# ENVIRONMENTAL POLICIES AND INSTITUTIONS IN FOOD-ENERGY-WATER NEXUS: STRUCTURAL AND REDUCED FORM APPROACHES

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## ABSTRACT

ENVIRONMENTAL POLICIES AND INSTITUTIONS IN FOOD-ENERGY-WATER NEXUS: STRUCTURAL AND REDUCED FORM APPROACHES

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Food, energy and water sectors are heavily affected by climate change. Multiple new technologies have been introduced to these sectors as mitigation strategies for climate change. This dissertation aims to study whether the use of these technologies in these sectors leads to unexpected environmental consequences and whether these consequences could be alleviated by properly-designed environmental policies and institutions. Different economic analysis tools, such as reduced-form econometrics, structural econometrics, and structural microeconomics simulation, are applied in the analysis.

I first study the interaction of environmental policies and technology improvements in food and water sectors. Irrigation technology is used as an example due to its ability to bridge the two sectors. Specifically, I study how institutions such as water rights complement new irrigation technologies in promoting the sustainability of US agriculture. Using data from the Ogallala-High Plains Aquifer (HPA) region of Kansas, I find that water extraction moderately increases after adoption of the more efficient LEPA irrigation. About half of the LEPA's rebound effects arise because adopters tend to irrigate more land and grow more water intensive crops, with the remaining half attributable to more intensive irrigation. More importantly, this rebound effect is in general higher for farmers with larger water rights. A 10% reduction of water rights will reduce water use by 6% in the long run, and if the reduction targets the majority of the water rights, which lie between 100 and 500 AF, LEPA's rebound effects decrease by 15.4%. Finally, farmers also have incentive to apply a small amount of water in order to preserve their water rights, but the associated water waste is insignificant.

A related policy question is how to effectively promote the adoption of more efficient irrigation technologies. Complementing the first study in the dissertation, a structural dynamic discrete

choice model is developed next to estimate adoption determinants and aggregate diffusion paths of LEPA technology in the Kansas HPA. The estimation results confirm that farmers value the option to delay adoption in the presence of uncertainties and sunk costs. Besides, behavioral biases such as inertia to change farming practices also significantly delay LEPA adoption by increasing perceived adoption costs. This inertia is reduced when more neighbors have adopted LEPA. Finally, under the same level of expected government budget, increase in average adoption probability under profit gain insurance policies is 10% higher than that under cost share subsidies.

The last study turns to the energy sector, which is critical in mitigating climate change. Specifically, it looks at how the projected fast decline in solar energy capacity costs affects renewable penetration and $CO_2$ emissions. Using both an analytical model and a dynamic structural simulation model, I show that wind energy capacity investment first increases and then decreases as solar costs decrease due to the complex interaction of wind and solar capacities. Results indicate that when solar costs drop from the 2030 projected level to 2050 projected level, $CO_2$ emissions increase by 12.9% because of the decline in wind energy investment, which indicates that cheaper solar cost does not necessarily imply a cleaner grid without any carbon policy interventions. The use of energy storage to increase renewable penetration in order to reduce carbon emissions, as is suggested in the literature, is economically infeasible as the high storage capacity costs currently prevent any storage investment. However, if the regulator requires that renewable penetration rate could not drop below 36%, the maximum renewable penetration obtained under all levels of possible future solar capacity costs, social welfare from renewable investment in 2050 would increase by \$0.77 billion/year due to a decrease in $CO_2$ emissions. This study illustrates the importance of a second-best-type policy in the energy sector facing future decline in solar capacity costs if a carbon tax is not politically available.

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# CHAPTER 1

# INTRODUCTION

The sectors of food, energy and water are related to each other in multiple ways. Greenhouse gas emissions from the energy sector contribute significantly to climate change, which reduces rainfall and increases drought occurrence. Not surprisingly, irrigation becomes increasingly important to raise crop yield. However, as groundwater levels of major aquifers continue declining, energy expenditures associated with irrigation water pumping go up.

Multiple new technologies have been introduced to these sectors to alleviate the threat of climate change. In the sectors of food and water, the use of more efficient and energy-saving irrigation technologies to water crops is encouraged, in hopes of saving the drying aquifers. In the energy sector, renewable energy technologies such as wind turbine and solar photovoltaic (PV) panels are gradually being used to generate $CO_2$-free energies in major electricity grids.

However, the use of these new technologies may lead to counterproductive results. Economists have long recognized the limitations of purely technological solutions to environmental problems, and argued that resilient and effective institutions and policies can be effective adaptation strategies. Given this observation, a study on the benefits of combining environmental policies and institutions with technological improvements in these sectors becomes necessary for effective policy design. Due to the significant role of renewable energies in preventing climate change and the ability of irrigation to connect food, energy and water sectors, the analyses in the dissertation are rooted in the context of irrigation agriculture and renewable energy development, in hopes of extending the lessons learned to other sectors in the food-energy-water nexus.

Using reduced-form panel data econometrics tools, the second chapter of this dissertation shows that the use of a more efficient irrigation technology, Low Energy Precision Application (LEPA), has increased, rather than decreased, groundwater extraction in the Kansas part of the High Plain Aquifer Area (HPA). The increased water use comes from irrigating more acreages and switching to more water-intensive crops such as corn, implying that policies reducing water use by corn growers could help ameliorate the rebound effects of LEPA. More importantly, this rebound effect is higher for farmers with larger water rights.[1] Thus, the unexpected water use rebound following LEPA adoption could also be alleviated by reducing farmers' water rights. Specifically, a 10% reduction of water rights will reduce LEPA's rebound effect by 15.4%. Recently, many areas inside Kansas HPA are considering to establish Local Enhanced Management Areas (LEMA) to reduce farmers' water rights inside the area for a number of years. The results in this chapter provide empirical support for this policy from the perspective of LEMA's impact on the social performance of efficient irrigation technologies.

The third chapter extends the second chapter by comparing the cost-effectiveness of different adoption promotion policies. Through estimating a structural dynamic discrete choice model, I show that delaying adoption is valuable in the presence of profit uncertainty and sunk costs, where profit uncertainty comes from farmers' uncertainty towards factors that determine LEPA's profit gains, such as energy price, crop price and rainfall. Across the U.S., two most commonly used policies to encourage agricultural technology adoption are cost share subsidies and insurance policies. While cost share policies direct reduce adoption costs, insurance policies promote adoption by reducing farmers' uncertainty towards the new technology's profit gain. A dynamic simulation using the estimated structural parameters show that the increase in average adoption probability under profit gain insurance policies is 10% higher than that under cost share subsidies, given the same level of expected government budget. Although LEPA diffusion in Kansas has already completed, the results obtained in the first two chapters are still useful for other regions that are considering promoting efficient irrigation technology adoption. Specifically, a profit insurance policy combined with policies that reduce water-intensive crops' water use or policies that reduce farmers' water rights would speed up diffusion while limiting water use rebound.

While the previous two chapters focus on technological and institutional (policy) adaptations to climate change, the fourth chapter focuses on preventing climate change in the energy sector through the use of renewable energies. It is widely expected that renewable energy penetration

[1] A water right is defined as a property right that specifies the maximum annual water extraction allowed for each irrigation well.

($CO_2$ emissions) will keep increasing (decreasing) facing the projected rapid decline in solar capacity costs. However, this is not guaranteed if the two emission-free renewable technologies, wind and solar, interact with each other. Although energy storage could also affect renewable penetration through affecting the values of wind and solar, investing in storage is not supported under a wide range of solar capacity costs as storage capacity is too expensive relative to its value. With both an analytical model and a microeconomics simulation model, I show that the value of wind energy decreases as solar capacity increases (i.e. they are substitutes) when the level of solar capacity is already high. Compared with the second chapter where the unexpected consequence comes from the use of a single technology, the interaction of multiple technologies leads to the unexpected consequence in this context. As a result, wind capacity investment decreases when solar capacity cost drops from its 2030 projected level to 2050 projected level if no carbon policies exist. Correspondingly, renewable penetration reduces by 6% and CO2 emissions go up by 12.9%. However, under a renewable energy policy that requires a minimum level of 36% renewable energy penetration, social welfare from renewable energy capacity investment in 2050 would increase by $0.77 billion/year due to an increase in renewable penetration and a decrease in $CO_2$ emissions.

Taken together, this dissertation demonstrates that purely technological solutions for environmental problems emerging in the food-energy-water nexus might be inefficient. These inefficiencies may come from the use of a single technology alone, or come from the interactions of multiple different technologies. However, the reduction in these inefficiencies could be economically significant when these technological solutions are combined with properly-designed environmental polices and institutions.

CHAPTER 2

# REBOUND EFFECTS OF NEW IRRIGATION TECHNOLOGIES: THE ROLE OF WATER RIGHTS (WITH JINHUA ZHAO)

## 2.1 Introduction

Irrigation is a major factor influencing modern agriculture's capacity to adapt to global climate change. Facing higher average temperature, greater variability in rainfall and increased likelihood and severity of droughts, production agriculture will be more dependent on irrigation in order to meet the increasing global food demand (Zilberman, Zhao, and Heiman, 2012). However, over 60% of the world's consumption of water is already used for irrigation (FAO, 2016; Wada and Bierkens, 2014), and there is worldwide depletion of surface and groundwater resources. For example, the recent California drought has resulted in increased irrigation using groundwater, leading to substantial groundwater depletion in Central Valley (Howitt et al., 2014). In the High Plains region, irrigation water use since 1930s has depleted over half of the aquifer capacity in the southern part of the Ogallala-High Plains aquifer (henceforth HPA) (Haacker, Kendall, and Hyndman, 2015; McGuire, 2009). Consequently, new irrigation technologies such as Low Energy Precise Application (LEPA) irrigation and drip irrigation have been called upon to improve irrigation efficiency, thereby reducing water needs while maintaining or raising agricultural outputs (Schoengold and Zilberman, 2007; Zilberman, Zhao, and Heiman, 2012).

However, more efficient irrigation technologies do not always reduce water use. Ward and Pulido-Velazquez (2008) finds that adoption of water conservation technologies may raise water use due to the conversion of more land into production agriculture. Pfeiffer and Lin (2014a) finds statistically significant rebound effects of LEPA in HPA: water use increased after farmers switched from center pivot to LEPA. Such rebound effects are inefficient because of the spatial externalities of groundwater extraction: when one farmer pumps water, the resulting groundwater depletion raises the pumping costs of other farmers. The rebound effects together with imperfect property rights governing groundwater use will limit the potential of new technologies in promoting agricultural adaptation and sustainability.

Economists have long recognized the limitations of purely technological responses to external changes, and argued that resilient and effective institutions can be effective adaptation strategies (Zilberman, Zhao, and Heiman, 2012). Examples of such institutions include property rights over both surface water and groundwater, water markets and trading, and water use organizations that help regulate water use. At least theoretically, effective institutions can not only promote the adoption and diffusion of efficient technologies but also limit or even eliminate undesirable rebound effects of these technologies.

In this article, we use a panel data set in the HPA region of Kansas that includes well level water use and water rights during 1991-2010 to study the interacting impacts of institutions and new technologies, focusing on the role of water rights in reducing water use, promoting the adoption of LEPA, and limiting the rebound effects of LEPA. First, we show that LEPA's effect of raising water use is heterogeneous across water rights: higher rebound effects tend to occur for wells with larger water rights. This result indicates that policies that reduce water right levels could help ameliorate LEPA's rebound effects in the long run. Second, we compare and quantify the channels through which water rights and LEPA adoption affect water use. We show that about two thirds of water rights' effect on water use is mediated by irrigated acreages: larger water right holders tend to irrigate larger areas of land. In contrast, around half of LEPA's effect on water use is mediated by both crop choices (i.e. LEPA adopters switching to more water-intensive crops) and irrigated acreages, and the other half is attributable to LEPA adopters simply irrigating more intensively. Moreover, the mediating patterns of crop choice and irrigated acreage vary as the water right level changes. Estimates of the mediation channels not only identify the behavioral changes that contribute to the rebound effects, but also shed light on other impacts of such behavioral changes and allow for more effective targeting in formulating policy responses. For example, our results show that the adoption of LEPA helped raise corn acreage in Kansas, which has important implications for fertilizer use and associated environmental impacts. Policies that reduce water use by corn growers will also help ameliorate the rebound effects of LEPA.

Finally, Kansas follows a prior appropriation water right system with a three-year use-it-or-lose-it (UIOLI) clause. We find that farmers have incentive to apply a small amount of water in order to preserve their water rights even when irrigation is not profit maximizing, and this incentive is slightly higher after LEPA is adopted. The potential water savings if UIOLI is removed, however, are rather small.

There is a sizable literature on the effects of new irrigation technologies on water use in general (Ellis, Lacewell, and Reneau, 1985; Hanak et al., 2010; Khanna, Isik, and Zilberman, 2002; Scheierling, Young, and Cardon, 2006; Ward and Pulido-Velazquez, 2008; Whittlesey and Huffaker, 1995) and in the HPA region of Kansas in particular (Hendricks and Peterson, 2012; Peterson and Ding, 2005; Pfeiffer and Lin, 2012; Pfeiffer and Lin, 2013; Pfeiffer and Lin, 2014a; Pfeiffer and Lin, 2014b). Our work is closest to Pfeiffer and Lin (2014a), which identifies the rebound effects of LEPA. Our innovations include explicitly modeling water rights and farmer incentives to preserve water rights, demonstrating the heterogeneity of LEPA's rebound effects in water right levels, and quantifying the channels through which the rebound effects arise by estimating the role of such mediators as crop choices and irrigated acreages. Further, our data span a longer time period (1991 – 2010 in our article vs. 1996 – 2005 in Pfeiffer and Lin (2014a)).

## 2.2 High Plains Aquifer and Water Rights in Kansas

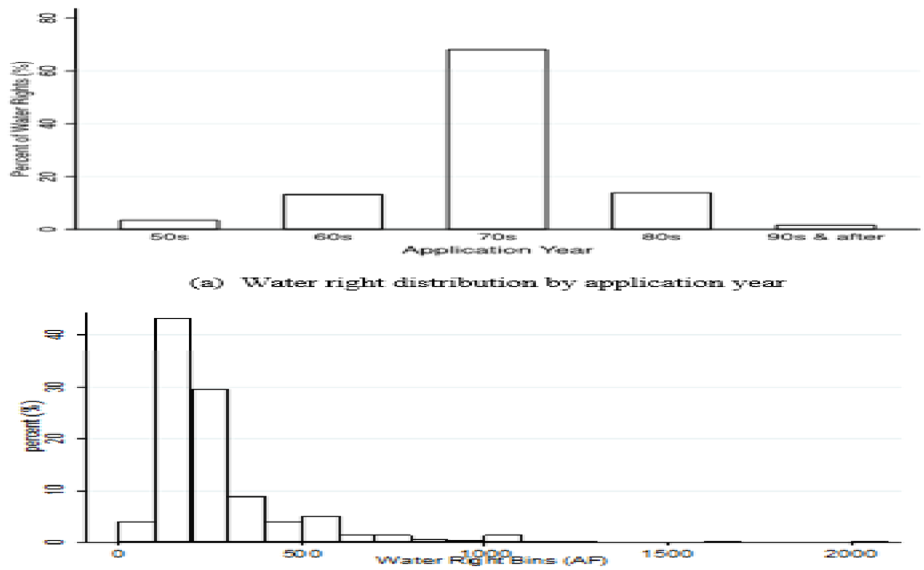
Our study area is the HPA region of Kansas, where production agriculture relies heavily on irrigation water withdrawal from HPA. HPA is the largest freshwater aquifer in the world (Miller and Appel, 1997) and has variable recharge rates from the north to the south. In most of the Kansas HPA, the recharge rate is low and irrigation is similar to mining a nonrenewable resource.

Kansas has a prior appropriation water right system (Peck, 1995; Peck, 2002; Peck, 2007), with each water right specifying the maximum amount of water that can be extracted from the HPA in a given year. The relationship between water rights and irrigation wells can be classified into four types: a single well assigned with a single water right (Type 1), a single well assigned with multiple water rights (Type 2), multiple wells sharing a single water right (Type 3), and multiple wells sharing multiple water rights (Type 4). We focus on Type 1-3 wells: they account for about 72% of the total number of wells and the associated water rights during our study period. Type 4 wells are not included in our analysis due to the complex relationship between water rights and wells. Section 4 and appendix B contain detailed descriptions of the linking procedure and the associated sample attrition.

The seniority of a water right is determined by the time when the water right application was recorded. Among the Type 1-3 water rights in our sample, most of the application dates are in 1970s. There is effectively a moratorium on new water right applications after 1990s (Peck, 1995). Figure 1.1(a) shows the distribution of Type 1-3 water rights by application dates. Since most applications for water rights occurred in 1970s and almost all water rights in our sample have application dates that are at least five years earlier than the beginning of our sample period, we take water rights as exogenous in our empirical estimations. In principle, when water availability cannot satisfy the demand, a well with a more senior water right can block wells with junior water rights from extracting water from the HPA. So far this type of blocking has never occurred so that a farmer's water use decisions are affected by his own water rights but not by the more senior water rights of other farmers.

Water rights in Kansas are not always strictly binding. First, water use is self-reported by farmers. Although water pumping is metered, it is possible that farmers misreport their actual water use. Second, farmers are allowed to go beyond the water right limits in drought years. Each year in our sample, about 10% - 30% of the wells reported water use above their water rights. However, as shown in figure 1.2, this percentage has generally been going down from 1991-2010.

The water right system in Kansas has a three-year use-it-or-lose-it (UIOLI) clause, implying that a water right is subject to cancellation if no water is used by the associated well(s) for three consecutive years. Under the Kansas Administrative Procedure Act, farmers can appeal to the Kansas Department of Water Resources to keep the water rights if they can establish a "due and sufficient cause for non-use" (Peck, 1995). Such cause includes sufficient rainfall, enough surface




(a) Water right distribution by application year

(b) Water right distribution by water right level

Figure 2.1: Distribution of Type 1-3 Water Rights

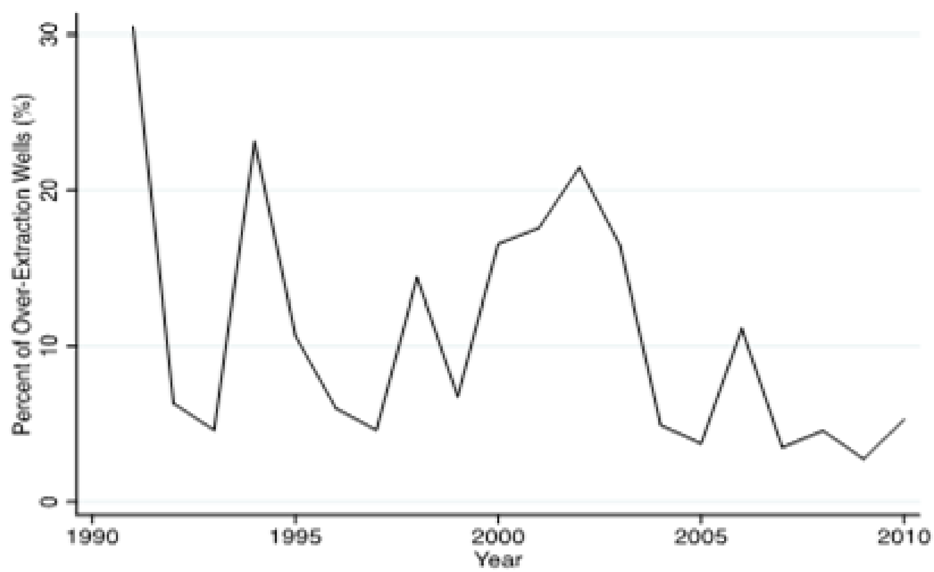



Figure 2.2: Annual percentage type 1-3 water rights experiencing over-extraction (1991-2010)

water as diversion sources, soil and water conservation such as CRP, etc. The burden of proof for establishing the due and sufficient cause for non-use lies with the farmers. Given the transaction costs involved, farmers might have incentive to use a small amount of water even when irrigation is not needed in order to preserve their water rights. Figure 1.3 shows the histogram of annual water extraction of Type 1-3 wells in our sample. In addition to a spike in zero water use, there is also a dis-proportionally large share of observations with a positive but small amount of water use. We will estimate farmer incentives to use a small amount of water in order to preserve their water rights, and evaluate their impacts on water use.

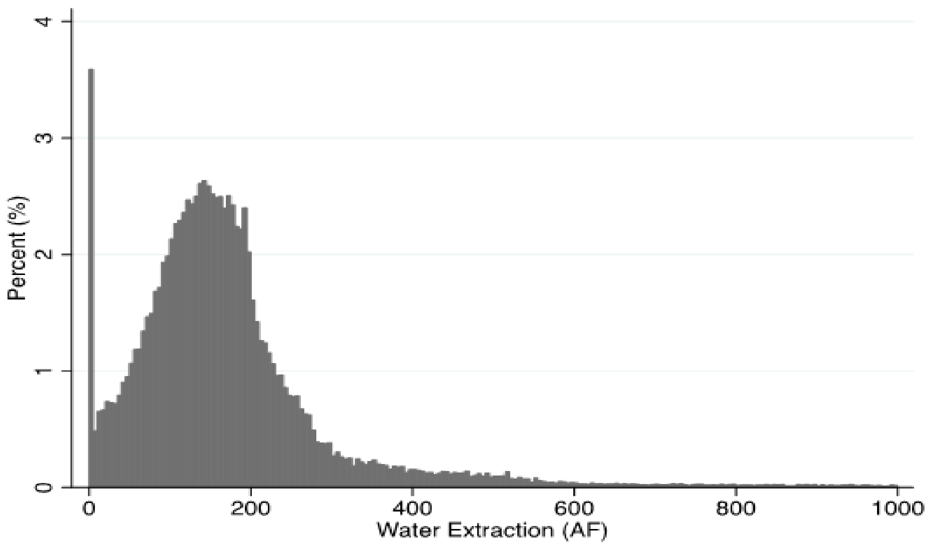



Figure 2.3: Histogram of water extraction of type 1-3 wells (1991-2010)

## 2.3 Model Specifications

The irrigation scheduling literature recognizes that a farmer typically irrigates a field multiple times during a single growing season, and the "optimal" intraseason scheduling depends on the stages of crop growth, soil characteristics, and irrigation technology (Scheierling, Cardon, and Young, 1997; Shani et al., 2009; Yaron and Dinar, 1982). During early stages of the growing season, the farmer might not know for sure how much irrigation water is needed for the reminder of the season due to weather uncertainties and future crop and energy prices. Constrained by his water rights, the farmer may decide to limit the amount of water applied during the early season and leave more options open in order to meet possible high water needs during the later season. Therefore, water rights can affect total irrigation water use of the entire growing season even when ex post the farmer ends up using less water than what the water rights allow.

There is a fixed cost associated with each irrigation application, arising from the minimum pressure required in order for the irrigation equipment to start. LEPA reduces the required water pressure – a reduction from 75 PSI for Center Pivot to 18 PSI for LEPA (Delano, Williams, and O'Brien, 1997), leading adopters to irrigate more frequently.[1] LEPA also greatly reduces evaporation loss, thereby raising irrigation efficiency and reducing the marginal cost of irrigation, leading farmers to irrigate more intensively under LEPA than under center pivot. The increased frequency and intensity of irrigation contribute to LEPA's rebound effects. These considerations and the existence of UIOLI clause lead to two hypotheses that we will test:

**Hypothesis 1 (H1):** *The rebound effects of LEPA on water use are partly attributable to increased irrigation intensity, and are lower for farmers with smaller water rights.*

**Hypothesis 2 (H2):** *Farmers have incentives to preserve water rights under UIOLI, and the incentives are stronger as future irrigation profitability rises and the associated water rights are larger.*

### 2.3.1 A Dynamic Joint Estimation Framework

We first develop and estimate a joint model of water use and water right preservation, focusing on LEPA replacing center pivot, i.e., using wells that have only used one or both technologies during our sample period. Our unit of analysis is wells, with each well treated as representing a single farmer. Let $y_{it}$ be the observed water extraction of well $i$ in year $t$. Farmers first decide whether to use water from the well in the current year and then decide how much water to use. Let $y_{it}^*$ be the latent variable representing the profit maximizing water extraction level without considering the fixed cost of irrigation. In reduced form, $y_{it}^*$ depends on the field characteristics, weather conditions, management practices, irrigation technology and water rights. To account for the nonlinear effects of water rights on water extraction, we divide the water right levels into eight bins, indexed by $j = 1, \ldots, 8 : (0, 100], (100, 200], \ldots, (600, 700]$, and greater than 700 acre-feet (AF), with the first

[1]Since farmers irrigate multiple times during a growing season, the reduction in the minimum water pressure of each irrigation run implies that, viewed from the perspective of the entire growing season, the variable cost (or marginal cost) of irrigation is also lower with LEPA.

bin (i.e. $j = 1$) set to be the base/default level. Figure 1.1(b) shows that over 90% of wells have water rights between 100 and 500 AF. Under a linear specification, we have

$$y_{it}^* = \sum_{j=2}^{8} R_i^j \rho_j + \sum_{j=1}^{8} LEPA_{it} * R_i^j \omega_j + \mathbf{AC}_{it}\boldsymbol{\beta}_1 + \boldsymbol{s}_i\boldsymbol{\beta}_2 + \boldsymbol{w}_{it}\boldsymbol{\beta}_3 + dtw_{it}\beta_4 + G_g + \varphi_t + c_i + \varepsilon_{it}, \quad (2.1)$$

In (2.1), $R_i^j = 1$ if well $i$'s water right falls into the $j^{th}$ water right bin ($j = 2, 3 \ldots, 8$), and $= 0$ otherwise. $LEPA_{it}$ is a dummy variable that equals 1 if the irrigation technology is LEPA and 0 if the technology is center pivot. We include the interaction of LEPA and $R_i^j$ to test part of Hypothesis 1, and the coefficient $\omega_j$ captures the moderating effect of a specific water right bin on LEPA's rebound effect. A larger $\omega_j$ means that LEPA's rebound effect is higher for wells in the $j^{th}$ bin. This specification allows us to estimate heterogeneous rebound effects for farmers with different amount of water right allocations. $\boldsymbol{AC_{it}}$ is a vector of acres of various crops irrigated by well $i$ in year $t$. $\boldsymbol{s_i}$ is a time invariant vector of soil characteristics of the field irrigated by well $i$. $dtw_{it}$ is the well's depth to groundwater, which affects the energy needed to extract the groundwater for irrigation.[2] $\boldsymbol{w_{it}}$ is a vector of weather conditions. $G_g$ and $\varphi_t$ capture the fixed effects of the groundwater management district (GMD) well $i$ belongs to and the time fixed effect, respectively. $c_i$ is a well-specific unobserved heterogeneity and $\varepsilon_{it}$ is an iid error term.

The dynamics of water use arises from the incentive to preserve one's water rights, which depends on the irrigation needs in future periods. Let $z_{it}^*$ be the latent variable describing the farmer's incentive to use water from well $i$ in year $t$. In reduced form, $z_{it}^*$ is specified as:

$$z_{it}^* = rc_i + 1\left(y_{it+1} > 0\right)\alpha_1 + x_{it}^y \alpha_2 + \eta_{it} \quad (2.2)$$

Two sets of factors affect this incentive: the need to irrigate in the current period, and the need to preserve the water right due to the UIOLI clause. In (2.2), $x_{it}^y$ includes all variables used in

[2]The depth to water measures the distance from soil surface to the top of the underground aquifer. Note that $dtw$ does not change even if a farmer deepens his well, and under perfect hydroconductivity (i.e., if water flows freely in the aquifer), the energy needed to extract water to the soil surface is determined by $dtw$ rather than by how deep the well is. dtw is related to a well's $saturatedthickness$, which measures the depth or thickness of water in the aquifer, i.e., the distance between the top and bottom of the aquifer. Saturated thickness affects the pump's water flow – more water is pumped per unit of time when there is more water underground, i.e., when the saturated thickness is larger. The sum of depth to water and saturated thickness equals the distance from the soil surface to the bottom of the aquifer, and remains unchanged through time. Since water right $R_i$ is also time invariant, only one of the depth to water and saturated thickness can be included in (2.1) to avoid perfect collinearity.

the extraction equation (2.1) except for crop acres and $c_i$, and captures the current period need to irrigate. The response to the UIOLI clause is captured by the need to irrigate next year $y_(it + 1)$: if the farmer expects that he will use water next year, his incentive to use water in the current year would be higher because doing so helps preserve his water rights.[3] Following Wooldridge (2000) and Biewen (2009), the coefficient $r$ on $c_i$ in (2) allows the unobserved heterogeneity to affect $y^*_{it}$ and $z^*_{it}$ differently.

In (2.2), we make the assumption of conditional "sequential exogeneity" of $1(y_{it+1} > 0)$: $\eta_{it}$ is uncorrelated with $y_{it}, y_{it+1}, \ldots, y_{iT}$ conditional on control variables $x^y_{it}$ and individual heterogeneity $c_i$.[4] This is a common assumption in nonlinear reduced-form dynamic estimation models (Akay, 2012; Contoyannis, Jones, and Rice, 2004; Deininger, Ali, and Alemu, 2011; Robone, Jones, and Rice, 2011; Stewart, 2007; Wooldridge, 2005), allowing for conditional maximum likelihood estimation for dynamic panels proposed by Wooldridge (2005). This assumption is plausible in our model for two reasons. First, we already control for a rich set of time-invariant variables, such as soil conditions, water rights, GMD fixed effects and individual heterogeneity $c_i$. Thus correlations of $y_{it+1}$ with unobserved time-invariant variables are controlled to a great extent. Second, the inclusion of weather conditions and year fixed effects in $x^y_{it}$ helps control for correlations of $y_{it+1}$ with time-varying unobserved variables.[5]

With data on annual water extractions from each well, we need to distinguish between water use for irrigation and water use for preserving water rights in order to connect the latent variables $y^*_{it}$ and $z^*_{it}$ to the observables. Let $\bar{S}$ be a water extraction threshold such that, because of the fixed

[3]Presumably the incentive to preserve water rights depends on water use in all future years beyond $y_{t+1}$. In (2.2), we do not include $y_{i\tau}, \tau \geq t + 2$, for two reasons. First, the impact of $y_{t+1}$ is likely to be much larger than that of $y_{i\tau}, \tau \geq t + 2$, since the water right in year $\tau$ can be preserved by using water in $\tau - 1$ instead of using water in year $t$. Second, $y_{it+1}$ and $y_{i\tau}, (\tau \geq t + 2)$ tend to be serially correlated, and including only $y_{it+1}$ means that the coefficient of $y_{it+1}$ captures the overall effect of all future water uses. In other words, we use $1(y_{it+1})$ as a sufficient statistics for all future water uses.

[4]Due to the forward looking nature of (2), our assumption is in fact an "inverse" sequential exogeneity. The typical sequential exogeneity assumption is that $\eta_{it}$ is uncorrelated with $y_{it}, y_{it-1}, y_{it-2}, \cdots, y_{i1}$

[5]One can imagine situations where $y_{it+1}$ might be endogenous without the inclusion of a rich set of controls. For example, a prolonged drought might raise the incentive to irrigate in year $t$ as well as water extraction in the next year. Conversely, low output prices over several years might reduce the current incentive to irrigate as well as future water use. In both cases, the inclusion of year fixed effects will help capture these time-varying effects, addressing the concern that $y_{it+1}$ might be endogenous.

cost of irrigation, it is profitable to irrigate if and only if $y_i t^* > \bar{S}$. Otherwise, if $y_{it}^*$ is lower than $\bar{S}$, the additional profit from irrigation cannot compensate for the fixed cost, and the farmer should not irrigate for the purpose of maximizing the current period profit. The observed water extraction $y_{it}$ then satisfies

$$y_{it} = \begin{cases} = y^* & y_{it}^* > \bar{S}, z_{it}^* > 0 \quad (c1) \\ \in (0, \bar{S}] & \text{if} \quad y_{it}^* \leq \bar{S}, z_{it}^* > 0 \quad (c2) \\ = 0 & z_{it}^* \leq 0 \quad (c3) \end{cases} \tag{2.3}$$

If $z_{it}^* \leq 0$, the farmer does not have any incentive to use water from well $i$ and $y_{it} = 0$ (case (c3)). If $z_{it}^* > 0$, the farmer has incentive to use water either because it is profitable to irrigate so that $y_{it} = y_{it}^*$ (case (c1)), and/or because he wishes to preserve his water rights (case (c2)). The former scenario occurs when the optimal water use $y_{it}^*$ exceeds $\bar{S}$, while the latter occurs when $y_i t^* \leq \bar{S}$. In case (c2), the farmer would apply a small amount of water in order to preserve the water rights, and the observed water use $y_{it} \in (0, \bar{S}]$. In our estimation, we set $\bar{S}$ to be 5 AF, in contrast to the mean extraction of 176 AF. We also conduct a series of robustness checks by varying $\bar{S}$ to show that our estimation results are not sensitive to the specific levels of $\bar{S}$.

