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Title: Effects of Water Scarcity, Climate Variability, and Risk Management Policy on Adaptive Agricultural Production Decisions.

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Water scarcity and extreme weather present substantial risks for agricultural production on the U.S. West Coast. Farmers adapt to water supply uncertainties and climate risks by changing water application rates, adjusting irrigated acres, adopting more efficient irrigation technology, and altering crop mix. Many policy options are available to attain sustainable agricultural development. The federal crop insurance program (FCIP) is a primary risk management tool for U.S. agriculture. Improving the design of risk management policy necessitates a deeper theoretical understanding and credible empirical measurement of production decisions connected with land and water use. To this end, we first examine the impact of water scarcity and climate variability on adaptive land use and irrigation strategies. We then investigate how alternative risk management policies affect production decisions.

We analyze how water availability, water supply institutions, and climate affect agricultural producers' land and water use decisions. We first present a theoretical model to characterize farmers' behavior in the presence of climate risk and water availability uncertainty. From the model, we derive the conditions for optimal production decisions and identify key parameters affecting land allocation, irrigation technology adoption, and water application rates. We then estimate a system of equations jointly to investigate how farmers adapt to different climate and water conditions with detailed irrigation and climate data for producers located in the states

of California, Oregon, and Washington. The estimation results add to our understanding of producers' adaptations to risks and contributes to improving water resource management.

Crop insurance may affect harvested acreage and yield by influencing producers' behavior such as land allocation and input use. Although specialty crops are a major source of farm income, especially on the U.S. west coast, they have not received as much attention as field crops in previous empirical studies. We assess the effect of moral hazard and adverse selection associated with the federal crop insurance program on the acreage and yield of major specialty crops in California. An econometric method that expands the switching regression model is developed to assess the effect. Results suggest that federal crop insurance can change specialty crop growers' production responses to climate and soil conditions. The moral hazard effect tends to increase the acreage and yield of the specialty crops, while the adverse selection effect tends to have the opposite effect. The overall effect of the federal crop insurance program on acreage and yield of specialty crops is found to be moderate.

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Effects of Water Scarcity, Climate Variability, and Risk Management Policy on Adaptive Agricultural Production Decisions

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APPROVED:

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Jian Shi, Author

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CONTRIBUTION OF AUTHORS

Chapter 3 investigates the effect of moral hazard and adverse selection associated with the federal crop insurance program on the acreage and yield of major specialty crops in California. I developed the empirical model, collected data, performed econometric analysis, and wrote the manuscript. Dr. JunJie Wu helped with developing the research idea, guided the project, and assisted in model design, results analysis, and manuscript editing. Beau Olen assisted with collection and interpretation of data and manuscript editing.

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Chapter 1 Introduction

1.1 Motivation and Objective

Agriculture is the largest water user on the U.S. West Coast, accounting for over 90% of human water consumption (USDA 2017). Water scarcity and extreme weather cause substantial economic losses to agricultural producers in the region. For example, the 2014 Central Valley drought reduced surface water availability by 6.6 million acre-feet in California, resulting in $2.2 billion economic losses to agriculture (Howitt et al. 2014). Water scarcity and extreme weather also impose significant stress on the environment and ecosystems on the West Coast, which in turn reduces agricultural productivity (Hoekstra 2014; IPCC 2014; Li et al. 2019). For example, to cope with demand for irrigation during the 2014 Central Valley drought, groundwater extraction increased by 5 million acre-feet, which lowered the groundwater level, deteriorated groundwater quality, and increased risk of land sinking. In addition, a deadly salmon parasite thrived in the drought and infected nearly all the juvenile Chinook salmon in the Klamath River in Northern California before they migrate to the ocean. The economic and environmental damages from drought and other extreme weather are anticipated to be more severe and frequent in the current context of climate change (Bates et al. 2008; Howitt et al. 2014).

Population increase, economic growth, and physical limit to water supply will lead to reduced water resources per capita on the West Coast. The influence of increasing population on water shortage is four times as important as the influence of water availability due to long-term climatic change (Kummu et al. 2010). Both over allocation of surface water and overdraft of groundwater contribute to uncertainty in water supply. California has allocated five times more surface water than the average annual streamflow (Grantham and Viers 2014), causing disputes over water ownership during times of water scarcity. Before the Sustainable Groundwater Management Act (SGMA) was passed in 2014, groundwater in California was an unregulated open access resource subject to the tragedy of the commons (Hardin 1968). NASA's GRACE satellite mission data shows that water reserves have significantly declined since 2003 in twenty-one of the thirty-seven largest aquifers in the world, mainly in the most prolific agricultural regions, such as the Central Valley of California (Richey et al. 2015).

Climate change intensifies water scarcity in a variety of ways and complicates the challenges faced by western agricultural producers. Changing patterns of precipitation and rising temperature are expected to decrease snowpack, cause earlier snowmelt runoff, increase the risk of winter flooding, and reduce spring and summer stream inflows on the U.S. West Coast, which will impact surface water availability (Hayhoe et al. 2004). In 2017, California had record level of precipitation after over five years of drought, with April snowpack approaching 200% of the normal level (NASA 2017). Agriculture is a climate-sensitive industry. Climate change and associated changes in water supply can affect the quantity (i.e. yield) and quality of agricultural products and alter agricultural landscape. For example, warmer temperature may shift ripening of wine grapes in California 1-2 months earlier, generating degraded quality and lower market value (Hayhoe et al. 2004; Jackson et al. 2011). Irrigated cropland decreased by about 0.8 million acres in the US from 2007 to 2012, with most of the decline occurring in the western states due to drought (USDA 2017).

Many policy options are available to cope with production risks and attain sustainable agricultural development, such as water pricing policy, institutional reforms, market-based mechanisms, and water use regulations. Some of them are complements. For example, an appropriate legal setting regarding water rights and flexible institutional arrangements may enhance participation in water trading (Libecap 2011; Li et al. 2018; Regnacq et al. 2016; Rosegrant and Bingswanger 1994). Other policy options are substitutable. For example, irrigation technology adoption can be a substitute of changing water price or water quota rates to reach similar level of water conservation (Dinar and Yaron 1990).

The federal crop insurance program (FCIP) is a primary risk management tool for US agriculture (Glauber 2013). Crop insurance can influence farmers' production behaviors through several channels. First, premium subsidies add to expected revenue for crop production. As such, subsidized crop insurance may create incentives for farmers to expand crop production to marginal lands (Claassen et al. 2017). Second, crop insurance reduces the riskiness of growing covered crops relative to other crops, thus potentially affecting farmers' crop mix (Wu 1999; Goodwin et al. 2004; Walters et al. 2012). Finally, crop insurance reduces farmers' production risk by cutting off the lower tail of the revenue distribution and therefore may change the use of risk-altering input such as fertilizer and pesticides (Babcock and Hennessy 1996; Young et al. 2001; Goodwin and Smith 2013). Both field crop and specialty crop producers have been increasingly relying on crop insurance for agricultural risk protection since 1990 (Lee and Sumner 2013). The USDA has been expanding coverage of the FCIP to more crops and regions. For example, cropland enrolled in the FCIP increased from 83.5 million acres to 296.3 million acres, with total liabilities growing from $11.2 billion to $119.6 billion from 1993 to 2013 (RMA 2013).

Adapting irrigation management is one of the primary mechanisms for the society to cope with water scarcity and climate change (Howden 2007). Farmers are exposed to uncertainties and risks associated with water, climate and price variability. To maintain profitability, they are incentivized to conserve water and alter production practices. Irrigated agricultural producers could respond to risks and policies in several major ways: (1) changing water application rates, (2) adjusting irrigated acres, (3) adopting more efficient irrigation technology, and (4) altering crop mix. Improving water management policy design necessitates a deeper theoretical understanding and credible empirical measurement of the impacts of water scarcity and climate variability on adaptive production decisions connected with agricultural land and water use.

The objective of this study is twofold: first to examine the impact of water scarcity and climate variability on adaptive production decisions on the West Coast (California, Oregon and Washington), including cropland allocation, water use, and irrigation technology adoption decisions; and second to examine how alternative risk management policies affect farmers' production decisions. Specific research questions are:

1. How do water supply uncertainties and climate risks affect farmers' land and water use decisions?

2. How does the federal crop insurance provision affect the harvested acreage and yield of specialty crops?

1.2 Research Summaries

This study consists of two essays that address these research questions. In the following, I provide a brief overview of each chapter.

In Chapter 2, we conduct both theoretical and empirical analysis to identify the major economic, climate, and institutional factors influencing farmers' production decisions on the U.S. West Coast. We first construct a farm-level theoretical model to characterize producers' behavior under water and climate risks at both the extensive margin (adjustments to irrigated share of cropland) and intensive margin (adjustments to water application rate). In particular, we capture production risks associated with extreme weather, such as drought, frost, and extreme heat. A formula of sufficient statistics representing optimal production decisions and key parameters in the adaptation strategies are derived. The conceptual framework informs empirical estimation and generates valuable insights into how farmers in irrigated agricultural production systems would respond and adapt to water scarcity and climate change.

Based on the theoretical model, we then conduct an empirical analysis to measure the relative importance of various economic, climate, and institutional factors influencing farmers' land and water use decisions, focusing on five major categories of crops in this region (forage, orchard/vineyard, potato, rice, and wheat). This study combines irrigation data from the Farm and Ranch Irrigation Survey (FRIS) developed by the USDA in 2013 and 2018, with climate data developed by the PRISM Climate Group at Oregon State University. With the unique crop-specific and growing-season-specific data of key water and climate variables, we estimate a farm-level modelling system. The estimation results add to our understanding of producers' adaptation to water scarcity, climate variability and institutional changes, and contributes to improving water resource management.

The FCIP is important to agricultural risk management. It affects producer behavior such as cropland allocation and input use. The effects of crop insurance on field crops have been well analyzed in previous empirical studies, whereas the effects on specialty crops have received much less attention, although specialty crops are a major source of farm income, especially on the West Coast. Therefore, in Chapter 3, we address the question how federal crop insurance provision affects the harvested acreage and yield of specialty crops. Specifically, we investigate into two questions: a) what are the main factors determining the provision of federal crop insurance to a specialty crop in a county? and b) how does the federal crop insurance availability affect the acreage and yield of specialty crops? We develop a simultaneous equation system for the models of federal crop insurance provision for specialty crops and their acreage and yield responses. The model is estimated with an econometric method that expands the standard endogenous switching regression model. This study provides a comprehensive treatment of moral hazard and adverse selection effects in insurance markets. Estimation results add to our understanding of the impacts of federal crop insurance provision on agricultural economies and inform the development of the FCIP for specialty crops.

Chapter 2

Mitigating Water Scarcity and Climate Risks: Adaptive Agricultural Land Use and Irrigation Strategies on the U.S. West Coast

Abstract: This paper analyzes how water availability, water supply institutions, and climate affect agricultural producers' land and water use decisions. We first present a theoretical model to characterize farmers' behavior in the presence of climate risk and water availability uncertainty. From the model, we derive the conditions for optimal production decisions and identify key parameters affecting land allocation, irrigation technology adoption, and water application rates. We then estimate a system of equations jointly to investigate how farmers adapt to different climate and water conditions with detailed irrigation and climate data for producers located in the states of California, Oregon, and Washington. Results suggest that water scarcity reduces irrigated share of selected crops and expands dryland production. Water scarcity encourages adoption of efficient irrigation technology sprinkler and drip, especially for crops with low adoption rates. Federal surface water supply makes farms irrigate more cropland and apply more water per acre. Climate risks, including excessive moisture, extreme heat, spring freeze and frost, and drought significantly influence irrigation strategies. The impact varies across crops. Weather conditions critically affect adaptations. Higher precipitation level decreases irrigated share and water application rates; whereas higher maximum temperature increases water application rates and discourages technology adoption.

Key words: water scarcity, climate variability, cropland allocation, water use, irrigation

2.1 Introduction

Adapting irrigation management is one of the primary mechanisms for the society to cope with water scarcity and climate change (Howden 2007). Farmers adapt to uncertainties and risks by changing water application rates, adjusting irrigated acres, adopting more efficient irrigation technology, and altering crop mix. Improving water management policy design necessitates a deeper theoretical understanding and credible empirical measurement of the impacts of water scarcity and climate variability on adaptive production decisions connected with agricultural water use. This chapter attempts to fulfill this need by addressing the following question: how do water supply uncertainties and climate risks affect farmers' cropland allocation, water application rates, and irrigation technology adoption for major crops on the West Coast (California, Oregon, and Washington)?

We identify specific climate risks for crop production, compile a comprehensive crop-specific dataset on key water and climate variables, distinguish between long-run and short-run responses, and estimate a system of equations on farmers' adaptations simultaneously for major field and specialty crops. Results suggest that water scarcity reduces irrigated share of selected crops and expands dryland production. We observe more elastic responses for crops with high surface water price (potato) or high groundwater pumping cost (forage and wheat). Water scarcity encourages adoption of efficient irrigation technology sprinkler and drip, especially for crops with low adoption rates (forage and wheat). Bureau of Reclamation provides more secured water supplies and subsidizes water use. Farms receiving water from BOR allocate 2.6% more cropland to irrigated production and use 11%~18% more water per acre than farms obtaining water elsewhere. Extreme weather events present key determinants of irrigation strategies. Excessive moisture risk discourages technology adoption for forage and wheat, encourages adoption for orchard/vineyard, and decreases water application rates for all crops. Extreme heat risk increases irrigated share and reduces technology adoption for forage and wheat. Orchard/vineyard producers mitigate freeze damage by using efficient irrigation technology and increasing water application rates. Wheat producers adapt to drought by irrigating a larger share of land, adopting efficient technology, and applying less water per acre. Weather expectations and observations are also critical to adaptations. Higher precipitation level reduces demand for irrigation, thus decreasing irrigated share and water application rates. Whereas high evaporative loss in hot weather increases water application rates by 2%~5% and decreases technology adoption by as much as 4%, given a 1°F increase in maximum temperature.

In Section 2, we provide some background information about previous research, our contributions to existing literature, and unique features of study region. In Section 3, we introduce the conceptual framework that models producers' behavior under water and climate risks and discuss major findings from a comparative statics analysis. In Section 4, we present an econometric implementation that measures the relative importance of various determinants of adaptation strategies. We present the empirical framework for modelling adaptations, discuss data source, expand on variable construction process, and identify model specifications and estimation methods. In Section 5, we interpret estimation results and provide policy implications. Section 6 concludes this chapter.

2.2 Background

2.2.1 Previous Studies

The effect of water scarcity and climate change on agriculture has been a focus in agricultural water resource economic research. Previous studies investigate a wide range of agricultural impacts. For example, Deschenes and Greenstone (2007) and Schlenker and Roberts (2009) examine the impacts of temperature, a type of short-run weather realizations, on crop yields and agricultural profits. Massetti and Mendelsohn (2011), Mendelsohn et al. (1994), Schuck et al. (2005), and Schlenker et al. (2007) find that expected climate and water supply variations alter land values. There are many studies measuring the economic impacts (e.g. producer surplus, profits) of agricultural water supply reductions and climate change. They conclude that the adverse impacts can be mitigated by good institutions, water pricing policies, and water market policies (Chen et al. 2001; Howden and Jones 2001; Kahil et al. 2016; Mejias et al. 2004; Sunding et al. 2002).

This analysis builds on previous research on how water availability and climate determine adaptation strategies. The existing literature on irrigation technology adoption is extensive and well developed (Dinar and Zilberman 1991; Green et al. 1996; Green and Sunding 1997; Lichtenberg 1989; Schuck and Green 2001; Shrestha and Gopalakrishnan 1993; Xu et al. 2018). Carey and Zilberman (2002), Caswell and Zilberman (1986), Connor et al. (2009), and Li et al. (2019) provide consistent evidence that the choice of irrigation technology depends on economic and physical conditions, such as well depth, soil quality, uncertainty in water supplies or water prices, access to water market etc. It is widely recognized that variable climate conditions are associated with different technical efficiency, which critically affect producers' irrigation technology choices. Dinar and Yaron (1990) find that higher temperature encourages adopting drip irrigation to offset the effect of higher evaporation rates. Negri and Brooks (1990) find that higher temperature discourages the adoption of water-saving technologies such as micro-sprinkler and solid-set sprinkler due to their high evaporative losses. Fleischer et al. (2011) find that Israel producers completely substitute capital (i.e. investment in water-saving irrigation technology) for a warmer climate. Frisvold and Deva (2013) compare the performance of gravity and sprinkler irrigation and find that sprinkler irrigation has higher adoption rates in regions with more rainfall and intense rain events than in drier climate.

Apart from irrigation technologies, other adaptation strategies include changing cropland allocations, altering crop mix, and adjusting irrigated acres. Surface water is an allocable input in agricultural production. In response to reduction in water supply and increases in water prices, farmers can reduce either cropland allocated to relatively low-value and water-intensive crops or irrigated acreage. The adjustments are more elastic at the crop level than at the farm level (Manning et al. 2017; Moore and Negri 1992; Moore et al. 1994; Sunding et al. 2002). For example, Sunding et al. (2002) find reduced acreage and scale of production in water-intensive crops, such as pasture, alfalfa, and wheat. The magnitude of the impacts depends primarily on the allocation of reductions among water users and water trading. Manning et al. (2017) find that agricultural producers in the western US respond to expected surface water supply variations through planting fewer acres of irrigated corn. Connor et al. (2009) find that the primary short-run response to a reduction in water supply is to decrease irrigated acres. Second, farmers adjust crop type and water use in response to long run climate expectations and short run weather realizations. Connor et al. (2009) find that in the long run and under a severe climate change scenario (a 4°C temperature increase) farmers choose to switch from perennial crop to annual crop production. Peck and Adams (2012) find that farmers adapt to climate change by adopting new crop varieties in the short run and investing in supplemental water supplies in the long run. Manning et al. (2017) find that producers respond to annual weather fluctuations by concentrating the application of available water to a subset of planted acreage to maintain high yields.

Relatively few studies have analyzed how water use and irrigation decisions respond to the risk of extreme weather events. Two notable exceptions are Olen et al. (2016) and Schuck et al. (2005). Olen et al. (2016) examine farm-level irrigation decisions and find that producers of orchards and vineyards are more likely to choose sprinkler irrigation and apply additional water to mitigate damage from drought, severe heat, or freeze. Schuck et al. (2005) find that to maintain crop yield, a larger share of farms adopt more technically efficient irrigation systems in response to droughts. Given that famers make land and water use decisions jointly (Howitt et al. 2014, 2015; Moreno and Sunding 2005; Sunding et al. 2002; Pfeiffer and Lin 2014), it is important to understand how the uncertainties in water availability and climate affect water use, land use, and irrigation decisions simultaneously. This paper complements literature by examining extreme weather events that are closely related to the volatility of water supplies and responsible for crop failure, and by modelling various adaptation strategies simultaneously.

2.2.2 Contributions

This study has several desirable features compared with existing literature. First, it is a farm-level, crop-specific analysis. The West Coast is one of the ten USDA Farm Production Regions, with significant spatial and temporal variations. There are many microclimates even within a small area due to the complex topography. The existing literature has focused on the effect of water supply uncertainties and climate risks on crop yield or output, as well as water management from the perspective of administrative agency at the macroscale (Deschenes and Greenstone 2007; Fischhendler and Heikkila 2010; Rosegrant and Binswanger 1994; Saleth and Dina 2000; Saleth 2004; Schlenker and Roberts 2009). The effect of climate risks on an individual farmer's land and water use decisions has received much less attention, due to lack of detailed farm-level data. Our micro-level modelling system attempts to explore how individual farmers with heterogeneous portfolios adapt to production risks. The crop-specific specification captures susceptibility of individual crops to alternative extreme weather events. For example, fruit blossoms can be damaged by spring freeze, making freeze risk one of the top drivers of crop loss for orchard/vineyards. As such, variation of freeze dates is a significant determinant of fruit tree growers' responses, since irrigation can be used to mitigate freeze damage. Furthermore, this system models the impacts of water scarcity and climate variability on cropland allocation, water use, and irrigation technology adoption decisions simultaneously. This approach presents a holistic framework to investigate individual famer's adaptation mechanisms and assess the magnitude of water scarcity and climate change effects. Estimation results provide valuable implications to promote development of efficient agricultural policies.

Second, the model explicitly distinguishes whether the decisions involved is a short-run or long-run response. Some of farmers' adaptations are short-run decisions, while others involve long-run investment. For example, in the short run, farmers can adjust water application rates or irrigated acres during the growing season in response to observed weather and water conditions. An array of climate statistics is developed for each month and season to represent observed variations of the agricultural growing season. However, it often entails long-run, quasi-irreversible capital investment to change irrigation technology or to convert from an annual crop to a perennial crop. Long-run decisions are more likely to respond to climate and water scarcity expectations, which can be represented by long-run averages for an array of climate statistics.

Third, this analysis differentiates annual crop and perennial crop. A perennial crop will be non-bearing or non-mature in the first several years, which may result in variations in water use. Lastly, this study examines specialty crop producers' behavior under risks and uncertainties. Specialty crops are a major source of farm income, especially on the West Coast. But they are not as well analyzed as field crops in literature. Also, there may be unique risks for growing specialty crops. For example, many specialty crops are perishable, making them susceptible to placement risk (Schieffer and Vassalos 2015). Finally, the 2014 Farm Bill authorizes the Risk Management Agency (RMA) to expand crop insurance to more specialty crops and more counties. Liability of specialty crops grew from around $7 billion in 2000 to almost $15 billion in 2014, accounting for 13.6% of total crop insurance liability in 2014 (FCIC 2015). More research about the impact of water supply uncertainties and climate risks on specialty crop producers' behavior can promote development of efficient agricultural policies.

2.2.3 Study Region

There are many microclimates even within a small area on the West Coast due to the complex topographic features. For example, the Cascade Range extends from northern California through Oregon and Washington to southern British Columbia. It creates a barrier between the maritime climate influences from the west and the continental climate influences from the east. This region's proximity to the Pacific Ocean and prevailing westerly winds bring substantial precipitation to the western slopes. However, as the air advances across the mountain top with little moisture left, the eastern slopes are cast in a shadow of dryness, which is geographically known as a rain-shadow effect (Ernst 2000). Besides, temperatures are mild throughout a year to the west of the Cascade Range. While the east side has larger annual variations, with colder winter and hotter summer. The Columbia River Basin is a vast agricultural production area extending across eastern Washington and northern Oregon, and through the Cascade Range. Irrigated crops such as potatoes, vegetables, and fruits appear on floodplains flanking the Columbia River. Agriculture is more rainfed oriented on higher-lying landscapes where there is no easy access to irrigation, and some of these upland fields are dormant in dry summer.

We focus on five crops/crop types: forage, orchard/vineyard, potato, rice, and wheat. These agricultural commodities are selected based on their acreage, water use, and sales receipts in each state of the West Coast. The selected crops account for 22%-54% of state cash receipts in 2018 (Economic Research Service, 2019). Some of the major crops in the orchard/vineyard category include grapes, almonds, apples, pears, and cherries. They rank among top five products in this category in terms of cash receipts by state (Economic Research Service, 2019). Figure 2-1 provides a visualization of the spatial distribution of selected crops across the West Coast. Orchard/Vineyard production is concentrated in the Columbia River Basin and west Oregon and California. The Columbia River Basin is a leading production region for apples, cherries, and pears. A more favorable and milder climate contributes to the popularity of wine grapes in west Oregon and west California. Almonds are popular in the middle of California, the San Joaquin Valley in particular because of better soils, less rainfall, and warmer temperatures. Rice production is almost exclusively concentrated in the Sacramento Valley in California. Potato and wheat production are concentrated in areas to the east of the Cascade Range, the Columbia River Basin in particular. Forage production, especially alfalfa is also concentrated in east Cascade Range due to the warm temperatures and well-drained soils. South California and the San Joaquin Valley are also top producing regions for alfalfa hay.

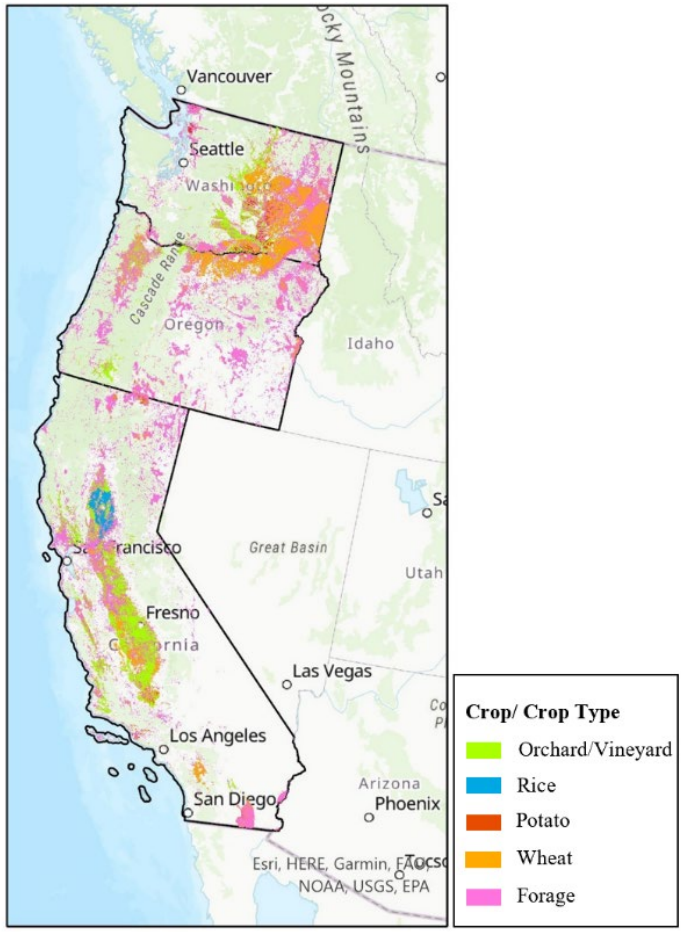

Figure 2-1. Spatial distribution of selected crops across the West Coast

2.3 The Theoretical Model

2.3.1 The Optimization Problem

Consider a multioutput producer, who makes production decisions, including cropland allocation, input use, and irrigation technology adoption to maximize his expected utility, subject to a land use constraint and a water availability constraint.

$$\max_{L_{ij}, r_{ij}, a_{ij}, z_{ij}} E[U_i(\textstyle\sum_j \pi_{ij}\left(L_{ij}, r_{ij}, a_{ij}, z_{ij} \middle| \theta, \varepsilon\right))],$$

$$\text{s.t. } \textstyle\sum_j L_{ij} \leq L_i,$$

$$\sum_j r_{ij} L_{ij} \leq E[\overline{W_i}\,|\varepsilon],$$

$$0 \leq a_{ij} \leq 1, \tag{2-1}$$

where $\pi_{ij} = [P_{ij}L_{ij}f_{ij}(r_{ij}a_{ij}, z_{ij}, \theta) - c_{ij}(\varepsilon)r_{ij}L_{ij} - \omega_{ij}z_{ij}L_{ij} - t_i a_{ij}]$. Profit from growing each crop equals the revenue ($P_{ij}L_{ij}f_{ij}(\cdot)$) minus costs from water use ($c_{ij}(\varepsilon)r_{ij}L_{ij}$), non-water input use ($\omega_{ij}z_{ij}L_{ij}$), and the equipment and installation costs of the efficient irrigation system ($t_i a_{ij}$), which is independent land allocated to each crop. Parameters and variables are defined in Table 2-1. Subscript i is dropped henceforth to simply notation.

Table 2-1. Definitions of Parameters and Variables in the Optimization Problem

Parameter	Explanation
i	Index of farm
j	Index of crop
θ	A random variable reflecting uncertainty associated with climate change
ε	A random variable reflecting uncertainty associated with water scarcity
L_{ij}	Land allocated to crop j
L_i	Total cropland
r_{ij}	Crop-specific per-acre water application rate
$\overline{W_i}$	Exogenous water use constraint
a_{ij}	Irrigation efficiency
α_i	Arrow-Pratt measure of risk aversion
P_{ij}	Output price
c_{ij}	Water price
ω_{ij}	Price of non-water input
z_{ij}	Crop-specific per-acre non-water input use
t_i	Cost of irrigation
β_j	Output elasticity of efficient water use
γ_j	Output elasticity of non-water input

Now we introduce specific functional forms and assumptions to examine the impacts of water scarcity and climate risks on optimal adaptation strategies. Specifically, we assume

$$U(\pi|\theta,\varepsilon) = -e^{-\alpha\pi}, \tag{2-2}$$

$$f_j = (r_j a_j)^{\beta_j} z_j^{\gamma_j} e^{\theta}. \tag{2-3}$$

Equation (2-2) presents a Von Neumann-Morgenstern utility function that exhibits constant absolute risk aversion (Morgenstern and Von Neumann 1953). It takes the form so that we can transform the optimization problem into maximizing the certainty equivalent $E[\pi] - \frac{1}{2}\alpha Var[\pi]$ (see Appendix A1 for derivation). This specification offers substantial mathematical tractability, simplifies calculation, and facilitates understanding how the marginal cost of risk bearing influences optimal decisions, which we will discuss later. Equation (2-3) gives a Cobb-Douglas production function on the average yield of crop j with uncertainty (Feldstein 1971). It reveals the relation between output and input use, including water application rates, irrigation technology, and non-water input. $r_j a_j$ represents average effective water application rates.[1] We assume that a producer chooses the share of land adopting the efficient irrigation technology. A larger share implies a higher average irrigation efficiency a_j, which in turn increases the productivity of water and increases output. Sum of output elasticities of inputs $\beta_j + \gamma_j$ is assumed to be positive but smaller than 1 to guarantee decreasing returns to scale in agricultural production. We also assume decreasing marginal productivity of input use to maintain concavity.

[1] Let s_j denote the share of land adopting the efficient irrigation technology. For the rest $1 - s_j$, the producer chooses between the less efficient technology with share h_j and dry land production with share $1 - h_j$. The water use efficiencies for the efficient and baseline technology are δ_{high} and δ_{low}, respectively. The average water use can be expressed as $r_j s_j \delta_{high} + r_j(1 - s_j)h_j\delta_{low} + 0 * (1 - s_j) * (1 - h_j) = r_j s_j(\delta_{high} - h_j\delta_{low}) + r_j h_j \delta_{low}$. The right hand side informs the average effective water application rate as an increasing function of s_j. Therefore, for simplicity we use a continuous variable a_j to indicate the relative efficiency of water use and rewrite the right hand side as $r_j a_j$.

