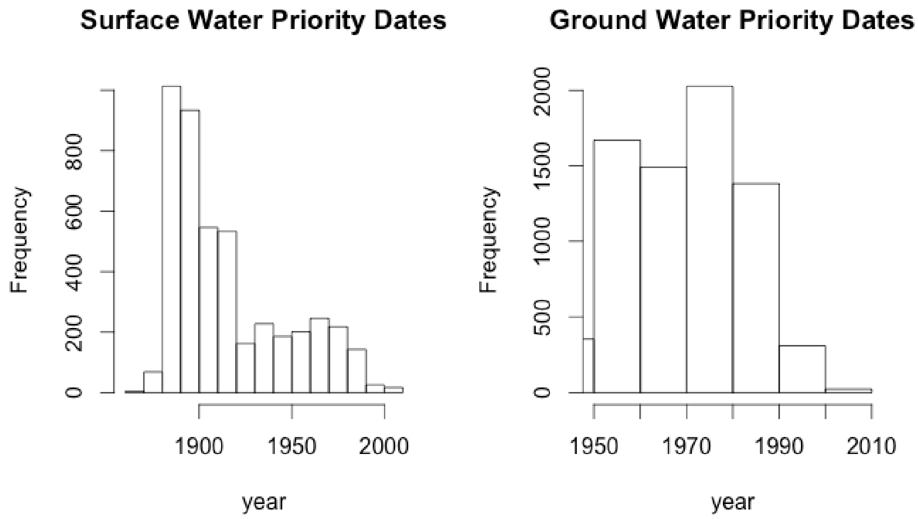

Figure 2.2: Water Rights Distribution Across Time. Left panel shows the appropriation date for surface water rights. Right panel shows the appropriation date for groundwater rights.

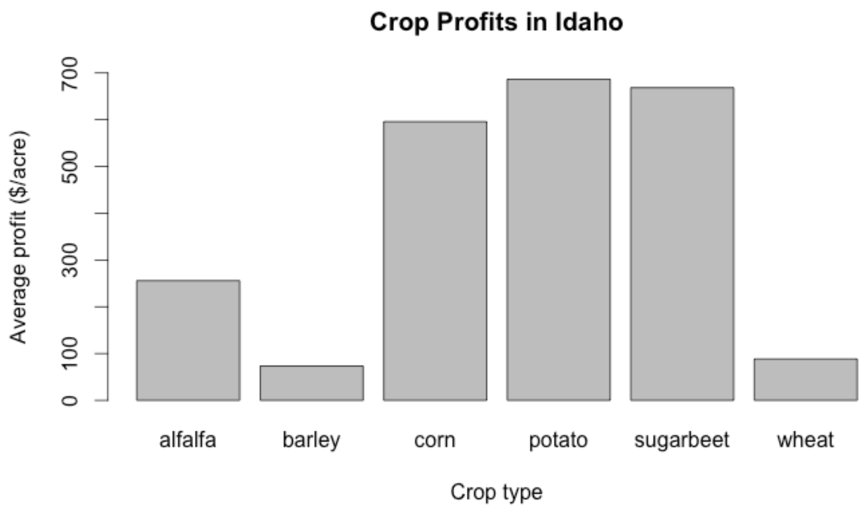

Figure 2.3: Average crop profits in Idaho, 2006-2013

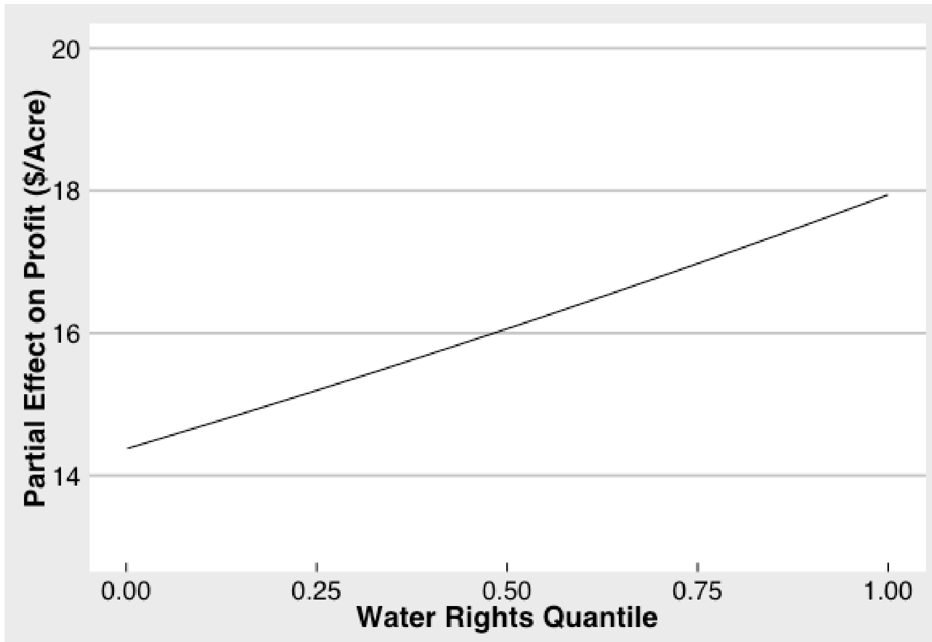

Figure 2.4: Partial effects of *IrrDist* at different levels of water rights quantile.The x-axis shows the distribution of water rights quantile, with 0 being the most senior, and 1 being the most junior water right. The y-axis shows the monetary value ($/acre) of the discrete effect of residing in an irrigation district.

Table 2.1: Description of Variable Names and Sources

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

Table 2.2: Summary Statistics of Variables. Number of observation N=7792.

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

Table 2.3: Sample Mean Comparison between Irrigation Districts and Individual Farmers

Variables	Irrigation Districts	Individual Farmers	Differences
corn	0.048	0.146	-0.098***
wheat	0.201	0.118	0.083***
barley	0.168	0.146	0.022
alfalfa	0.374	0.471	-0.097***
sugarbeet	0.065	0.018	0.046***
potato	0.101	0.053	0.048***
fallow	0.044	0.048	-0.004
exml3	7.373	12.104	-4.731**
gddl3	1379.96	1499.109	-119.149***
precl3	65.611	52.064	13.547***
GrndSurf	0.133	0.103	0.031
QmeanSurf	0.573	0.54	0.032
QsdSurf	0.102	0.04	0.062*
icclass	3.314	3.398	-0.084
nicclass	5.578	5.558	0.02
slope	2.813	2.76	0.053
ydwheat	76.386	78.21	-1.824
ydcorn	52.907	66.073	-13.165*
claypc	12.817	12.035	0.781
kfactor	0.305	0.27	0.036

[a] Column 2-4 corresponds to sample means for irrigation districts, individual farmers, and differences in sample means.

[b] Sample means and t-tests for time-invariant variables (water rights and soil variables) are computed based on one single year of observation for each water right. Sample means and t-tests for time-variant variables (land allocation and climate) are computed by pooling all observations.

[c] Two sample t-test results are represented by asterisks on mean differences. A triple asterisk indicates $p < 0.001$; a double asterisk indicates $p < 0.01$; a single asterisk indicates $p < 0.05$.

Table 2.4: Fractional multinomial logit parameter estimates

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

Number of Obs: 7792

Log pseudo-likelihood: -10525.69

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

Table 2.5: Average partial effects of fractional multinomial logit estimates

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

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

Table 2.6: Model estimates of average partial effect on profits ($/acre)

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

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

Table 2.7: Fractional multinomial logit model estimates on farm area variables

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

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

Chapter 3

The Effect of Climate Change on Irrigated Agriculture: Water-Temperature Interactions and Adaptation in the Western U.S.

3.1 Introduction

Changing global climate has broad implications for agricultural productions globally, and it is of great policy concern to assess the impact of climate change on agriculture (Intergovernmental Panel on Climate Change, 2014a,b). Among all climate factors, temperature and water are two of the most important variables that affect agricultural production. Numerous studies have focused on the non-linear effects of temperature on agricultural yield (e.g. Schlenker and Roberts, 2009; Lobell et al., 2013), land rent indicators (Deschênes and Greenstone, 2007; Mendelsohn and Dinar, 2009; Wang et al., 2009), farmland value (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005, 2007; Timmins, 2006), and land allocation decisions (Kurukulasuriya, Mendelsohn et al., 2008; Seo and Mendelsohn, 2008; Wang et al., 2010). Studies have also found that water availability positively contributes to agricultural production (e.g. Buck, Auffhammer, and Sunding, 2014; Mukherjee and Schwabe, 2015; Manning, Goemans, and Maas, 2017, Chapter 2 of this dissertation) as long as water is not excessive (Hendricks, 2018).

Previous studies have also pointed out that water and temperature complement each other in shaping agricultural production (Fezzi and Bateman, 2015; Hendricks, 2018). Yet the literature attributes this complementarity mainly to the physiological impact of water and temperature on yields. This confounds potential adaptation mechanisms that may also respond jointly towards shifts in water and temperature conditions. In this study, we argue that the observed complementarity actually reflects a combination of two distinct mechanisms. At the intensive margin, water and temperature complement each other in determining crop yields. When facing a hotter climate, farmers with limited water supply will suffer greater yield losses or smaller gains (Morison, 1996; Fezzi and Bateman, 2015). At the extensive margin, farmers may adapt to climate change via changing crop mixes (Kurukulasuriya, Mendelsohn et al., 2008; Mendelsohn and Massetti, 2017), and the capacity to do so in response to a hotter climate depends crucially on water availability.[1] Studies have shown that when facing a hotter climate, farmers are able to reallocate their crop mixes, and/or adopt new types of crops if they are presented with extra sources of irrigation water (Hornbeck and Keskin, 2014; Pfeiffer and Lin, 2014, Chapter 2 of this dissertation). The real impact of water and temperature will depend on the combination of these two factors.

Our analysis consists of two parts. In the first part, we construct a theoretical model of land and water allocation, which explicitly incorporates the physical complementarity of water and temperature. We show that the marginal effect of temperature on land allocation, i.e., the direction of adaptation, depends on the trade-off between two factors: 1) relative crop suitability, i.e. different crops perform differently under normal and extreme heat temperatures, and 2) the physiological water-temperature complementarity, i.e. crops grow better under higher temperatures when presented with more water, as introduced in

[1]We use crop choice, crop mix and land allocation interchangeably in this paper. All these phrases refer to farmers' choice of 1) which crop type to grow on their land, and 2) what fractions of land are assigned to each selected crop type.

Fezzi and Bateman (2015). When facing higher temperatures, producers will adjust their land allocation to the water and heat-intensive crop if the suitability effect dominates, and vice versa. We also show that when land allocation is adjustable, the water-temperature interaction effect on farm profit is purely driven by the relative suitability effect, and not by the complementarity effect between water and temperature.

In the second part of the analysis, we empirically examine the joint effects of water and temperature on agricultural adaptation by modeling land allocation dynamics in response to temperature and water availability in the Eastern Snake River Plain of Idaho. We assemble a detailed geospatial dataset spanning the period 2007-2016 on land allocation, water availability, and climate at the spatial scale of individual prior appropriation water right. Following previous economic literature, we decompose the nonlinear effect of temperature into growing degree-days (GDD) and extreme degree-days (EDD). We include three measures of water availability and access: precipitation, priority of surface water rights, and access to groundwater.

To summarize the cumulative effect of changes in multi-crop farms, we estimate farm profit as a function of field-scale land allocation, annual crop prices, and region-specific costs of production. Using this measure as a dependent variable, we estimate two sets of models. The first set of models mimics the Ricardian regression framework (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005; Mendelsohn and Massetti, 2017), where we explain expected farm profit using long term climate and water norms in pooled cross-sectional ordinary least squares (OLS) and panel random-effect (RE) models. To explain the long term land-allocation dynamics in response to temperature and water availability, we also estimate a pooled cross-sectional fractional multinomial logit (FMNL) model that explains the share of land allocated to the region's major crops and fallow as a function of temperature and water variables. The second set of models mimics studies that draws inference via short-term weather shocks (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). We estimate the short term response of land allocation to random weather shocks using panel fixed-effect (FE) models.

Our empirical results show that land allocation significantly responds to temperature and water availability differences both in the long term and in the short term. In the long term, estimated farm profits, induced by land allocation differences, respond positively to increases in GDD, EDD, precipitation, and groundwater access. A one degree-day increase in GDD increases estimated farm profit per acre by 0.4%, whereas a one degree-day increase in EDD increases estimated farm profit by 0.9%. We also find that farmers switch from alfalfa and barley towards potatoes and wheat when facing higher GDD, and switch from alfalfa towards corn and sugarbeets when facing higher EDD. This supports our hypothesis that in the long term, crop suitability effects drive land allocation differences, and its magnitudes are larger than the water-temperature complementarity effect. In the short term model, we find that farmers' responses to weather shocks mimic those in the long term case, but that magnitude of the responses is much smaller. A one-degree day increase in EDD increases estimated farm profit by only 0.4%, and the effects of GDD is negligible. Finally, we find that land allocation itself responds to the water-temperature interaction. When facing a hotter climate, farmers with greater water availability and access tend to allocate more land to drought-tolerant crops and fallow more. In the long term this interaction effect is dominated by variations in precipitation and access to groundwater, whereas in the short term the interaction effect is dominated by variations in the priority of water rights.

This study makes three major contributions to the literature on the economics of agriculture and climate. First, We analyze and empirically test the joint role of water and temperature in determining agricultural adaptation to climate change. We show that this joint effect is not only driven by the physical complementarity of water and temperature, but rather determined by the combination of adjustments at both the intensive and the extensive margins. This complements the limited studies on how water and temperature can jointly affects agricultural production and adaptation to climate change.

Second, this study provide estimates for both the long term and the short term effect of land allocation to climatic differences. Due to data constraints, most previous studies on land allocation estimated the long term effect (e.g. Seo and Mendelsohn, 2008; Kurukulasuriya, Mendelsohn et al., 2008; Wang et al., 2010). We show that land allocation responses in the short term differs greatly from those in the long term in the size of the effect, as well as in the dominant components of temperature and water availability. This complements the literature estimating land allocation responses, and more broadly to the estimation of both short term and long term responses to climate change.

Third, this study adds to the growing literature (e.g. Buck, Auffhammer, and Sunding, 2014; Brent, 2017, Chapter 2 of this dissertation) on understanding the value of water availability to agricultural production. We show that the value of water differs systematically with temperature, and especially so in EDD. We also show that the short term and long term contribution of different water sources may be different. The effect of surface water availability on land allocation differs with temperature only in the short term, while the effect of groundwater access differs with temperature only in the long term.

3.2 Literature Review

The Joint and Non-linear Effect of Water and Temperature

Agriculture production depends heavily on the realization of climate variables, with temperature and water availability being two of the most important factors.[2] Studies have shown that the effect of temperature on yield is highly non-linear (e.g. Schlenker, Hanemann, and Fisher, 2007; Schlenker and Roberts, 2009; Lobell et al., 2013; Bertone Oehninger et al., 2016b). Temperature has positive impacts on crop development between a certain range, usually from 5.5°C to 32°C(the GDD threshold), whereas temperatures above and below that range will harm the crop (Lobell et al., 2013; Olen, Wu, and Langpap, 2015). The literature also investigated the impact of variations in water availability, realized solely through precipitation in rain-fed agriculture (e.g. Deschênes and Greenstone, 2007; Lobell et al., 2013), and a combination of precipitation, water storage, surface water and groundwater supply in irrigated agriculture (Schlenker, Hanemann, and Fisher, 2007; Buck, Auffhammer, and Sunding, 2014; Mukherjee and Schwabe, 2014; Bertone Oehninger et al., 2016a, Chapter 2 of this dissertation). These studies have generally found positive impacts of water availability on agricultural productivity, especially in arid/semi-arid regions where water is a scarce resource.

Besides the direct impact mentioned above, there is one additional impact that water and temperature can affect agricultural production: through the complementary effect of water and temperature. Physiological studies suggest that increasing temperature raises water demands for crops to develop, as evapotranspiration becomes larger under higher

[2] Zhang, Zhang, and Chen (2017) argued that other variables, such as wind speed and humidity, are also important. This is not the main concern of this paper though.

temperature (Monteith and Moss, 1977; Schauberger et al., 2017). This means that warming leads to larger gains/smaller losses in crop yields when water is sufficient, and water becomes more valuable when temperature is higher (Tack, Barkley, and Hendricks, 2017). Traditional reduced-form estimations on the impact of climate change, no matter on crop yield, profit or adaptation, may leads to biased estimates or confounding results if this complementarity is ignored (Fezzi and Bateman, 2015).

The water-temperature complementary effect has been investigated by a limited number of studies in the economic literature, including Fezzi and Bateman (2015) and Hendricks (2018). Both studies focus on identifying the impact of water and temperature from a Ricardian land rent perspective. Fezzi and Bateman (2015) proposed a cross-sectional hedonic regression in the UK with an interaction term between water and temperature. They found that there exists a positive interaction effect between temperature and precipitation after disaggregating the data to the individual farm level. Hendricks (2018) modeled land rental rates in the Eastern U.S. using cross-sectional Ricardian regression. He proposed to dissect the joint effect into three distinct components: heat stress, water deficit, and water surplus. The physiological complementarity between water and temperature is captured through the water deficit component, which explicitly incorporates reference evapotranspiration, a key factor determining physiological water demand under different temperature scenarios. Hendricks (2018) found that water deficit contributes to about 33% of climate-related damages.

Nevertheless, we argue that the Ricardian land rent approach taken by Fezzi and Bateman (2015) and Hendricks (2018) is not able to comment on specific mechanisms of which climate may affect agricultural production. Both studies mainly focus on how the physiological complementary effect between water and temperature may affect crop yields. Yet the impact of the complementary effect not only affects crop yields at the intensive margin, but also triggers corresponding adjustments at the extensive margin through changing land allocation. For example, under a warmer climate, farmers with sufficient water supply have the capacity to grow high-value, water-sensitive crops by mitigating water stress through irrigation. Attributing the interaction effect solely to the gains/losses at the intensive margin will miss a critical part of the calculus.

In this study, we argue that the empirical interaction effect in Fezzi and Bateman (2015) in a Ricardian farmland values regression should actually be attributed to the combination of the physiological impact on yield and the corresponding land allocation adjustments. We complement Fezzi and Bateman (2015) and Hendricks (2018)'s study by theoretically modeling farmers' decision-making when land allocation is flexible, and empirically estimating land allocation adjustments to climate change. We are able to show how agricultural adaptation also differs with respect to water, temperature, and their interactions. This helps fully understand the underlying mechanisms how water and temperature can jointly affect land allocation.

Land Allocation as an Adaptation Mechanism

Various measures can be taken by agricultural producers to adapt to changing climate conditions (Howden et al., 2007; Ortiz-Bobea and Just, 2012). These measures include changing farming practices (Ding, Schoengold, and Tadesse, 2009; Huang, Wang, and Wang, 2015), selecting crop variaties (Tack et al., 2016), adjusting agricultural land base (Manning, Goemans, and Maas, 2017). Yet adaptation via crop switching is one of the most important strategies farmer can use to adapt to climate change. Several studies have estimated the impact of climatic variables on land allocation decisions (e.g. Seo and Mendelsohn, 2008; Kurukulasuriya, Mendelsohn et al., 2008; Wang et al., 2010). For example, Kurukulasuriya, Mendelsohn et al. (2008) found that farmers in Africa are more likely to grow maize-beans and sorghum in cooler regions, and cowpea and millet in hotter regions. Wang et al. (2010) found that farmers in China are more likely to choose cotton and maize, but less likely to choose soybeans, and vegetables in warmer regions. All these studies confirm that temperature and precipitation have significant impact on farmers' crop choices.

Most existing studies on farm level land allocation rely on survey data in the developing countries, with observations from one cross-section, with records only for the main type of crop grown on the farm (e.g. Seo and Mendelsohn, 2008; Wang et al., 2010; Mendelsohn and Massetti, 2017). This brings up several limitations. First, identification of climate impact relies solely on variation in climate between different farmers. As Auffhammer and Schlenker (2014) argued, omitted variable bias is a haunting problem for these Ricardian-type studies. The author has to show that climate is uncorrelated with other location-specific factors that may also influence land allocation. Second, these studies can only retrieve long term effects of climate change, but not the short term effects. This ignores adaptation mechanisms that may only exist in the short term, such as storage or water leasing through short-term contracts. It is also hard to compare and reconciliate the effects of long term adaptation with the majority of studies that estimates short term effects at the intensive margin. Third, using categorical crop type as the dependent variable confounds the marginal changes in crop mixes in response to changes in climate conditions, which is the more realistic case in a multi-crop irrigated agriculture system. We propose remedies to all three shortcomings by leverage a farm-level dataset on land allocation fractions spanning multiple years. This allows us to apply different econometric methods to overcome the above shortcomings.