The remaining issue is to model individual heterogeneity $c_i$. Since water rights as well as soil characteristics are time invariant for a specific well, we use a random effects rather than a fixed effects specification at the well level in order to identify the coefficients of the time-invariant variables. We adopt the correlated random effect (CRE) framework of the Chamberlain-Mundlak Device suggested by Wooldridge (2002) that makes the following distributional assumption for $c_i$:

$$c_i = \gamma_0 + \sum_j \overline{LEPA_i} * R_t^j \gamma_{1j} + \overline{\boldsymbol{AC}}_{i\gamma_2} + \overline{\boldsymbol{w}}_i \gamma_3 + \overline{dtw_i} \gamma_4 + 1\left(y_T > 0\right) \gamma_5 + a_i \tag{2.4}$$

where $a_i \sim N(0, \sigma_a^2)$ and is independent of the explanatory variables. The bars over variables indicate time averages of time-varying variables across all sample periods for a well. By including these averages, we allow for arbitrary correlations between $c_i$ and the time-varying variables in (2.1) and (2.2), which is analogous to that of a fixed effects specification.[6] Because the joint

[6]In fact, the CRE specification reduces to a fixed effects specification if (2.1) - (2.2) are estimated through linear models.

estimation model is dynamic, the "end condition" $1(y_T > 0)$ is included to capture the potential correlation between $y_T$ and $c_i$. This "end condition" is analogous to the "initial condition" used in the dynamic panel estimation approach proposed by Wooldridge (2002) and Wooldridge (2005). The only difference is that the dynamics in our model "goes backwards" (i.e. $y_{it}$ is influenced by $y_{it+1}$ but not $y_{it-1}$) so that an "end condition" rather than an "initial condition" is included. The conditional maximum likelihood estimation of the CRE specification in a dynamic setting gives consistent estimates of the model parameters, as shown in Wooldridge (2002) and Wooldridge (2005).

Equations (2.1) - (2.4) describe a forward-looking dynamic system in which decisions are characterized by double hurdles (0 for $z_{it}^*$ and $\bar{S}$ for $y_{it}^*$) with two latent variables. The likelihood function is derived in appendix A. Our model structure goes beyond the commonly used dynamic panel models in Wooldridge (2005), which are either linear or Probit/Tobit models. Most double hurdle models are applied to the analysis of cross-sectional data (Newman, Henchion, and Matthews, 2003; Yen, 1993), and the few applications of double hurdle models to panel data, such as Dong and Kaiser (2008), Dong, Chung, and Kaiser (2001), and Ricker-Gilbert, Jayne, and Chirwa (2011), have much simpler dynamic structures. For example, Dong and Kaiser (2008) assumes that each agent only makes participation decision once over the study period, though purchasing quantity decisions are made every year. In Dong, Chung, and Kaiser (2001), the dynamic structure is represented by autocorrelations in one of the error terms, whereas in our model the influence of $y_{it+1}$ on $y_{it}$ is introduced explicitly. There are no dynamic decisions in Ricker-Gilbert, Jayne, and Chirwa (2011).

### 2.3.2 Separate Estimation of (2.1) and (2.2)

The dynamic joint estimation of (2.1) and (2.2) is consistent and efficient, but suffers from two limitations. First, we need to establish causality of LEPA on water use but the econometric literature has not developed an effective methodology to test and correct for the endogeneity of explanatory variables in a nonlinear dynamic model with unobserved heterogeneities. Second, it is difficult to calculate the marginal effects of key variables. In (2.1) - (2.4), as $z_{it}^*$ is a function of $y_{it+1}$ and the value of $y_{it+1}$ depends on $z_{it+1}^*$, $E(y_{it}|c_i)$ is a complex function of $y_{it+1}$. Specifically, when we take the derivative of $E(y_{it}|c_i)$ with respect to a particular $x_{it}$ that affects both $y_{it}^*$ and $y_{it+1}^*$ (e.g. time-invariant variables such as water rights), we also need to calculate the derivative of $z_{it}^*$ with respect to $y_{it+1}$ in (2.2). However, $y_{it+1}$ again depends nonlinearly on $y_{it+1}^*$ and $z_{it+1}^*$. The marginal effects thus involve evaluating a nonlinear chain of derivatives. The computation burden is further increased since we have to integrate $c_i$ out of the marginal effects. Finally, since the marginal effects are highly nonlinear, we will have to rely on bootstrap methods instead of the delta method to calculate the standard errors of the marginal effects. Bootstrapping is essentially impossible given the computation burdens involved.

To address these limitations, we also estimate the two decisions in (2.1) and (2.2) separately, and use the separate models to test the exogeneity of LEPA adoption and to evaluate the marginal effects of key variables. Specifically, we use the correlated random effect (CRE) Tobit method to estimate (2.1), with (2.4) replaced by

$$c_i = \theta_0 + \sum_j \overline{LEPA}_{it} * R_i^j \theta_{1j} + \overline{\boldsymbol{AC}}_i \theta_2 + \overline{\boldsymbol{w}}_i \theta_3 + \overline{dtw}_i \theta_4 + a_i^u, \tag{2.5}$$

which excludes $y_T$ because (2.1) by itself is a static model so that the ending period condition is not needed. In separately estimating (2.2), we use $d_i$ to represent the unobserved heterogeneity:

$$z_{it}^* = d_i + 1\left(y_{it+1} > 0\right)\alpha_1 + x_{it}^y \alpha_2 + \eta_{it}, \tag{2.6}$$

with $d_i = \varphi_0 + \sum_j \overline{LEPA}_i * R_i^j \varphi_{1j} + \overline{dtw}_{it} \varphi_2 + \overline{\boldsymbol{w}}_i \varphi_3 + z_T \varphi_4 + a_i^z$. Define $z_{it} = 1$ if $z_i^* > 0$ (or equivalently $y_{it} > 0$), and $z_{it} = 0$ otherwise, we know that (2.6) is equivalent to

$$z_{it}^* = rc_i + z_{it+1}\alpha_1 + x_{it}^y \alpha_2 + \eta_{it}, \tag{2.7}$$

which reduces to a standard CRE dynamic Probit model.

Since separate estimations are biased and less efficient, we compare the estimation results of the joint dynamic model with those of the separate models to assess the magnitude of the bias and the efficiency loss. We find that the estimates of the key variables are close across the two models.

### 2.3.3 Mediators of the Effects of LEPA and Water Rights

Pfeiffer and Lin (2014a) shows that LEPA adoption could raise water extraction through adopters expanding the irrigated acreage and switching to more water intensive crops. To more formally study the channels through which LEPA and water rights affect water use, we adopt the three-step procedure of a mediation effect model with two mediators, crop choices and irrigated acreage. Specifically, in Step 1, we regress water use on LEPA and water rights without the mediators, i.e., we estimate the model in (2.1) and (2.5) without the crop acreages. In Step 2, we regress the mediators on LEPA and water rights. Finally in Step 3, we estimate the model in (2.1) and (2.5) but with the mediators included.

Since the estimation model in (2.1) and (2.5) is nonlinear, we cannot rely on the Sobel test to estimate the magnitude of the mediation effects as in, for example, Hendricks and Peterson (2012), which conducts a Sobel test to evaluate the effects of water price on water demand. Instead, we follow the general rule that mediation effects are present if the marginal effects of LEPA and water rights are significant in Step 1, but their magnitudes and/or significance levels are reduced in Step 3 (relative to Step 1), and they are significant in Step 2. The logic is that the independent variables (LEPA and Water Rights) affect the mediators (crop choices and irrigated acreage), which in turn affect the dependent variable (water use). We compare the changes in the marginal effects on water extraction of LEPA and water rights, with and without the mediators (i.e., in Steps 1 and 3). The reduction in their marginal effects when the mediating variables are included show how much of their effects on water use manifest through the mediators.

### 2.3.4 Issues of Endogeneity

One might be concerned that $dtw_{it}$ is endogenous in (2.1) as the depth to water is greater in areas where more water was extracted in the past. However, our regression analysis shows that an individual well's water extraction has little impact on annual changes in $dtw_{it}$ – the larger influence comes from the aggregate water extraction of all wells above the aquifer. This spatial externality of water extraction, however, might in itself lead to endogeneity of $dtw_{it}$. Well i's water extraction might be influenced by its neighbor wells in two ways. First, farmers might engage in a simultaneous move game of water extraction so that their water extraction levels in a Nash equilibrium are mutually dependent. Second, one well's extraction affect the depth to water of other wells. Explicitly including $dtw_{it}$ in (2.1) addresses the second reason but not the first. Due to the large number of wells above the aquifer, we expect the strategic incentives in the first reason to be moderate. Thus we treat $dtw_{it}$ as exogenous, similar to Pfeiffer and Lin (2014a), Pfeiffer and Lin (2014b) and Hendricks and Peterson (2012).

The adoption of LEPA might also be endogenous in (2.1) – it is possible that unobserved factors raise water use as well as promote LEPA adoption. It is difficult to come up with valid instrument variables.[7] Instead, we take an indirect approach that combines several methodologies developed in the literature for linear models, to establish that LEPA adoption is exogenous in a linear model of (2.1). Once we establish the exogeneity in the linear model, we then argue that the exogeneity will carry over to nonlinear CRE Tobit estimation since the latter includes more controls such as individual heterogeneity.

Our methodology for the linear model is based on the following identity:

$$\begin{aligned}\mathrm{Cov}\,(\Delta LEPA_{it}, \Delta\varepsilon_{it}) &= \mathrm{Cov}\,(LEPA_{it}, \varepsilon_{it}) - \mathrm{Cov}\,(LEPA_{it-1}, \varepsilon_{it}) \\ &\quad - \mathrm{Cov}\,(LEPA_{it}, \varepsilon_{it-1}) + \mathrm{Cov}\,(LEPA_{it-1}, \varepsilon_{it-1}) \\ &= 2\,\mathrm{Cov}\,(LEPA_{it}, \varepsilon_{it}) - \mathrm{Cov}\,(LEPA_{it-1}, \varepsilon_{it}) - \mathrm{Cov}\,(LEPA_{it}, \varepsilon_{it-1})\end{aligned}, \quad (2.8)$$

where $\Delta LEPA_{it} = LEPA_{it} - LEPA_{it-1}$ and $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$. The second equality in (2.8) follows from the stationarity of $\varepsilon_{it}$ (which implies that $\mathrm{Cov}\,(LEPA_{it}, \varepsilon_{it}) = \mathrm{Cov}\,(LEPA_{it-1}, \varepsilon_{it-1})$). The exogeneity of $LEPA_{it}$ in (2.1), i.e., $Cov(LEPA_{it}, \varepsilon_{it}) = 0$, is equivalent to $\mathrm{Cov}\,(\Delta LEPA_{it}, \Delta\varepsilon_{it}) +$

[7] Pfeiffer and Lin (2014a) uses county level subsidy expenditures for LEPA adoption as the instrument in a fixed effects model and shows that correcting for the endogeneity of LEPA makes a small but statistically significant difference. One potential issue about this IV is that the subsidy expenditures of a county are partly driven by that county's adoption rate, which in turn might be correlated with individual adoption decisions within the county. Another possible IV is the adoption decisions of one's neighbors in previous years: the technology diffusion literature provides rich evidence about neighbor influences (Zhao, 2007). However, the validity of this IV requires controlling for correlated unobservables among neighbors and location-specific time trends, which is difficult to implement. In fact, regression analysis of our data provides evidence against the validity of this IV. (Details of the analysis is available from the authors upon request.)

$\text{Cov}(LEPA_{it-1}, \varepsilon_{it}) + \text{Cov}(LEPA_{it}, \varepsilon_{it-1}) = 0$, according to (2.8). We will test a stronger version of this condition:

**Hypothesis 3 (H3):** $\text{Cov}(LEPA_{it-1}, \varepsilon_{it}) = 0, \text{Cov}(LEPA_{it}, \varepsilon_{it-1}) = 0\, and\, \text{Cov}(\Delta LEPA_{it}, \Delta\varepsilon_{it}) = 0$.

Compared with testing the sum of the covariances being zero, Hypothesis 3 has a higher probability of being rejected, resulting in a test with a higher statistical power. That is, if we fail to reject Hypothesis 3, we will also fail to reject the hypothesis of $\text{Cov}(\Delta LEPA_{it}, \Delta\varepsilon_{it}) + \text{Cov}(LEPA_{it-1}, \varepsilon_{it}) + \text{Cov}(LEPA_{it}, \varepsilon_{it-1}) = 0$. We will test each of the three conditions separately and obtain the associated p-values, and then draw conclusions about the joint hypothesis.

Specifically, to test the first condition in Hypothesis 3, we follow the strategy suggested by Wooldridge (2002) and Wooldridge (2005): we add $LEPA_{it-1} * R_i^j, j = 1, \ldots, 8$ to equation (2.1) and run a fixed effect regression. We fail to reject the null of $\text{Cov}(LEPA_{it-1}, \varepsilon_{it}) = 0$ if the F-test of the coefficients of $LEPA_{it-1} * R_i^j, j = 1, \ldots, 8$ being zero is not statistically significant.[8] Similarly, to test the second condition in Hypothesis 3, which is equivalent to $\text{Cov}(LEPA_{it+1}, \varepsilon_{it}) = 0$, we run the same FE regression but with $LEPA_{it-1}$ replaced by $LEPA_{it+1}$.

To test the third condition in Hypothesis 3, we follow another strategy suggested by Wooldridge (2002, p308-309) and adopted by Hendricks and Peterson (2012), which applies an IV strategy to linear first difference (FD) models. Specifically, consider the linear first differencing of (2.1).

$$\Delta y_{it} = \sum_{j=1}^{8} \Delta LEPA_{it}^{*} R_i^j \omega_j + \Delta \mathbf{AC}_{\pi}\beta_1 + \Delta \boldsymbol{w_{it}}\beta_3 + \Delta dtw_{it}\beta_4 + \Delta\varphi_t + \Delta\varepsilon_{it}, \tag{2.9}$$

where $\Delta$ means first differencing. A Hausman test can be performed to test the exogeneity of $\Delta LEPA_{it}$ in (2.9), i.e., $\text{Cov}(\Delta LEPA_{it}, \Delta\varepsilon_{it}) = 0$, if we can find a valid IV for $\Delta LEPA_{it} * R_i^j$. One IV that is often used is the lagged explanatory variable, i.e., $LEPA_{it-2} * R_i^j$. The argument is that

[8]The setup in Wooldridge (2002) is to test whether $\varepsilon_i t$ is correlated with the lead of the independent variable ($x_{it}$), not the lag, in order to test the strict exogeneity of $x_{it}$. The rationale is the same in our model where we perform the test using lagged independent variables. This method has been extended by Su, Zhang, and Wei (2016) to allow for more periods of lags and leads. The test also requires that $LEPA_{it}$ be exogenous. This condition is satisfied under the null of Hypothesis 3: when all three covariance terms are equal to zero, (2.8) implies that $Cov(LEPA_{it}, \varepsilon_{it}) = 0$.

a farmer's LEPA adoption decision in previous periods, although possibly correlated with $y_{it-1}$ and $y_{it}$, should have no impact on the cross period changes in water use shocks in future periods (i.e. $\text{Cov}(LEPA_{it-2}, \Delta\varepsilon_{it}) = 0$), especially after a number of covariates have been controlled for in (2.1), Thus, we use $LEPA_{it-2} * R_i^j$ as an IV to conduct a Hausman test of the endogeneity of $\Delta LEPA_{it} * R_i^j$ in the FD equation of (2.1). We fail to reject the null that $\text{Cov}(\Delta LEPA_{it}, \Delta\varepsilon_{it}) = 0$ if the Hausman test statistics is not statistically significant.

Moving from the linear model to the CRE Tobit estimation, we note that in the CRE specification of the unobserved heterogeneity $c_i$ in equation (2.5), $LEPA_{it}$ is uncorrelated with the projection error $a_i^u$ by construction (Chamberlain, 1982; Mundlak, 1978; Wooldridge, 2002).[9] Therefore, as long as the tests above show that LEPA is exogenous to the idiosyncratic error $\varepsilon_{it}$, it will also be exogenous to $a_i^u + \varepsilon_{it}$.

## 2.4 Data

The data used for our estimation are drawn from multiple sources. Information about wells and water rights is drawn from the Water Information Management and Analysis System (WIMAS) maintained by the Kansas Water Office. Among the four types of wells, we focus on Type 1-3 wells for two reasons: (i) the aggregation of information about wells and water rights is relatively straightforward, and (ii) little information will be lost due to the high proportion of Type 1-3 wells in our sample: among 24961 wells in total, 17903 wells are of Types 1-3, accounting for 72% of all wells. For Type 2 and 3 wells, we aggregate water rights and well characteristics to form one-to-one well-water right pairs. The detailed aggregation procedure is described in appendix B.). In contrast, multiple wells are associated with multiple water rights for Type 4 wells, making it hard to aggregate relevant information. The appendix also describes the subsequent steps of data cleaning towards the unbalanced sample of 11,099 wells and 175,373 observations as well as the final balanced sample of 4,663 wells and 93,260 observations. It shows the summary statistics and regression results used to ensure representation and consistency as data points are removed.

[9] A well-known implication of this fact is that estimates for time-varying variables (both the estimated coefficients and standard errors) in linear CRE models are the same as those in FE models.

Spatially explicit soil characteristics are obtained from SSURGO soil survey on the website of USDA Natural Resources Conservation Service. These characteristics include detailed soil information about surface soil slope, available water capacity, irrigated capacity class and saturated hydraulic conductivity. Data on depth to water are obtained from the output files of Haacker, Kendall, and Hyndman (2015). Weather data are obtained from the North America Land Data Assimilation System (NLDAS) maintained by NASA that reports geo-referenced information about annual precipitation and potential evapotranspiration.

Finally, the well and water right data obtained from WIMAS are matched to soil and weather data using the spatial join function in ArcGIS. Table 2.1 presents the summary statistics of the variables used in our estimation based on the balanced panel.

## 2.5 Estimation Results

Table 2.2 presents the dynamic joint estimation and separate estimation results for water extraction in (2.1) and incentive to use water in (2.2). Comparing the first two columns of table 2.2, we find that the two estimation approaches lead to similar estimates and significance levels for most variables. Specifically, (i) the estimated coefficient of LEPA interacted with the water right bins follow the same pattern of first increasing and then decreasing, peaking at the $(300, 400]$ bin. (ii) The estimated coefficients of the water right bins follow a similar pattern as the water right levels increase. (iii) The estimated coefficients of the weather and soil variables are similar. Relatively large differences between the two approaches arise for two sets of coefficients. (i) The coefficients of crop acres in the separate estimation roughly equal those in the joint dynamic estimation plus 0.30 for all crops. One possible reason is that the total acreage of planted crops is almost perfectly correlated with the incentive to use water, and in joint estimation the indicator variable of using water $1(y_{it+1} > 0)$ partly captures the crop acreage effect. (ii) The coefficients of the time-invariant water right bins differ to some extent across the two approaches, possibly because the individual heterogeneities in (2.1) and (2.2) are time-invariant and are allowed to be correlated with each other in the joint estimation but not in the separate estimations, making time-invariant variables more

**Table 2.1:** Summary Statistics

| Variables (units) | Balanced Panel 1991-2010 | | | | | |
|---|---|---|---|---|---|---|
| | **Definition** | **N** | **Mean** | **Std.D** | **Min** | **Max** |
| Water Extraction (AF) | Annual groundwater extraction | 93,260 | 176.03 | 142.24 | 0 | 1720.66 |
| Center Pivot | | 44,845 | 170.74 | 142.05 | 0 | 1720.66 |
| LEPA | | 48,415 | 180.92 | 142.24 | 0 | 1349 |
| Water Right (AF) | Annual water use cap | 93,260 | 274.72 | 182.51 | 0.1 | 2074 |
| Acres Irrigated (Acres) | Annual acres irrigated | 93,260 | 150.61 | 84.69 | 0 | 640 |
| Center Pivot | | 44,845 | 146.6 | 82.98 | 0 | 640 |
| LEPA | | 48,415 | 154.32 | 86.08 | 0 | 640 |
| Extraction per acre (AF/Acre) | Water Extraction\Acres Irrigated | 90,304 | 1.15 | 0.51 | 0 | 33.03 |
| Center Pivot | | 43,119 | 1.14 | 0.55 | 0 | 33.03 |
| LEPA | | 47,185 | 1.15 | 0.47 | 0 | 6.71 |
| LEPA | =1 if LEPA is used; 0 otherwise | 93,260 | 0.52 | 0.5 | 0 | 1 |
| Precipitation (in) | Annual rainfall | 93,260 | 25.28 | 5.94 | 10.86 | 50.06 |
| Depth to Water (ft) | Distance from land surface to top of aquifer | 93,260 | 94.48 | 115.79 | 0 | 3151.42 |
| Slope (% of distance) | Ground surface gradient | 93,260 | 2.93 | 3.3 | 0 | 20 |
| Potential Evapotranspiration (in) | Crop water evaporation and transpiration | 93,260 | 52.23 | 3.92 | 40.51 | 61.38 |
| Saturated Hydroconductivity | Rate of water moving in saturated soil | 93,260 | 36.54 | 35.66 | 0 | 92 |
| Available Water Capacity (cm/cm) | Soil's ability to retain water | 93,260 | 0.16 | 0.045 | 0 | 0.23 |
| Irrigated Capability Class (dummy) | =1 if soil is suitable for Irrigation; 0 otherwise | 93260 | 0.31 | 0.46 | 0 | 1 |
| **Percent of wells planting certain crops** | | | | | | |
| Corn | | 93,260 | 42.47% | | | |
| Soybeans | | 93,260 | 8.48 | | | |
| Alfalfa | | 93,260 | 9.17 | | | |
| Corn and Wheat | | 93,260 | 3.22 | | | |
| Corn and Soy | | 93,260 | 3.09 | | | |
| Wheat | | 93,260 | 3.46 | | | |
| Sorghum | | 93,260 | 2.01 | | | |
| Fallow/Dryland Crop | | 93,260 | 2.58 | | | |
| Other Crops | | 93,260 | 25.53 | | | |
| # Observations with water extraction = 0 (AF) | | 2956 | | | | |
| # with extraction in (0,5] | | 393 | | | | |
| # with extraction in (0,10] | | 851 | | | | |
| # with extraction in (0,20] | | 2076 | | | | |

prone to differ across the two approaches.

**Table 2.2:** Dynamic Joint Estimation and Separate Estimation Results

| | **Water Extraction** | | **Incentive to Use Water** | |
|---|---|---|---|---|
| **Variables** | Dynamic Joint | Separate | Dynamic Joint | Separate |
| $1(y_{it+1} > 0)$ | | | 2.26*** | 1.73*** |
| | | | -0.034 | -0.057 |
| $LEPA * 1[0 < R \leq 100]$ | -4.92* | -4.29 | 0.14* | 0.19* |
| | (2.73) | (2.62) | (0.08) | (0.11) |
| $LEPA * 1[100 < R \leq 200]$ | -0.72 | 0.15 | 0.18*** | 0.24*** |
| | (0.84) | (0.82) | (0.04) | (0.06) |
| $LEPA * 1[200 < R \leq 300]$ | 2.38** | 2.19** | 0.23*** | 0.29*** |
| | (0.95) | (0.93) | (0.05) | (0.66) |
| $LEPA * 1[300 < R \leq 400]$ | 7.32*** | 5.90*** | 0.31*** | 0.33*** |
| | (1.59) | (1.55) | (0.08) | (0.11) |
| $LEPA * 1[400 < R \leq 500]$ | 6.09** | 4.40* | 0.22* | 0.16 |
| | (2.40) | (2.35) | (0.12) | (0.14) |
| $LEPA * 1[500 < R \leq 600]$ | -1.72 | -4.51** | -0.076 | 0.0062 |
| | (2.05) | (2.00) | (0.11) | (0.16) |
| $LEPA * 1[600 < R \leq 700]$ | -5.62 | -6.83* | 0.34 | 0.24 |
| | (3.93) | (3.85) | (0.20) | (0.20) |
| $LEPA * 1[R > 700]$ | -2.38 | -2.99 | 0.33** | 0.33* |
| | (2.40) | (2.34) | (0.15) | (0.18) |
| $1[100 < R \leq 200]$ | 10.70** | 18.92*** | 0.36*** | 0.55*** |
| | (4.93) | (6.55) | (0.06) | (0.12) |
| $1[200 < R \leq 300]$ | 15.38*** | 24.17*** | 0.40*** | 0.70*** |
| | (5.19) | (6.85) | (0.07) | (0.14) |
| $1[300 < R \leq 400]$ | 29.54*** | 26.00*** | 0.36*** | 0.65*** |
| | (7.26) | (8.23) | (0.09) | (0.16) |
| $1[400 < R \leq 500]$ | 26.30*** | 18.39* | 0.25** | 0.65*** |
| | (7.42) | (10.60) | (0.11) | (0.22) |
| $1[500 < R \leq 600]$ | 47.74*** | 41.71*** | 0.26** | 0.83*** |
| | (9.76) | (9.91) | (0.12) | (0.22) |
| $1[600 < R \leq 700]$ | 18.12** | -13.02 | -0.09 | 0.46* |
| | (9.11) | (13.99) | (0.15) | (0.27) |
| $1[R > 700]$ | 144.74*** | 76.33*** | 0.42*** | 0.91*** |
| | (8.46) | (11.16) | (0.13) | (0.29) |
| Precipitation | -1.86*** | -1.82*** | -0.0014 | -0.0047 |
| | (0.11) | (0.10) | (0.00) | (0.01) |
| Depth to Water | -0.62*** | -0.57*** | -0.0044*** | -0.0032* |
| | (0.03) | (0.03) | 0.00 | (0.00) |
| Potential Evapotranspiration | 4.21*** | 4.21*** | 0.010*** | 0.049*** |

Table 2.2 (cont'd)

| | | | | |
|---|---|---|---|---|
| | (0.26) | (0.25) | (0.00) | (0.02) |
| Irrigated capacity class | -0.41 | -2.17 | 0.035 | 0.045 |
| | (1.56) | (1.65) | (0.03) | (0.04) |
| Slope | 3.03*** | 2.59*** | 0.0035 | 0.0062 |
| | (0.25) | (0.27) | (0.01) | (0.01) |
| Available water capacity | -152.97*** | -162.51*** | -0.64 | -1.04 |
| | (27.48) | (28.32) | (0.54) | (0.70) |
| Saturated hydroconductivity | 0.036 | 0.058* | 0.00027 | 0.00062 |
| | (0.04) | (0.04) | (0.00) | (0.00) |
| Corn Acres | 0.62*** | 0.97*** | | |
| | (0.01) | (0.01) | | |
| Soybeans Acres | 0.57*** | 0.93*** | | |
| | (0.01) | (0.01) | | |
| Alfalfa Acres | 0.63*** | 0.98*** | | |
| | (0.01) | (0.01) | | |
| Corn-Wheat Acres | 0.55*** | 0.88*** | | |
| | (0.01) | (0.01) | | |
| Corn-Soybeans Acre | 0.61*** | 0.95*** | | |
| | (0.01) | (0.01) | | |
| Wheat Acres | 0.12*** | 0.48*** | | |
| | (0.01) | (0.01) | | |
| Sorghum Acres | 0.37*** | 0.73*** | | |
| | (0.01) | (0.01) | | |
| Other Crop Acres | 0.50*** | 0.85*** | | |
| | (0.01) | (0.01) | | |
| Constant | 38.02 | 81.03 | | -2.76* |
| | (66.01) | (60.97) | | (1.57) |
| r | | | 0.68*** | |
| | | | -0.031 | |
| **Marginal Effects** | | | | |
| $1[100 < R \leq 200]$ | | 19.36*** | | 0.028** |
| | | (6.01) | | (0.01) |
| $1[200 < R \leq 300]$ | | 25.25*** | | 0.034** |
| | | (6.32) | | (0.02) |
| $1[300 < R \leq 400]$ | | 28.79*** | | 0.033** |
| | | (7.65) | | (0.01) |
| $1[400 < R \leq 500]$ | | 20.95** | | 0.029* |
| | | (9.86) | | (0.02) |
| $1[500 < R \leq 600]$ | | 38.48*** | | 0.030* |
| | | (9.34) | | (0.02) |
| $1[600 < R \leq 700]$ | | -12.62 | | 0.026 |
| | | (12.36) | | (0.02) |

Table 2.2 (cont'd)

| | | | | |
|---|---|---|---|---|
| $1[R > 700]$ | | 72.64*** | | 0.038** |
| | | (10.76) | | (0.02) |
| LEPA (overall) | | 0.81 | | |
| | | (0.59) | | |
| @$0 < R \leq 100$ | | -3.84* | | 0.0064 |
| | | (2.33) | | (0.00) |
| @$100 < R \leq 200$ | | 0.14 | | 0.0078*** |
| | | (0.76) | | (0.00) |
| @$200 < R \leq 300$ | | 2.05** | | 0.0092*** |
| | | (0.87) | | (0.00) |
| @$300 < R \leq 400$ | | 5.55*** | | 0.010*** |
| | | (1.46) | | (0.00) |
| @$400 < R \leq 500$ | | 4.09* | | 0.0055 |
| | | (2.19) | | (0.00) |
| @$500 < R \leq 600$ | | -4.29** | | 2.36E-03 |
| | | (1.90) | | (0.00) |
| @$600 < R \leq 700$ | | -5.91* | | 0.008 |
| | | (3.31) | | (0.01) |
| @$R > 700$ | | -2.92 | | 0.010** |
| | | (2.29) | | (0.00) |
| $1(y_{it+1} > 0)$ | | | | 0.206*** |
| | | | | (0.02) |
| Time Fixed Effect | Yes | Yes | Yes | Yes |
| GMD Fixed Effect | Yes | Yes | Yes | Yes |
| N | 88597 | 93260 | 88597 | 88597 |

*Note:* Standard errors are reported in parentheses in the first three columns. The last column reports cluster robust standard errors (clustered at the well level). Significance levels: $*** = 1\%$, $** = 5\%$, and $* = 10\%$

Comparing the last two columns of table 2.2, we find that the estimated coefficients of LEPA interacted with the water right bins again follow similar patterns across the two approaches, and the same holds true for the estimated coefficients of water right bins themselves. Further, the estimated coefficients of LEPA interacted with the water right bins have similar magnitudes across the two approaches. The estimated coefficients of the water right bins do differ across the two approaches, again due to the correlation of individual heterogeneities in (2.1) and (2.2).

Overall, the coefficients of key variables (e.g., LEPA interacted with different water right bins) are similar in magnitude and trend between the joint and separate estimation approaches, showing that the bias of separate estimation is limited. We will thus rely on the separate estimation results in subsequent discussions and analyses.

### 2.5.1 Water Extraction and the Rebound Effects of LEPA

The CRE Tobit estimates of the water extraction decisions in (2.1) and (2.5) are reported in the second column of table 2.2. The estimated coefficients of most variables have expected signs. Water extraction goes up as the irrigated crop acreages rise, and this effect is larger for water intensive crops including corn, soybeans, alfalfa and corn/soybeans rotation. Water extraction also rises in potential evapotranspiration (a higher value of which represents a higher demand for water by crops), in saturated hydraulic conductivity (which measures how easy water flows through the aquifer and thus out of pumps), and in slope of the land (since more sloped land requires more water to irrigate due to more runoff). On the other hand, water extraction decreases in precipitation, in depth to water (since more depth means more energy expenditure needed to extract water to soil surface), and in available water capacity (a higher value of which indicates more water is stored in a crop's root zone for crop needs).

Regarding the rebound effects of LEPA, the second column of table 2 reports the estimated coefficients of LEPA interacted with the water right bins, as well as the estimated marginal effects of LEPA, both overall and at different water right bins.[10] The rebound effect is most pronounced for water rights between 200 and 500 AF, but is negative for extremely small (below 100 AF) and large water rights (above 500 AF). Thus, the adoption of LEPA raises water extraction for farmers with "moderate" water rights (between 100 and 500 AF) but reduces water extraction for those with extremely small and large water rights (below 100 AF and over 500 AF). As discussed earlier, a farmer's intraseason irrigation decisions are inherently dynamic: facing possibly binding water rights, the farmer will likely restrict water extraction during the early growing season in order to

[10]Since the Tobit model is nonlinear, the coefficients of LEPA*water right bins in (2.1) and the corresponding marginal effects can differ in both their estimated magnitudes and statistical significance. For example, while the coefficient to of $LEPA * 1(0 < R \leq 100]$ is -4.29 and not significant, the marginal effect of LEPA at water right of $(0, 100]$ is -3.84 and significant. This kind of difference often occurs when calculating marginal effects in nonlinear models, see, for example, Dowd, Greene, and Norton (2014).