Assume there is price-taking behavior and no uncertainty in output price. Let water price $c_j(\varepsilon) = c_j + \varepsilon^2$, where $E(\varepsilon) = 0$ and $Var(\varepsilon) = \sigma_\varepsilon^2$. There is no assumption imposed on the distributional form of ε, which creates flexibility for the model as it proceeds. This specification implies that water scarcity increases expected water price. Assume the production uncertainty associated with climate change θ follows a normal distribution, $\theta \sim N(0, \sigma^2)$. From this assumption, we derive that revenue for growing each crop $P_j L_j f_j(\cdot)$ follows a log normal distribution. $\pi = \sum_j \pi_j$ is normally distributed with mean $E[\pi]$ and variance $Var[\pi]$.[2] Accordingly we calculate the distributional statistics of π as $E[\pi] = \sum_j [P_j L_j (r_j a_j)^{\beta_j} z_j{}^{\gamma_j} e^{\frac{1}{2}\sigma^2} - (c_j + \sigma_\varepsilon^2) r_j L_j - \omega_j z_j L_j - t a_j]$ and $Var[\pi] = e^{\sigma^2}(e^{\sigma^2} - 1) \sum_j [P_j L_j (r_j a_j)^{\beta_j} z_j{}^{\gamma_j}]^2$.[3] The objective function can be expressed as an increasing function of the certainty equivalent $E[\pi] - \frac{1}{2}\alpha Var[\pi]$: $E[U(\pi|\theta, \varepsilon)] = -e^{-\alpha\left(E[\pi] - \frac{1}{2}\alpha Var[\pi]\right)}$. Therefore, the risk premium is $R = \frac{1}{2}\alpha Var[\pi]$.

Solving the optimization problem (2-1), we obtain:

$$r_j^* = \frac{\lambda \beta_j}{(1-\beta_j-\gamma_j)(c_j+\sigma_\varepsilon^2+\eta)}, \tag{2-4}$$

$$z_j^* = \frac{\lambda \gamma_j}{\omega_j(1-\beta_j-\gamma_j)}, \tag{2-5}$$

$$a_j^*: P_j r_j^{*\beta_j} z_j^{*\gamma_j}(1-\beta_j-\gamma_j) a_j^{*\beta_j} \lambda \beta_j e^{\frac{1}{2}\sigma^2} - \left[P_j r_j^{*\beta_j} z_j^{*\gamma_j}(1-\beta_j-\gamma_j)\right]^2 a_j^{*2\beta_j+1} \alpha e^{\sigma^2}\left(e^{\sigma^2}-1\right)(t+\tau) = \lambda^2 \beta_j, \tag{2-6}$$

$$L_j^* = \frac{(1-\beta_j-\gamma_j)(t+\tau)}{\lambda \beta_j} a_j^*, \tag{2-7}$$

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[2] We can also derive the joint distribution of (θ, ε) and the conditional distribution of ε.

[3] The covariance of revenue from different crops are assumed to be zero for simplicity.

where a_j^* is characterized by the implicit function in equation (2-6) and λ, η, and τ are the shadow prices assigned to the land, water supply, and share constraint, respectively. Detailed derivations and explanations are provided in Appendix A2.

2.3.2 A Comparative Analysis

An assessment of the impact of water availability and climate change on production decisions requires a clear and direct measure of risks. In this study, an increase in risks is reflected by an increase in risk premium. At a given risk aversion level α, changes in risks can be attributed to changes in variability of climate σ^2 or variability in water supply σ_ε^2. In the following we discuss some comparative statics results and implications.

2.3.2.1 Impact of Climate Risks

(1) We find that climate variability encourages technology adoption for a producer with high irrigation efficiency and for a crop with high market value.

First, the sign of the marginal effect $\frac{\partial a_j^*}{\partial \sigma^2}$ is determined by the magnitude of the optimal irrigation efficiency a_{ij}^* compared to a threshold level $\bar{a}_J$, where $\bar{a}_J = \frac{1-\beta_j-\gamma_j}{\delta\beta_j\gamma_j}\left[\frac{\left(4e^{\sigma^2}-1\right)\lambda}{\left(3e^{\sigma^2}-1\right)P_j(1-\beta_j-\gamma_j)}\right]^{\frac{1}{\beta_j}}\left[\frac{\omega_j(1-\beta_j-\gamma_j)}{\lambda\gamma_j}\right]^{\frac{\gamma_j}{\beta_j}}(c_j+\sigma_\varepsilon^2+\eta)$. When $a_j^* < \bar{a}_J$, $\frac{\partial a_j^*}{\partial \sigma^2} < 0$; otherwise, when $a_j^* > \bar{a}_J$, $\frac{\partial a_j^*}{\partial \sigma^2} > 0$. The detailed derivation is presented in Appendix A3. The implication is that for a producer who adopts the efficient irrigation technology for a smaller share of land and thus having a lower irrigation efficiency, a more variable climate tends to discourage adoption, indicating the efficient irrigation technology as a risk-increasing input for him. The producer initially self-selects to a low adoption rate due to some inherent features that may reduce irrigation efficiency. For example, the cropland may have low water-holding capacity or the water salinity is high. In this case, the expectation of increasing climate risks makes him more concerned with the effectiveness of technology and hence less willing to invest in technology adoption. In contrast, if the adoption rate is high above the threshold level, increasing climate variability incentivizes the producer to increase the use of the efficient irrigation technology, in an effort to mitigate the adverse impacts of climate change. Under this circumstance, the water-saving irrigation technology is a risk-reducing input. It improves the relative efficiency of water use, reduces the effects of climate change such as uncertain rainfall on production, and reduces the implicit cost of risks.

Second, under climate change technology adoption favors crop with high market price. The threshold is mainly affected by the output elasticities, output and input prices, and shadow prices of the constraints. In particular, the threshold level is negatively impacted by output price, which suggests a low threshold for a crop with high market value. Hence there is a higher probability that optimal irrigation efficiency is above the threshold. Consequently, producer is more likely to increase adoption given a more variable climate. This result is very straightforward in that producer chooses to invest in a crop that can bring high marginal returns. This result can also be understood using second order derivatives. $\frac{\partial^2 a_j^*}{\partial \sigma^2 \partial P_j} > 0$, meaning that producer increases adoption more (or reduces adoption less) for a crop with high market price.

(2) In response to increasing climate risks, a producer allocates more land to a crop that he predominantly grows, and that has high output price or low water price.

First, climate change makes a producer grow more of a crop that is already dominant in his production. The sign of the marginal effect $\frac{\partial L_j^*}{\partial \sigma^2}$ is influenced by the optimal land allocation L_j^* relative to a threshold level, which is defined as $\overline{L_j} = \frac{(1-\beta_j-\gamma_j)^2}{\lambda {\beta_j}^2 \gamma_j} \left[\frac{\left(4e^{\sigma^2}-1\right)\lambda}{\left(3e^{\sigma^2}-1\right)P_j(1-\beta_j-\gamma_j)}\right]^{\frac{1}{\beta_j}} \left[\frac{\omega_j(1-\beta_j-\gamma_j)}{\lambda\gamma_j}\right]^{\frac{\gamma_j}{\beta_j}} (c_j + \sigma_\varepsilon^2 + \eta)(t+\tau)$. Below the threshold, a producer self-selects to allocates less land to a certain crop because of some inherent reasons. More uncertainties in climate decreases marginal productivity of land even more and hence incentivize him to reduce the planted acreage of the crop

($\frac{\partial L_j^*}{\partial \sigma^2} < 0$). Above the threshold, the producer chooses to largely produce crop j. $\frac{\partial L_j^*}{\partial \sigma^2} > 0$, meaning he continues to expand production of crop j in accordance with the increase in technology adoption. Intuitively, the producer predominantly grows a certain crop as a result of self-selection. For instance, he either has more farming experience for this crop or he is expecting more economic returns. In response to more climate risks, he would increase the share of land planted to the crop he has more confidence in.

We can also interpret these results using the shadow price of the land constraint λ. As shown in Appendix A3, the threshold level $\overline{L_j}$ is negatively associated with a threshold for the shadow price $\bar{\lambda}$. When the plated acreage L_j^* is small for crop j (i.e. $L_j^* < \overline{L_j}$), the marginal benefit of land use is high (i.e., $\lambda > \bar{\lambda}$), and producer switches to grow a dominant crop. Whereas when the shadow price of land is below $\bar{\lambda}$, land is not much of an "expensive" resource, so producer tends to expand production given an expectation of more climate risks.

Second, climate change makes a producer allocate more land to a crop with high market price and low water price. The threshold level $\overline{L_j}$ decreases with output price. That is, for a high-value crop, threshold is lower, optimal planted acreage L_j^* is more likely to go beyond the threshold, wherefore the producer is more likely to increase its planted acreage given climate change. From a second order derivative perspective, it implies the producer expands production more (or cuts production less) for a crop with high market price. In addition, a higher water price c_j for a crop increases the threshold, thus making the producer more likely to reduce its acreage. It makes intuitive sense in that with increasing production risks, producer grows less of a crop with more expensive water supply.

(3) The impact of climate variability on water application rates is indeterminate. A producer increases water application rates if he adjusts technology adoption more than he adjusts planted acreage.

Irrigation efficiency and total volume of water use are substitutes as agricultural inputs. The first order conditions inform that $a_j^*(t+\tau) = (c_j + \sigma_\varepsilon^2 + \eta)L_j^* r_j^*$. It means the opportunity cost for technology adoption (left hand side) should achieve the same results as spent on applying more water (right hand side). From this condition we have $\frac{\partial a_j^*/\partial(\sigma^2)}{a_j^*} = \frac{\partial L_j^*/\partial(\sigma^2)}{L_j^*} + \frac{\partial r_j^*/\partial(\sigma^2)}{r_j^*}$. Detailed derivation is presented in Appendix A4. It means if a producer improves irrigation efficiency by adopting better technology in response to climate risks, he can equivalently increases the absolute amount of water use to maintain the same level of productivity.

As such, if there is relatively more adjustments in technology adoption than in land use ($\frac{\partial a_j^*/\partial(\sigma^2)}{a_j^*} > \frac{\partial L_j^*/\partial(\sigma^2)}{L_j^*}$), producer increases water application rates ($\frac{\partial r_j^*}{\partial \sigma^2} > 0$) to compensate for the difference. Specifically, there are two cases when water application rates increase. First, when technology adoption and cropland allocation change in opposite direction ($\frac{\partial a_j^*/\partial(\sigma^2)}{a_j^*} > 0 > \frac{\partial L_j^*/\partial(\sigma^2)}{L_j^*}$), producer increases technology adoption and reduces planted acreage. Both adjustments save him water so that he can apply more water per acre. Intuitively it means the producer concentrates water use to a smaller share of land to maintain high yields. Second, when they change in the same direction with more adjustments in technology adoption ($\frac{\partial a_j^*/\partial(\sigma^2)}{a_j^*} > \frac{\partial L_j^*/\partial(\sigma^2)}{L_j^*} > 0$ or $0 > \frac{\partial a_j^*/\partial(\sigma^2)}{a_j^*} > \frac{\partial L_j^*/\partial(\sigma^2)}{L_j^*}$), better efficiency (when both positive) saves the producer water even though he needs to distribute water to a larger area. With more water available he can meet the irrigation requirements for more cropland and meanwhile increase the water application rates.

2.3.2.2 Impact of Water Scarcity

Reductions in water supply are specified to increase expected water price by a magnitude of its variance σ_ε^2. Now we examine the effects of more expensive water supply on adaptation strategies.

(1) We find that water scarcity reduces water application rates.

Water scarcity influences production behavior by changing water price. With this specification, the shadow prices for land and water supply constraints λ and η are not affected by water scarcity. Therefore, we can easily derive the marginal effect on water use as $\frac{\partial r_j^*}{\partial \sigma_\varepsilon^2} = -\frac{\lambda \beta_j}{(1-\beta_j-\gamma_j)(c_j+\sigma_\varepsilon^2+\eta)^2} < 0$. It suggests that as the uncertainty in water supply increases, producers cut the volume of water applied per-acre. This makes intuitive sense in that as water becomes more expensive due to reduced supply, producers have lower demand.

(2) Water scarcity encourages technology adoption for a producer with low irrigation efficiency and for a crop with high price.

The sign of the marginal effect $\frac{\partial a_j^*}{\partial \sigma_\varepsilon^2}$ depends on the optimal adoption a_j^* relative to a threshold level $\overline{a_j^\varepsilon}$. When $a_j^* < \overline{a_j^\varepsilon}$, $\frac{\partial a_j^*}{\partial \sigma_\varepsilon^2} > 0$; otherwise, $\frac{\partial a_j^*}{\partial \sigma_\varepsilon^2} < 0$. Detailed derivation is presented in Appendix A5. When a producer adopts the irrigation technology for a small share of land and uses water in a less efficient way, he responds to more expensive water supply by improving irrigation efficiency. Higher water price discourages him from using water. To maintain productivity, he substitutes with technology to offset the reduction in average effective water application rates. Whereas a producer with high irrigation efficiency is more likely to decrease investment in technology given water supply uncertainty. Since we assume decreasing marginal productivity, additional investment in technology adoption is not necessarily covered by the benefit (i.e. marginal product value) from increasing adoption. In other words, increasing adoption may cause loss in net returns. Therefore, higher water price drives him to reduce adoption.

Second, under water shortage technology adoption favors crop with high market price. $\frac{\partial^2 a_j^*}{\partial \sigma_\varepsilon^2 \partial P_j} > 0$, meaning if a crop has higher price, it is more likely that

$\frac{\partial a_j^*}{\partial \sigma_\varepsilon^2} > 0$. Given more limited water supply, a producer is more willing to increase adoption (or less willing to reduce adoption) of the efficient irrigation technology for a high-value crop. This result is also straightforward in that capital investment favors a crop that can bring high marginal returns.

(3) In response to water scarcity, a producer allocates more land to a crop that is not largely produced. The expansion in acreage increases with output price.

The threshold level is correspondingly defined by $\overline{L_j^\varepsilon}$ (or $\overline{\lambda^\varepsilon}$). When $L_j^* < \overline{L_j^\varepsilon}$ ($\lambda > \overline{\lambda^\varepsilon}$), land has a high marginal productivity. Hence, a producer has an incentive to expand production of the crop. When $L_j^* > \overline{L_j^\varepsilon}$ ($\lambda < \overline{\lambda^\varepsilon}$), the production scale is sufficiently large. An extra unit of land cannot bring enough benefit to cover the extra cost of input use. Under this circumstance, if a producer expects increasing water price, he responds by decreasing planted acreage, in accordance with decreased water application rate and decreased technology adoption. This reduction in acreage goes to crops that are not massively produced (i.e. with small L_j^*), implying a more diversified crop portfolio.

Likewise, informed by the second order derivatives, the acreage reduction tends to happen to a crop with low output price. That is, water scarcity makes producers concentrate on limited cropland and more expensive water supply to high-value crops.

2.3.3 Summary: Key Parameters

Climate change and water scarcity are anticipated to affect irrigated agriculture production on the West Coast. In response, producers can adapt by altering land allocations, adjusting water application rates, and adopting efficient irrigation technologies. This analysis constructs a theoretical framework to explore a multioutput producer’s adaptive strategies under uncertainties. Comparative statics results are summarized in Table 2-2. There are several interesting findings.

Table 2-2. Comparative Statics Analysis[a]

Parameters	Sign $(\frac{\partial a_j^*}{\partial(\cdot)})$	Sign $(\frac{\partial L_j^*}{\partial(\cdot)})$	Sign $(\frac{\partial r_j^*}{\partial(\cdot)})$
Climate variability σ^2	$(+)$ if $a_j^* > \overline{a}_j$	$(+)$ if $L_j^* > \overline{L}_j$, i.e. $\lambda < \bar{\lambda}$	$(+)$ if $\frac{\partial a_j^*/\partial(\cdot)}{a_j^*} > \frac{\partial L_j^*/\partial(\cdot)}{L_j^*}$
Water availability σ_ε^2	$(-)$ if $a_j^* > \overline{a_j^\varepsilon}$	$(-)$ if $L_j^* > \overline{L_j^\varepsilon}$, i.e. $\lambda < \overline{\lambda^\varepsilon}$	$(-)$

Note: [a] Differentiate the optimal solutions and/or first order conditions with respect to each parameter. The detailed derivation and proof are provided in Appendix A3-A5.

First, climate variability and water scarcity have opposite impacts on irrigation technology adoption. As an agricultural input, more efficient irrigation technology improves the relative efficiency of water use, mitigates crop damage from climate risks such as uncertain rainfall, and reduces the implicit cost of risk bearing. Meanwhile, it requires irreversible capital investment, generating a marginal cost that is not necessarily paid back by its marginal product value especially under uncertainties. There are two cases when a producer chooses to increase adoption. 1) If he has a high irrigation efficiency and anticipates a more variable climate, he will manage risk exposure by applying the technology to a larger share of cropland. 2) If he has a low adoption rate and expects increasing water price, he will enhance the use of technology to improve irrigation efficiency and compensate for reduced water supply. Under both circumstances, the producer is more likely to invest in technology adoption (or less likely to cut investment in technology adoption) for a crop with high market price.

Second, cropland allocation responds to climate variability and water scarcity in opposite ways as well. Consider a producer who predominantly grows a certain crop. 1) On one hand, large production scale is a result of self-selection; meanwhile low shadow price indicates land as a “cheap” resource. If he expects more climate risks, he increases the share of land allocated to this crop and decreases the scale of other crops that he does not massively grow. 2) On the other hand, due to decreasing marginal productivity, an extra unit of land does not guarantee high marginal benefit. If he expects water shortage, he decreases planted acreage of this crop and instead diversifies crop portfolio. In both cases, production risks make him expand production scale of a crop with high price.

Lastly, in response to climate variability, a producer increases water application rates if he adjusts technology adoption more than he adjusts planted acreage. Irrigation efficiency and total volume of water use are substitutes in agricultural production. 1) If he increases adoption and decreases scale, higher efficiency and less water demand saves him water so that he increases water application rates. 2) If he increases adoption more than he increases scale, the water saved by increasing irrigation efficiency is more than enough to cover the irrigation demand for a larger area, so that he increases water application rates. Whereas water scarcity leads to a decline in water application rates, regardless of the characteristics specific to producer or crop.

2.4 The Empirical Analysis

2.4.1 Empirical Model

Building on the theoretical framework, we perform an empirical analysis of farmers' adaptive land allocation and irrigation practices conditional on water scarcity (***S***), water supply institutions (***I***), climate and weather conditions (***C***), farm characteristics and farmer demographics (***D***), and expected output and input prices (***P***). As informed by equations (2-4)~(2-7), ***S*** and ***C*** include measurements of climate and water availability risks, and ***D*** each farm's unique property and personal characteristics. Hence, the empirical models of interest are:

$$DRY_{it} = g(\boldsymbol{S_{it}}, \boldsymbol{I_{it}}, \boldsymbol{C_{it}}, \boldsymbol{D_{it}}, \boldsymbol{P_{it}}), \tag{2-8}$$

$$IS_{it}^{j} = h^{j}(\boldsymbol{S_{it}}, \boldsymbol{I_{it}}, \boldsymbol{C_{it}}, \boldsymbol{D_{it}}, \boldsymbol{P_{it}}), \tag{2-9}$$

$$TC_{it}^{j} = l^{j}(\boldsymbol{S_{it}}, \boldsymbol{I_{it}}, \boldsymbol{C_{it}}, \boldsymbol{D_{it}}, \boldsymbol{P_{it}}), \tag{2-10}$$

$$AR_{it}^{j} = m^{j}(\boldsymbol{S_{it}}, \boldsymbol{I_{it}}, \boldsymbol{C_{it}}, \boldsymbol{D_{it}}, \boldsymbol{P_{it}}), \tag{2-11}$$

where

DRY_{it} = share of total harvested cropland allocated to dryland crops in farm i and year t,

IS_{it}^{j} = share of total harvested cropland allocated to irrigate crop j in farm i and year t,

TC_{it}^{j} = irrigation technology adoption choice of crop j in farm i and year t,

AR_{it}^{j} = per-acre water application rate of crop j in farm i and year t.

For this study, $j = 1, \dots, 5$ is an index of crop/crop typ. $t = 2008, 2013$ indexes year. We include $j = 0$ in equation (2-9) to represent the share of cropland allocated to irrigate all other non-selected crops. Equations (2-8) and (2-9) jointly characterize a producer's land use decisions by modelling share of irrigated cropland vs dry land, and how irrigated cropland are allocated to individual crop. Equations (2-9), (2-10), and (2-11) define a producer's irrigation strategy specific to selected crops, including share of land irrigated, technology adoption, and water use.

Water availability $\boldsymbol{S}$ is measured by both economic and physical variables. The economic variable measuring water availability includes cost of off-farm surface water. The physical variables include a) depth to groundwater; and b) pump capacity for irrigation, i.e., well water discharge rate. We calculate the per-acre cost of off-farm surface water as an economic indicator of surface water availability. We use average depth to well water at the start of irrigation season to represent groundwater pumping cost. It is a weighted average of well water depth for all wells pumped, with weights measured by the share of pump capacity discharge from each well in total pump capacity. Variations in pump capacity also translate into changing groundwater availability. It is calculated as an average well water discharge rate for each farm.

We construct several variables to measure the nature of surface water supply institutions, denoted as vector ***I***. Water supply institutions affect farmers' water availability and costs and therefore influence their land use and irrigation decisions. We include a variable for whether some/all off-farm surface water is supplied by federal agencies, specifically the U.S. Bureau of Reclamation (BOR). We also include an interaction term of BOR surface water supply and water price to examine how institutions affect farmers' response to water scarcity.

Vector ***C*** includes county-level climate and weather variables. Different crops are sensitive to different types of extreme weather, such as excess moisture, extreme heat, spring freeze, and drought. We assume farmers make decisions based on both long-run expected climate conditions and short-run observed weather conditions. For example, irrigation technology adoption decision is made before the growing season conditional on climate expectations. While water application rates is a short-run response that can be adjusted during the growing season conditional on realized weather conditions. Therefore, we develop crop-specific climate risk measurements, climate expectations, and weather realizations. For example, excessive moisture risk is captured by a 30-year precipitation variability. Expected precipitation level is formulated as a 5-year average during specific months. While average precipitation in each production year represents realized precipitation level.

Farm characteristics and farmer demographics ***D*** includes land characteristics that may affect land use and irrigation decisions, such as cropland quality. We also control for farm size. We develop a variable for tenure to characterize the demographic feature of farmer, which is calculated as the share of land owned in total acreage operated. We also include a state identifier in ***D*** as there may be different policies varying across states.

Vector ***P*** includes the expected output prices at the time when the planting decisions are made, measured by lagged market prices. Both winter wheat and spring wheat are grown in Oregon and Washington[4]. We use wheat price in general to

[4] California grows winter wheat only.

represent this category. Price of the orchard/vineyard category is represented by a weighted average price for the top sales perennial crops in each state. We include the input prices farmers pay at the start of the growing season, such as the indexes of prices paid for commodities, services, interest, taxes, and wage rates.

More detailed variable construction process and description are available in the following data section.

2.4.2 Data

2.4.2.1 Data Source

This analysis uses farm-level cross-sectional data on water and climate for the states of California, Oregon, and Washington. Our dataset is obtained from three main sources. The first one is the Cause of Loss (COL) data collected by the U.S. Department of Agriculture Risk Management Agency (USDA-RMA). The COL data report the county-level causes and timing of crop loss for all insured commodities under the federal crop insurance program (FCIP). The COL data provide a comprehensive summary of insurance information (e.g., total premium, subsidy, liability, indemnity, loss ratio, coverage category (i.e. buy-up or CAT)) associated with each insured commodity and insurance plan, as well as detailed information about the year and month when the loss occurs. The FCIP is the primary risk management tool for U.S. agriculture (Glauber 2013; Shi et al. 2019), making the COL data a reliable source to evaluate the relative risks for agricultural production.

With the COL data, we analyze the specific causes and timing of crop loss, as captured by indemnity payments, by state and by crop using historical data files from 1989-2018 (USDA-RMA 2019). We summarize the key adverse climate and weather conditions influencing each of the five crops/crop type. Figure 2-2 provides a visual presentation that there are various risks for growing each crop at each of the three states. In Table 2-3, each cell identifies the specific timing of climate or weather risks that affect production. Two percentages in parentheses represent the share of specific indemnity payments in total weather-related indemnity payments and the ratio of specific indemnity payments to total liabilities, respectively. For example, forage production in California is susceptible to excessive moisture from December to March. Indemnified losses caused by excess moisture accounts for 77% of all weather-relevant indemnities and 33% of total liabilities. As shown in Table 2-3, the top causes of crop loss on the West Coast are excess moisture, heat, freeze and frost, and drought. For a particular crop and location, these major causes comprise 48%-77% of total weather-related indemnity payments and at least 13% of insurance liability for each crop, indicating that climate and weather variability imposes a significant risk to agricultural production.

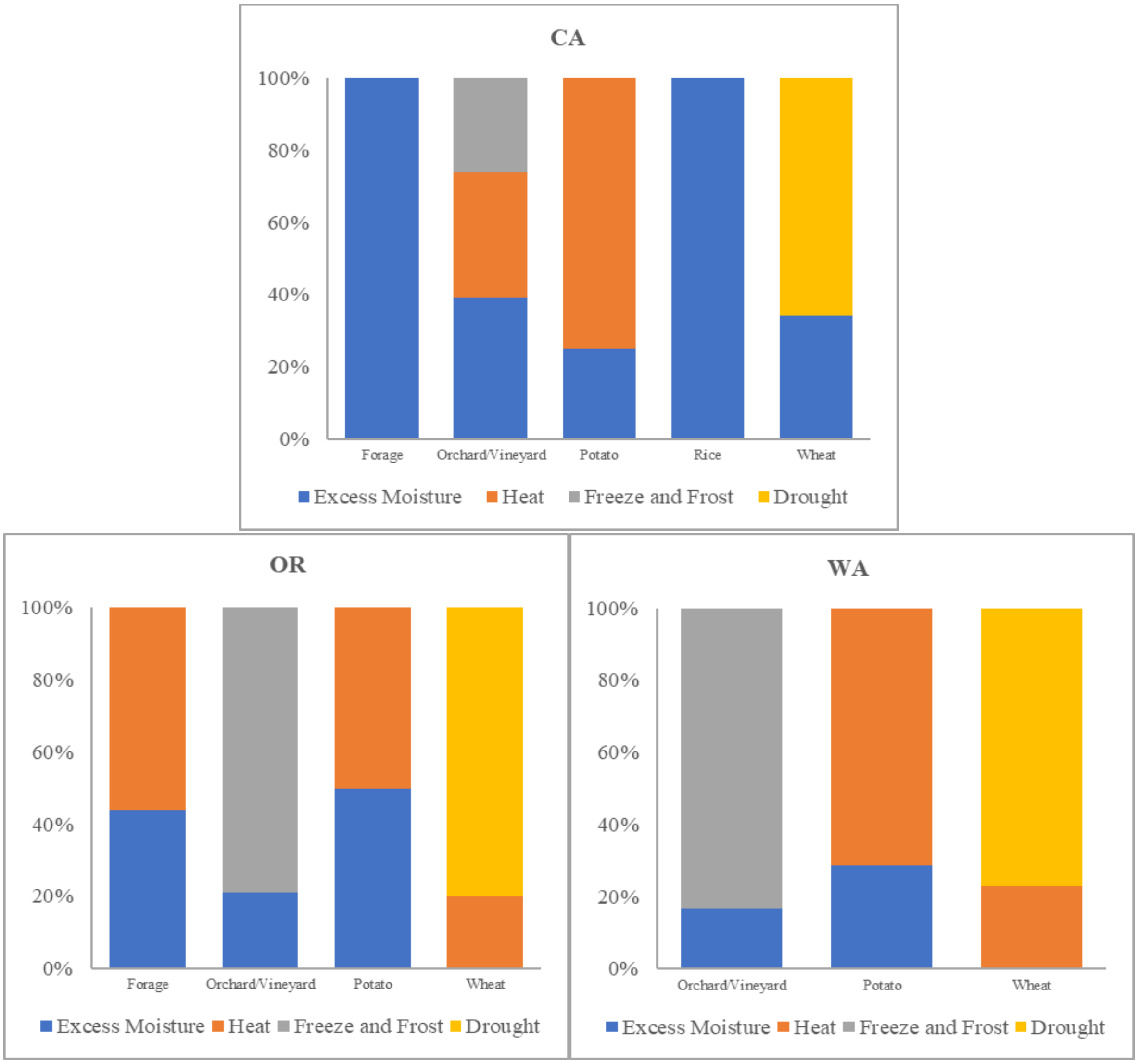

Figure 2-2. Various risks for growing each crop by state

Table 2-3. Top Drivers of Crop Loss for Selected Crops on the West Coast 1989-2018

		Excess Moisture	Heat	Freeze and Frost	Drought
	CA[a]	Dec-Mar (77%, 33% [b])			
Forage	OR[a]	June-Aug (25%, 7%)	June-Oct (31%, 9%)		
	WA[a]				
	CA	Feb-May (26%, 9%)	Mar-Aug (24%, 8%)	Mar-May (18%, 6%)	
Orchard/Vineyard	OR	June-Aug (12%, 4%)		Mar-May (41%, 15%)	
	WA	June-Aug (9%, 3%)		Mar-May (39%, 15%)	
	CA	Apr-July (12%, 3%)	May-Aug (36%, 9%)		
Potato	OR	May-Oct (29%, 9%)	May-Aug (31%, 9%)		
	WA	May-Oct (18%, 6%)	May-Aug (45%, 15%)		
	CA	Mar-May (76%, 28%)			
Rice	OR				
	WA				
	CA	Dec-May (26%, 13%)			Dec-May (48%, 25%)
Wheat	OR		May-July (16%, 6%)		Mar-Aug (60%, 24%)
	WA		May-July (13%, 3%)		Mar-Aug (43%, 10%)

Note: [a] State abbreviation, CA, OR, and WA stand for California, Oregon, and Washington, respectively.
[b] In parentheses are two percentages with the former representing the share of indemnified loss caused by each factor in total weather-related indemnity payments, and the latter representing the ratio to total liabilities.

The COL analysis suggests that different crops are sensitive to different types of extreme weather. The losses also reflect the self-selection of producers choosing different crops in different locations. To develop measures of climate risks that are truly exogenous, we generate county-level climate and weather variables specific to individual crop using climate data developed from the PRISM system, capturing both spatial and temporal variations of important climate variables on the West Coast. PRISM datasets are recognized world-wide as the highest-quality spatial climate datasets currently available and provide the USDA with their official 30-year digital climate maps (Daly 2006; Daly et al. 2012; 2008; 2002; Daly et al. 1994). The PRISM system produces continuous, digital grid estimates of daily, monthly, yearly, and event-based climatic parameters. Our climate data for each county is extracted using an agricultural land mask so that data does not include mountainous area or other non-agricultural lands. A unique feature of our climate data is that they reflect both expected climate and observed weather conditions. As mentioned in the last section, long run adaptations are responsive to climate expectations while short run adjustments are affected by weather realizations. Hence, we develop recent 5-year averages for an array of climate statistics for each month of the year to represent long-run expectations, and an array of climate statistics for each month and season for short-run observations.