3.3 Theoretical Framework

In this section we propose a theoretical model to demonstrate the effect of water and temperature on agricultural land allocation and farm profit. Following Hornbeck and Keskin (2014), we set up a two-crop maximization problem where farmers adjust both land and water allocation when facing changing climates. As an extension, we explicitly model crop's physiological complementarity, which allow us to mimic farmer's crop allocation process. We are able to demonstrate that, how land allocations adjust to changing temperature conditions depends on the trade-off between two factors: 1) which crop is more suitable to grow under higher temperatures, i.e. the suitability effect. and 2) crops' increasing demand for water under higher temperature, i.e. the physiological complementarity effect. Additionally, under our theoretical assumptions, the interaction effect of temperature and water on farm profit comes solely from the suitability effect, and not from the physiological complementarity effect. The latter has already been capitalized through adjustments made in land allocation and water intensities.

Model Setup

Consider a price-taking farmer who maximizes profit by allocating two types of crops (type 1 and 2) and a fixed amount of water $\bar{w}$ on a unitary land with constant return to scale.[3] The farmer possesses two crop-specific restricted profit function, $y_1(w_1, T)$ and $y_2(w_2, T)$ for the two crops, both of them depend on temperature realizations T and water intensities w_1 and w_2. Following previous literature (e.g. Schlenker and Roberts, 2009; Lobell et al., 2013; Moore and Lobell, 2014), assume that the non-linear temperature effect on profit can be

[3]Here we implicitly assume that the amount of water supply $\bar{w}$ is uncorrelated with temperature realizations since modeling factors for water supply is not the focus of this study.

captured by two additively separable parts: growing degree days, G; and extreme degree days, D, so that $T \equiv \{G, D\}$. Without loss of generality, let crop 1 be more water-intensive, and more heat-intensive than crop 2.[4] We can think of crop 1 as more suitable to grow with irrigation in hotter, wetter climates with higher profits, and crop 2 is more suitable to grow in dryland in temperate, arid climates with lower profits.

The farmer's maximization problem can be written as:

$$\begin{aligned} \max_{w_1, w_2, L_1, L_2} \quad & \pi = y_1(w_1, T)L_1 + y_2(w_2, T)L_2 \\ s.t. \quad & L_1 + L_2 = 1; \quad L_1 w_1 + L_2 w_2 = \bar{w} \end{aligned} \tag{3.1}$$

where L_1 and L_2 are land allocated to crop 1 and 2 respectively.

We assume farmers can freely adjust their land allocation L_1 and L_2 with respect to changes in water and temperature conditions. Under our assumptions, the first-order conditions are:

$$\begin{aligned} \frac{\partial y_1}{\partial w_1} &= \frac{\partial y_2}{\partial w_2} \\ y_1 - y_2 &= \frac{\partial y_1}{\partial w_1}(w_1 - w_2) \end{aligned} \tag{3.2}$$

where land allocation is implicitly determined by water intensities w_1 and w_2. Because we assume land has constant return to scale, optimal conditions for the long term model that an increase in water availability $\bar{w}$ leads to adjustments only at the extensive margin with increasing land allocated to the first crop, $\frac{\partial L_1}{\partial \bar{w}} > 0$, but not at the intensive margin of which

[4]Here we introduce three assumptions regarding the two restricted profit functions. First, crop 1 has higher marginal product of water than crop 2, $\frac{\partial y_1}{\partial w_1} > \frac{\partial y_2}{\partial w_2} > 0$. Second, for an increase in growing degree days G, marginal profitability is positive and crop1 increases faster for than crop 2, $\frac{\partial y_1}{\partial G} > \frac{\partial y_2}{\partial G} > 0$. Third, for an increase in extreme degree days D, marginal profitability is negative and crop 1 decreases slower than crop 2, $\frac{\partial y_2}{\partial D} < \frac{\partial y_1}{\partial D} < 0$.

water intensities remain constant, $\frac{\partial w_1}{\partial \bar{w}} = \frac{\partial w_2}{\partial \bar{w}} = 0$.[5] In other words, at a given level of temperature conditions, farmers will just need to follow a pair of optimal water intensities w_1^* and w_2^* that does not change with respect to total water availability, which is to some extent realistic.

Effects on Land Allocation

Of particular interest, we find the marginal effect of temperature on water intensities and land allocations are ambiguous. The marginal effect is given by:

$$\begin{aligned}
\frac{\partial w_1}{\partial T} &= -\frac{\frac{\partial^2 y_2}{\partial w_2^2}}{|H|}\Big[\overbrace{\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T}}^{\text{Suitability}} - \overbrace{\frac{\partial^2 y_1}{\partial T \partial w_1}(w_1 - w_2)}^{\text{Complementarity}}\Big] \\
\frac{\partial w_2}{\partial T} &= -\frac{\frac{\partial^2 y_1}{\partial w_1^2}}{|H|}\Big[\underbrace{\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T}}_{\text{Suitability}} - \underbrace{\frac{\partial^2 y_2}{\partial T \partial w_2}(w_1 - w_2)}_{\text{Complementarity}}\Big]
\end{aligned} \tag{3.3}$$

and

$$\frac{\partial L_1}{\partial T} = -\Big[\frac{\bar{w} - w_2}{(w_1 - w_2)^2}\frac{\partial w_1}{\partial T} + \frac{w_1 - \bar{w}}{(w_1 - w_2)^2}\frac{\partial w_2}{\partial T}\Big] \tag{3.4}$$

where $|H|$ in Equation 3.3 is the determinant of the Hessian matrix. Readers are referred to the appendix for proof of the above comparative statics.

From equation 3.3, we can see that the marginal effect of temperature on both water intensities, $\frac{\partial w_1}{\partial T}$ and $\frac{\partial w_2}{\partial T}$, are governed by the trade-off between two effects: 1) the relative crop suitability effect, $\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T}$; 2) the water-temperature complementarity effect, $\frac{\partial^2 y_1}{\partial T \partial w_1}(w_1 - w_2)$. Both effects are positive for temperature increases in GDD and EDD. Due to suitability

[5] If land has decreasing return to scale, then an increase in total water availability will result in an increase in water intensity for the first crop. See Hornbeck and Keskin (2014) for further details.

effect, farmer will allocate more land to crop 1 under a higher temperature. At the same time, due to the existence of complementarity effect, farmer will talk advantage of the higher temperature by applying extra water to both crops which pushes land allocation away from crop 1

Combining Equation 3.3 and 3.4 , we have:

$$\begin{aligned} &\frac{\partial L_1}{\partial T} > 0 \quad \text{if} \quad \frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} > \frac{\partial^2 y_1}{\partial T \partial w_1}(w_1 - w_2) \\ \text{and} \quad &\frac{\partial L_1}{\partial T} < 0 \quad \text{if} \quad \frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} < \frac{\partial^2 y_2}{\partial T \partial w_2}(w_1 - w_2) \end{aligned} \tag{3.5}$$

Overall, the direction of adjustments in land allocation depend on which of the two effects is dominating. If the suitability effect dominates the complementarity effect, then land allocation will adjust to increase allocation for the water and heat-intensive crop when temperature increases, and vice versa.

Comparative Statics of water-temperature interaction pattern

The water-temperature interaction pattern is also important when considering the outcomes of land allocation. According to our results, the interaction effect is also ambitious:

$$\frac{\partial^2 y_1}{\partial T \partial \bar{w}} = \frac{1}{(w_1 - w_2)^2}(\frac{\partial w_2}{\partial T} - \frac{\partial w_1}{\partial T}) \lesseqgtr 0 \tag{3.6}$$

The sign of cross-derivative of temperature and water availability on land allocation, $\frac{\partial^2 y_1}{\partial T \partial \bar{w}}$, depends on the relative changes of marginal water intensities for the two crops. A positive cross-derivative indicates that the first crop gets comparatively less water comparing to the second crop, and a negative cross-derivative indicates that the first crop gets comparatively more water (less reduction) than the second crop.

Effects on farm Profit

Different than the ambiguous effects of land allocation, water and temperature have deterministic effects on farm profit. We find that water and growing degree days have positive effects on farm profit, extreme degree days have negative effects on farm profit. For water-temperature interaction, the effect is also positive.[6] The water-temperature interaction effect on farm profit is no longer driven by the physiological complementarity effect. That effect have already been capitalized through adjustments made in land allocation and water intensities. Equation 3.7 shows the cross-derivative of water availability and temperature on farm profit, $\frac{\partial^2 \pi}{\partial T \partial \bar{w}}$. For both normal temperature and extreme heat conditions, the cross-derivatives are irrelevant to the original complementarity effect in the crop-specific restricted profit function. Rather, it reflects the crop suitability effect, i.e., which crop grows better at higher temperature levels.

$$\frac{\partial^2 \pi}{\partial T \partial \bar{w}} = \frac{1}{w_1 - w_2}\left(\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T}\right) > 0 \tag{3.7}$$

For a stark contrast, consider a plausible special case of the model by restricting land allocation to be a fixed input. Equation 3.8 gives the cross-derivative on profit when crop allocations are fixed:

$$\frac{\partial^2 \pi_0}{\partial T \partial \bar{w}} = a * \frac{\partial^2 y_1}{\partial T \partial w_1} + (1 - a) * \frac{\partial^2 y_2}{\partial T \partial w_2} > 0 \tag{3.8}$$

[6] See appendix for detailed formula and proof.

where a is a normalizing constant bounded by 0 and 1.[7] Equation 3.8 suggests that if land allocation is fixed, then the cross-derivative of water and temperature on farm profit, $\frac{\partial^2 \pi_0}{\partial T \partial \bar{w}}$, is purely driven by the complementary effect $\frac{\partial^2 y_1}{\partial T \partial w_1}$ and $\frac{\partial^2 y_2}{\partial T \partial w_2}$. Farmers can fully enjoy the benefit of having more water available when facing a rising temperature. However, this comes at the cost that expected profit is sub-optimal comparing to the case when land allocation is flexible. In fact, if farmers can freely choose their crop mixes, then the water-temperature complementarity effect will be absorbed by shifts in land allocation changes with respect to changes in water and temperature.[8]

We should note that our model has several limitations. First, we assume that land has constant returns to scale, which is not necessarily the case in empirical settings. Second, our model assumes that temperature and water are deterministic, which ignores the effect of risk and stochasticity in decision making. Planting conservatively can be beneficial if farmers are risk-averse, and wish to mitigate downside risks. We expect the interaction effect of temperature and water on farm profit to come from both suitability and physiological complementarity effects if any of these assumptions are violated in empirical settings. In this sense, our model demonstrates a special case of which the physiological complementarity effect is completely absorbed. Nevertheless, our model provides insights on the importance of including the possibility of crop allocation when evaluating the marginal impact of temperature and water availability on agricultural production.

[7] $a = \frac{L_1 \frac{\partial^2 y_2}{\partial w_2^2}}{\frac{\partial^2 y_1}{\partial w_1^2} L_2 + \frac{\partial^2 y_2}{\partial w_2^2} L_1}$ to be exact.

[8] This stems from the observation that the global optimal for our particular problem requires adjustments to land allocation for both water and temperature changes. A constraint on land allocation in the short term model is thus always sub-optimal.

3.4 Empirical Framework

Our empirical exercise probes the effects of water availability and temperature on agricultural land allocation decisions. We model land allocation by aggregating land allocation fractions into expected farm profits, constructed as a function of field-scale land allocation, annual crop prices, and region-specific costs of production.[9] Main variation in our dependent variable comes from the differences in the land allocated to different type of crops. Since land allocation decisions are made prior to the realization of crop prices and yields, we use lagged prices and yields to proxy farmers' expectation of these factors at the time of their planting.

Our main regression model is given by Equation 3.9:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_1 prec_{it} + \beta_2 prec_{it}^2 + \beta_3 senior_i + \beta_4 grndwater_i \\ &\quad + \gamma_4 gdd_{it} + \gamma_5 gdd_{it}^2 + \gamma_6 edd_{it} + \gamma_7 edd_{it}^2 \\ &\quad + \eta_1 prec_{it} \times g(e)dd_{it} + \eta_2 senior_i \times g(e)dd_{it} + \eta_3 grndwater_i \times g(e)dd_{it} \\ &\quad + \delta' \mathbf{Z} + u_i + v_t + \varepsilon_{it} \end{aligned} \tag{3.9}$$

where the expected profit for farm i in year t, y_{it}, is regressed on quadratic growing season precipitation $prec_{it}$, water seniority $senior_i$, access to groundwater $grndwater_i$, quadratic growing degree days gdd_{it}, quadratic extreme degree days edd_{it}, as well as linear interaction effects between the three water variables and extreme degree days. To avoid severe multicollinearity, we do not put GDD and EDD interactions in the same model, and instead estimate two separate groups of models where GDD and EDD interactions appear separately in one group of models.

We use two measures of temperature, growing degree days (GDD) and extreme degree

[9] We are not able to get observed farm profits data.

days (EDD), to reflect the non-linear effect of temperature on crop development. This strategy is widely used in the previous literature (e.g. Schlenker, Hanemann, and Fisher, 2007; Schlenker and Roberts, 2009; Lobell et al., 2013; Moore and Lobell, 2014; Fezzi and Bateman, 2015). We also use three measures of water availability: growing season precipitation, water rights seniority, and access to groundwater.

We fit three sets of models on each of our specifications: ordinary least squares (OLS), panel random-effect model (RE), and panel fixed-effect model (FE). These methods differ not only in their identifying assumptions, but more fundamentally in the underlying effects that they recover. OLS and RE recovers long term adaptation behaviors through variations between cross-sections, whereas FE recovers short term adaptation behaviors through random weather shocks. Each approach has its own advantages and weaknesses, which we will discuss below.

The OLS model aims at estimating the long term response of land allocation to climate through exploiting variations between different farmers. This approach mimics the Ricardian and semi-Ricardian regression framework pioneered by Mendelsohn, Nordhaus, and Shaw (1994), and subsequently adopted by other studies (e.g. Schlenker, Hanemann, and Fisher, 2005; Seo and Mendelsohn, 2008; Wang et al., 2010; Moore and Lobell, 2014). Ideally, OLS reveals the long term equilibrium outcome caused by differences in climate conditions across different farmers. It has the ability to incorporate crucial adaptation measures, in our case land allocation decisions, as a result of those differences in climate and water availability (Mendelsohn and Massetti, 2017).

However, one fundamental challenge of the semi-Ricardian approach is to address omitted variable bias. Farmers settling in two specific locations differ not only in climate conditions, but also in other land-specific characteristics that correlates with both climate and agricultural land allocation. Two of the most prevalent confounding factors are soil conditions and access to irrigation water, both known to be correlated with average temperature (e.g. see Schlenker, Hanemann, and Fisher, 2005; Fezzi and Bateman, 2015). A correctly specified cross-sectional regression will have to include all these confounding factors in order to ensure unbiased estimates for the climate variables.

The FE model, on the other hand, aims at estimating the short term response through exploiting variations in land allocation by the same farmer in reaction to stochastic weather shocks (Blanc and Schlenker, 2017). In our particular case, the source of variation comes from changes in the expectation of climate variations, represented by changes in the recent realization of weather shocks. It has the advantage of controlling for time-invariant confounding factors (Auffhammer et al., 2013). By differencing out individual specific heterogeneity terms, FE achieves plausible identification as long as omitted confounding factors are not variant both with time and individual.

However, there are two main factors that causes FE to underestimate the long term adaptation to climate and water supply. First, using variations in weather only captures short term responses to weather shocks, where important long term adjustments can be omitted from the approach (Fisher et al., 2012). For example, crop rotation may put constraints on flexible adjustments of land allocation towards weather shocks. Technological changes in water supply may also be available to farmers only in the long term, but not in the short term. These changes include switching from flood to sprinkler or drip irrigation, or acquiring groundwater rights for irrigation. Without considering these long term adaptation mechanisms, the FE estimator will underestimate the impact of climate change on land allocation, and (potentially) over-estimate the impact on profit (e.g. Deschênes and Greenstone, 2007).

Secondly, for the FE approach to be valid in our particular application of estimating land allocations, farmers have to update their expectations on climate at least partly from short term weather shocks. Since land allocations are made *ex ante* to temperature and water supply realizations, farmers will make decisions based on their expectation of these factors rather than the actual realization of those factors. If farmers' expectations are formed solely from the long term mean temperature and water distributions, then year-to-year land allocations will be independent from weather shocks. On the other hand, the short term effect will be as large as the long term effect if farmers form expectations by updating their beliefs based on recent weather shocks.[10] Literature has suggested that weather shocks can influence beliefs towards climate change(Deryugina, 2013), and induces behavioral changes accordingly (Ding, Schoengold, and Tadesse, 2009; Kelly, Kolstad, and Mitchell, 2005). Nevertheless, as long as long term climate normals are still part of farmers' consideration, the estimated effects using FE will be smaller than the effects estimated by the cross-sectional model since FE wipes out the effects of long term averages through within transformation.

For the above reasons, we expect our results from OLS, RE and FE to differ. The three models are essentially different weighing schemes regarding within variations and between variations. Since the two sources of variations are generated through different mechanisms, the underlying effects estimated from the two sources should be different. This will cause the three models to diverge even if there exist no individual heterogeneities. In this sense, the difference between OLS, RE and FE should not be viewed as inconsistencies in the models with stronger assumptions (OLS and RE), as we would in traditional Hausman-type tests.

To further decompose long term adaptation mechanisms, we fit a cross-sectional fractional multinomial logit (FMNL) model on the percentage of each land use categories. This

[10] From a Bayesian learning perspective, this means that farmers form posterior beliefs that put most weights on recent realizations of weather and water availability rather than long term averages.

allows us to track land allocation dynamics in response to climate and water differences. The FMNL model, a generalized version of multinomial logit model, has been widely used in the literature to model land allocation fractions (Kala, Kurukulasuriya, and Mendelsohn, 2012; Fiszbein, 2017, Chapter 2 of this dissertation). Previous literature estimating impacts of land allocation on climate change usually treats land allocation decisions as a categorical choice (Seo and Mendelsohn, 2008; Wang et al., 2010). The FMNL improves upon that literature by treating land allocation as fractions, which provide a natural link to our theoretical model on land shares, while at the same time better mimics the actual land allocation dynamics in our study region.

The proposed FMNL model is still cross-sectional in nature, which means that it shares the same advantages and disadvantages of the traditional Ricardian framework. We are not able to expand the FMNL framework to a panel because of econometric constraints. Nevertheless, if omitted variable bias can be properly controlled in the model, then FMNL recovers the same long term adaptation effects of climate and water supply on agriculture.

3.5 Data

Our empirical exercise focuses on the East Snake River Plain (ESRP) in Southeast Idaho (see Figure 3.1). ESRP mainly falls into temperate, cold semi-arid climate, with cold winters and warm but not too hot summers. With insufficient precipitation during the growing season, agricultural production in the ESRP relies heavily on irrigation water: 74.7% of farmlands are irrigated (National Agricultural Statistics Service, 2012) and irrigated agriculture accounts for 85.6% of water withdrawals in the ESRP (Kenny et al., 2009). The region grows six primary crops, including alfalfa, barley, corn, potatoes, sugar beets, and spring and winter wheat, which cover more than 97% of all cropland in the region (National Agricultural Statistics Service, 2007-2016). Both surface water flows and groundwater recharge relies heavily on winter precipitation and snowmelt. Surface water is mainly drawn from Snake River and its tributaries, whereas groundwater is extracted from the Eastern Snake Plain Aquifer underneath the plain.

[Insert Figure 3.1 here.]

One of the most important reasons why we focus on the ESRP is that Idaho maintains a geo-referenced database for adjudicated water rights.[11] The database not only provides detailed information on the priority date and the source of water for each water right. More importantly, from this database we are able to extract the geographical boundaries of each water right in ESRP. This enables us to spatially match individual water rights with a series of geo-referenced datasets that document field-level land allocation decisions, climate and weather patterns, and soil conditions. We use water rights as the cross-section in our analysis following previous studies (e.g. Xu, Lowe, and Adams, 2014; Browne, 2017, Chapter 2 of this dissertation).[12]

From all individual water rights in the ESRP, We exclude water users who hold only groundwater titles from the analysis because groundwater users do not usually face curtailment risks from the appropriation system, which makes their water supply more reliable than surface water. We also exclude all observations with fewer than five pixels in the cropland data layer (CDL) in a given year.[13] Our final sample is an unbalanced panel spanning 10

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

[12] The boundaries of water rights do not necessarily line up with the boundaries of the actual farms. Unfortunately due to data constraints we are not able to describe the latter. Yet as Chapter 2 of this dissertation argues, water right can be used an individual unit of observation because water right boundaries delineate the land base over which water rights are enforced and water is a quasi-fixed input to production (Moore, Gollehon, and Carey, 1994).

[13] Five pixels translates to approximately 3.8 acres of cropland from 2007 to 2009, and 1.1 acres from 2010

years between 2007-2016, with 961 individual water right. Equation 3.9 describes the main linear and FMNL model estimated in our empirical analysis. Table 3.1 provides summary statistics of variables included in our model.

Growing degree days and extreme degree days are non-linear transformation of temperature, which assumes that plant growth is linear only between moderate temperature ranges from 8°C to 32°C(Ritchie and NeSmith, 1991), and detrimental in hot temperature higher than 32°C(Lobell et al., 2013).[14] The use of growing degree days is common in estimating agroeconomic models (e.g. Schlenker, Hanemann, and Fisher, 2007; Deschênes and Greenstone, 2007), and is suggested by literature as a preferred method than using monthly average temperature (Schlenker, Hanemann, and Fisher, 2007). Extreme heat conditions are detrimental to crop growth, and will significantly reduce crop yield (Burke and Emerick, 2016). Extreme heat conditions also contribute to increasing rates of plant evapotransporation, which cause increase water demands for crops as a result. Growing season cumulative precipitation measures the supplemental water supply provided by precipitation process, which offsets demands for irrigation water.