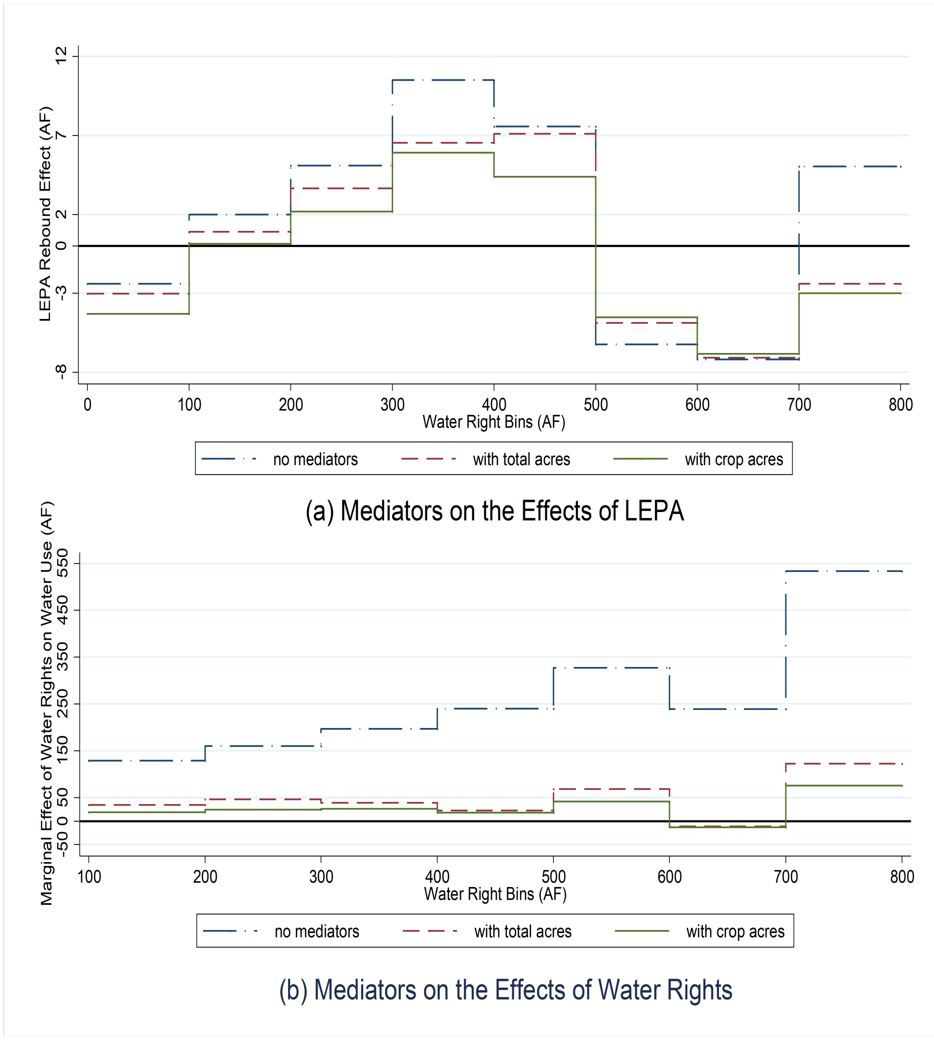
leave more options open to increase water use during the later season. For those with moderate water rights, the higher irrigation efficiency of LEPA means that farmers have access to more "effective water," i.e., water that is available to be used by crops, so that he has more flexibility of increasing the effective water to crops when given the same amount of available water. Thus, with the adoption of LEPA, he has incentive to use more water during the early season since doing so will be less costly in restricting the options during the later season. This intuition provides a dynamic explanation for the rebound effects of new technologies, over and above the static reasons discussed in, for example, Ward and Pulido-Velazquez (2008).[11] For those with extremely large water rights, it is likely that they already apply too much water, e.g., to maximize crop yields instead of profit. LEPA, with its higher irrigation efficiency, can reduce the extracted water that is needed to maximize the yields. Conversely, those with extremely small water rights may have already exceeded their water rights, and the adoption of LEPA can help mitigate violations of water rights without reducing the effective water received by the crops.[12] In these two cases, LEPA reduces water use and has no rebound effects.[13]

The rebound effect of LEPA follows a nonlinear pattern as water rights change: it first increases as water rights rise up to about 500 AF, and then decreases as water rights further rise. This pattern is also graphed in figure 2.4 (the solid lines). Since almost 90% of the wells in our sample have water rights below 500 AF, the overall pattern depicts the rebound effects of LEPA increasing in water rights. Again, this pattern is consistent with the framework of intraseasonal dynamic irrigation decisions. For those with smaller water rights, there is a higher probability of the water rights being binding and the incentive to restrict water use in the early season is higher, leading to lower total water use even if ex post the water rights are not binding. The larger the water rights, the

[11]This dynamic explanation is speculative as testing it requires intraseasonal irrigation scheduling data, which are not available. Nevertheless, the agronomy literature shows that for some crops such as corn, the yield is more sensitive to water deficits later in the season, especially during tasseling and grain filling periods, than early in the season (NeSmith and Ritchie, 1992a; NeSmith and Ritchie, 1992b).

[12]About 62% of wells with water rights in (0, 100] AF have exceeded their water right allocations in at least one year during the periods when they use center pivot, but this percentage drops to 48% during the periods when they use LEPA. In contrast, for wells with significant rebound effects, the percentages are respectively 43% and 38% for those in (200, 300], and 24% and 20% for those in (300, 400].

[13]Formal tests of these explanations require dynamic and structural estimation of the irrigation decisions, and are beyond the scope of this article.




(a) Mediators on the Effects of LEPA

(b) Mediators on the Effects of Water Rights

Figure 2.4: Marginal Effects of LEPA and Water Rights in Mediation Test

more room the farmer has in adjusting water use later in the season, raising the farmer's incentive to use more water early in the season. These results confirm part of Hypothesis 1, and highlight the importance of institutional approaches such as restricting water rights in ameliorating the rebound effects of LEPA. We will conduct a series of counterfactual analysis of reducing water rights later in this article.

Overall, conditional on crop choices, the rebound effect of LEPA is positive (at 0.81) but not statistically significant – we will come back to this issue below when we discuss the mediation results.

### 2.5.2 Mediators of LEPA and Water Rights

To investigate the channels through which LEPA and water rights affect water extraction, we conduct the three step regressions used in formal mediation tests with two possible mediators, acres irrigated and crop choices (tables 2.3 - 2.5). Tables 2.3 and 2.4 show that the two independent variables, LEPA and water rights, do affect the two mediators. In table 2.3, the marginal effects of water rights and LEPA on acres irrigated are positive and significant. In table 2.4, LEPA raises the acreage of corn, soybeans and alfalfa, three water intensive crops. Compared to farmers with water rights between 0 and 100 AF (the base water right bin), acreages of water intensive crops (corn, soybean, alfalfa, and mixture of corn with other crops) are larger for wells in higher water right bins.

**Table 2.3:** Mediation Test: Marginal Effect of LEPA and Water Rights on Acres Irrigated (Panel Tobit)

| Variables | Marginal Effects |
|---|---|
| R1 | 80.29*** |
| | (4.49) |
| R2 | 97.11*** |
| | (4.80) |
| R3 | 135.35*** |
| | (6.59) |
| R4 | 183.82*** |
| | (9.36) |
| R5 | 224.84*** |
| | (8.24) |
| R6 | 210.17*** |
| | (13.18) |
| R7 | 365.31*** |
| | (8.89) |
| LEPA | 2.39*** |
| | (0.32) |

Note: Standard errors are reported in parentheses. Significance levels: $***$ = 1%, $**$ = 5%, and $*$ = 10%.

**Table 2.4:** Mediation Test: Effect of LEPA and Water Rights on Crop Acres (Linear RE)

| | LEPA | Water Right Bins (lower bound upper bound) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Marginal Effects** | | **100<br>200** | **200<br>300** | **300<br>400** | **400<br>500** | **500<br>600** | **600<br>700** | **>700** |
| Corn | 3.82*** | 41.83*** | 61.66*** | 51.40*** | 43.08*** | 64.78*** | 32.81** | 65.16*** |
| | (0.93) | (3.21) | (3.83) | (6.99) | (11.66) | (10.12) | (14.76) | (16.60) |
| Soybeans | 0.77** | 12.67*** | 10.72*** | 9.11*** | 5.74** | 8.31*** | 6.32*** | 8.75** |
| | (0.38) | (1.77) | (1.75) | (2.24) | (2.67) | (2.03) | (2.18) | (3.83) |
| Alfalfa | 1.17* | 7.06*** | 5.05* | 5.83* | 2.36 | 36.55*** | 5.55 | 65.92*** |
| | (0.66) | (2.46) | (2.83) | (3.01) | (4.14) | (10.64) | (7.11) | (19.58) |
| Corn | -0.55 | 0.59 | 1.96 | 13.81*** | 23.21** | 26.72*** | -0.98 | 14.02* |
| & Wheat | (0.56) | (1.14) | (1.99) | (4.90) | (10.30) | (10.04) | (10.09) | (7.62) |
| Corn | -0.35 | 2.71*** | 5.22*** | 9.63*** | 10.48*** | 4.01* | 3.56** | 7.41*** |
| & Soy | (0.31) | (1.02) | (1.12) | (2.63) | (3.27) | (2.08) | (1.39) | (2.60) |
| Wheat | -0.83** | 4.02*** | 1.75 | 3.26* | -1.7 | 1.72 | 6.96 | 0.03 |
| | (0.33) | (1.11) | (1.30) | (1.78) | (2.95) | (2.41) | (8.61) | (2.41) |
| Sorghum | 0.022 | 2.35** | 1.33 | 1.14 | 1.53 | 0.68 | 3.21 | 1.43 |
| | (0.25) | (0.98) | (1.15) | (1.35) | (1.52) | (1.20) | (3.64) | (1.53) |
| Others | -1.95* | 12.19*** | 12.87*** | 45.58*** | 104.05*** | 84.61*** | 159.03*** | 205.23*** |
| | (1.03) | (3.74) | (4.20) | (8.42) | (19.52) | (15.17) | (43.96) | (29.67) |

Note: Clustered robust standard errors are reported in parentheses (clustered at well level). Significance levels: $*** = 1\%, ** = 5\%$, and $* = 10\%$.

In table 2.5, the first column reports the marginal effects of various water right bins (relative to the default bin) as well as those of LEPA at each of these bins when both mediators are excluded from the regression; the second column contains these marginal effects when one of the mediators, acres irrigated per well, is added as an explanatory variable; and the third column reproduces the marginal effects reported in column two of table 2.2, which contain all the mediators.[14] These marginal effects are also plotted in figure 2.4, with panel (a) showing the marginal effects of LEPA and panel (b) showing those of water right bins. The effects without the mediators, i.e., those corresponding to the first column of table 2.5, are plotted as broken lines, those with only the total irrigated acres included (corresponding to the second column of table 2.5) are plotted as dashed

[14] Instead of adding the irrigated acreage and the crop choices (excluding a default crop) as separate variables, the third column simply contains the irrigated acreage of all crops. The results of the two approaches are equivalent.

lines, and those with crop acreages included (corresponding to the last column of table 2.5) are plotted as solid lines.

**Table 2.5:** Mediation Test: Comparison of Estimates with and without Mediators (Marginal Effects of Panel Tobit)

| **Variables** | **Water Extraction Estimation With/Without Mediators** | | |
|---|---|---|---|
| | **No Mediators** | **With Acres Irrigated** | **With Crop Acres** |
| 1[$100 < R \leq 200$] | 92.38*** | 32.44*** | 19.36*** |
| | (5.50) | (6.68) | (6.01) |
| 1[$200 < R \leq 300$] | 122.09*** | 45.22*** | 25.25*** |
| | (6.17) | (7.05) | (6.32) |
| 1[$300 < R \leq 400$] | 159.89*** | 39.56*** | 28.79*** |
| | (9.24) | (8.65) | (7.65) |
| 1[$400 < R \leq 500$] | 201.16*** | 25.05** | 20.95** |
| | (13.86) | (11.19) | (9.86) |
| 1[$500 < R \leq 600$] | 281.11*** | 61.73*** | 38.48*** |
| | (12.25) | (10.73) | (9.34) |
| 1[$600 < R \leq 700$] | 192.57*** | -11.11 | -12.62 |
| | (19.94) | (13.74) | (12.36) |
| 1[$R > 700$] | 492.76*** | 115.96*** | 72.64*** |
| | (13.29) | (12.44) | (10.76) |
| LEPA (overall) | 3.09*** | 1.69*** | 0.81 |
| | (0.63) | (0.60) | (0.59) |
| @$0 < R \leq 100$ | -1.13 | -2.59 | -3.84* |
| | (1.34) | (2.30) | (2.33) |
| @$100 < R \leq 200$ | 1.78** | 0.83 | 0.14 |
| | (0.80) | (0.78) | (0.76) |
| @$200 < R \leq 300$ | 4.76*** | 3.44*** | 2.05** |
| | (0.95) | (0.90) | (0.87) |
| @$300 < R \leq 400$ | 10.23*** | 6.11*** | 5.55*** |
| | (1.66) | (1.49) | (1.46) |
| @$400 < R \leq 500$ | 7.50*** | 6.47*** | 4.09* |
| | (2.54) | (2.22) | (2.19) |
| @$500 < R \leq 600$ | -6.22*** | -4.66** | -4.29** |
| | (2.18) | (1.96) | (1.90) |
| @$600 < R \leq 700$ | -7.09* | -5.84* | -5.91* |
| | (4.16) | (3.23) | (3.31) |
| @$R > 700$ | 5.05** | -2.36 | -2.92 |
| | (2.57) | (2.38) | (2.29) |

Note: Standard errors are reported in parentheses. Significance levels: $*** = 1\%, ** = 5\%$, and $* = 10\%$.

When Acres Irrigated is added to the explanatory variables (comparing between the first and second columns of table 2.5, and between the broken and dashed lines in figure 2.4(b)), the marginal effects of water rights on water extraction decrease by 65%-76% for different water right bins. In contrast, when crop choices are added (comparing between the second and third columns, or dashed and solid lines), the marginal effects of water rights decrease slightly, by about 10% on average. These results indicate that *about two thirds of the effects of water right on water extraction operate through irrigated acreage*. That is, farmers with larger water rights tend to use more irrigation water mainly because they irrigate larger areas of land.

For the rebound effect of LEPA, both the irrigated acreage and crop choices are significant mediators over the range of water rights between 100 and 500 AF, and the mediators' effects are heterogeneous across the water right bins (table 2.5 and figure 2.4(a)). For wells with small water rights (in $(100, 200]$), the mediators together explain over 90% of LEPA's effects on water use, while for those with water rights in $(200, 500]$, the mediators together explain about 50% of LEPA's effects. The results confirm part of Hypothesis 1: even after expanded irrigation acreage and more water intensive crop choices are accounted for, about half of LEPA's rebound effect is attributable to farmers simply irrigating more intensively under LEPA than under center pivot for the majority of farmers (those with water rights between 200 and 500 AF). Further, comparing the marginal effects of LEPA across the three columns of table 2.5, we find that the effects of each mediator vary across water right bins: the effects of irrigated acreage seems to dominate those of the crop choices for water rights in $(100, 400]$, while the opposite is true for water rights in $(400, 500]$.

The first column of table 2.5 shows that when crop acreages are not included as explanatory variables, the estimated overall marginal effect of LEPA on water use is 3.09 and is statistically significant. This estimate is close to those obtained in Pfeiffer and Lin (2014a), which does not include crop acreages: 3.95 and 3.60 in fixed effects models with and without instrumenting for LEPA adoption. Our results show that a large share of the marginal effects can be attributed to the mediators including irrigated acreage and crop choices, and that the effects vary greatly across water right levels.

### 2.5.3 Tests of the Exogeneity of LEPA

The p-values of the three regressions used to test the three conditions in Hypothesis 3 are respectively 0.62 (F-test of the coefficients of $LEPA_{it-1} * R_i^j, j = 1, \ldots, 8$), 0.35 (F-test of the coefficient of $LEPA_{it+1} * R_i^j, j = 1, \ldots, 8$) and 0.65 (Hausman test with $LEPA_{it-2}$ ad the IV). Thus, we fail to reject each of the three individual hypotheses. The p-value for the joint Hypothesis 3 depends on how the test statistics of the three individual hypotheses are correlated with each other. For example, if the three test statistics are independent, then the p-value of the joint hypothesis equals $1-(1-p_1)(1-p_2)(1-p_3) = 0.91$.[15] But in general the test statistics of the individual hypotheses are correlated, and the classical approach to control for this is the Bonferroni method (Shaffer, 1995). Specifically, let $\alpha$ be the significance level of the joint hypothesis (i.e., rejecting Hypothesis 3 if and only if the p-value is less than $\alpha$). Then the joint hypothesis is rejected if the p-value of each of the three separate tests is less than $\alpha/3$. We fail to reject Hypothesis 3 even if we choose a high significant level, e.g., $\alpha = 10\%$, since the p-value of each individual hypothesis far exceeds 0.10/3=0.033. There are different variations of the Bonferroni method (e.g., with different weights and orders attached to the three individual tests) but the same conclusion holds: we fail to reject the null hypothesis that LEPA is exogenous in (2.1). This finding is largely consistent with Pfeiffer and Lin (2014a), which controls for the potential endogeneity of LEPA adoption using fixed effects 2SLS: the estimated coefficients of LEPA with and without the instrument variable are close to each other.

### 2.5.4 Decision to Preserve Water Rights

The last column of table 2.2 reports the panel Probit regression results of the decision to use water (equation (2.2)). Confirming part of Hypothesis 2 that farmers' decisions are influenced by expectations about future water use, the coefficient of the indicator variable of water use in the next

---

[15]Let $H_0$ denote the joint hull hypothesis, i.e., Hypothesis 3, and $H_{0i}$ be the $i^{th}$ individual hypothesis. Then the p-value of the joint hypothesis = Prob (reject $H_0$ | $H_0$ is true) = Prob (reject $H_{01}$ OR reject $H_{02}$ OR reject $H_{03}$ | $H_{0i}$ is true, $i = 1, 2, 3$) = 1 – Prob (fail to reject $H_{01}$ AND fail to reject $H_{02}$ AND fail to reject $H_{03}$ | $H_{0i}$ is true, $i = 1, 2, 3$) = $1 - (1 - p_1)(1 - p_2)(1 - p_3)$.

period ($y_{it+1} > 0$) is positive and significant. That is, farmers have more incentive to preserve their water rights in the current period if they expect that they will again irrigate the next year.

The bottom part of the column reports the marginal effects of water rights and LEPA on the incentive to use water. LEPA has a positive influence on the incentive for all levels of water rights and this effect is significant for water rights between 100 and 400 AF, although the magnitudes of the effects are small. For example, the marginal effect of LEPA is 0.0078 for water rights in $(100, 200]$, implying that on average a farmer with these levels of water right is 0.78% more likely to preserve his water rights if LEPA has been adopted than if center pivot is still used.

Relative to the base water right bin of $(0, 100]$, the marginal effects of other water right bins are positive and generally significant. Again their magnitudes are modest, possibly because we have controlled for a large number of covariates in the estimation and because farmers view water rights as providing irrigation services with limited values over and above the irrigation services. In other words, once future irrigation water use is controlled for, the water rights only represent a modest value to the farmer and thus do not significantly affect their incentives to preserve the water rights.

### 2.5.5 Robustness Checks

In estimating the water extraction decisions in (2.1) and (2.5), we introduced the water extraction threshold $\bar{S}$ to interpret whether observed water use is for irrigation in the current period or for preserving water rights (cf. (2.3)). We set $\bar{S} = 5$ AF in our estimation, but this threshold could be at other values. We re-estimate (2.1) and (2.5) using different values of $\bar{S}$ (at 5, 10, and 20 AF) and report the estimation results in appendix C (table C.1 and figure C.1). The results show that the estimated coefficients and marginal effects of key variables (e.g., LEPA interacted with water right bins) remain largely unchanged, establishing that our estimates are robust to different values of $\bar{S}$.

Since water right applications occurred much earlier than our study period (cf. figure 2.1(a)), water rights are treated as being exogenous in our regression analysis. One might argue that farmers with higher water extraction applied for larger water rights, and serial correlation in water extraction could cause water rights to be endogenous. We are less concerned about this potential endogeneity because we control for a wide range of factors affecting water extraction, including soil and weather characteristics, crops and depth to water, as well as time and groundwater management district fixed effects. Nevertheless, in case there are unobserved variables correlated with water rights, we conduct a robustness check in which only wells with water right application dates prior to 1980 are included. The estimation results are also reported in appendix C (table C.1 and figure C.1). Again, our estimation results are robust to this restriction.

## 2.6 Policy Simulations of Changing Water Governing Institutions

While it is important to recognize the existence of the rebound effects of more efficient technologies such as LEPA, it is perhaps even more important to investigate what can be done in response to such rebound effects. The previous discussions highlight the importance of water governing institutions: the rebound effects of LEPA tend to be lower for farmers with smaller water rights. Further, farmers do respond to the use-it-or-lose-it clause by using water in order to preserve their water rights. If water is used only to preserve the water rights instead of for profitable irrigation, removing the UIOLI clause might help save water. In this section, we conduct a series of counterfactual simulations to evaluate how water use will be affected as the water rights are reduced and as the UIOLI clause is removed.

Since the water rights are fixed during our sample period, the estimated effects of the water rights are due to cross-sectional variation and thus represent the long-term impacts of differing water rights that would have incorporated such adjustments as growing different crops and adopting LEPA. To simulate such long-term impacts, we rely on the CRE Tobit estimates of (2.1) without the mediators, i.e., we use the coefficients underlying the marginal effects reported in the first column of table 2.5. As established in the mediation tests (tables 2.3 and 2.4), long-term changes in water rights will indeed influence irrigated acreage and crop choices, which in turn affect water extraction. Excluding the mediators allows us to capture the long-run effects of water rights, after farmers have adjusted their irrigated acreage and planted crops.

To account for possible adjustments through the adoption of LEPA, we could re-estimate (2.1)

**Table 2.6:** Effects of Water Rights on LEPA Adoption

| **Water Right Bins** | **Marginal Effects** |
|---|---|
| $1[100 < R \leq 200]$ | 0.097*** |
| | (0.018) |
| $1[200 < R \leq 300]$ | 0.098*** |
| | (0.019) |
| $1[300 < R \leq 400]$ | 0.097*** |
| | (0.021) |
| $1[400 < R \leq 500]$ | 0.111*** |
| | (0.025) |
| $1[500 < R \leq 600]$ | 0.111*** |
| | (0.024) |
| $1[600 < R \leq 700]$ | 0.083** |
| | (0.033) |
| $1[R > 700]$ | 0.124*** |
| | (0.025) |
| Precipitation | -0.0017*** |
| | (0.001) |
| Depth to Groundwater | 0.00022* |
| | (0.000) |
| Potential Evapotranspiration | -0.0036*** |
| | (0.001) |
| Irrigated capacity class | -0.0064 |
| | (0.009) |
| Slope | -0.00028 |
| | (0.001) |
| Available water capacity | 0.081 |
| | (0.150) |
| Saturated hydroconductivity | 0.00032* |
| | (0.000) |

Note: Standard errors are reported in parentheses. Significance levels: $*** = 1\%$, $** = 5\%$, and $* = 10\%$.

without LEPA, or capture any effects that water rights might have on LEPA adoption. We take the latter approach since LEPA is a primary interest of our study. Specifically, we regress LEPA adoption on water rights as well as the weather and soil characteristics, using a CRE panel linear probability model, a CRE panel Probit model, and a CRE pooled Probit model. These models lead to similar estimation results, and table 2.6 reports those from the CRE panel linear probability model. The water right bins over 100 AF all have positive and significant coefficients, and their coefficients are of similar magnitudes. That is, although farmers with water rights exceeding 100 AF are more likely to adopt LEPA than those with water rights below 100 AF, the incentive to adopt LEPA is similar among the former so that when water rights are reduced within this group, the incentive to adopt LEPA will not change. This observation will likely carry over to the entire sample given the small percentage of farmers with water rights lower than 100 AF, making it feasible to condition the long-term effects of water rights on irrigation technologies.

We estimate the expected reductions in water extraction when water rights for all wells are reduced by 5%, 10% and 15% respectively for three technology scenarios of all wells using center pivot in all sample years, all wells using LEPA, and wells using technologies given in our data. We first calculate each observation's expected water extraction given the existing water rights using the coefficients underlying the first column of table 2.5, and recalculate the expected water extraction when each well's water right is reduced. A well's expected water extraction will change if and only if its water right falls in a different water right bin after the reduction.[16] We find that that *a 10% reduction in water rights leads to about 6% reduction in water extraction*, and this relationship is about linear within the range of water right reduction levels. The reduction in water extraction is slightly more pronounced if all wells use LEPA than if all use center pivot, consistent with the earlier finding that reducing water rights helps limit the rebound effects of LEPA. If the government specifically targets the water rights with positive rebound effects, e.g., reducing by 10% of the

[16]Since we divide the water right levels into eight water right bins, a well's water extraction varies only if its water right level moves across bins as it is reduced. This is of course an artifact of the discretization of water right levels. While for each individual well the effects are under- or over-estimated, the estimated average effects tend to be accurate; in fact, the marginal effects of water right reductions for all wells remain similar across the three water right reduction magnitudes of 5%, 10%, and 15%. Note that water right reductions affect water extraction even if the water right is not binding, due to the dynamic nature of intraseasonal irrigation scheduling.

water rights between 100 and 500 AF, then their water extraction will decrease by about 4.6%, and LEPA's rebound effect will decrease by about 15.4%.

Water is wasted when it is not profitable to irrigate but water is nevertheless extracted in order to preserve the water rights, i.e., when $y^*_{it} < \bar{S}$ and $z^*_{it} > 0$. The actual waste equals a small amount not higher than $\bar{S}$. If we assume that the waste is at the upper bound of $\bar{S}$, then the expected water waste per well equals:

$$Prob(y^*_{it} < \bar{S}, z^*_{it} > 0) \times \bar{S} \tag{2.10}$$

Since the error terms of $y^*_{it}$ and $z^*_{it}$ (i.e. $\varepsilon_{it} + a^u_i$ and $\eta_{it} + a^z_i$) specified in equations (2.1) and (2.2) are both normally distributed, the joint probability in (2.10) could be calculated as long as we know the correlation coefficient of $\varepsilon_{it} + a^u_i$ and $\eta_{it} + a^u_i$.[17] We calculate the expected waste in (2.10) and bootstrap its standard errors using -1, 0.5, 0, 0.5 and 1 as the correlation coefficients between $\varepsilon_{it} + a^u_i$ and $\eta_{it} + a^Z_i$.

We find that the annual expected water waste per well is rather small, at about 0.25-0.35 AF per year for each well, and this result is not sensitive to the correlation coefficients. Although this amount is significantly different from zero, it is insignificant in magnitude compared with the average annual water extraction of 176 AF per well. Even if the amount applied each time is higher, say, at 10 (or 20) AF, the resulting annual waste of 0.5-0.7 (or 1-1.4) AF is still small. We therefore conclude that the UIOLI clause has not resulted in significant water waste.

## 2.7 Conclusions

In this article we investigate how institutions can complement new technologies in promoting the sustainability of US agriculture using irrigation as an example. Specifically, we study the role of water rights in limiting the rebound effects of LEPA and affecting farmer incentives to preserve their water rights in the HPA region of Kansas. We find that water extraction moderately increases after LEPA adoption, and the rebound effect is heterogeneous across farmers with different levels

[17]The correlation coefficient could be estimated through joint dynamic estimation of the water extraction and water use incentive equations while allowing for the error terms to be correlated. However, since the standard errors can only be estimated through bootstrapping, the computation time involved is prohibitively long.

of water rights. It is negative for the few farmers with very small (<100 AF) and very large water rights (>500 AF), but is positive for the majority of farmers, i.e., those with water rights between 200 and 500 AF. For these farmers, LEPA's rebound effects are larger for those with larger water rights, implying that policies restricting water rights can help ameliorate LEPA's rebound effects in the long run. Specifically, a 10% reduction of water rights for all wells will in the long run reduce water use by about 6%. If the 10% reduction is targeted at the medium water rights between 100 and 500 AF, their expected water use will decrease by 4.6% and LEPA's rebound effect will decrease by 15.4%. Further, restricting water rights will not affect the incentives to adopt LEPA among farmers with water rights exceeding 100 AF. Thus, institutional changes such as reducing water rights can limit the undesirable rebound effects of new technologies such as LEPA without hurting incentives to adopt them.

We also find that on average about a half of the effects of LEPA in raising water extraction across a wide range of water right levels arises from the channel of crop choices and expansion in irrigated acreage: farmers using LEPA are more likely to grow water intensive crops such as corn, soybean and alfalfa as well as irrigate more lands compared with those using center pivot. The remaining half of LEPA's rebound effect is attributable to more intensive irrigation. In contrast, about two thirds of the effects of water rights on water extraction operate through irrigated acreage: famers with larger water rights will irrigate larger areas of their fields. Crop choices explain about 10% of the effects of water rights: farmers with larger water rights tend to plant more water intensive crops. The remaining quarter of the effects is attributable to more intensive irrigation by farmers with larger water rights.

We find that farmers have incentive to preserve their water rights even when no irrigation is needed, in response to the use-it-or-lose-it clause of the water right system. This incentive is higher if the farmer expects to irrigate in the next period. Nevertheless, we find that the associated water waste is insignificant, at about 0.25-0.35 AF per well each year, relative to the annual water extraction of 176 AF.

# APPENDICES

## APPENDIX A

## MAXIMUM LIKELIHOOD ESTIMATION OF THE DYNAMIC MODEL

Assuming that $\varepsilon_{it} \sim iidN\left(0,\sigma_{\varepsilon}^{2}\right), \eta_{it} \sim, iidN(0,1)$, and $\operatorname{cov}(\varepsilon_{it},\eta_{it}) = 0$,[1] we know the period $t$ density function for $y_{it}$ has three possible cases. Under condition (c1),

$$f_{c1}\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right) = \frac{1}{\sigma_{\varepsilon}}\phi\left(\frac{y_{it}-c_i-x_{it}^{y}\beta}{\sigma_{\varepsilon}}\right)\Phi\left(\frac{rc_i+1\left(y_{it+1}>0\right)\alpha_1+x_{it}^{y}\alpha_2}{\sigma_{\eta}}\right) \tag{A.1}$$

Under condition (c2),

$$f_{c2}\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right) = \left[1-\Phi\left(\frac{c_i+x_{it}^{y}\beta-\overline{S}}{\sigma_{\varepsilon}}\right)\right]\Phi\left(\frac{rc_i+1\left(y_{it+1}>0\right)\alpha_1+x_{it}^{y}\alpha_2}{\sigma_{\eta}}\right) \tag{A.2}$$

Finally, under condition (c3),

$$f_{c3}\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right) = 1-\Phi\left(\frac{rc_i+1\left(y_{it+1}>0\right)\alpha_1+x_{it}^{y}\alpha_2}{\sigma_{\eta}}\right) \tag{A.3}$$

Together, the likelihood function for a particular well $i$ in specific year $t$ is:

$$\begin{aligned} f\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right) = &\left[f_{c1}\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right)\right]^{1\left(y_{it}>\overline{S}\right)} \\ &* \left[f_{c2}\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right)\right]^{1\left(0<y_{it}\leq\overline{S}\right)} * \left[f_{c3}\left(y_{it+1}\right)y_{it+1},x_{it}^{y}\right)]^{1(y_n=0)} \end{aligned} \tag{A.4}$$

Note that, due to the dynamic structure in equation (2.2) in the main text, the likelihood function in period $t$ depends on $y_{it+1}$. Utilizing the property of conditional density functions, the full likelihood function (conditional on $c_i$) of well $i$ over all years is given by the product of per-period likelihood functions:

$$f\left(y_i|y_{iT},c_i,x_{it}^{y}\right) = \prod_{t=1}^{T_i-1} f\left(y_{it}|y_{it+1},c_i,x_{it}^{y}\right) \tag{A.5}$$

Using the distribution of $c_i$ in equation (2.3) specified in the main text, the unconditional likelihood contribution becomes:

$$f\left(y_i|y_{iT},x_{it}^{y}\right) = \int f\left(y_i|y_{iT},c_i,x_{it}^{y}\right)h\left(c_i|x_i,y_{T_i},\theta\right)dc_i \tag{A.6}$$

[1]We also make the typical assumption that $\sigma_{\eta}^{2} = 1$ in order to identify the model.

## APPENDIX B

## DATA ISSUES

In this appendix, we describe how we aggregate information for Types 2-3 wells, and the data cleaning procedures.

## B.1 Well-Water Right Data Aggregation

For Type 2 wells, i.e., cases where a single well is associated with multiple water rights, we sum the amount of water extraction caps specified by all associated water rights and treat the sum as the "single" water right for the well. For Type 3 wells, i.e., cases where multiple wells share the same water rights, their soil and weather characteristics (e.g., precipitation and dtw) are similar as the wells are located close to each other. The averages of these characteristics are used as those of the "aggregate well." For water extraction, acres irrigated and crops planted, we sum up the reported levels of individual wells to obtain the corresponding levels of the aggregate well. In cases where different crops are planted for the individual wells (constituting about 9% of Type 3 wells), we represent the planted crop of the aggregate well as "other crops." For the irrigation technology of the aggregate well, we take the most advanced technology of the individual wells.[1]

## B.2 Data Cleaning Procedures

We drop wells that do not report any irrigation technology during the study period and those that do not have annual extraction caps on record,[2] resulting in an unbalanced panel of 12459 wells and 233206 observations in total. We also drop a small number of wells for which the reported water

[1]We also tried to use the most frequently used technology among the individual wells, and the regression results are almost the same.

[2]Typically, when water rights are abandoned, the whole histories of their relevant information (except for water right IDs) are dropped from the WIMAS system. WIMAS records the year when the water rights were abandoned, but this information could not be downloaded. Instead, one needs to go into the WIMAS website and manually check this information from the "Action Trail" menu for each selected water right. We manually checked 1000 randomly selected abandoned water rights and found that about 80% of these water rights were abandoned before or during 1980s. Since our study period spans from 1991 to 2010, dropping abandoned water rights from our sample does not affect our results.

extraction is positive but no planted crops are reported (1,610 observations in total). It is required that farmers must report the crop they are irrigating if they report a positive water use.[3] Thus, these observations are treated as having missing data, rather than as farmers simply using some water to preserve their water rights. Similar to Pfeiffer and Lin (2014a), we exclude observations that use flood irrigation during our study period, resulting in an unbalanced sample with 11,220 wells and 177,195 observations. The sample means of key variables up to this data-cleaning step is presented in column 1 of table B.1.