Finally, the USDA Farm and Ranch Irrigation Survey (FRIS) is the primary data for characterizing the variability in water availability, water supply institutions, farm characteristics, farmer demographics, water use, and irrigation technology adoption across farms on the West Coast. This study generates a representative sample of farms on the West Coast with data in production years 2013 and 2018 (the two most recent surveys). The West Coast is one of the ten USDA Farm Production Regions. The FRIS provides the most comprehensive profile of irrigation in the U.S. because it is delivered to all irrigated farms as a supplement to the Census of Agriculture. It contains detailed farm-level data on water sources (e.g., groundwater and surface water), water supply institutions, farm characteristics, farmer demographics, and a variety of irrigation management practices, including technology adoption, water use, water recycling and reclamation, and whether irrigation was used to mitigate damage from extreme weather such as freeze and heat stress.

Variables complementing the FRIS data and PRISM data are developed from other sources. We obtain the commodity price and input price data from USDA National Agricultural Statistics Service (NASS). It provides state-level price received in each marketing year for potato, rice, wheat, and forage. We rank commodities in orchard/vineyard category by cash receipts in 2018, select top 3 crops in this category for each state, and calculate weighted averages to represent category price, with weights measured by the relative cash receipts. Output prices are adjusted for inflation with 1982-1984 as base year. All input prices are normalized by the index of prices paid by farmers for commodities, services, interest, taxes, and wage rates at the start of the growing season (USDA 2014). Cropland quality variables are generated from the 1997 Natural Resources Inventory and the 2011 National Land Cover Database. Specifically, we collect GIS data on the amount of land in Land Capability Class 1-8 and use a shape file for agricultural land from the National Land Cover Database to construct a variable for the amount of agricultural land in each of the eight Land Capability Classes. Lower Land Capability Class values indicate higher quality soils with less use restrictions and better suitability for agricultural production.

2.4.2.2 Variable Construction and Description

Table 2-4 presents detailed explanations for the variables. We quantify excess moisture risk as precipitation variability. For example, excess moisture from December to March is identified as a primary cause of loss for forage in California. We construct average of monthly standard deviation of precipitation over the previous 30 years. These monthly mean standard deviations are then averaged across specific months, i.e. December to March to capture variability. For each crop/county combination, we also calculate 5-year mean precipitation averaged over specific months to represent the expectation of precipitation in the long run. Short run production decisions are affected by short run weather realizations. As such, we create mean precipitation averaged over specific months in each production year to represent short-run precipitation levels.

Table 2-4. Definitions for Dependent and Independent Variables

Dependent Variables	
Dry land share, DRY_{it}	Share of dry land production in total harvested acreage [0,1][a]
Irrigated share, IS_{it}^{j}	Crop-specific share of irrigated land harvested in total harvested acreage [0,1][a]
Technology adoption, TC_{it}^{j}	Crop-specific adoption of efficient irrigation technology (0/1)[b]
Water application rate, AR_{it}^{j}	Crop-specific quantity of water applied (acre-feet per acre)
Independent Variables	
Water scarcity, ***S***	
Surface water cost	Price of off-farm surface water ($1000 per acre-foot)
Well water depth	Depth to well water at the start of irrigation season (1000 feet)
Pump capacity	well water discharge rate (1000 GPM)
Water supply institutions, ***I***	
BOR	Off-farm surface water supplied by the BOR (0/1)
BOR*Surface water cost	Interaction term of BOR surface water supply and water price
Climate and weather, ***C***	
Excessive moisture risk	30-year mean of monthly standard deviation of precip. averaged over specific months (inches)
Extreme heat risk	30-year mean of monthly standard deviation of daily max. temperature averaged over specific months (°F)
Spring freeze and frost risk	Median of last spring freeze date over 30 years (days)
Drought risk	Percentage of months when actual precip. smaller than average precip. by one std. dev. over 30 years [0,1]
Precipitation, expected	5-year average of monthly mean of precip. averaged over growing season (inches)
Precipitation, observed	monthly mean of precip. of the year averaged over growing season (inches)
Max. temperature, expected	5-year average of monthly mean of daily max. temperature averaged over growing season (°F)
Max. temperature, observed	monthly mean of daily max. temperature of the year averaged over growing season (°F)
Farm characteristics and farmer demographics, ***D***	
Cropland quality	Share of cropland in Land Capability Classes 1, 2, or 3 [0,1]
Scale	Total acreage of land that could be used for crops without additional improvement (1000 acres)
Tenure	Ratio of land owned relative to the total land owned, rented, and leased [0,1]
Prices, ***P***	
Output price	1-year lagged output price of the marketing year
Input price	Indexes of price paid for commodities, services, interest, taxes, and wage rates

Note: [a] The shares add to 1, altogether characterizing a producer's cropland allocation decision.
[b] Benchmark is gravity (0); efficient technology is sprinkler and drip (1).

Extreme heat risk is characterized by variability in daily maximum temperature. We first calculate the standard deviation of daily maximum temperature for a specific month over a 30-year period, then calculate the average of standard deviation across specific months. For each crop/county combination, we also construct a 5-year average of monthly mean daily maximum temperature averaged across months to represent expectation and calculate the monthly mean of daily maximum temperature (averaged across months in a given year) to represent the maximum temperature condition in a year.

Spring freeze presents a considerable risk to orchard/vineyard production on the West Coast. We use 32°F as the break point for freeze data. We generate a 30-year median of the date when the last spring freeze occurred on agricultural land to measure the expected spring freeze risk for growing orchard/vineyard in a county.

Lastly, we treat drought risk as a relatively high probability of extremely low precipitation, which is captured by the left tail of precipitation distribution. We use the percentage of months during which precipitation is below the average precipitation by more than the standard deviation throughout a 30-year period to represent drought risk for producing wheat in a county.

Table 2-5 reports summary statistics for the dependent variables. We have 4480 farms in total that irrigate at least one of the selected crops, with 1646 observations from 2013 FRIS and 2834 from 2018.[5] Irrigation is an essential component of farming practices in our sample. On average, a representative producer allocates 5.2% of cropland to dryland crops, 74.7% to irrigate selected crops, and 20.1% to irrigate other non-selected crops. Irrigated share is relatively large for producers irrigating forage and orchard/vineyard and small for potato and wheat. More than 90% of orchard/vineyard and potato farms adopt the efficient irrigation technology, sprinkler and drip. Adoption rates are lower for forage and wheat farms. There is less variation in water application rates, with forage and rice irrigation using more water per acre. All rice is irrigated, exclusively with the benchmark technology, gravity. Beside, rice production is almost exclusively concentrated in the Sacramento Valley in California. Given these features, there is little variation in dependent variables for rice. Therefore, we decide to drop rice from selected crops even though rice is a water-intensive crop.

[5] 4526 farms in 2013 and 7974 farms in 2018 participate in the survey on the West Coast. Our sample represent 36% of producers in the study region.

Table 2-5. Descriptive Statistics for Dependent Variables

Variable (units)		Irrigated land: Forage	Orchard/Vineyard	Potato	Rice	Wheat	Other	Dry land
Cropland allocation [0,1]		0.239 (0.380)	0.470 (0.467)	0.015 (0.084)	0.030 (0.162)	0.036 (0.116)	0.201 (0.318)	0.052 (0.165)
Technology adoption	% Gravity	43	10	5	100	38	--	--
	% Sprinkler & Drip	57	90	95	0	62	--	--
Water application rate (acre-feet/acre)		2.450 (1.331)	2.066 (1.280)	1.847 (1.044)	4.384 (1.432)	1.925 (0.893)	--	--
Observations		1645	2629	294	170	658	4407	4480

Note: Reported are sample means. In parentheses are standard deviations.

Table 2-6 reports summary statistics for the independent variables. The unit cost of off-farm surface water is highest for orchard/vineyard and lowest for wheat, indicating surface water availability is more of a concern for orchard/vineyard producers. On the contrary, depth to well water is smallest for orchard/vineyard and second largest for wheat, pump capacity smallest for orchard/vineyard and largest for wheat. The difference implies relatively lower groundwater pumping cost for orchard/vineyard producers; while groundwater is less accessible for wheat producers. These distinctions in water scarcity perfectly coincide with the fact that a higher proportion of orchard/vineyard and potato farms use groundwater (63% and 59%, respectively), while a majority of wheat and forage farms use off-farm surface water (71% and 64%, respectively). There is a similar pattern in water supply institutions. Wheat farms rely heavily on surface water, with 39.3% of them obtaining surface water from BOR. While only 17.4% of orchard/vineyard farms receive BOR surface water supply. Table 2-3 summarizes the climate risks that are critical to the health of each crop. Table 2-6 provides a comparison across crops. For example, excessive moisture risk presents more of a threat to orchard/vineyard than to wheat. Extreme heat risk is highest for growing potato and lowest for forage. Land quality is highest for potato and lowest for wheat. Farm size is significantly larger for potato and wheat than other crops. Tenure is highest for orchard/vineyard and lowest for wheat, suggesting that farmers growing perennial crops tend to own cropland rather than rent or lease from others. Variables without variation are not reported, such as input prices.

Table 2-6. Descriptive Statistics for Independent Variables

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)
Water scarcity[a]				
Off-farm surface water cost ($1000/acre-foot)	0.047 (0.085)	0.166 (0.224)	0.091 (0.180)	0.041 (0.067)
Depth to well water (1000 feet)	0.153 (0.099)	0.143 (0.086)	0.193 (0.135)	0.189 (0.127)
Pump capacity (1000 GPM)	1.154 (0.506)	0.971 (0.561)	1.175 (0.527)	1.255 (0.521)
Water supply institutions				
BOR surface water supply (0/1)	0.291 (0.454)	0.174 (0.379)	0.270 (0.445)	0.393 (0.489)
Climate and weather				
Excessive moisture risk (inches)	22.181 (24.045)	36.173 (20.225)	17.793 (10.081)	13.643 (20.284)
Extreme heat risk (°F)	1.926 (2.418)	3.097 (1.611)	4.445 (0.511)	2.913 (2.314)
Spring freeze and frost risk (days)	--	89.159 (27.449)	--	--
Drought risk [0,1]	--	--	--	0.060 (0.122)
Precipitation, expected (inches)	19.277 (14.538)	15.050 (15.096)	28.278 (22.627)	16.011 (11.321)
Precipitation, observed (inches)	17.835 (14.429)	12.082 (14.254)	27.101 (22.095)	16.012 (13.210)
Max. temperature, expected (°F)	28.284 (3.850)	30.174 (3.468)	26.513 (3.560)	28.995 (3.908)
Max. temperature, observed (°F)	28.947 (3.515)	30.321 (3.244)	27.314 (3.335)	29.762 (3.580)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	0.255 (0.280)	0.298 (0.326)	0.373 (0.256)	0.244 (0.255)
Scale (1000 acres)	2.023 (5.381)	1.057 (3.317)	3.825 (7.329)	3.900 (6.977)
Tenure [0,1]	0.584 (0.316)	0.766 (0.290)	0.602 (0.320)	0.483 (0.287)
Price				
Output price ($/ton)	44.684 (4.036)	637.001 (248.230)	38.877 (13.719)	58.746 (9.207)

Note: [a] Outliers in water scarcity variables are replaced with the values at 95% percentile. Missing observations are replaced with county-level or state-level averages, by assuming that farms in the same county have similar water availability.

2.4.3 Estimation Strategy

2.4.3.1 A Farm-level Analysis

The FRIS provides detailed farm-level data on irrigation. However, for confidentiality reason the survey doesn't reveal a farm identifier, which prevent us from merging different surveys into a panel. To deal with this situation, we test two types of estimation methods. First, we stack the samples from 2013 and 2018 to create a pooled cross-sectional dataset and treat farms that might have participated in both surveys as independent observations. The model specification of equations (2-8)~(2-11) takes the form

$$Y_{it}^{j} = \boldsymbol{\beta_1^j S_{it}} + \boldsymbol{\beta_2^j I_{it}} + \boldsymbol{\beta_3^j C_{it}} + \boldsymbol{\beta_4^j D_{it}} + \boldsymbol{\beta_5^j P_{it}} + u_t^j + \varepsilon_{it}^j, if\ Y_{it}^j = DRY_{it}, IS_{it}^j, AR_{it}^j, \quad (2\text{-}12)$$

$$Prob(Y_{it}^j = 1) = \frac{\exp\left(\boldsymbol{\beta_1^j S_{it}} + \boldsymbol{\beta_2^j I_{it}} + \boldsymbol{\beta_3^j C_{it}} + \boldsymbol{\beta_4^j D_{it}} + \boldsymbol{\beta_5^j P_{it}} + u_t^j + \varepsilon_{it}^j\right)}{1 + \exp\left(\boldsymbol{\beta_1^j S_{it}} + \boldsymbol{\beta_2^j I_{it}} + \boldsymbol{\beta_3^j C_{it}} + \boldsymbol{\beta_4^j D_{it}} + \boldsymbol{\beta_5^j P_{it}} + u_t^j + \varepsilon_{it}^j\right)}, if\ Y_{it}^j = TC_{it}^j, \quad (2\text{-}13)$$

where the superscript j can be ignored when $Y_{it}^j = DRY_{it}$. u_t^j and ε_{it}^j represent year fixed effects and the error term, respectively.

Endogeneity issue and selecting functional forms raise a challenge to econometric estimation. First, we deal with endogeneity caused by simultaneity using instruments. We use depth to well water at the start of irrigation season to represent groundwater availability, which affects and is affected by adaptations. We adopt an IV approach to address the simultaneity-induced endogeneity bias given that groundwater is a non-exclusive open access good, a farm's pumping practices bear the consequence of neighboring farms' pumping behavior. Following Irwin and Bockstael (2002) and Pfeiffer and Lin (2012), we use average well water depth of neighboring farms (i.e. all other farms within the same county) as an instrument for well water depth. Pump capacity is similarly instrumented by the average pump capacity of neighboring producers. Per-acre cost of off-farm surface water reflects surface water availability. Water price is usually treated as exogenous as individual farms do not have a significant effect on price. However, we consider the potential endogeneity bias and develop instrumental variables on neighboring farms' surface water cost.

Second, we identify model specifications and estimators. Specifically, the dependent variables DRY_{it} and IS_{it}^{j} jointly model producers' land use decisions, including allocation of cropland between irrigated production and dryland production, and allocation of irrigated cropland to individual crops. They are estimated using OLS. Since they are specified as shares, we also test a fractional logit (FL) model. In addition, the majority of the farms in the sample irrigate at least one of the selected crops, generating many zeros in the share of dry land (around 85% of the sample). So we also test a Tobit model on dry land share, see the following subsections for detailed discussion. Our survey data identifies the primary method of irrigation for each crop. The irrigation technology adoption variable TC_{it}^{j} is estimated as a discrete choice model using binomial logit. Water application rates variable AR_{it}^{j} is estimated with OLS.

Third, we address endogeneity resulting from correlation across equations. Producers make land and irrigation decisions jointly, which gives rise to correlated error terms. So we estimate this system of equations simultaneously using seemingly unrelated estimation.

We implement a 3-stage estimation procedure that sequentially addresses these econometric challenges to obtain consistent and efficient estimates.

1st stage: Regress the endogenous water scarcity variables on all the exogenous regressors and instruments with OLS and get predicted values;

2nd stage: Regress the dependent variables on all the exogenous regressors and fitted values of endogenous variables, using selected functional forms and estimators

3rd stage: Estimate producers' responses as a system.

2.4.3.2 A County-level Analysis

Alternatively, we sacrifice the microscale model for a panel structure. The smallest geographic identifier for each surveyed farm is the county they belong to. Hence, we aggregate data to county-level for each variable and generate a panel dataset. Specific panel construction methods are provided in Table 2-7. We estimate the equation system as

$$Y_{ct}^{j} = \boldsymbol{\beta_1^j S_{ct}} + \boldsymbol{\beta_2^j I_{ct}} + \boldsymbol{\beta_3^j C_{ct}} + \boldsymbol{\beta_4^j D_{ct}} + \boldsymbol{\beta_5^j P_{ct}} + a_c^j + b_t^j + \varepsilon_{ct}^j, \ \forall\, Y_{ct}^j, \quad (2\text{-}14)$$

where subscript c indexes county and a_c^j and b_t^j represent county and year fixed effects, respectively. Compared with the farm-level model, we get to treat unobserved heterogeneity but we lose the richness of data by aggregation. Besides, this panel specification weakens the interpretation on individual farmer's heterogeneous responses to climate and water conditions.

Table 2-7. Panel Construction: Aggregation Methods for Dependent and Independent Variables

Dependent Variables	
Dry land share, DRY_{ct}	Weighted average of dry land share DRY_{it}, weight same as above [0,1]
Irrigated share, IS_{ct}^{j}	Weighted average of irrigated share IS_{it}^{j}, weight measured by share of total harvested cropland of each farm in the county [0,1]
Technology adoption, TC_{ct}^{j}	Share of farms adopting efficient irrigation technology [0,1]
Water application rate, AR_{ct}^{j}	Weighted average of water application rate AR_{it}^{j}, weight measured by share of irrigated acreage of each farm in total irrigated acreage of the county (acre-feet per acre)
Independent Variables	
Water scarcity, ***S***	
Surface water cost	Weighted average of cost, weight measured by share of expenditure on surface water of each farm in total expenditure of the county ($1000 per acre-foot)
Well water depth	County average (1000 feet)
Pump capacity	County average (1000 GPM)
Water supply institutions, ***I***	
BOR	Share of farms obtaining off-farm surface water from BOR [0,1]
Climate and weather, ***C***	No aggregation needed
Farm characteristics and farmer demographics, ***D***	
Cropland quality	No aggregation needed
Scale	County total (1000 acres)
Tenure	Weighted average of tenure, weight same as that of irrigated share [0,1]
Prices, ***P***	No aggregation needed

The estimation strategy remains same as farm-level analysis except for the following aspects, see Table 2-8 for a detailed comparison. First, TC_{ct}^{j} is specified as the share of farms within a county adopting efficient irrigation technology. So we test both OLS and FL on this dependent variable. Second, there are non-linear specifications in the second stage for the farm-level model. Therefore, we perform a seemingly unrelated estimation on the system using a 2-step GLS approach and adjust the variance-covariance matrix to get the correct standard errors in the third stage. However, at county-level, we have the option to use OLS for all dependent variables in stage 2. This allows using MLE for seemingly unrelated regression, where the estimators are iterated to convergence. The estimates from GLS and MLE are asymptotically equivalent, but not numerically identical. Lastly, we perform a two-way fixed effects estimation on this panel.

Table 2-8. A Comparison of Estimation Methods

		Pooled Data Models			Panel Data Models		
Dependent variables		DRY_{it}, IS_{it}^{j}	TC_{it}^{j}	AR_{it}^{j}	DRY_{ct}, IS_{ct}^{j}	TC_{ct}^{j}	AR_{ct}^{j}
Estimation methods	1st stage	OLS			OLS		
	2nd stage	OLS/FL/Tobit	Binomial logit	OLS	OLS/FL/Tobit	OLS/FL	OLS
	3rd stage	Seemingly unrelated regression GLS			Seemingly unrelated regression MLE		
Fixed effects		Year			County, year		
Obs.		4481			239		

2.4.3.3 Identifying the Best Model Specifications and Estimators

We perform several tests to determine the best model specifications and estimation methods and assess the robustness of estimation results. First, we test different estimators on the equations of dry land production and irrigated share, including OLS, FL, and Tobit (only for dry land share). Table 2-9 provides a detailed comparison across different estimators for dry land share. In the case of OLS regression, we report parameter estimates, standard errors, and significance levels from a 3-stage estimation. In the cases of nonlinear models, we run first two steps of estimation, perform post-estimation predictions, calculate the marginal effects and their standard errors using numerical derivatives, as reported in Table 2-9. We then run the third stage estimation using coefficients from previous stages, adjust their standard errors, and report significance levels. We prefer the significance of coefficients that are adjusted by seemingly unrelated regression over the significance of marginal effects for the following reasons: 1) from a technical perspective, marginal effects are nonlinear functions of all the parameter estimates and explanatory variables; and 2) marginal effects are estimated with a nonstandard vce (delta method standard error), they cannot be adjusted by seemingly unrelated regression.

Table 2-9. A Comparison between Three Estimators for the Share of Dry Land Production

Variable (units)	OLS Coef. (Std. Err.)	Fractional Logit dy/dx (Std. Err.)	Tobit dy/dx (Std. Err.)
Water scarcity			
Off-farm surface water cost ($1000/acre-foot)	-0.014 (0.022)	-0.035 (0.029)	-0.260** (0.117)
Depth to well water (1000 feet)	0.154*** (0.053)	0.097** (0.044)	0.601*** (0.192)
Pump capacity (1000 GPM)	0.001 (0.008)	-0.001 (0.008)	0.011 (0.032)
Water supply institutions			
BOR surface water supply (0/1)	-0.026*** (0.006)	-0.031*** (0.012)	-0.146*** (0.041)
BOR*surface water cost	0.045 (0.033)	0.074 (0.081)	0.435 (0.293)
Climate and weather			
Excessive moisture risk (inches)	-2.07E-4 (2.56E-4)	7.06E-5 (0.000)	-0.002 (0.001)
Extreme heat risk (°F)	-0.012 (0.021)	0.002 (0.018)	0.071 (0.083)
Spring freeze and frost risk (days)	0.002*** (0.001)	0.001 (0.001)	0.004 (0.003)
Drought risk [0,1]	0.715*** (0.216)	0.545*** (0.152)	2.717*** (0.704)
Precipitation, expected (inches)	0.003*** (0.000)	0.001 (0.000)	0.007*** (0.001)
Max. temperature, expected (°F)	-4.02E-4 (0.001)	-0.006*** (0.002)	-0.036*** (0.009)
Farm characteristics and farmer demographics			
Cropland quality [0,1]	0.012 (0.012)	0.007 (0.014)	0.009 (0.057)
Scale (1000 acres)	0.002*** (0.001)	0.001*** (0.000)	0.011*** (0.003)
Tenure [0,1]	-0.037*** (0.010)	-0.035*** (0.011)	-0.217*** (0.045)
Year: 2018	0.021*** (0.006)	0.023*** (0.008)	0.114*** (0.033)
State: OR	-0.018 (0.041)	-0.019 (0.036)	-0.349** (0.159)
State: WA	-0.023 (0.018)	-0.010 (0.024)	-0.253*** (0.086)
Hausman Test of the Null Hypothesis that the Difference in Coefficients Is Not Systematic			
χ^2 Test Statistic	--	126.84	
Prob > χ^2	--	0.00	
Result	--	Rejected at 1% level of confidence	

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. The values reported are coefficient estimates from OLS regression, marginal effects from Fractional Logit model, and marginal effects from Tobit model, respectively. In parentheses are standard errors.

The marginal effects from FL and Tobit have different magnitudes but same signs except for two estimates that are statistically insignificant. We perform a Hausman specification test to see whether there is systematic difference between them and find that FL estimator is consistent and efficient, while Tobit is inconsistent. The parameters from OLS and the average marginal effects from FL are very close in magnitude and don't switch signs except for three insignificant estimates. Since we cannot adjust the standard errors of marginal effects with SUR, a simple OLS model is more desirable as it requires less assumption and treatment. This conclusion holds for the share equations of selected crops and other crops.

Second, we test the performance of instruments. The parameter estimates for instruments from the first stage regression are mostly statistically significant, indicating them as relevant to the endogenous variables. Besides, the instruments pass weak identification tests. The Stock-yogo F-stats (Kleibergen-Paap rk Wald stats for county-level) are greater than 10, which supports that we choose strong and adequate instruments and technically overcome the endogeneity issue.

2.5 Estimation Results

2.5.1 Evidence from Farm-level Analysis

2.5.1.1 Adaptation to Water Scarcity and Climate Risks: Land Use

Table 2-10 reports the marginal effects of water scarcity and climate risks on cropland allocation. First, intensified water scarcity, measured by increasing surface water price and groundwater pumping cost, reduces irrigated share of selected crops and expands dryland production. We observe more elastic response to water scarcity in selected crops with high water price. Summary statistics show that potato producers pay high surface water and groundwater cost and irrigate the smallest share of land, indicating water as a less accessible or affordable input. If they expect a 1% increase in surface water price, they reduce irrigated share of by 1.5%. Wheat and forage production are heavily dependent on surface water. They have the lowest surface water costs while paying more for groundwater extraction. Increasing surface water price doesn't significantly affect irrigated share of wheat and forage. However, reduced groundwater availability discourages farmers from irrigating wheat and forage. A 1% increase in well water depth and pump capacity decreases the irrigated share of both crops by 0.1%. Irrigation is essential to orchard/vineyard production. They irrigate the largest share of land, predominantly using groundwater. Besides, it is more costly to adjust their irrigated share given the perennial nature and sunk cost. As such, water scarcity doesn't have a significant effect on the irrigated share of perennial crops. Overall, these reductions in irrigated share of selected crops go to either dryland crops or other crops. Expansion in dryland production is intuitive in that water scarcity lessens water demand. Producers switch to irrigate other crops plausibly due to the relative profitability. There may be some non-selected crops that are less water-intensive or have higher marginal productivity in land and water use, making it more profitable to expand their irrigated acreage.

Table 2-10. OLS Parameter Estimation Results for the Share of Dry Land Production and Irrigated Cropland

Variable (units)	Dry Land	Irrigated Land				
		Forage	Orchard/Vineyard	Potato	Wheat	Other
Water scarcity						
Off-farm surface water cost ($1000/acre-foot)	-0.014 (0.022)	0.075 (0.133)	0.027 (0.042)	-0.162*** (0.055)	0.075 (0.185)	0.078** (0.036)
Depth to well water (1000 feet)	0.154*** (0.053)	-0.608*** (0.131)	0.010 (0.127)	-0.126 (0.112)	0.020 (0.109)	-0.164** (0.073)
Pump capacity (1000 GPM)	0.001 (0.008)	-0.031 (0.022)	-0.005 (0.017)	-0.001 (0.028)	-0.064** (0.028)	0.044*** (0.012)
Water supply institutions						
BOR surface water supply (0/1)	-0.026*** (0.006)	-0.078*** (0.022)	-0.080*** (0.022)	0.042 (0.043)	-0.069*** (0.019)	0.105*** (0.014)
BOR*surface water cost	0.045 (0.033)	0.068 (0.242)	0.136 (0.099)	0.076 (0.706)	0.109 (0.253)	-0.307*** (0.081)
Climate and weather						
Excessive moisture risk (inches)	-2.07E-4 (2.56E-4)	-0.002** (0.001)	0.002*** (0.001)	-0.008 (0.007)	0.001 (0.001)	0.003*** (0.000)
Extreme heat risk (°F)	-0.012 (0.021)	0.143** (0.061)	0.009 (0.031)	0.026 (0.040)	0.241*** (0.076)	-0.103*** (0.033)
Spring freeze and frost risk (days)	0.002*** (0.001)	--	-3.93E-4 (0.000)	--	--	-0.002*** (0.001)
Drought risk [0,1]	0.715*** (0.216)	--	--	--	0.031 (0.115)	0.719** (0.264)
Precipitation, expected (inches)	0.003*** (0.000)	-0.005*** (0.001)	-0.007*** (0.001)	0.002 (0.003)	-0.003* (0.002)	0.004*** (0.001)
Max. temperature, expected (°F)	-4.02E-4 (0.001)	-0.017*** (0.004)	0.017*** (0.001)	0.004 (0.006)	-0.006 (0.006)	0.014*** (0.002)
Farm characteristics and farmer demographics						
Cropland quality [0,1]	0.012 (0.012)	-0.004 (0.041)	0.077*** (0.028)	2.73E-5 (0.067)	-0.034 (0.054)	9.76E-5 (0.022)
Scale (1000 acres)	0.002*** (0.001)	-0.014*** (0.003)	-0.016*** (0.003)	0.001 (0.001)	-0.003*** (0.001)	0.007*** (0.001)
Tenure [0,1]	-0.037*** (0.010)	0.185*** (0.028)	0.289*** (0.028)	-0.025 (0.045)	0.070*** (0.028)	-0.210*** (0.018)
Price						
Output price ($/ton)	--	0.027*** (0.003)	5.27E-5 (0.000)	0.002 (0.003)	0.007* (0.004)	--
Year: 2018	0.021*** (0.006)	0.237*** (0.033)	0.034 (0.033)	0.024 (0.045)	0.121 (0.080)	-0.074*** (0.012)
State: OR	-0.018 (0.041)	-0.620** (0.308)	0.201* (0.121)	0.034 (0.107)	-1.029*** (0.374)	0.205*** (0.063)
State: WA	-0.023 (0.018)	-0.018 (0.053)	0.200* (0.111)	0.111 (0.097)	-0.971*** (0.350)	0.155*** (0.030)
R-squared	0.21	0.82	0.88	0.56	0.64	0.39

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. In parentheses are standard errors.

Second, BOR surface water supply increases the total share of irrigated cropland but does not affect producers' land use response to water scarcity. BOR indicates water rights seniority as BOR is instrumental in the early development of irrigated agriculture in western U.S. under the prior appropriation doctrine (Moore 1991). BOR distributes water according to a priority-based sharing system, which follows the chronological order in which water rights are established. At times of water shortage, water right seniority guarantees an advantage to receive water from BOR over juniors. Senior water right holders can irrigate more acreage of land and are less likely to have curtailed allotment while junior holders tend to predominantly bear the costs of water scarcity (Brent 2017; Burness and Quirk 1979; Hutchins 1968, 1977; Libecap 2011; Li et al. 2017, 2018; Schlenker et al. 2007; Xu and Li 2016). Therefore, farms receiving water from BOR have more secured surface water supplies. Results suggest that BOR supply significantly reduces dry land share by 2.6%, which is a 50% reduction relative to average dry land share. Specifically, farms getting water from BOR allocate more cropland to irrigate other crops. However, water supply institutions do not have a significant effect on changing farmers' land use responses to water scarcity except making irrigated share of other crops more sensitive to water shortage. Given \$100 higher water cost, farms with BOR supply allocate 2.02% less cropland to irrigate other crops than farms without BOR supply.