Growing season precipitation is defined as total precipitation from April to September, which reflects the agroeconomic scenario of the study area. We use a dummy variable for access to groundwater. Following Chapter 2 of this dissertation, we use standardized priority year on a scale between zero and one to indicate surface water right priority, where zero indicates the most senior water right, and one means the most junior water right.

We obtain land allocation data from National Agricultural Statistics Service (NASS)'s Cropland Data Layer (CDL). CDL is a crop-specific land cover dataset for the continental

to 2014.

[14]We check the robustness of using different cutoff temperatures for GDD and EDD, as well as using temperature bins in regression. Our result is robust against cutoff changes in GDD and EDD.

US based on satellite imagery and calibrated classification algorithms (National Agricultural Statistics Service, 2007-2016). It provides a moderate resolution imagery that classifies agricultural land use types. The dataset is available from year 2007 onwards. For each farm entity, we are able to identify the percentage of land allocated to six major crops of the region: alfalfa, barley, corn, potato, sugarbeet and wheat, as well as land idlement.

Soil data is obtained from the SSURGO database, a soil database developed by USDA-NRCS. The SSURGO dataset contains a crop-specific yield estimate for each soil type, and from which we construct an average irrigated crop yield map for wheat and corn. This allows us to capture the possibility that a parcel of land is especially suitable for certain crops but not for others, which may explain some of the empirical cropping choices. We also include common soil quality indicators in our model, such as irrigated and non-irrigated soil capacity class, percent of clay, percent of slopes, and the k-factor.[15]

Daily temperature and precipitation data is obtained from the PRISM climate dataset developed by Oregon State University, which provide medium-scale climate maps and estimates. PRISM is the most comprehensive dataset to date that covers the continental US, and is used in almost every previous climate impact studies. We construct growing degree days, extreme degree days, and growing season precipitation by accumulating PRISM data data products.

We calculate a regional average expected profit for each crop as a function of lagged crop prices, production costs and crop yields. The expected profit from each water right is then calculated by multiplying the regional-average profit with the fraction of each crop for that water right. Figure 3.2 shows the average expected profit for each water right, overlaid by the realizations of GDD, EDD, and growing season precipitation in 2007. Downstream

[15]k-factor measures the erodibility of soils.

Water rights around Twin Falls and Milner area have on average the highest profit, followed by upstream water rights around Idaho Falls, and finally water rights around Hurley and along the Big Lost River. Coincidentally, the Twin Falls / Milner area has the highest GDD and EDD over the basin, while the Hurley / Big Lost River area has the lowest GDD and EDD.

[Insert Figure 3.2 here.]

3.6 Results

The long term Case

Table 3.2 presents the main estimation results with different specifications in the long term case. The three climate variables, GDD, EDD and precipitation all show consistently positive impact on expected farm profit. Specifically, a one degree-day increase in GDD increases farmers' expected profit by \$1.4-1.9 per acre, or 0.5-0.7% annually. The FMNL models, presented in Table 3.3 and 3.4, shows that when facing higher GDD, farmers plant less alfalfa, barley and fallow less, while planting more corn, potato, sugarbeet and wheat. Since alfalfa and barley are among two of the three low-profit crops, and idled land earns no profit, the sign of the expected profit goes unambiguously to the positive. This result is agronomically reasonable since alfalfa mainly grows in the temperate climate, while corn and potato are suitable for warmer climates. This result indicates that for temperature increases within GDD ranges, the crop suitability effect is positive, and its magnitude larger than the water-temperature complementary effect.

Results on extreme degree days depict a similar picture to the case of GDD. A one degree-day increase in EDD increases farmers' expected profit by \$ 0.7-1.4 per acre, or 0.3-0.5% annually. A one mm increase in growing season precipitation increases farmers' expected profit by \$ 2.8-3.7 per acre, or 1.0-1.4% annually. On average, when facing increasing EDD, farmers switch out of alfalfa into planting corn on about half of the marginal land, and a mix of barley, potato, and wheat on the other half. This indicates that the crop suitability effect is also positive in the EDD range, and its magnitude larger than the water-temperature complementary effect.

We should note that our result only shed light on the relative direction of agricultural adaptation to climate change, but not the yield/profit gains from GDD and water availability, and losses from EDD. That is why a positive coefficient on EDD does not mean that extreme heats are beneficial to agricultural production. Rather, it suggests that farmers adapt to extreme heats by switching from lower-valued crops to higher-valued crops.

Still, our result on EDD differs from some of the other studies on climate impact. For example, Hornbeck and Keskin (2014) found that in the long term, agricultural production could become more sensitive to drought if presented with extra water supply, i.e., a negative crop suitability effect. However, we believe that our results differ from Hornbeck and Keskin (2014)'s for several reasons. First, the set of crops farmers can choose from in our study area is much larger than that in Hornbeck and Keskin (2014)'s. In our study we observe farmers growing six different types of crops, each with non-trivial fractions. In contrast, in Hornbeck and Keskin (2014) farmers only switch between corn and wheat. The opportunity of finding the most suitable crop under a particular climate scenario increases dramatically when farmers have a larger set of crop to choose from. This is exactly what we see from our analysis: farmers switch from alfalfa towards almost all other major crop types, which are generally more suitable than alfalfa under extreme heat conditions. Second, technological innovation such as heat-resistant crop varieties help mitigate yield loss from extreme heat (e.g. Hendricks, 2018). These advances are more likely to be developed for high value, widely grown crops such as corn and potato rather than region-specific crops like alfalfa.

Water availability have generally positive impacts on farmers' expected profits. Having access to groundwater increases farm profit by \$17-33 per acre, or 6.3-12.3% annually. Having one mm more precipitation on average increases farm profit by \$1.5-3.6 per acre, or 0.5-1.4% annually. Parameter estimates on mean surface water priorities are not significant in all model specifications. With more water available, farmers are able to switch from low-profit crops (alfalfa, barley and wheat) towards high-profit crops, which are usually more water-intensive.

Finally, our model indicates that GDD is the most influential climate variable. In other words, differences in GDD is the primary driver of long term differences in planting decisions. This can be viewed in two ways. Statistically speaking, the t-statistics on GDD and GDD^2 is much smaller than EDD and precipitation, indicating that GDD has more explanatory power in the model. In terms of climate impact, a one-standard deviation increase in GDD doubles the expected profit, while a one-standard deviation change in EDD and precipitation only increases the expected profit by a quarter.

The short term Case

Table 3.5 presents a set of models using short-term weather patterns to explain expected farm profits.[16] The signs of major variables in the short term models remain the same as in

[16] We only present results from EDD interactions as model with GDD interaction terms to save space, noting that the patterns are similar with the models presented here. Also, GDD interaction models are not

the long term model: temperature and water availability positively contributes to expected profit, and the water-temperature interaction terms show negative effects on expected profit. However, we find three key differences in the short term models when comparing with the long term models.

The first key difference is that, the fixed-effect models (column (3) and (6) Table 3.5) are extremely poor predictors of expected farm profits, and the estimated effects of climate variables in the short term models are much smaller than those in the long term models. Only 0.4% of total within variations can be explained by short-term weather shocks, a sharp drop from models considering between variations, which explains about 35% of the total between variations. This result is not surprising for two reasons. First, a large portion of within variations come from crop rotation patterns, which are quasi-fixed over a period of several years, and are thus less affected by weather shocks. Secondly, since our study draws inference on disaggregated farm-level observations, the influence of crop rotation patterns will be even larger comparing to studies using county-level observations (e.g. Deschênes and Greenstone, 2007), which may average out cropping patterns by different individual farms.

The second key difference is that, in the short term farmers respond to a different set of water and temperature variables comparing to the long term case. Variations in the year-to-year realizations of GDD has no significant impact farmers' land allocation decision in the short term. This is in sharp contrast with the long term case, when GDD is the dominating factor in determining land allocation. Instead, the primary driver of farmers' year-to-year adjustments on land allocation is shocks in EDD, while by precipitation. Going from OLS to random-effect to fixed-effects, the effect of GDD becomes smaller, whereas the effects of EDD and precipitation become larger. In the case of the fixed-effect models, GDD is not

stable due to multicollinearity.

significant at all in both models. This indicates that farmers adapt to a normal warming climate (within GDD range) only in the long term but not in the short term. However, if the warmer climate does lead to drought, then farmers will adapt based on recent experiences to drought. Reactions to short term shocks comes mainly in the form of heat stress induced by EDD, which is as large as 40-80% of the size of long term adaptation towards EDD. Reactions to water stress have a much smaller magnitude, at about 1-7% of the size of long term adaptation towards precipitation.

There could be several underlying reasons for the observed divergence between short term and long term adaptations to climatic variables. From a behavioral perspective, farmers may overreact to extreme events with small probability like drought or water shortage, and underreact to regular events like growing degree-day changes (Tversky and Kahneman, 1974). Also, droughts and water shortages cause dramatic losses in yields, where GDD has a positive, but marginal impact on crop yield. If farmers are loss-averse, they will respond to EDD and precipitation more dramatically than to GDD (Kahneman, Knetsch, and Thaler, 1991). Both of these behavioral abnomolies lead to overreaction to EDD in the short term. Another possibility is that yield and profit losses are easier to be causally linked to extreme heat conditions and abnormal rainfall, whereas marginal increases in yield can be attributed to multiple factors besides regular warming. Thus farmers are more likely to be aware of the impact of extreme events on farm profit, and thus make corresponding adaptation measures in the following year(s).

Third, we find that although in all models water-temperature interactions have negative effects on expected profit, the influence of different water sources diverge between short term and long term. Surface water availability is the only statistically significant interaction term in the short term fixed-effect models (column (3) and (6) in Table 3.5). This differs sharply from the long term models, which show that the interaction term of precipitation and access to groundwater are significant, while water right priority is not. Additionally, water right priority shows positive impact to farmers' land allocation in the random-effect model using three year lagged weather variables (column (5) in Table 3.5). In all long term models water right priority appears to be insignificant.

Two conclusions can be drawn from the above observation on water availability. First, the direction of which farmers adapt to water availability are the same across water sources and time spans. For all three water sources, and in all model specifications, the impact of water availability on expected profit is positive and declining with temperature increases. Second, the impact of different water sources diverges between short term and long term. Groundwater availability impact land allocation only in the long term, surface water availability impact land allocation only in the short term, and precipitation impacts land allocation in both short and long terms. One possible explanation to this phenomenon is that this reflects the risk and uncertainty associated with the three water sources. Groundwater sources are the most stable water sources with virtually no uncertainty.[17] Because of that, within variations for the same individual farmer cannot be explained by the constant availability to groundwater. In contrast, surface water irrigators face continued risk of curtailment. If those irrigators update their expectations on surface water availability based on most recent realizations, then land allocations will be affected by water right priorities in the short term.[18]

[17]In very rare cases, junior groundwater rights are curtailed to recharge senior surface water flows.

[18]In another paper we show that farmers indeed update their expectations on water availability based on recent curtailment events.

3.7 Discussion and Implication

In this paper we explore the joint effect of water and temperature on agricultural land allocation decisions in irrigated agriculture. We show theoretically that crop suitability and water-temperature complementarity are two counter-balancing factors that shapes land allocation decisions when facing different climate scenarios. We also show that the effect of physiological complementarity on farm profit will be fully capitalized through changes in land allocation if land allocation is flexible. We then empirically demonstrate that water and temperature conditions significantly affects land allocation decisions in irrigated agriculture. Farmers plant crop mixes that are more profitable with larger GDD, EDD, and water availability. Furthermore, we found that the effect of water and temperature on empirical land allocation differs between the long term and the short term. Long term differences in land allocation are mainly driven by GDD, whereas short term differences are driven by EDD. Also, surface water availability only affects land allocation in the short term, whereas access to groundwater only affects land allocation in the long term.

Our paper has several policy implications. First, it stresses the need to consider potential adaptation mechanisms when evaluating the real impact of climate change to agriculture. Studies on crop yield can overestimate the impact of climate change if farmers adapt at the extensive margin through changing planted acreages (Manning, Goemans, and Maas, 2017) or crop mixes.

Second, our study illustrates the need to consider short term behavioral responses to climate change. We find that short term weather shocks have non-negligible influence on farmers' decision making, and that influence likely comes from (over)updating expectations based on recent shocks. Estimating climate impact based on long term climate normals can underestimate the impact from climate change, especially if climate change causes increasing frequency of extreme weather events.

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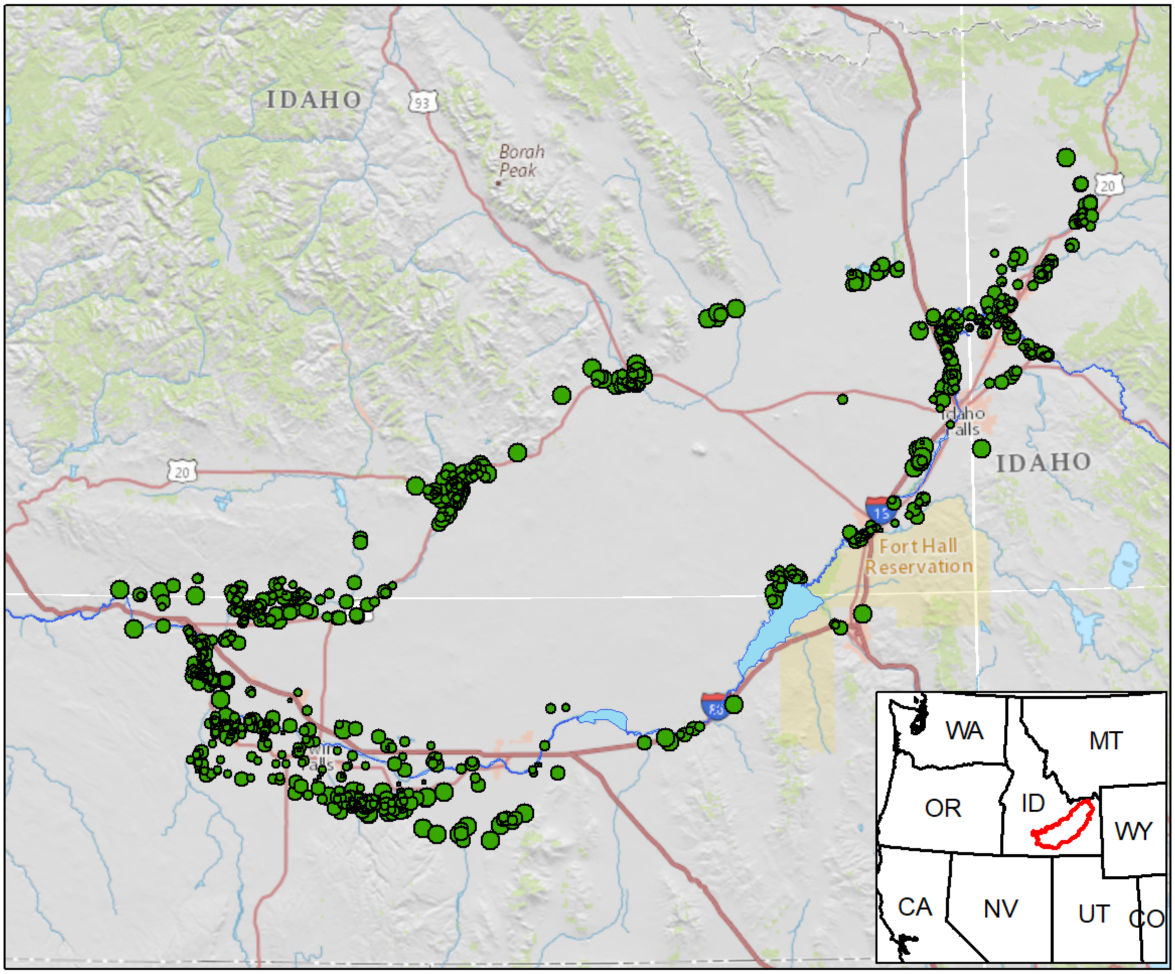

Figure 3.1: Map of Water Rights in ESRP. Each green dot denotes one water right. Size of the dot indicates relative size of the water right. Blue line denotes the main stem of the Snake River. Lower-right panel denotes the relative location of the ESRP (Red line denotes the watershed boundary of ESRP.)

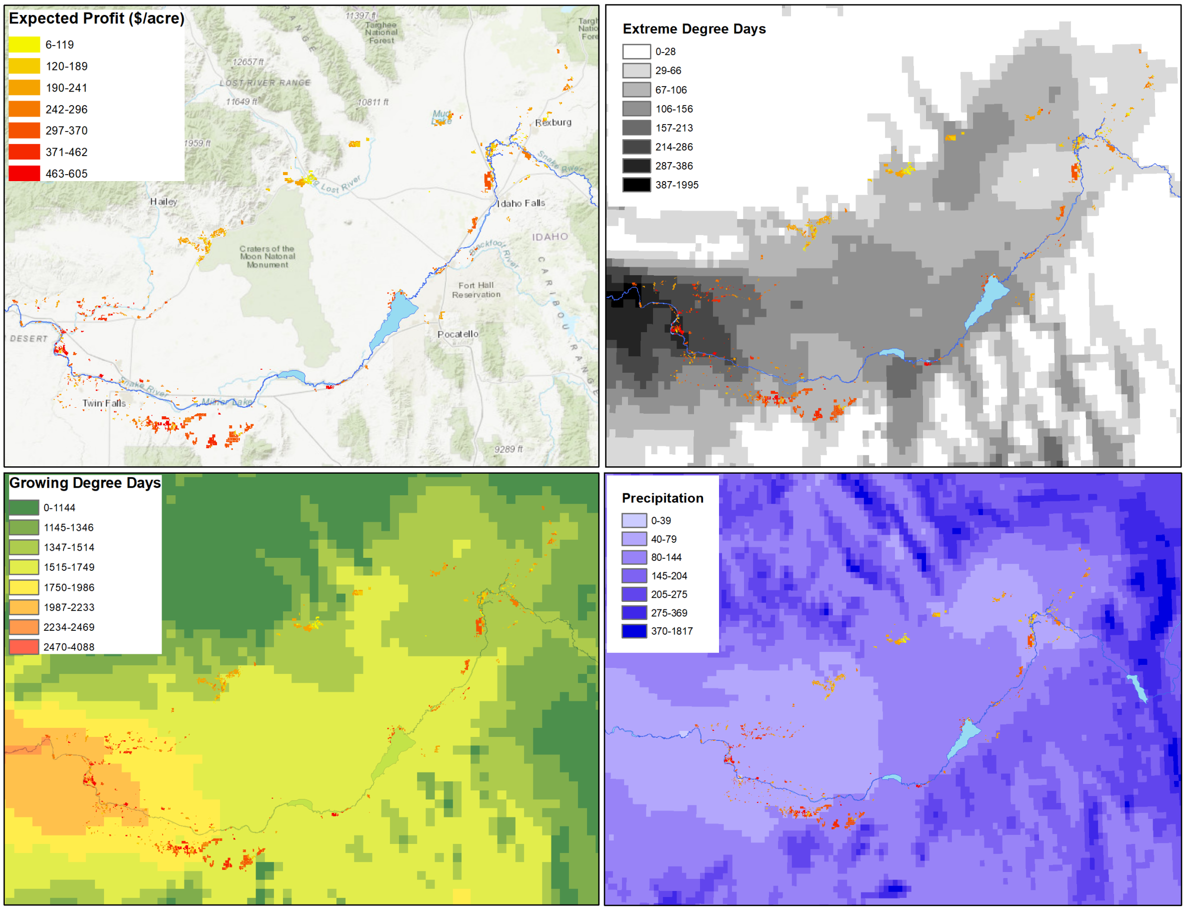

Figure 3.2: Farm Profit versus climate. Upper left panel plots average expected profit (over 10 years) for all water rights. Lower left panel overlays growing degree days in 2007 on average expected profit. Upper right panel overlays extreme degree days in 2007 on average expected profit. Lower right panel overlays growing season precipitation in 2007 on average expected profit. Scale of average expected profit is shown in the upper left panel, and remains unchanged for all four panels. Scales of GDD, EDD and precipitation are shown in each respective panel. Blue line denotes the main stem of Snake River.