Similar to Pfeiffer and Lin (2014a), we remove outlier wells by excluding those with the maximum irrigated acres in the study period exceeding 640. Doing so reduces the sample size to 11,099 wells and 175,373 observations. The sample mean of key variables up to this step is listed in the second column of table B.1. A quick comparison of the first two columns of table B.1 shows that the number of observations drops only by 1.03% after excluding the outlier wells, and the sample means remain largely unchanged for most key variables. The sample means of water extraction and water rights slightly decrease after outliers are dropped. The exclusion of the outliers helps prevent the estimation results from being skewed by a small amount of extreme observations.

Our analysis that uses pooled data will be based on the unbalanced sample of 11,099 wells and 175,373 observations. However, our correlated random effects model specified in Section 3 can only be applied to balanced samples. For these models, we drop those wells with missing data for some of the sample years, resulting in a balanced sample of 4,663 wells and 93,260 observations. The associated sample means of the balanced sample are shown in the last column of table B.1. Comparing the last two columns of table B.1 shows that the average water rights and dtw are relatively lower in the balanced sample, while the other attributes are similar across the two samples.

Since the sample size drops significantly going from the unbalanced to the balanced sample, we run a linear fixed effects variation of equation (2.1) specified in the main text using the two samples to check whether the two samples lead to significantly different estimates of LEPA's rebound effects.

[3] Personal communication with Brownie Wilson, the GIS/Support Services Manager for Kansas WIMAS database and Kansas Geological Survey.

**Table B.1:** Sample Mean Comparison for Unbalanced and Balanced Samples

| | Sample Mean | | |
|---|---|---|---|
| **Samples** | **Unbalanced** | **Unbalanced** | **Balanced** |
| **Max Irrigated Acres Outliers** | **Include** | **Exclude** | **Exclude** |
| Water Extraction (AF) | 180.04 | 175.37 | 176.03 |
| Center Pivot Irrigation | 172.51 | 168.26 | 170.74 |
| LEPA Irrigation | 185.46 | 180.49 | 180.92 |
| Water Right (AF) | 306.35 | 299.07 | 274.72 |
| Acres Irrigated (Acres) | 155.86 | 151.97 | 150.61 |
| Center Pivot Irrigation | 149.7 | 146.12 | 146.6 |
| LEPA Irrigation | 160.3 | 156.19 | 154.32 |
| Extraction per acre (AF/Acre) | 1.14 | 1.14 | 1.15 |
| Center Pivot Irrigation | 1.14 | 1.14 | 1.14 |
| LEPA Irrigation | 1.15 | 1.15 | 1.15 |
| LEPA | 0.58 | 0.58 | 0.52 |
| Precipitation (in) | 24.49 | 24.52 | 25.28 |
| Depth to Water (ft) | 116.1 | 115.66 | 94.48 |
| Slope (% of distance) | 2.46 | 2.44 | 2.93 |
| Potential Evapotranspiration (in) | 52.6 | 52.58 | 52.23 |
| Saturated Hydroconductivity | 29.21 | 29.13 | 36.54 |
| Available Water Capacity (cm/cm) | 0.17 | 0.17 | 0.16 |
| Irrigated Capability Class (dummy) | 0.39 | 0.39 | 0.31 |
| **Percent of Wells planting Certain Crops** | | | |
| Corn | 40.46% | 40.70% | 42.47% |
| Soybeans | 7.22 | 7.28 | 8.48 |
| Alfalfa | 7.6 | 7.61 | 9.17 |
| Corn and Wheat | 5.32 | 5.29 | 3.22 |
| Corn and Soy | 3 | 3.02 | 3.09 |
| Wheat | 3.66 | 3.67 | 3.46 |
| Sorghum | 1.98 | 1.99 | 2.01 |
| Fallow/Dryland Crop | 3.26 | 3.28 | 2.58 |
| Other Crops | 27.5 | 27.15 | 25.53 |
| N | 177,195 | 175,373 | 93,260 |
| # Wells | 11220 | 11099 | 4663 |
| # Observations with water use = 0 | 7194 | 7159 | 2956 |
| # Observations with water use $\in (0, 5]$ | 1303 | 1303 | 393 |

Unlike the CRE Tobit model, the linear FE model does not require a balanced panel. The first two columns of table B.2 show the regression results using the unbalanced and balanced panels respectively. Figure B.1 graphs the estimated LEPA's rebound effects for different water right bins, with the solid line representing the effects estimated using the unbalanced panel and the dashed line representing those using the balanced panel. To further compare the estimated rebound effects of LEPA between the two samples, we re-run the linear FE model using cubic splines of water rights instead of the water right bins, in order to "smooth out" the nonlinear effects.[4] Figure B.2 plots the estimated rebound effects of LEPA for the two samples.[5]

**Table B.2:** Estimations for Unbalanced and Balanced Samples

| Method | Unbalanced Linear FE | Balanced Linear FE | Balanced CRE Tobit |
|---|---|---|---|
| N | 175373 | 93260 | 93260 |
| Number of Wells | 11099 | 4663 | 4663 |
| $LEPA * 1[0 < R \leq 100]$ | -3.47* | -5.22** | -4.29 |
| | (1.81) | (2.45) | (2.62) |
| $LEPA * 1[100 < R \leq 200]$ | 1.83*** | -0.53 | 0.15 |
| | (0.68) | (0.80) | (0.82) |
| $LEPA * 1[200 < R \leq 300]$ | 2.02*** | 1.49* | 2.19** |
| | (0.73) | (0.91) | (0.93) |
| $LEPA * 1[300 < R \leq 400]$ | 4.81*** | 5.38*** | 5.90*** |
| | (1.07) | (1.52) | (1.55) |
| $LEPA * 1[400 < R \leq 500]$ | 4.30*** | 4.70** | 4.40* |
| | (1.64) | (2.29) | (2.35) |
| $LEPA * 1[500 < R \leq 600]$ | -5.58*** | -5.01*** | -4.51** |
| | (1.54) | (1.96) | (2.00) |
| $LEPA * 1[600 < R \leq 700]$ | -6.21*** | -7.62** | -6.83* |
| | (2.12) | (3.78) | (3.85) |
| $LEPA * 1[R > 700]$ | -2.47 | -2.78 | -2.99 |
| | (1.73) | (2.30) | (2.34) |
| $1[100 < R \leq 200]$ | | | 18.92*** |
| | | | (6.55) |
| $1[200 < R \leq 300]$ | | | 24.17*** |

[4]Specifically, we replace $\sum_{j=2}^{8} LEPA_{it} * R_i^j$ in equation (2.1) by $LEPA_{it} * \sum_{k=1}^{K} \alpha_k \theta_k (R_i)$, where $\theta_k(\cdot)$ is the $k^{th}$ basis function defined over the sample range of water right levels and $\alpha_k$ is the coefficient of the $k^{th}$ basis function to be estimated. Therefore, $\sum \hat{\alpha}_k \theta_k(r)$ is the estimate of the rebound effect of LEPA for a well with water right $R_i = r$. In our estimation, we set the number of basis functions to be $K = 10$.

[5]We do not use the cubic spline method in our main analysis due to the difficulty in calculating the marginal effects of water rights and the associated standard errors in the CRE Tobit model.

Table B.2 (cont'd)

| | | | |
|---|---|---|---|
| | | | (6.85) |
| $1[300 < R \leq 400]$ | | | 26.00*** |
| | | | (8.23) |
| $1[400 < R \leq 500]$ | | | 18.39* |
| | | | (10.60) |
| $1[500 < R \leq 600]$ | | | 41.71*** |
| | | | (9.91) |
| $1[600 < R \leq 700]$ | | | -13.02 |
| | | | (13.99) |
| $1[R > 700]$ | | | 76.33*** |
| | | | (11.16) |
| Precipitation | -1.46*** | -1.76*** | -1.82*** |
| | (0.077) | (0.100) | (0.100) |
| Depth to Water | -0.52*** | -0.54*** | -0.57*** |
| | (0.020) | (0.025) | (0.026) |
| Potential Evapotranspiration | 4.29*** | 4.04*** | 4.21*** |
| | (0.190) | (0.250) | (0.250) |
| Irrigated capacity class | | | -2.17 |
| | | | (1.650) |
| Slope | | | 2.59*** |
| | | | (0.270) |
| Available water capacity | | | -162.51*** |
| | | | (28.320) |
| Saturated hydroconductivity | | | 0.058* |
| | | | (0.035) |
| Corn Acres | 0.78*** | 0.83*** | 0.97*** |
| | (0.005) | (0.007) | (0.008) |
| Soybeans Acres | 0.73*** | 0.78*** | 0.93*** |
| | (0.007) | (0.009) | (0.010) |
| Alfalfa Acres | 0.81*** | 0.84*** | 0.98*** |
| | (0.006) | (0.008) | (0.009) |
| Corn-Wheat Acres | 0.69*** | 0.74*** | 0.88*** |
| | (0.005) | (0.008) | (0.009) |
| Corn-Soybeans Acre | 0.76*** | 0.80*** | 0.95*** |
| | (0.008) | (0.011) | (0.011) |
| Wheat Acres | 0.30*** | 0.32*** | 0.48*** |
| | (0.007) | (0.010) | (0.011) |
| Sorghum Acres | 0.53*** | 0.57*** | 0.73*** |
| | (0.009) | (0.013) | (0.013) |
| Other Crop Acres | 0.68*** | 0.71*** | 0.85*** |
| | (0.005) | (0.007) | (0.008) |
| **Marginal Effects** | | | |

Table B.2 (cont'd)

| | | | |
|---|---|---|---|
| **LEPA** | 1.21** | 0.193 | 0.81 |
| | (0.480) | (0.620) | (0.590) |

*Note:* Standard errors are reported in parentheses. Significance levels: $***$ = 1%, $**$ = 5%, and $*$ = 10%

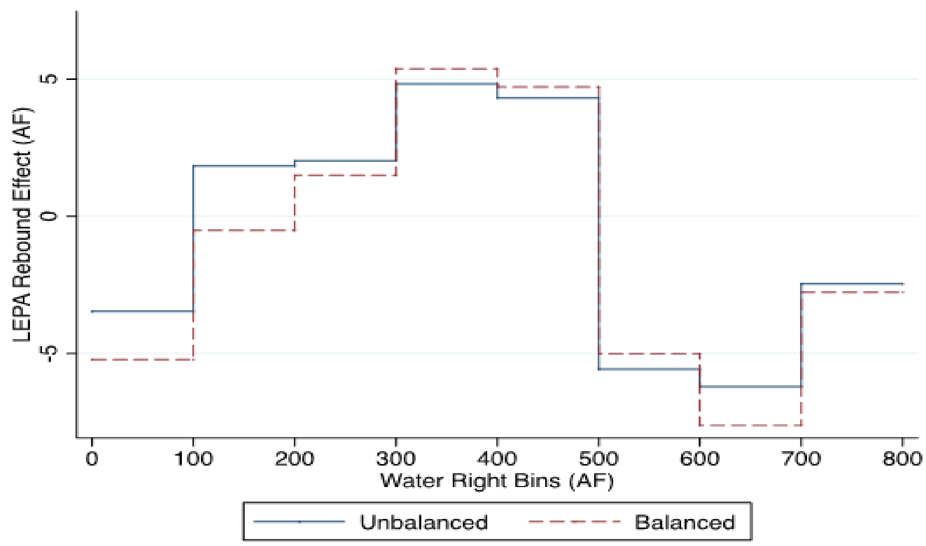



Figure B.1: LEPA Rebound Effect for Different Water Right Bins (Discrete)

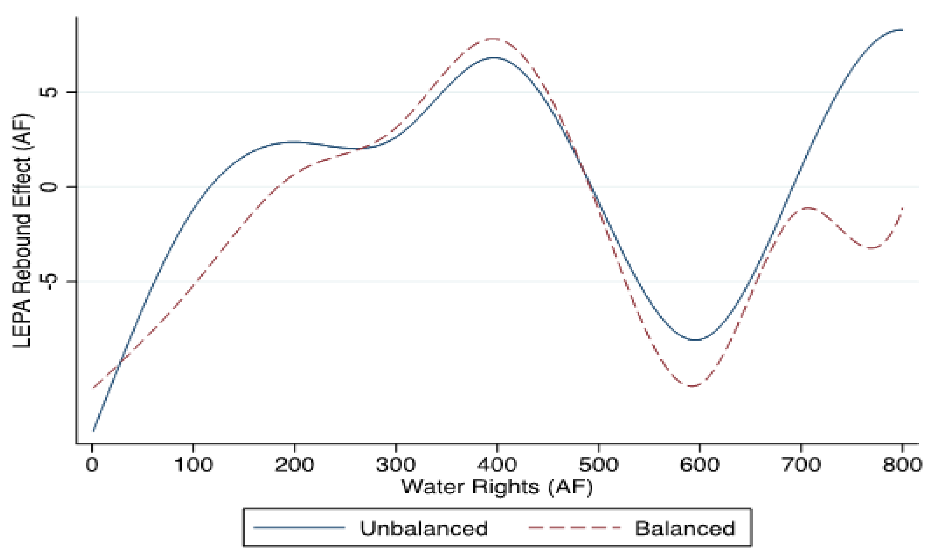



Figure B.2: LEPA Rebound Effect for Different Water Right Levels (Smooth)

Table B.2, figures B.1 and B.2 show that the estimates are similar across the unbalanced and balanced samples. The general pattern of LEPA's rebound effects first increasing and then decreasing in water rights is the same, and the magnitudes of LEPA's rebound effects obtained from the two samples are close for water rights below 600 AF, which constitute the majority of our data (cf. figure 2.1(b) in the main text).[6] Finally, we also compare the estimates using the balanced sample of both the linear and CRE Tobit models (the last two columns of table B.2), and find that the key estimates and the general pattern of LEPA's rebound effects are similar.

[6]The rebound effects do differ significantly across the balanced and unbalanced samples for water rights exceeding 600 AF. This difference underlies the difference in the estimated marginal effects of LEPA in the last row of table B.2.

## APPENDIX C

## RESULTS OF ROBUSTNESS CHECKS

In this section, we report the estimation results of the robustness checks with respect to the threshold value $\bar{S}$ and the sample restriction to water right application dates prior to 1980. The first three columns of table C.1 show that the estimated coefficients and marginal effects of key variables (e.g., LEPA interacted with water right bins) remain largely unchanged, establishing that our estimates are robust to different values $\bar{S}$. The estimated marginal effects of LEPA across different water right bins for the three specifications are plotted in figure C.1.

**Table C.1:** Robustness: Estimating (2.1) for Different Values of $\bar{S}$ and Samples (Panel Tobit)

| | **Water Extraction** | | | |
|---|---|---|---|---|
| **Variables** | All years | All years | All years | Before 1980 |
| $LEPA * 1[0 < R \leq 100]$ | -4.29 | -3.47 | -2.14 | -6.54** |
| | (2.620) | (2.660) | (2.770) | (3.150) |
| $LEPA * 1[100 < R \leq 200]$ | 0.15 | 0.17 | 0.23 | 0.3 |
| | (0.820) | (0.830) | (0.830) | (0.920) |
| $LEPA * 1[200 < R \leq 300]$ | 2.19** | 2.11** | 2.13** | 3.15*** |
| | (0.930) | (0.930) | (0.940) | (0.990) |
| $LEPA * 1[300 < R \leq 400]$ | 5.90*** | 5.84*** | 5.87*** | 6.66*** |
| | (1.550) | (1.560) | (1.570) | (1.630) |
| $LEPA * 1[400 < R \leq 500]$ | 4.40* | 4.33* | 4.42* | 4 |
| | (2.350) | (2.360) | (2.370) | (2.500) |
| $LEPA * 1[500 < R \leq 600]$ | -4.51** | -4.52** | -4.52** | -5.25** |
| | (2.000) | (2.000) | (2.020) | (2.090) |
| $LEPA * 1[600 < R \leq 700]$ | -6.83* | -6.90* | -6.96* | -4.77 |
| | (3.850) | (3.860) | (3.880) | (4.170) |
| $LEPA * 1[R > 700]$ | -2.99 | -2.98 | -2.88 | -3.57 |
| | (2.340) | (2.350) | (2.360) | (2.540) |
| $1[100 < R \leq 200]$ | 18.92*** | 28.46*** | 40.12*** | 22.57*** |
| | (6.550) | (6.630) | (6.810) | (8.610) |
| $1[200 < R \leq 300]$ | 24.17*** | 33.78*** | 45.54*** | 28.45*** |
| | (6.850) | (6.930) | (7.100) | (8.840) |
| $1[300 < R \leq 400]$ | 26.00*** | 36.01*** | 48.42*** | 30.88*** |
| | (8.230) | (8.290) | (8.440) | (10.090) |
| $1[400 < R \leq 500]$ | 18.39* | 28.58*** | 40.84*** | 23.43* |
| | (10.600) | (10.650) | (10.790) | (12.350) |

Table C.1 (cont'd)

| | | | | |
|---|---|---|---|---|
| 1[500 < $R$ ≤ 600] | 41.71*** | 51.29*** | 63.35*** | 41.30*** |
| | (9.910) | (9.960) | (10.080) | (11.670) |
| 1[600 < $R$ ≤ 700] | -13.02 | -2.62 | 10.63 | -18.84 |
| | (13.990) | (14.040) | (14.150) | (16.030) |
| 1[$R$ > 700] | 76.33*** | 85.88*** | 98.03*** | 80.53*** |
| | (11.160) | (11.210) | (11.320) | (13.030) |
| Precipitation | -1.82*** | -1.83*** | -1.86*** | -1.87*** |
| | (0.100) | (0.100) | (0.110) | (0.110) |
| Depth to Water | -0.57*** | -0.57*** | -0.57*** | -0.60*** |
| | (0.026) | (0.026) | (0.026) | (0.028) |
| Potential Evapotranspiration | 4.21*** | 4.23*** | 4.29*** | 4.22*** |
| | (0.250) | (0.250) | (0.260) | (0.280) |
| Irrigated capacity class | -2.17 | -2.24 | -2.33 | -2.63 |
| | (1.650) | (1.650) | (1.650) | (1.820) |
| Slope | 2.59*** | 2.58*** | 2.58*** | 2.45*** |
| | (0.270) | (0.270) | (0.270) | (0.300) |
| Available water capacity | -162.51*** | -164.52*** | -167.21*** | -164.14*** |
| | (28.320) | (28.350) | (28.430) | (31.450) |
| Saturated hydroconductivity | 0.058* | 0.057 | 0.054 | 0.087** |
| | (0.035) | (0.035) | (0.035) | (0.039) |
| Corn Acres | 0.97*** | 0.96*** | 0.95*** | 0.97*** |
| | (0.008) | (0.008) | (0.008) | (0.009) |
| Soybeans Acres | 0.93*** | 0.92*** | 0.90*** | 0.93*** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Alfalfa Acres | 0.98*** | 0.97*** | 0.96*** | 0.98*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Corn-Wheat Acres | 0.88*** | 0.87*** | 0.86*** | 0.87*** |
| | (0.009) | (0.009) | (0.009) | (0.010) |
| Corn-Soybeans Acre | 0.95*** | 0.94*** | 0.92*** | 0.94*** |
| | (0.011) | (0.012) | (0.012) | (0.013) |
| Wheat Acres | 0.48*** | 0.47*** | 0.44*** | 0.48*** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Sorghum Acres | 0.73*** | 0.72*** | 0.70*** | 0.72*** |
| | (0.013) | (0.013) | (0.013) | (0.014) |
| Other Crop Acres | 0.85*** | 0.84*** | 0.82*** | 0.84*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Constant | 81.03 | 69.02 | 53.36 | 98.84 |
| | (60.970) | (61.020) | (61.200) | (67.820) |
| **Marginal Effects** | | | | |
| 1[100 < $R$ ≤ 200] | 19.36*** | 27.44*** | 36.93*** | 23.76*** |
| | (6.010) | (5.980) | (5.990) | (7.800) |
| 1[200 < $R$ ≤ 300] | 25.25*** | 33.34*** | 42.91*** | 30.65*** |

Table C.1 (cont'd)

| | | | | |
|---|---|---|---|---|
| | (6.320) | (6.290) | (6.290) | (8.030) |
| $1[300 < R \leq 400]$ | 28.79*** | 37.28*** | 47.45*** | 34.69*** |
| | (7.650) | (7.630) | (7.640) | (9.270) |
| $1[400 < R \leq 500]$ | 20.95** | 29.58*** | 39.64*** | 26.39** |
| | (9.860) | (9.860) | (9.890) | (11.410) |
| $1[500 < R \leq 600]$ | 38.48*** | 46.58*** | 56.41*** | 38.54*** |
| | (9.340) | (9.320) | (9.330) | (10.840) |
| $1[600 < R \leq 700]$ | -12.62 | -3.85 | 6.97 | -15.5 |
| | (12.360) | (12.380) | (12.440) | (13.930) |
| $1[R > 700]$ | 72.64*** | 80.75*** | 90.73*** | 77.17*** |
| | (10.760) | (10.740) | (10.750) | (12.410) |
| LEPA (overall) | 0.81 | 0.8 | 0.87 | 1.20* |
| | (0.590) | (0.590) | (0.600) | (0.650) |
| $@0 < R \leq 100$ | -3.84* | -3.04 | -1.82 | -5.79** |
| | (2.330) | (2.320) | (2.350) | (2.770) |
| $@100 < R \leq 200$ | 0.14 | 0.16 | 0.21 | 0.28 |
| | (0.760) | (0.770) | (0.770) | (0.850) |
| $@200 < R \leq 300$ | 2.05** | 1.97** | 1.99** | 2.95*** |
| | (0.870) | (0.870) | (0.880) | (0.930) |
| $@300 < R \leq 400$ | 5.55*** | 5.49*** | 5.52*** | 6.26*** |
| | (1.460) | (1.470) | (1.480) | (1.540) |
| $@400 < R \leq 500$ | 4.09* | 4.03* | 4.11* | 3.72 |
| | (2.190) | (2.200) | (2.210) | (2.330) |
| $@500 < R \leq 600$ | -4.29** | -4.30** | -4.29** | -4.97** |
| | (1.900) | (1.900) | (1.910) | (1.970) |
| $@600 < R \leq 700$ | -5.91* | -5.98* | -6.05* | -4.04 |
| | (3.310) | (3.320) | (3.350) | (3.510) |
| $@R > 700$ | -2.92 | -2.91 | -2.81 | -3.48 |
| | (2.290) | (2.290) | (2.310) | (2.470) |

*Note:* Standard errors are reported in parentheses. Significance levels: $*** = 1\%, ** = 5\%$, and $* = 10\%$

The estimation results for the subsample with water right application dates prior to 1980 are reported in the last column of table C.1, and the marginal effects of LEPA are plotted in figure C.1. The trends of the marginal effects of LEPA across different water right bins are the same between the full sample and the prior to 1980 sample. The magnitudes of the rebound effects are also rather close to each other over a wide range of water right bins, so are the magnitudes of the water right bins themselves.

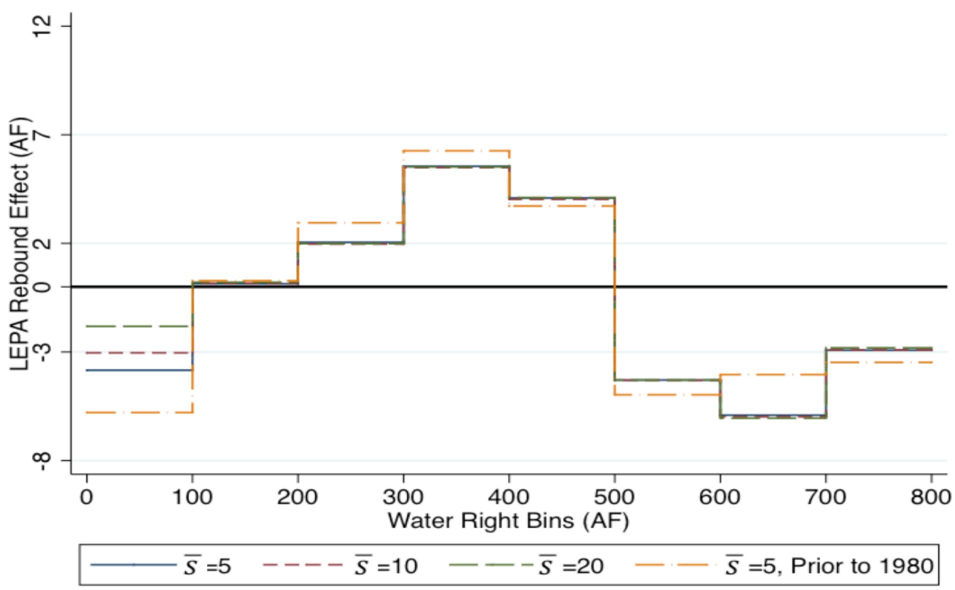



Figure C.1: LEPA Rebound Effect for Different Water Right Bins (Prior 1980, Discrete)

# APPENDIX D

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# CHAPTER 3

# WHAT DRIVES (NO) ADOPTION OF NEW IRRIGATION TECHNOLOGIES: A STRUCTURAL DYNAMIC ESTIMATION APPROACH (WITH JINHUA ZHAO)

## 3.1 Introduction

Agriculture is among the most vulnerable sectors to global climate change. With the prospect of greater variabilities in rainfall and higher frequencies of serious droughts, irrigation is becoming increasingly important as an adaptation strategy to climate change (Zilberman, Zhao, and Heiman, 2012). However, throughout the world, irrigation is facing the major challenge of declining groundwater, and this is the most serious in semi-arid agricultural zones such as California and the High Plain Aquifer (HPA) area in the US. For example, half of groundwater storage in the southern Ogallala aquifer underlying the HPA has been depleted, threatening agricultural sustainability in this important production area (Haacker, Kendall, and Hyndman, 2015). As a result, more efficient irrigation technologies are needed in many parts of the world in order to preserve water resources while maintaining and even raising agricultural outputs and profits.

Better technologies are not always adopted; there is a rich economics literature documenting the slow diffusion of efficient new technologies, including irrigation technologies (Sunding and Zilberman, 2001; Zilberman, Zhao, and Heiman, 2012). One example, which is the subject of this paper, is the adoption and diffusion of Low Energy Precision Application (LEPA) in the Kansas portion of HPA: it took more than 20 years before LEPA diffusion was completed. A major reason for the slow diffusion, especially at the early stages, is the combination of sunk adoption costs, which include the upfront purchasing, installing and learning costs, and uncertainties regarding the new technology's profitability. A forward-looking farmer has incentive to wait and obtain more information about the new technology's profit gains before incurring the irreversible (sunk) adoption costs (Carey and Zilberman, 2002; Zhao, 2007). In other words, farmers do not simply choose whether or not to adopt. Instead, they also have the option to delay the adoption decision until more information is available so that they are more certain about the technology's profitability (Taylor and Zilberman, 2015). Thus, waiting is treated as a "real option" for farmers. This real options framework has been applied to a wide range of investment and policy decisions beyond technology adoption (Dixit and Pindyck, 1994). Besides these rational considerations, certain irrational behavioral biases could also lead to slow technology diffusion. For example, farmers might have psychological inertia in choosing alternative farming practices. Such inertia raises switching cost and significantly reduces the incentive to adopt new technologies (Handel, 2011; Hortaccsu, Madanizadeh, and Puller, 2017; Ito, Ida, and Tanaka, 2016).

In this paper, we study the underlying farm-level incentives that drive LEPA diffusion in the Kansas part of HPA by structurally estimating a dynamic technology adoption model that incorporates uncertainty, learning, irreversibility, inertia and delay. We are able to provide an in-depth understanding of irrigation technology adoption behavior by incorporating a number of potential adoption determinants in a theoretical-consistent framework. We first develop a real options model of LEPA adoption, and then structurally estimate the underlying parameters using observed LEPA diffusion data. The structural modeling framework also allows us to make out-of-sample predictions and conduct counterfactual policy simulations.

We find empirical evidence that LEPA profit gain level, profit gain uncertainty and upfront adoption costs are all important determinants of LEPA adoption behaviors. Specifically, farmers do value the option to delay adoption when they are making an irreversible adoption decision and when they are uncertain about LEPA's profit gain. Consistent with the predictions of the real options adoption model, this option significantly decreases LEPA diffusion speed. If farmers simply choose whether or not to adopt LEPA in each year but do not consider the option to delay adoption, average LEPA adoption rate would increase by as much as 42%, and the time it takes to reach the long-run diffusion rate observed in the sample would shrink by over 50%.

We also find evidence that peer effects positively affect LEPA adoption, which is consistent with the findings in Sampson and Perry (2018). The interpretation of peer effects in our model is fairly flexible due to our flexible model specification regarding peer effects. One such interpretation is that the presence of more neighbor LEPA adopters significantly reduces farmers' inertia to choose alternative farming practices. Unlike the rational incentive to delay adoption created by profit gain uncertainty and adoption irreversibility, inertia represents a form of behavioral bias that raises farmers' subjective adoption costs. By reducing inertia, peer effects reduce perceived adoption costs and increase LEPA adoption probability.

Many important agricultural districts across U.S and across the world are subsidizing or are considering subsidizing water-saving irrigation technology adoptions. For example, Arizona, California, Colorado, Texas and Utah have received nearly half of Environmental Quality Incentives Program's (EQIP) funding to promote irrigation efficiency improvement (Nixon, 2013). As another example, the Comprehensive Water Management Plan (CWMP) issued by Chinese government in 2006 also requires the central government to subsidize a major part of water management equipment construction (Yao, Zhao, and Xu, 2017). We study the relative cost-effectiveness of two frequently used subsidy policies through counterfactual simulations: a LEPA profit gain insurance policy that guarantees a minimum annual per-acre profit gain level, and a cost share policy that directly reduces LEPA adoption costs. Simulation results show that insurance policies are always more cost-effective than the cost share policies in promoting LEPA adoption, given the same government budget.

To our knowledge, this is the first paper that decomposes the effects of profit gain level, profit gain uncertainty and adoption costs on irrigation technology adoption. Most empirical work utilizes reduced-form techniques to study irrigation technology adoption (Alcon, Miguel, and Burton, 2011; Caswell and Zilberman, 1986; Dinar and Yaron, 1992; Foltz, 2003; Koundouri, Nauges, and Tzouvelekas, 2006; Kulecho and Weatherhead, 2006; Salazar and Rand, 2016; Shrestha and Gopalakrishnan, 1993). While reduced-form studies can estimate the *overall* effects of a certain factor on adoption decisions, the pathways through which the causality relationship is established remains unclear due to the lack of variation in uncertainty levels across farmers and lack of true adoption cost data. Our study, on the other hand, employs a structural dynamic estimation approach to overcome these difficulties.

Despite their advantages, structural dynamic models are less often used in the literature than reduced-form models for two main reasons. The first is the curse of dimensionality (Rust, 1987): computational cost increases exponentially as the number of state variables increases. Technology adoption decisions are affected by multi-dimensional uncertainties such as input and output price uncertainties, and incorporating all of them (as state variables) typically leads to a Bellman equation that cannot be evaluated numerically. The second challenge facing structural dynamic models is the lack of robustness (Arcidiacono and Miller, 2011): the estimation results are typically more sensitive to model specification than reduced form models. A main reason is that structural dynamic models typically assume that a parsimonious set of parameters can capture all underlying incentives, while reduced form models can resort to such tools as fixed effects models using panel data to deal with the many individual characteristics not captured by available data.

In this paper, we adapt the novel methodology proposed by Arcidiacono and Miller (2011), which simultaneously addresses both issues of dimensionality and unobserved individual heterogeneity. The importance of accounting for individual heterogeneity in technology adoption studies has been documented by Suri (2011), which shows that individual heterogeneity explains large variations in the adoption of hybrid maize in Kenya. In addition, unobserved heterogeneity introduces a special pattern of serial correlation in error terms and represents a form of dynamic selection, which could bias the estimation of other parameters if not properly accounted for. The difficulty of incorporating individual heterogeneity in structural dynamic discrete choice models, similar to that of incorporating multiple state variables, mainly arise from the computational burden, which is alleviated in Arcidiacono and Miller (2011) by combining reduced form techniques with structural estimation in a novel fashion. Our paper represents the first application of their methodology to irrigation technology adoption. Other applications include Chung, Steenburgh, and Sudhir (2013), which studies sale force responses to a bonus-based compensation plan and Scott (2013), which studies agricultural land use dynamics in the U.S.

We construct a large well-level panel dataset of LEPA adoption for the estimation. In the literature, cross sectional (Caswell and Zilberman, 1986; Foltz, 2003; Koundouri, Nauges, and

Tzouvelekas, 2006) and aggregate time-series datasets (Alcon, Miguel, and Burton, 2011) have been used to study irrigation technology adoption decisions. Cross sectional data, being a snapshot of the diffusion process, provide little information on the diffusion process. Time series data, on the other hand, depicts the aggregate diffusion process without information on individual decisions and individual heterogeneity. The panel dataset enables a more comprehensive investigation of individual adoption decisions and aggregate diffusion processes. Only a few studies in the irrigation adoption literature use panel datasets, e.g., Shrestha and Gopalakrishnan (1993), and Genius et al. (2014), but even with these studies, the datasets contain either too few study periods or too few cross-sectional observations (i.e. farmers).