Third, climate and weather have a mixed but significant influence on land use decisions. Different crop producers adapt in different ways to various climate risks. 1) As shown in Table 2-3, forage production is susceptible to excessive moisture and extreme heat. Given a perception of increasing excessive moisture risk, forage producers are concerned with crop loss and reduce irrigated share. A higher probability of extreme heat increases the needs for irrigation to avoid crop failure, hence increasing its irrigated share. 2) Excessive moisture, extreme heat, and spring freeze and frost are responsible for crop loss in orchard/vineyard production. Excessive moisture increases water availability and enables expanding irrigated share at a lower cost, making orchard/vineyard producers increase irrigated share. They respond to extreme heat by increasing irrigated share as there is more demand for irrigation. Spring freeze and frost risk switches farms from irrigated production to dry land production, but does not have a discernible impact on orchard/vineyard even though it presents a critical threat to the health of orchard/vineyard. 3) Potato production is vulnerable to excessive moisture and extreme heat. Potato producers are concerned with crop loss and reduce irrigated share given a perception of increasing excessive moisture risk. Whereas they increase irrigated share if anticipating a higher probability of extreme heat. 4) Excessive moisture, extreme heat, and drought are major causes of loss for wheat producers. Similar to orchard/vineyard farmers, they expand irrigated share if expecting more excessive moisture and extreme heat risks. In response to drought risk, wheat farms increase the irrigated share to guarantee productivity, but the positive effect is insignificant.

Likewise, different crop producers adapt in different ways to various weather expectations. More precipitation in the growing season implies less demand for irrigation to maintain crop yield. If a producer expects a 1-inch increase, he reduces irrigated share by 0.3%~0.7%, depending on which crop he irrigates. On average, he allocates 0.3% more land to dryland production. On the other hand, more precipitation indicates more recharge of surface and ground water. Increased water availability results in an increasing irrigated share of other crops by 4%. Similarly, if a producer expects higher maximum temperature, he irrigates more land in an effort to offset the effect of high evapotranspiration rates in hot climate. Irrigated share of orchard/vineyard rises by 1.7% in response to a 1°F increase. In contrast, forage producers might be concerned with evapotranspiration loss and low irrigation efficiency. They adapt by allocating 1.7% less cropland to irrigate forage.

Cropland quality has a positive effect on the irrigated share of perennial crops, indicating that cropland is a complement of irrigation as agricultural inputs. Better cropland quality (e.g. better water-holding capacity) results in better performance of irrigation and higher productivity of water. Perennial crop producers expand irrigated area as they expect more economic returns from investing in irrigation on high quality land. Farm size has a negative impact on the irrigated share of selected crops and positive on other crops, suggesting that larger farms have a more diversified crop profile. Besides, large farms have more dry land probably due to high marginal operation costs. Tenure has a positive effect on irrigated share, suggesting that landownership encourages investing in irrigation to get long-run benefits. Lastly, driven by higher expected output price, producers irrigate more cropland to increase productivity and profits. If output price is higher by 1%, irrigated share of forage and wheat rises by 1.2% and 0.4%, respectively.

2.5.1.2 Adaptation to Water Scarcity and Climate Risks: Irrigation Technology Adoption

Table 2-11 reports the marginal effects of water scarcity and climate risks on the probability of efficient irrigation technology adoption. Coefficient estimates are reported in Appendix A-6. The irrigation technology equation correctly predicts adoption in at least 78% of observations for all crops, indicating equation (2-13) fits the observed data well. Predicted probabilities of adoption are identical to observed mean values in Table 2-5. The marginal effects suggest that both water scarcity and climate variability play an important role in technology adoption decisions.

Table 2-11. Marginal Effects on Probability of Efficient Irrigation Technology Adoption

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
Water scarcity				
Off-farm surface water cost ($1000/acre-foot)	1.894*** (0.297)	0.141** (0.059)	0.600** (0.401)	0.629 (0.633)
Depth to well water (1000 feet)	0.030 (0.175)	0.251** (0.133)	-0.137** (0.112)	0.526** (0.279)
Pump capacity (1000 GPM)	0.058** (0.025)	0.012 (0.019)	0.079** (0.040)	0.074 (0.052)
Water supply institutions				
BOR surface water supply (0/1)	0.058** (0.027)	-0.075*** (0.019)	0.004 (0.039)	-0.094** (0.040)
BOR*surface water cost	-1.459*** (0.392)	0.545 (0.209)	0.146 (0.923)	0.394 (0.661)
Climate and weather				
Excessive moisture risk (inches)	-0.001 (0.001)	0.002** (0.001)	-0.004 (0.007)	-0.003* (0.002)
Extreme heat risk (°F)	-0.250** (0.080)	-0.015 (0.036)	0.044 (0.044)	-0.065 (0.177)
Spring freeze and frost risk (days)	--	0.001 (0.000)	--	--
Drought risk [0,1]	--	--	--	0.947** (0.384)
Precipitation, expected (inches)	0.003 (0.002)	-3.42E-4 (0.001)	-4.14E-4 (0.003)	0.011 (0.006)
Max. temperature, expected (°F)	-0.041*** (0.006)	-0.004 (0.004)	-0.020 (0.010)	-0.023* (0.012)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	0.030 (0.048)	0.043 (0.033)	0.059 (0.096)	-0.207 (0.126)
Scale (1000 acres)	-0.001 (0.002)	0.031*** (0.007)	0.006* (0.004)	-0.001 (0.002)
Tenure [0,1]	-0.047 (0.032)	-0.006 (0.023)	-0.021 (0.046)	0.100** (0.049)
Price				
Output price ($/ton)	-0.033** (0.014)	-2.32E-4 (0.000)	0.005 (0.005)	0.036* (0.020)
Year: 2018	-0.244** (0.109)	-0.020 (0.047)	0.099 (0.075)	0.410** (0.051)
State: OR	0.693** (0.025)	-0.092 (0.306)	0.103 (0.320)	0.678 (0.452)
State: WA	0.266*** (0.051)	-0.130 (0.320)	0.074 (0.325)	0.754 (0.334)
Predicted Probability	0.57	0.90	0.95	0.62
Correct Prediction	78%	88%	94%	83%

Note: The benchmark is gravity irrigation technology. Sprinkler and drip are efficient technologies. We first perform a seemingly unrelated regression (SUR) and obtain the significance level of the coefficient estimates, as shown in the table. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. We then perform post-estimation predictions and calculate the marginal effects using numerical derivatives. In parenthesis are standard errors. We do not report the significance level of marginal effects because marginal effects are estimated with a nonstandard vce (delta method standard error), they cannot be adjusted with SUR. From a technical perspective, marginal effects are non-linear functions of all the parameter estimates and explanatory variables. So we prefer the significance of coefficients that are adjusted by SUR over the significance of marginal effects.

First, farms switch to the water-saving technology to improve technical efficiency if they have a higher degree of water shortage. Both surface water and groundwater scarcity encourage producers to adopt the efficient irrigation technology sprinkler and drip. A \$10 higher surface water price increases the probability of adoption by 0.1%-1.9%. Reducing the measures of groundwater availability by 1% results in higher probability of adoption by less than 0.1% for all crops. The margin is comparatively larger for forage and wheat. A plausible explanation is the relative low adoption rates for these crops (57% and 62%, respectively), implying more variation in data. This is consistent with our theoretical finding that when a producer has low adoption rate and uses water in a less efficient way, he responds to more expensive water supply by improving irrigation efficiency. Higher water price discourages forage producers from using water. To maintain productivity, they substitute with technology to compensate for the decline in effective water use.

Second, BOR surface water supply has a mixed effect on technology adoption. Forage farms with BOR supply are 5.8% more likely to adopt the efficient technology, while orchard/vineyard and wheat farms have a lower probability of adoption by 7.5% and 9.4%, respectively. Furthermore, BOR supply makes forage producers less responsive to water scarcity, i.e. it disincentivizes technology adoption. A \$10 rise in surface water price increases the probability of adoption by 1.9% and 0.5% for farms without and with BOR supply. Farms with BOR supply are less likely to adopt efficient technology because of the relatively secured surface water supplies guaranteed by the institution. Consequently, they feel it less necessary to adjust irrigation decisions as much.

Third, technology adoption is more responsive to climate risks than to expected weather conditions. Besides, climate and weather have a more significant effect on technology adoption for forage and wheat than orchard/vineyard and potato, due to high adoption rates and fewer variations for the latter two crops. Excessive moisture risk, as measured by a higher variability in precipitation increases the probability of adoption for orchard/vineyard while decreases that for wheat. This is consistent with our theoretical finding that climate variability incentivizes a crop producer with high adoption rates to increase the use of the efficient technology, while discourages adoption for a producer with low adoption rates. 90% of orchard/vineyard farms use the efficient technology as a risk-reducing input. It improves the relative efficiency of water use, reduces the adverse effects of climate change on production, and reduces the implicit cost of risks. Whereas wheat farms self-select to a relatively low adoption rate (62%) due to some inherent features that may reduce irrigation efficiency. For instance, their cropland may have low water-holding capacity or the water salinity is high. In this case, the expectation of more variable precipitation makes them more concerned with the effectiveness of technology and hence less willing to invest in technology adoption. This also explains the effect of extreme heat risk on adoption. Extreme heat increases evaporative loss and reduces irrigation efficiency, thus significantly discouraging adoption for forage, a crop with a low adoption rate of 57%. Orchard/vineyard producers mitigate crop damage from spring freeze and frost risk by adopting efficient irrigation technology. Likewise, wheat farms adapt to drought by switching to the water-saving technology. A 1% increase in drought risk leads to a higher probability of adoption by 0.9%. Finally, higher expected maximum temperature discourages farmers from adopting efficient technology. A 1°F increase in maximum temperature decreases adoption probability by 4.1% and 2.3% for forage and wheat farms, respectively. Previous studies find that evaporative losses from the sprinkler irrigation are approximately 15% in warmer environments (Finkel and Nir 1983; Negri and Brooks 1990). Out of the concern that evapotranspiration causes economic loss, producers are less willing to invest in technology.

Farm size has a positive impact on technology adoption for orchard/vineyard and potato, as large farms are more likely to be able to afford the initial investment in better irrigation equipment and other input cost. Tenure has a positive impact on technology adoption for wheat, as landownership creates incentives for investing in irrigation facilities to get long-run returns. Lastly, if output price is higher by 1%, probability of adoption decrease by 1.5% for forage and increases by 2.1% for wheat, respectively.

2.5.1.3 Adaptation to Water Scarcity and Climate Risks: Water Application Rates

Table 2-12 reports the marginal effects of water scarcity and climate risks on water application rates. First, the effect of water scarcity on short-run irrigation decisions differs from that on long-run irrigation decisions, and producers adapt to surface water and groundwater scarcity in different ways. Potato farms have the highest surface and ground water costs, and the smallest share of irrigated crops, and use the least amount of water per acre. Their irrigated share is responsive to water scarcity but water application rates are not significantly affected. Nevertheless, other selected crops are more water-demanding. Higher surface water price does not change their irrigated share but reduces per-acre water application rates. These results correspond to the increase in technology adoption, which eliminates the need for intensive water use. Greater well depth indicates higher pumping cost and hence decreases water application rates, but the effect is not statistically significant. Increasing pump capacity increases technology adoption and water application rates. In other words, higher engineering cost of pumping groundwater makes it more beneficial to improve irrigation efficiency. Producers concentrate available water on existing irrigated area to maintain high yields rather than expanding irrigation area.

Table 2-12. OLS Parameter Estimation Results for Water Application Rates

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
Water scarcity				
Off-farm surface water cost ($1000/acre-foot)	-1.097***	-0.687***	0.016	-0.792*
	(0.413)	(0.140)	(0.439)	(0.424)
Depth to well water (1000 feet)	-0.279	-0.009	0.140	-0.357
	(0.315)	(0.316)	(0.453)	(0.264)
Pump capacity (1000 GPM)	0.128**	0.161***	-0.172	0.023
	(0.062)	(0.046)	(0.112)	(0.060)
Water supply institutions				
BOR surface water supply (0/1)	0.294***	0.366***	0.334***	0.209***
	(0.079)	(0.081)	(0.135)	(0.083)
BOR*surface water cost	-3.577***	-0.693	-6.261***	-3.257***
	(1.056)	(0.686)	(1.808)	(0.837)
Climate and weather				
Excessive moisture risk (inches)	-0.003	-0.011***	-0.034**	-0.008**
	(0.003)	(0.003)	(0.017)	(0.004)
Extreme heat risk (°F)	-0.045	-0.086	-0.004	0.317
	(0.210)	(0.120)	(0.149)	(0.297)
Spring freeze and frost risk (days)	--	0.002	--	
		(0.001)		
Drought risk [0,1]	--	--	--	-0.615
				(0.457)
Precipitation, observed (inches)	-1.99E-4	-0.006**	-0.003	-0.002
	(0.004)	(0.003)	(0.006)	(0.005)
Max. temperature, observed (°F)	0.120***	0.051***	0.069**	0.099***
	(0.018)	(0.015)	(0.030)	(0.023)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	0.120	0.189*	-0.113	-0.338
	(0.150)	(0.108)	(0.304)	(0.244)
Scale (1000 acres)	0.006**	0.021***	0.014**	-0.006*
	(0.003)	(0.006)	(0.006)	(0.003)
Tenure [0,1]	-0.054	-0.066	2.38E-4	0.242**
	(0.098)	(0.084)	(0.153)	(0.116)
Price				
Output price ($/ton)	-0.012	0.001***	0.003	-0.012
	(0.014)	(0.000)	(0.014)	(0.013)
Year: 2018	-0.189*	0.252**	-0.012	-0.115
	(0.115)	(0.106)	(0.182)	(0.233)
State: OR	-0.450	-0.632	0.760	-1.688
	(1.055)	(0.434)	(0.496)	(1.487)
State: WA	-0.633***	-0.136	0.873**	-1.490
	(0.187)	(0.408)	(0.436)	(1.380)
R-squared	0.83	0.77	0.85	0.87

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. In parentheses are standard errors.

Second, water supply institutions have a consistent and significant effect on water application rates across crops. As the largest surface water supplier in the U.S., BOR does not charge interest on project cost repayment and charges producers based on their ability to pay (Moore, 1999). That is, the BOR subsidizes agricultural water use. As a result, farms that obtain off-farm surface water from BOR use 11%-18% more water per-acre. In this sense, BOR is a successful and effective institution. However, BOR does not provide a good institutional design for adapting to water scarcity in terms of water use. In fact, it makes water use more responsive to surface water price. Farms with BOR supply tend to use too much water per acre due to the price advantage. In times of water scarcity, these farms reduce water application rates by a larger margin than farms without, even though they have relatively more secured water supplies. We infer that there exists other water suppliers, such as some state, municipal, or private water projects that don't necessarily provide price advantages but protect producers in certain ways against water scarcity.

Third, there is a consistent effect of climate risks and observed weather conditions on agricultural water use across crops. Both excessive moisture and higher observed precipitation level significantly reduce water application rate as irrigation requirements can be easily met. Extreme heat risk doesn't significantly influence water use. Extreme heat increases the irrigated share of forage, which creates the need for more water; meanwhile, extreme heat discourages adopting the efficient technology for forage, which implies decreasing irrigation efficiency. Forage producers have to distribute water to a larger area at a lower efficiency. So they choose to reduce water application rates, the effect is insignificant though. While observed maximum temperature increases water application rates. In response to a 1°F increase in maximum temperature, producers use 2%~5% more water per acre to offset the evapotranspiration in hot weather. Farmers use irrigation to mitigate damage from freeze and frost through soil heat retention and latent heat transfers (Longstroth 2012; Vasquez and Fidelibus 2013). Perennial crops producers respond to freeze by increasing technology adoption and reducing irrigated share. Both adaptations save them water so that they can increase water application rates. That is, they concentrate water use to a smaller share of land to maintain high yield if expecting more freeze risk. Drought decreases water application rates of wheat farms due to reduced water availability and more adoption of efficient irrigation technology, the effect is insignificant though.

Cropland quality has a positive effect on water application rates of perennial crops, which again supports that cropland is a complement of irrigation as agricultural inputs. Corresponding to the expansion in irrigated share, perennial crop producers expect higher productivity of water on high quality land with better water-holding capacity. Therefore, they apply more water per acre to achieve higher yield and higher economic returns. Farm scale has a positive effect on water application rates for most crops. Large farms find it more profitable to improve irrigation efficiency than to expand irrigation area. They can afford and are willing to adopt efficient technology and apply more water per acre. Tenure increases water use in a similar way. Landownership encourages investment in irrigation to receive returns in the future. Lastly, higher price of perennial crops leads to an inelastic response in water application rates. Water use rises by 0.4% given a 1% price increase.

2.5.2 Evidence from County-level Analysis

Table 2-13 reports summary statistics for the dependent variables at county level. They display a similar pattern to farm-level statistics. We have a panel of 239 counties that irrigate at least one of the selected crops, with 113 observations from 2013 FRIS and 126 from 2018. Irrigation is an essential component of farming practices in our sample. On average, a representative producer allocates 16% of cropland to dryland crops, 59% to irrigate selected crops, and 25% to irrigate other non-selected crops. Irrigated share is relatively large for producers irrigating forage and orchard/vineyard and small for potato and wheat. More than 90% of orchard/vineyard and potato farms adopt the efficient irrigation technology, sprinkler and drip. Adoption rates are lower for forage and wheat farms. There is less variation in water application rates, with forage and rice irrigation using more water per acre. For same reasons as farm-level analysis, rice is dropped from estimation. Independent variables preserve the same pattern when aggregated to county level. Detailed statistics are provided in Appendix A6.

Table 2-13. Descriptive Statistics for Dependent Variables

Variable (units)	Irrigated land						Dry land
	Forage	Orchard/Vineyard	Potato	Rice	Wheat	Other	
Cropland allocation [0,1]	0.24 (0.31)	0.27 (0.32)	0.02 (0.06)	0.02 (0.09)	0.04 (0.08)	0.25 (0.26)	0.16 (0.25)
Technology adoption [0,1]	0.65 (0.40)	0.93 (0.16)	0.92 (0.24)	0 (0)	0.62 (0.42)	--	--
Water application rate (acre-feet/acre)	2.33 (1.10)	1.76 (1.16)	1.42 (0.96)	4.18 (0.69)	1.76 (0.72)	--	--
Observations	172	192	104	19	101	239	239

Note: Reported are sample means. In parentheses are standard deviations.

Overall, we compare county-level estimation results with farm-level results and find a consistency in farmers' responses, suggesting that individual farms largely preserve the same pattern when aggregated to county level. In terms of sign, estimated marginal effects that are significant across both models do not switch signs, with only a few exceptions.[6] In terms of magnitude, we observe similar level of marginal effects in technology adoption. While for land allocation and water application rates, producers exhibit more elastic responses to climate and weather whereas less elastic responses to water scarcity and water supply institutions. Specifically, when aggregated to county level, major differences include: 1) producers are less responsive to reduced groundwater availability, especially higher pump capacity; 2) water supply institutions are not a key factor influencing adaptations; and 3) climate risks and expected or observed weather conditions have a larger impact on agricultural land and water use. In the following we expand on the county-level results and discuss the differences in detail.

[6] For all selected crops, 2 marginal effects from land use equations, 1 from technology adoption equations, and 3 from water application rates equations switch signs across models.

2.5.2.1 Adaptation to Water Scarcity and Climate Risks: Land Use

Table 2-14 reports the marginal effects of water scarcity and climate risks on cropland allocation. First, increasing surface water price diverts farms from irrigated production to dryland production. If producers expect surface water price to increase by 10%, they reduce irrigated share by 0.1%~0.3%, depending on the crop, while expanding dry land share by 0.4%. Variations in groundwater availability or water supply institutions do not have a statistically significant effect on land use, except that higher pump capacity encourages producers to allocate more land to irrigate potato and other crops. Counties comparably have lower input cost as production increases than individual farms. Due to economies of scale and their market control, counties are not as sensitive to water supply reductions as individual farms.

Table 2-14. OLS Parameter Estimation Results for the Share of Dry Land Production and Irrigated Cropland

Variable (units)	Dry Land	Irrigated Land				
		Forage	Orchard/Vineyard	Potato	Wheat	Other
Water Scarcity and institutions						
Off-farm surface water cost ($1000/acre-foot)	0.485***	-0.524**	-0.081	-0.138*	-0.132	-0.301**
	(0.142)	(0.247)	(0.218)	(0.074)	(0.112)	(0.118)
Depth to well water (1000 feet)	-0.218	0.078	-0.120	0.043	0.120	0.143
	(0.216)	(0.409)	(0.372)	(0.134)	(0.158)	(0.184)
Pump capacity (1000 GPM)	-0.041	0.085	0.021	0.074***	0.040	0.072*
	(0.042)	(0.073)	(0.060)	(0.023)	(0.029)	(0.038)
BOR surface water supply [0,1]	0.102	0.012	0.046	-0.017	-0.017	-0.088
	(0.092)	(0.164)	(0.167)	(0.057)	(0.066)	(0.121)
Climate and weather						
Excessive moisture risk (inches)	-0.002	-0.002	0.014***	0.002	0.001	1.06E-4
	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)	(0.002)
Extreme heat risk (°F)	0.113	0.228	-0.504***	-0.055**	0.211***	-0.283**
	(0.105)	(0.173)	(0.085)	(0.027)	(0.068)	(0.133)
Spring freeze and frost risk (days)	-0.005	--	0.005***	--	--	0.012**
	(0.004)		(0.001)			(0.005)
Drought risk [0,1]	-1.474***	--	--	--	-0.336***	1.387**
	(0.453)				(0.097)	(0.584)
Precipitation, expected (inches)	0.003	0.001	0.004	-0.003	0.004**	6.57E-4
	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)
Max. temperature, expected (°F)	-0.001	-0.030***	0.047***	-0.002	0.012	0.020***
	(0.005)	(0.012)	(0.009)	(0.004)	(0.008)	(0.006)
Farm characteristics and farmer demographics						
Cropland quality [0,1]	0.269**	-0.201	0.069	0.101	0.010	0.103
	(0.121)	(0.226)	(0.207)	(0.069)	(0.087)	(0.163)
Scale (1000 acres)	-1.31E-4	-0.001**	0.001**	3.24E-5	2.72E-5	2.86E-4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure [0,1]	0.049	0.043	0.078	-0.102*	0.006	-0.393***
	(0.090)	(0.171)	(0.166)	(0.059)	(0.069)	(0.125)
Price						
Output price ($/ton)	--	0.026***	-1.06E-4	0.003*	-0.007	--
		(0.008)	(0.000)	(0.002)	(0.004)	
Year: 2018	-0.027	0.307***	-0.096	0.080**	-0.167*	0.035
	(0.034)	(0.102)	(0.068)	(0.033)	(0.091)	(0.046)
State: OR	-0.139	-1.402	-2.276***	0.190***	-0.892***	0.468*
	(0.203)	(0.903)	(0.370)	(0.078)	(0.349)	(0.254)
State: WA	-0.035	-0.345**	-2.128***	0.263***	-0.831***	0.092
	(0.097)	(0.164)	(0.340)	(0.073)	(0.330)	(0.123)
R-squared	0.73	0.62	0.66	0.72	0.72	0.86

Note: In parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Second, climate and weather have a mixed but significant influence on land use decisions. Different crop producers adapt in different ways to various climate risks. 1) Forage production is susceptible to excessive moisture and extreme heat. Given a perception of increasing excessive moisture risk, forage producers are concerned with crop loss and reduce irrigated share. A higher probability of extreme heat increases the needs for irrigation to avoid crop failure, hence increasing irrigated share. 2) Excessive moisture, extreme heat, and spring freeze and frost are responsible for crop loss in orchard/vineyard production. Excessive moisture increases water availability and enables expanding irrigated share at a lower cost, making orchard/vineyard producers increase irrigated share. Extreme heat leads to high evaporative loss and incentivizes them to reduce irrigated share. Orchard/vineyard producers use irrigation to mitigate crop damage from spring freeze and frost. If they expect an additional day when the last spring freeze occurs, indicating a longer freezing season affecting spring blossoms, they allocate 0.5% more land to irrigation. 3) Potato producers adapt in a similar manner, by irrigating more land if expecting excessive moisture and less land if expecting extreme heat and high evapotranspiration rate. 4) Excessive moisture, extreme heat, and drought are major causes of loss for wheat producers. They expand irrigated share if expecting more excessive moisture and extreme heat risks. In response to drought risk, wheat farms expect reductions in water supply and hence decrease irrigated share.

Likewise, different crop producers adapt in different ways to various weather expectations. If a producer expects more precipitation in the growing season, there is less demand for irrigation to maintain crop yield, which results in a shift from irrigating selected crops to dry land production. On the other hand, more precipitation indicates more recharge of surface and ground water. Increased water availability makes producers allocate more land to irrigation. A 1-inch increase in expected precipitation level changes the share of each irrigated crop or dryland crop by -0.3%~0.4%. Similarly, if a producer expects higher maximum temperature, he irrigates more land in an effort to offset the effect of high evapotranspiration rates in hot climate. Irrigated share of orchard/vineyard rises by 4.7% in response to a 1°F increase. In contrast, forage producers might be concerned with evapotranspiration loss and low irrigation efficiency. They adapt by allocating 3% less cropland to irrigate forage.

Cropland quality has a positive effect on the share of dryland production and irrigated share of most selected crops. With better land quality comes less demand for irrigation, thus increasing dry land share. On the other hand, with better land quality also comes better performance of irrigation and higher productivity of water, making producers expand irrigated share. Farm scale has a mixed impact on the irrigated share of selected crops. Counties with larger farm size tend to irrigate more perennial crops and less forage, probably due to the high market price and economic returns from irrigating perennial crops. Tenure has a negative effect on irrigated share of potato, a crop with the lowest price among selected crops. A plausible explanation is that landownership encourages producers to allocate more land to irrigate high-value crops. Lastly, driven by higher expected output price, producers irrigate more cropland to increase productivity and profits. If output price is higher by 1%, irrigated share of forage and potato rises by 1.2% and 0.1%, respectively.

2.5.2.2 Adaptation to Water Scarcity and Climate Risks: Irrigation Technology Adoption

Table 2-15 reports the marginal effects of water scarcity and climate risks on the share of farms adopting efficient irrigation technology in a county. First, producers switch to the water-saving technology to improve technical efficiency in times of water shortage. Both surface water and groundwater scarcity encourage producers to adopt the efficient irrigation technology sprinkler and drip. A $10 higher surface water price increases the share of farms adopting the efficient irrigation technology by 0.03%~0.2%. Reducing the measures of groundwater availability by 1% results in a higher share of adoption by 0.01%~0.31% for selected crops. However, water supply institutions do not significantly affect technology adoption. Again, we observe less elastic and significant responses to water scarcity in counties than in individual farms due to economies of scale.

Table 2-15. OLS Parameter Estimation Results for the Share of Efficient Irrigation Technology Adoption

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
Water Scarcity and institutions				
Off-farm surface water cost ($1000/acre-foot)	0.059 (0.253)	0.026 (0.095)	0.146 (0.307)	0.201 (0.171)
Depth to well water (1000 feet)	0.515 (0.387)	0.245* (0.143)	0.224 (0.575)	-0.032 (0.232)
Pump capacity (1000 GPM)	0.165** (0.075)	0.038 (0.026)	0.289*** (0.103)	0.011 (0.047)
BOR surface water supply [0,1]	0.100 (0.148)	-0.041 (0.060)	-0.011 (0.245)	-0.145 (0.095)
Climate and weather				
Excessive moisture risk (inches)	-0.003 (0.002)	0.004*** (0.001)	0.044** (0.021)	-0.008*** (0.002)
Extreme heat risk (°F)	0.586*** (0.227)	0.025 (0.047)	0.071 (0.126)	-0.346*** (0.119)
Spring freeze and frost risk (days)	--	0.002*** (0.001)	--	--
Drought risk [0,1]	--	--	--	0.054 (0.168)
Precipitation, expected (inches)	0.011*** (0.004)	0.002 (0.001)	-0.012 (0.009)	-0.002 (0.003)
Max. temperature, expected (°F)	-0.020 (0.014)	0.013*** (0.005)	0.021 (0.018)	-0.057*** (0.012)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	0.074 (0.212)	0.014 (0.076)	0.046 (0.300)	-0.083 (0.126)
Scale (1000 acres)	1.67E-4 (0.000)	9.08E-5 (0.000)	-6.40E-5 (0.001)	3.47E-4 (0.000)
Tenure [0,1]	-0.339** (0.153)	-0.077 (0.059)	-0.124 (0.252)	0.200** (0.098)
Price				
Output price ($/ton)	0.013 (0.011)	7.85E-5 (0.000)	-0.013 (0.009)	0.033*** (0.007)
Year: 2018	0.130 (0.114)	-0.003 (0.028)	-0.142 (0.154)	0.596*** (0.145)
State: OR	-2.618** (1.163)	0.233 (0.199)	-0.139 (0.362)	2.020*** (0.599)
State: WA	0.413*** (0.166)	0.223 (0.184)	-0.197 (0.344)	1.993*** (0.567)
R-squared	0.96	1.00	0.92	0.99

Note: In parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Second, technology adoption are more responsive to climate risks than to expected weather conditions. Excessive moisture risk, as measured by a higher variability in precipitation increases the share of adoption for orchard/vineyard and potato while decreases that for forage and wheat. This results is consistent with our theoretical finding that climate variability incentivizes a crop producer with high adoption rates (orchard/vineyard 93% and potato 92%) to increase the use of the efficient technology, while discourages adoption for a producer with low adoption rates (forage 65% and wheat 62%). We observe the largest impact on technology adoption for potato because as a shallow-rooted crop, potato is vulnerable to variations in soil moisture and thus highly dependent on sprinkler and drip irrigation. The marginal effect of extreme heat risk on technology adoption is different. Extreme heat increases evaporative loss and reduces irrigation efficiency, thus significantly discouraging technology adoption for wheat producers. On the other hand, forage farms switch to the efficient irrigation technology to avoid crop failure from extreme heat. Orchard/vineyard producers mitigate spring freeze damage by adopting efficient irrigation technology. Given an additional day when spring freeze last occurs, the percentage of farms adopting the efficient technology increases by 0.2%. Likewise, wheat farms adapt to drought by switching to the water-saving technology. A 1% increase in drought risk leads to a higher share of adoption by 5.4%.

Frisvold and Deva (2013) find that sprinkler irrigation has higher adoption rates in regions with more rainfall and intense rain events than in drier climate. Similarly, we estimate that higher expected precipitation level encourages forage producers to adopt the efficient irrigation technology. A 1-inch increase in expected precipitation increases share of adoption by 1.1%. Finally, higher expected maximum temperature discourages forage and wheat farms from adopting efficient technology. A 1°F increase in maximum temperature decreases percentage of adoption by 2.0% and 5.7% for forage and wheat farms, respectively. Previous studies find that evaporative losses from the sprinkler irrigation are approximately 15% in warmer environments (Finkel and Nir 1983; Negri and Brooks 1990). Out of the concern that evapotranspiration causes economic loss, these producers are less willing to invest in technology. On the contrary, specialty crop producers increases adoption by 1.3% given a 1°F increase in maximum temperature. They respond to warmer temperature in an opposite way because a majority of them (79%) adopt drip irrigation technology, while forage and wheat producers prefer sprinkler over drip.[7] Previous research find that higher temperature encourages drip irrigation to offset the effect of higher evaporation rates (Dinar and Yaron 1990; Finkel and Nir 1983; Negri and Brooks 1990). Consistently, we estimate a positive effect of maximum temperature on technology adoption for specialty crops.