Table 3.1: Summary Statistics of Variables

Variable	Mean	Median	Min	Max	Std Dev
% Land Alfalfa	0.47	0.43	0.00	1.00	0.39
% Land Barley	0.15	0.01	0.00	1.00	0.27
% Land Corn	0.14	0.00	0.00	1.00	0.28
% Land Potato	0.05	0.00	0.00	1.00	0.17
% Land Sugarbeet	0.02	0.00	0.00	1.00	0.11
% Land Wheat	0.11	0.00	0.00	1.00	0.23
% Land Fallow	0.05	0.00	0.00	1.00	0.16
GDD	1521.93	1483.86	849.07	2133.30	280.51
EDD	64.81	45.10	0.17	312.05	58.36
Precipitation	59.65	49.95	7.78	234.41	38.65
Surface Water Right Quantile	0.54	0.55	0.00	1.00	0.28
Access to Groundwater	0.10	0.00	0.00	1.00	0.30
Irrigated Capacity Class	3.39	3.10	2.00	6.00	0.69
Non-Irrigated Capacity Class	5.56	6.00	3.00	6.00	0.94
Slope of Land	2.75	2.02	1.00	15.82	2.16
Wheat Yield on Soil	78.25	80.00	30.00	120.00	21.34
Corn Yield on Soil	66.02	60.00	40.00	149.88	27.06
% Clay in Soil	12.07	11.67	1.50	42.25	7.56
k-factor	0.27	0.25	0.02	0.57	0.13
log(Area)	4.59	4.55	0.85	8.78	1.12

Table 3.2: Models on Expected Profit Using Long-term Climate Norms

Variables/Model	(1) OLS	(2) RE	(3) FMNL	(4) OLS	(5) RE	(6) FMNL
Growing Degree Days	2.838***	2.853***	2.71***	4.270***	4.309***	3.65***
	(0.256)	(0.445)	(7.94e-38)	(0.572)	(1.062)	(2.76e-139)
GDD^2	-0.000450***	-0.000453***	-0.000439***	-0.000591***	-0.000596***	-0.000534***
	(4.48e-05)	(7.67e-05)	(2.27e-8)	(7.29e-05)	(0.000134)	(1.01e-11)
Extreme Degree Days	4.690***	4.819**	4.17*	0.564	0.582	0.332
	(1.113)	(2.185)	(2.23)	(0.465)	(0.720)	(3.87)
EDD^2	-0.00293**	-0.00310	-0.00139	0.00137	0.00131	0.00199***
	(0.00136)	(0.00262)	(0.00366)	(0.000861)	(0.00143)	(0.000222)
Precipitation	7.123***	7.333	8.52	19.24***	19.63*	10.4***
	(2.512)	(4.905)	(10)	(5.908)	(11.24)	(3.74e-16)
$Precipitation^2$	-0.00983	-0.0103	-0.0173	-0.0150*	-0.0155	-0.000762
	(0.00695)	(0.0137)	(0.0394)	(0.00861)	(0.0165)	(0.0023)
Priority Quantile	11.3	11.23	2.31	22.09	21.95	-8.82
	(8.267)	(17.01)	(16.6)	(32.53)	(67.02)	(163)
Access to Groundwater	62.77***	61.63***	43.4***	64.80**	61.42	137***
	(8.004)	(16.20)	(8.85)	(30.71)	(64.71)	(32.8)
	(0.00136)	(0.00262)	(0.00366)	(0.000861)	(0.00143)	(0.000222)
EDD × Precipitation	-0.0494***	-0.0508**	-0.0483			
	(0.0140)	(0.0254)	(0.147)			
EDD × Priority Quantile	0.101	0.104	0.006			
	(0.111)	(0.206)	(0.12)			
EDD × Groundwater	-0.540***	-0.527**	-0.402***			
	(0.133)	(0.244)	(0.137)			
GDD × Precipitation				-0.00929***	-0.00948*	-0.00583***
				(0.00266)	(0.00495)	(9.78e-06)
GDD × Priority Quantile				-0.00673	-0.00661	0.00626
				(0.0225)	(0.0442)	(0.0129)
GDD × Groundwater				-0.0204	-0.0184	-0.0738*
				(0.0218)	(0.0434)	(0.0338)
Observation	9,568	9,568		9,568	9,568	
R^2	0.211	0.205		0.21	0.203	

Note: Robust standard error reported in parenthesis. FMNL standard errors are calculated via the Krinsky-Robb method. Quadratic terms are generated using Chebyshev polynomials to avoid multicollinearity. Year dummies and controls for soil quality are suppressed from reporting. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

Table 3.3: Marginal Effects from FMNL on Crop Fractions, EDD Interaction

	alfalfa	barley	corn	potato	sugarbeet	wheat	fallow
Growing Degree Days	-0.000618***	-0.00132***	0.00288***	0.00142***	0.000334***	0.000556***	-0.00325
	(2.59e-51)	(1.08e-41)	(5.93e-80)	(1.29e-64)	(6.79e-118)	(4.95e-53)	(0.00655)
GDD^2	1.56e-6***	2.83e-6***	-4.12e-6***	2.91e-6***	-5.73e-7***	-1.85e-6***	5.06e-6
	(0)	(5.63e-16)	(1.19e-15)	(2.3e-15)	(2.19e-15)	(9.67e-16)	(0.000123)
Extreme Degree Days	-0.0259***	0.00628***	0.0115***	0.0043***	0.000172	0.005***	-0.00133
	(0.00748)	(0.000147)	(2.39e-08)	(1.32e-05)	(0.00172)	(5.08e-05)	(0.00108)
EDD^2	3.07e-05***	-9.76e-06**	-9.32e-06*	-3.42e-06	3.98e-08	-7.29e-06**	-9.11e-07
	(2.66e-07)	(1.8e-05)	(5.99e-05)	(2.43e-06)	(2.48e-05)	(1.46e-06)	(1.59e-05)
Precipitation	-0.0618***	0.0155**	0.0303***	0.00594	0.000623	0.00734	0.00206
	(0.000252)	(0.00783)	(2.96e-09)	(0.00864)	(0.012)	(0.00928)	(0.00942)
$Precipitation^2$	0.00018***	-5.55e-05***	-8.42e-05	-9.76e-06***	-2.4e-06	-7.75e-06***	-2.01e-05
	(2.66e-07)	(1.8e-05)	(5.99e-05)	(2.43e-06)	(2.48e-05)	(1.46e-06)	(1.59e-05)
Priority Quantile	0.0483**	-0.0901***	-0.0178	0.00158	0.00388***	0.0391**	0.015*
	(0.0226)	(0.0267)	(0.0205)	(0.0136)	(0.000998)	(0.0172)	(0.00898)
Access to Groundwater	0.0251	-0.0436***	0.0449***	0.0211***	0.00407***	-0.0428***	-0.00869
	(0.0209)	(0.0156)	(0.00784)	(0.00729)	(0.000742)	(0.0125)	(0.00586)
	(4.4e-06)	(3.99e-06)	(5.1e-06)	(2.34e-06)	(6.59e-07)	(2.84e-06)	(8.5e-07)
EDD $\times$ Precipitation	0.000308***	-0.000241***	-0.000192***	-1.77e-06	8.3e-07	6.48e-05	6.15e-05
	(2.14e-05)	(2.12e-07)	(1.21e-08)	(6.47e-05)	(0.000209)	(5.19e-05)	(8.4e-05)
EDD $\times$ Priority Quantile	-0.00123***	0.000999***	0.00031***	0.000139	-3.84e-05	-8.38e-05	-9.9e-05
	(0.000322)	(0.000211)	(7.55e-05)	(1e-04)	(2.69e-05)	(0.000182)	(7.58e-05)
EDD $\times$ Groundwater	0.000265	0.000325	-0.000503***	-0.00024*	-6.99e-05***	0.000194	2.83e-05
	(0.000292)	(0.00032)	(0.000112)	(0.000128)	(1.82e-05)	(0.000184)	(9.15e-05)

Note: Independent variables are long-run climate normals. Robust standard error reported in parenthesis, calculated via the Krinsky-Robb method. Quadratic terms are generated using Chebyshev polynomials to avoid multicollinearity. Year dummies and controls for soil quality are suppressed from reporting. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

Table 3.4: Marginal Effects from FMNL on Crop Fractions, GDD Interaction

	alfalfa	barley	corn	potato	sugarbeet	wheat	fallow
Growing Degree Days	-0.000323***	0.00316***	0.00406***	0.00124***	0.000296***	0.000389***	-0.00882
	(6.94e-146)	(3.26e-154)	(0)	(7.36e-145)	(2.61e-156)	(3.07e-143)	(0.015)
GDD^2	4.43e-08***	-1.65e-07***	-5.01e-07***	-2.72e-07***	-4.87e-08***	-1.71e-07***	1.11e-06
	(0)	(3.79e-19)	(7.98e-19)	(4.29e-19)	(1.26e-18)	(2.33e-19)	(2.61e-06)
Extreme Degree Days	-0.00382***	-0.0121***	-0.00279***	0.00408	0.00018	0.0106*	0.00384*
	(1.17e-05)	(8.76e-07)	(7.53e-05)	(0.00544)	(0.00138)	(0.00482)	(0.0018)
EDD^2	6.85e-06***	1.17e-05***	4.57e-06***	-3.02e-06***	-5.26e-08***	-1.4e-05***	-6.07e-06***
	(5.05e-07)	(7.72e-08)	(5.41e-08)	(2.31e-07)	(1.28e-08)	(8.84e-07)	(4.87e-07)
Precipitation	-0.0264***	0.0533***	0.0143***	0.00424***	0.000642***	0.0155***	-0.0615
	(8.55e-38)	(8.78e-48)	(2.03e-38)	(3.39e-34)	(5.59e-19)	(8.89e-42)	(0.129)
Precipitation^2	5.62e-05***	-6.35e-05***	-5.97e-07	-8.06e-06***	-2.24e-06	-3.51e-05***	5.34e-05
	(2.76e-08)	(4.55e-09)	(2.17e-06)	(3.59e-07)	(2.82e-06)	(1.92e-08)	(0.000102)
Priority Quantile	0.186**	-0.293	-0.0502	-0.0473	0.0227***	0.139	0.0429
	(0.0583)	(0.152)	(0.189)	(0.17)	(0.000518)	(0.103)	(0.0463)
Access to Groundwater	0.0397	-0.118*	0.211***	0.0173	0.0123***	-0.119*	-0.044*
	(0.0886)	(0.0551)	(0.0243)	(0.026)	(0.00177)	(0.0483)	(0.0171)
GDD × Precipitation	6.65e-06***	-3.24e-05***	-9.61e-06***	6.61e-07***	-1.58e-08***	1.48e-06***	3.33e-05
	(0)	(1.7e-17)	(8.69e-18)	(6.21e-18)	(1.46e-12)	(5.43e-18)	(8.14e-05)
GDD × Priority Quantile	-0.000142*	0.000171***	3.16e-05	3.86e-05**	-1.39e-05	-6.8e-05	-1.73e-05
	(7.2e-05)	(1.59e-05)	(1.66e-05)	(1.35e-05)	(0.000189)	(3.72e-05)	(1.44e-05)
GDD × Groundwater	-8.22e-06	5.74e-05	-0.00012**	-6.28e-06	-7.98e-06	5.71e-05	2.76e-05
	(5.42e-05)	(4.92e-05)	(3.82e-05)	(2.87e-05)	(6.18e-06)	(3.97e-05)	(1.51e-05)

Note: Independent variables are long-run climate normals. Robust standard error reported in parenthesis, calculated via the Krinsky-Robb method. Quadratic terms are generated using Chebyshev polynomials to avoid multicollinearity. Year dummies and controls for soil quality are suppressed from reporting. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

Table 3.5: Models on Expected Profit Using Short-term Weather Shocks

Dependent Variables	1 Year Lagged Weather			3 Year Lagged Weather		
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) RE	(6) FE
Growing Degree Days	0.500***	0.175**	0.0650	1.015***	0.254**	-0.0569
	(0.0801)	(0.0799)	(0.0829)	(0.118)	(0.128)	(0.142)
GDD^2	-7.25e-05***	-3.04e-05**	-1.91e-05	-0.000155***	-4.57e-05**	-1.45e-05
	(1.41e-05)	(1.33e-05)	(1.37e-05)	(2.07e-05)	(2.18e-05)	(2.44e-05)
Extreme Degree Days	0.162	0.367*	0.479**	0.441	0.636**	0.665*
	(0.192)	(0.189)	(0.205)	(0.300)	(0.299)	(0.340)
EDD^2	0.000287	-0.000234	-0.000424*	0.000528	-0.000336	-0.000575
	(0.000282)	(0.000249)	(0.000257)	(0.000473)	(0.000457)	(0.000486)
Precipitation	0.176	0.323	0.466**	0.116	0.298	0.146
	(0.193)	(0.197)	(0.199)	(0.525)	(0.517)	(0.525)
Precipitation^2	-0.000210	-0.000704	-0.00106**	0.00207	-6.80e-06	0.000127
	(0.000474)	(0.000482)	(0.000488)	(0.00155)	(0.00159)	(0.00162)
Priority Quantile	-11.96	-18.25		-9.442	-24.59*	
	(7.765)	(13.09)		(8.095)	(14.80)	
Access to Groundwater	42.63***	36.66***		47.60***	37.10***	
	(7.484)	(11.84)		(7.824)	(13.57)	
EDD × Precipitation	-0.000418	-0.000968	-0.00151	-0.00428	-0.00401	-0.00182
	(0.00135)	(0.00120)	(0.00121)	(0.00291)	(0.00271)	(0.00283)
EDD × Priority Quantile	0.143	0.240**	0.300**	0.168*	0.338**	0.611**
	(0.0895)	(0.115)	(0.140)	(0.0971)	(0.152)	(0.238)
EDD × Groundwater	-0.280***	-0.172	-0.0710	-0.328***	-0.152	0.162
	(0.105)	(0.127)	(0.150)	(0.115)	(0.173)	(0.257)
Observations	9,568	9,568	9,568	9,568	9,568	9,568
R^2	0.179	0.174	0.04	0.184	0.176	0.005

Note: Independent variables for column (1)-(3) are weather shocks for the past year. Independent variables for column (4)-(6) are average weather shocks in the past three years. Quadratic terms are generated using Chebyshev polynomials to avoid multicollinearity. Year dummies and controls for soil quality are suppressed from reporting. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

Theory Appendix

Consider a price-taking farmer who maximizes profit by allocating two crops and a fixed amount of water $\bar{w}$ on a unitary land. The farmer possesses two restricted profit function, $y_1(w_1, T)$ and $y_2(w_2, T)$ for the two crops, both of them depend on temperature realizations T and water intensities w_1 and w_2. Assume that the non-linear temperature effect on profit can be partitioned into two additively separable parts: growing degree days, G; and extreme degree days, D. The farmer's maximization problem can be written as:

$$\begin{aligned} max \quad & \Pi = y_1(w_1, G, D)L_1 + y_2(w_2, G, D)L_2 \\ s.t. \quad & L_1 + L_2 = 1; \quad L_1 w_1 + L_2 w_2 = \bar{w} \end{aligned} \tag{A.1}$$

Here assume that the restricted profit functions $y_1(.)$ and $y_2(.)$ are globally concave, with six additional assumptions:

1. The marginal product of water is higher for the first crop:

   $\partial y_1/\partial w_1 > \partial y_2/\partial w_2 > 0$.

2. The marginal product of water declines slower for the first crop:

   $\partial^2 y_2/(\partial w_2)^2 < \partial^1 y_1/(\partial w_1)^2 < 0$.

3. Normal temperature increase productivity for both crops, but more so for the first crop.

   $\partial y_1/\partial G > \partial y_2/\partial G > 0$

4. Normal temperature increases marginal productivity of water for both crops, but more so for the first crop:

$\partial^2 y_1/\partial G \partial w_1 > \partial^2 y_2/\partial G \partial w_2 > 0.$

5. Extreme heat decreases productivity for both crops, but more so for the second crop:

   $\partial y_2/\partial D < \partial y_1/\partial D < 0.$

6. Extreme heat increases marginal productivity of water for both crops, and more so for the first crop:

   $\partial^2 y_1/\partial D \partial w_1 > \partial^2 y_2/\partial D \partial w_2 > 0.$

Under these assumptions, the first-order conditions are:

$$\begin{aligned} \frac{\partial y_1(w_1, G, D)}{\partial w_1} &= \frac{\partial y_2(w_2, G, D)}{\partial w_2} \\ y_1(w_1, G, D) - y_2(w_2, G, D) &= \frac{\partial y_2(w_2, G, D)}{\partial w_2}(w_1 - w_2) \end{aligned} \tag{A.2}$$

From assumption 1, at the optimal we have $w_1^* > w_2^*$, the water-intensive crop gets more water per unit. To see the effect of total water availability, totally differentiate the FOC with respect to $\bar{w}$ and simplify:

$$\frac{\partial^2 y_2(w_2, G, D)}{(\partial w_2)^2} \frac{\partial w_2}{\partial \bar{w}}(w_1 - w_2) = 0 \tag{A.3}$$

Since $w_1 > w_2$ at the margin, the only possible solution is that $\frac{\partial w_1}{\partial \bar{w}} = \frac{\partial w_2}{\partial \bar{w}} = 0$. This means that adjustments to water availability only occur at the extensive margin by adjusting land allocations L_1 and L_2, but not at the intensive margin by adjusting water intensity w_1 and w_2.

From that, we can solve for the optimal land allocation, which is given as,

$$L_1^*(\bar{w}) = \frac{\bar{w} - w_2}{w_1 - w_2} \tag{A.4}$$

And since changing water supply only causes adjustments on the extensive margin, we conclude that farm profit and land allocated to the water intensive crop increases with the amount of water suuply,

$$\begin{aligned} \frac{\partial L_1}{\partial \bar{w}} &= \frac{1}{w_1 - w_2} > 0 \\ \frac{\partial \pi}{\partial \bar{w}} &= \frac{y_1 - y_2}{w_1 - w_2} > 0 \end{aligned} \tag{A.5}$$

Effect on Land Allocation

Shifts in temperature patterns not only shifts the marginal productivity of both crops, but also the marginal productivity of water with respect to both crops. How will overall farm profit and land allocation adjust to changes in 1) temperature, and 2) the temperature water interaction, remains unanswered. We derive the following comparative statics using Cramer's rule:

$$\begin{aligned} \frac{\partial w_1}{\partial T} &= -\frac{\partial^2 y_2}{\partial w_2^2}\big[\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} - \frac{\partial^2 y_1}{\partial T \partial w_1}(w_1 - w_2)\big]/|H| \\ \frac{\partial w_2}{\partial T} &= -\frac{\partial^2 y_1}{\partial w_1^2}\big[\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} - \frac{\partial^2 y_2}{\partial T \partial w_2}(w_1 - w_2)\big]/|H| \end{aligned} \tag{A.6}$$

where $|H|$ is the determinant of the Hessian matrix, given by:

$$|H| = \begin{vmatrix} \frac{\partial^2 y_1}{\partial w_1^2} & -\frac{\partial^2 y_2}{\partial w_2^2} \\ 0 & -\frac{\partial^2 y_2}{\partial w_2^2}(w_1 - w_2) \end{vmatrix} = -\frac{\partial^2 y_1}{\partial w_1^2}\frac{\partial^2 y_2}{\partial w_2^2}(w_1 - w_2) < 0 \tag{A.7}$$

Land allocation changes with respect to temperature changes are transmitted through changes in water application rates, i.e.,

$$\begin{aligned} \frac{\partial L_1}{\partial T} &= \frac{\partial L}{\partial w_1}\frac{\partial w_1}{\partial T} + \frac{\partial L}{\partial w_2}\frac{\partial w_2}{\partial T} \\ &= -\left[\frac{\bar{w} - w_2}{(w_1 - w_2)^2}\frac{\partial w_1}{\partial T} + \frac{w_1 - \bar{w}}{(w_1 - w_2)^2}\frac{\partial w_2}{\partial T}\right] \end{aligned} \tag{A.8}$$

For increases in both GDD and EDD, the sign of $\frac{\partial L_1}{\partial T}, \frac{\partial w_1}{\partial T}$ and $\frac{\partial w_2}{\partial T}$ are determined by the tradeoff between productivity increases at the extensive margin, $\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} > 0$, versus productivity decrease at the intensive margin, $\frac{\partial^2 y_1}{\partial T \partial w_1} > 0$ and $\frac{\partial^2 y_2}{\partial T \partial w_2} > 0$. If extensive margin dominates, i.e. $\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} > \frac{\partial^2 y_1}{\partial T \partial w_2}(w_1 - w_2)$, farmers will choose to plant more land to the water-intensive crop while decreasing water application rates for both crops, i.e.

$$\frac{\partial L_1}{\partial T} > 0; \quad \frac{\partial w_1}{\partial T} < 0; \quad \frac{\partial w_2}{\partial T} < 0 \quad \text{if} \quad \frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} > \frac{\partial^2 y_1}{\partial T \partial w_1}(w_1 - w_2) \tag{A.9}$$

If intensive margin dominates, i.e. $\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} < \frac{\partial^2 y_2}{\partial T \partial w_2}(w_1 - w_2)$, farmers will choose to plant less land to the water-intensive crop while increasing water application rates for both crops.

$$\frac{\partial L_1}{\partial T} < 0; \quad \frac{\partial w_1}{\partial T} > 0; \quad \frac{\partial w_2}{\partial T} > 0 \text{if} \quad \frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T} < \frac{\partial^2 y_2}{\partial T \partial w_2}(w_1 - w_2) \tag{A.10}$$

We can also derive the cross-derivatives of water and temperature on land allocation, i.e.,

$$\begin{aligned} \frac{\partial L_1^2}{\partial T \partial \bar{w}} &= \frac{\partial}{\partial T \partial \bar{w}} \frac{\bar{w} - w_2}{w_1 - w_2} \\ &= \frac{1}{(w_1 - w_2)^2} (\frac{\partial w_2}{\partial T} - \frac{\partial w_1}{\partial T}) \end{aligned} \tag{A.11}$$

The sign of this cross-derivative reflects the relative magnitude of water application rate changes with respect to temperature. We are unable to comment on the specific sign of this cross-derivative.