The remainder of the paper proceeds as follows. We review the relevant literature in section 3.2 and construct a conceptual real options adoption model in section 3.3. We introduce the study area and the dataset we use in section 3.4. Section 3.5 enriches the conceptual model to make it feasible for empirical implementation, given data available to us. Section 3.6 explains our estimation strategies. We present and discuss estimation results in section 3.7 and conduct a set of counterfactual simulations in section 3.8. The paper concludes in section 3.9.

## 3.2 Literature Review

This paper brings together two branches of literature, namely the literature on technology adoption and that on the estimation of structural dynamic discrete choice models.

Since the seminal work of Griliches (1957), technology adoption has been characterized as a rational behavior that is driven by the new technology's profitability. The S-shaped diffusion pattern of many new technologies is shown to be a result of profit gain heterogeneity among potential adopters (David, 1966; Mansfield, 1961; Rogers, 1995; Sunding and Zilberman, 2001; Weir, Knight, et al., 2000). In a study of hybrid maize adoption in Kenya, Suri (2011) finds strong evidence that the adoption decisions are rational and could be explained well by both observed and unobserved heterogeneous net benefits of the technology. With a structural dynamic model, Ryan and Tucker (2012) also finds that observable heterogeneities in benefits and adoption costs are important determinants of intra-firm video-call technology diffusion.

When technology adoption is treated as a dynamic decision, not only a new technology's profitability, but also decision makers' uncertainty towards its profitability would affect its adoption pattern. As explained by Dixit and Pindyck (1994), decision makers not only choose between adopting or not adopting in a given period, but also choose whether or not to delay the adoption/investment decision to the future until more information becomes available (Taylor and Zilberman, 2015). In one setting, potential adopters are uncertain about the technology itself. For example, how to best operate the technology. Consequently, economic agents have incentive to obtain more information, e.g., through other agents' experience of using the technology (Besley and Case, 1994; Conley and Udry, 2010; Foster and Rosenzweig, 1995; Goolsbee and Klenow, 2002). If the agent expects that many of his neighbors will adopt soon, he might want to delay adoption until his neighbors adopt first(Foster and Rosenzweig, 1995; Zhao, 2003). This delaying behavior is known as "strategic delay". In another setting, decision makers have perfect information about the technology itself but are uncertain about future realizations of exogenous factors (e.g. output prices) that determine the net profit of the new technology (Farzin, Huisman, and Kort, 1998). Thus, they would not adopt the technology until its profit gain raises to a fairly high level such that they are more or less sure that it would not drop to very low levels in the future. Examples of this case includes but are not limited to studies on electricity generator investment (Reedman, Graham, and Coombes, 2006), oil drilling (Kellogg, 2014), and choice among competing new technologies (Kauffman and Li, 2005).

Irrigation technology adoption is among one of the most frequently studied technology adoption topics in the literature. Most empirical studies on irrigation technology adoption take reduced-form approaches (e.g. Probit/Logit and duration models). Exogenous factors that affect new irrigation technology profits such as well depth, water price, land quality, crop price, farmer characteristics, credit availability and peer effects are found to be important drivers of irrigation technology adoption (Alcon, Miguel, and Burton, 2011; Caswell and Zilberman, 1986; Dinar and Yaron, 1992; Foltz, 2003; Genius et al., 2014; Koundouri, Nauges, and Tzouvelekas, 2006; Kulecho and Weatherhead, 2006; Salazar and Rand, 2016; Sampson and Perry, 2018; Sampson and Perry, 2019; Shrestha and Gopalakrishnan, 1993). However, we are not aware of structure estimation papers that fully account for the dynamic nature of irrigation technology adoption.

Traditionally, the Nested Fixed Point Algorithm (NFXP) proposed by Rust (1987) has been used to estimate structural dynamic discrete choice models. A significant drawback of this approach is the high computational burden involved, since the highly nonlinear dynamic programming problem has to be solved for every observation for each iteration of parameter search. With many observations, the execution speed is extremely slow. More importantly, accounting for unobserved heterogeneity could make NFXP computationally infeasible (Arcidiacono and Miller, 2011). Alternatively, two-step procedures in Hotz and Miller (1993) and Bajari, Benkard, and Levin (2007) have been developed to reduce computational burden associated with NFXP. The idea is to estimate reduced-form conditional choice probabilities (CCPs) of choosing each option as a flexible function of state variables in the first step. These estimated probabilities are subsequently used as inputs in a second step estimation to recover structural parameters. In particular, the value functions could be re-formatted as functions of state variables and CCPs in the second step, eliminating the need to solve the dynamic programming problem for each iteration. This approach is used frequently in industrial organization studies. For example, Ryan (2012) uses the model to study the effects of environmental regulation on cement firm competition and their entry/exit decisions. Bajari et al. (2013) studies the impacts of income and credit constraints on housing demand. However, this approach cannot deal with unobserved heterogeneity, which is critically important for understanding technology adoption.

Unobserved heterogeneities in dynamic discrete choices are successfully controlled for in Arcidiacono and Miller (2011). This approach, through a combination of Expectation-Maximization (E-M) algorithm and the two step-procedures similar to Hotz and Miller (1993) and Bajari, Benkard, and Levin (2007), incorporates unobserved individual heterogeneities without substantially increasing computational burden. We adopt this approach in this study, offering one of the first applications of this estimation method to technology adoption.

## 3.3 Theoretical Framework: A Real Options Approach

This section outlines a model of irrigation technology adoption for farmers who follow real options decision rule. Specifically, each farmer decides the optimal time to replace his current CP (P) irrigation system with a more efficient substitute, LEPA (L). While this simple model abstracts away from many details of the real decision problem, we extend it in section 3.5 to make it more realistic for empirical implementation.

At the beginning of each year ($t$), a farmer ($i$) who has not adopted LEPA considers whether or not to adopt LEPA in the current year. If he adopts LEPA, he starts to use LEPA immediately after paying the upfront adoption costs. LEPA adoption is assumed to be irreversible – farmers never switch back to CP once LEPA has been adopted.[1] Therefore, farmers who adopted LEPA in previous years do not make adoption decisions again. On the other hand, if he chooses not to adopt LEPA in year $t$, he continues to make adoption decision in the next year. The farmer solves a single-agent dynamic programing problem to maximize the sum of discounted expected lifetime profits by determining the optimal time to adopt LEPA.

### 3.3.1 LEPA Adoption Profit Gain and Learning

Farmer $i$'s profit gain from using LEPA (compared to using CP) in year $t$ is $\pi^D_{it}$, which varies across farmers and years. Additionally, $\pi^D_{it}$ follows a transition process that is known to the farmer:

$$\pi^D_{it+1} = \gamma_0 + \gamma_1 \pi^D_{it} + \gamma_2 \pi^D_{it-1} + \gamma_3 t + \eta_{it+1}. \tag{3.1}$$

where $\eta_{it} \sim i.i.dN(0, \sigma_\eta)$. In addition, we assume that future profit gain realizations are positively correlated with previous years' profit gain realizations. That is, $\gamma_1 > 0$ and $\gamma_2 > 0$. Thus, current and past profit gain realizations are informative about its realizations in the future. This represents a form of learning that is used frequently in real options models. This transition structure has three important features:

[1] In the data, farmers seldom switch back from LEPA to CP because LEPA is almost always more profitable than CP due to the increased efficiency and reduced energy expenditures. Once adopted and the sunk adoption costs have been incurred, there is no reason for farmers to switch back to CP.

First, although a farmer could observe his profit gain realizations in the current year ($\pi^D_{it}$) and in the past ($\pi^D_{it-1}$) , he could not predict perfectly those in the future. The random noise $\eta_{it+1}$ captures both profit gain volatility and the farmer's uncertainty toward future profit gain realizations.

Second, due to this volatility, it is always possible for $\pi^D_{it+1}$ to drop to very low levels, even though $\pi^D_{it}$ and/or $\pi^D_{it-1}$ are relatively high.

Third, as $\pi^D_{it+1}$ is positively correlated with $\pi^D_{it}$ and $\pi^D_{it+1}$, the probability of $\pi^D_{it+1}$ dropping to a very low level is lower when $\pi^D_{it}$ and $\pi^D_{it-1}$ are higher.

These three features have important implications on farmers' adoption behaviors, as will be discussed later in this section.

### 3.3.2 LEPA Adoption Costs

Converting from CP irrigation to LEPA requires purchasing water-delivering nozzles and attaching the nozzles to the CP frame. The amount and/or type of nozzles to purchase depend on many factors such as the initial CP frame's size and age. Besides, the conversion also requires a change in farming practices such as constructing round furrows and performing conventional tillage. Again, the costs of such changes are different for different farmers depending on their initial farming practices. We assume that the various cost components above are time-constant and denote these heterogeneous upfront adoption costs by $C_i$.

Moreover, farmers may have psychological inertia in choosing alternative irrigation systems and farming practices, which is a form of perceived adoption cost. The role of inertia as an "implicit" switching cost has been well-documented (Handel, 2011; Hortaccsu, Madanizadeh, and Puller, 2017; Ito, Ida, and Tanaka, 2016). This inertia, however, is lower when farmers are surrounded by more neighbor LEPA adopters. The effects of neighbor adopters on inertia (peer effects) is represented by $f(n_{it})$, where $n_{it}$ is the number of neighbor LEPA adopters for farmer $i$ at the beginning of year $t$ (or equivalently, at the end of year $t-1$). Consequently, the complete characterization of adoption costs is:

$$C_{it} = C_i + f(n_{it}). \tag{3.2}$$

The interpretation of neighbor LEPA adopters' effects on LEPA adoption is flexible. Besides reducing perceived adoption costs, peer effects could take multiple other forms. For example, farmers could derive utility not only from profit gains of using LEPA, but also from their neighbor adopters. It is possible that the appearance of neighbor adopters simply makes farmers feel comfortable about adopting LEPA, even though it does not really affect profit gains. It is also possible that farmers are not familiar with the performance of the technology and learn from his neighbor adopters about this information. Even though they may not be able to observe their neighbors' profit gain realizations, number of neighbor adopters could also provide them with additional information on the merits of the new technology. Under these alternative settings, $C_{it} = C_i$, but the annual profit gain function could be modified as $\pi_{it}^D + f(n_{it})$, where now $f(n_{it})$ translates utility gains from witnessing more neighbor adopters into a monetary value. Although we incorporate $f(n_{it})$ in the adoption cost function rather than the profit function in our model, this choice does not affect parameter estimations in the empirical model, a point that will be made more clear in section 3.6.

### 3.3.3 Value of Immediate LEPA Adoption

If a farmer adopts LEPA in the current year (i.e. year $t$), he will accumulate profit gain from LEPA adoption for all periods $\tau \geq t$ (since LEPA adoption is irreversible). Without considering adoption costs, the value of adopting LEPA in year $t$ is simply the summation of discounted expected LEPA profit gain from the current year on:

$$V_L(\Gamma_{it}) = E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^D \right\} = \pi_{it}^D + \beta E \left\{ V_L(\Gamma_{it+1}) | \Gamma_{it} \right\}, \tag{3.3}$$

where $\beta$ is the annual discount factor. In addition, $\Gamma_{it} = \{\pi_{it}^D, \pi_{it-1}^D\}$, which means that the expectation is taken with respect to $\pi_{it+1}^D$ conditional on $\pi_{it}^D$ and $\pi_{it-1}^D$, according to (3.1).

If the farmer follows Net Present Value (NPV) rule in making adoption decision, he would adopt LEPA in year $t$ as long as the ex-ante expected NPV of adoption in year $t$ is positive: $V_L(\Gamma_{it}) - C_{it} > 0$. By doing so, the farmer only compares the value of adopting LEPA now (i.e.

$V_L(\Gamma_{it}) - C_{it}$) and the value of never adopting (i.e. 0). However, he ignores the value of the option to remake adoption decision in the future if he gives up adopting LEPA in this year. In this sense, the farmer is myopic.

Delaying adoption decision is valuable when farmers are uncertain about future LEPA profit gain realizations and when LEPA adoption is irreversible. As discussed in section 3.3.1, even if current year's ex-ante expected NPV of adoption is positive, there is always a chance that ex-post profit gain in the future drops to a fairly low level due to its inherent volatility, and the adoption costs might not be recouped if adoption has already occurred. If this situation happens, the farmer would regret of having adopted LEPA previously, even though the ex-ante expected NPV of adoption at that time used to be positive. The irreversibility of LEPA adoption and uncertainty about future profit gain realizations together render a positive value of delaying adoption until more positive information about future profit gain realizations arrives.

### 3.3.4 Value of Delay and The Adoption Decision

Formally, the value of the option to delay adoption decision to the next year could be expressed as:

$$V_P(\Gamma_{it}, C_{it}) = \beta E\left\{\max[V_P(\Gamma_{it+1}, C_{it}), V_L(\Gamma_{it+1}) - C_{it}]|\Gamma_{it}\right\}. \tag{3.4}$$

In other words, a farmer will adopt LEPA in the next year if the realized conditions next year favor LEPA, but he could choose to continue waiting if otherwise.

Note that $C_{it}$, rather than $C_{it+1}$, appears in the right hand side of (3.4). Since the only time-varying component in $C_{it}$ is inertia, we implicitly assume that farmers do not think/realize that their inertia levels would change in the next year if more neighbors adopt LEPA this year.[2] In other words, we do not model strategic delay. At the beginning of each year, inertia levels are set after farmers observe how many of their neighbors have already adopted LEPA, but they do not consider the possibility that their inertia levels could be further reduced if they delay adoption until more neighbors adopt.

[2]This assumption does not rule out that farmers are forward-looking in other aspects. For example, the farmer is still projecting $\pi^D_{it+1}$ based on their current and past profit gain realizations.

The model would be extended to a dynamic game model among farmers if strategic delay is considered. When making his adoption decision in one year, a farmer needs to predict how many neighbors are going to adopt LEPA in that year. However, his neighbors' adoption behaviors are also affected by many other farmers (i.e. his neighbor's neighbors), whose behaviors again are affected by another set of farmers. As there is a large set of farmers in the region, each farmer would take a very large number of other farmers' adoption behaviors into account, which makes empirical implementation infeasible. Therefore, we assume that farmers do not practice strategic delay in reality and leave the test of this assumption in future research.

### 3.3.5 Adoption Decision

Given the model structure above, farmer $i$ would adopt LEPA in year $t$ if and only if:

$$V_L(\Gamma_{it}) - C_{it} > V_P(\Gamma_{it}, C_{it}). \tag{3.5}$$

That is, he will only adopt LEPA if the current year's expected NPV from LEPA adoption is higher than that from delaying adoption decision to the future. Another interpretation of (3.5) comes from rewriting it as $V_L(\Gamma_{it}) > C_{it} + V_P(\Gamma_{it}, C_{it})$. That is, the sum of discounted expected profit gains from LEPA adoption must be high enough to compensate both adoption costs and the option value. This situation will happen if year $t$ profit gain is high enough such that the farmer is more or less certain that it would not drop to a fairly low level in the future.

## 3.4 Study Region and Data

Our study region is the Kansas part of HPA, which spans more than 30,000 square miles across western Kansas. Irrigation agriculture accounts for more than 90 percent of total agricultural production in this area and groundwater is almost the only irrigation water source. Information on well locations and irrigation technologies is drawn from the Water Information Management and Analysis System (WIMAS) maintained by the Kansas Water Office. Our sample contains a large number of irrigation wells in this area – 7251 in total. The data also spans a long time period – from 1997 to 2010.

Spatially explicit data on depth to groundwater are obtained from the output files of Haacker, Kendall, and Hyndman (2015). Geo-referenced precipitation and temperature data are obtained from the North America Land Data Assimilation System (NLDAS) maintained by NASA. We match the well-level data with these spatially explicit data in ArcGIS according to each well's geographical coordinates. Finally, information on crop price comes from NASS quick stats and information on natural gas price is obtained from EIA. All price data are converted to 2010 dollar values, adjusting for inflation rate.

**Table 3.1:** Summary Statistics (1997-2010)

| | **N** | **Mean** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|---|
| **Variables** | | | | | |
| Water Use (feet/acre) | 35,332 | 1.05 | 0.59 | 0 | 17.42 |
| LEPA | 6,533 | 1.13 | 0.50 | 0 | 5.10 |
| CP | 28,799 | 1.02 | 0.59 | 0 | 17.42 |
| Real Corn Price ($/Bu) | 35,332 | 2.86 | 0.59 | 2.27 | 4.95 |
| Real Gas Price ($/Mcf) | 35,332 | 5.89 | 2.53 | 3.59 | 13.65 |
| Depth to Water (ft) | 35,332 | 113.36 | 89.65 | 0 | 386.51 |
| Effective Precipitation (feet/year) | 35,332 | 1.01 | 0.19 | 0.43 | 1.54 |
| Number of Neighbor LEPA Adopters | 28081 | 15.88 | 7.45 | 0 | 30 |
| Monthly Average Temperature (°C) | | | | | |
| May | 35,332 | 19.32 | 1.49 | 15.36 | 23.02 |
| Jun | 35,332 | 24.56 | 1.39 | 21.04 | 28.75 |
| Jul | 35,332 | 28.19 | 1.24 | 24.52 | 31.23 |
| Aug | 35,332 | 27.08 | 1.61 | 22.71 | 30.65 |
| Sep | 35,332 | 22.45 | 2.18 | 17.68 | 27.38 |
| Oct | 35,332 | 14.49 | 1.49 | 7.78 | 17.83 |
| Nov | 35,332 | 7.08 | 2.36 | -0.86 | 11.58 |
| # Wells | 7,251 | | | | |
| # Wells that Adopted LEPA | 6,533 | | | | |
| LEPA Adoption Year | | | | | |
| Full Sample | 6,533 | 1999.85 | 3.14 | 1997 | 2010 |
| Post-1997 Adopters | 4,658 | 2001.02 | 3.04 | 1998 | 2010 |

Table 3.1 presents the summary statistics of the variables. The major crop in this region is corn. Western Kansas has a semi-arid climate with average annual precipitation around 1 foot/year, which could not meet water demand for most crops. Therefore, irrigation is an important factor determining crop yields. Prior to the introduction of LEPA in 1991, Center Pivot (CP) was the

dominant irrigation technology in the study region. Compared to CP, LEPA is more efficient[3] and requires less energy to lift groundwater. Therefore, LEPA is in general more profitable.

Figure 3.1 depicts LEPA's diffusion path. A sudden jump in total number of adopters is observed in 1997, which is mainly caused by inconsistent definition of LEPA before and after 1997.[4] We only use data after 1997 in our empirical exercise for internal consistency.

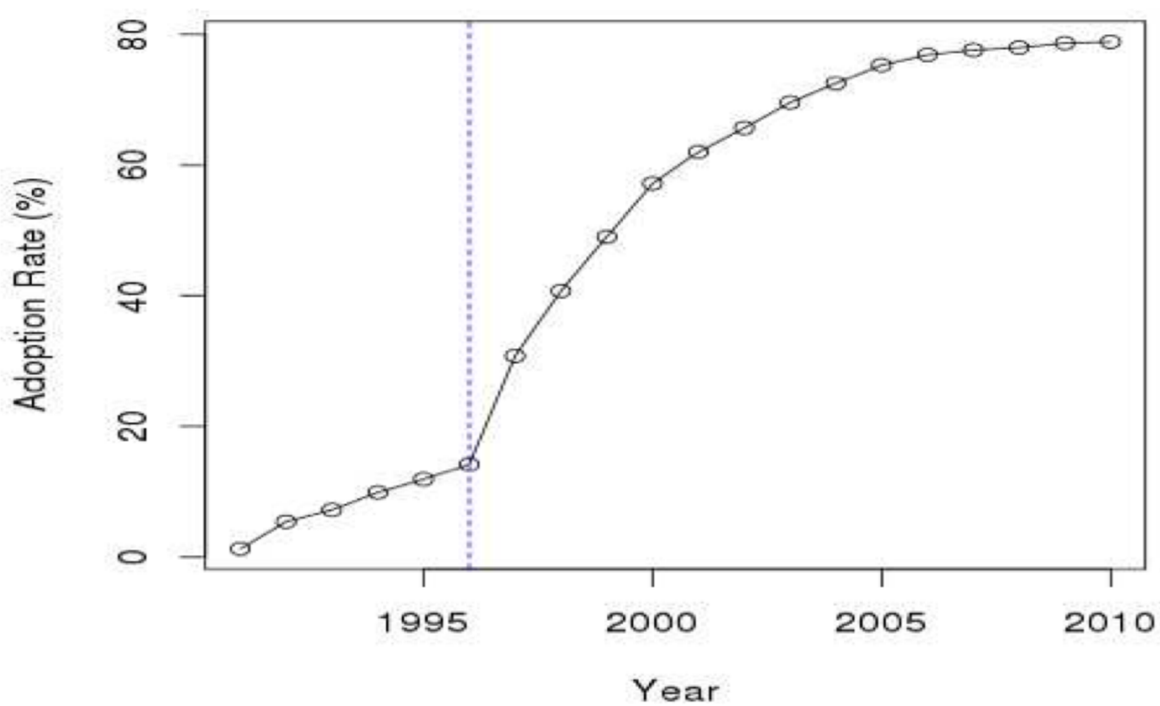



Figure 3.1: LEPA Diffusion Path in Kansas HPA

Another potential reason for the sudden jump might be that the state of Kansas started to provide cost shares to a small number of adopters after 1996. We do not have information on exactly who received the subsidy, but we do know the total number of farmers who received the subsidy in each

[3]efficiency = $\frac{\text{amount of water utilized by crop}}{\text{total water extraction}}$ (Pfeiffer and Lin, 2014). The efficiency level is always less than 1 because part of irrigation water is lost due to evaporation, soil water percolation and wind drift.

[4]Before 1997, only Center Pivot with LEPA nozzles was classified as LEPA in the dataset. However, all Center Pivot systems equipped with dropped nozzles were classified as LEPA after 1997. The different types of nozzles have similar efficiency levels, with the most significant difference between them being the ability to be adapted to local farming conditions (personal communication with Dr. Danny H. Rogers, Kansas State University Research and Extension, Department of Biological and Agricultural Engineering).

year. Across all sample years, only around 12% of LEPA adopters received the subsidy from 1996 to 2010 and the average cost share per farmer is \$16/acre. Figure (3.2) plots the annual percent of new LEPA adopters who received cost share subsidies. In each year during 1997-2006, a period when most LEPA adoptions happen, the share of LEPA adopters who received cost share subsidies is relatively low, varying between 7% to 20%. This share drops to 0 after 2007. Given this low cost share subsidy reception rate and low average cost share amount, we ignore the cost share program in our empirical model.

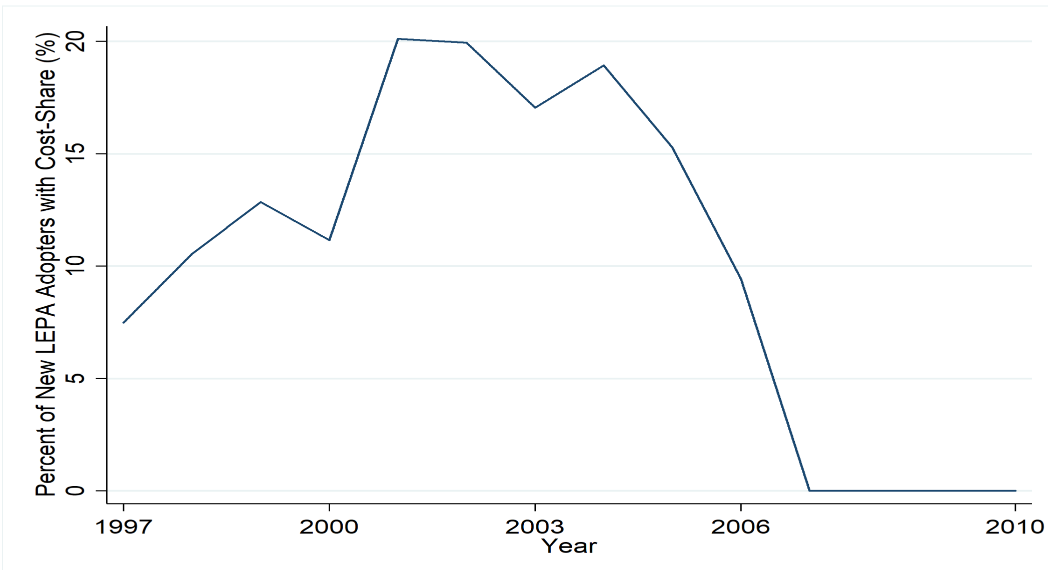



Figure 3.2: Percent of New LEPA Adopters Who Received Cost-Share Subsidies Among All New LEPA Adopters by Year

## 3.5 Empirical Adoption Model

This section enriches the theoretical model outlined in section 3.3 to make it feasible for empirical implementation. We first derive the expression of $\pi_{it}^{D}$ from the underlying production and cost functions, whose parameters are empirically estimated in section 3.6. We also distinguish variables that are observed by both farmers and econometricians from variables that are only observed by farmers. Finally, we show a transformation of Bellman equations associated with the adoption decision, which forms the basis of the dynamic discrete choice estimation strategy in section 3.6.

### 3.5.1 Profit Gain Following LEPA Adoption

#### 3.5.1.1 Production Function Specification

The first step in calculating profit gain following LEPA adoption is to specify a crop production function. Since our focus is on irrigation technologies, we model water as the single variable input, with other inputs optimally chosen given water application rates. In order to maintain flexibility, we specify a concave per-acre crop-water production function, following many agronomic studies (Martin, Watts, and Gilley, 1984; Tong and Guo, 2013):

$$q_{ijt}(w_{ijt}) = \alpha_{0it} + \alpha_{1it} * (\theta_j * w_{ijt} + r_{it}) + \alpha_2(\theta_j * w_{ijt} + r_{it})^2, \quad \text{for } j \in \{P, L\}, \tag{3.6}$$

where $w_{ijt}$ is annual water extraction, $r_{it}$ is annual rainfall, and $\theta_j$ is water use efficiency of technology $j \in \{P, L\}$, which equals the percentage of total water extraction that is utilized by the crop. Therefore, $\theta_j * w_{ijt} + r_{it}$ is the total effective water from irrigation and rainfall that is utilized by the crop. LEPA is more efficient than CP: the same level of effective water is reached with less water extraction when LEPA is used. We set $\theta_P = 0.85$ and $\theta_L = 0.95$ following Amosson et al. (2001) and Irmak et al. (2011). We assume that the concavity parameter $\alpha_2$ is constant but allow $\alpha_{0it}$ and $\alpha_{1it}$ to be heterogeneous across farmers or years to capture the effects of unobservables on crop yields.[5]

Revenue per acreage equals the output in (3.6) multiplied by crop price. Although farmers plant a variety of crops in Kansas HPA, corn is the dominant crop. According to USDA NASS statistics, corn production ranks top1 or top2 in each year during 1996-2010 in the study area. Although we have data on self-reported crop code in WIMAS database, the information is noisy. Reported crop type often represents a combination of multiple crops (e.g. corn, wheat and barley), and the areas planted to different crops in the combination are not reported, making it difficult to utilize this information. We treat the production function in (3.6) as a generic production function without distinguishing among different crops and use corn price as crop price. The cost of this simplification

[5] $\alpha_{0it}$ will finally be canceled out when calculating profit difference between LEPA and CP.

is low: corn dominates the production region, and heterogeneity of $\alpha_{1it}$ across farmers and years can also capture farm-specific and year-specific crop choices.

We next specify the production cost function. Following Rogers and Alam (2006) and Pfeiffer and Lin (2014), the variable cost to pump one acre-foot of groundwater is specified as a linear function of total water extraction:

$$c_{ijt}(w_{ijt}) = p^{e}_{ijt} * w_{ijt} = \eta * p^{gas}_{t} * (dtw_i + 2.31 * PSI_j) * w_{ijt}, \quad j \in \{P, L\}, \tag{3.7}$$

with $p^{e}_{ijt}$ being energy cost to lift one acre-foot of groundwater for farmer $i$ using technology $j$ in year $t$. Energy cost is calculated from the engineering relationship between the amount of natural gas needed to lift one acre-foot groundwater up for one foot ($\eta = 0.022$), natural gas price ($p^{gas}_{t}$), irrigation well's depth to groundwater ($dtw_i$) and water pressure required to operate irrigation system ($PSI_j$). LEPA requires less energy to operate than CP – the required water pressure to operate the system decreases from around 75 PSI for CP to 18 PSI for LEPA (Delano, Williams, and O'Brien, 1997). Similar to Hendricks and Peterson (2012), we assume that all farmers use natural gas to power their irrigation equipment.[6] Even though farmers face the same natural gas price in a given year, different wells have different levels of depth to water and uses different irrigation systems, so the energy cost per unit water extraction is farm-and-technology specific. Finally, the cost of water pumping is known to both farmers and econometricians.

Combining (3.6) and (3.7), farmer $i$'s per-acre profit from using irrigation system $j$ is

$$\pi^{j}_{it}(w_{ijt}) = p_t * q_{ijt}(w_{ijt}) - c_{ijt}(w_{ijt}), \tag{3.8}$$

where $p_t$ is crop price in year $t$.

#### 3.5.1.2 Optimal Water Extraction

In each year, water extraction decisions are made after farmers haven selected irrigation technologies. Groundwater is a common pool resource, shared by multiple farmers over the same aquifer. A

[6]The public available database in WIMAS does not contain information on irrigation well level energy source.

single farmer's water use im a given year has insignificant effects on the aquifer level, and even less effect on his future water use and profits. Therefore, we assume that a farmer's water use does not influence his well's depth to groundwater in the future (i.e, $dtw_i$ is time-constant).[7] Consequently, the water extraction decision is static. Maximize (3.8) with respect to $w_{ijt}$, the first order condition (FOC) gives optimal water extraction per acre for farmer $i$ in year $t$ with irrigation technology $j$:

$$w^*_{ijt} = -\frac{\alpha_{1it}}{2\alpha_2\theta_j} + \frac{1}{2\alpha_2}\frac{p^e_{ijt}}{\theta_j^2 p_t} - \frac{r_{it}}{\theta_j}. \tag{3.9}$$

Plugging $w^*_{ijt}$ into equation (3.8) gives the optimal per-period profit function $\pi^j_{it}(x_{it})$, where $x_{it} = \{p^e_{ijt}, p_t, r_{it}\}$ is the set of state variables that affect optimal water extraction. Finally, annual profit gain from using LEPA (compared to using CP) is expressed as:

$$\pi^D_{it} = \pi^L_{it}(x_{it}) - \pi^P_{it}(x_{it}). \tag{3.10}$$

### 3.5.2 Adoption Decision in the Empirical Model

The adoption decision in the empirical model is the same as that in the theoretical model specified in section 3.3 except that we add another component, $\varepsilon_{it}$, to the per-period profit gain function:

$$\pi^D_{it}(x_{it}, \varepsilon_{it}) = \pi^D_{it} + \varepsilon_{it} \tag{3.11}$$

Unlike $\pi^D_{it}$ which is observable to both farmers and econometricians, $\varepsilon_{it}$ is only observed by farmers. Following Rust (1987), we interpret this term as a per-period profit gain shock. If all state variables observed by farmers could also be observed by econometricians, then two farmers' adoption decisions should be exactly the same if all their state variables coincide. This is rarely the case observed in the data. The goal of adding an additional state variable that is unobservable to econometricians is to rationalize different adoption decisions observed when observable state variables are the same. We assume $\varepsilon_{it}$ conforms to an $i.i.d$ logistic distribution with location parameter zero and scale parameter $\sigma_\varepsilon$.

[7]During our study period, the average depth to groundwater $dtw$ across the study region only increased by 5 feet, compared to the average depth to groundwater level of 108 feet.

Under this enriched setup, the choice-specific value functions [8] corresponding to (3.3) and (3.4) are:

$$\begin{aligned} v_L(\Gamma_{it}) &= \pi_{it}^D + \beta E\left[v_L(\Gamma_{it+1}) + \varepsilon_{it+1}|\Gamma_{it},\varepsilon_{it}\right] \\ &= \pi_{it}^D + \beta \int v_L(\Gamma_{it+1}) f(\Gamma_{it+1}|\Gamma_{it}) d(\Gamma_{it+1}) \end{aligned}, \tag{3.12}$$

and

$$\begin{aligned} v_P(\Gamma_{it}, C_{it}) &= \beta E\left\{\max[v_P(\Gamma_{it+1}, C_{it}), v_L(\Gamma_{it+1}) - C_{it} + \varepsilon_{it+1}]|\Gamma_{it},\varepsilon_{it}\right\} \\ &= \beta\sigma_\varepsilon \int ln\left\{exp\left(\frac{v_L(\Gamma_{it+1}) - C_{it}}{\sigma_\varepsilon}\right) + exp\left(\frac{v_P(\Gamma_{it+1}, C_{it})}{\sigma_\varepsilon}\right)\right\} f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1} \end{aligned}, \tag{3.13}$$

where the second equality follows from the $i.i.d$ logistic distribution assumption of $\varepsilon_{it}$ (Arcidiacono and Miller, 2011). Moreover, we parameterize LEPA adoption costs $C_{it}$ as:

$$C_{it} = C_i + f(n_{it}) = C_i + \gamma_N n_{it}. \tag{3.14}$$

Further, each farmer knows his own $C_i$, but this information is not observed by econometricians. We assume there are two levels of $C_i$ – high ($C^H$) and low ($C^L$), and each farmer has non-negative probabilities of belonging to each cost group ($\tau_i^H$ and $\tau_i^L$).[9] We assume, however, that there is no correlation between $C_i$ for different farmers after conditioning on a bunch of observable variables.