Tenure has a positive impact on technology adoption for wheat and a negative impact for forage. Wheat has a higher market price than forage, suggesting higher economic returns. As such, landownership creates incentives for wheat producers to invest in irrigation facilities to get long-run benefits. Lastly, if output price is higher by 1%, share of wheat farms adopting the efficient technology increases by 1.9%.

2.5.2.3 Adaptation to Water Scarcity and Climate Risks: Water Application Rates

Table 2-16 reports the marginal effects of water scarcity and climate risks on water application rates. First, producers adapt to water scarcity by adjusting irrigation strategies, specifically effective irrigation water use. In response to surface water shortage, they apply less amount of water per acre; in response to groundwater shortage, they adopt better irrigation technology, which improves irrigation efficiency and in turn eliminates the need for intensive water use. Intensified surface water scarcity, as measured by increasing water price decreases water application rates. Given a 10% increase in surface water price of orchard/vineyard and wheat, water application rates decline by 1.6% and 0.6%, respectively. Increasing groundwater pumping cost, represented by greater well water depth and pump capacity also reduces water application rates for most selected crops, but the effect is statistically insignificant. In addition, there is a negative impact of BOR surface water supply on water application rates. As discussed earlier, BOR subsidizes agricultural water use, thus providing a price advantage over other water supply institutions. Therefore producers who receive surface water from BOR have higher water application rates

[7] Among the orchard/vineyard farms that adopt the efficient irrigation technology, 79% adopt the drip technology while 21% adopt the sprinkler technology. The percentages for forage, potato, and wheat farms are 2% vs 98%, 28% vs 72%, and 5% vs 95%, respectively.

than producers who don't. However, this institutional advantage disappears when aggregated to county level. Forage has the largest average water application rates among selected crops. If there is 1% more forage farms receiving water from BOR, water application rates decrease by 0.4%.

Table 2-16. OLS Parameter Estimation Results for Water Application Rates

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
Water Scarcity and institutions				
Off-farm surface water cost ($1000/acre-foot)	-0.023 (0.611)	-5.095*** (1.044)	-0.092 (1.003)	-2.488*** (0.592)
Depth to well water (1000 feet)	1.235 (0.890)	-0.337 (1.343)	-2.134 (1.699)	-0.052 (0.819)
Pump capacity (1000 GPM)	-0.068 (0.176)	0.290 (0.246)	-0.108 (0.343)	-0.027 (0.158)
BOR surface water supply [0,1]	-0.997*** (0.372)	0.352 (0.592)	-0.362 (0.699)	-0.510 (0.350)
Climate and weather				
Excessive moisture risk (inches)	0.015*** (0.004)	0.044*** (0.014)	-4.92E-4 (0.049)	-0.013** (0.006)
Extreme heat risk (°F)	-1.642*** (0.545)	-2.025*** (0.505)	0.228 (0.384)	0.808** (0.420)
Spring freeze and frost risk (days)	--	0.023*** (0.007)	--	
Drought risk [0,1]	--	--	--	-2.088*** (0.568)
Precipitation, observed (inches)	-0.009 (0.006)	0.035*** (0.012)	-0.053*** (0.018)	-0.009 (0.007)
Max. temperature, observed (°F)	0.166*** (0.033)	0.141*** (0.045)	0.066 (0.057)	0.114*** (0.040)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	-1.468*** (0.507)	-0.350 (0.730)	1.773** (0.902)	1.384*** (0.462)
Scale (1000 acres)	-0.001 (0.001)	0.003* (0.001)	-2.87E-5 (0.002)	-0.001 (0.001)
Tenure [0,1]	-0.125 (0.379)	-0.825 (0.586)	-1.167* (0.719)	-0.115 (0.352)
Price				
Output price ($/ton)	-0.037 (0.025)	0.003* (0.002)	0.006 (0.034)	-0.008 (0.022)
Year: 2018	-0.681*** (0.244)	0.881*** (0.328)	-0.336 (0.552)	0.006 (0.414)
State: OR	8.626*** (2.783)	-8.794*** (1.992)	0.933 (1.121)	-4.611** (2.127)
State: WA	0.788** (0.392)	-6.507*** (1.852)	1.363 (1.104)	-4.252** (2.022)
R-squared	0.98	0.92	0.88	0.96

Note: In parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Second, climate risks and observed weather conditions are major factors influencing agricultural water use. Since excessive moisture increases water availability, forage producers adapt by increasing water application rates. In response to extreme heat, they adopt the efficient technology to avoid crop loss, which in turn decreases water application rates. Orchard/vineyard farms adapt in the same way to excessive moisture and extreme heat. Besides, they use the efficient irrigation technology to mitigate spring freeze damage through soil heat retention and latent heat transfers. This adaptation strategy saves them enough water so that they choose to apply more water application per acre and achieve high yields. Given an additional day when spring freeze last occurs, water application rates for specialty crops increase by 1.3%. On the contrary, excessive moisture reduces the demand for irrigation water use, hence decreasing water applications rates of wheat farms. Wheat farms increase water application rates to offset the effect of evaporative loss if they expect more extreme heat risks. They apply less water per acre in response to drought due to reduced water supply and more adoption of efficient irrigation technology. A 1% increase in drought risk leads to a lower water application rate by 1.2%.

Orchard/vineyard is more water-demanding than potato. If precipitation during the growing season is 1 inch higher, which contributes to increasing water availability, perennial crop producers increase their water application rates by 2%; whereas potato producers decrease by 4% as irrigation requirements can be easily met. Observed maximum temperature increases water application rates for all selected crops. In response to a 1°F increase in maximum temperature, producers apply 5%~8% more water per acre to offset evapotranspiration and maintain productivity.

Cropland quality has a significant and mixed effect on water application rates. For potato and wheat, cropland is a complement of irrigation as agricultural inputs. With better land quality comes better performance of irrigation and higher productivity of water. Therefore, producers are willing to use more water to improve yield. For forage production, cropland is a substitute of irrigation. With better land quality comes less demand for irrigation and lower water application rates. Farm scale has a positive effect on water application rates for specialty crops. Counties with larger farm size are more likely to be able to afford the expenditures on increasing water application. Lastly, higher price of the specialty crops leads to an inelastic response in water application rates. Water use rises by 0.8% given a 1% price increase.

2.6 Conclusion

Water scarcity and extreme weather present substantial risks for agricultural production on the west coast. This paper examines how water availability and climate variability affect producers' adaptive land use and irrigation strategies. We measure specific risks for crop production, compile a comprehensive crop-specific dataset on key water and climate variables, distinguish between long-run and short-run responses, and estimate a system of equations on cropland allocation, irrigation technology adoption, and water application rates simultaneously for major field and specialty crops. Main empirical findings are as follows.

Water scarcity reduces irrigated share of selected crops, expands dry land production scale, encourages adoption of efficient irrigation technology, and has a mixed effect on water application rates. First, we find a more elastic response to water scarcity in cropland allocation when water price is high. For producers paying high surface water price (e.g. potato), reduced surface water availability diverts them to irrigate other crops. For producers paying high pumping cost and are not dependent on groundwater (e.g. forage and wheat), reduced groundwater availability diverts them to expand dry land production. Second, water scarcity increases adoption of efficient irrigation technology sprinkler and drip, by the largest margin for crops with low adoption rates (e.g. forage and wheat). Third, producers respond to higher surface water price by reducing water application rates. In response to groundwater shortage, they adopt better irrigation technology, which improves irrigation efficiency and in turn eliminates the need for intensive water use. Finally, we observe more elastic responses to water scarcity in individual farms than in counties.

Water supply institutions significantly influence adaptations. Farms receiving surface water from BOR have more secured water supplies and subsidized water use. So they allocate 50% less cropland to dryland crops compared with farms obtaining water elsewhere (2.6% vs 5.2%); meanwhile, they use 11%~18% more water per acre. An effective institutional design should function in a way that mitigates the adverse impact of water scarcity. However, there is no such effect in BOR; if any, it only makes producers more sensitive to water scarcity. Farms receiving water from BOR tend to use a large amount of water given the price advantage and therefore cut on water use by a larger margin in times of water shortage. Moreover, when aggregated to county level, most of these institutional influence disappears. Due to data limitations, we cannot investigate the effect of other water supply institutions, such as state, municipal, or private water projects, which proposes a topic for future research.

Climate risks present a significant determinant of irrigation strategies. The effect varies across long-run and short-run responses and across crops. First, excessive moisture risk results in significant crop loss for forage, thus reducing its irrigated share and discouraging technology adoption. Excessive moisture increases water availability and enables expanding irrigated share at a lower cost, making orchard/vineyard and wheat farms increase irrigated share. Orchard/vineyard and potato producers increase technology adoption whereas wheat producers do not have an incentive to adopt as they are concerned with the effectiveness of technology given more variable precipitation. For all crops, water application rates decrease as it is easier to meet irrigation requirements with excessive moisture. Second, extreme heat necessitates increasing irrigated share of forage and wheat to avoid crop failure. Due to evaporative loss in hot climate, extreme heat discourages technology adoption for forage and wheat producers. Third, spring freeze and frost risk switch farms from irrigated production to dry land production. Orchard/vineyard producers mitigate freeze damage by using efficient irrigation technology and increasing water application rates. Lastly, in response to drought, wheat producers irrigate a larger share of land and are more likely to increase technical efficiency with better technology. Meanwhile, they apply less water per acre due to reduced water supply.

Both expected and observed weather conditions play an essential role in producer decisions. On one hand, more precipitation indicates less demand for irrigation to maintain crop yield, thus increasing dry land share while reducing the irrigated share and water application rates of selected crops. On the other hand, more precipitation increases water supply, thus increasing the irrigated share of other crops. A 1-inch increase in expected precipitation level changes the share of each irrigated crop or dryland crop by -0.7%~0.4%. Likewise, to offset the effect of higher evapotranspiration rates in hot weather, producers adapt by increasing irrigated share of orchard/vineyard and water application rates for all selected crops. Given a 1°F increase in maximum temperature, irrigated share of orchard/vineyard increases by 1.7% (4.7% at county-level) while water application rates increase by 2%~5% (5%~8% at county-level), depending on the crop. On the other hand, producers are concerned with high evaporative loss and low irrigation efficiency, and hence low economic returns of irrigation investment. A 1°F increase leads to 1.7% (3% at county-level) reductions in irrigated share for forage and discourages adoption by 4.1% and 2.3% (2.0% and 5.7% at county-level) for forage and wheat farms, respectively. Finally, we estimate more elastic responses to climate risks and weather conditions in counties than in individual farms.

Cropland is a complement to irrigation as agricultural inputs. Higher land quality implies higher productivity of water and thus increases irrigated share and water application rates of perennial crops. Large farms are more likely to adopt efficient technology and use more water per acre as they can afford the capital investment on irrigation equipment and various input costs. Tenure increases irrigated share, technology adoption, and water use, indicating that landownership encourages investment in irrigation for long-run benefits. Lastly, driven by higher expected output price, producers invest in irrigation to improve productivity and profits. They expand irrigated share, adopt efficient technology, and increase water application rates.

Overall, this study shows that agriculture production is vulnerable to water scarcity and climate variability. Producers manage risk exposure by changing land use decisions and irrigation practices. An effective policy design can affect producers' adaptations, protect them against risks, and ultimately promote sustainable resource management and agricultural development. This study can be improved and expanded in several aspects. First, we can extend the conceptual model by relaxing some assumptions and modifying specifications. We impose several assumptions on parameters and functional forms, such as a Von Neumann-Morgenstern utility function, a Cobb-Douglas production function with uncertainty, exogenous output price, normal distributions of climate risks and profits. These assumptions are not essential, but they offer substantial mathematical tractability and facilitate identifying the key factors relevant to optimal production decisions. Furthermore, we model the discrete choice of technology adoption as a continuous variable for the share of land irrigated with the efficient irrigation technology, which is mathematically represented by irrigation efficiency. This identification facilitates a quantitative analysis given that other choice variables are continuous and that the production decisions are jointly made. This approximation can weaken the model's power in explaining producer behavior. It is debatable and it is possible to be extended.

In addition, we can expand the econometric analysis and provide more empirical evidence. For example, we currently use irrigation data from two most recent FRIS surveys 2013 and 2018. We can update the dataset with earlier or prospective surveys to form a stronger and more balanced panel.

Last but not least, building on the empirical results, we can evaluate the impact of the impact of alternative policy options for encouraging water conservation and adoption of efficient irrigation technology. We can identify alternative water policies and climate scenarios, e.g., changes in water pricing policies, changes in type or frequency of extreme weather patterns, etc. We then apply the modelling system to assess the effect of the policy options and climate patterns on cropping patterns and irrigation practices. Farmers' technology adoption in response to climate change (e.g., drought, frost, extreme heat) is of particular interest, since there is lack of study in literature about how the risk of extreme weather events affects irrigation decisions. To improve the predictability of optimal policy design, we can incorporate various scenario specifications and explore the possibility of more intertwined policy combinations. Given agriculture's sensitivity to water scarcity and climate and weather conditions, it is meaningful to evaluate irrigated agricultural performance under various scenarios. This analysis provides a framework to identify the challenges and options for adaptive agricultural management in irrigated production systems. It presents an interesting and important topic for future research.

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Chapter 3

Assessing Effects of Federal Crop Insurance Supply on Acreage and Yield of Specialty Crops

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Abstract: Crop insurance may affect harvested acreage and yield by influencing producers' behavior such as land allocation and input use. Although specialty crops are a major source of farm income, especially on the U.S. west coast, they have not received as much attention as field crops in previous empirical studies. This paper assesses the effect of moral hazard and adverse selection associated with the federal crop insurance program on the acreage and yield of major specialty crops in California. An econometric method that expands the switching regression model is developed to assess the effect. Results suggest that federal crop insurance can change specialty crop growers' production responses to climate and soil conditions. The moral hazard effect tends to increase the acreage and yield of the specialty crops, while the adverse selection effect tends to have the opposite effect. The overall effect of the federal crop insurance program on acreage and yield of specialty crops is found to be moderate.

Key words: specialty crops, insurance supply, moral hazard, adverse selection, acreage, yield

3.1 Introduction

The focus of U.S. agricultural policy has shifted from direct price and income support towards risk management over the last 20 years (Claassen et al. 2017). With the elimination of direct government payments in the 2014 Farm Bill (i.e., the Agricultural Act of 2014), the federal crop insurance program (FCIP) has become the primary risk management tool for U.S. agriculture (Glauber 2013). Along with the growth of the FCIP have come more insurance programs for specialty crops, including crop-specific programs introduced in the 1980s and 1990s and the Whole Farm Revenue Protection (WFRP) program established by the 2014 Farm Bill. In 2017, 12.4 million acres of specialty crops were enrolled in the FCIP, with $17.1 billion of liabilities to the federal government (U.S. Department of Agriculture 2017).

Crop insurance can influence farmers' production behaviors through several channels. First, premium subsidies add to expected revenue for crop production. As such, subsidized crop insurance may create incentives for farmers to expand crop production to marginal lands (Claassen et al. 2017). Second, crop insurance reduces the riskiness of growing covered crops relative to other crops, thus potentially affecting farmers' crop mix (Goodwin et al. 2004; Walters et al. 2012; Wu 1999). Finally, crop insurance reduces farmers' production risk by cutting off the lower tail of the revenue distribution and therefore may change the use of risk-altering input such as fertilizer and pesticides, as well as adoption of certain seed technologies (Babcock and Hennessy 1996; Goodwin and Smith 2013; Young et al. 2001).

Although the effects of crop insurance on field crops have been well analyzed in previous studies, the effects on specialty crops have received much less attention. An objective of this paper is to analyze the effect of federal crop insurance on the acreage and yield of specialty crops. The specific research questions for this paper are: a) What are the main factors determining the provision of federal crop insurance to a specialty crop in a county? and b) How does the federal crop insurance availability affect the acreage and yield of specialty crops? To address these questions, we construct a simultaneous-equation system consisting of equations of federal crop insurance provision for specialty crops and their acreage and yield responses. Crop insurance provision decisions and farmers' responses intertwine due to moral hazard and adverse selection effects, causing endogeneity issues. An econometric method that expands the standard endogenous switching regression model is developed to address the endogeneity issues and to measure moral hazard and adverse selection effects. The method is applied to estimate the effects of federal crop insurance provision on acreage and yield of five major types of specialty crops in California (apples, wine grapes, dry plums, English walnuts, and dry beans), using county-level data from 1980 to 2017.

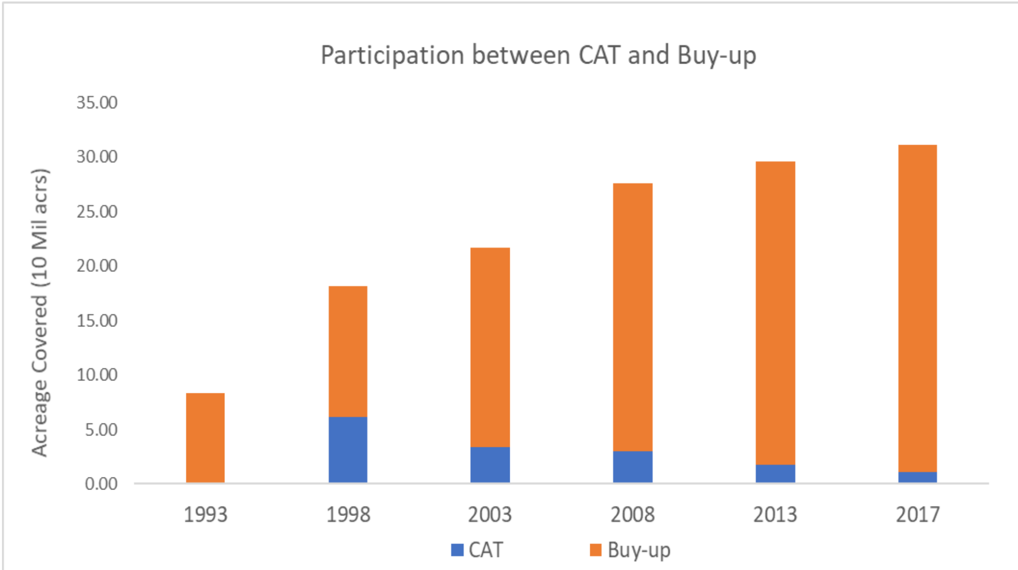
This paper focuses on the links between crop insurance and production of specialty crops for several reasons. First, the 2014 Farm Bill authorizes the Risk Management Agency (RMA) to expand crop insurance to more specialty crops and more counties. Liability of specialty crops grew from around \$7 billion in 2000 to \$17 billion in 2017, accounting for 16.1% of total crop insurance liability in 2017 (FCIC 2019). As such, there is an increasing demand for information about the impacts of insurance for specialty crops, and more research on specialty crop insurance would help to inform the development of the FCIP for specialty crops. For example, one of California's 2018 Farm Bill recommendations is to "continue emphasis on research and development priorities, specifically the Whole Farm Diversified Risk Management Insurance Plan" (State of California 2017). Second, as mentioned before, specialty crops have not received as much attention as field crops in previous empirical studies, but are major sources of U.S. farm income. For example, specialty crops account for more than 30% of cash receipts for U.S. crop sales in 2014 (USDA-ERS 2016). Besides, consumption of specialty crops is conducive to improvement in dietary habits, which is a concern for a growing proportion of consumers. Finally, there may be unique risks for growing specialty crops. For example, planting perennial crops can be risky because they are unproductive for their first several years. Many specialty crops are perishable, making them susceptible to placement risk (Schieffer and Vassalos 2015). These distinct risk features affect demand for and supply of crop insurance to specialty crops.

3.2 Background for the Empirical Analysis

In this section, we provide some background information for the empirical analysis, including a brief description of the evolution of the FCIP and specialty crop insurance and a review of previous studies that examine the effect of the FCIP.

3.2.1 Evolution of the FCIP and Specialty Crop Insurance

The FCIP has developed significantly since it was first authorized by Congress in the 1930s. Until the 1980s, participation in the FCIP had been low. Since then Congress has made major changes to the FCIP to encourage participation and expand the insurance pool. The Federal Crop Insurance Act of 1980 expanded coverage to more crops and regions. In 1994, catastrophic coverage (CAT) was created to provide coverage for 50% of the approved yield indemnified at 55% of the price election or protected price. The premium for CAT coverage is paid by the federal government; however, a producer must pay a $300 administrative fee. CAT was so popular that in 1998, shortly after it was first introduced, it covered around one thirds of total insured acreage (see Figure 3-1). In the mid-1990s, revenue insurance was introduced and has since become the most popular form of insurance. The Agricultural Risk Protection Act of 2000 induced significant growth in the size and cost of the FCIP. The 2000 farm bill increased premium subsidies for buy-up coverage that exceeds the basic CAT coverage. Consequently, the dominance of buy-up coverage returned, as indicated by the growing participation rate in buy-up coverage since 2003 (see Figure 3-1). The 2014 Farm Bill eliminated direct payments and introduced “shallow loss” revenue insurance programs for major commodities, a margin protection program for dairy, and the Whole Farm Revenue Insurance Program. Ever since, the FCIP has become the primary agricultural risk management tool in the US.

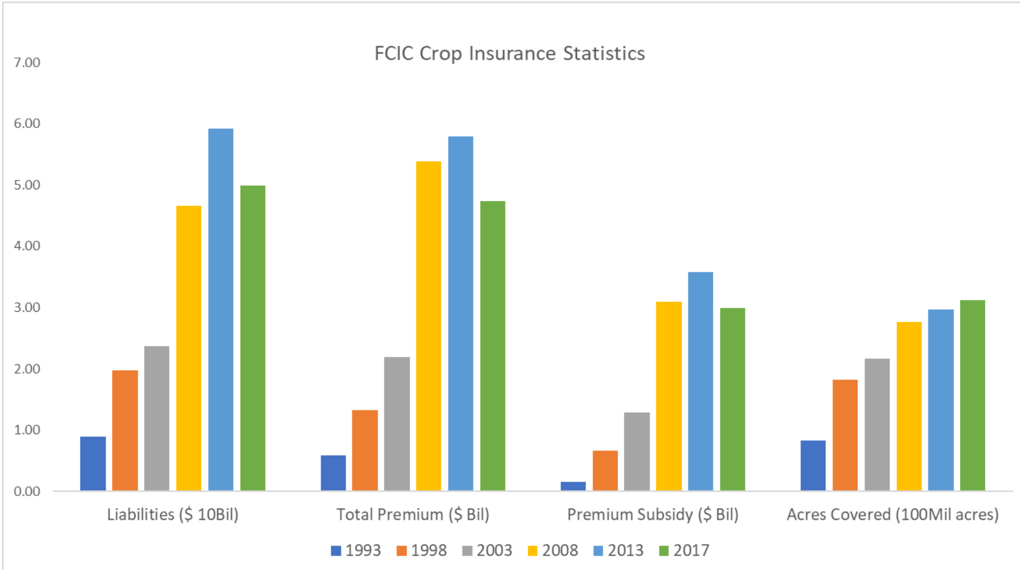


Data source: RMA, Summary of Business Reports and Data, https://www.rma.usda.gov/data/sob.html

Figure 3-1. A comparison between CAT and buy-up coverage

The FCIP has been growing rapidly in the past three decades in terms of covered acreage and federal liability (see Figure 3-2).[8] From 1993 to 2017, crop land enrolled in the FCIP increased from 83.5 million acres to 311.6 million acres, total liabilities grew from $11.2 billion to $106.1 billion, total premiums increased from $0.75 billion to $10.07 billion, and premium subsidies rose from $0.20 billion to $6.36 billion. The USDA is continuing its efforts to expand the role of the FCIP in agricultural risk management for crop producers.

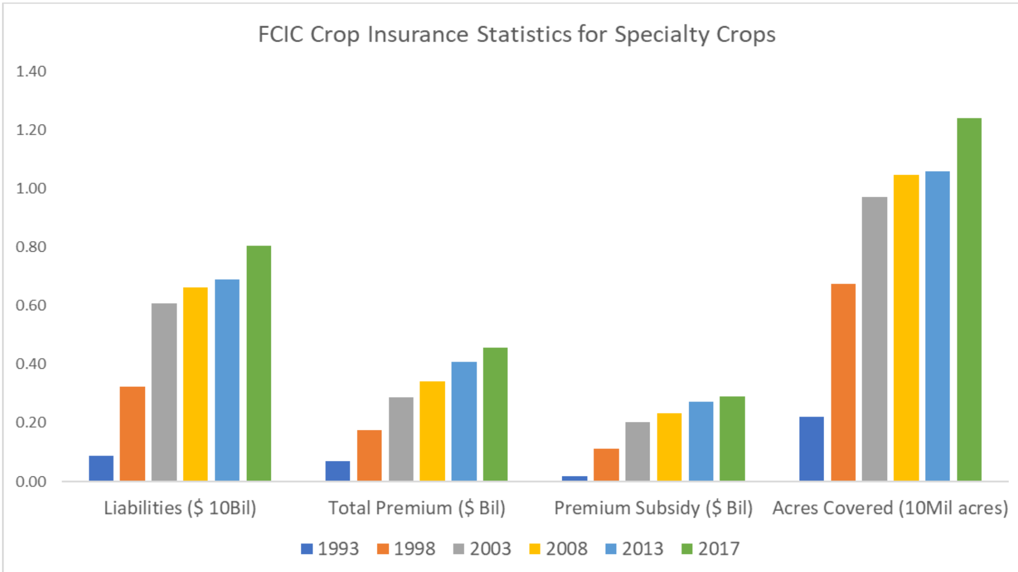
[8] All dollar values in figures, tables, and estimation are adjusted for inflation with 1982-1984 as base year.



Data source: RMA, Summary of Business Reports and Data, https://www.rma.usda.gov/data/sob.html

Figure 3-2. Selected FCIC crop insurance statistics for all crops, 1993-2017

Like field crop producers, specialty crop producers have been increasingly relying on crop insurance for risk protection since 1990 (Lee and Sumner 2013). The number of specialty crops and regions covered by the FCIP has increased significantly over the past three decades. From 1993 to 2017, total liabilities, premiums and premium subsidies all increased significantly (see Figure 3-3). Covered acreage rose from 2.2 million acres to 12.4 million acres from 1993 to 2017. In 2017, 74% of specialty crop acreage was covered (FCIC 2019). Insurance for specialty crops has become an important component of the federal crop insurance portfolio. The share of specialty crop liability rose from less than 10% in 1993 to more than 20% in the early 2000s, and about 16% in 2017 (RMA 2019; FCIC 2019). The 2014 Farm Bill authorized the RMA to broaden insurance coverage to more specialty crops and more counties. With the RMA's efforts to expand risk management programs for specialty crops, this share is expected to grow.



Data source: RMA, Summary of Business Reports and Data, https://www.rma.usda.gov/data/sob.html

Figure 3-3. Selected FCIC crop insurance statistics for specialty crops, 1993-2017

Table 3-1 provides specific information about insurance for the five selected crops. Insurance was initially offered to each crop in 1980s. These 5 crops have exclusively used yield insurance plans; mostly Actual Production History (APH) but there has been very limited use of Supplemental Coverage Option-Yield Protection (SCO-YP) starting in 2016. Changes in subsidy rates across time reflect major changes in the evolution of the FCIP. For example, the design of CAT in 1994 induced a significant jump in subsidy rates for all the crops analyzed. The 2000 farm bill also increased the amount of subsidies, enabling continued growth in subsidy rates. Corresponding to the major program changes, the share of buy-up policies in total liability tells the same story as Figure 3-1. During 1980-1994, CAT was not available, so 100% of the liability was for buy-up policies. After 1995, buy-up policy lost its dominate role in insurance coverage. But this downward trend didn’t last long until 2000 when premium subsidy rates for buy-up increased. Farmers were incentivized to switch back to buy-up policy ever since, making buy-up regain its popularity. All selected crops experienced a similar pattern, with apples and prune having the highest buyup liability share and walnuts having the lowest.

Table 3-1. Descriptive Statistics of Insurance for Selected Crops

		Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Year when insurance initiated		1988	1980	1986	1984	1982
Total Liability ($B)[a]		0.5	15.3	1.8	3.0	0.2
Total Premium ($M)[a]		52.3	656.8	251.4	94.4	19.3
Average Loss Ratio[a]		1.9	0.6	1.7	0.9	1.8
# of Counties Covered in 2017		14	26	13	22	18
Insurance Plans		APH	APH, SCO-YP	APH, SCO-YP	APH, SCO-YP	APH, SCO-YP
Average Subsidy Rate	1980-1994	0.20	0.23	0.23	0.23	0.22
	1995-2000	0.79	0.82	0.54	0.81	0.81
	2001-2014	0.67	0.74	0.62	0.79	0.79
	2015-2017	0.69	0.63	0.61	0.67	0.63
Buyup Liability Percentage (%)	1980-1994	100	100	100	100	100
	1995-2000	32	29	67	27	34
	2001-2014	76	56	91	42	58
	2015-2017	92	74	92	49	77

Note: [a] For all the counties and years when a crop insurance program is available for the crop.

Furthermore, apples and dry plums are the latest to have insurance product. They cover the least number of counties. Even though the subsidy rates became stable and similar in recent years, apples and dry plums used to have comparatively lower subsidy rates in history. And lastly, apples, dry plums and dry beans have the largest loss ratio, implying a higher ratio of indemnity payments. These findings are consistent with the fact that apples and dry plums have relatively small scale of production compared to other crops, as indicated by the acreage of harvested land in Table 3-2. In contrast, grape is the earliest to have insurance policy, has the maximum amount of total liability and premium, has the smallest loss ratio, covers more counties, and has relatively higher subsidy rate. It is reasonable to say that insurance policy favors grapes, which in large owes to the massive and concentrated grape production within California.

Table 3-2. Descriptive Statistics of Variables

	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Number of Observations	697	1,026	497	805	588
Provision of Insurance (0/1)[a]	0.25 (0.43)	0.54 (0.50)	0.69 (0.46)	0.61 (0.49)	0.57 (0.50)
Harvested Acreage (acres)	1,102 (1,452)	15,738 (21,366)	5,147 (5,410)	10,155 (11,727)	4,782 (5,603)
Harvested Yield (tons/acre)	9.42 (6.26)	5.21 (3.11)	2.16 (0.85)	1.37 (0.78)	1.09 (0.32)

Note: The values are sample means. In parentheses are standard deviation.
[a] The RMA's insurance provision decision (1=supply, 0=no supply).