Effects on Farm Profit

We are also interested in how farm profit reacts to changes in temperature, water availability, and their interactions. First, we argue that farm profit increases with increasing water availability,

$$\begin{aligned} \frac{\partial \pi}{\partial \bar{w}} &= \frac{\partial}{\partial \bar{w}} L_1 y_1 + \frac{\partial}{\partial \bar{w}} (1 - L_1) y_2 \\ &= \frac{\partial L_1}{\partial \bar{w}} y_1 - \frac{\partial L_1}{\partial \bar{w}} y_2 \\ &= \frac{y_1 - y_2}{w_1 - w_2} = \frac{\partial y_1}{\partial \bar{w}} > 0 \end{aligned} \tag{A.12}$$

using the fact that at the optimal, water intensities remain constant with respect to total water availability.

Secondly, farm profit increases with growing degree days, and decreases with extreme weather conditions.

$$\begin{aligned}\frac{\partial \pi}{\partial T} &= \frac{\partial}{\partial T} L_1 y_1 + (1-L_1) y_2 \\ &= \frac{\partial L_1}{\partial T} y_1 - \frac{\partial L_1}{\partial T} y_2 + L_1 \frac{\partial y_1}{\partial T} + (1-L_1)\frac{\partial y_2}{\partial T} + L_1 y_1^W \frac{\partial w_1}{\partial T} + (1-L_1) y_2^W \frac{\partial w_2}{\partial T} \\ &= L_1 \frac{\partial y_1}{\partial T} + (1-L_1)\frac{\partial y_2}{\partial T} - [\frac{\bar{w}-w_2}{(w_1-w_2)^2}\frac{\partial w_1}{\partial T} + \frac{w_1-\bar{w}}{(w_1-w_2)^2}\frac{\partial w_2}{\partial T}](y_1-y_2) \\ &+ [\frac{\bar{w}-w_2}{w_1-w_2}\frac{\partial w_1}{\partial T} + \frac{w_1-\bar{w}}{w_1-w_2}\frac{\partial w_2}{\partial T}]\end{aligned} \tag{A.13}$$

Notice that the last two terms cancels out using the first order condition, and we have:

$$\frac{\partial \pi}{\partial T} = L_1 \frac{\partial y_1}{\partial T} + (1-L_1)\frac{\partial y_2}{\partial T} \tag{A.14}$$

which is positive for growing degree days $\frac{\partial \pi}{\partial G} > 0$, and negative for increases in extreme degree days $\frac{\partial \pi}{\partial D} > 0$.

Finally, the cross-derivative of water and temperature on farm profit is given by:

$$\begin{aligned}\frac{\partial^2 \pi}{\partial T \partial \bar{w}} &= \frac{\partial}{\partial \bar{w}} L_1 \frac{\partial y_1}{\partial T} + (1-L_1)\frac{\partial y_2}{\partial T} \\ &= \frac{1}{w_1-w_2}(\frac{\partial y_1}{\partial T} - \frac{\partial y_2}{\partial T})\end{aligned} \tag{A.15}$$

again using the fact that at the optimal, water intensities remain constant with respect to total water availability. The cross-derivative is positive for both growing degree day and extreme degree day increases.

Comparative Statics when Land Allocation is Fixed

For some reason, farmers may not be able to adjust crop mixes in reaction to shifts in climate patterns. The farmer's problem now becomes to maximize profit by allocating only water between the two crops, i.e.

$$\begin{aligned} max \quad \pi &= L_1 y_1(w_1, G, D) + L_2 y_2(w_2, G, D) \\ s.t. \bar{L}_1 w_1 + \bar{L}_2 w_2 &= \bar{w}; \quad L_1 = \bar{L}_1; \quad L_2 = \bar{L}_2 \end{aligned} \tag{A.16}$$

The FOC of the problem is given by:

$$\frac{\partial y_1(w_1, G, D)}{\partial w_1} = \frac{\partial y_2(w_2, G, D)}{\partial w_2} \tag{A.17}$$

Using implicit function theorem one can arrive at the following comparative statics:

$$\begin{aligned} \frac{\partial \pi}{\partial T} &= L_1 \frac{\partial y_1}{\partial T} + L_2 \frac{\partial y_2}{\partial T} \\ \frac{\partial \pi}{\partial \bar{w}} &= y_1^W = y_2^W \\ \frac{\partial^2 \pi}{\partial \bar{w} \partial T} &= \frac{\partial^2 y_1}{\partial T \partial w_1} \frac{L_1 \frac{\partial^2 y_2}{\partial w_2^2}}{L_1 \frac{\partial^2 y_2}{\partial w_2^2} + L_2 \frac{\partial^2 y_1}{\partial w_1^2}} + \frac{\partial^2 y_2}{\partial T \partial w_2} \frac{L_2 \frac{\partial^2 y_1}{\partial w_1^2}}{L_1 \frac{\partial^2 y_2}{\partial w_2^2} + L_2 \frac{\partial^2 y_1}{\partial w_1^2}} \end{aligned} \tag{A.18}$$

Specifically, the cross-derivative of water and temperature on farm profit is a weighted mean of the cross-derivatives for the two restricted profit function, $\frac{\partial^2 y_1}{\partial T \partial w_1}$ and $\frac{\partial^2 y_2}{\partial T \partial w_2}$. Intuitively, no adjustment is made at the extensive margin, then farmers with more water supply are able to achieve larger yields (suffer less loss) at the intensive margin when temperature increases.

Chapter 4

Weather Fluctuations, Expectation Formation, and Short-run Behavioral Responses to Climate Change

4.1 Introduction

There has been widespread interest in the economic literature on understanding the impacts of climate change on economic outcomes and corresponding adaptation measures. A popular approach to do so is to use random weather fluctuations to identify the effects of climate change on economic outcomes, such as agricultural production (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009), gross domestic product (Dell, Jones, and Olken, 2012), and long-run adaptation (Deschênes and Greenstone, 2011). One premise adopted in most studies is that weather fluctuations affect economic outcomes contemporaneously. For example, extreme heat events decrease crop yields (e.g. Schlenker and Roberts, 2009; Lobell et al., 2013), but this negative effect applies only to the particular year in which the extreme heat event occurs. However, under certain circumstances the impact of weather fluctuations in the current year can be carried over into the future. Studies have showed that extreme weather realizations can affect future economic output (Dell, Jones, and Olken, 2012) and induce and intensify political instability, human conflicts and wars in the future (Zhang et al., 2008; Hsiang, Burke, and Miguel, 2013; Zheng et al., 2014; Iyigun, Nunn, and Qian, 2017).

One particular pathway through which past weather fluctuations can affect future economic outcomes is the process of expectation formation. Not only do weather fluctuations affect contemporaneous outcomes, they also shape what people expect for future climate. Both economists and psychologists have established that recent realizations of an event can disproportionately affect human perceptions on the underlying probability of that event happening (e.g. Tversky and Kahneman, 1974; Kahneman, Knetsch, and Thaler, 1991; Camerer and Loewenstein, 2011). Studies have found that subjective expectations to climate are inconsistent with rational behaviors (Cameron, 2005), such that people significantly over-adjust their expectations to climate in response to the occurrence of recent, local, and extreme weather events (Marx et al., 2007; Deryugina, 2013; Konisky, Hughes, and Kaylor, 2016; Lee, Loveridge, and Winkler, 2018). Through expectation formation, economic decisions that require forward-looking inference on climate may be subject to a disproportionately large influence from past weather fluctuations. In that sense, weather fluctuations can cause short-run economic losses due to sub-optimal decision-making based on over-adjusted expectations over climate.

Using agricultural production as an example, we empirically investigate how expectations are formed and updated over previous realizations of weather, and how economic agents adjust and adapt their decision making in response to those shifts in expectations. Agricultural production is uniquely affected by weather fluctuations and the corresponding expectation formation process. Many agricultural production decisions are made prior to the realization of weather. Examples include decisions on acreage, crop allocation, planting time, seed variety, and tillage method. These *ex ante* decisions are made based on subjective expectations over climate rather than the realization of weather. Previous studies have found that climate change induces long-run adaptation in acreage (Cohn et al., 2016; Cui, 2017) and crop-allocation decisions (Seo and Mendelsohn, 2008; Wang et al., 2010, Chapter 3 of this dissertation). This literature usually focuses on the response of farmers to long-run climate normals, which ignores the fact that recent realizations can have a disproportionately large role on subjective expectations to climate. Indeed, other studies have found that agricultural production decisions can also be affected by various types of short-run expectation shifters, among them monsoon patterns (Miller, 2016), spring snowpack forecasts (Manning, Goemans, and Maas, 2017), and previous realizations of temperature (Miao, Khanna, and Huang, 2015), precipitation (Ding, Schoengold, and Tadesse, 2009; Kala, 2017), and water availability (Buck, Auffhammer, and Sunding, 2014). There is scant literature that comments on the specific mechanisms by which previous realizations enter the expectation formation process, how they may affect multiple *ex ante* decisions, and how expectation-induced adaptation can be affected by multiple endowments.

Our empirical analysis focuses on two *ex ante* agricultural production decisions: 1) acreage decisions, i.e., how much land to plant; and 2) crop-allocation decisions, i.e., what type(s) of crop to grow on land in production. We estimate fixed-effect models on acreage, crop allocation, and their aggregate effect using farm-level data for an irrigated, multi-crop agricultural system. We use multiple lags of growing degree days (GDD), extreme degree days (EDD), precipitation, and surface water availability (as governed by prior appropriation water rights) as independent variables to identify the effects of past weather realizations on agricultural decision making. A unique feature of our dataset is that irrigation water is distributed by collective water providers, whose water is acquired under prior appropriation water rights. As such, cross-sectional variation in surface water availability comes from differences in water right attributes held by water providers, whereas time-series variations in surface water availability are mainly governed by stochastic natural inflows that determine the total water supply available to be allocated in the system. Our identification strategy relies on time-series variation for each individual farmer by differencing out cross-sectional variations using fixed effects. This approach allows us to control for average climate and water right attributes, while simultaneously controlling for other unobserved individual-specific heterogeneity, such as risk attitudes that may drive insurance adoption. This allows us to capture the effect of shifting expectations due to individual-specific fluctuations in weather and surface water availability, and the subsequent behavioral responses by that same individual.

Using the above empirical strategy, we test four types of expectation formation mechanisms (heuristics) in this paper. Our starting hypothesis is that farmers form expectations using Bayesian updating from a long history of weather realizations. Bayesian updating dictates that expectations are primarily governed by long-run climate and surface water availability. If Bayesian updating applies, the effect of a recent shock on posterior expectations, and thus *ex ante* production decisions in subsequent years, will be small, time-independent in magnitude, and long-lasting in duration. We test for Bayesian updating versus three other wide-spread heuristics from the behavioral economics literature. Among them are 1) the availability heuristic, which predicts that the effect from recent shocks is time-dependent; 2) the recency heuristic, which predicts that the effect is larger for more recent shocks and dissipates for shocks farther away; and 3) the reinforcement strategy, which predicts the effect to be cyclical.

We assemble a novel farm-level dataset in the Upper Snake River Basin in Idaho spanning 2007-2016. For each farm, we identify the geographical location and match that with high-resolution geospatial datasets documenting field-level cropland acreage, crop allocation, temperature, and precipitation. We separately acquire data on daily water curtailment and deliveries for each farm. To summarize the cumulative effect of crop allocation in multi-crop farms, we estimate expected farm profit as a function of field-scale land allocation, annual crop prices, and region-specific costs of production following Chapter 2 and 3 of this dissertation.

Our results indicate that previous shocks in weather and surface water availability significantly affect both acreage and crop-allocation decisions. On average, an increase in GDD in past years induces adjustments towards extra acreage as well as water-intensive, higher-profit crops, while an increase in EDD in past years reduces cropland acreage but does not significantly change crop allocation. In contrast to temperature shocks, we find that past precipitation shocks do not have significant effects on acreage or crop allocation. We find evidence that farmers respond to all endowment shocks in a cyclical way, but especially so for water availability shocks. A longer water curtailment in prior years leads to under-placement of higher-profit crops in the first year and over-placement in the second year. In the first year following a shock, we do not find a change in cropland acreage, but we find that farmers decrease cropland acreage in the second year and increase cropland acreage in the third year.

These results provide evidence to reject the hypothesis that farmers use strict Bayesian updating over climate and surface water availability. Instead, our results support alternative expectation-formation heuristics to various degrees. We find that the timing of weather and water shocks affect farmers' adaptation strategies, which is consistent with the availability heuristic. Limited evidence supports the recency heuristic, as our model suggests that previous endowment shocks continue to affect farmers' decision making for at least three years and as long as five to six years. Finally, we present evidence that farmers adopt the reinforcement strategy when making inferences on future climate conditions. Responses to previous weather shocks exhibit cyclical behaviors in almost all models, a key characteristic consistent with reinforcement learning.

This study makes several major contributions to the existing literature. First, we show that *ex ante* economic decision-making can be disproportionately affected by past weather fluctuations through cognitive heuristics other than Bayesian updating. This complements the existing literature assessing the economic impact of climate change by demonstrating a mechanism through which past weather fluctuations may affect future economic decisions and outcomes. Second, our study emphasizes the need to incorporate short-run behavioral responses into the assessment of climate change impacts. We show that weather fluctuations create the potential for an over-adjustment cost as farmers overreact to short-run weather signals. The existing approaches to modeling climate change impacts, such as Ricardian regression, contemporaneous fixed-effect, or long-differences, are not able to identify this short-run response. Our results are particularly relevant given that climate change models project a change in long-run averages as well as increased variation, particularly in temperature. As weather shocks become more frequent and larger in magnitude, this over-adjustment cost may also increase. Third, this study links two important threads in the economic literature, one from the behavioral economics literature on learning mechanisms, the other from the climate change economics literature on agricultural adaptation to climate change. Previous studies in these areas either investigate subjective perceptions over climate change without linking them to behavioral responses, or demonstrate adaptive responses to past weather fluctuations without tracing them back to their underlying learning mechanisms.

4.2 Expectation Formation

In the section below, we formally lay out mechanisms by which expectations are formed and updated using previous weather and water availability realizations. Imagine a representative farmer who holds a single natural endowment governed by a random variable W, which is independently and identically distributed (i.i.d) with some mean μ and variance σ^2. The expectation formation process can be generalized as a process of assigning weights to previous realizations, i.e.,

$$E_t(W) = \sum_{s=1}^{T} \beta_s w_{t-s} \tag{4.1}$$

where the expectation of the endowment at time t, $E_t(W)$, is learned from T previous realizations, w_{t-T} to w_{t-1}, with a set of weights $\beta_T, ..., \beta_1$. We present four different types of learning mechanisms in this section: Bayesian updating, the availability heuristic, the recency heuristic, and the reinforcement strategy. All four of them are essentially different sets of weights with respect to previous realizations.

We begin with the Bayesian updating rule, a standard tool used by economists to model rational probability updating behaviors (Camerer and Loewenstein, 2011). The Bayesian updating rule states that an agent's posterior belief is formed by combining its prior belief and the observed data with a specific set of weights, i.e.,

$$Pr(event|data) \propto Pr(event) \times Pr(data|event) \tag{4.2}$$

The validity of the Bayesian updating rule has been extensively examined in the literature. Some studies have found that decision-makers may deviate from strict application of Bayes' Rule (e.g. Barberis, Shleifer, and Vishny, 1998; Charness and Levin, 2005; Rabin, 2002; Chiang et al., 2011), while others confirm that Bayes' rule applies in their application

(Anwar and Loughran, 2011). Nevertheless, the Bayesian updating hypothesis serves as a common starting point for numerous studies on learning and decision-making under risk and uncertainty.

One characteristic of Bayesian updating is that if T is relatively large or if the farmer uses a non-informative prior, then the posterior mean will be close to the maximum likelihood estimator (MLE), which is the sample average over the entire history of previous realizations, $\bar{w}$.[1] We write this as:

$$E_t(W) \simeq \bar{w} = \sum_{s=1}^{T} \frac{1}{T} w_{t-s} \tag{4.3}$$

which indicates that any single year of realization w_{t-s} will shift the expectation by a factor of approximately $\frac{1}{T}$ when T is large.[2] This can be formally written as:

$$\frac{dw_{t-s}}{dE_t(w)} \simeq \frac{1}{T} \quad \text{for any } s \in 1, ..., T \tag{4.4}$$

Several hypotheses can be drawn if the farmer follows the Bayesian updating rule. First, given a long stream of previous realizations, the realization for any single year has a relatively small effect on the expectation. This is because each single realization is diluted by a weight of $\frac{1}{T}$, which results in a small influence on the posterior expectation if T is sufficiently large. Second, no matter how distant (lagged) the realization, each enters the expectation with the same weight. Thus the effect of each realization on the expectation is independent from its timing.

[1] The assumption of a non-informative prior is not needed for our empirical study, because any individual-specific prior will be subsumed by the inclusion of individual level fixed-effects.

[2] The specific form of this weight depends on the shape of the distribution as well as the prior used for inference. For example, if W$\sim$Normal(μ, σ^2), then the weight will be exactly $\frac{1}{T}$. If W$\sim$Bernoulli(μ), then the weight will be $\frac{1}{T+2}$ under a non-informative prior $Beta(1, 1)$.

Literature on cognitive psychology and behavioral economics has pointed out multiple alternative heuristics, i.e., learning mechanisms, that deviate from the strict application of Bayes' rule in belief updating. One such heuristic is the availability heuristic, proposed by Tversky and Kahneman (1974). The availability heuristic describes the phenomenon in which individuals place higher probability on events that are foremost in their memory. For example, recent observation of a car accident increases a person's subjective perception of the probability of car accidents, even if the underlying probability of car accidents remains unchanged. In the case of agricultural production, Marx et al. (2007) found that when drawing inference on weather patterns, Ugandan farmers often turn to familiar patterns from the past two agricultural seasons, or to those happening at the same time as other memorable events, such as the independence of the Republic of Uganda in 1962. In our particular application, the availability heuristic implies unequal weights between different realizations, i.e.

$$E_t(W) = \sum_{s=1}^{T} \beta_s w_{t-s} = \beta_1 w_{t-1} + \beta_2 w_{t-2} + ... + \beta_T w_{t-T} \tag{4.5}$$

where the weights β_s for each realization w_{t-s} are not necessarily equal. A stronger version of the availability heuristic dictates that farmers place higher weights on realizations that happened more recently, i.e., $\beta_1 \geq \beta_2 \geq ... \geq \beta_T$.

A closely related concept is the recency bias, which suggests that farmers draw inference only from experiences in the recent past instead of using the entire history of realizations. Marx et al. (2007) found that farmers use weather information dating back to at most five years when drawing inference on future climate. The recency bias implies a shorter stream of historical realizations are used by the farmer, i.e.

$$E_t(W) = \sum_{s=1}^{S} \beta_s w_{t-s} = \beta_1 w_{t-1} + \beta_2 w_{t-2} + ... + \beta_S w_{t-S} \tag{4.6}$$

where $S \leq T$, such that farmers only use S years of observations instead of T years. Another interpretation of the recency bias is that every realization longer than S years ago has zero weight in the expectation, i.e., $\beta_s = 0$ for any $s > S$. Under recency bias, the average weight of each realization included in the expectation is larger than under the Bayesian updating case, since the farmer now uses fewer observations to infer his/her expectation. Both the availability and recency heuristics cause farmers to under-utilize the history of realizations at their disposal. The end result is that farmers put too much weight on the most recent shocks, and as a result over-react to weather fluctuations comparing to the reaction predicted by Bayesian updating.

Finally, we consider the reinforcement strategy, sometimes referred to as the "win-stay, lose-shift" heuristic. Under the reinforcement strategy, an individual expects a shock they have personally experienced to recur in the future (Roth and Erev, 1995; Camerer and Ho, 1999; Chiang et al., 2011). When a previous realization deviates from the individual's expectation, he/she will expect that positive or negative shock to be carried over to future realizations. Although rational Bayesian updating exhibits some positive feedbacks, reinforcement learning amplifies those feedbacks to a degree that is inconsistent with rational behavior.