A farmer adopts LEPA in year $t$ if and only if the value of adopting LEPA net of adoption costs is higher than the value of delaying adoption. Let $d_{iLt} \in \{0, 1\}$ denote whether farmer $i$ adopts LEPA in year $t$. The adoption decision in the empirical model becomes:

$$\begin{cases} v_L(\Gamma_{it}) - C_{it} + \varepsilon_{it} \geq v_P(\Gamma_{it}, C_{it}) \Leftrightarrow d_{iLt} = 1 \\ v_L(\Gamma_{it}) - C_{it} + \varepsilon_{it} < v_P(\Gamma_{it}, C_{it}) \Leftrightarrow d_{iLt} = 0 \end{cases}. \tag{3.15}$$

## 3.6 Estimation Strategies

There are three sets of parameters in the model specified in Section 3.5: $\Omega_1 = \{\alpha_{1it}, \alpha_{2i}\}$, parameters in the production function in (3.6); $\Omega_2 = \{\gamma_0, \gamma_1, \gamma_2, \gamma_3\}$, parameters in $f(\Gamma_{it+1}|\Gamma_{it})$, the

[8]Following Rust (1987), the choice-specific value functions are the lifetime expected profits without considering $\varepsilon_{it}$.

[9]Assuming discrete supports for unobserved heterogeneities (a.k.a "finite mixture") is a common practice in the dynamic discrete choice estimation literature, which provides a good approximation to the true distributions. See for example Mroz (1999), Arcidiacono and Miller (2011) and Chung, Steenburgh, and Sudhir (2013).

transition function of profit gain; and $\Omega_3 = \{C^H, C^L, \tau_i^H, \sigma_\varepsilon, \gamma_N\}$, the collection of $C_i$ distribution parameters, the standard deviation of per-period profit shocks, and the effect of neighbor LEPA adopters on farmers' inertia. In this section, we discuss the estimation strategies employed to estimate these three sets of parameters.

### 3.6.1 Production Function Estimation

Due to the lack of individual farmer level crop yield data, we could not estimate the production function in (3.6) directly. Instead, we rely on (3.9), the optimality condition associated with annual water extraction, to identify parameters in production function (3.6). Rearranging (3.9), we have

$$\theta_j w_{ijt}^* + r_{it} = -\frac{\alpha_{1it}}{2\alpha_2} + \frac{1}{2\alpha_2}\frac{p_{ijt}^e}{\theta_j p_t}. \tag{3.16}$$

$\alpha_{1it}$ is further parameterized as follows:

$$\alpha_{1it} = \alpha_{1i} + \alpha_{1gt} D_t * g_i + \alpha_{1temp} temp_{it} + \mu_{it}, \tag{3.17}$$

where $\alpha_{1i}$ is a farmer-level fixed effect, $D_t$ is a series of year dummies, $g_t$ is a series of groundwater management district (GMD) dummies,[10] $temp_{it}$ is a vector of monthly average temperatures in the growing season, and $\mu_{it}$ is an idiosyncratic unobserved term. The estimation equations in (3.16) and (3.17) are broadly consistent with the reduced-form water use estimation equations in Hendricks and Peterson (2012), Pfeiffer and Lin (2014), and Li and Zhao (2018).

Ideally, equation (3.16) could be estimated with a fixed effects model. However, crop price is only available at the whole state level, rather than at individual farmer level, leading to possible measurement errors associated with crop prices. For identification, we use the annual log of ethanol demand in Kansas as the IV for crop price. This choice of IV is reasonable because large share of corn is used in ethanol production. The output of this estimation step is $\hat{\Omega}_1 = \{\hat{\alpha}_{1it}, \hat{\alpha}_2\}$.

[10]The Kansas HPA is divided into five GMDs for groundwater monitoring and regulation purpose. Areas within the same GMD share similar hydrological and climatically conditions.

### 3.6.2 Profit Gain Transition Rule Estimation

Using $\hat{\Omega}_1 = \{\hat{\alpha}_{1it}, \hat{\alpha}_2\}$, we predict annual water extraction if farmer $i$ uses CP ($\hat{w}^*_{iPt}$) or LEPA ($\hat{w}^*_{iLt}$) in year $t$ according to (3.9). Plugging ($\hat{w}^*_{iPt}$) and ($\hat{w}^*_{iLt}$) into (3.8), we obtain the predicted profits, $\hat{\pi}^P_{it}$ and $\hat{\pi}^L_{it}$, as well as the predicted per-period profit difference between LEPA and CP for farmer $i$ in year $t$:

$$\hat{\pi}^D_{it} = \hat{\pi}^L_{it} - \hat{\pi}^P_{it}.$$

According to (3.1), farmers forecast $\pi^D_{it+1}$ based on $\pi^D_{it}$, $\pi^D_{it-1}$, as well as a time trend. We enrich (3.1) by adding the predicted fixed effects component of $\alpha_{1it}$ in (3.17) to the prediction equation:

$$\hat{\pi}^D_{it+1} = \gamma_0 + \gamma_1\hat{\pi}^D_{it} + \gamma_2\hat{\pi}^D_{it-1} + \gamma_3\hat{\alpha}_{1i} + \gamma_4 t + \eta_{it}. \tag{3.18}$$

Equation (3.18) is estimated via OLS. The output of this step is $\hat{\Omega}_2 = \{\hat{\gamma}_0 - \hat{\gamma}_4, \hat{\sigma}_\eta\}$. Equation (3.18) assumes a transition function analogous to that of an AR(2) process, and transition rule functional form selection issues are discussed in appendix H. Note that instead of estimating the transition function for $x_{it}$ (underlying variables that determines $\pi^D_{it}$), we estimate the transition function for $\pi^D_{it}$ directly. This approach has two advantages. First, the dimension of the state space is reduced from nine (i.e. current and past values of the crop price, gas price and precipitation, year dummies, depth to groundwater as well as $\alpha_{1i}$) to only four (i.e. the current and past profit gains, a time trend, and $\alpha_{1i}$), greatly reducing computational burden in estimating and simulating the dynamic discrete choice model. Second, it is more realistic to assume that farmers forecast future profit gains based on current and past profit gains instead of all underlying variables that affect profit gain, because the latter approach would require farmers to possess fairly high levels of computational power and cognitive ability (Hendel and Nevo, 2006). See Gowrisankaran and Rysman (2012) and Murphy (2018) for similar approaches.

### 3.6.3 Dynamic Discrete Choice Estimation

The remaining set of parameters $\Omega_3 = \{C^H, C^L, \tau^H_i, \sigma_\varepsilon, \gamma_N\}$ are estimated through the dynamic LEPA adoption model (3.12) - (3.15). Rust (1987) pioneered the Nested Fixed Point Algorithm

(NFXP) to structurally estimate dynamic stochastic discrete choice models. For each iteration of model parameter search, the NFXP solves the dynamic programming problem defined by (3.12)-(3.15) and computes choice-specific value functions. However, the computational burden of NFXP is relatively high due to this repeated solution of dynamic programming problems, especially for problems with multiple state variables. More Importantly, unobserved heterogeneity, which is represented in our model by individual-specific part of adoption costs (i.e. $C_i$), could make NFXP computationally infeasible (Arcidiacono and Miller, 2011). Instead, we follow Hotz and Miller (1993), Bajari, Benkard, and Levin (2007) and Arcidiacono and Miller (2011) to estimate (3.12) - (3.15) without explicitly solving the dynamic programming model. To proceed, we rearrange equation (3.13) as:

$$v_P(\Gamma_{it}, C_i, n_{it}) = \beta \int [v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it} - \sigma_\varepsilon ln Pr_L(\Gamma_{it+1}, C_i, n_{it})] f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1}, \tag{3.19}$$

where $Pr_L(\Gamma_{it+1}, C_i, n_{it})$ is the probability of choosing LEPA in year $t+1$ given $\Gamma_{it+1}$:

$$\begin{aligned} Pr_L(\Gamma_{it+1}, C_i, n_{it}) &= \frac{exp[\frac{v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it}}{\sigma_\varepsilon}]}{exp[\frac{v_P(\Gamma_{it+1}, C_i, n_{it})}{\sigma_\varepsilon}] + exp[\frac{v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it}}{\sigma_\varepsilon}]} \\ &= \frac{1}{1 + exp[\frac{v_{Pt+1} - (v_{Lt+1} - C_i - \gamma_N n_{it})}{\sigma_\varepsilon}]}. \end{aligned} \tag{3.20}$$

Subtracting (3.19) from the value of LEPA in (3.12) and adoption cost $C_{it}$, we get

$$\begin{aligned} v_L - C_i - \gamma_N n_{it} - v_P = \pi^D_{it} + \beta\sigma_\varepsilon \int [ln Pr_L(\Gamma_{it+1}, C_i, n_{it})] f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1} \\ - (1-\beta)(C_i + \gamma_N n_{it}), \end{aligned} \tag{3.21}$$

which is a function of the per-period profit gain of using LEPA ($\pi^D_{it} = \pi^L_{it} - \pi^P_{it}$) and the next period's probability of adopting LEPA (if LEPA is not adopted in the current period). Details of the derivation are presented in appendix E.1.

Since $\pi^D_{it}$ and $n_{it}$ enter (3.21) linearly,[11] the interpretation of peer effects becomes very flexible, as discussed in section 3.3. For example, if peer effects are interpreted as utility gains

[11] $\pi^D_{it}$ and $n_{it}$ enter (3.21) nonlinearly in the second term through $Pr_L(\Gamma_{it+1}, C_i, n_{it})$. However, as will be shown in appendix E.2, this term is treated as known when estimating (3.21).

from witnessing more neighbor LEPA adopters, (3.21) becomes $v_L - C_i - v_P = [\pi_{it}^D + \tilde{\gamma}_N n_{it}] + \beta\sigma_\varepsilon \int [lnPr_L(\Gamma_{it+1}, C_i, n_{it})] f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1} - (1-\beta)C_i$, where $\pi_{it}^D + \tilde{\gamma}_N n_{it}$ is annual utility gain from LEPA adoption. Given the same structure of this equation and (3.21), estimates of parameters other than $\gamma_N$ and $\tilde{\gamma}_N$ are not affected. $\tilde{\gamma}_N$ is also obtained by a simple constant-scale transformation of $\gamma_N$: $\tilde{\gamma}_N = (\beta - 1)\gamma_N$. Obviously, peer effects could also be easily interpreted as neighbor adopters' effect on utility gains, even though it is currently interpreted as neighbor adopters' effect on adoption costs in our model (through its effect on inertia).

According to (3.15), the likelihood of observing farmer $i$ whose unobserved portion of adoption costs being $C_i \in \{C^H, C^L\}$ choosing irrigation technology $j \in \{P, L\}$ in year $t$ is:

$$l_{ijt}(\Gamma_{it}; C_i, n_{it}, \sigma_\varepsilon) \equiv Pr_j(\Gamma_{it}; C_i, n_{it}) = \begin{cases} Pr[v_L(\Gamma_{it}) - C_i + \varepsilon_{it} > v_P(\Gamma_{it}, C_i, n_{it})], \ j = L \\ Pr[v_L(\Gamma_{it}) - C_i + \varepsilon_{it} < v_P(\Gamma_{it}, C_i, n_{it})], \ j = P \end{cases}. \tag{3.22}$$

Therefore, the likelihood contribution of this farmer in year $t$ is:

$$l_{it}(d_{it}, \Gamma_{it+1}|\Gamma_{it}, C_i, n_{it}; \sigma_\varepsilon) = \prod_{j \in \{P,L\}} [l_{ijt}(\Gamma_{it}, C_i, n_{it}; \sigma_\varepsilon)]^{d_{ijt}} f(\Gamma_{it+1}|\Gamma_{it}). \tag{3.23}$$

Integrating out $C_i$ in (3.23), the full likelihood contribution of farmer $i$ is:

$$l_i(d_i, \Gamma_i|\Gamma_{i1}, n_i, \sigma_\varepsilon) = \tau_i^H \prod_{t=1}^{T_i} l_{it}(d_{it}, \Gamma_{it+1}|\Gamma_{it}, C^H, n_{it}, \sigma_\varepsilon) + \tau_i^L \prod_{t=1}^{T_i} l_{it}(d_{it}, \Gamma_{it+1}|\Gamma_{it}, C^L, n_{it}, \sigma_\varepsilon), \tag{3.24}$$

where $T_i$ is the number of years that farmer i waited until he adopted LEPA. In addition, $d_i = \{d_{i1}, d_{i2} \dots d_{iT_i}\}$, $\Gamma_i^D = \{\Gamma_{i1}^D, \Gamma_{i2}^D \dots \Gamma_{iT_i}^D\}$ and $n_i = \{n_{i1}, n_{i2} \dots n_{iT_i}\}$. To complete the model, we parameterize the probability of farmer $i$ falling into adoption class $H$ as:

$$\tau_i^H = \tau^H(\Gamma_{i1}; \delta) = \frac{exp(\delta_0 + \delta_1 \Gamma_{i1})}{1 + exp(\delta_0 + \delta_1 \Gamma_{i1})}. \tag{3.25}$$

The E-M CCP algorithm in Arcidiacono and Miller (2011) is taken to estimate the model parameters. Details of the algorithm are presented in at appendix E.2. Standard errors of parameters estimated by the dynamic discrete choice model are obtained via nonparametric panel bootstrapping with 380 bootstrap runs.[12]

One problem in the empirical model above is that the number of neighbor adopters ($n_{it}$) might be endogenous due to correlated unobservables between a farmer and his neighbors. One solution in the context of identifying peer effects on groundwater appropriation and irrigation technology adoption with reduced-form techniques is to include a detailed list of control variables in the estimation to capture as much correlation among neighbors as possible (Sampson and Perry, 2018; Sampson and Perry, 2019). In our model, annual profit gains $\pi_{it}^{D}$ is a function of various factors such as crop price, gas price, depth to groundwater and precipitation. We also allow marginal productivity of water's slope to be farmer(well)-specific and time-specific to control for time-constant and time-varying correlated unobservables among farmers and their neighbors. Therefore, we are controlling for a large set of observed and unobserved variables that might be correlated with farmers and their neighbors. Consequently, we believe that the problem of endogeneity in estimation results are minimized even though we could not completely rule out all potential sources of endogeneity in $n_{it}$. We provide more discussion on this issue in section 3.7.

## 3.7 Empirical Results

In this section, we present the estimation results of production function parameters ($\hat{\Omega}_1$) from (3.16), state variable transition function parameters ($\hat{\Omega}_2$) from (3.18), and dynamic parameters ($\hat{\Omega}_3$) from (3.24) and (3.25). Each step relies on the estimation results of the previous steps. We conduct robustness checks at each step to ensure that robust estimation results are used in the subsequent steps.

[12] Due to the randomness in selecting wells in each bootstrap sample, it is possible to resemble a sample with all (or almost all) farmers/wells falling into the low adoption cost or high adoption cost class. With little adoption class heterogeneity in the drawn bootstrap sample, the estimated $C^L$, $C^H$, and corresponding class probabilities will be very imprecise. To avoid this situation, we initially draw 500 bootstrap samples. After all bootstrap runs, we delete 120 runs whose estimated $\tau_i^H$ (or $\tau_i^L$) are very close to 1 (or that give extremely large $\delta_0$ and $\delta_1$ estimates) when calculating standard errors, leaving us 380 effective bootstrap runs.

### 3.7.1 Production Function Estimation Results

Production function estimation results are reported in Table 3.2. The results in column (I) and (III) are obtained by applying a farm-level fixed effects model to the first order condition of profit maximization (3.16), using ethanol production as the instrument variable for corn price. As a robustness check, columns (II) and (IV) reports direct estimates of (3.6) using county level yield data.

From (3.17), the intercept of effective water's marginal product ($\alpha_{1it}$) depends on farmer fixed effects and year-by-GMD fixed effects, and would also depend on the monthly temperature in the growing season. Column (I) reports the second stage estimation results of the 2SLS estimation of (3.16), excluding monthly temperature in (3.17), while column (III) reports the results with the temperatures included. The first stage estimates are reported in Table 3.3. The first column in Table 3.3 corresponds to specification (I) in Table 3.2, while the second column corresponds to specification (III). The instrument passes both under-identification test and weak instrument test. The slope of water's marginal product ($\alpha_2$) is around -33 in both specifications, which is negative and statistically significant, confirming that the production function is concave in effective water.

Column (III) indicates that while a higher temperature improves yields in May and June, it reduces the yield during the hot summer months of July - September. Between columns (I) and (III), the average $\alpha_{1it}$ across farmers and years are very close, at around 143.

We estimated the production function in (3.6) indirectly through (3.16) due to the lack of farm level yield data. As a robustness check, we also provide a direct production function estimation using county-level crop yield data. Specifically, we estimate the following adaptation of (3.6) to county level data:

$$q_{ct}(w_{ct}) = \alpha_{0ct} + \alpha_{1ct} W_{it}^{e} + \alpha_{2ct} W_{it}^{e2} + \mu_{ct}, \tag{3.26}$$

where subscript $c$ indexes county in the study region and $W^e$ is effective water calculated from individual farmer-level water use averaged to county level.[13] We use a county level fixed effects

[13]Specifically, we calculate annual effective water for farmer $i$, $\theta_{it} w_{it} + r_{it}$, for each farmer in our dataset and obtain effective water in county $c$ in year $t$ by averaging effective water for farmers in that county.

**Table 3.2:** Production Function Estimation Results

| | **Without Temperature** | | **With Temperature** | |
|---|---|---|---|---|
| Identification Strategy | Water Use FOC (I) | County-Level Yield (II) | Water Use FOC (III) | County-Level Yield (IV) |
| $\alpha_2$ | -33.03*** | -29.9* | -32.91*** | -37.04* |
| | (0.87) | (17.81) | (0.88) | (22.07) |
| $\alpha_{1it}$ | | | | |
| $\alpha_{1temp5}$ | | | 2.37*** | -0.05 |
| | | | (0.49) | (2.38) |
| $\alpha_{1temp6}$ | | | 1.83*** | -2.60 |
| | | | (0.45) | (2.48) |
| $\alpha_{1temp7}$ | | | -2.95*** | -0.44 |
| | | | (0.42) | (2.09) |
| $\alpha_{1temp8}$ | | | -0.91* | -0.99 |
| | | | (0.51) | (2.31) |
| $\alpha_{1temp9}$ | | | -1.76*** | 2.02 |
| | | | (0.48) | (1.97) |
| $\alpha_{1temp10}$ | | | -8.52*** | 9.32*** |
| | | | (0.59) | (2.53) |
| $\alpha_{1temp11}$ | | | 2.64*** | -0.58 |
| | | | (0.41) | (1.84) |
| Farmer FE | Y | | Y | |
| County FE | | Y | | Y |
| Year-by-GMD FE | Y | Y | Y | Y |
| $\alpha_{oit}$ | | | | |
| County FE | | Y | | Y |
| Year FE | | Y | | Y |
| $E(\alpha_{1it})$ | 143.20 | 120.64 | 142.71 | 152.62 |
| $R^2$ | 0.130 | 0.804 | 0.132 | 0.823 |
| Obs | 35332 | 333 | 35332 | 333 |

*Notes*: Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 3.3:** Fixed Effect Instrumental Variable Production Function Estimation – First Stage

| Dependent Variable: $pE/(\theta_j * pC)$ | (I) | (III) |
|---|---|---|
| $pE/(\theta_j * log(ethanol))$ | 2.81*** | 2.84*** |
| | (0.0012) | (0.0052) |
| Monthly Average Temperature | N | Y |
| Farmer FE | Y | Y |
| Year-by-GMD FE | Y | Y |
| F-statistic | 2.8e+05 | 3.0E+05 |
| Under-identification test (Anderson canon. corr. LM P-value) | 0.000 | 0.000 |
| Weak-instrument-robust inference (Anderson-Rubin Wald test p-value) | 0.000 | 0.000 |

*Notes*: Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

model to estimate (3.26) and the results are shown in columns (II) and (IV) in Table 3.2. Most of the temperature variables in (IV) are insignificant, possibly due to the small number of observations. The estimated slope of marginal product ($\alpha_2$) and the average of the intercept of marginal product ($\alpha_1$) across farmers (or counties) and time are similar to each other across specifications (I) - (IV), providing strong support that our identification strategy based on individual water use data works well in identifying production function parameters. We rely on the results of specification (I) in subsequent estimations. We do not use the direct yield function estimation results in specification (II) and (IV) because farmer-level fixed effects estimation allows us to estimate farmer-specific intercept of effective water's marginal product (i.e. $\alpha_{1i}$).

The importance of accounting for individual level heterogeneity has been well documented by Suri (2011). One such farmer-level heterogeneities comes from heterogeneity in farmers' profit gains from using LEPA, which in turn comes from farmers' heterogeneous production functions. Indeed, the histogram of estimated $\hat{\alpha}_{1it}$ across farmers and years in the upper panel of Figure 3.3 exhibits strong heterogeneity in $\alpha_1$. This heterogeneity is then passed on to the heterogeneity of annual profit gain in the lower panel of figure 3.3. The mean and standard deviation of annual profit gain are $24.07/acre and $14.25/acre, respectively.

As a final robustness check, we calculate the average elasticity of water extraction per acre with

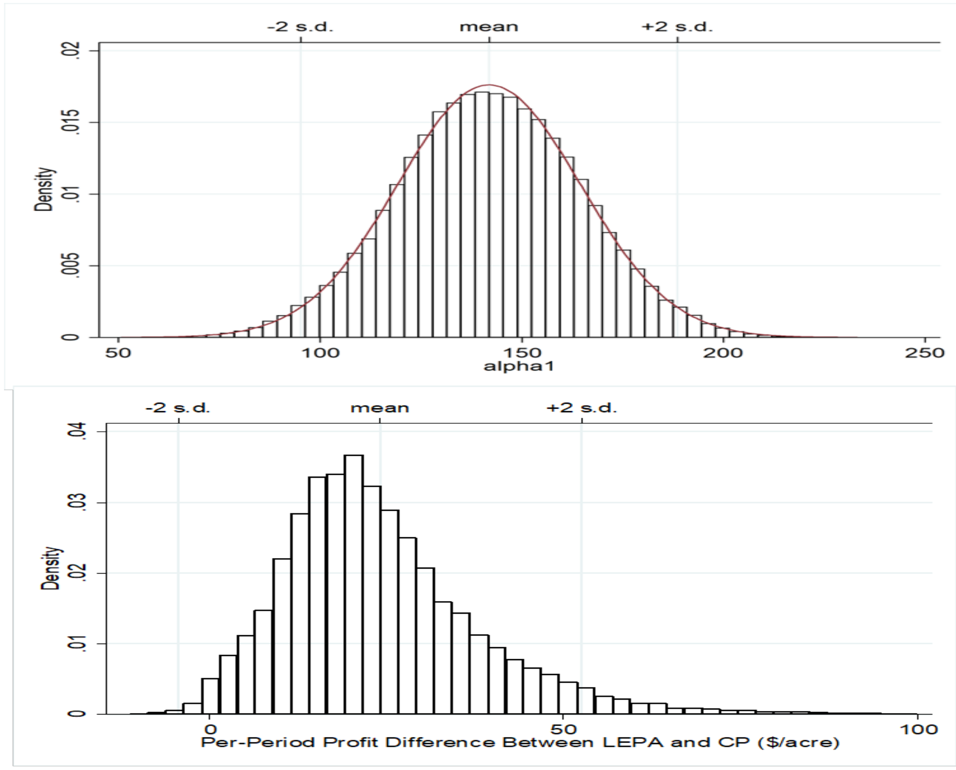



Figure 3.3: Histogram of $\hat{\alpha}_{1it}$ in Production Function (upper) and Per-period Profit Difference Between LEPA and CP across Farmers and Years (lower)

respect to energy cost. The elasticity is -0.562 for farmers who uses CP and -0.279 for those using LEPA. Using a similar dataset in the same study region, Hendricks and Peterson (2012) estimates the average elasticity across all farmers and all years in their sample to be -0.09. However, they do not take the energy requirement to start irrigation equipment into account (i.e. $PSI_j$ in (3.7)) when calculating the energy costs. After such factor is incorporated into energy cost calculation, Pfeiffer and Lin (2014) shows that the estimated elasticity for CP becomes -0.577 (Pfeiffer and Lin, 2014), which is about the same as our estimate of -0.562.

### 3.7.2 Profit Gain Transition Rule Estimates

The estimated AR(2)-type transition process for profit gains is presented in table 3.4. Most variables used to predict future profit gain realizations are statistically significant. In particular, current and past profit gain realizations ($\pi^D_{it}$ and $\pi^D_{it-1}$) are positively correlated with future profit gain realizations. The uncertainty of profit gain transition is captured by $\sigma_{\varepsilon}$. The more uncertain farmers are about the future realizations of these variables, the more dispersed is the distribution represented by the probability density function $f(\pi_{it+1}|\pi_{it}, \pi_{it-1}, \alpha_{1i}, t)$.

**Table 3.4:** Profit Gain Transition Rule Estimation Results

| Dependent Variable: $\hat{\pi}^D_{it+1}$ | Estimates |
|---|---|
| $\pi^D_{it}$ | 0.21*** |
| | (0.0059) |
| $\pi^D_{it-1}$ | 0.55*** |
| | (0.0069) |
| $\alpha_{1i}$ | 6.04*** |
| | (0.1789) |
| t | 0.031 |
| | (0.025) |
| constant | -5.25** |
| | (.4715) |
| $\sigma_{\eta}$ | 8.82 |

*Notes*: Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### 3.7.3 Dynamic Parameter Estimation Results

#### 3.7.3.1 Parameter Estimates

The estimation results for adoption cost distribution parameters and per-period profit gain shock's scale parameter are shown in table 3.5. All estimated parameters have the expected signs and are statistically significant. We discuss several important lessons learned from the estimation results.

First, 66% of farmers fall into the low adoption cost class and 34% of farmers fall into the high cost class on average. The large difference between the two cost classes and the nontrivial probability of each class demonstrate the importance of accounting for cost heterogeneities in adoption models.

Second, the unobserved adoption costs for farmers with low adoption costs are estimated to be \$74.15/acre, which falls in the \$40-\$77.37/acre equipment and installation cost range (converted to 2010 dollar) used in agronomic studies (Delano, Williams, and O'Brien, 1997; Hutton et al.,

**Table 3.5:** Dynamic Parameter Estimation Results

| | **Parameter Estimates** |
|---|---|
| **Adoption Cost** $C_{it} = C_i + \gamma_N n_{it}$ **($/acre)** | |
| $C^L$ | 74.15*** |
| | (28.77) |
| $C^H$ | 277.70*** |
| | (88.72) |
| $\gamma_N$ | -2.7** |
| | (1.3) |
| **Cost Class Probability** | |
| $C = C^L$ | 64% |
| $C = C^H$ | 36% |
| **Profit Shock Scale Parameter** | |
| $\sigma_\varepsilon$ | 33.49*** |
| | (5.28) |
| Obs | 28081 |

*Notes*: Bootstrapped standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1989; Peters, Neibling, and Stroh, 2016). However, estimated adoption costs for farmers with high adoption costs are $277.7/acre, which is much higher than the upper bound of the range above.[14] Adoption costs in our model include not only equipment and installation cost, but also include farmers' inertia to change their current farming systems. Shown by the cost range in the agronomic literature, equipment and installation costs do not vary too much. Therefore, farmers with high adoption costs are likely to have higher psychological inertia towards changing their current farming practices than other farmers. Thus, allowing adoption costs to be heterogeneous across farmers captures this irrational behavioral bias.[15]

Third, similar to Sampson and Perry (2018), which studies peer effects on LEPA adoption using reduced-form estimation with the same data source, we also find statistically significant evidence of peer effects. As the number of neighbor LEPA adopters increases, inertia level decreases, and

[14]We also tried to increase the number of classes to three and four, but the estimated population level probabilities of the third and forth classes turn out to be close to zero.

[15]We interpret inertia as a behavioral bias because inertia itself does not bring any profit/utility gains to farmers.

perceived adoption costs decrease. As discussed in section 3.3 and section 3.6, we can also interpret peer effects as a farmer's utility gain from observing more neighbor adopters: if more neighbors adopt LEPA, I am more comfortable of adopting LEPA myself. Compared to Sampson and Perry (2018), our study utilizes a structural estimation model that not only quantifies peer effects, but also the effects of profit gain level, profit gain uncertainty and adoption costs on LEPA diffusion.

Lastly, as the deterministic part of the per-period profit difference is estimated in the previous step, the per-period profit shock scale parameter $\sigma_{\varepsilon}$ can be identified. The estimated scale parameter is relatively large – around \$33.49/acre, higher than the mean of the per-period per-acre profit gain from using LEPA (\$24.07/acre). This finding is consistent with studies that use the same dataset to study LEPA adoption decisions with reduced-form estimation techniques. For example, after controlling for a rich set of control variables, the $R^2$ in a fixed effects linear probability model is still only around 0.1 in Sampson and Perry (2018). The relatively large scale parameter estimate indicates that there are possibly many other factors that affect per-period LEPA profit gains that are not captured by the model. As we have controlled for a rich set of climate factors and economic factors in the profit function, one possible source of the missing information is the deviation of farmers' perceived profit gain from the objective profit gain. Another possible explanation is that farmers may not be extremely rational when making adoption decisions and a rational dynamic programming model here is not able to capture all irrational behaviors. Although we introduce behavioral bias in adoption costs through inertia, there might still be other forms of irrational behaviors. For example, farmers might be yield-maximizing rather than profit-maximizing. Such behaviors might be related to factors such as farmers' socioeconomic characteristics. Unfortunately, we could not identify such behavioral biases given the information in the dataset, but a future extension that incorporates more irrational behaviors into the modeling framework here is valuable.

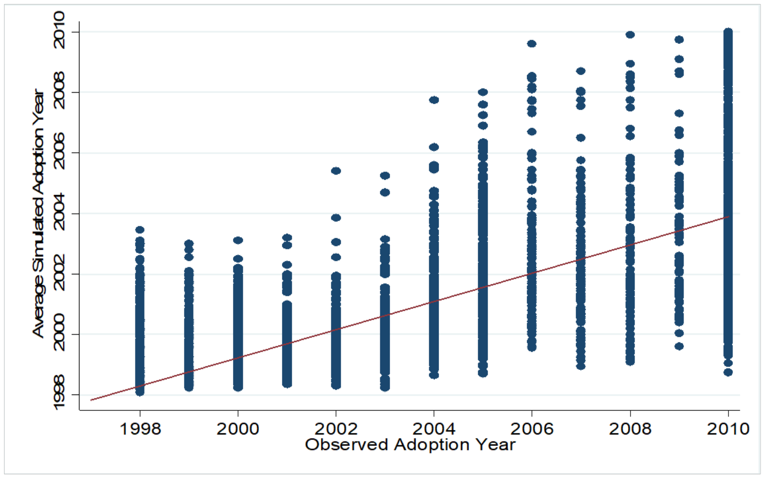
#### 3.7.3.2 Model Validity

To check how well the structural adoption model works, we test model validity by comparing the observed LEPA diffusion path to the path predicted by our model. To do so, we parameterize the model in (3.12) to (3.15) with the estimated model parameters and solve explicitly the dynamic programming model faced by each farmer in each year using collocation method described by Miranda and Fackler (2004). In a nutshell, the simulation follows the procedure below:

- Decide each farmer's adoption cost (high or low) according to the estimated individual farmer's probability of belonging to each adoption cost class ($\pi_i^H$). We set a farmer to be a high-adoption-cost farmer if $\pi_i^H > 0.5$ and to be a low-adoption-cost farmer otherwise.
- Randomly draw the per-period profit shock for each farmer in each year according to the estimated shock distribution.
- Calculate the deterministic part of the per-period profit gain based on observed variables such as crop price, energy price and precipitation.
- Solve $v_P$ and $v_L$ defined in (3.12) and (3.13) by collocation method.
- Decide whether to adopt LEPA for each farmer in each year according to (3.15). If adopt, record adoption year and this farmer would not make adoption decisions again in the future. If not, continue to the next year.
- Repeat the previous procedure for each year in the sample.
- Iterate the procedure above over different draws of per-period profit shocks.
- Across all the draws, calculate the average of each farmer's adoption years and obtain the average new and cumulative adopters in each year.

Figure 3.4 plots each irrigation well's simulated LEPA adoption year against its observed adoption year. A linear regression line is also fitted in the figure. All the points would stay on the 45°line for a perfectly fit model. A clear upward sloping trend is observed in the figure, meaning that the model predicts individual-level diffusion patterns relatively well.

Figure 3.5 presents the comparison between the simulated and observed number of total adopters (upper panel) and the number of new adopters (lower panel) in each year. The solid lines represent observed paths and the dashed lines represent simulated paths. In general, the predicted trends of




*Note: each dot in the figure represents an observed-simulated adoption year combination for an irrigation well. The line in the figure is the line fit of wells' simulated adoption years on observed adoption years.*

Figure 3.4: Simulated Average Adoption Year v.s. Observed Adoption Year

both total adopters and new adopters over time are similar to the trends observed in the data. The combined evidence from figures 3.4 and 3.5 implies that the model does a relatively good job in terms of predicting both average adoption pattern and individual well-level LEPA diffusion pattern.