Based on our review of the history and evolution of the FCIP for specialty crops, our study period (1980-2017) can be divided into four subperiods during which the insurance program for specialty crops was largely unchanged: 1980-1994, 1995-2000, 2001-2014, and 2015-2017. Premium subsidies were initiated in the Federal Crop Insurance Act of 1980 and were significantly increased in the Federal Crop Insurance Reform Act of 1994. CAT, a new and fully subsidized insurance plan, was introduced in 1994 to expand coverage. From 2000 to 2014, new premium rates and new insurance products were developed to encourage further enrollment. For example, the Agricultural Risk Protection Act of 2000 increased premium subsidies for buy-up coverage that exceeds the basic CAT coverage (O'Donoghue 2014). The 2014 farm bill established the WFRP program.

3.2.2 Previous Studies on Federal Crop Insurance

Much research focuses on federal crop insurance, but mostly in the context of field crops. Some of the research analyzes the demand for crop insurance (e.g., Coble et al. 1996; Goodwin 1993; Hazell et al. 1986; Mishra and Goodwin 2003, 2006) or producer responses to crop insurance (e.g., Du et al. 2014; Du et al. 2017; Miao et al. 2016; Quiggin et al. 1993), while others explore the feasibility and design of the federal crop insurance program (e.g., Annan et al. 2014; Chambers 1989; Coble et al. 1997; Coble et al. 2017; Gardner and Cramer1986; Goodwin and Ker 1998; Goodwin

2001; Ker and Goodwin 2000; Ker et al. 2016; Nelson and Loehman 1987; Quiggin et al. 1993; Skees and Reed 1986; Woodard et al. 2011; Woodard et al. 2012; Woodard and Verteramo 2017).

Many studies also explored the economic and environmental impacts of federal crop insurance. In particular, the effect of federal crop insurance on fertilizer and pesticides use has received a lot of attention because of its environmental implications. Crop insurance may affect fertilizer and pesticides use at both the intensive margin (i.e., through changes in application rates) and extensive margin (i.e., through changes in land use) (Babcock and Hennessy 1996; Chang and Mishra 2012; Horowitz and Lichtenberg1993; Mishra et al. 2005; Smith and Goodwin1996; Weber et al. 2016). Several studies have estimated the intensive-margin effect of crop insurance. Horowitz and Lichtenberg (1993) found that the Midwestern corn farmers who purchased crop insurance increased fertilizer use by 19% and pesticide expenditure by 21%, while Smith and Goodwin (1996) and Babcock and Hennessy (1996) concluded that crop insurance decreased fertilizer and chemical application rates. Mishra et al. (2005) found that revenue insurance purchases reduced expenditure on fertilizer, but not on pesticide. Chang and Mishra (2012) found that crop insurance had a positive effect on fertilizer/chemical expenses and that the effect was robust across the entire distribution of fertilizer/chemical expenses. Weber et al. (2016) found that expanded crop insurance coverage had little effect on productivity (value of production per acre), and fertilizer and chemical use.

Crop insurance may also affect fertilizer and pesticides use by affecting crop mix. Wu (1999) finds that providing crop insurance for corn shifts land from hay and pasture to corn, which increases fertilizer and pesticides use at the extensive margin, and this effect is of greater importance in affecting total chemical use and environmental quality than the effect at the intensive margin. Since the publication of this study, many other researchers have estimated the effect of federal crop insurance on land allocation, and results suggest that crop insurance subsidies have modest impacts on land use at the extensive margin, and that these land reallocations generate small to moderate environmental effects, which can be locally significant (Claassen et al. 2011; Goodwin et al. 2004; Lubowski et al. 2006; Miao et al. 2016; O'Donoghue et al. 2009; Walters et al. 2012; Weber et al. 2016). For example, in a recent study, Claassen et al. (2017) found that federal crop insurance has a small effect on conversions of non-cropland to cropland and more significant effects on crop choice and crop rotation, and that changes in land use and cropping systems have small to moderate effects on soil erosion, nitrogen runoff and leaching, and soil carbon sequestration.

There's a dearth of literature on the effects of specialty crop insurance. Two noticeable exceptions are Richards (2000), who studies the demand for crop insurance for California grapes; and Ligon (2011), who estimates the effects of specialty crop insurance supply on output and prices of the insured crops. Richards (2000) found that premium increases are likely to reduce participation in federal crop insurance programs by California grape producers and cause a significant change in coverage levels among growers. Ligon (2011) found a significant effect of crop insurance supply on the output of perennial crops, and a small but significant effect on the prices of insured crops. Lee and Sumner (2013) examined the evolution of insurance availability for specialty crops, farmer participation over time, and potential financial payoffs to insurance participation. They found that specialty crop growers have a lower return on investment in crop insurance, as measured by indemnity-to-premium ratios, and lower participation rates than field crop growers.

A major reason for the lack of study of specialty crop insurance is data shortage. Specialty crops are not as widely grown as field crops, which may result in fewer observations and less resources devoted to data collection. While research on field crops provides some conceptual foundations and empirical guidance, implications or findings cannot be easily applied to specialty crops due to their distinct product characteristics, production practices, and risk profiles. To inform the development of specialty crop insurance policies, there needs to be more research on the effects of specialty crop insurance, including the acreage and yield responses of specialty crops to federal crop insurance provision. In the next section, we will present an empirical model to address this need.

3.3 Empirical Model and Estimation

3.3.1 Empirical Model

This paper constructs a simultaneous-equation system consisting of crop insurance provision for specialty crops and their acreage and yield responses. The following equations are used to characterize the Risk Management Agency's (RMA) provision of specialty crop insurance and producers' acreage and yield responses:

$$I_{ijt}^{*} = \boldsymbol{X}_{\boldsymbol{ijt}}^{'}\boldsymbol{\xi} - u_{ijt} \tag{3-1}$$

$$I_{ijt} = \begin{cases} 1, & if\ I_{ijt}^{*} > 0 \\ 0, & otherwise \end{cases} \tag{3-2}$$

$$A_{ijt} = \sum_{k=1}^{4} \theta_{1i}^{k} I_{ijt} D_t^k + \sum_{k=1}^{4} I_{ijt} D_t^k \boldsymbol{Z}_{\boldsymbol{ijt}}^{'} \boldsymbol{\theta}_{\boldsymbol{2i}}^{\boldsymbol{k}} + \boldsymbol{Z}_{\boldsymbol{ijt}}^{'} \boldsymbol{\theta}_{\boldsymbol{3i}} + \nu_{ijt} \tag{3-3}$$

$$Y_{ijt} = \sum_{k=1}^{4} \beta_{1i}^{k} I_{ijt} D_t^k + \sum_{k=1}^{4} I_{ijt} D_t^k \boldsymbol{W}_{\boldsymbol{ijt}}^{'} \boldsymbol{\beta}_{\boldsymbol{2i}}^{\boldsymbol{k}} + \boldsymbol{W}_{\boldsymbol{ijt}}^{'} \boldsymbol{\beta}_{\boldsymbol{3i}} + \varepsilon_{ijt} \tag{3-4}$$

where

i = an index of crop (apples, wine grapes, dry plums, English walnuts, and dry beans);

j = an index of county;

t = an index of year, with t=1980, …, 2017;

k = 1, …, 4 indicates the four time periods during which the FCIP for specialty crops remains largely unchanged;

D_t^k = a dummy variable for period *k*, which equals one if year *t* is in period *k* and zero otherwise;

I_{ijt}^{*} = a latent variable for crop insurance supply;

I_{ijt} = an index indicating whether crop insurance is supplied to crop *i* in county *j* in year *t*;

A_{ijt} = harvested acreage of crop *i* in county *j* in year *t*;

Y_{ijt} = average yield per harvested acre for crop *i* in county *j* in year *t*;

$X_{ijt}, Z_{ijt}, W_{ijt}$ = vectors of independent variables;

$u_{ijt}, v_{ijt}, \epsilon_{ijt}$ = error terms.

To identify the independent variables included in X_{ijt}, Z_{ijt}, and W_{ijt}, we rely on policy guidelines and previous analyses. The RMA makes crop insurance provision decisions on a crop-by-crop and county-by-county basis, taking into account factors affecting both the demand for crop insurance and the feasibility for developing an actuarially fair crop insurance program. Thus, the availability of crop insurance for a specialty crop varies not only over time but also cross counties. The RMA makes specialty crop insurance provision decisions based on a set of criteria (General Accounting Office 1999, Appendix III). First, the crop must be "economically significant" in the county. A crop is considered economically significant if the total market value of the crop is at least one of the following: 1) \$3 million in the agricultural statistics district where it will be covered (8 in California); 2) \$9 million in the state where it will be covered; 3) \$15 million in the RMA administrative region (10 nationally); or 4) \$30 million nationally. There is a gap between when the RMA considers providing an insurance plan to a crop-county and when the insurance product is officially offered. The process of offering an insurance product usually starts with a pilot program, which is conducted for about three years in order for RMA to gain experience and test the program components before it becomes more widely available. Thus, we use own-crop values at the county, agricultural statistic district, state, and national levels in year t−3 to represent the RMA's expected degree of economic significance for the crop at different spatial scales. If a crop's value is relatively concentrated in an area, the area is more likely to be supplied with insurance. Second, there must be “producer interest.” Producer interest is indicated to the RMA through recommendations by RMA regional offices as well as high levels of noninsured disaster payments (General Accounting Office 1999). We use standard deviation of per-acre revenue to represent producer interest. The variation in revenue captures the inherent risk of crop production, thus reflecting the demand for crop insurance. A larger variation indicates higher production risks, implying more producer interest. Third, supplying the policy must be “feasible.” To the RMA, supplying an insurance product may be technically infeasible if, for example, there are inadequate data to evaluate the actuarial soundness of the product, if mechanisms to market the product are lacking, or if the proposed product is too complicated (General Accounting Office 1999). In this analysis, feasibility is reflected by the length of historical production data available. It provides a direct measurement of whether there is enough data to design and assess an insurance product. If there is a longer production history in record, it would be easier to establish an insurance policy, making crop insurance supply more feasible.

RMA’s insurance provision decisions consider factors affecting both the demand for insurance and the feasibility for developing an insurance program. Producer interest directly reflects demand for insurance. Farmers are more interested in an insurance product if the specialty crop is risky to produce or is of higher value. Technical feasibility and budget constraint represent RMA’s considerations from a supplier’s perspective. Therefore, equation (3-1) is a reduced-form equation that describes the outcomes of RMA’s crop insurance supply decisions, rather than a conventional supply function.

The independent variables in the acreage and yield response functions (3) and (4) can be identified by examining producers’ decision problems that maximize expected utility under production risks (Claassen et al. 2011; Goodwin et al. 2004; Walters et al. 2012; Weber et al. 2016). Independent variable vectors Z and W consist of output and input prices, land quality and climate conditions. We also include age structure of perennial crops as an independent variable in the harvested acreage and yield response equations. The share of non-bearing grape acreage in county j in year t is an explanatory variable in the harvested acreage response equation for grapes because non-bearing land is not harvested. The share of bearing, non-mature crop land is an explanatory variable in the yield response equation for grapes because non-mature crops have lower yields than mature crops.

The dummy variables D in the acreage and yield response equations capture major structural and quantitative changes in the FCIP over the study period. As mentioned in the section Evolution of the FCIP and Specialty Crop Insurance, premium subsidies were initiated in the Federal Crop Insurance Act of 1980 and were significantly increased in the Federal Crop Insurance Reform Act of 1994. CAT, a new and fully subsidized insurance plan, was introduced in 1994 to expand coverage. From 2000 to 2014, new premium rates and new insurance products were developed to encourage further enrollment. For example, the Agricultural Risk Protection Act of 2000 increased premium subsidies for buy-up coverage that exceeds the basic CAT coverage (O'Donoghue 2014). The 2014 farm bill established the WFRP program. Given the evolution of the insurance program, 4 major time periods are specified as 1980-1994, 1995-2000, 2001-2014, and 2015-2017. Each represents a period during which the insurance program for specialty crops is largely unchanged. With 1980-1994 as the baseline, three dummy variables can be constructed to reflect how changes in the FCIP affect farmers' insurance participation and production decisions.

3.3.2 Estimation Methods

Moral hazard and adverse selection raise a big challenge to the estimation of the equation system. Arrow (1984) defines moral hazard as 'hidden action' of an insured agent, and adverse selection as 'hidden knowledge' available to the insured agent about his probability of loss. In the context of FCIP, moral hazard occurs when an insured farmer adjusts his input use and crop mix to take advantage of the insurance policy (Smith and Goodwin 1996; Wu 1999). Adverse selection occurs when a farmer who is more likely to suffer from crop loss is also more likely to be supplied with crop insurance. The potential loss is based on asymmetric information known to the farmer, but unknown to the insurer (Wu 1999).

Due to adverse selection, RMA's decisions to provide crop insurance to specialty crops may be endogenous in the acreage and yield response equations. Moral hazard also causes endogeneity issue because of simultaneity. Crop insurance availability may affect a farmer's possibility of adjusting cropping patterns. On the other hand, farmers' opportunity to adjust cropping patterns may change possibility of being supplied with crop insurance. In this case, a simple OLS estimation of response equations would produce biased estimates.

An endogenous switching regression model is often used to account for moral hazard and adverse selection effects. But a standard switching regression model deals with simultaneous-equation systems consisting of two equations with correlated unobserved error terms (Fuglie and Bosch 1995; Maddala 1983; Wu 1999). To estimate the equation system with three equations, an econometric method that expands the switching regression model is developed. Assume the error terms u_{ijt}, v_{ijt} and ε_{ijt} follow a multivariate normal distribution, i.e., $(u, v, \varepsilon) \sim N(0, \Sigma)$, with

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix}$$

where σ_{11} is normalized to one.

From equation (3-3), the expected harvested acreage for a particular crop (dropping subscripts to simplify notations), given insurance supply, equals

$$E(A|I = 1) = \boldsymbol{D'\theta_1} + \boldsymbol{D'Z'\theta_2} + \boldsymbol{Z'\theta_3} + E(v|u < \boldsymbol{X'\xi})$$

$$= \boldsymbol{D}' \ \boldsymbol{\theta_1} + \boldsymbol{D}' \ \boldsymbol{Z}' \ \boldsymbol{\theta_2} + \boldsymbol{Z}' \ \boldsymbol{\theta_3} - \sigma_{12} \frac{\phi(\boldsymbol{X'}\xi)}{\Phi(\boldsymbol{X'}\xi)} \qquad (3\text{-}5)$$

where $\boldsymbol{D'} = (D_t^1, \dots, D_t^4)$, $\boldsymbol{\theta_1}' = (\theta_1^1, \dots, \theta_1^4)$, $\phi(\cdot)$ and $\Phi(\cdot)$ are probability density function and cumulative distribution function of the standard normal. Similarly, the expected harvested acreage, given no insurance supply, can be derived in a similar way:

$$E(A|I=0) = \boldsymbol{Z}'\boldsymbol{\theta}_{\boldsymbol{3}} + E(v|u \geq \boldsymbol{X}'\boldsymbol{\xi}) = \boldsymbol{Z}'\boldsymbol{\theta}_{\boldsymbol{3}} + \sigma_{12}\frac{\phi(\boldsymbol{X}'\xi)}{1-\Phi(\boldsymbol{X}'\xi)} \tag{3-6}$$

Combining equations (3-5) and (3-6) gives

$$E(A) = P(I=1)E(A|I=1) + P(I=0)E(A|I=0)$$

$$= \Phi(\boldsymbol{X}'\boldsymbol{\xi})E(A|I=1) + [1-\Phi(\boldsymbol{X}'\boldsymbol{\xi})]E(A|I=0). \tag{3-7}$$

Substituting (5) and (6) into (7), we obtain the expected acreage equation:

$$E(A) = \Phi(\boldsymbol{X}'\boldsymbol{\xi})(\boldsymbol{D}'\boldsymbol{\theta}_{\boldsymbol{1}} + \boldsymbol{D}'\boldsymbol{Z}'\boldsymbol{\theta}_{\boldsymbol{2}}) + \boldsymbol{Z}'\boldsymbol{\theta}_{\boldsymbol{3}}. \tag{3-8}$$

Similarly, we can derive the expected yield equation:

$$E(Y) = \Phi(\boldsymbol{X}'\boldsymbol{\xi})(\boldsymbol{D}'\boldsymbol{\beta}_{\boldsymbol{1}} + \boldsymbol{D}'\boldsymbol{W}'\boldsymbol{\beta}_{\boldsymbol{2}}) + \boldsymbol{W}'\boldsymbol{\theta}\boldsymbol{\beta}_{\boldsymbol{3}}. \tag{3-9}$$

A two-stage procedure can be used to estimate this simultaneous-equation system (3-1), (3-8), (3-9). In the first stage, the reduced form equation of insurance provision (1) is estimated, which provides estimates of ξ. In the second stage, equations (3-8) and (3-9) are estimated simultaneously after substituting $\boldsymbol{X}'\hat{\boldsymbol{\xi}}$ for $\boldsymbol{X}'\boldsymbol{\xi}$. Estimating these two equations simultaneously with full information maximum likelihood method (FIML) provides consistent estimates of model coefficients and standard errors (Lokshin and Sajaia 2004).

The effect of crop insurance on acreage can be derived by subtracting (6) from (5):

$$\Delta E(A) = E(A|I=1) - E(A|I=0)$$

$$= (\boldsymbol{D}'\boldsymbol{\theta}_{\boldsymbol{1}} + \boldsymbol{D}'\boldsymbol{Z}'\boldsymbol{\theta}_{\boldsymbol{2}}) - \sigma_{12}\left[\frac{\phi(\boldsymbol{X}'\xi)}{\Phi(\boldsymbol{X}'\xi)} + \frac{\phi(\boldsymbol{X}'\xi)}{1-\Phi(\boldsymbol{X}'\xi)}\right], \tag{3-10}$$

where the first term on the right-hand side measures the moral hazard effect, and the rest measures the adverse selection effect, i.e., the difference in harvested acreage between an insured farm and a randomly selected uninsured farm with the same characteristics.[9] Likewise, the effect of crop insurance on crop yield can be decomposed into a moral hazard effect and an adverse selection effect:

$$\Delta E(Y) = E(Y|I=1) - E(Y|I=0)$$

$$= (\boldsymbol{D}'\boldsymbol{\beta_1} + \boldsymbol{D}'\boldsymbol{W}'\boldsymbol{\beta_2}) - \sigma_{13}\left[\frac{\phi(\boldsymbol{X}'\xi)}{\Phi(\boldsymbol{X}'\xi)} + \frac{\phi(\boldsymbol{X}'\xi)}{1-\Phi(\boldsymbol{X}'\xi)}\right], \tag{3-11}$$

In the next section, we discuss the data used to estimate the system of equations and the insurance effects.

3.4 Data

This analysis uses county-level data on crop insurance and crop production for the state of California from 1980-2017. The data, in pooled cross-sectional form, varies by year, county, and crop. The data is obtained from two main sources. The first source is the Summary of Business Reports (1980-2017) by the USDA RMA. The reports provide crop-specific information at the county level, such as type of insurance plan, number of policies sold, total liability, premium before application of subsidies, subsidized premium and total indemnity. The data are used to generate the dependent variable in the crop insurance supply equation (3-2). It is a binary variable equal to one if insurance is offered to crop *i* in county *j* in year *t*, zero otherwise. The data show that whenever an insurance policy was offered, a positive number of insurance policies were sold. Therefore, the terms “offering” and “supplying” insurance to crop i in county j in year t are used interchangeably. The second major source of data is disaggregated agricultural production data (1980-2017) collected by California’s Agricultural Commissioners. The production data include crop-specific output price, harvested acreage and yield at the county level. A variable construction procedure resulted in the insurance and production data for the five crops analyzed in

[9] We assume that when aggregating to county level, moral hazard and adverse selection effects are pronounced enough and exhibit the same pattern as in producer level.

this article: apples, wine grapes, English walnuts, dry plums (i.e., prunes), and dry beans (see Appendix A1).

The crop insurance and production databases, together with data collected from other sources, are also used to generate the independent variables for the crop insurance supply equation and the acreage and yield response equations. As discussed in the last section, the independent variables for the insurance supply equation include variables that measure economic significance of the crop, producer interest, feasibility to provide crop insurance, and budget of the FCIP. We use own-crop values at the county, agricultural statistic district, state, and national levels in year t−3 to represent the economic significance of the crop. Data on crop values for apples, wine grapes, and dry beans are developed from the U.S. Department of Agriculture's *Crop Values Annual Summary*. Crop values for other crops are generated by using prices, harvested acreages and yields from the Agricultural Commissioners' data.

Independent variables included in the acreage and yield response equations include input and output prices, crop age structure, climate and weather, and land quality. Data on input and output prices comes from the Agricultural Prices Summary. To represent the prices paid by farmers at the start of the growing season, we collect indexes of input price paid in April for feeds, livestock and poultry, seeds, fertilizers, chemicals, fuels, supplies and repairs, autos and trucks, building materials, interest on farm real estate and farm non-real estate debt, farm real estate taxes, and wage rates. To represent the prices received at the end of the growing season for substitutes and complements, we collect indexes of output prices received in October for food grain, oilseed, fruit and nuts, vegetables and melons, meat, dairy, and poultry and eggs. Because of lack of futures markets and support prices for specialty crop, we use the lagged output price (p_{t-1}) as the expected price in the harvested acreage and yield equations.

Data on the age distribution of grape vines is obtained from the California Grape Acreage Reports, which are published by the California Field Office of the USDA NASS. To construct a variable for the quantity of land with bearing, non-mature grape vines, which are vines that are 4-6 years old, we add newly planted acres in t−3, t−4, and t−5. To construct a variable for the quantity of land with non-bearing grape vines, which are vines that are 1-3 years old, we add newly planted acres in t, t−1, and t−2.

The 1997 Natural Resources Inventory and the 2011 National Land Cover Database are used to generate soil quality variables. Specifically, we collect GIS data on the amount of land in Land Capability Class 1-8 and use a shape file for agricultural land from the National Land Cover Database to construct a variable for the amount of agricultural land in each of the eight Land Capability Classes. Lower Land Capability Class values indicate higher quality soils with less use restrictions and better suitability for agricultural production. Climate data is collected from the PRISM Climate Group's Data Explorer for every county in California and month of the year from 1950 to 2017. Most of the crops we are modelling are orchard and vineyard crops. Olen and Wu (2014) found that the most frequent causes of loss for insured orchard/vineyard in California were freeze (27%), excess moisture (21%), and heat (16%). As such, we selected four major types of climate variables: April minimum temperature (frost risk), July maximum temperature (heat risk), mean growing season temperature, May precipitation (excess moisture risk). For modelling acreage response, we constructed long-term historical climate averages (1950-1979) to represent expectations for each risk and the growing season temperature. For modelling yield response, we constructed annual deviation to represent observed weather conditions. Both soil quality variables and climate variables enter the harvested acreage and yield equations (3-3) and (3-4) as independent variables.

Some descriptive statistics for the dependent variables are given in Table 3-2. There is significant variation in insurance supply, harvested acreage, and yield for all crops, as indicated by standard deviation.

3.5 Estimation Strategies

In this section, we provide a brief description of the model specifications and estimators that we choose to estimate the equation system (3-1)-(3-4). A more detailed description of the procedures and justifications for selecting these specifications and estimators is given in Appendix A2.

3.5.1 Federal Crop Insurance Supply

We test several specifications to determine a) which spatial scales of crop values should be included in the model, and b) whether absolute crop values or relative shares of crop value are better indicators of economic significance. We find that the specification containing absolute crop values at various spatial scales provides the best fit model.

Tests are also performed to determine the appropriate method for estimating the insurance equation for each crop. We compare the estimation results from four different estimators: pooled probit with unclustered standard errors, pooled probit with cluster-robust standard errors, panel probit using random-effect estimator, and panel probit using correlated-random-effect estimator (i.e., Mundlak's approach). Table 3-3 provides a detailed comparison across different estimators for dry beans. The major findings are as follows: 1) panel probit estimators outperform pooled probit estimators. As evidenced by the likelihood-ratio test, pooled probit method does not provide consistent estimates because it neglects county-specific effects; it is also inefficient when standard errors are not adjusted to solve the problem of serial correlation induced by time-invariant county characteristics. 2) random-effect estimators perform better than correlated-random-effect estimators. As supported by the Hausman specification test, there is no significant correlation between the unobserved time-invariant county-specific effects and the regressors, implying the random-effect estimator as consistent and more efficient. This conclusion is confirmed by a Wald test on the coefficients from the correlated-random-effect model. The unobserved heterogeneity is uncorrelated with regressors, indicating random-effect estimators as both consistent and efficient. Therefore, the test statistics reveal that the random-effect panel probit estimator is the best estimator for insurance supply equation. This conclusion holds for all selected crops.

Table 3-3. A Comparison between Four Estimators of Insurance Supply to Dry Beans

Variable (units)	dy/dx			
	Pooled Probit		**Panel Probit**	
	Robust unclustered std. error	Robust clustered std. error	Random effect	Correlated random effect
Economic Significance				
County Value ($B)	37.300*** (4.020)	37.300*** (7.390)	12.300*** (4.570)	6.700 (23.600)
Statistic District Value ($B)	-0.813 (1.070)	-0.813 (2.760)	-1.660*** (0.435)	-2.740*** (0.390)
California Value ($B)	-3.730*** (1.280)	-3.730** (1.760)	-2.440*** (0.015)	-1.720*** (0.041)
U.S. Value ($B)	-0.179 (0.206)	-0.179 (0.180)	-0.207*** (0.000)	-0.165*** (0.000)
Producer Interest				
Variation of Revenue	-0.003*** (0.000)	-0.003*** (0.001)	-0.002** (0.001)	-0.003*** (0.001)
Technical Feasibility				
Length of Historical Production Data	0.006*** (0.002)	0.006 (0.006)	0.010* (0.005)	0.003 (0.006)
FCIP Budget				
Trend (year)	0.011*** (0.003)	0.011** (0.005)	0.009*** (0.003)	0.008*** (0.003)
Obsv.	588	588	588	588
R^2	0.42	0.42	—	—
Pred. Prob. Of Supply	0.57	0.57	0.55	0.55
Correct Prediction	82%	82%	87%	90%
Likelihood-ratio Test of the Null Hypothesis $\rho = 0$				
ρ	—	—	0.82	0.80
$\bar{\chi}^2$ Test Statistic	—	—	165.78	154.77
Prob >= $\bar{\chi}^2$	—	—	0.000	0.000
Result			Rejected at the 1% level of confidence	
Hausman Test of the Null Hypothesis that the Difference in Coefficients Is Not Systematic				
χ^2 Test Statistic	—	—	3.92	
Prob > χ^2	—	—	0.270	
Result			Not rejected at the 10% level of confidence	
Wald Test of the Null Hypothesis that Unobserved Heterogeneity Is Uncorrelated with Regressors				
χ^2 Test Statistic	—	—	4.55	
Prob > χ^2	—	—	0.102	
Result			Not rejected at the 10% level of confidence	

Note: In parentheses are Delta-method robust standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

3.5.2 Harvested Acreage and Yield Response Equations

The model specifications for the harvested acreage and yield equations are identified as follows. First, we add interaction terms between the predicted probability of insurance provision and explanatory variables in the estimation. These interaction terms capture the mechanisms through which farmers' cropping decisions are affected by crop insurance supply. Based on the coefficients on the interaction terms, we can assess how acreage and yield respond differently to changes in explanatory variables due to provision of crop insurance.

The harvested acreage equation and yield equation are estimated simultaneously. We perform Hausman tests to check if the unobserved error term is correlated with the regressors. Test statistics indicate that correlation between the county effect and the independent variables results in an endogeneity issue only in the yield equation of walnuts and dry beans. We use least squares dummy variable estimators to deal with county fixed effects in these equations. For the rest, county fixed effects lead to an auto-correlation problem, and they can be treated as random parameters. The pooled OLS method with cluster robust standard errors is used to address serial correlation. It outperforms the random-effect estimator in that it does not require additional assumption on the specific form of the variance-covariance matrix and that it allows for arbitrary heteroscedasticity.

3.6 Estimation Results

3.6.1 Federal Crop Insurance for Specialty Crops

The estimation results from the model of federal crop insurance provision are presented in Table 3-4. The crop insurance provision equation correctly predicts supply in at least 80% of observations for all crops, indicating the estimated equation (3-1) fits the observed data well. The predicted probability of crop insurance provision is close to the observed mean values for all crops. The marginal effects indicate that both the demand and supply side of the crop insurance market play a role in the RMA's decisions.

Table 3-4. Marginal Effects for the Models of Insurance Supply to Specialty Crops

Variable (units)	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Economic Significance					
County Value ($B)	-2.320 (2.200)	2.390*** (0.406)	-0.840 (1.610)	2.720 (2.190)	12.300*** (4.570)
Statistic District Value ($B)	1.880* (1.030)	-0.321*** (0.015)	-2.590*** (0.142)	2.790*** (0.062)	-1.660*** (0.435)
California Value ($B)	1.160* (0.620)	0.225*** (0.000)	2.000*** (0.001)	-0.191*** (0.000)	-2.440*** (0.015)
U.S. Value ($B)	-0.220*** (0.000)	-0.117*** (0.000)	—	—	-0.207*** (0.000)
Producer Interest					
Variation of Revenue	0.0002*** (0.000)	-0.0004*** (0.0002)	-0.001*** (0.000)	-0.0003 (0.0003)	-0.002** (0.001)
Technical Feasibility					
Length of Historical Production Data	0.005 (0.005)	0.019*** (0.007)	0.041*** (0.008)	—	0.010* (0.005)
FCIP Budget					
Trend (year)	0.019*** (0.004)	0.010*** (0.002)	0.023*** (0.003)	0.023*** (0.003)	0.009*** (0.003)
Obsv.	697	1,026	497	805	588
Pred. Prob. Of Supply	0.22	0.53	0.66	0.62	0.55
Correct Prediction	91%	80%	94%	91%	87%

Note: Models estimated with robust standard errors. In parentheses are Delta-method standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

First, economic significance is a significant determinant of federal crop insurance supply to a crop in a county. Higher economic value reflects higher market demand for insurance. The economic significance variables that are statistically significant are increasingly negative at larger spatial scales, except for dry plums, and their coefficients decrease in absolute value. All economic significance variables that are statistically significant at the county level are positive and have relatively large coefficients, while most of the statistically significant variables at the national level are negative and have relatively small coefficients. For example, own-crop value at the county level has a positive and significant effect on crop insurance supply for grapes and dry beans. If county value is 10% higher, probability of insurance supply for these crop increases by 1.5% and 6.7%, respectively. Own-crop value at the agricultural statistic district level has a discernibly positive effect on crop insurance supply for apples and walnuts. Therefore, the estimation results support our expectation that if a crop's value is relatively concentrated in an area, the area is more likely to be supplied with insurance.

Second, when revenue from producing a crop displays a larger standard variation, either the price or yield or both must be volatile, risk averse producers would be more interested in insurance products to manage the risk. Through recommendations by RMA regional offices, there is a higher probability of crop insurance supply. However, only the variation of revenue for apples has the expected positive marginal effect on insurance supply. In fact, the estimated marginal effects are very small in magnitude for all crops, with elasticity ranging from -0.35% to 0.08%. It suggests that variation in revenue has a comparatively indiscernible impact on the RMA's decision to provide insurance.