We formally express the reinforcement strategy as the farmer over-adjusting his/her expectation by reinforcing the most recent shock, i.e., the difference between the most recent realization, w_{t-1}, and the expectation prior to that realization, $E_{t-1}(W)$:

$$E_t(W) = \sum_{s=1}^{T} \beta_s w_{t-s} + \gamma\big[w_{t-1} - E_{t-1}(W)\big] \tag{4.7}$$

where $\gamma > 0$ measures the magnitude of the reinforcement behavior. Simplifying Equation 4.7 by expanding the previous expectation term $E_{t-1}(W)$ yields:

$$E_t(W) = \sum_{s=1}^{T} \tilde{\beta}_s w_{t-s} \tag{4.8}$$

where $\tilde{\beta}_s$ takes the following form:

$$\begin{aligned} \tilde{\beta}_1 &= \beta_1 + \gamma \\ \tilde{\beta}_s &= \beta_s - \gamma\tilde{\beta}_{s-1} \quad \text{for any } s > 2 \end{aligned} \tag{4.9}$$

Equation 4.9 suggests that the reinforcement strategy causes weights to be cyclical. The key reason for cyclical weights is that the farmer adjusts his/her expectations based on the shock $w_{t-1} - E_{t-1}(W)$. As such, the farmer relies too heavily on the realization in the year prior t-1, w_{t-1}, but puts too little weight on the shock at t-2, w_{t-2}, which was the key component in forming the year t-1 expectation, $E_{t-1}(W)$. Expanding the iterated expectations leads us to conclude that the farmer will also over-utilize w_{t-3}, under-utilize w_{t-4}, etc. If γ is sufficiently large, it is even possible that the weights for even years, i.e., $\tilde{\beta}_2$, $\tilde{\beta}_4$, etc., can become negative.

The mechanism for reinforcement learning can be also understood by linking it with *ex ante* production decisions through a win-stay-lose-shift strategy. Say a farmer perceives a positive shock of precipitation last year (year t-1) relative to what he/she expected. He/she could have planted more acres if he/she knew the shock was going to be exceed the expectation. Using the reinforcement strategy, this year (year t) he/she will over-adjust by planting more acres, in expectation that this year's precipitation is going to be more like last year. This will likely lead to a larger-than-optimal acreage because, on average, precipitation will not be as good as last year. Perceiving a negative precipitation shock for this year, the farmer over-adjusts back to a smaller-than-optimal acreage in the next year (t+1). From the above, we see a positive shock in year t-1, i.e., two years before, can lead to a negative adjustment two years after in year t+1.

We formally write the hypotheses for the four learning mechanisms as follows:

Hypothesis 1 (Bayesian Updating) Given a long stream of previous realizations, the realization from any single year has a relatively small impact on the expectation.

Hypothesis 2 (Bayesian Updating) The timing of the realization is irrelevant with respect to the effect on the expectation.

Hypothesis 3 (Availability Heuristic) Each realization will have different weights in the expectation, depending on how long ago the realization occurred.

Hypothesis 4 (Recency Bias) More recent realizations will have positive weights, whereas more distant realizations will have zero weight.

Hypothesis 5 (Reinforcement Strategy) Past realizations enter the expectation with cyclical weights.

Under the assumption that annual realizations of endowments are randomly drawn from i.i.d climate patterns, the best estimators for the endowments are simply the long-run normals, i.e., the average of realizations over a long period of time.[3] These long-run normals are close to the expectations formed by Bayesian updating, which simply results in a moving average. Indeed, most previous studies use long-run climate normals as an approximation of farmers' expectations over climate (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005; Burke and Emerick, 2016). Since there are minimal shifts in long-run normals from year to year, economic decisions made from Bayesian-updated expectations should not deviate from the optimal decisions, *ceteris paribus*.[4] On the other hand, deviation from strict Bayesian updating leads to expectations that differ from long-run normals, especially if recent realizations are heavily used. As such, we expect that alternative learning mechanisms are likely to result in economic losses due to sub-optimal decision making.

4.3 Data

Our empirical analysis focuses on Water District #1 (WD1) in the State of Idaho, which governs water allocation for the upper Snake River from Minidoka Dam to Milner Dam, as well as tributaries along that segment of the Snake River. WD1 is the largest water district in Idaho, accounting for water deliveries to nine major reservoirs and approximately 350 water users (Olenichak, 2015). Among the 350 water users, around 200 are individual irrigators, and the rest are various forms of collective water management institutions, including public

[3]Climate change shifts the long-run underlying distribution of temperature, precipitation, as well as surface water availability. However these shifts take place over a much longer period of time from the perspective of annual expectation formation, and the magnitudes of the shifts in underlying distributions are minimal compared to variations in the annual realizations of weather. For these reasons we do not consider shifting climate patterns, and instead assume an i.i.d underlying climate distribution. We control for shifting climate patterns using polynomial time trends in the empirical models.

[4]There will still be year-to-year variations at least for crop-allocation decisions because of crop rotation. But similar logic can be readily extended to crop-rotation decisions, i.e. crop rotation patterns are unaffected by recent temperature realizations because they are *ex ante* decisions.

irrigation districts and private irrigation and canal companies. Water is used predominantly for agricultural irrigation in WD1.

We choose WD1 for our analysis because the district operates and keeps the longest and the most accurate information regarding water availability and curtailment decisions in the State of Idaho. Records on daily water calls for each river segment are available dating back to 1988, including detailed information on how water calls are determined (See Olenichak, 2015).[5] Using these records as well as the adjudicated water rights database from Idaho Department of Water Resources (IDWR), we are able to reconstruct daily water availability for every water user within WD1.

We collect data for 589 unique farms for 2007-2016, with information on farm boundaries, attributes for water rights held by respective water providers, and daily water calls. We then spatially match the farms with geo-referenced databases on land use and crop allocation, temperature, and precipitation. Our data assembling strategy is similar to those used in previous studies, including Leonard and Libecap (2016); Browne (2017) and Chapter 2 of this dissertation. Table 2 provides summary statistics.

[Insert Table 4.1 here.]

Surface Water Availability

Irrigation water allocation in WD1 is administered under the prior appropriation doctrine, which is based on the principle of ”first in time, first in right.” Available water in the district

[5] Only Water District #11, the governing body of Bear River, has similar temporal coverage regarding water calls in Idaho. WD11 is not an ideal study site because the river is collectively managed by Idaho, Utah and Wyoming, which leads to complex water right structures.

is prioritized to fulfill senior water rights, or those that are established earlier in time. Junior water rights are curtailed if there is not enough water to fulfill senior water rights in any given day. An individual farmer either possess his/her own water rights, or can receive water deliveries from an irrigation water provider, such as an irrigation district, irrigation company, or canal company. In the latter case, the water provider serves as the "middle-man" between WD1 and the farmer. The water provider acquires water from WD1 through water rights owned in common by all farmers within the district, and distributes water to its members (shareholders).

We obtain daily curtailment records for each farm in our dataset from 1988-2017. Curtailment decisions in WD1 are made using a computerized water accounting model that calculates water availability in each of 36 unique river segments in the district (hereby referred to as "reaches"). Each day, the district calculates water availability over the entire sub-basin. It then issues a cutoff priority date for each reach following the prior appropriation rule, with the goal of allocating all available water to the most senior water right holders throughout the entire district. Figure 4.1 shows the illustrative positions of the reaches in WD1. For each reach, the cutoff priority date corresponds to any water right junior to the last right fulfilled. Depending on the spatial and temporal distribution of water flows in the basin, the cutoff priority date can differ across different reaches and/or on different days. Table 4.2 shows a sample output from the water accounting model on May 20th. On that specific day, reaches on most of the main stem of the Snake River, as well as reaches on upstream tributaries of the Grey River, Salt River, Henry's Fork, and Falls River, share a curtailment priority date of December 14, 1891. Reaches on the Teton River, Willow Creek, as well as the lower main stem of the Snake River have a priority date that differs from the main stem.

[Insert Figure 4.1 here.]

[Insert Table 4.2 here.]

We also construct a database of water right portfolios using administrative records from WD1 and the Idaho Department of Water Resources (IDWR). A water portfolio is a combination of one or more water rights owned by the same farm. Water rights in a water portfolio share the same geographical place of use, with each water right having (potentially) different priority dates, diversion points, and diversion rates.[6] Almost all collective irrigation institutions hold a water portfolio that contains multiple water rights. We then combine water curtailment records with the water portfolio database, from which we are able to determine daily curtailment decisions for each water portfolio. Although curtailment decisions for a single water right are binary on any given day, i.e. either curtailed or filled, a water portfolio with multiple water rights may be partially filled, with some water rights in the portfolio curtailed and others fulfilled. We characterize daily curtailment decisions for a water portfolio as the percentage of permitted diversions.

Since acreage and crop allocation decisions are made over the entire growing season, we need to aggregate daily curtailments into annual realizations. In order to fully characterize water availability over the entire year, we count the annual number of curtailment days using 12 distinct measurements by combining the following three characteristics: 1) total number of days (TND) curtailed vs. longest curtailment streak (Streak); 2) Growing Season (April to October) vs. Summer Months (June to August); and 3) 100% vs. more than 80% vs. more than 50% percent of permitted diversions curtailed.

Our dataset on curtailments improves upon previous studies on prior appropriation water rights in both spatial and temporal coverage. In terms of spatial coverage, previous

[6]Geographical boundaries are extrapolated from the water rights place of use (WRPOU) database from IDWR. Diversion point, diversion volume, and priority date are from Olenichak (2015). These two are then merged through common water right numbers.

studies usually proxy the underlying distribution of curtailments through direct comparison of priority dates (Lee, Rollins, and Singletary, 2017) or some order-preserving transformation over priority date (Xu, Lowe, and Adams, 2014; Brent, 2017, Chapter 2 of this dissertation). Yet priority date only preserves the order of water seniority within each reach, but can differ widely in the probability distributions of curtailment across reaches and sub-basins.By directly measuring water availability using curtailment records, we eliminate the concern that spatial heterogeneity in water availability for the same priority date across reaches may be correlated with some location-specific unobservables, which can potentially bias statistical inferences in previous studies. In terms of temporal coverage, most previous studies rely on time-invariant attributes of water rights (e.g. Mukherjee and Schwabe, 2015; Brent, 2017; Lee, Rollins, and Singletary, 2017, Chapter 2 of this dissertation) or some long-run expectations over water delivery (e.g. Schlenker, Hanemann, and Fisher, 2007), which cannot capture dynamically evolving expectations over water deliveries. Two exceptions are Buck, Auffhammer, and Sunding (2014) and Manning, Goemans, and Maas (2017), which measure the amount of water delivered and called, respectively, over a growing season at the county level. Our dataset improves upon those two by quantifying variation at the level of the water right and by creating various measures of water curtailment attributes.

Farm Boundaries

Farm boundary data were purchased from FarmMarketID, a private firm that collects data on farm characteristics for marketing purposes. We obtain geo-referenced farmland ownership in year 2016, where each farm in our sample owns one or more common land units (CLU).[7]

[7] According to the definition from USDA-Farm Service Agency, a CLU is an individual contiguous farming parcel, which is the smallest unit of land that has four characteristics: 1. a permanent, contiguous boundary; 2. common land cover and land management; 3. a common owner, and/or 4. a common producer association.

For the purpose of this study, we use farms that are serviced by only one collective water provider, either an irrigation district or an irrigation or canal company.[8] By doing so, we exclude farms that have access to any individual water rights, or those that are within the service boundaries of more than one water provider. These measures ensure that water availability and farm boundaries are clearly defined for the farms in the analysis. Figure 4.2 shows illustrates the locations of the farms included in our analysis.

[Insert Figure 4.2 here.]

We make several assumptions regarding water rights and farm boundaries. First, we assume that farm boundaries remain constant from 2007-2016. Due to data availability constraints, we are unable to obtain farm boundaries earlier than 2016. We do not expect this to jeopardize our main inference if farmland sales are accompanied by the sale of corresponding right(s) to be serviced by water providers, which is usually true. Second, We assume that within each irrigation district, water is allocated proportionally to each farm. This assumption is widely adopted by previous studies, including Schlenker, Hanemann, and Fisher (2007) and Buck, Auffhammer, and Sunding (2014). Our main inference will not be jeopardized as long as water is not allocated using a seniority-based system within each irrigation district. As Chapter 2 of this dissertation documented, water within irrigation districts is usually allocated to members in proportion to the share(s) owned by each. Similar share systems are widely adopted by irrigation and canal companies in our sample.[9]

[8] We define this using the criteria that over 90% of the total land mass of the farm is covered by that provider.

[9] Personal communication with Brian Olmstead, General Manager of the Twin Falls Canal Company, 6/16/2016.

Acreage and Crop Allocation

Acreage and crop-allocation data are obtained from the USDA Cropland Data Layer (CDL), a field scale remote sensing product developed for the continental U.S. using satellite imagery and calibrated classification algorithms. For each farm, we identify the percentage of land allocated to six major crops in the region: alfalfa, barley, corn, potato, sugarbeets, and wheat, as well as land in fallow. These six crops and fallow account for over 98% of the total land area allocated to agriculture in WD1 (National Agricultural Statistics Service, 2007-2016). Therefore, we do not expect the exclusion of lands in other crops to affect our results. Our farm level fixed-effect approach offers additional safeguards against omitted crop types as well as general misclassification in the CDL, as time-invariant mis-classifications will be eliminated by the transformation.

Climate and Weather

We obtain daily temperature and precipitation data from the PRISM climate dataset, a medium-scale geo-referenced weather dataset. PRISM has been used extensively in previous studies on climate change, such as Schlenker, Hanemann, and Fisher (2007). Growing degree days (GDD), extreme degree days (EDD), and growing season precipitation are inferred from PRISM data by accumulating daily temperature and precipitation over the growing season. Following previous economic literature, we evaluate GDD using cutoffs of 8°C and 32°C (Ritchie and NeSmith, 1991) because temperatures in that range are generally beneficial to crop growth (Schlenker and Roberts, 2009). We calculate EDD using a cutoff temperature of 32°Cbecause extreme heat above that level is detrimental to crop development(Lobell et al., 2013; Burke and Emerick, 2016). We calculate growing season precipitation as the cumulative amount precipitation between April and September, which reflects the standard duration of the growing season in the region.

4.4 Empirical Strategy

Our empirical question examines how previous realizations in weather and water availability, transmitted through the expectation formation process, affect agricultural producers' *ex ante* decision making. We model three outcomes of interest in our empirical models: 1) the fraction of non-cropland, which reflects a farm's decision to expand or shrink farm acreage on marginal lands; 2) the expected profit on land in crop production, which reflects aggregated differences in expected profit due to crop-allocation decisions; and 3) total expected profit, which summarizes both cropland acreage and crop-allocation decisions. Expected profit is constructed as a function of field-scale crop allocation decisions, annual state-level crop prices, and region-specific costs of production.[10] All three outcome variables reflect farmers' *ex ante* production decisions undertaken early in the growing season.

We first motivate our econometric strategy conceptually. One inherent problem for many agricultural decisions, such as acreage and crop allocation, is the timing mismatch between decision making earlier in the growing season and the realization of key endowments later during the season. In the planting stage of year t, farmer i maximizes expected profit, $E_{it}\Pi(\mathbf{y}_{it};\mathbf{W})$, by making *ex ante* production decisions, $\mathbf{y}_{it}$, based on his/her subjective expectations over a vector of J natural endowments $E_{it}\mathbf{W}$, $\mathbf{W} \equiv W_1, ..., W_J$. At harvest, realizations of climate and water at year t, $\mathbf{W}_{it}$, are observed, and the farmer earns

[10]We assume zero profit from fallowed cropland as well as non-cropland. This simplification is necessary since we do not have data on yield gains following fallow or on profit from non-agricultural land uses, such as grassland or forests.

profit $\Pi(\mathbf{y}_{it}; \mathbf{w}_{it})$. Assuming that the marginal effects of endowments are separable from each other, previous studies have shown theoretically that under certain conditions, the first-stage maximization problem yields a series of linear marginal effects between optimal production decisions and the expected level of endowments (Moore and Negri, 1992; Cui, 2017, Chapter 3 of this dissertation).[11] Our conceptual model can be written as:

$$\begin{aligned} y_{it} &= \sum_{j} \alpha_j E_{it}(W_j) + \gamma \mathbf{X}_{it} \\ E_{ijt}(W) &= \sum_{s=1}^{T} \beta_{js} w_{i,j,t-s} \end{aligned} \tag{4.10}$$

where the farmer's decision y_{it}, is a linear function of expectations over each natural endowment $E_{it}(W_j)$, and a set of control variables $\mathbf{X}_{it}$.

The expectation formation process follows Equation 4.8, where each of the previous T shocks, $w_{i,j,t-s}$, contributes to the expectation with a weight of β_{js}. These unspecified weights nest the four learning mechanisms presented in the previous section. Combining the two steps and adding in different types of natural endowments, our final empirical equation becomes:

$$\begin{aligned} y_{it} =& \sum_{s=1}^{T} \beta_{1s} \text{GDD}_{i,t-s} + \sum_{s=1}^{T} \beta_{2s} \text{EDD}_{i,t-s} + \sum_{s=1}^{T} \beta_{3s} \text{Precipitation}_{i,t-s} + \sum_{s=1}^{T} \beta_{4s} \text{IrrigationWater}_{i,t-s} \\ &+ \mu_i + f(t) + \varepsilon_{it} \end{aligned} \tag{4.11}$$

where y_{it} is the outcome of interest for farm i at year t; $\text{GDD}_{i,t-s}$ is the s years' lag of growing degree days; $\text{EDD}_{i,t-s}$ is the s years' lag of extreme degree days; $\text{Precipitation}_{i,t-s}$ is the s

[11] The separability assumption has first order impact on a farm profit model (Fezzi and Bateman, 2015; Hendricks, 2018), but second order impact on a production decision model (Chapter 3 of this dissertation). Thus assuming separability is likely to have minimal impact to our result.

years' lag of growing season precipitation, and Irrigation_Water$_{i,t-s}$ is the s years' lag of irrigation water availability, which depends on water curtailments under prior appropriation. The model also includes a farm-level fixed effect μ_i and a five-degree polynomial time trend $f(t)$. Here the coefficient of lag s for endowment j, β_{js}, identifies the product of the marginal effect of an endowment on the decision, α_j, and the lag-specific weight, β_{js}, both of which appear in Equation 4.10. We are not able to separately identify α_j and β_{js} from our empirical model in Equation 4.11, but since α_j remains constant for each endowment over time, we are able to identify the relative weights for different lags.

Equation 4.11 can be used to test for all four learning mechanisms we have laid out in the previous section. Specifically, if a farmer is a Bayesian updater using long history, we expect all lagged coefficients on an endowment to be equal, and to be non-different from zero, i.e., $\beta_1 = \beta_2 = ... = \beta_T \simeq 0$. If a farmer engages in availability heuristic, we expect coefficients to be larger when the shocks happen closer to the current period, i.e. $\beta_1 \geq \beta_2 \geq ... \geq \beta_T$. If a farmer engages in recency heuristic, we expect coefficients to be different from zero for lags closer to the current period, but to be non-different from zero for lags farther away from the current period, i.e., $|\beta_s| > 0$ for some $s \leq S$ and $\beta_s \simeq 0$ for $s > S$. If a farmer engages in reinforcement heuristic, we expect coefficients to be cyclical, as documented in Equation 4.8 and 4.9.

We employ a panel fixed-effect approach to identify our main effect of interest by exploiting time-series variation in previous weather and water availability shocks for each individual. This approach offers two advantages over cross-sectional methods. First, by only comparing the same individual at different time periods, we are able to simultaneously control for the effect of location-specific average temperature and precipitation, as well as water-right-specific average curtailments. Although realizations of water availability vary from year to year, the underlying water portfolios for the same farm remain constant, and thus the long-run mean water availability should also remain constant.[12] Second, since weather and water availability shocks are plausibly random, we eliminate concerns about time-invariant omitted variable biases, which plague empirical studies using cross-sectional regressions (Blanc and Schlenker, 2017).

One potential confounding factor for our empirical approach is the role of crop insurance in protecting farmers against weather-related crop losses. Studies have shown that subsidized crop insurance provides a disincentive to adapt, such that producers significantly under-adjust to climate change, and as a result suffer greater sensitivity to extreme heat (Annan and Schlenker, 2015). Data on crop insurance at the scale of individual farm are not available to us. However, we do not believe that omitting insurance from the model will significant undermine our results. This is because our inclusion of individual fixed effects soaks up any time-invariant determinants of insurance adoption, such as risk attitudes, soil conditions, or long-run climate and water conditions. At the same time, our flexible time trend controls for potential structural changes in crop insurance, such as changes in premium or subsidy rates. In addition, even if insurance adoption is time-varying and correlates with weather shocks, omitting insurance adoption will only understate the impact of climate expectations on agricultural decision-making, because insurance adoption is likely to discourage adaptation than encourage it. For example, a bad weather shock encourages insurance adoption, which in turn discourages the farmer from shrinking acreage or switching to a less profitable crop allocation. In this sense, insurance adoption counter-balances over-adjustment by hedging against the risk of weather shocks. As such, if we are still able to find significant responses to short-run weather, our result will be robust from the influence

[12] Water portfolios were established from the late 1800s through the mid-1900s and rarely include new rights with priority dates after year 2000. These newer water rights have close to zero probability of receiving water during the growing season. Thus we can safely claim that water portfolios remain largely unchanged during our study period.

of crop insurance.