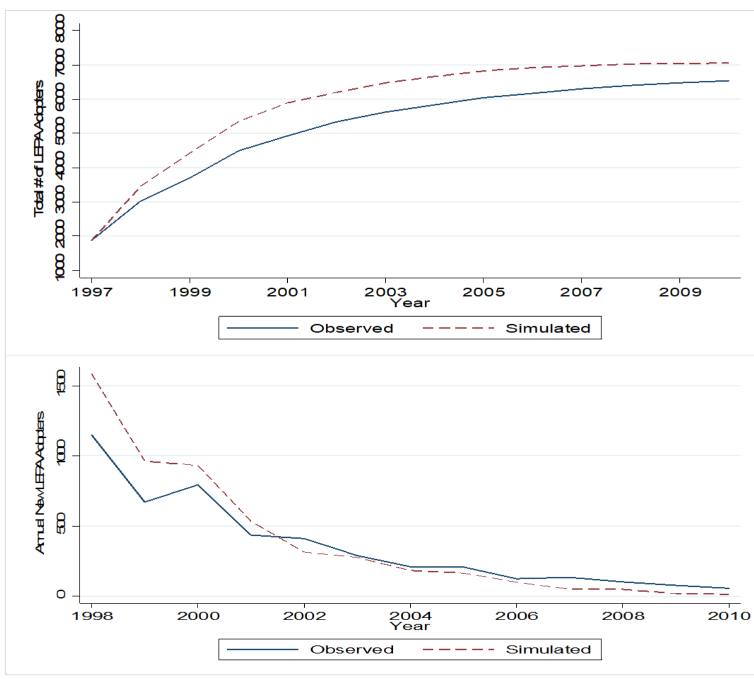



Figure 3.5: Simulated v.s. Observed Number of Cumulative Adopters (upper) and New Adopters (lower)

One possible reason that could bias the estimation results and harm model validity is the potential endogeneity in the number of neighbor LEPA adopters. As we have discussed at the end of section 3.6, we could not completely rule out the possibility that the number of neighbor adopters is endogenous due to correlation in unobservables, even though we have included a rich set of control variables in both the main regression equation (3.21) and adoption class distribution equation (3.25). However, we still use the estimation results reported above in our subsequent analysis because: (1) the overall adoption patterns predicted by the model are relatively reasonable shown by figures 3.4 and 3.5, and (2) it is difficult to find a suitable IV for neighbor adopters in this context and the approach we take (i.e. including a detailed list of control variables to identify peer effects) is consistent with the approach commonly used in the literature (Sampson and Perry, 2018; Sampson and Perry, 2019). We check whether our estimation results are sensitive to our definition of neighbors in appendix F.

#### 3.7.3.3 Effects of Uncertainty and Adoption Costs on Adoption Rate

In this section, we consider the effects of adoption costs, number of neighbor LEPA adopters, profit gain level and profit gain uncertainty on LEPA adoption rate. Specifically, we calculate the elasticities of adoption probability with respect to adoption costs and state variable uncertainties.

Elasticity with respect to adoption costs is relatively straightforward to calculate. In practice, we increase estimated unobserved adoption costs by one percent and calculate the percent change in adoption probability for each individual in each year through simulating the model defined by (3.10)-(3.15). The mean percent change in adoption probability across all farmers and all years is reported in the first row in table 3.6 as an estimate of the elasticity.

Ideally, standard errors of the elasticity estimates could also be obtained if we bootstrap the simulation, which is computationally costly. Instead, we report the standard deviation of this percent change across farmers and years in parenthesis in table 3.6. As this standard deviation is not the standard error of the estimated elasticity, we could not calculate p-value and show statistical significance. However, it gives a broad idea about how disperse the estimated elasticities are for

**Table 3.6:** Adoption Probability Elasticities

| | **Elasticities** |
|---|---|
| **Adoption Cost** | |
| Overall | -1.75 |
| | (1.44) |
| High Adoption Cost Class | -2.53 |
| | (1.23) |
| Low Adoption Cost Class | -0.49 |
| | (0.66) |
| **# of Neighbor LEPA Adopters** | |
| Level | 0.42 |
| | (0.26) |
| **Natural Gas Price** | |
| Level | 0.48 |
| | (0.33) |
| Uncertainty | -0.034 |
| | (0.14) |
| **Crop Price** | |
| Level | 0.17 |
| | (0.18) |
| Uncertainty | -0.1 |
| | (0.29) |
| **Growing Season Precipitation** | |
| Level | -0.73 |
| | (0.42) |
| Uncertainty | 0.027 |
| | (0.055) |
| **Profit Gain** | |
| Level | 0.68 |
| | (0.34) |
| Uncertainty | -0.10 |
| | (0.033) |

*Notes*: elasticities are calculated as the percent change in adoption rate (i.e. adoption probability) with respect to 1 percent change in stata variable level or uncertainty. For example, if initial probability of adoption is 40%, an elasticity of 1 means one hundred percent increase in the variable being considered leads to 100% increase in adoption probability, resulting in an adoption probability of 80%.

different farmers in different years. A 1% increase in adoption cost will lead to a 1.75% reduction in adoption rate on average.[16] The mean of this elasticity across farmers and years is not too much larger than its standard deviation, meaning that the effect of increasing adoption costs on adoption probability is relatively dispersed across farmers. To investigate the source of dispersion, we also report separately the elasticity estimates (and their standard deviations) for farmers with high adoption costs and with low adoption costs.[17] Shown by the results, the effect of increasing adoption costs on adoption probability is much higher for farmers with high adoption costs than those with low adoption costs. This is partly because the level of high adoption costs is much higher than that of low adoption costs. Therefore, one percentage change in the level of high adoption costs is also higher than that of low adoption costs, leading to more changes in adoption probability.

The procedure of calculating adoption probability elasticity with respect to the number of neighbor adopters is the same as the one above. We increase the amount of neighbor adopters for each farmer in each year by one percent and calculate percent change in adoption probability. The mean and standard deviation of this elasticity are also reported in table 3.6. As expected, increase in the number of neighbor LEPA adopters increases adoption rate because it lowers down farmers' perceived adoption costs through reducing inertia.

To calculate elasticities with respect to profit gain uncertainties and profit gain levels, we first decompose overall profit gain uncertainty into uncertainties in the underlying factors (i.e. gas price, crop price, precipitation, and profit shocks). We estimate the following AR(2) transition rule for each underlying factor:[18]

$$x_{it+1} = \phi_0 + \phi_1 x_{it} + \phi_2 x_{it-1} + \nu_{it}.$$

We define the elasticity of adoption probability with respect to an underlying variable's uncertainty as the percentage change in adoption rate with respect to one percentage change in the

[16]Note that this is a percentage reduction in percentage. For example, if the initial adoption probability is 50%, then a 1.75% reduction in adoption rate gives an adoption probability of $50\% * (1 - 0.0175) = 49.13\%$.

[17]We assign farmers whose probability of falling into high adoption cost class is greater than 0.5 to be farmers with high adoption costs.

[18]Our data shows that precipitation does not demonstrate strong serial correlation. Therefore, precipitation is assumed to be normally distributed across farmers and years.

standard deviation of $v_{it}$ ($\sigma_v$).[19] Similarly, the adoption probability elasticities with respect to underlying variables' levels are calculated as the percentage changes in adoption rate with respect to one percentage change in the levels of $x_{it}$.

The estimated elasticities with respect to underlying variables' levels and uncertainties are reported in table 3.6. The signs of the elasticities with respect to these variables' levels are as expected: increases in natural gas price and crop price lead to increases in adoption rate because such increases make LEPA more profitable compared to CP. On the other hand, an increase in precipitation reduces adoption rate because irrigation demand is lower with more precipitation, so there is less need to adopt more efficient irrigation technologies.

The effects of natural gas price, crop price and precipitation uncertainties are relatively smaller than the effects of their levels. Holding profit gain level constant, higher uncertainty in profit gain is expected to reduce adoption probability because it raises the threshold of profit gain above which adoption happens. However, increasing precipitation uncertainty increases, rather than decreases, adoption probability. Moreover, the mean of each elasticity across farmers and years is smaller than the corresponding standard deviation (reported in parentheses). Indeed, increases in levels/uncertainties of gas price, crop price and precipitation do not necessarily translate in to the same change in profit gain uncertainty due to the nonlinear relationship between profit gain and underlying variables that affect profit gains. Therefore, we also directly calculate the elasticities of adoption probability with respect to profit gain's level and uncertainty (refer to (3.18)). The results are shown in the last two rows of table 3.6. As expected, increase in profit gain level increases adoption probability, while increase in profit gain uncertainty decreases adoption probability. The means of these elasticities are also much higher than their standard deviations (reported in parentheses).

[19]Specifically, we simulate the paths for all state variables in each year based on the new transition rule and calculate LEPA profit gains. To be consistent with the estimation procedure, we then use the calculated profit gains to fit a profit gain transition rule. With this transition rule, we numerically solve the dynamic programming problem and calculate the probability of adoption under different magnitudes of $\sigma_v$, holding the levels of profit gain constant at the observed levels.

## 3.8 Counterfactual Simulations

In section 3.7.3.3, we calculate the elasticity of LEPA adoption probability with respect to profit gain level, profit gain uncertainty, neighbor adopters and adoption costs. These elasticity estimates could be regarded as "marginal effects".

In this section, we ask two questions: (1) what is the effect of the incentive to delay adoption created by profit gain uncertainty and adoption irreversibility on adoption rate? (2) what kind of policy is the most cost-effective in promoting efficient irrigation technology adoption? Answering these two questions requires changing certain model parameters "non-marginally". One merit of structural models is the ability to evaluate the effects of non-marginal changes in key variables on adoption decisions through simulation. We lay out the details of the simulations used to answer theses two questions and discuss the simulation results in the following two subsections.

### 3.8.1 Option to Delay and Adoption Rate

According to the Net Present Value (NPV) rule, a farmer should adopt LEPA as long as the expected sum of discounted future profit gains from LEPA is higher than the adoption costs. To put it in another way, NPV rule only considers whether or not to adopt now, but not the option to delay adoption decision to the future.

However, this other option (i.e. option to delay) is important when farmers are uncertain about future profit gain realizations and when the adoption procedure is irreversible. Even if the NPV of adoption is positive now, there is always a chance that profit gain drops to a fairly low level in the future due to its inherent volatility, and adoption costs might not be recouped if this happens but adoption has already occurred.

By real options theory, farmers do not simply choose whether or not to adopt now, but also consider the option to delay the decision until better information is available (Taylor and Zilberman, 2015). If he does not adopt this year, he still has the option to make adoption decision in the future. But if he adopts now, he would not have the chance to recoup the upfront adoption costs if profit gains become very low in the future. This "option value" creates incentive for forward looking farmers to delay adoption even though adoption is profitable through the lens of NPV rule. Therefore, it is possible that a farmer should adopt LEPA in a given year by NPV rule, but should not adoption by real options rule. A rational farmer tends to delay adoption until profit gain realization in the current year is high enough such that the probability that it drops to a low level later is small.

Formally, the NPV decision rule is to adopt LEPA as long as:

$$E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^{D} \right\} - C_{it} > 0. \tag{3.27}$$

On the other hand, the real-option decision rule is to adopt if:

$$v_L(\Gamma_{it}) - v_P(\Gamma_{it}, C_{it}) - C_{it} > 0. \tag{3.28}$$

For each observation in the dataset, we simulate $V_L(\Gamma_{it}) = E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^{D} \right\}$, $v_L(\Gamma_{it}) - v_P(\Gamma_{it}, C_{it})$ and $C_{it} = C_i + \gamma_N n_{it}$ using observed state variables and estimated structural parameters in table 3.4 and table 3.5. Figure 3.6 plots average of $E \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^{D} \right\}$, average of $v_L(\Gamma_{it}) - v_P(\Gamma_{it}, C_{it})$, and average of $C_{it}$ in two axes, one for farmers with low adoption costs and the other for farmers with high adoption costs. All averages above are taken across farmers and years in the sample.

Obviously, $V_L(T_{it}) = E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^{D} \right\}$ is always greater than $v_L(\Gamma_{it}) - v_P(\Gamma_{it}, C_{it})$ because $v_P(\Gamma_{it}, C_{it})$ represents the value of the option to make adoption decisions in the future, which is positive and is killed once LEPA is adopted. For farmers with low adoption costs (upper panel), adoption costs are higher than $v_L(\Gamma_{it}) - v_P(\Gamma_{it}, C_{it})$ but is much lower than $E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^{D} \right\}$, which means that farmers should adopt LEPA if they follow NPV rule, but should not adopt if they follow real options rule instead. For those with high adoption costs (lower panel), adoption costs are higher than $v_L(\Gamma_{it}) - v_P(\Gamma_{it}, C_{it})$ and is about the same as $E \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau} \pi_{i\tau}^{D} \right\}$. Therefore, they are also unlikely to adopt under real options decision rule unless a fairly high profit realization is observed, and they are on the margin of adoption under NPV rule. Taking these two cases together, if all farmers follow NPV rule, average adoption probability across farmers and years would be higher.

Figure 3.7 shows that if all farmers had followed NPV rule, average LEPA adoption rate across all farmers and all sample periods would have increased by 13%. More specifically, the increase in average adoption rate in the first two years (i.e. 1998 and 1999) would have been as high as 42% and the diffusion process would have been completed by as early as 1999. The huge difference in the two adoption paths shows that the option to delay adoption decision until more information arrives significantly reduces adoption rate.

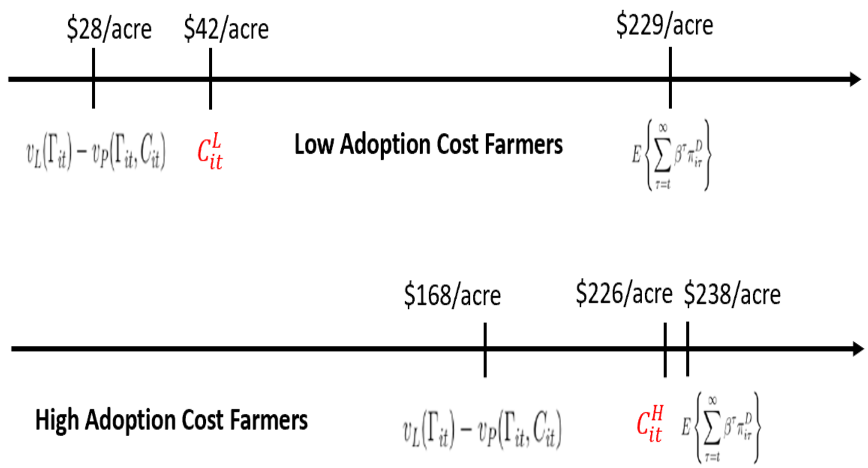



Figure 3.6: NPV and Real Option Decision Rule Critical Values

If farmers are not uncertain towards LEPA's profit gain (i.e. they know perfectly profit gain realizations in the future), there will be no incentive to delay adoption. Thus, adoption paths produced by NPV rule and real option rule would be the same. Given the large difference between the two predicted adoption patterns, profit gain uncertainty is an important factor that lowers down adoption rate (through creating an option value to delay). Even though the marginal effect of profit gain uncertainty is relatively small as shown in table 3.6, the total effects of uncertainty are important given the highly nonlinear nature of Bellman equations.

### 3.8.2 Insurance, Cost-Share Programs and Adoption

Two commonly adopted approaches to promote technology adoption are to provide (i) cost share payments to reduce initial adoption costs (Isik, 2004; Seo et al., 2008), and (ii) insurance to reduce profit uncertainties (Freudenreich and Mußhoff, 2018; Salazar et al., 2017). Utilizing a dynamic simulation framework, Song (2018) shows that profit insurance program is more cost-effective than adoption cost subsidies in promoting the adoption of energy crops such as switchgrass. Profit

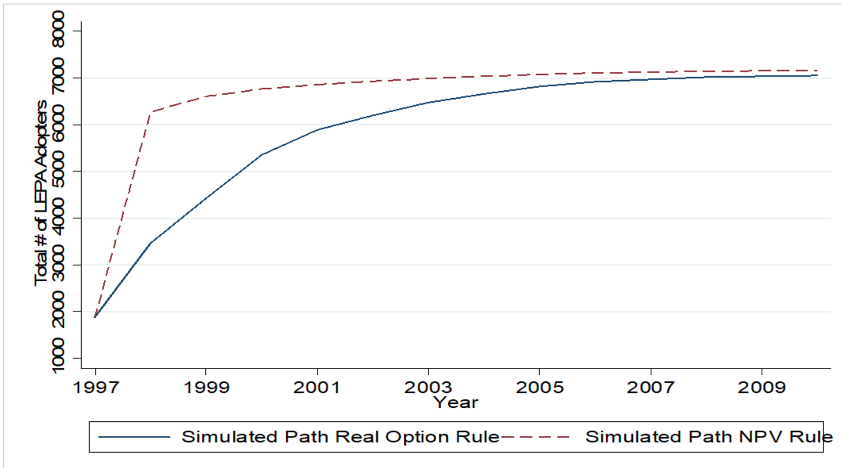



Figure 3.7: Simulated Adoption Path – NPV and Real Option Decision Rule

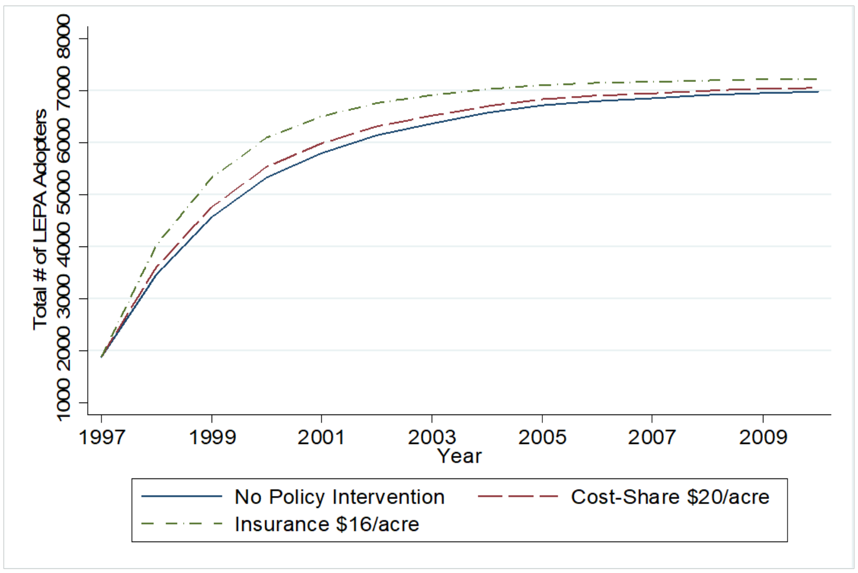
insurance, while reducing profit uncertainty, also increases profit levels when the actual profit level drops below the insured level. Thus, the overall effects of profit insurance tend to be larger than that of cost-share in their application.

However, performances of profit insurances and cost-share subsidies in terms of efficient irrigation technology promotions have not been compared in the literature. In this section, we evaluate the cost-effectiveness of a LEPA profit gain insurance policy and a cost share subsidy program. Under the insurance policy, LEPA adopters will receive the insured LEPA profit gain once the level of the observed profit gain drops below this insured level. Under the cost share policy, farmers receive a one-time reimbursement of a fraction of adoption costs after they adopt LEPA.

For the cost share counterfactual policy, we set cost share rate at \$20/acre.[20] The simulation procedure is the same as the one described in section 3.7.3.2, except that $C_{it}$ in (3.13) is replaced by $C_{it} - 20$. For the counterfactual insurance policy simulation, the choice of insurance rate (\$$R$/acre) is a bit trickier. To make the comparisons between cost share policy and insurance policy meaningful, the two policies should have the same level of expected government budget. Therefore, we first run the cost share policy counterfactual simulation and record the expected government expenditure under this policy. Then, we pick an arbitrary insurance rate, run the simulation, and

[20]The average cost-share rates among farmers who received the payments under the real Kansas program is around \$16/acre.

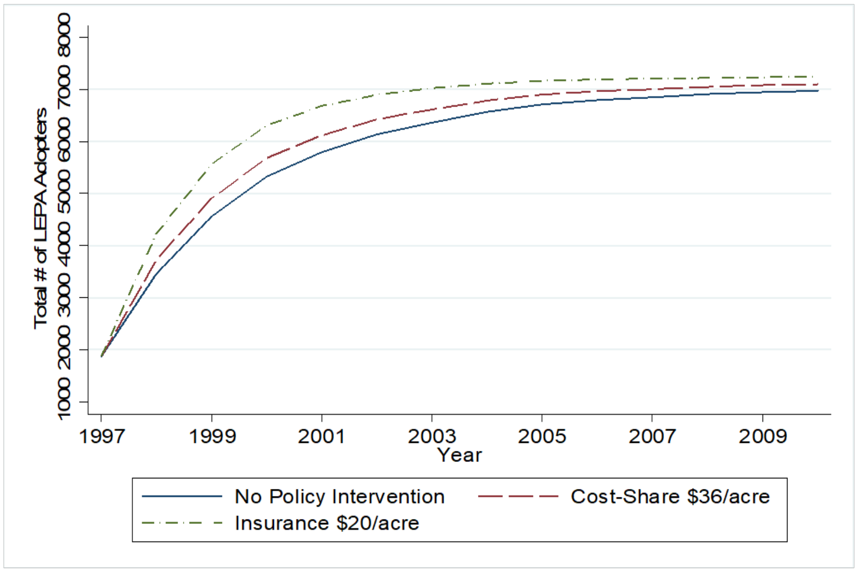
calculate government expenditure under this rate. If this expenditure is lower (higher) than the one under the cost share policy, we adjust up (down) the insurance rate until the level of expected government budget under the insurance policy equals to that under the cost share policy. Following this procedure, the selected insurance rate is $R$ = \$16/acre. Again, the simulation procedure is the same as the one described in section 3.7.3.2, except that $\pi_{it}^{D}$ in (3.12) is replaced by $\max\{\pi_{it}^{D}, R\}$.




*Note: The expected net govern present payments to farmers under the insurance and cost-share policy are both \$11.4 million.*

Figure 3.8: Effect of Insurance and Cost-Share Payments on Adoption Rate

The results are plotted in figure 3.8. The solid line represents the simulated adoption path without policy interventions, the dashed line is the simulated adoption path under the \$20/acre cost-share policy, and the dash-dotted line is the simulated adoption path under the \$16/acre insurance program. Both policies cost the government around \$11.4 million in expectation. It is straightforward to tell from the figure that the insurance policy is more efficient than the cost-share subsidy. More precisely, the average adoption probability over all sampling periods increases by 11.9% under the insurance program, but it only increases by 1.8% under the cost-share program. There are two possible explanations for why insurance program works more efficiently. First, as discussed above, profit insurance affects adoption probability by both reducing profit uncertainty and increasing profit levels when the actual profit level drops below the insured level. Second, even




*Note: The expected net govern present payments to farmers under the insurance and cost-share policy are both $20.9 million.*

Figure 3.9: Effect of Insurance and Cost-Share Payments on Adoption Rate

though the marginal effects of profit gain level and profit gain uncertainty are smaller than that of adoption costs shown in table 3.6, the total effects could be reversed given the highly nonlinear nature of bellman equation.

To make sure that this result does not change when the level of government budget changes, we perform the same exercise except that we set a new cost share rate to $36/acre[21] and a new insurance rate to $20/acre. The levels of expected government expenditure for the two policies are both $20.9 million. The adoption path comparison is shown in figure 3.9. Again, the insurance program is the more cost-effective option.

## 3.9 Conclusions and Future Directions

Climate change and the continuing exhaustion of groundwater resources in many important agricultural zones impose significant challenges to modern agriculture. Adopting more efficient irrigation technologies is an effective adaptation strategy facing the challenges. However, the

[21]This is the 95th percentile of cost-share payments received by farmers under the real Kansas program during 1996-2014

diffusions of these technologies are typically very slow. The effectiveness of various policies that promote adoption depend on the underlying incentives of potential adopters. Being able to identify the most important adoption drivers helps promote the diffusions of these technologies, but it is difficult to achieve this goal with traditional reduced-form estimation approaches.

This paper develops and estimates a structural dynamic discrete choice model that explicitly accounts for LEPA's profit gains, profit gain uncertainties, individual-specific adoption costs and peer effects on adoption decisions. Our estimation results confirm that farmers value the option to delay adoption when they face uncertainties and sunk costs. Profit gain uncertainty and irreversibility of LEPA's adoption together make it more attractive to delay adoption until more information about future profit gain arrives. Had farmers ignored the option to delay adoption and used NPV decision rule instead of real options rule when making LEPA adoption decisions, average adoption probability would have increased by 13% to 42% in different sampling years.

Besides the rational incentive to delay adoption created by profit gain uncertainty, we also find evidence that LEPA adoption rate has been driven down by farmers' behavioral biases, namely, farmers' inertia to change farming practices. Inertia adds up significantly to some farmers' perceived adoption costs, making them less likely to adopt LEPA, *ceteris paribus*. However, such inertia could be reduced when more neighbors of the farmer adopt LEPA, which is consistent with the literature on peer effects.

Following many local governments' increasing interest to promote efficient irrigation technology adoption through subsidies, we perform counterfactual policy simulations based on our model to test the relative cost-effectiveness of two policies that are commonly used: a cost-share policy and a profit gain insurance policy. Simulation results show that insurance policies are more cost-effective than cost-share programs under the same levels of expected government budget. In particular, increase in adoption probability following the implementation of the insurance policy is around 10% higher than that of the cost-share program.

There are several directions to extend the analyses in this study. First, we ignore strategic delay when modeling the effects of neighbor adopters on farmers' adoption decisions. As stated in section 3.3, the main reason of ignoring strategic delay is that farmers need to predict a large number of other farmers' adoption decisions when making their own adoption decisions. It might help to justify this simplification if a model with strategic delay is estimated using a small subset of farmers (e.g. farmers in a township) and we test the strength of strategic delay based on this model. However, with much fewer observations, the power of statistical test might drop significantly, unless a dataset with much more detailed farmer-level information such as the one used in Besley and Case (1994) is obtained. Second, farmers use either natural gas or electricity in this region to power their irrigation system. As we do not have information on individual farmers' energy sources, we assume that natural gas is the only energy source in the region following the literature. A natural extension of this paper is to get nonpublic energy source data from Kansas government and examine the differences in adoption behaviors between farmers who rely on natural gas and who rely on electricity to operate their irrigation systems. Finally, we have illustrated that LEPA adoption behaviors might also be affected by certain irrational behavioral biases that are not captured in the model. A fruitful future research direction is to identify these irrational components, which probably requires obtaining information on farmers' socioeconomic characteristics.

**APPENDICES**

## APPENDIX E

## DYNAMIC DISCRETE CHOICE ESTIMATION DETAILS

This section shows how to derive alternative representations of choice specific value functions and the details of the E-M CCP algorithm proposed by Arcidiacono and Miller (2011), tailored to our technology adoption model.

## E.1 Alternative Choice-Specific Value Function Representation

This section shows how to derive equation (3.19) from equation (3.13):

$$\begin{aligned}
v_P(\Gamma_{it}, C_i, n_{it}) &= \beta E\left\{\max[v_P(\Gamma_{it+1}, C_i, n_{it}), v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it} + \varepsilon_{it+1}]|\Gamma_{it}, \varepsilon_{it}\right\} \\
&= \beta\sigma_\varepsilon \int ln\left\{exp\left(\frac{v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it}}{\sigma_\varepsilon}\right)\right. \\
&\qquad \left. + exp\left(\frac{v_P(\Gamma_{it+1}, C_i, n_{it})}{\sigma_\varepsilon}\right)\right\} f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1} \\
&= \beta\sigma_\varepsilon \int ln\left\{exp\left(\frac{v_{Lt+1} - C_i - \gamma_N n_{it}}{\sigma_\varepsilon}\right)\right. \\
&\qquad \left. \left[1 + exp\left(\frac{v_{Pt+1} - [v_{Lt+1} - C_i - \gamma_N n_{it}]}{\sigma_\varepsilon}\right)\right]\right\} f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1} \\
&= \beta \int [v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it} - \sigma_\varepsilon ln Pr_L(\Gamma_{it+1}, C_i, n_{it})] f(\Gamma_{it+1}|\Gamma_{it}) d\Gamma_{it+1}
\end{aligned} \tag{E.1}$$

where the last line follows from the fact that:

$$\begin{aligned}
Pr_L(\Gamma_{it+1}, C_i, n_{it}) &= \frac{exp[\frac{v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it}}{\sigma_\varepsilon}]}{exp[\frac{v_P(\Gamma_{it+1}, C_i, n_{it})}{\sigma_\varepsilon}] + exp[\frac{v_L(\Gamma_{it+1}) - C_i - \gamma_N n_{it}}{\sigma_\varepsilon}]} \\
&= \frac{1}{1 + exp[\frac{v_{Pt+1} - (v_{Lt+1} - C_i - \gamma_N n_{it})}{\sigma_\varepsilon}]}.
\end{aligned}$$

## E.2 E-M CCP Estimation Algorithm

If $C_i$ is observable, a simple two-step CCP approach is feasible. In a first step, one perform a reduced-form flexible logit regression of LEPA adoption decision on state variables in $\Gamma_{it}$ and $n_{it}$ to get predicted $\hat{Pr}_L(\Gamma_{it+1}, n_{it})$. In the second step, plug $\hat{Pr}_L(\Gamma_{it+1}, n_{it})$ into equation (3.21) and apply Maximum Likelihood Estimation (MLE) to estimate $\sigma_\varepsilon$ and $\gamma_N$. However, as adoption costs are unobserved by econometricians, the two steps needs to be modified following the EM-CCP approach in Arcidiacono and Miller, 2011.

To initiate the estimation procedure, recall that we assume that their are two possible realizations of the unobserved part of adoption costs (i.e. $C_i \in \{C^H, C^L\}$), so we replicate the dataset twice. The two replications share exactly the same variable values except that they have different unobserved $C_i$ – one group with $C^H$ and another with $C^L$. Next, we give arbitrary starting values to parameters in $\Omega_3$. Denote these starting values as $\Omega_3^{(0)} = \{C^{H(0)}, C^{L(0)}, \delta^{(0)}, \sigma_\epsilon^{(0)}, \gamma_N^{(0)}\}$, where the (0) superscripts stand for *iteration (0)*. In addition, we also give arbitrary starting values to $q_{iC^k}^{(0)}$, the probability of farmer $i$ falling in adoption cost category $C^k \in \{C^H, C^L\}$. We then perform parameter iterations until the algorithm converges. The steps in each iteration and the convergence criterion are defined as follows. In ***iteration (m+1)***:

*Step 1*: perform a reduced-form flexible logit regression of LEPA adoption decision on $\pi_{it}^D$, $\pi_{it-1}^D$, $\alpha_{1i}$, $n_{it}$, time trend $t$, $C^{H(m)}$ and $C^{L(m)}$, using $q_{iC}^{(m)}$ as sampling weights. Variables other than $\pi_{it}^D$ and $n_{it}$ are also included in the regression because they are used by farmers to predict future profit gains. Using the estimated parameters, we predict $\hat{Pr}_L^{(m+1)}(\Gamma_{it+1}, C^{k(m)}, n_{it})$, the probability that farmer $i$ whose unobserved adoption costs are $C^k \in \{C^H, C^L\}$ with $n_{it}$ neighbor LEPA adopters at the beginning of year $t$ will adopt LEPA in year $t+1$.

*Step 2*: this step of CCP estimation is to update the structural parameters that maximize the likelihood function derived from the dynamic programming problem, given the predicted $Pr_L^{(m+1)}(\Gamma_{it+1}, C^{k(m)}, n_{it})$ and $q_{iC^k}^{(m)}$. Plug $Pr_L^{(m+1)}(\Gamma_{it+1}, C^{k(m)}, n_{it})$ into equation (3.21), then plug equation (3.21) into equation (3.20), we obtain the per-period likelihood of observed choices for farmer $i$ with unobserved adoption costs being $C^k$ as $l_{it}^{(m)}(d_{it}|\Gamma_{it}, n_{it}, \hat{Pr}_{Lit+1}^{(m+1)}; C_i = C^k, \sigma_\varepsilon, \gamma_N)$, which is analogues to equation (3.23) except it is augmented with $\hat{Pr}_{Lit+1}^{(m+1)}$ and $f(\Gamma_{it+1}|\Gamma_{it})$ is dropped.[1] The theoretical-consistent likelihood contribution for farmer i with unobserved adoption

[1]Take log with respect to equation (3.23), it is straightforward to see that $f(\Gamma_{it+1}|\Gamma_{it})$ is additively separable from the other parts of log likelihood function. Therefore, it does not influence the final MLE estimation. Thus, the transition rule is separately estimated in section 3.6.2.

costs being $C^k$ across all years becomes:

$$l_i^{(m)}(d_i|\Gamma_i, n_i, \hat{P}r_{Li}^{(m+1)}; C_i = C^k, \sigma_\varepsilon, \gamma_N) = \prod_{t=1}^{T_i} l_i^{(m)}(d_{it}|\Gamma_{it}, n_{it}, \hat{P}r_{Lit+1}^{(m+1)}; C_i = C^k, \sigma_\varepsilon, \gamma_N) \quad \text{(E.2)}$$

According to the $E-M$ algorithm, the structural parameters $\{C^{H(m+1)}, C^{L(m+1)}, \sigma_\varepsilon^{(m+1)}\ \gamma_N^{(m+1)}\}$ that maximize the likelihood function derived from the dynamic programming problem are found by maximizing:

$$\sum_i \sum_{C^k \in \{C^H, C^L\}} q_{iC^k}^{(m)} ln l_i^{(m)}(d_i|\Gamma_i, n_i, \hat{P}r_{Lit+1}^{(m+1)}; C_i = C^k, \sigma_\varepsilon, \gamma_N) \quad \text{(E.3)}$$

with respect to $\{C^H, C^L, \sigma_\varepsilon, \gamma_N\}$.