Third, we assume that if there is enough data to design and evaluate an insurance policy, it would be more technically feasible to offer crop insurance. As evidenced by the positive marginal effects of the technical feasibility variable for all crops, a longer production history contributes to a higher probability of insurance supply. This impact is statistically significant for all crops except for apples.

Finally, there is evidence that the FCIP's budget constraint affects crop insurance supply to specialty crops. Liability of specialty crops grew from around $7 billion in 2000 to almost $17 billion in 2017, accounting for 16.1% of total crop insurance liability in 2017 (FCIC 2019). The FCIP's indemnity payment increased by more than 650% to nearly $7.5 billion from 1990 to 2011 (Glauber 2013). Premium subsidies rose from only $23 million in 1993 to more than $620 million by 2017 (U.S. Department of Agriculture 2019). This rapid expansion in specialty crop insurance is made possible by increasing funding for the federal crop insurance program and is captured by the positive marginal effects of the time trend variable for all crops.

3.6.2 Acreage and Yield Response Functions

The estimation results from the model of harvested acreage and yield response are reported in Table A3 and Table A4, respectively, in the appendix. Panel A of each table presents parameter estimates for the interaction terms, and panel B presents parameter estimates for the non-interaction terms, thus reflecting the marginal impact of each variable in the case of no crop insurance supply. Both the acreage and yield response models have high goodness of fit, with R2 ranging from 0.62 to 0.95. Several results from the tables are highlighted below.

First, the estimated results suggest that both harvested acreage and crop yield are more responsive to soil and climate variables, than to price variables. Different crops may require different soil and climate conditions. In addition, some crops may have comparative advantages on low quality land (i.e., more profitable to grow those crops), and others have comparative advantages on high quality land. Thus interpretation of the coefficients on soil and climate variables must bear these points in mind. Input and output prices have no discernible effect on crop production, except that an increase in fertilizer price significantly lowers crop yield for apples and walnuts.

Second, the age distribution of grape vines has a statistically significant effect on grape acreage and yield. Bearing but non-mature crops have lower yields. Non-insured farmers with a larger share of non-mature cropland tend to have lower yield and smaller harvested acreage. The effect of non-mature cropland shares on yield and harvested acreage tends to be smaller in farms with crop insurance.

Finally, most of the coefficients of the interaction terms are significant at 10% level or higher, indicating that crop insurance significantly affects harvested acreage and yield by influencing the effect of climate and soil quality on farmers' production decisions. Below, we discuss the acreage and yield effects in detail.

3.6.3 Effects of Crop Insurance on Acreage

Using the estimated models and equations (3-10) and (3-11), we estimate the effect of crop insurance on acreage and yield for each of the five crops from 1980-2017. The average results across counties and the study period are summarized in Table 3-5. The first row of the table shows the moral hazard effect on harvested acreage of the selected crop. For all the crops, farmers expand harvested acreage when crop insurance becomes available to take advantage of the reduced risk. The second row of Table 3-5 shows the self-selection effect on harvested acreage. The self-selection effect is negative for all crops because farmers who are supplied with crop insurance are more likely to suffer from crop losses and therefore tend to harvest fewer acreages compared with a randomly selected farmer with the same characteristics. Conversely, farmers without crop insurance tend to harvest more acreage than a randomly selected farmer with the same characteristics. The moral hazard effect dominates the adverse selection effect for apples, grapes and dry plums, making the overall effect of crop insurance on acreage of these crops positive. While for walnuts and dry beans, the adverse selection effect outweighs the moral hazard effect.

Table 3-5. Average Effects of Crop Insurance on Harvested Acreage and Yield across Counties in California, 1980-2017

	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Acreage (acres)					
Moral Hazard Effect	269.8 (1113.3)	3179.1 (1917.5)	878.1 (101.4)	2110.7 (1045.2)	247.9 (796.6)
Adverse Selection Effect	-247.9 (152.6)	-1417.1 (833.0)	-706.1 (508.4)	-2446.8 (1337.1)	-610.3 (513.0)
Total Acreage Effect ($\Delta E(A)$)	21.9 [2.1%]	1762.0 [11.2%]	172.0 [3.3%]	-336.1 [-3.3%]	-362.4 [-7.6%]
Yield (tons/acre)					
Moral Hazard Effect	4.88 (3.51)	0.23 (0.23)	0.11 (0.05)	0.44 (0.36)	0.06 (0.23)
Adverse Selection Effect	-4.02 (2.47)	-0.10 (0.01)	-0.08 (0.61)	-0.47 (0.25)	-0.07 (0.06)
Total Yield Effect ($\Delta E(Y)$)	0.86 [9.3%]	0.13 [2.5%]	0.03 [1.4%]	-0.03 [-2.2%]	-0.01 [-0.9%]

Note: In brackets are percent changes in acreage or yield. In parentheses are standard deviations.

If we compare horizontally, the effects vary across the five selected crops. This may reflect that each crop has a distinct production practice and risk profile. Our data show that the revenues from producing apples, grapes and dry plums have a much larger standard deviation than revenues from producing walnuts and dry beans. This suggests that it is riskier to produce the first three crops than the last two. Therefore, producers of the first three crops are more likely to have some “hidden action” in production practices, making the moral hazard effect dominate for these crops. The last two crops are less prone to moral hazard, making the adverse selection effect dominate for the last two crops. The overall effect of crop insurance on acreage and yield is positive for apples, grapes and dry plums, and negative for the other two crops.

Among the first three crops, insurance has the largest influence on grapes. As shown in Table 3-1, grape is the first among the three that is covered by a crop insurance policy, has the maximum amount of total liability and premium, has the smallest loss ratio, covers more counties, and has a relatively higher subsidy rate. Due to the massive and concentrated grape production in California, insurance policy favors grapes. With better policy design and higher participation rates, adverse selection is less of an issue to grapes. A big, positive moral hazard effect, and a small, negative adverse selection effect make grape producers expand harvested acreage to the largest extent.

The estimated acreage response model also reveals the channels through which crop insurance affects the harvested acreage of the specialty crops. First, the impacts of crop insurance on harvested acreage can manifest through producers' responses to climate variables. Farmers are significantly affected by climate conditions when making acreage decisions. However, most of the coefficients for the climate variables change signs or significance after crop insurance is offered. For example, the estimation results indicate that crop insurance supply changes farmers' responses to frost risk, represented by minimum temperature. Without insurance, expectation of more freezing temperature makes farmers harvest fewer acres of apples and grapes. With crop insurance, farmers may respond differently to frost risks because crop insurance helps protect farmers from such risk. As a result, the effect of frost risk on harvested acreage is smaller when crop insurance is available.

3.6.4 Effects of Crop Insurance on Yield

Table 3-5 also reports the effect of crop insurance on yield of the five crops. Crop yield can increase or decrease under crop insurance, ranging from -0.9%-9.3% and depending on the crop. With crop insurance, apples, grapes and dry plums have higher harvested yield. While farmers growing walnuts and dry beans have lower yield. Crop insurance supply has a mixed effect on yield for the following reasons. Farmers may grow on marginal lands, where yield is lower under crop insurance. Changes in crop mix, including changing from one crop variety to another, can either increase or decrease yield. Farmers may change the rate of replanting perennial crops, thereby affecting the age distribution of the orchard and the yield, especially in the first several years when the perennial crops are either non-bearing or bearing but non-mature. Furthermore, crop insurance can affect the use of chemical or labor inputs, but its relation to yield change depends on whether the input is risk-increasing or risk-decreasing.

In Table 3-5, we also decompose the total yield effect into a moral hazard effect and an adverse selection effect. In response to insurance supply, hidden actions lead to higher yield. For all selected crops, counties with crop insurance tend to have lower yield than a randomly selected county with the same characteristics. Therefore, the resulting aggregate self-selection effect is negative for all crops. Lastly, the total effect on crop yield has the same sign as total acreage effect.

The yield effect of crop insurance supply also varies across the five selected crops. Apples and dry plums have unique characteristics that involve riskier production practices. They are more prone to hidden action, such as increasing the use of risk-increasing input. While grapes have better policy support and higher participation rate. They have less severe adverse selection issue. Hence crop insurance provision increases average yield for these crops. On the contrary, relatively small moral hazard effects and large adverse selection effects lead to reduced yield for walnuts and dry beans. The estimated yield response model indicates that crop insurance affects yield mainly through climate interaction terms. Both precipitation and average temperature have a quadratic relation with yield, with the shape depending on crop. Extreme heat has an adverse effect on crop yield. For example, grape production is more restricted by maximum temperature than other crops. A 1°F increase in maximum temperature is associated with a 4.8% reduction in yield. However, crop insurance mitigates the negative impact of extreme heat. With crop insurance, farmers have different perceptions on climate risks. Adaptations in production behavior make yield less responsive to changes in climate conditions. When supplied with crop insurance, grape yield decreases by 3.3% for a 1°F increase in maximum temperature.

3.6.5 Changes in Crop Insurance Effects over Time

So far we have focused on the average effect of crop insurance over the study period. In Table 3-6, we report the effect of changes in crop insurance in the last three periods, which feature different crop insurance programs for specialty crops. Each percentage indicates the change in harvested acreage or yield comparing to the period before. Compared with the base period 1980-1994, increased premium subsidies and benefits associated with enrollment in CAT in 1995-2000 encourage acreage expansion for all crops except apples. Policy changes in 2001-2014, including reduced premium rates and higher coverage levels, motivated more walnut producers to participate in the insurance program, with participation rates increasing from 0.54 (1995-2000) to 0.68. Walnut producers expand acreage by 32.1%. Besides, apple producers respond so strongly to this policy change that by 2014, harvested acreage exceeds the level before the decline in 1995. The 2014 farm bill reverses the trend for most crops. The WFRP program benefits apple, grape and dry plum producers more than others. In fact, the WFRP program attempts to address the adverse selection issues by providing a wide variety of coverage levels and enlarging the insurance pool (Olen and Wu 2017). This may reflect that apples, grapes and dry plums may be less prone to adverse selection problems.

Table 3-6. Effects of Policy Changes in the FCIP on Harvested Acreage and Yield, Relative to the Previous Period

	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Acreage (acres)					
1995-2000	-28.3%	2.0%	0.8%	14.0%	3.3%
2001-2014	1.0%	-16.4%	-13.1%	32.1%	7.0%
2015-2017	4.5%	21.9%	11.5%	-25.5%	-5.1%
Yield (tons/acre)					
1995-2000	-26.6%	5.8%	-1.6%	2.9%	1.5%
2001-2014	5.5%	12.0%	12.4%	6.8%	3.4%
2015-2017	4.6%	10.7%	10.1%	-7.1%	-4.2%

Major policy changes influencing farmers' participation decisions are also manifested in yield changes. The impacts of the policy changes move in the same direction as the total yield effects reported in Table 3-5. Corresponding to the decline in harvested acreage, average yield of apples for 1995-2000 declined 27% compared with the average yield in the previous period for counties with insurance supply. The average yield increased for all crops, apples included, with the changes in crop insurance programs in the 2000 farm bill. This upward trend continues in apples, grapes and dry plums after the establishment of the WFRP program.

3.7 Conclusion

Federal crop insurance for specialty crops is important to agricultural risk management for many states in the US. Specialty crops are an increasingly important contributor to farm income and human health. With the expansion in crop insurance programs, policymakers need better information on specialty crop producers' behavior in subsidized insurance markets. However, there is a significant knowledge gap in the literature about the impacts of specialty crop insurance on land allocation and crop yield.

This paper analyzes the main factors affecting federal crop insurance supply to specialty crops in California and the impact of the supply on the acreage and yield of five major types of specialty crops in California (apples, wine grapes, dry plums, English walnuts, and dry beans). The analysis provides several interesting results.

First, both the demand and supply affect the RMA's decision to provide insurance for a specialty crop in a county. Higher economic value of a crop, more concentrated production within a county, more technical feasibility, and the FCIP's increasing budget all contribute to a higher probability of crop insurance provision in a county.

Second, crop insurance provision affects farmers' acreage response to climate conditions and soil quality. Crop insurance reduces growers' financial risks and encourages them to expand crop production to areas with less favorable soil and climate conditions. Apples and dry plums involve riskier production practices. They are more prone to hidden action. Grapes have better policy support and higher participation rate and are less prone to adverse selection problems. Hence crop insurance provision increases harvested acreage of these crops. On the contrary, smaller moral hazard effect and larger adverse selection effect lead to reduced acreage for walnuts and dry beans.

Third, crop insurance supply can increase or decrease the yield of a specialty crop. With crop insurance supply, the average yields of apples, grapes and dry plums increase, while the average yields of walnuts and dry beans decrease. These results parallel with the changes in harvested acreage. These results may reflect that crop insurance encourages crop production on marginal lands (which tends to reduce the average yield), but increases the use of risk-increasing input (which tends to increase the average yield).

In response to crop insurance supply, famers may adopt less efficient practices, such as growing riskier crops or growing on marginal lands. For all selected crops, moral hazard and adverse selection problems lead to discernible acreage and yield changes. These acreage and yield responses may cause poor actuarial performance of the insurance policy and increase government costs. Some index-based insurance policies can be effective at mitigating moral hazard and adverse selection effects in insurance markets. These policies make payments based on objective measurements rather than farm-level or county-level yield. Hence, producers' hidden knowledge about their management practices cannot affect the chance of a payment. There will be low levels of information asymmetry. Besides, the WFRP program also addresses adverse selection problems in the FCIP by providing a wide variety of coverage levels and enlarging the insurance pool (Olen and Wu 2017).

Federal crop insurance can significantly affect acreage and yields of specialty crops, thus influencing their prices and output. This suggests that crop insurance can influence the consumption of specialty crops such as fruits and nuts, which may have important public health implications. Changes in land use and fertilizer and pesticides application under crop insurance may also have important environmental consequences. A better understanding of the public health and environmental implications will lead to a better design of the federal crop insurance program and therefore should be an important topic for future research.

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Chapter 4 Conclusion

Irrigation management is a primary mechanism for improving sustainability of water use and coping with climate change in the arid U.S. West (Howden 2007; USDA 2016). Many policy options are available to cope with production risks and attain sustainable agricultural development. The federal crop insurance program (FCIP) is a primary risk management tool for U.S. agriculture (Glauber 2013). Improving water and risk management policy design necessitates a thorough understanding of the impacts of water scarcity and climate variability on adaptive production decisions connected with agricultural land and water use. We conduct both theoretical and empirical analysis to identify the major economic, climate, and institutional factors influencing production decisions and evaluate producers' responses to risk management policies.

Chapter 2 examines how water availability and climate variability affect producers' adaptive land use and irrigation strategies. Conceptually, we construct a farm-level theoretical model to explore a multioutput producer's behavior under uncertainties. In particular, we capture production risks associated with extreme weather, such as drought, frost, and extreme heat. A formula of sufficient statistics representing optimal production decisions and key parameters in the adaptation strategies are derived. Comparative analysis suggests that climate variability encourages technology adoption for a producer with high irrigation efficiency and for a crop with high market value. A producer allocates more land to a crop that he predominantly grows and a crop with high output price or low water price if he anticipates a more variable climate. In response to climate variability, a producer increases water application rates if he adjusts technology adoption more than he adjusts planted acreage. We find a similar pattern in the effects of water scarcity on adaptations. If a producer has a low adoption rate and expects increasing water price, he will enhance the use of technology to improve irrigation efficiency and compensate for reduced water supply. Due to decreasing marginal productivity of input use, a producer chooses to diversify crop portfolio and switches to a crop that he does not massively grow given more expensive water supply. The expansion in planted acreage increases with output price. Reductions in water supply cause a decline in water application rates, regardless of the characteristics specific to producer or crop.

The conceptual framework informs empirical estimation and generates valuable insights into how farmers in irrigated agricultural production systems would respond and adapt to water scarcity and climate change. Empirically, we measure specific risks for crop production, compile a comprehensive crop-specific dataset on key water and climate variables, distinguish between long-run and short-run responses, and estimate a system of equations on cropland allocation, irrigation technology adoption, and water application rates simultaneously for major field and specialty crops. Results suggest that water scarcity reduces irrigated share of selected crops and expands dryland production. We observe more elastic responses for crops with high surface water price (potato) or high groundwater pumping cost (forage and wheat). Water scarcity encourages adoption of efficient irrigation technology sprinkler and drip, especially for crops with low adoption rates (forage and wheat). Bureau of Reclamation provides more secured water supplies and subsidizes water use. Farms receiving water from BOR allocate 2.6% more cropland to irrigated production and use 11%~18% more water per acre than farms obtaining water elsewhere. Extreme weather events present key determinants of irrigation strategies. Excessive moisture risk discourages technology adoption for forage and wheat, encourages adoption for orchard/vineyard, and decreases water application rates for all crops. Extreme heat risk increases irrigated share and reduces technology adoption for forage and wheat. Orchard/vineyard producers mitigate freeze damage by using efficient irrigation technology and increasing water application rates. Wheat producers adapt to drought by irrigating a larger share of land, adopting efficient technology, and applying less water per acre. Weather expectations and observations are also critical to adaptations. Higher precipitation level reduces demand for irrigation, thus decreasing irrigated share and water application rates. Whereas high evaporative loss in hot weather increases water application rates by 2%~5% and decreases technology adoption by as much as 4%, given a 1°F increase in maximum temperature.

Federal crop insurance for specialty crops is important to agricultural risk management for many states in the U.S. Specialty crops are an increasingly important contributor to farm income and human health. With the expansion in crop insurance programs, policymakers need better information on specialty crop producers' behavior in subsidized insurance markets. However, there is a significant knowledge gap in the literature about the impacts of specialty crop insurance on land allocation and crop yield. Chapter 4 analyzes the main factors affecting federal crop insurance supply to specialty crops in California and the impact of the supply on the acreage and yield of five major types of specialty crops in California (apples, wine grapes, dry plums, English walnuts, and dry beans). Results suggest that both the demand and supply affect the RMA's decision to provide insurance for a specialty crop in a county. Higher economic value of a crop, more concentrated production within a county, more technical feasibility, and the FCIP's increasing budget all contribute to a higher probability of crop insurance provision in a county. Crop insurance provision affects farmers' acreage response to climate conditions and soil quality. Crop insurance reduces growers' financial risks and encourages them to expand crop production to areas with less favorable soil and climate conditions. Crop insurance supply can increase or decrease the yield of a specialty crop. With crop insurance supply, the average yields of apples, grapes and dry plums increase, while the average yields of walnuts and dry beans decrease.

This study makes several contributions to literature. First, it is a farm-level, crop-specific analysis. Our micro-level modelling system explores how individual farmers with heterogeneous portfolios adapt to production risks. The crop-specific specification captures susceptibility of individual crops to alternative extreme weather events. Furthermore, this system models the impacts of water scarcity and climate variability on cropland allocation, water use, and irrigation technology adoption decisions simultaneously. Second, the model explicitly distinguishes whether the decisions involved is a short-run or long-run response. Third, this analysis differentiates annual crop and perennial crop. A perennial crop will be non-bearing or non-mature in the first several years, which may result in variations in water use. Lastly, this study examines specialty crop producers' behavior under risks and uncertainties. Specialty crops are a major source of farm income, especially on the West Coast. But they are not as well analyzed as field crops in literature. Also, there may be unique risks for growing specialty crops. The 2014 Farm Bill authorizes the RMA to expand crop insurance to more specialty crops and more counties. More research about the impact of water supply uncertainties and climate risks on specialty crop producers' behavior can promote development of efficient agricultural policies.

Overall, this study shows that agriculture production is vulnerable to water scarcity and climate variability. Producers manage risk exposure by changing land use decisions and irrigation practices. An effective policy design can affect producers' adaptations, protect them against risks, and ultimately promote sustainable resource management and agricultural development. This study can be improved and expanded in several aspects. First, we can extend the conceptual model by relaxing some assumptions and modifying specifications. We impose several assumptions on parameters and functional forms, such as a Von Neumann-Morgenstern utility function, a Cobb-Douglas production function with uncertainty, exogenous output price, normal distributions of climate risks and profits. These assumptions are not essential, but they offer substantial mathematical tractability and facilitate identifying the key factors relevant to optimal production decisions. Furthermore, we model the discrete choice of technology adoption as a continuous variable for the share of land irrigated with the efficient irrigation technology, which is mathematically represented by irrigation efficiency. This identification facilitates a quantitative analysis given that other choice variables are continuous and that the production decisions are jointly made. This approximation can weaken the model's power in explaining producer behavior. It is debatable and it is possible to be extended.

Second, we can expand the econometric analysis and provide more empirical evidence. For example, we currently use irrigation data from two most recent FRIS surveys 2013 and 2018. We can update the dataset with earlier or prospective surveys to form a stronger and more balanced panel. In addition, building on the empirical results, we can evaluate the impact of the impact of alternative policy options for encouraging water conservation and adoption of efficient irrigation technology. We can identify alternative water policies and climate scenarios, e.g., changes in water pricing policies, changes in type or frequency of extreme weather patterns, etc. We then apply the modelling system to assess the effect of the policy options and climate patterns on cropping patterns and irrigation practices. Farmers' technology adoption in response to climate change (e.g., drought, frost, extreme heat) is of particular interest, since there is lack of study in literature about how the risk of extreme weather events affects irrigation decisions. To improve the predictability of optimal policy design, we can incorporate various scenario specifications and explore the possibility of more intertwined policy combinations. Given agriculture's sensitivity to water scarcity and climate and weather conditions, it is meaningful to evaluate irrigated agricultural performance under various scenarios. This analysis provides a framework to identify the challenges and options for adaptive agricultural management in irrigated production systems. It presents an interesting and important topic for future research.

Third, federal crop insurance can significantly affect acreage and yields of specialty crops, thus influencing their prices and output. This suggests that crop insurance can influence the consumption of specialty crops such as fruits and nuts, which may have important public health implications. Changes in land use and fertilizer and pesticides application under crop insurance may also have important environmental consequences. A better understanding of the public health and environmental implications will lead to a better design of the federal crop insurance program and therefore should be an important topic for future research.

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APPENDIX

A1 Derivation of Expected Utility

π is normally distributed with mean $E[\pi_i]$ and variance $Var[\pi_i]$. Denote the probability density function of π_i as $g(\pi_i)$.

$$E[U_i(\pi)] = \int U(\pi_i)g(\pi_i)d\pi_i$$

$$= \int (-e^{-\alpha\pi_i}) \frac{1}{\sqrt{2\pi_i Var[\pi_i]}} e^{-\frac{(\pi_i - E[\pi_i])^2}{2Var[\pi_i]}} d\pi_i$$

$$= \frac{1}{\sqrt{2\pi_i Var[\pi_i]}} \int \left(-e^{-\frac{(\pi_i - E[\pi_i] + \alpha_i Var[\pi_i])^2 + 2E[\pi_i]\alpha_i Var[\pi_i] - (\alpha_i Var[\pi_i])^2}{2Var[\pi_i]}}\right) d\pi_i$$

$$= \frac{1}{\sqrt{2\pi_i Var[\pi_i]}} e^{-E[\pi_i]\alpha_i + \frac{1}{2}\alpha_i{}^2 Var[\pi_i]} \int \left(-e^{-\frac{(\pi_i - E[\pi_i] + \alpha_i Var[\pi_i])^2}{2Var[\pi_i]}}\right) d\pi_i$$

$$= -e^{-\alpha\left(E[\pi_i] - \frac{1}{2}\alpha_i Var[\pi_i]\right)}. \tag{A1-1}$$

A2 Derivations of the Optimal Solutions in Equations (2-4) ~ (2-7)

A Lagrangian function, denoted LA_i, states the optimization problem as:

$$LA_i = E[U_i(\pi)] + \lambda_i\left(L_i - \sum_j L_{ij}\right) + \eta_i\left(E[\overline{W_i}\,|\varepsilon] - \sum_j r_{ij}L_{ij}\right) + \tau_i(1 - a_{ij}), \tag{A2-1}$$

where λ_i, η_i, and τ_i are the shadow prices assigned to the land, water supply, and share constraint, respectively. The necessary first order conditions for the optimal solutions are:

$$P_{ij}\left(r_{ij}a_{ij}\right)^{\beta_j} z_{ij}{}^{\gamma_j} e^{\frac{1}{2}\sigma^2} - \left(c_{ij} + \sigma_\varepsilon^2\right)r_{ij} - \omega_{ij}z_{ij} - \lambda_i - \eta_i r_{ij} = \alpha_i e^{\sigma^2}\left(e^{\sigma^2} - 1\right)P_{ij}{}^2 L_{ij}\left(r_{ij}a_{ij}\right)^{2\beta_j} z_{ij}{}^{2\gamma_j}, \tag{A2-2}$$

$$\beta_j P_{ij} a_{ij}{}^{\beta_j} r_{ij}{}^{\beta_j - 1} z_{ij}{}^{\gamma_j} e^{\frac{1}{2}\sigma^2} - \left(c_{ij} + \sigma_\varepsilon^2\right) - \eta_i = \alpha_i e^{\sigma^2}\left(e^{\sigma^2} - 1\right)\beta_j P_{ij}{}^2 L_{ij} a_{ij}{}^{2\beta_j} r_{ij}{}^{2\beta_j - 1} z_{ij}{}^{2\gamma_j}, \quad \text{(A2-3)}$$

$$\gamma_j P_{ij}\left(r_{ij} a_{ij}\right)^{\beta_j} z_{ij}{}^{\gamma_j - 1} e^{\frac{1}{2}\sigma^2} - \omega_{ij} = \alpha_i e^{\sigma^2}\left(e^{\sigma^2} - 1\right)\gamma_j P_{ij}{}^2 L_{ij}\left(r_{ij} a_{ij}\right)^{2\beta_j} z_{ij}{}^{2\gamma_j - 1}, \quad \text{(A2-4)}$$

$$\beta_j P_j L_{ij} r_{ij}{}^{\beta_j} a_{ij}{}^{\beta_j - 1} z_{ij}{}^{\gamma_j} e^{\frac{1}{2}\sigma^2} - t_i - \tau_i = \alpha_i e^{\sigma^2}\left(e^{\sigma^2} - 1\right)\beta_j P_{ij}{}^2 L_{ij}{}^2 r_{ij}{}^{2\beta_j} a_{ij}{}^{2\beta_j - 1} z_{ij}{}^{2\gamma_j} \quad \forall j. \quad \text{(A2-5)}$$

These conditions are informative. First, at the optimal solutions, the shadow price of each constraint equals the marginal net benefit of each resource, which is defined as the expected value of the marginal product of the resource minus extra cost of input use and extra risk premium. For example, equation (A2-2) states that the optimal acreage allocated to a crop L_{ij}^* is such that the shadow price of the land availability constraint λ_i equals the marginal net benefit of land. The marginal net benefit is defined as the difference between expected value of marginal product of land ($P_{ij}\left(r_{ij} a_{ij}\right)^{\beta_j} z_{ij}{}^{\gamma_j} e^{\frac{1}{2}\sigma^2}$) and extra cost of water ($\left(c_{ij} + \sigma_\varepsilon^2\right) r_{ij} + \eta_i r_{ij}$), extra cost of non-water input ($\omega_{ij} z_{ij}$), and finally extra risk premium ($\alpha_i e^{\sigma^2}\left(e^{\sigma^2} - 1\right) P_{ij}{}^2 L_{ij}\left(r_{ij} a_{ij}\right)^{2\beta_j} z_{ij}{}^{2\gamma_j}$). Equation (A2-3) states that the optimal per-acre water use of a crop r_{ij}^* is determined at the level where the shadow price of the water availability constraint η_i equals the per-acre marginal net benefit of water. The marginal net benefit is similarly defined as the difference between expected value of per-acre marginal product of water ($\beta_j P_{ij} a_{ij}{}^{\beta_j} r_{ij}{}^{\beta_j - 1} z_{ij}{}^{\gamma_j} e^{\frac{1}{2}\sigma^2}$) and extra cost of water use ($c_{ij} + \sigma_\varepsilon^2$), extra per-acre risk premium ($\alpha_i e^{\sigma^2}\left(e^{\sigma^2} - 1\right)\beta_j P_{ij}{}^2 L_{ij} a_{ij}{}^{2\beta_j} r_{ij}{}^{2\beta_j - 1} z_{ij}{}^{2\gamma_j}$). Equation (A2-5) states that the optimal irrigation efficiency a_{ij}^* is at the level where the marginal net benefit is equal to its shadow price τ_i.

Second, optimal water and non-water input use follow a fixed expansion path $\frac{z_{ij}^*}{r_{ij}^*} = \frac{c_{ij}+\sigma_\varepsilon^2+\eta_i}{\omega_{ij}}\frac{\gamma_j}{\beta_j}$, which is affected by the output elasticities β_j and γ_j, non-water input price ω_{ij}, water price $c_{ij} + \sigma_\varepsilon^2$, and its shadow price η_i.

Third, optimal cropland allocation changes proportionally to the optimal adoption of the water-saving irrigation technology. That is, if the producer decides to apply more efficient irrigation to a larger share of land, i.e., increase irrigation efficiency for a certain crop, he will also allocate more land to this crop. And the expansion in the production scale is positively affected by the cost associate with the efficient irrigation technology $t_i + \tau_i$, and limited by sum of output elasticities of inputs $\beta_j + \gamma_j$, shadow price of land λ_i, and output elasticity of efficient water use β_j. It makes intuitive sense as if it is more expensive to install the efficient irrigation system, the producer will plant more of the crop given the high sunk cost and irreversible investment. However, if land is a relatively "expensive" resource, meaning a large λ_i, he will not expand planted acreage as much.

The conditions generate the optimal solutions:

$$r_{ij}^* = \frac{\lambda_i\beta_j}{(1-\beta_j-\gamma_j)(c_{ij}+\sigma_\varepsilon^2+\eta_i)}, \tag{A2-6}$$

$$z_{ij}^* = \frac{\lambda_i\gamma_j}{\omega_{ij}(1-\beta_j-\gamma_j)}, \tag{A2-7}$$

$$a_{ij}^*: P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j){a_{ij}^*}^{\beta_j}\lambda_i\beta_j e^{\frac{1}{2}\sigma^2} - \left[P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j)\right]^2{a_{ij}^*}^{2\beta_j+1}\alpha_i e^{\sigma^2}\left(e^{\sigma^2}-1\right)(t_i+\tau_i) = {\lambda_i}^2\beta_j, \tag{A2-8}$$

$$L_{ij}^* = \frac{(1-\beta_j-\gamma_j)(t_i+\tau_i)}{\lambda_i\beta_j}a_{ij}^*, \tag{A2-9}$$

where a_{ij}^* is characterized by the implicit function in equation (A2-8).