The effect we capture here differs from those recovered in popular empirical approaches, including the Ricardian approach (e.g. Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005), the long-difference approach (e.g. Burke and Emerick, 2016; Mcwilliams, 2016), and the contemporaneous fixed-effect approach (e.g. Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). The Ricardian approach draws inference from cross-sectional variation in climate, which recovers the long-run difference in economic outcomes for different individuals as well as any corresponding adaptation responses. Similarly, the long-difference approach also recovers the long-run impact of climate, but through time-series variations in long-run climate normals for the same individual. Our approach is most similar to the contemporaneous fixed-effect approach, yet there are still subtle differences between the two. The contemporaneous fixed-effect approach recovers the impact of weather shocks on contemporaneous economic outcomes, as well as any short-run adaptation responses that are contemporaneous or *ex post* to weather realizations. In contrast, our approach captures short-run adaption responses prior to weather fluctuations by using fixed-effect models with lagged dependent variables. In addition, our approach directly tests for the effect of weather fluctuations on resource-allocation decisions, while most contemporaneous fixed-effect studies focus on the combined effect of these decisions and actual weather and water availability, such as crop yield or revenue.

Variable Selection

While the economic literature has examined many approaches to summarizing climate variables, there is limited guidance as to which aggregation method(s) best approximate the effect of water availability on agricultural production. That is why we create 12 variables that characterize three aspects of the water curtailments, namely the percentage of water curtailed relative to permitted diversions (50%, 80% vs. 100%), the time frame of the aggregation (growing season vs. summer), as well as measuring streaks versus total number of days (Streak vs. TND). Yet having multiple measurements of water availability means that we need to carefully select which measurement to be included in empirical models. Including multiple measurements for the same year is problematic because these measurements are highly correlated. To choose systematically which among these multiple measurements of water availability to include in the empirical model, we turn to machine learning techniques.

We use a class of shrinkage estimators known as generalized lasso (least absolute shrinkage and selection operator). Shrinkage estimators reduce the set of variables by penalizing redundant variables through a regularizing function (Hastie, Tibshirani, and Friedman, 2009). Formally, the shrinkage estimator can be written in the following form:

$$\hat{\boldsymbol{\beta}} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} (y_i - \sum_{j=1} p x_{ij} \beta_j)^2 + \lambda R(\boldsymbol{\beta}) \tag{4.12}$$

where the coefficients $\boldsymbol{\beta}$ are estimated by minimizing the square loss function plus a regularizing function $R(\boldsymbol{\beta})$ times a penalty parameter λ. Common regularizers used in the literature include the L1-norm, i.e. $R(\boldsymbol{\beta}) = ||\beta||_1 = \sum_{j=1}^{p} |\beta_j|$, which corresponds to the lasso estimator; and the L2-norm, i.e., $R(\boldsymbol{\beta}) = ||\beta||_2 = \sum_{j=1}^{p} \beta_j^2$, which corresponds to the ridge estimator. In general, the lasso estimator shrinks coefficients faster towards zero than the ridge estimator. The lasso estimator is known to perform poorly under multicollinearity, while the ridge estimator alleviates the multicollinearity problem.

To simultaneously overcome variable shrinkage and the multicollinearity problem, we use a hybrid version of lasso and ridge estimator, known as the elastic net regression (Zou and Hastie, 2005). Elastic net regression uses a regularizer of $R(\boldsymbol{\beta}) = (1-\alpha)||\beta||_2 + \alpha||\beta||_1$, with α defined as the elastic net mixing parameter. In the special case when $\alpha = 1$, elastic net converges to ridge regression; in the case when $\alpha = 0$, elastic net converges to lasso regression. In order to mimic the fixed-effect approach in our main model, we fit a elastic net regression using within-transformed independent and dependent variables at the farm level. Since our focus is mainly on water availability variables, we include all 12 measurements of water availability for the current year, eight lagged years, and one lead year. We also include GDD, EDD and precipitation for three lagged years, and time trends as a fifth-degree polynomial. We fix the elastic net mixing parameter $\alpha = 0.5$ to balance the tradeoff between multicollinearity and variable shrinkage, and tune the penalty parameter λ by comparing out-of-sample performance using 10-fold cross validation for different values of λ. The optimal λ is then selected by the "one-standard-deviation" rule suggested by Hastie, Tibshirani, and Friedman (2009).

The elastic net procedure points us towards a subset of candidate variables to include in the empirical model. We then run a fixed-effect regression using variables that have been selected using the elastic net. We refer to this as the naive "post-elastic-net" model. Our main econometric model is selected by including one measurement of water availability for each lagged year that has the most predictive power in the post-elastic-net model. If for some years, none of the measurements are selected using the elastic net procedure, we include a measurement for that year with a different set of aggregation methods from its neighboring lagged years to minimize multicollinearity. Our final models include three lags for GDD, EDD, and precipitation, and five lags for water availability.

4.5 Results

Results from our main model are presented in column (1) of Table 4.3, 4.5 and 4.6. We first presents results on crop-allocation decisions in Table 4.3. Our main model (column 1) suggests that among the three weather variables, crop-allocation decisions only respond to shocks in GDD. A one degree-day increase in GDD increases expected farm profit by 0.13/acre for both the first and the third lag. The second lag in GDD has a negative sign and is not statistically significant. The impacts of EDD and precipitation on crop allocation are not significant for all three lags.

[Insert Table 4.3 here.]

We find that short-term reactions to water availability exhibit cyclical patterns. The first and third lag of water curtailment days have negative and significant impacts on crop allocation, while the second and fourth lag have positive and significant impacts. The fifth lag is not significant. This is to say, farmers react to an increase in curtailment days by planting less profitable crop mixes in the first and third year, but more profitable crop mixes in the second and the fourth year. To facilitate comparison of the results for different water availability measurements, we calculate the discrete effect of a one-standard-deviation shift in each measurement, and present that in column (1) of Table 4.4. We find that a one-standard-deviation increase in water curtailments decreases expected farm profit by \$16.6/acre in the first year, increases it by \$21.3/acre in the second year, decreases it by \$19.0/acre in the third year, and increases it by \$23.07/acre in the fourth year.

To see the aggregate effect of a water curtailment shock on *ex ante* production decisions, we generate two measures of the medium-run impact. The first measure involves summing up estimates of the discrete effects for the first three lags or all five lags. This is presented in Table 4.4. We find that the aggregate impact of a water shock is negative and significant when adding up the first three lags, but is not significant for the sum of all five lags. The significance for the three-year lag is an artifact of the number of estimates included in the summation: the three-year summation include two lags with a negative effect on crop allocation, but only one lag with a positive effect on crop allocation, which results in a net negative effect across years. For the five-year lag, the number of positive and negative lags more closely offset one another, resulting in a statistically insignificant aggregate result. Based on the five-year result, it is reasonable to view the cumulative effect of a water curtailment shock as neutral in the medium run.

The second method we use to measure a medium-run effect is to re-estimate the model using three-year moving averages (MA3) as independent variables instead of the first three lags. The results using this approach are presented in column (3) of Table 4.3. We find that the MA3 of water curtailment is statistically insignificant. This corresponds to our result that water availability has no statistically significant aggregate impact on crop-allocation decision in the medium run.

[Insert Table 4.4 here.]

We present the results for acreage decisions in Table 4.5. We find that a one-unit increase in EDD for the first and third lags significantly increases non-cropland acreage by 0.24% and 0.23%, while the second lag is insignificant. A one-unit increase in GDD for the first and third lags significantly reduces non-cropland acreage by 0.05% and 0.02%, while the second lag is again insignificant. The direction of the effect for both GDD and EDD are as expected: greater GDD increases crop yields, which encourages the allocation of marginal lands to crop production; greater EDD decreases crop yields, which discourages the use of marginal lands in crop cultivation. Precipitation has a positive effect on non-cropland acreage for the first lag, but not for the second and the third lag.

[Insert Table 4.5 here.]

We also find that shocks in water curtailments significantly affect non-cropland acreage. We find that the second lag and the fifth lags are positive and significant, the third lag is negative and significant, and the first and fourth lags are insignificant. We find that a one-standard-deviation increase in water curtailment in the second lag increases non-cropland area by 3.7%, which is the largest effect for all five lags. A one-standard-deviation increase in water curtailment also decreases non-cropland area by 1.2% for the third lag, and increases non-cropland area by 1.7% for the fifth lag.

Similarly to the acreage model, we generate two aggregate measures for the medium-run effects on acreage in production. When adding lags up, we find that decreasing water availability significantly decreases cropland acreages in the medium run (three or five years). A one standard-deviation increase in water curtailments significantly increases non-cropland area by 3.3% over three years, and 5.9% over five years. The MA3 model depicts a similar story (presented in column (3) of Table 4.5), where the MA3 for water curtailment is positive and significant. The direction of effect for water curtailment is such that less secure water availability leads to fewer acres planted. The benefit from reducing acreage planted is that it allows for an increase in irrigation intensity on existing lands in production when holding the total amount of available water constant.

Finally we turn to the models of total profits, presented in Column (1) of Table 4.6.[13] We find that all three weather variables have significant impacts on total profits, which capture the combined effects of crop allocation and acreage. A one-unit increase in the first

[13] The reader is referred to Table A1 for a demonstration of the post elastic-net results, which we use to select water curtailment variables.

and third lags of EDD significantly decreases total profit by \$0.809 and \$0.717 /acre, and the second lag of EDD is not significant. A one-unit increase in the first and third lags of GDD significantly increases total profit by \$0.218 and\$0.128 /acre respectively, and the second lag of GDD is not significant. In contrast, a one millimeter increase in precipitation is insignificant for the first and third lags, but the second lag increases total profit by by \$0.221/acre.

[Insert Table 4.6 here.]

We again find evidence of a cyclical response in total profit to water availability shocks. Water curtailment days have negative effects on total profit for the first, third, and fifth lags, and have positive effects for the second and fourth lags. A one-standard-deviation increase in curtailment days significantly decreases total profit by \$11.57/acre in the first year, increases it by \$11.74/acre in the second year, and increases it by \$10.70/acre in the fourth year. The third and fifth lags are not statistically significant. We again generate two aggregate measures for the medium-run impacts on total profit. By adding lags up, we find that water availability has statistically insignificant impact on total farm profit over both three- and five-year time horizons. This result holds for the MA3 model.

Overall, we find that agricultural producers significantly respond to recent shocks in natural endowments by changing *ex ante* production decisions in the short run. These responses generally differ between different kinds of natural endowments. A GDD shock has a positive effect on total profit, which comes from expansion in cropland acreage combined with a more profitable crop allocation. An EDD shock has a negative impact on total profit, which comes solely from a reduction in cropland acreage, but not from a change in crop allocation. A precipitation shock has a positive effect on total profit, which arises from a reduction in cropland acreage, but a shift towards more profitable crops. A water curtailment shock shrinks cropland acreage, but has no impact on crop allocation or total profit over the medium run.

Expectation Formation Mechanisms

Our results suggest that agricultural producers deviate from the Bayesian learning hypothesis in several ways. First, we find *ex ante* adaptation behaviors significantly respond to previous shocks in endowments. Responses to previous shocks are persistent across different types of endowments, as well as across different adaptation mechanisms. This contradicts the hypothesis that farmers' expectations are formed through Bayesian updating using a long history of realizations, and the hypothesis that the expectations are drawn from long-run normals. Second, we find that the magnitudes of adaptation responses vary widely for different lags. This further contradicts the Bayesian updating hypothesis, which suggests that each lagged realization should enter the posterior expectation with equal weight.

Instead, we find evidence that suggests, to varying degrees, support for alternative heuristics. All three models are consistent with the availability heuristic, which states that different lags enter the expectation formation process with different weights. However we find limited evidence to support the stronger version of the availability heuristic, which states that more recent shocks carry greater weight than more distant shocks. Coefficient estimates for the first lag of GDD are significantly larger than the rest of the lag in the overall profit and acreage models, and so is the coefficient estimate for the second lag of water curtailment in the acreage model. However, coefficient estimates for GDD and water curtailment in the other models, and for EDD and precipitation in all models, do not exhibit this pattern.

We also find mixed evidence with respect to the recency heuristic, which predicts that more distant lags will not be considered as part of the expectation formation process. For GDD, EDD, and precipitation, we find no support for the recency heuristic over the course of three lags. In multiple models regarding weather variables, we are able to reject the hypothesis that the third lag is different from zero. For water curtailment, we find significant responses to the first three lags. Coefficient estimates on water curtailment fall to zero by lag five for the overall profit and crop-allocation models, and at lag six for the acreage model. This suggests that farmers' expectation formation processes at least incorporate endowment shocks for the last three years, and most likely considers shocks over five to six years.

We find evidence consistent with some form of reinforcement learning, which predicts that previous shocks enter expectations in a cyclical fashion. The cyclical pattern appears for all four variables: GDD, EDD, precipitation and water availability, and in multiple models. For GDD, the first and the third lags are large in magnitude, while the second lag are small. The same pattern holds for EDD, though (as expected) the direction of adjustment is the opposite from that of GDD. The cyclical pattern in lags is best illustrated by the estimated coefficients for lagged water curtailments on crop-allocation decisions, which exhibits the strongest cyclical pattern. In the first year, the farmer reacts to a drought by adjusting the crop allocation towards less water-intensive (and lower profit) crops. This is likely an over-reaction since the long-run distribution of water curtailment has not changed significantly. In the second year, the farmer realizes that his/her strategy under-performs by planting too little to water-intensive crops, and over-correct his/her belief and plant more water-intensive crops. In the third year, the farmer under-performs again by planting too much of the water-intensive crop comparing to the long-run normals, and again over-corrects in the opposite direction. As such, the reinforcement strategy causes the farmer to move back and forth in his/her expectations and the corresponding adjustments in crop mix.

The three alternative heuristics capture more pronounced reactions to weather and water shocks over the very short run, relative to the Bayesian expectation formation process. We argue that using medium or long-run differences to estimate the impact of climate change, such as is common in Ricardian regression or the long-difference method (Burke and Emerick, 2016; Mcwilliams, 2016), may fail to capture this effect. The problem is especially severe if reinforcement learning dominates the learning process, as we have seen for shocks in water curtailment. While there exists cyclical patterns of water curtailment on crop allocation and overall profit, the effects are masked completely in the MA3 models. This observation echoes that in Buck, Auffhammer, and Sunding (2014), which suggests that farmland prices are only significantly affected by water delivery shocks by the first two orders of moving averages, but not by MA3 or higher orders of moving averages.

Predictability of Weather Fluctuations

So far, we have assumed that conditional on individual-specific long-run normals, shocks in the realizations of weather and water availability cannot be predicted. This assumption justifies our claim that short-run adaptation to endowment shocks are over-reactions due to behavioral heuristics rather than rational responses based on predictions of weather and water curtailments. In the following section, we check for two possible violations that could undermine this assumption. We find our assumption to be valid for both cases.

First, we test whether the current endowment shock can be predicted by previous shocks, with a specific focus on water availability. While the realizations of temperature and precipitation are largely random, one could argue that water availability is temporally dependent. For example, if a water provider engages in inter-year water management, then water shortage/abundance in one year can be carried over to the next year through water storage decisions.

We check this possibility using a leave-one-out validation strategy. For each year from 2007-2016, we train a best prediction model using data for the past 15 years, and omit the year in question. The prediction model is constructed using the elastic net algorithm with 10-fold cross-validation, identical to what we use for variable selection. We then use the post-elastic-net prediction model to generate a prediction for the water curtailment shock, and compare that with the actual shock for the year we have left out. If the predictive model is able to explain some variations for the current shock, then our assumption is violated.

Table 4.7 presents the result for the leave-one-out strategy. Though the models performs well on in-sample prediction, they perform poorly for the year we have left out. All prediction models increases the variations for the test sample rather than decreasing it, indicating that these models have no predictive power over future water curtailments. Thus, previous shocks to water realization cannot be used to accurately predict the shock in an upcoming growing season.

[Insert Table 4.7 here.]

Second, we check whether current endowment shocks can be predicted by some factors that are unobserved or omitted by our model. For example, temperature and precipitation can be predicted using El Nino/La Nina cycles. We are especially worried about omitting spring snowpack in our model, as Manning, Goemans, and Maas (2017) have shown that spring water forecasts can affect farmers' expectations on summer water calls, and thus alter their *ex ante* planting decisions in spring. If these factors are also correlated with previous endowment shocks, then our estimates will be biased.

We address this concern by directly including current endowment shocks in our model as a placebo test. If the current shock is somehow predictable at the time of planting, for example by spring water supply forecast, we should see significant adaptation responses to the current shock. Column (2) of Table 4.3, 4.5 and 4.6 presents the results. We find that current year shocks in water availability have no effect on farmers' *ex ante* production decisions in all three models. The same applies to current year shocks in GDD and EDD. In fact, 11 out of 12 current-year shock variables are statistically insignificant. This evidence suggests that our results are unlikely to be influenced by unobserved predictive capacity.

4.6 Conclusion

A weather fluctuation is the realization of climate at a certain point in time, but the economic impacts of weather fluctuations have the potential to affect agricultural production for growing seasons into the future. In this study, we show that past weather fluctuations can affect future agricultural decision making through the mechanism of expectation formation. Using a fixed-effect approach, we find significant behavioral responses in acreage and crop-allocation decisions to past shocks in natural endowments, including temperature, precipitation, and water availability. This suggests that instead of using rational Bayesian learning, agricultural producers use alternative learning mechanisms that rely more heavily on recent weather realizations than on long-run normals. This weighting of recent realizations can result in economic losses if farmers over-react to recent signals by making acreage and crop-allocation decisions that are sub-optimal relative to those made under expectations based on a longer and more representative history of weather observations.

There are several policy implications that follow from this study. First, our results stress the need to incorporate short-run behavioral responses into the assessment of climate change impacts. Economic decisions are made by agents who are prone to various cognitive biases when evaluating future uncertainties. Assuming textbook rationality from economic agents overlooks an important behavioral response to weather fluctuations. Second, our study shows that the impact of climate change is caused not only by shifts in the mean, but also by shifts in climate variability. As the magnitude of weather fluctuations becomes larger, so do shifts in the subjective expectations over future climate, which may increase the economic losses from short-run behavioral responses. Third, our study provides an example of the economic value of information regarding future uncertainty. Reliable forecasts of future climate and water availability, in the form of long-run climate normals, spring snowpack forecasts, monsoon or El Niño patterns, as well as extension programs that focus on the proper use of these sets of information, reduce biases when predicting future weather and water realizations. As a result, access to these types of information can alleviate the economic losses induced by cognitive biases from the expectation formation process.

This study can be extended in several directions. First, our study can be used as a foundation to consider other types of *ex ante* adaptation decisions that require forward-looking inference regarding climate or other types of uncertainty. For example, one could consider the effect of a recent heat wave on the adoption of irrigation, farmland value, or air-conditioner purchases. All of these behaviors require agents to form expectations over future climate, which are subject to the influence of recent shocks. Second, it remains an important empirical question to provide quantitative estimates on the economic losses from over-adjustment. For this study we show only the behavioral changes due to weather fluctuation, but we do not estimate the associated economic losses. Evaluating the latter question requires field level crop-specific yield data, which we do not have at this time. Future research can try to quantify these welfare through the use of of new remote sensing methods to capture field-level crop yield observations (Donaldson and Storeygard, 2016; Chance et al., 2017).

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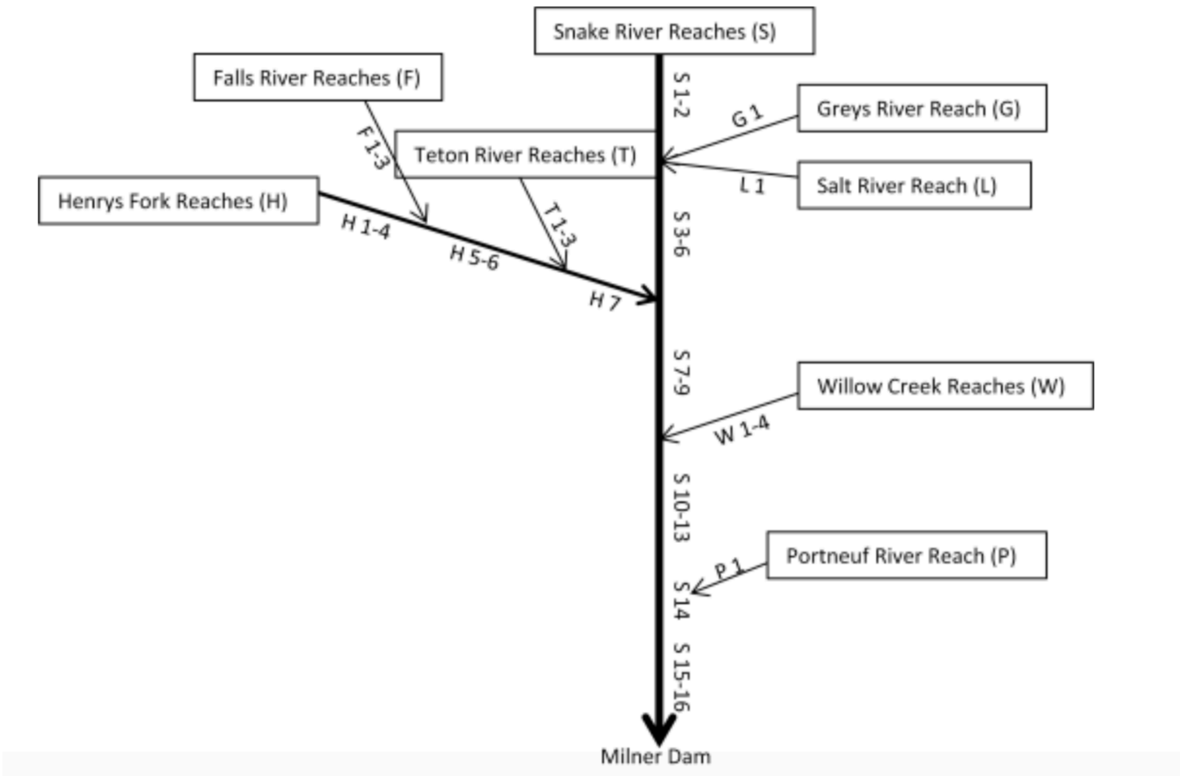

Figure 4.1: Schematic Illustration of Relative Positions of Snake River and Tributary Reaches in the Upper Snake River Basin (from Olenichak, 2015).