A3 Determining the Sign: the Effect of Climate Variability on Technology Adoption

The sign of the derivative is determined in the following way. $\frac{\partial a_{ij}^*}{\partial \sigma^2} = \frac{a_{ij}^*[\left(3e^{\sigma^2}-1\right)\left(P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2}-\lambda_i\right)-\lambda_i e^{\sigma^2}]}{2(e^{\sigma^2}-1)[\lambda_i\beta_j+(1+\beta_j)(\lambda_i-P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2})]}$ is derived from equation (A2-8).

First, we prove that $\frac{\partial a_{ij}^*}{\partial \alpha_i} > 0$. The sign is determined in the following way. $\frac{\partial a_{ij}^*}{\partial \alpha_i} = \frac{a_{ij}^*\left(P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2}-\lambda_i\right)}{\alpha_i\left[\lambda_i\beta_j+(1+\beta_j)\left(\lambda_i-P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2}\right)\right]}$ is derived from equation (A2-8). $\frac{\partial^2 a_{ij}^*}{\partial \alpha_i \partial \lambda_i} < 0$, which means $\frac{\partial a_{ij}^*}{\partial \alpha_i}$ is decreasing in λ_i. When $\lambda_i = P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}\left(1 - \beta_j - \gamma_j\right){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2}$, $\frac{\partial a_{ij}^*}{\partial \alpha_i} = 0$. Since the second term on the left-hand side of equation (A2-8) is positive, $\lambda_i < P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}\left(1 - \beta_j - \gamma_j\right){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2}$. So $\frac{\partial a_{ij}^*}{\partial \alpha_i} > 0$.

Since $\frac{\partial a_{ij}^*}{\partial \alpha_i} > 0$ and the numerator of $\frac{\partial a_{ij}^*}{\partial \alpha_i}$ is positive, the denominator of $\frac{\partial a_{ij}^*}{\partial \alpha_i}$ is also positive. The denominator of $\frac{\partial a_{ij}^*}{\partial \sigma^2}$ has the same sign with the denominator of $\frac{\partial a_{ij}^*}{\partial \alpha_i}$, which is also positive. The threshold level $\overline{a_{ij}} = \frac{1-\beta_j-\gamma_j}{\delta\beta_j\gamma_j}\left[\frac{\left(4e^{\sigma^2}-1\right)\lambda_i}{\left(3e^{\sigma^2}-1\right)P_{ij}\left(1-\beta_j-\gamma_j\right)}\right]^{\frac{1}{\beta_j}}\left[\frac{\omega_{ij}(1-\beta_j-\gamma_j)}{\lambda_i\gamma_j}\right]^{\frac{\gamma_j}{\beta_j}}(c_{ij} + \sigma_\varepsilon^2 + \eta_i)$ is derived by setting the numerator of $\frac{\partial a_{ij}^*}{\partial \sigma^2}$ equal to zero.

When $\left(3e^{\sigma^2} - 1\right)\left(P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}\left(1 - \beta_j - \gamma_j\right){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2} - \lambda_i\right) - \lambda_i e^{\sigma^2} = 0$, $\overline{\lambda_i} = \frac{3e^{\sigma^2}-1}{4e^{\sigma^2}-1}P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}\left(1 - \beta_j - \gamma_j\right){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2}$, $a_{ij}^* = \overline{a_{ij}}$.

When $a_{ij}^* < \overline{a_{ij}}$, i.e. when $\lambda_i > \overline{\lambda_i}$, $\frac{\partial a_{ij}^*}{\partial \sigma^2} < 0$.

Otherwise, when $a_{ij}^* > \overline{a_{\iota J}}$, i.e. when $\lambda_i < \overline{\lambda_\iota}$, $\frac{\partial a_{ij}^*}{\partial \sigma^2} > 0$.

A4 Determining the Sign: the Effect of Climate Variability on Water Application Rates

The sign of the derivative is complicated by how the shadow price λ_i change with climate variability. Therefore we take a different approach. We derive from the first order conditions that $a_{ij}^*(t_i + \tau_i) = (c_{ij} + \sigma_\varepsilon^2 + \eta_i)L_{ij}^* r_{ij}^*$. From this condition, we derive the marginal effect as $\frac{\partial r_{ij}^*}{\partial \sigma^2} = \frac{(t_i+\tau_i)}{(c_{ij}+\sigma_\varepsilon^2+\eta_i)} \frac{\frac{\partial a_{ij}^*}{\partial \sigma^2} * L_{ij}^* - \frac{\partial L_{ij}^*}{\partial \sigma^2} * a_{ij}^*}{{L_{ij}^*}^2}$. When $\frac{\partial a_{ij}^*}{\partial \sigma^2} * L_{ij}^* - \frac{\partial L_{ij}^*}{\partial \sigma^2} * a_{ij}^* > 0$, i.e. when $\frac{\partial a_{ij}^*/\partial \sigma^2}{a_{ij}^*} > \frac{\partial L_{ij}^*/\partial \sigma^2}{L_{ij}^*}$>0, $\frac{\partial r_{ij}^*}{\partial \sigma^2} > 0$. Otherwise, $\frac{\partial r_{ij}^*}{\partial \sigma^2} < 0$.

Alternatively, we take derivative on both sides of the equation $a_{ij}^*(t_i + \tau_i) = (c_{ij} + \sigma_\varepsilon^2 + \eta_i)L_{ij}^* r_{ij}^*$ with respect to σ^2 and get $\frac{\partial a_{ij}^*/\partial(\sigma^2)}{a_{ij}^*} = \frac{\partial L_{ij}^*/\partial(\sigma^2)}{L_{ij}^*} + \frac{\partial r_{ij}^*/\partial(\sigma^2)}{r_{ij}^*}$. Hence, $\frac{\partial r_{ij}^*/\partial(\sigma^2)}{r_{ij}^*} = \frac{\partial a_{ij}^*/\partial(\sigma^2)}{a_{ij}^*} - \frac{\partial L_{ij}^*/\partial(\sigma^2)}{L_{ij}^*}$. The sign of the marginal effect depends on the difference of adaptations in technology adoption and cropland allocation.

A5 Determining the Sign: the Effect of Water Scarcity on Technology Adoption

The sign of the derivative is determined in the following way. $\frac{\partial a_{ij}^*}{\partial(\sigma_\varepsilon^2)} = \frac{a_{ij}^*[{\lambda_i}^2\beta_j - 2\beta_j {r_{ij}^*}^{\beta_j} {a_{ij}^*}^{\beta_j+1} P_{ij} {z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j)\alpha_i e^{\frac{1}{2}\sigma^2}(e^{\sigma^2}-1)(t_i+\tau_i)]}{r_{ij}^*[P_{ij} {z_{ij}^*}^{\gamma_j}(1-\beta_j-\gamma_j)\alpha_i e^{\frac{1}{2}\sigma^2}\left(e^{\sigma^2}-1\right)(t_i+\tau_i){r_{ij}^*}^{\beta_j}{a_{ij}^*}^{\beta_j+1}(1+2\beta_j) - {\lambda_i}^2\beta_j]} \cdot \frac{\partial r_{ij}^*}{\partial \sigma_\varepsilon^2}$ is derived from equation (A2-8). The denominator of the first term on the right-hand side can be transformed into $\frac{\lambda_i\beta_j}{a_{ij}^*}[\lambda_i\beta_j + (1+\beta_j)(\lambda_i - P_{ij}{r_{ij}^*}^{\beta_j}{z_{ij}^*}^{\gamma_j}\left(1-\beta_j-\gamma_j\right){a_{ij}^*}^{\beta_j}e^{\frac{1}{2}\sigma^2})]$, which is positive according to A3. The numerator can be rewritten as

$$\frac{\lambda_i \beta_j}{P_{ij} {z_{ij}^*}^{\gamma_j} (1-\beta_j-\gamma_j) {r_{ij}^*}^{\beta_j} {a_{ij}^*}^{\beta_j}} [P_{ij} {r_{ij}^*}^{\beta_j} {z_{ij}^*}^{\gamma_j} (1-\beta_j-\gamma_j) {a_{ij}^*}^{\beta_j} e^{\frac{1}{2}\sigma^2} (2-{a_{ij}^*}^{\beta_j}) - 2\lambda_i].$$

When the numerator is set equal to zero, $\overline{a_{ij}^{\varepsilon}} = [1 - \sqrt{1 - \frac{2\lambda_i}{P_{ij} {r_{ij}^*}^{\beta_j} {z_{ij}^*}^{\gamma_j} (1-\beta_j-\gamma_j) e^{\frac{1}{2}\sigma^2}}}]^{\frac{1}{\beta_j}}$

and $\overline{\lambda_i}^{\varepsilon} = \frac{P_{ij} {r_{ij}^*}^{\beta_j} {z_{ij}^*}^{\gamma_j} (1-\beta_j-\gamma_j) {a_{ij}^*}^{\beta_j} e^{\frac{1}{2}\sigma^2} (2-{a_{ij}^*}^{\beta_j})}{2}$.

When $a_{ij}^* < \overline{a_{ij}^{\varepsilon}}$, i.e. when $\lambda_i > \overline{\lambda_i}^{\varepsilon}$, the numerator is negative. Since $\frac{\partial r_{ij}^*}{\partial \sigma_{\varepsilon}^2} < 0$, $\frac{\partial a_{ij}^*}{\partial \sigma_{\varepsilon}^2} > 0$.

Otherwise, when $a_{ij}^* > \overline{a_{ij}^{\varepsilon}}$, i.e. when $\lambda_i < \overline{\lambda_i}^{\varepsilon}$, $\frac{\partial a_{ij}^*}{\partial \sigma_{\varepsilon}^2} < 0$.

A6. Supporting Statistics and Estimation Results

The coefficient estimates for the nonlinear model equation (2-13) are reported in Table A1. The summary statistics for independent variables at county level are presented in Table A2.

Table A1. Parameter Estimates of Efficient Irrigation Technology Adoption

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
Water scarcity				
Off-farm surface water cost ($1000/acre-foot)	14.091***	1.733**	13.986**	5.648
	(2.334)	(0.744)	(5.955)	(5.569)
Depth to well water (1000 feet)	0.221	3.080**	-3.189**	4.716**
	(1.222)	(1.574)	(1.519)	(2.254)
Pump capacity (1000 GPM)	0.434**	0.143	1.831**	0.663
	(0.184)	(0.205)	(0.768)	(0.529)
Water supply institutions				
BOR surface water supply (0/1)	0.430**	-0.925***	0.088	-0.845**
	(0.199)	(0.307)	(0.841)	(0.352)
BOR*surface water cost	-10.857***	6.692	3.395	3.535
	(3.245)	(4.256)	(20.581)	(6.028)
Climate and weather				
Excessive moisture risk (inches)	-0.008	0.026**	-0.086	-0.031*
	(0.006)	(0.012)	(0.157)	(0.018)
Extreme heat risk (°F)	-1.859**	-0.178	1.017	-0.584
	(0.879)	(0.399)	(0.992)	(1.715)
Spring freeze and frost risk (days)	--	0.007	--	--
		(0.007)		
Drought risk [0,1]	--	--	--	8.497**
				(3.834)
Precipitation, expected (inches)	0.019	-0.004	-0.010	0.103
	(0.014)	(0.014)	(0.061)	(0.065)
Max. temperature, expected (°F)	-0.308***	-0.049	-0.475	-0.207*
	(0.054)	(0.057)	(0.309)	(0.114)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	0.220	0.533	1.367	-1.855
	(0.404)	(0.466)	(2.136)	(1.367)
Scale (1000 acres)	-0.009	0.384***	0.137*	-0.013
	(0.011)	(0.098)	(0.084)	(0.013)
Tenure [0,1]	-0.347	-0.068	-0.493	0.898**
	(0.237)	(0.288)	(0.963)	(0.408)
Price				
Output price ($/ton)	-0.242**	-0.003	0.124	0.320*
	(0.105)	(0.002)	(0.162)	(0.177)
Year: 2018	-1.747**	-0.249	2.036	6.708**
	(0.787)	(0.576)	(1.660)	(3.462)
State: OR	10.105**	-0.907	1.905	5.261
	(4.342)	(2.419)	(4.124)	(8.267)
State: WA	2.492***	-1.184	1.075	6.271
	(0.423)	(2.246)	(3.852)	(7.655)
Intercept	18.725***	4.172	3.755	-19.110
	(5.349)	(3.111)	(8.311)	(12.871)
Observations	1645	2629	294	658
Likelihood Ratios χ^2 (df)	830.43 (16)	189.24 (17)	28.87 (16)	404.29 (17)
Prob > χ^2	0.00	0.00	0.02	0.00

Note: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. In parentheses are standard errors.

Table A2. Descriptive Statistics for Independent Variables

Variable (units)	Forage	Orchard/Vineyard	Potato	Wheat
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)
Water Scarcity and institutions [a]				
Off-farm surface water cost ($1000/acre-foot)	0.054 (0.105)	0.097 (0.157)	0.093 (0.166)	0.042 (0.094)
Depth to well water (1000 feet)	0.139 (0.084)	0.143 (0.080)	0.160 (0.099)	0.146 (0.096)
Pump capacity (1000 GPM)	1.113 (0.485)	1.058 (0.490)	1.070 (0.511)	1.145 (0.465)
BOR surface water supply [0,1]	0.304 (0.276)	0.251 (0.267)	0.309 (0.278)	0.361 (0.263)
Climate and weather				
Excessive moisture risk (inches)	30.235 (34.913)	34.593 (24.684)	21.419 (10.984)	18.433 (24.943)
Extreme heat risk (°F)	1.692 (2.312)	1.980 (2.051)	4.302 (0.610)	2.764 (2.397)
Spring freeze and frost risk (days)	--	109.042 (34.524)	--	--
Drought risk [0,1]	--	--	--	0.091 (0.142)
Precipitation, expected (inches)	28.506 (23.347)	30.171 (23.585)	34.116 (26.065)	21.373 (15.585)
Precipitation, observed (inches)	26.200 (23.555)	26.536 (23.849)	31.953 (26.900)	20.685 (18.050)
Max. temperature, expected (°F)	27.174 (4.028)	26.901 (4.163)	26.112 (4.328)	28.218 (3.800)
Max. temperature, observed (°F)	27.823 (3.775)	27.474 (3.925)	26.838 (4.045)	28.873 (3.463)
Farm characteristics and farmer demographics				
Cropland quality [0,1]	0.404 (0.320)	0.453 (0.316)	0.403 (0.288)	0.353 (0.321)
Scale (1000 acres)	35.153 (59.454)	27.914 (57.057)	39.157 (68.692)	55.561 (69.908)
Tenure [0,1]	0.567 (0.234)	0.625 (0.246)	0.614 (0.238)	0.546 (0.215)
Price				
Output price ($/ton)	44.335 (4.021)	497.261 (324.277)	42.999 (16.700)	56.676 (9.851)

Note: [a] Outliers in water scarcity variables are replaced with the values at 95% percentile. Missing observations are replaced with county-level or state-level averages, by assuming that farms in the same county have similar water availability.

A7. Variable Construction

We start with all crops included in the database and drop the ones from the analysis that exhibit any of the following features: (1) it is not a specialty crop (i.e., not fruit, nut, vegetable, nursery and floriculture); (2) it has never been supplied with insurance or has always been supplied with insurance (thus the variation is not large enough for empirical analysis); (3) it has data for insurance but not for production; and (4) there are ambiguous crop categories. For example, at points in time the insurance policies for citrus crops were divided into more specific categories, transitioning from policies for “citrus”, to “citrus” and “special citrus”, and finally to a wide variety of more crop-specific policies. This ambiguity presents identification issues for determining the incidence of insurance supply to different crops across time. Finally, several crops were dropped from the database because they have few observations. These procedures resulted in the insurance and production data for the five crops analyzed in this article: apples, wine grapes, English walnuts, dry plums (i.e., prunes), and dry beans.

A8. Identifying the Best Model Specifications and Estimators

A8.1 Federal Crop Insurance Supply

The model specifications are determined in the following way. First, only county level own-crop values are used to represent economic significance. Then crop values at the agricultural statistic district level, state level, and national level are added to the estimation successively. This process generates four specifications for each crop insurance equation. We perform Wald tests of coefficients and find that economic significance variables are jointly significant only if crop values at all spatial levels are included. This result holds for all crops. Therefore, the specification that includes all spatial level crop values provides the most fit model.

Apart from selection of spatial scales, the measurements of economic significance need to be determined as well. First, absolute crop values at different spatial scales are used as measurements. Then relative shares of county value in each spatial scale are also used to measure economic significance. A comparison of marginal effects under these two model specifications suggests absolute crop values are better indicators of economic significance. Wald test results show that for all crops, the explanatory variables are jointly significant when absolute crop values are included in the estimation.

Tests are also performed to determine the appropriate method for estimating the insurance equation for each crop. Table 3-3 reports the estimation results of the marginal effects from four different estimators for the insurance equation for grapes. The insurance equation is first estimated using the pooled probit method, with both unclustered standard errors and cluster-robust standard errors.

The pooled probit method ignores the panel structure of the data. It does not exploit variation between counties. The results from the pooled probit method are inconsistent if there are fixed county effects, and are also inefficient if standard errors are not adjusted to solve the problem of serial correlation induced by time-invariant county characteristics.

We then estimate the insurance equation as a panel probit model using both the random-effect and correlated-random-effect estimators. The error term u_{ijt} in the insurance supply equation (3-1) can be decomposed into two components,

$$u_{ijt} = a_{ij} + b_{ijt}, \tag{A8-1}$$

where a_{ij} capturesunobserved time-invariant county specific effects. The random-effect estimator assumes a_{ij} to be uncorrelated with explanatory variables X'_{ijt}, while the correlated random effect estimator (i.e., Mundlak's approach) accounts for correlation between a_{ij} and X'_{ijt}.

The test statistics reported in Table 3-3 show that the random effect estimator is better than the correlated random effect estimator. We run the Hausman specification test to see whether there is systematic difference between the two sets of panel probit estimates. The null hypothesis means both the random and correlated random effect models would be consistent, and the random effect model is also efficient. The null hypothesis that there is no correlation between county-specific effects and the regressors cannot be rejected, indicating that the random-effect estimator is consistent and more efficient. We also perform a Wald test on the coefficients from the correlated random effect model. The result shows that they are jointly insignificant. That is, the assumption for the random effects model that the unobserved heterogeneity is uncorrelated with regressors is valid. The Wald test result confirms the conclusion from Hausman test that random effect estimator is consistent and efficient.

The test statistics reported in Table 3-3 also reveal that the random-effect panel probit estimator performs better than the pooled probit estimators. ρ is the proportion of the total variance contributed by the county specific effects. According to the likelihood-ratio test, ρvalues are significantly different from zero, reflecting the importance of inter-county variance. This suggests that the pooled probit method does not provide consistent estimates for this model as it neglects county fixed effects in the data. Indeed, most marginal effects estimated using the pooled probit estimators are statistically insignificant.

The above analysis and tests of model specifications and estimation methods are performed for each crop. The results confirm that the random-effect panel probit estimator is also the best estimator for other crop insurance supply equations.

A8.2 Harvested Acreage and Yield Response Equations

The model specifications for the harvested acreage and yield equations are determined in the following way. First, the predicted probability of insurance provision is the only policy variable included in the estimation of the equation system; no interaction terms are included. To explore the mechanisms through which farmers' cropping decisions are affected by crop insurance supply, interaction terms are then added to the estimation. According to equation (3-3), the coefficient on the interaction term, θ_i, measures the difference in the marginal effect of the independent variable with and without insurance supply. Similarly, the coefficient on the interaction term in equation (3-4), β_i, defines the effect of crop insurance supply on yield. Based on the estimated coefficients on the interaction terms, we can assess how acreage and yield respond differently to changes in explanatory variables due to provision of crop insurance. The interaction terms are selected in the following manner. First, all interaction terms between crop insurance provision and explanatory variables are included in the estimation. Those that are insignificant for all crops are dropped. Then the equation system is re-estimated simultaneously.

The harvested acreage equation and yield equation are estimated simultaneously. We perform Hausman specification tests to check if unobserved county heterogeneity is correlated with regressors. The error terms in equation (3-3) and (3-4) are both decomposed into time-invariant and time-varying parts:

$$\nu_{ijt} = c_{ij} + d_{ijt}, \tag{A8-2}$$

$$\varepsilon_{ijt} = e_{ij} + f_{ijt}. \tag{A8-3}$$

According to the Hausman test results, correlation between county effect and the independent variables results in an endogeneity problem in the acreage equation of dry beans, and yield equation of grapes and dry plums. We use least squares dummy variable estimators to deal with county fixed effects in these equations. For the rest, county-fixed effects c_{ij} and e_{ij} lead to an auto-correlation problem instead of the endogeneity problem, and they can be treated as random parameters. The pooled OLS method with cluster robust standard errors is used to deal with serial correlation. It outperforms the random effect estimator in that it does not require additional assumption on the specific form of the variance-covariance matrix and that it allows for arbitrary heteroscedasticity.

A9. Estimation Results

The estimation results from the harvested acreage and yield response models are presented in Table A3 and Table A4.

Table A3. SUR Estimates of the Harvested Acreage Response Models

Variable (units)	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Panel A: $\theta's$					
$I^* * \text{Own Price } (\$/ton)$	3.103** (1.290)	7.512 (6.686)	-1.095 (3.800)	10.080*** (3.392)	15.630*** (4.277)
$I^* * \text{LCC } [1-2](\%)$	-466.310 (338.490)	1,351 (1,606)	-8,370*** (1,061)	9,607** (1,300)	4,919* (2,652)
$I^* * \text{LCC } [1-3](\%)$	-65.300*** (9.745)	-499.280*** (68.540)	30.790* (18.400)	-48.860** (21.070)	28.350 (28.920)
$I^* * \text{LCC } [1-4](\%)$	9.453 (8.047)	308.930*** (102.640)	518.850*** (58.570)	195.590*** (45.670)	156.250*** (42.760)
$I^* * \text{PPT } (inches)$	85.040 (108.700)	-5,173*** (932.600)	-507.400 (456.600)	-2,660*** (374.300)	-340.100 (1,203)
$I^* * \text{PPT}^2\ (inches^2)$	-2.722 (1.769)	73.300*** (14.650)	14.380* (7.814)	37.840*** (5.817)	-15.290 (32.630)
$I^* * \text{Min Temp. (°F)}$	-15,736*** (4,383)	-251,347*** (40,387)	118,663*** (22,437)	-188,751*** (19,191)	-135,184*** (24,683)
$I^* * \text{Min Temp.}^2\ (\text{°F}^2)$	125.200 (98.440)	3,847*** (903.200)	-603.800 (525.700)	-1,742*** (246.400)	-1,276*** (430.000)
$I^* * \text{Max Temp. (°F)}$	11,642*** (3,856)	280,130*** (33,573)	286,486*** (26,220)	182,492*** (21,244)	255,183*** (38,089)
$I^* * \text{Max Temp.}^2\ (\text{°F}^2)$	-119.800* (66.110)	-1,325* (702.500)	-1,586*** (516.600)	-3,640*** (314.700)	-3,466*** (563.000)
$I^* * \text{D}_{1995-2000}$	-1,440 (2,419)	1,977 (7,810)	250.100 (1,850)	8,292** (3,893)	852.200 (2,717)
$I^* * \text{D}_{2001-2014}$	-817.700 (2,479)	-5,309 (8,833)	-1,704 (2,046)	11,698*** (4,155)	1,348 (3,003)
$I^* * \text{D}_{2015-2017}$	-974.000 (2,341)	11,332* (6,499)	-1,311 (1,777)	10,021*** (3,002)	1,838 (2,937)
$I^* * \text{Non-bearing Land } (\%)$		1,619*** (307.400)			

Table A3. SUR Estimates of the Harvested Acreage Response Models (Cont.)

Variable (units)	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Panel B: η′s					
Own Price ($\$/ton$)	-0.916* (0.516)	8.758** (4.138)	1.883 (3.198)	-0.597 (2.090)	2.916** (1.283)
LCC $[1-2]$(%)	-37.260** (18.660)	-1,176 (924.000)	5,768*** (803.880)	1,242 (934.490)	441.760 (622.250)
LCC $[1-3]$(%)	12.790*** (2.307)	264.580*** (37.630)	-12.800 (14.570)	-5.082 (11.880)	-53.360*** (19.170)
LCC $[1-4]$(%)	-3.082 (2.964)	40.160 (66.110)	-487.260*** (47.350)	-65.050** (32.600)	-70.000*** (25.550)
PPT ($inches$)	80.560*** (23.310)	2,039*** (561.400)	138.800 (353.500)	121.600 (230.400)	-81.370 (422.100)
PPT^2 ($inches^2$)	-0.650* (0.356)	-26.930*** (8.758)	0.677 (5.952)	-1.670 (3.343)	-4.580 (10.610)
Min Temp. (°F)	1,320 (1,988)	213,624*** (41,405)	139,573*** (20,620)	44,294** (17,343)	1,450 (16,961)
Min $\mathrm{Temp.}^2$ ($°\mathrm{F}^2$)	-126.500*** (22.720)	-687.400 (454.900)	1,674*** (377.700)	426.000*** (139.000)	-519.100*** (185.200)
Max $\mathrm{Temp.}^2$ ($°\mathrm{F}^2$)	-67.050*** (15.980)	1,075*** (344.900)	2,048*** (340.300)	564.700*** (144.800)	-317.000 (199.200)
Average Temp. (°F)	-651.100 (2,001)	-204,326*** (39,512)	-194,490*** (31,492)	-48,654** (22,236)	-3,010 (20,176)
Average $\mathrm{Temp.}^2$ ($°\mathrm{F}^2$)	174.600*** (32.950)	-865.100 (744.200)	-3,304*** (727.800)	-978.400*** (261.700)	792.200** (373.700)
Trend ($year$)	-8.107 (8.267)	592.800** (243.900)	1,197*** (311.400)	232.600 (180.900)	54.490 (121.600)
Non − bearing Land (%)		-307.800** (148.400)			
County Dummies	No	No	No	No	No
Obsv.	697	1,022	497	1,056	588
R^2	0.62	0.71	0.84	0.76	0.70

Note: In parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A4. SUR Estimates of the Yield Response Models

Variable (units)	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Panel A: β's					
$I^* * \text{LCC}\,[1-2](\%)$	-0.009 (1.302)	0.353* (0.202)	0.110 (0.195)	0.164* (0.088)	-0.084*** (0.025)
$I^* * \text{LCC}\,[1-3](\%)$	-0.041 (0.036)	0.013 (0.009)	-0.001 (0.003)	-0.007*** (0.002)	0.003** (0.001)
$I^* * \text{LCC}\,[1-4](\%)$	-0.035 (0.025)	-0.061*** (0.012)	0.004 (0.011)	0.010*** (0.003)	-0.008*** (0.002)
$I^* * \text{Max Temp.}\,(°\text{F})$	-8.823 (30.200)	-1.270 (9.185)	-11.440*** (4.229)	-1.515 (2.157)	0.237 (1.424)
$I^* * \text{Max Temp.}^2\ (°\text{F}^2)$	0.293 (0.623)	0.083*** (0.015)	0.063 (0.076)	0.004 (0.041)	-0.021 (0.040)
$I^* * \text{Average Temp.}\,(°\text{F})$	9.787 (29.670)	-2.667 (9.127)	11.320*** (4.216)	-1.481 (2.147)	-0.101 (1.421)
$I^* * \text{Average Temp.}^2\ (°\text{F}^2)$	1.101* (0.624)	-0.826*** (0.175)	-0.010 (0.081)	-0.036 (0.040)	0.003 (0.031)
$I^* * \text{D}_{1995-2000}$	-11.810 (10.490)	1.918* (1.084)	-0.211 (0.432)	0.231 (0.337)	0.086 (0.179)
$I^* * \text{D}_{2001-2014}$	-5.516 (10.870)	2.179* (1.232)	-0.623 (0.482)	0.330 (0.357)	0.145 (0.201)
$I^* * \text{D}_{2015-2017}$	-2.167 (9.609)	0.878 (0.876)	0.235 (0.412)	0.070 (0.249)	0.155 (0.199)
$I^* * \text{Non}-\text{mature Land}\ (\%)$		0.006*** (0.002)			

Table A4. SUR Estimates of the Yield Response Models (Cont.)

Variable (units)	Apples	Grapes	Plums, Dry	Walnuts	Beans, Dry
Panel B: $\gamma's$					
Own Price ($\$K/ton$)	-8.430***	-0.212	0.811	0.169	-0.161**
	(1.830)	(0.452)	(0.683)	(0.181)	(0.081)
Fertilizer Price ($\$K/ton$)	-13.800**	0.683	0.627	-2.760*	-0.789
	(6.630)	(3.520)	(2.200)	(1.510)	(0.654)
LCC $[1-2](\%)$	-0.249***	-0.352***	-0.343**		0.018***
	(0.057)	(0.116)	(0.162)	—	(0.007)
LCC $[1-3](\%)$	0.055***	-0.012**	0.002	-0.004	-0.003***
	(0.009)	(0.005)	(0.003)	(0.004)	(0.001)
LCC $[1-4](\%)$	-0.022**	-0.029***	-0.026***	-0.081***	0.003***
	(0.009)	(0.008)	(0.010)	(0.018)	(0.001)
PPT ($inches$)	0.005	-0.001	0.004	-0.002	0.001
	(0.028)	(0.018)	(0.011)	(0.005)	(0.004)
PPT^2 ($inches^2$)	-0.0017*	-0.0009	-0.0006**	0.0001	-0.0002
	(0.0009)	(0.0006)	(0.0002)	(0.0002)	(0.0001)
Min Temp. (°F)	2.515	0.643	-12.660***	-0.441	0.158
	(9.655)	(5.432)	(3.504)	(1.549)	(0.906)
Min Temp.^{2} (°F^2)	0.025	0.223**	0.061	-0.001	-0.007
	(0.187)	(0.088)	(0.051)	(0.024)	(0.022)
Max Temp. (°F)	-2.338	-1.044	12.570***	0.441	-0.023
	(9.631)	(5.409)	(3.490)	(1.544)	(0.907)
Max Temp.^{2} (°F^2)	0.222	-0.253**	-0.025	-0.020	0.011
	(0.186)	(0.100)	(0.057)	(0.024)	(0.017)
Average Temp. (°F)	-5.589	-1.614	25.230***	0.921	-0.372
	(19.290)	(10.860)	(6.996)	(3.091)	(1.822)
Average Temp.^{2} (°F^2)	0.073	-0.544***	-0.068	-0.021	0.046
	(0.379)	(0.196)	(0.112)	(0.051)	(0.040)
Trend ($year$)	0.013*	-0.003	0.008***	-0.005***	0.002***
	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)
Non − mature Land (%)		-0.002*			
		(0.001)			
County Dummies	No	No	No	Yes	Yes
Obsv.	697	1,022	497	1,056	588
R^2	0.84	0.90	0.92	0.86	0.95

Note: In parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.