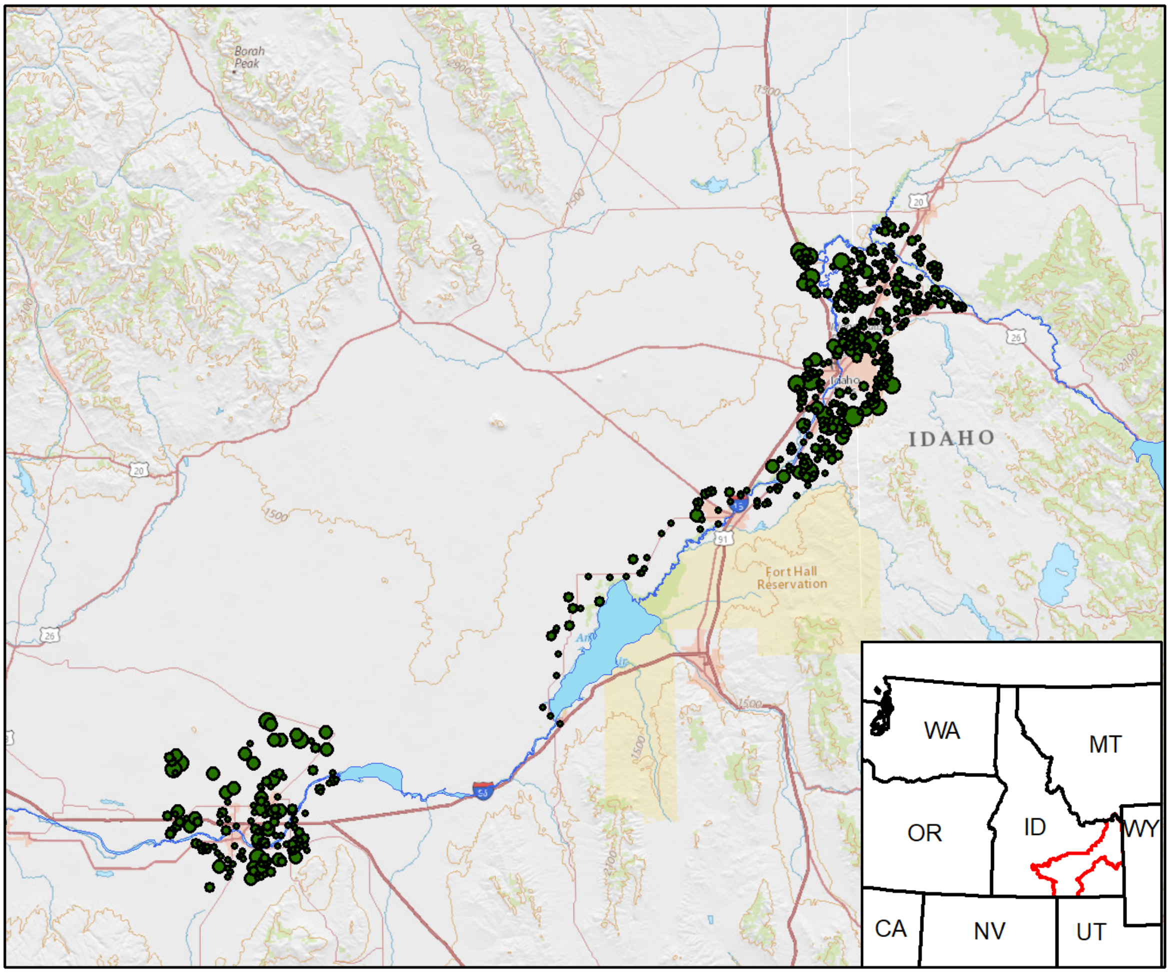

Figure 4.2: Map of Farms in WD1. Each green dot denotes one farm. Size of the dot indicates relative size of the farm. Blue line denotes the main stem of the Snake River. Lower-right panel denotes the relative location of water district 1 (Red line denotes the boundary of the district.)

Table 4.1: Summary Statistics of Variables

	mean	median	min	max	std_dev
Overall Expected Profit	191.57	183.28	0.19	686.28	114.17
Expected Profit from Cropland	240.01	248.04	4.41	686.28	118.72
% Area Not Cropland	0.20	0.13	0.00	0.99	0.21
Growing Degree Days	1370.96	1357.72	1017.66	1739.65	158.00
Extreme Degree Days	31.52	23.99	1.43	144.44	25.47
Growing Season Precipitation	137.18	134.35	31.38	264.42	51.14
No. Days, 100% Curtailment, Season	43.02	0.00	0.00	214.00	66.32
No. Days, 100% Curtailment, Summer	21.28	0.00	0.00	92.00	31.82
Longest Streaks, 100% Curtailment, Season	34.56	0.00	0.00	214.00	54.65
Longest Streaks, 100% Curtailment, Summer	19.60	0.00	0.00	92.00	30.16
No. of Days, 50% Curtailment, Season	63.72	53.00	0.00	214.00	63.88
No. of Days, 50% Curtailment, Summer	34.17	27.00	0.00	92.00	32.79
Longest Streaks, 50% Curtailment, Season	49.22	31.00	0.00	214.00	53.40
Longest Streaks, 50% Curtailment, Summer	29.85	20.00	0.00	92.00	30.86
Farm Area (Acre)	96.98	52.22	4.58	1572.89	139.07

Table 4.2: Sample Water Accouting Record in WD1

Reach	Actual Date	Actual Reach Flow	Reach Gain	Total Natural Reach Flow	Reach Diver-sion	Natural Flow Diversion	Remaining Natural Flow	Last Right Priority
Snake River								
S1	May 15	1,690	685	685	0	0	685	1891-12-14
S2	May 15	3,810	2,120	2,805	0	0	2,805	1891-12-14
Grey's River								
G1	May 15	488	488	488	0	0	488	1891-12-14
Salt River								
L1	May 15	483	483	483	0	0	483	1891-12-14
Snake River								
S3	May 16	9,380	773	4,549	0	0	4,549	1891-12-14
S4	May 16	10,200	842	5,391	22	20	5,371	1891-12-14
S5	May 16	5,999	0	5,391	4,201	3,340	2,031	1891-12-14
S6	May 16	5,570	85	5,476	514	430	1,686	1891-12-14
Henry's Fork								
H1	May 13	40	10	10	0	0	10	1891-12-14
H2	May 14	1,410	512	522	0	0	522	1891-12-14
H3	May 15	2,220	818	1,340	8	8	1,332	1891-12-14
H4	May 15	2,216	0	1,340	4	0	1,332	1891-12-14
Falls River								
F1	May 15	20	10	10	0	0	10	1891-12-14
F2	May 15	902	882	892	0	0	892	1891-12-14
F3	May 15	474	69	961	497	490	471	1891-12-14
Henry's Fork								
H5	May 15	1,560	-100	2,201	1,030	550	1,153	1891-12-14
H6	May 15	901	0	2,201	659	490	663	1891-12-14
Teton River								
T1	May 15	347	354	354	7	7	347	1885-06-01
T2	May 15	0	163	517	510	510	0	1885-06-01
T3	May 15	0	34	551	34	34	0	1885-10-17
Henry's Fork								
H7	May 16	1,480	579	3,331	0	0	1,242	1891-12-14
Snake River								
S7	May 16	7,010	-40	8,767	0	0	2,888	1891-12-14
S8	May 16	6,180	581	9,348	1,411	1,400	2,069	1891-12-14
S9	May 16	5,970	0	9,348	210	203	1,866	1891-12-14
Willow Cr								
W1	May 16	31	41	41	10	10	31	1883-04-01
W2	May 16	64	-4	37	0	0	27	1883-04-01
W3	May 16	28	-16	21	20	11	0	1883-04-01
W4	May 16	28	0	21	0	0	0	1883-04-01
Snake River								
S10	May 17	5,640	86	9,455	444	330	1,622	1891-12-14
S11	May 17	2,920	-332	9,123	2,388	1,173	117	1891-12-14
S12	May 17	2,788	0	9,123	132	117	0	1891-12-14
S13	May 18	2,795	7	9,130	0	0	7	1900-10-11
Portneuf River								
P1	May 18	55	55	55	0	0	55	1900-10-11
Snake River								
S14	May 19	10,868	2,440	11,625	188	0	2,502	1900-10-11
S15	May 19	8,850	-78	11,547	1,838	10	2,414	1900-10-11
S16	May 20	0	149	11,696	9,100	2,563	0	1900-10-11

Note: Table shows the curtailment record for May 20th (Time at Milner, ID). The water right accounting system displays the ”actual date” for each reach of when the block of water arriving at Milner on May 20th passed through the reach and how it was distributed (diverted) according to the reach priority date occurring on the actual date displayed for each reach (Olenichak, 2015).

Table 4.3: Parameter Estimates for Crop-allocation Decisions

Dependent Variable: Expected Profit ($/acre) from Crop-Allocation			
Variable	(1)	(2)	(3)
EDD		0.431	
		(0.375)	
lag1(EDD)	-0.224	-0.574	
	(0.31)	(0.338)	
lag2(EDD)	-0.0631	0.197	
	(0.232)	(0.356)	
lag3(EDD)	-0.325	-0.282	
	(0.312)	(0.322)	
MA3(EDD)			-0.589
			(0.445)
GDD		-0.0134	
		(0.0631)	
lag1(GDD)	0.129*	0.18**	
	(0.0567)	(0.0619)	
lag2(GDD)	-0.12	-0.2*	
	(0.0684)	(0.0908)	
lag3(GDD)	0.13*	0.0242	
	(0.0653)	(0.0683)	
MA3(GDD)			0.371***
			(0.101)
prec		0.285**	
		(0.108)	
lag1(prec)	-0.137	0.0594	
	(0.0949)	(0.11)	
lag2(prec)	0.194	0.234*	
	(0.103)	(0.109)	
lag3(prec)	0.15	0.226	
	(0.109)	(0.124)	
MA3(prec)			0.301*
			(0.12)
TND.summer.80%		-0.0205	
		(0.12)	
lag1(TND.season.80%)	-0.266**	-0.257**	
	(0.0817)	(0.0819)	
lag2(TND.summer.100%)	0.686***	0.718***	
	(0.162)	(0.168)	
lag3(Streak.season.50%)	-0.338***	-0.395***	
	(0.0894)	(0.0901)	
MA3(TND.season.80%)			-0.0675
			(0.169)
lag4(Streak.summer.100%)	0.764***	0.852***	0.176
	(0.181)	(0.203)	(0.156)
lag5(Streak.season.80%)	-0.0434	-0.0383	0.156
	(0.102)	(0.11)	(0.0808)
n	5890	5890	5890
R-squared	0.039	0.042	0.025

a. Time trends are added in the model as 5-degree polynomials, and are suppressed from table. Robust standard errors in parenthesis, clustered at the individual level. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

b. “lag#” denotes number of years that the variable in question took place prior to the current growing season. “MA3” denotes the 3 year moving average of a variable, i.e. the average of the last 3 lags.

c. Water curtailment varialbes are structured as the following: “TND” or “Streak” denotes total number of days vs longest streaks of water curtailment; “season” or “summer” denotes whether days of curtailments are accumulated for the entire growing season or just in summer months, and percentage denotes what percentage of water (in total volume) is curtailed.

Table 4.4: Partial Effect of Dependent Variables with One Standard Deviation Shift in Water Curtailments

Lags	Crop-Allocation($/acre)	% Non-Cropland	Total Profit ($/acre)
1	-16.63**	0.0084	-11.57**
2	21.33***	0.0370***	11.74*
3	-18.96***	-0.0123**	-4.58
4	23.07***	0.0092	10.70*
5	-2.43	0.0165**	-7.01
3-year Aggregate	-4.41	-14.26**	0.033***
5-year Aggregate	-0.71	6.38	0.0589***

Table 4.5: Parameter Estimates for Percentage of Non-cropland Area

Dependent Variable: % Non-Cropland Area			
Variable	(1)	(2)	(3)
EDD		-0.000134	
		(0.000403)	
lag1(EDD)	0.00241***	0.00242***	
	(0.000444)	(0.000465)	
lag2(EDD)	9.1e-06	8.15e-05	
	(0.000315)	(0.000445)	
lag3(EDD)	0.00238***	0.00233***	
	(0.00043)	(0.000451)	
MA3(EDD)			0.0038***
			(0.000725)
GDD		3.02e-06	
		(7.26e-05)	
lag1(GDD)	-0.00046***	-0.000471***	
	(8.15e-05)	(9.55e-05)	
lag2(GDD)	-0.000139	-0.000205*	
	(7.75e-05)	(0.000102)	
lag3(GDD)	-0.00021**	-0.000213**	
	(7.11e-05)	(8.13e-05)	
MA3(GDD)			-0.000793***
			(0.000135)
prec		9.36e-05	
		(0.000146)	
lag1(prec)	-0.000228*	-0.000212	
	(0.000112)	(0.000161)	
lag2(prec)	-0.000121	-0.000105	
	(0.000111)	(0.000113)	
lag3(prec)	0.000206	0.000208	
	(0.00015)	(0.000158)	
MA3(prec)			-4.19e-05
			(0.000148)
TND.season.80%		-1e-04	
		(0.000136)	
lag1(TND.season.80%)	0.000135	0.000101	
	(0.00011)	(0.00013)	
lag2(Streak.summer.80%)	0.00128***	0.0012***	
	(0.000202)	(0.000218)	
lag3(Streak.season.50%)	-0.000219**	-0.000207*	
	(8.48e-05)	(9.04e-05)	
MA3(Streak.summer.80%)			0.00101*
			(0.000471)
lag4(TND.summer.50%)	0.000279	0.00023	0.000152
	(0.000145)	(0.000155)	(0.000111)
lag5(Streak.season.80%)	0.000295**	0.00028*	0.000429***
	(0.000113)	(0.00012)	(9.45e-05)
n	5890	5890	5890
R-squared	0.265	0.266	0.253

a. Time trends are added in the model as 5-degree polynomials, and are suppressed from table. Robust standard errors in parenthesis, clustered at the individual level. A triple asterisk indicates p < 0.01; a double asterisk indicates p < 0.05; a single asterisk indicates p < 0.1.

b. “lag#” denotes number of years that the variable in question took place prior to the current growing season. “MA3” denotes the 3 year moving average of a variable, i.e. the average of the last 3 lags.

c. Water curtailment varialbes are structured as the following: “TND” or “Streak” denotes total number of days vs longest streaks of water curtailment; “season” or “summer” denotes whether days of curtailments are accumulated for the entire growing season or just in summer months, and percentage denotes what percentage of water (in total volume) is curtailed.

Table 4.6: Parameter Estimates for Total Profit

Dependent Variable: Total Profit ($/acre)			
Variable	(1)	(2)	(3)
EDD		-0.0103	
		(0.335)	
lag1(EDD)	-0.809**	-0.892**	
	(0.292)	(0.307)	
lag2(EDD)	-0.0971	-0.118	
	(0.206)	(0.324)	
lag3(EDD)	-0.717*	-0.722*	
	(0.29)	(0.3)	
MA3(EDD)			-1.44**
			(0.44)
GDD		0.0177	
		(0.0574)	
lag1(GDD)	0.218***	0.235***	
	(0.0486)	(0.0551)	
lag2(GDD)	-0.0206	-0.0127	
	(0.0649)	(0.0857)	
lag3(GDD)	0.128*	0.0987	
	(0.0549)	(0.0612)	
MA3(GDD)			0.416***
			(0.092)
prec		0.0744	
		(0.103)	
lag1(prec)	0.0332	0.129	
	(0.0889)	(0.105)	
lag2(prec)	0.22*	0.221*	
	(0.086)	(0.0919)	
lag3(prec)	0.0331	0.0449	
	(0.106)	(0.116)	
MA3(prec)			0.202
			(0.115)
TND.summer.50%		0.0447	
		(0.104)	
lag1(TND.season.80%)	-0.185**	-0.173*	
	(0.0716)	(0.0723)	
lag2(TND.season.50%)	0.188*	0.226**	
	(0.0788)	(0.0871)	
lag3(Streak.season.100%)	-0.135	-0.177	
	(0.0982)	(0.1)	
MA3(TND.season.80%)			-0.0289
			(0.158)
lag4(Streak.summer.100%)	0.361*	0.364	0.0832
	(0.163)	(0.188)	(0.145)
lag5(TND.season.50%)	-0.108	-0.116	0.0238
	(0.0779)	(0.0793)	(0.0742)
N	5890	5890	5890
R-squared	0.037	0.039	0.032

a. Time trends are added in the model as 5-degree polynomials, and are suppressed from table. Robust standard errors in parenthesis, clustered at the individual level. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

b. "lag#" denotes number of years that the variable in question took place prior to the current growing season. "MA3" denotes the 3 year moving average of a variable, i.e. the average of the last 3 lags.

c. Water curtailment varialbes are structured as the following: "TND" or "Streak" denotes total number of days vs longest streaks of water curtailment; "season" or "summer" denotes whether days of curtailments are accumulated for the entire growing season or just in summer months, and percentage denotes what percentage of water (in total volume) is curtailed.

Table 4.7: Predictive Model of TND.Season.100%

year	R^2 within sample	R^2 out of sample
2007	0.280	-0.151
2008	0.239	-0.262
2009	0.203	-1.176
2010	0.396	-0.860
2011	0.303	-0.424
2012	0.238	-0.812
2013	0.329	-0.165
2014	0.170	-0.395
2015	0.132	-1.319
2016	0.136	-1.194

a. Training samples are constructed using observations within 15 years to the year of interest. Testing samples are observations of the year of interest. Elastic net mixing parameter α is fixed at 0.5. Lasso penalty parameter λ is selected as 1-standard-deviation larger than the optimal λ that minimizes prediction error.

b. Both within sample and out of sample r^2 are calculated as $1 - RSS/TSS$.

Appendix Table

Table A1: Post-Lasso Estimates on Overall Expected Profit

Dependent Variable: Overall Expected Profit			
Variables	Estimates	Variables	Estimates
lag1(gdd)	0.103***	lag2(TND.summer.100%)	0.097
	(0.017)		(0.158)
lag3(gdd)	0.041**	lag2(TND.summer.50%)	-0.347
	(0.018)		(0.213)
lead1(TND.season.100%)	0.128	lag4(Streak.summer.100%)	0.507***
	(0.174)		(0.194)
lead1(Streak.season.100%)	0.11	lag4(Streak.season.80%)	0.158
	(0.145)		(0.129)
TND.summer.50%	0.03	lag6(TND.summer.100%)	0.278
	(0.117)		(0.180)
lag1(TND.season.50%)	-0.002	lag6(Streak.summer.80%)	0.017
	(0.117)		(0.163)
lag1(TND.season.100%)	0.004	lag7(TND.season.100%)	-0.446***
	(0.183)		(0.151)
lag1(Streak.summer.80%)	-0.445*	lag7(Streak.season.50%)	0.305***
	(0.239)		(0.100)
lag1(TND.summer.100%)	0.023	lag8(TND.summer.100%)	-0.399
	(0.289)		(0.384)
lag2(TND.season.50%)	0.498**	lag8(Streak.summer.100%)	0.187
	(0.200)		(0.403)
lag2(TND.season.80%)	-0.112		
	(0.144)		
N	5890		
R-squared	0.0396		
Elastic net mixing parameter α	0.5		
Lasso penalty parameter λ	2.236		

a. Post-lasso fixed-effect regression on overall expected profit. Presented variables are selected by the elastic net algorithm through 10-fold cross validation. Elastic net mixing parameter α is fixed at 0.5. Lasso penalty parameter λ is selected as 1-standard-deviation larger than the optimal λ that minimizes prediction error.

b. Time trends are added in the model as 5-degree polynomials, which is suppressed from the output. Standard errors in parenthesis. A triple asterisk indicates $p < 0.01$; a double asterisk indicates $p < 0.05$; a single asterisk indicates $p < 0.1$.

c. "lag#" denotes number of years that the variable in question took place prior to the current growing season. "MA3" denotes the 3 year moving average of a variable, i.e. the average of the last 3 lags.

d. Water curtailment varialbes are structured as the following: "TND" or "streak" denotes total number of days vs longest streaks of water curtailment; "season" or "summer" denotes whether days of curtailments are accumulated for the entire growing season or just in summer months, and percentage denotes what percentage of water (in total volume) is curtailed.