*Step 3*: this step updates the parameters of population-level unobserved adoption cost distribution, $\delta^{(m+1)}$, and update the probability of farmer $i$ falling in unobserved cost category $C^k$, $q_{iC^k}^{(m+1)}$. Given $\{C^{H(m+1)}, C^{L(m+1)}, \sigma_\varepsilon^{(m+1)}, \gamma_N^{(m+1)}\}$, calculate:

$$\begin{aligned} l_i^{(m)}(d_i, C_i = C^{k(m+1)}|\Gamma_i, n_i, \hat{P}r_{Lit+1}^{(m+1)}; \delta, \sigma_\varepsilon^{(m+1)}, \gamma_N^{(m+1)}) &= \tau(C^k|\Gamma_{i1}, \delta) \\ &* \prod_{t=1}^{T_i} l_i^{(m)}(d_i|\Gamma_i, \hat{P}r_{Lit+1}^{(m+1)}; C_i = C^{(m+1)}, \sigma_\varepsilon^{(m+1)}) \end{aligned} \quad \text{(E.4)}$$

Maximize the equation above with respect to $\delta$ gives $\delta^{(m+1)}$. Finally, $q_{iC^k}^{(m+1)}$ is updated as:

$$q_{iC^k}^{(m+1)} = \frac{l_i^{(m+1)}(d_i, C_i = C^{k(m+1)}|\Gamma_i, n_i, \hat{P}r_{Lit+1}^{(m)}; \delta^{(m+1)}, \sigma_\varepsilon^{(m+1)}, \gamma_N^{(m+1)})}{\sum_{C^k \in \{C^H, C^L\}} l_i^{(m+1)}(d_i, C_i = C^{k(m+1)}|\Gamma_i, n_i, \hat{P}r_{Lit+1}^{(m)}; \delta^{(m+1)}, \sigma_\varepsilon^{(m+1)}, \gamma_N^{(m+1)})} \quad \text{(E.5)}$$

The iterative inner loop and outer loop continues until function (E.3) converges.[2]

[2]Convergence is obtained if the difference between the value of function (E.3) in two consecutive iterations is less than $10^{-7}$.

## APPENDIX F

## DISCUSSION: ENDOGENEITY IN NUMBER OF NEIGHBOR LEPA ADOPTERS

In our main specification, we define neighbors are the nearest 30 wells around each well. We test whether the estimation results are sensitive to our definition of neighbors in this section. In an alternative specification, we define neighbors as the 21st-30th nearest wells around each well. In a third specification, we also define neighbors to be the nearest 30 wells around each well, but restrict that only the new adopters last year influence farmers' adoption decisions.

Total number of adopters in each year and annual new adopters predicted by the initial model and the two alternative specifications are plotted in figure F.1 (parameter estimation results are omitted here).

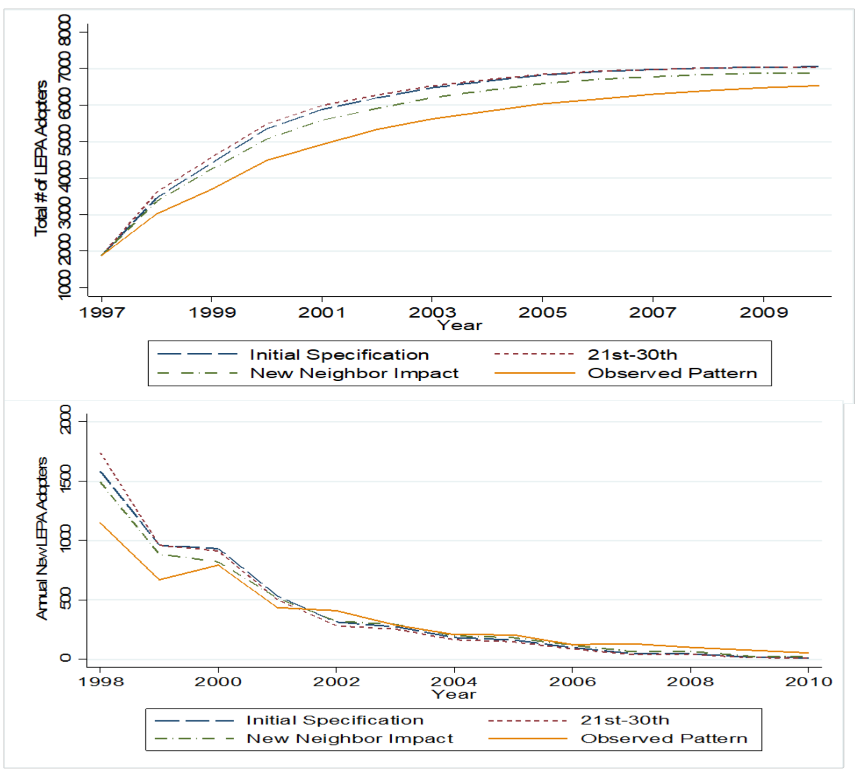
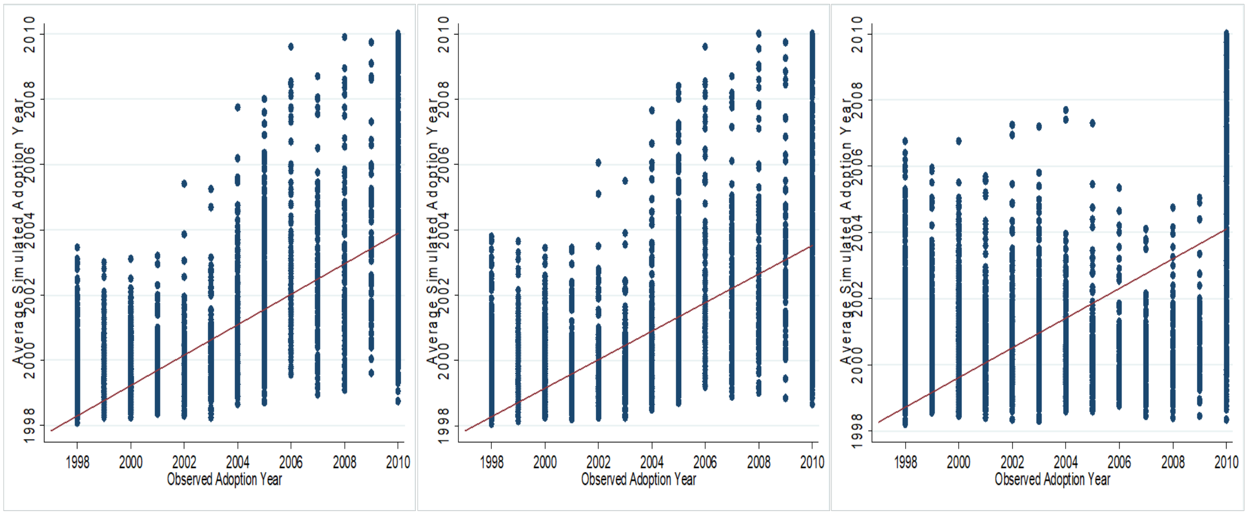



Figure F.1: Simulated v.s. Observed Number of Cumulative Adopters (upper) and New Adopters (lower)

The predicted patterns for the initial specification and the first alternative (21st-30th nearest




Initial Specification | $21^{st}$-$30^{th}$ | New Neighbor Impact

Figure F.2: Simulated Average Adoption Year v.s. Observed Adoption Year

wells as neighbors) are very similar. When we restrict that only new adopters last year influence adoption decisions, the predicted aggregate adoption path moves closer to the observed path, but the difference between this path and the previous two paths are not very large. However, shown by figure F.2, the individual farmer (or well) level adoption year predictions are much worse when only last year's new neighbor adopters are allowed to affect farmers' adoption decisions.

The comparisons above reveal that the predicted aggregate adoption pattern is insensitive to neighbor definition. However, the prediction power with respect to individual level adoption decisions is stronger when we allow all past neighbor adopters to affect farmers' adoption decisions. The results of this exercise lend support to our inclusion of total neighbor adopters in the adoption model.

## APPENDIX G

## OTHER POSSIBLE LEPA ADOPTION MODEL SPECIFICATIONS

### G.1 No Adoption Cost Heterogeneity

This section contains LEPA adoption model without considering individual heterogeneity in adoption costs. The estimation of this model is straightforward, which follows the procedure described in the first paragraph in appendix E.2. The estimation results are shown in the first column of table G.1. The estimation results of the preferred model in table 3.5 are also duplicated in the second column of table G.1 to facilitate comparison.

**Table G.1:** Ignoring Adoption Cost Heterogeneity in LEPA Adoption Model

| | **No Heterogeneity in Adoption Cost** | **Preferred Model** |
|---|---|---|
| **Adoption Cost** $C_{it} = C_i + \gamma_N n_{it}$ **($/acre)** | 503.7*** | |
| | (56.2) | |
| $C^L$ | | 74.15*** |
| | | (28.77) |
| $C^H$ | | 277.70*** |
| | | (88.72) |
| $\gamma_N$ | 20.69*** | -2.7** |
| | (4.77) | (1.3) |
| **Cost Class Probability** | | |
| $C = C^L$ | | 64% |
| $C = C^H$ | | 36% |
| **Profit Shock Scale Parameter** | | |
| $\sigma_\varepsilon$ | 66.14*** | 33.49*** |
| | (6.12) | (5.28) |
| Obs | 28081 | 28081 |

*Notes*: Bootstrapped standard errors are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Without modeling adoption cost heterogeneity, the estimated adoption costs goes to $503.7/acre, which is unreasonably high. The scale parameter of profit shock ($66.14/acre) is also much higher than the one estimated when adoption cost heterogeneity is modeled. We also estimate the adoption model by the BBL method in Bajari, Benkard, and Levin (2007) without accounting for adoption cost heterogeneity. The results (not shown here, available upon request) are consistent with those shown in column 1 here. Intuitively, If farmers all have the same adoption costs, the observable LEPA profit gain at which farmers adopt LEPA should be similar, *ceteris paribus*. If adoption cost heterogeneity presents, the observable profit gain level above which farmers adopt LEPA will be higher for farmers with high adoption costs and lower for those with low adoption costs. When such heterogeneity is not properly accounted for, a large profit gain shock dispersion is needed to justify the large dispersion of observed profit gains at which different farmers adopt LEPA. The unreasonably high adoption costs and profit shock scale parameter estimates shown in column 1 further illustrate the importance of modeling adoption cost heterogeneity.

# APPENDIX H

## PROFIT GAIN TRANSITION RULE SELECTION

Selecting a correct transition rule for profit difference is a critical step in dynamic structural estimation. This section discusses the procedures we follow to make such selection.

We fit a fixed effects linear probability model in table (H.1), where the dependent variable is whether a farmer adopts LEPA in each year, whereas the independent variables are LEPA profit gains in the current and past years. The results show that profit gains in year $t$, $t-1$ and $t-2$ all have significant impacts on LEPA adoption probability, while the influence of that in year $t-3$ becomes insignificant. According to the dynamic discrete choice problem defined by equation (3.12) to (3.15), past realizations of LEPA profit gain (i.e. $\pi^D_{it-1}, \pi^D_{it-2}, \pi^D_{it-3}$, etc) could only affect LEPA adoption probability in year $t$ through their influence on LEPA profit gain's transition rule. Therefore, possible LEPA profit gain realization in the next year should be a function of its current realization and its realizations in the past two years, which gives an AR(3) type of transition rule.

**Table H.1:** Reduced-Form Evidence on Profit Gain Transition Rule Selection

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\pi^D_{it}$ | 0.0032*** | 0.0027*** | 0.0015*** | 0.0015*** |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| $\pi^D_{it-1}$ | | 0.0016*** | 0.0016*** | 0.0012** |
| | | (0.001) | (0.001) | (0.001) |
| $\pi^D_{it-2}$ | | | 0.0018*** | 0.0023*** |
| | | | (0.001) | (0.001) |
| $\pi^D_{it-3}$ | | | | -0.0003 |
| | | | | (0.0007) |
| Farmer FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| $R^2$ | 0.1650 | 0.1623 | 0.1452 | 0.1394 |

*Notes*: Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

However, we finally select an AR(2) transition rule specified by equation (3.18) because it gives us an additional year in the estimation compared to if we choose and AR(3) rule. The first year in the dynamic estimation is 1998 if an AR(2) transition rule is selected and is 1999 if an AR(3) transition rule is selected instead. Additionally, it also reduces the dimension of the discrete choice model by one. Finally, shown by table H.2, the difference between dynamic estimation results with AR(1) and AR(2) transition rules is very large, while the difference between results with AR(2) and AR(3) transition rules is small. Therefore, the results from using the AR(2) type transition rule is reported in the main text and all the subsequent analyses are based on these results.

**Table H.2:** Estimation Results with AR(1), AR(2) and AR(3) Transition Rules

| | **AR(1)** | **AR(2)** | **AR(3)** |
|---|---|---|---|
| **Adoption Cost** $C_it = C_i + \gamma_N n_{it}$ **(\$/acre)** | | | |
| $C^L$ | -101.93*** | 74.15*** | 80.12*** |
| | (14.97) | (20.13) | (24.13) |
| $C^H$ | 431.65*** | 277.70*** | 285.78*** |
| | (61.44) | (17.77) | (14.76) |
| $\gamma_N$ | -20.36*** | -2.7*** | -2.4*** |
| | (7.34) | (1.3) | (1.3) |
| **Cost Class Probability** | | | |
| $C = C^L$ | 68% | 64% | 61% |
| $C = C^H$ | 32% | 36% | 39% |
| **Profit Shock Scale Parameter** | | | |
| $\sigma_\varepsilon$ | 241.55*** | 33.49*** | 31.45*** |
| | (97.28) | (5.28) | (5.37) |

*Notes*: Bootstrapped standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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## CHAPTER 4

## CHEAPER SOLAR, CLEANER GRID?

### 4.1 Introduction

Thanks to the declining renewable energy costs and various federal support programs, renewable energies' share of electricity generation across the U.S has more than doubled from 2007 to 2017. Texas, for example, has already reached its 2025 renewable capacity goal specified by the state's Renewable Portfolio Standard (RPS) in 2009. Although wind capacity costs are not expected to experience large changes in the near future, the decline in solar capacity costs is still strong, with a 62% decline expected in only thirty years (Augustin et al., 2018). As solar capacity costs continue declining, it is widely expected that renewable energy penetration[1] would further increase, even without stricter RPS requirements.

However, although solar capacity is expected to grow with the fast decline in its capacity costs, the overall change in renewable energy penetration also depends on how the capacity levels of other renewable resources, such as wind and energy storage, are adjusted correspondingly. If the expansion of solar capacity increases their values (i.e. solar complements wind and storage), the capacities of all renewable resources and renewable energy penetration will increase. If they are substitutes instead, increase in solar capacity will push the capacities of other renewable resources down. Consequently, the change in renewable energy penetration becomes ambiguous.

This chapter studies the relationships between solar, wind and energy storage, both analytically and empirically. I then investigate how renewable energy penetration, carbon emissions and social welfare are affected by the projected decline in solar capacity costs. I first build a three-period analytical model where wind, solar, storage and fossil-fuel energy generators compete to supply electricity (energy).[2] On the one hand, different renewable energy resources substitute each other

[1]Renewable energy penetration is defined as the share of electricity generated from renewable energy sources.
[2]Throughout the chapter, "electricity" and "energy" are used interchangeably.

because the energy supply from one resource is a perfect substitute for that from another.[3] On the other hand, they can also complement each other through influencing outputs of fossil-fuel energies. Wind and solar energies are intermittent – they are only produced when wind blows and the sun is shining. Facing almost perfectly inelastic real-time electricity demand, fossil-fuel power generators must be changing output frequently to meet the increasingly fluctuating residual demand due to renewable expansion, which imposes high output adjustment costs (i.e. ramping costs and startup costs) on these generators. Fortunately, wind and solar energy resources share complementary production patterns (Slusarewicz and Cohan, 2018). Mixing wind and solar capacities helps smoothing out aggregate renewable energy production and reducing fossil fuel generation capacities' output adjustment costs (Shaner et al., 2018; Slusarewicz and Cohan, 2018; Solomon, Kammen, and Callaway, 2016; Solomon, Faiman, and Meron, 2010). Due to the reduction in ramping costs, increasing the capacity of one renewable resource increases the value of the other. In equilibrium, whether renewable energy resources complement or substitute each other depends on the relative strengths of these two countering forces. The strength of the complementarity effect, in particular, depends on the capacity levels of different renewable energy resources, which affect fossil-fuel energy capacities' output ramping patterns. Finally, the analytical model predicts that solar complements (substitutes) wind when the level of solar capacity is relatively low (high). While storage never substitutes wind, it only complements solar when the level of solar capacity is relatively high.

A dynamic simulation model is then developed to simulate daily operation decisions of electricity generation capacities in the ERCOT electricity market. The relationships between wind, solar and storage predicted by the analytical model are all confirmed by the simulation results. The results from the operation simulation model are then combined with a stylized investment model to decide optimal wind/solar/storage capacities as well as renewable energy penetrations at different levels of solar capacity costs. Solar capacity level is low when solar capacity costs are high. At low solar levels, solar and wind are complements and solar cost reduction increases both solar capacity

[3]An exception is energy storage, it complements other resource in the period when it is charging because it demands, rather than supplies, energy.

and wind capacity, driving up renewable energy penetration. However, solar and wind become substitutes as solar costs gradually go down (and solar capacity becomes high). A decline in solar costs then increases solar capacity but decreases wind capacity. Fixing the capacity costs of wind at its long-term average,[4] renewable energy penetration first goes up from 22% to 36% when solar costs decline from the 2016 projection to the 2030 projection, and then goes down to 30% as solar costs keep declining to the 2050 projection. Correspondingly, carbon emissions first decrease by 22%, but then increase by 12.9% from the minimum point. Due to the lack of carbon policies, social welfare from renewable energy investment (i.e. benefits of energy consumption net of fossil-fuel energy generators' operation costs, renewable energy investment costs and social damage of carbon emissions) reduces by $0.57 billion/year as solar costs decrease from the 2030 projection to the 2050 projection. If, on the other hand, renewable energy penetration is not allowed to drop below 36%, the highest penetration level achieved over the range of solar capacity costs being studied, social welfare would increase by $0.77 billion/year when the capacity costs of solar drop to the 2050 projection. Thus, solar cost reduction alone does not guarantee a cleaner grid and a better off electricity market. Environmental policies are needed to reduce the unexpected consequence of solar cost decline and improve social welfare.

The simulation model also shows that it is not optimal to invest in energy storage if solar capacity costs fall in the range used in this study. However, As solar capacity costs decline from the 2016 projection to the 2050 projection, a 92.5% increase in the value of storage is observed because solar complements storage at high solar capacity levels. It is reasonable to expect that more storage capacity would be added to the grid if solar capacity costs continuous to decline after 2050, and if storage capacity costs could be driven down due to future technological improvements. As storage complements solar at high solar capacity levels, the presence of storage capacity by the time when solar capacity costs are very low would further increase renewable penetration and is likely to drive carbon emissions down.

This study is related to the literature in several ways. First, by investigating how the values of

[4]Unlike solar, the projected average capacity costs of wind is almost constant from 2016 to 2050.

wind, solar and energy storage depend on each other's capacity level, this study looks into how the expansion of one renewable resource affects optimal capacities of other renewable resources and renewable energy penetration. This is in contrast with Cullen and Reynolds (2017) and other studies that investigate how fossil-fuel energy capacities are affected by renewable energy expansions (Bushnell, 2010; Gowrisankaran, Reynolds, and Samano, 2016; Verdolini, Vona, and Popp, 2018). There is also a large literature in quantifying the marginal values of renewable energy and energy storage (emission offsets and/or production cost savings) using reduced-form econometrics techniques (Abrell, Kosch, and Rausch, 2019; Callaway, Fowlie, and McCormick, 2018; Carson and Novan, 2013; Cullen, 2013; Graff-Zivin, Kotchen, and Mansur, 2014; Kaffine, McBee, and Lieskovsky, 2013; Novan, 2015). However, none of these studies investigate the interactions of wind energy, solar energy, and energy storage, which directly affect equilibrium capacity of each renewable resource.

Second, it combines two literatures that study the effects of mixing different renewable resources on renewable energy penetration. In one literature, the share of each renewable resource in the mixture is arbitrarily chosen (Lew et al., 2013). A detailed maximization problem that determines fossil-fuel energy capacity's output is solved, taking fossil-fuel capacities' operation costs (i.e., production costs and startup costs) into consideration. The share of renewable energy output in total energy generation is then calculated. Due to the ignorance of renewable resources' investment costs, the mixture arbitrarily chosen may not be supported in an economic equilibrium. In the other literature, the share of each resource in the mixture is decided by maximizing renewable energy output while satisfying a "limited curtailment" constraint and keeping investment costs as low as possible (Shaner et al., 2018; Solomon, Kammen, and Callaway, 2016; Solomon, Faiman, and Meron, 2010). This approach, however, ignores the impact of renewable energy production on fossil-fuel energy generators' operations, which in turn affect the values of renewable energies and optimal investment. Moreover, this literature does not study how renewable penetration changes as investment costs decline. This study combines the two literatures by adopting an approach similar to that used in Cullen and Reynolds (2017), where optimal investment decisions are solved after optimal daily operation decisions for each possible renewable capacity combination are first decided based on fossil-fuel energy generators' production costs and startup costs. This exercise is then performed multiple times to decide the changes in renewable energy penetration and carbon emissions as the capacity costs of solar keep declining.

Finally, this study also fits into a growing literature that emphasizes the effects of dynamic frictions on renewable energy valuation. Comparing simulation results obtained by a dynamic simulation model that accounts for fossil-fuel energy generators' startup costs (i.e. costs incurred when a generator is started up from zero production) and a static model that does not, Cullen (2015) and Cullen and Reynolds (2017) show that ignoring startup costs significantly overestimates the value of wind energy because the intermittency of wind increases fossil-fuel energy generators' total startup costs. Similar arguments have also been made in several other studies (Eser et al., 2016; Kopiske, Spieker, and Tsatsaronis, 2017; Milligan and Kirby, 2009). I extend this literature by showing both analytically and empirically that startup costs not only affect the values of renewable resources themselves, but also influence the effect of one renewable resource on the value of another. In a similar study, Castro (2018) looks into the interaction of wind energy and energy storage with a simulation model, but ignores startup costs in the analysis. Without startup costs, the simulated relationships between wind, solar and storage capacities would be biased. For example, aggregate renewable energy output smoothing through mixing wind and solar energies is not valuable anymore because fossil-fuel energy capacities' output changes are costless. Consequently, the degree of substitution between wind and solar would be overestimated due to the loss of this complementarity effect.

The rest of the paper is organized as follows. A three-period model is analyzed in section 4.2 to show why and how the values of wind energy, solar energy and energy storage depend on each other's capacity when fossil-fuel energy generators' output adjustment costs are considered. Section 4.3 presents the details of the daily dynamic simulation model used to empirically quantity the interactions between different renewable resources and energy storage. The stylized investment model that determines renewable energy penetrations under different solar capacity costs is also presented. Section 4.4 shows the data and procedure used to calibrate the simulation model. Model validation results are shown in chapter 4.5. Section 4.6 shows and discusses the implications of the simulation results. Finally, section 4.7 concludes the paper and proposes several future research directions.

## 4.2 Analytical Model: Value Dependence

In this section, I analyze why and how do the values of wind, solar and energy storage depend on each other in a multi-period daily operation model. I first lay out demand and supply in the electricity market. Then, social planner's problem regarding electricity generation in each period, facing given levels wind, solar, storage and fossil-fuel energy capacities, is presented. Values of wind energy, solar energy and energy storage are then derived from the value function associated with the social planner's optimal operation decisions. Based on the previous two steps, I analyze complementarity/substitution relationships among wind energy, solar energy and energy storage.

### 4.2.1 Daily Operation Model Setup

In the market, there is one wind turbine with capacity $k_w$, one solar PV with capacity $k_{so}$, and a battery storage with capacity $k_s$. For simplicity, I assume that there is only one type of fossil-fuel power generation technology with unlimited capacity.

Given these capacity levels, a social planner maximize the payoff from electricity production and consumption in a representative day, which is divided into three periods ($t = 1, 2, 3$). For each $t \in \{1, 2, 3\}$, benefit from electricity consumption is a concave function of total electricity production, $B_t(Q_t)$. Demand is given by a downward-sloping linear function $p_t(Q_t) = B'_t(Q_t) = a_t - bQ_t$, where $b > 0$. Wind and solar energy outputs in period $t$ are $\alpha_t^w k_w$ and $\alpha_t^{so} k_{so}$, where $\alpha_t^w$ and $\alpha_t^{so}$ are wind and solar energy capacity factors that are exogenously given. In contrast, energy storage is charged during period(s) when price(s) is(are) low, and is discharged during period(s) when price(s) is(are) high.

In the representative day, period 1 corresponds to early morning period (4:00am to 9:00am), where electricity demand is low, wind energy production is high, and solar energy is not being produced. Period 2 corresponds to mainly daytime hours (9:00am to 18:00pm), when both electricity demand and solar energy production are high, but wind energy production is low. Finally, period 3 corresponds to late afternoon and early night hours (18:00pm to 22:00pm), when solar energy generation quickly drops to zero, but wind energy production and demand remain largely unchanged. Given this, it is assumed that $a_1 < a_2 = a_3$, $\alpha_1^w > \alpha_2^w = \alpha_3^w > 0$ and $\alpha_2^{so} > \alpha_1^{so} = \alpha_3^{so} = 0$, respectively.

Renewable energy generation does not incur any costs, but fossil-fuel energy production is costly. The total fossil-fuel energy generation costs summed across all periods is:

$$C(q_1, q_2, \ldots, q_T) = \sum_{t=1}^{T} C_P(q_t) + \sum_{t=2}^{T} \tilde{C}_r(q_t - q_{t-1}), \tag{4.1}$$

where $C_P(q_t)$ represents production costs and $\tilde{C}_r(q_t - q_{t-1})$ represents intertemporal output adjustment costs (or ramping costs), which has the following form:

$$\tilde{C}(x) = \begin{cases} 0, & x < 0 \\ C_r(x), & x \geq 0 \end{cases}, \tag{4.2}$$

where $C_P(.)$ and $C_r(.)$ are assumed to be convex, increasing and quadratic functions (i.e. $C_P' > 0, C_r' > 0$, $C_P'' = constant > 0$ and $C_r'' = constant > 0$). The form of the outcome adjustment costs implies that the production technology favors small positive (or no/negative) intertemporal output changes than large ones. Further, I assume $C_r'(0) > 0$, which implies that increasing output from the previous period is not always profitable for fossil-fuel power generators, even if price in the current period is relatively high.

### 4.2.2 Social Planner's Operation Decision and Values of Wind, Solar and Storage

The social planner's daily operation problem is to choose energy production from fossil-fuel energy capacities and energy storage to maximize the surplus from electricity production and consumption:

$$max_{q_1,q_2,q_3,s_1,s_2,s_3} \sum_{t=1}^{3} B_t(Q_t) - C(q_1, q_2, q_3). \tag{4.3}$$

subject to:

$$Q_t = q_t + E_t, \tag{4.4}$$

where $s_t$ is energy supply from storage in period $t$ and $E_t = \alpha_t^w k_w + \alpha_t^{so} k_{so} + s_t$ is the aggregate energy output from non-fossil energy sources. For the ease of explanation, define energy storage's capacity factor in each period as $\alpha_t^s = \frac{\partial s_t^*}{\partial k_s}$. Finally, carbon emission costs are not included in (4.3) because no carbon taxes (or other carbon polices) exit in ERCOT, the study region of the empirical model presented later.

The optimized value of (4.3) is the value function associated with the social planner's optimal operation decisions. Denote this value by $V(k_w, k_{so}, k_s)$. The value of type $i \in \{w, so, s\}$ capacity is $V_{k_i}$ and the effect of type $j$ capacity on the value of type $i$ is $V_{k_i k_j}$.[5] The focus of the analytical analysis is to sign $V_{k_i k_j}$, for $i, j \in \{w, so, s\}$ and $i \neq j$.

Both $V_{k_i}$ and $V_{k_i k_j}$ could be obtained after the social planner's problem defined by (4.3) and (4.4) is solved. Analytically solving this maximization problem is complicated by the kink at $q_t = q_{t-1}$ in $C(q_1, q_2, q_3)$ specified in (4.1) and (4.2). Thus, solving the social planner's problem requires an ordering of $q_1^*, q_2^*$ and $q_3^*$.[6] This ordering, in particular, changes with varying levels of renewable energy/energy storage capacity. Many possible orderings exist, at least in theory.

Fortunately, $q_1^* < q_3^*$ and $q_2^* < q_3^*$ hold in almost all situations according to the later empirical simulation results. Therefore, I only focus on the cases where these two inequalities are satisfied in the following analytical analysis. So, we are left with four quantity orderings: (1) $q_1^* < q_2^* < q_3^*$, (2) $q_1^* < q_2^* = q_3^*$, (3) $q_1^* = q_2^* < q_3^*$ and (4) $q_1^* > q_2^*$, $q_1^* < q_3^*$. As solar energy produces only in period 2, the magnitude of $q_2^*$ is largely driven by the amount of solar capacity.

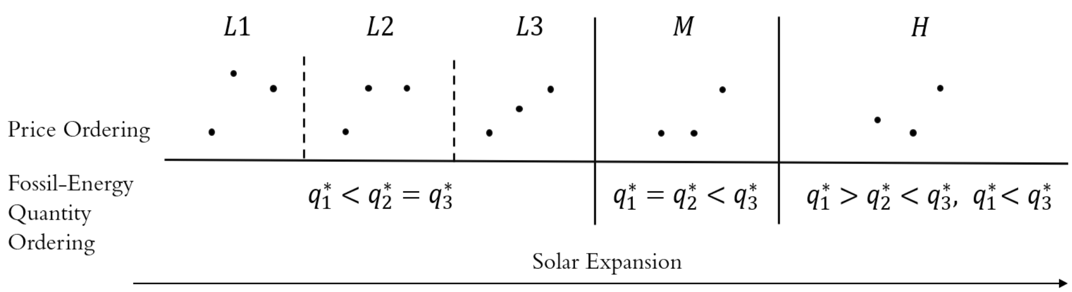
As discussed earlier, the operation of energy storage depends critically on the electricity price in each period. Similar to the quantity orderings, there are also many possible price orderings. However, $p_3 > p_1$ happens in almost all situations according to the later empirical simulation results. Therefore, I only focus on the cases where this inequality is satisfied. Now, price ordering

[5] Notationally, $V_{k_i} = \frac{\partial V}{\partial k_i}$ and $V_{k_i k_j} = \frac{\partial^2 V}{\partial k_i \partial k_j}$.

[6] The "*" superscript means "optimal choice".

depends only on the magnitude of $p_2$ relative to $p_1$ and $p_3$. Consequently, we are left with the same set of five price orderings for each quantity ordering. Namely, $p_1 < p_2 > p_3$, $p_1 < p_2 = p_3$, $p_1 < p_2 < p_3$, $p_1 = p_2 < p_3$ and $p_1 > p_2 < p_3$.

However, only the quantity-price orderings shown in figure 4.1 happen frequently in the empirical simulation defined later in section 4.3 using model parameters that are calibrated to fit the real ERCOT power system. Since demand in period two is higher than that in period one and solar energy produces only in period two, a relatively large solar capacity is needed to drive $p_2$ drop below $p_1$. But this also tends to push $q_2^*$ below $q_1^*$. Therefore, $p_1 \geq p_2$ is very unlikely to happen if $q_1^* < q_2^*$. Similarly, to keep $p_2$ above $p_1$, the amount of solar capacity must not be too high, which makes $q_1^* > q_2^*$ difficult to achieve. Therefore, $p_1 < p_2$ is also unlikely to happen if $q_1^* \geq q_2^*$.




*Note: In each possible price ordering, the first, second and third dots represent prices in period one, two and three, respectively. The height of the dots represents corresponding price levels.*

Figure 4.1: Quantity-Price Orderings in the Analytical Model

In the subsequent analytical analysis, I only focus on quantity-price ordering combinations denoted as $L_1$, $L_2$, $L_3$ and $H$ in figure 4.1. As solar capacity is an important determinant of which combination happens in equilibrium, I refer to these combinations as the *low-low solar*, *low-medium solar*, *low-high solar*, and *high solar* scenarios, respectively.[7] Since scenarios $L_1, L_2$ and $L_3$ share the same quantity ordering $q_1^* < q_2^* = q_3^*$, I denote the union of these three scenarios as $L = \{L_1, L_2, L_3\}$, and refer to it as *low solar scenarios*.

The mechanism that drives the relationships between wind, solar and storage under scenario

[7]Alternatively, I can also analytically solve out the conditions under which each of the twenty cases happen (five price orderings for four quantity orderings), which is straightforward but tedious because they depend on the (nonlinear) relationships between all model parameters.

$M$ (i.e. the *medium solar* scenario) is similar to that under scenario $L_2$ (i.e. the *low-medium solar* scenario). Therefore, I will simply mention the results under this scenario in the analytical analysis, without providing detailed discussions. Ignoring other quantity-price orderings would barely affect the analysis results because they are unlikely to happen under the model parameters that are calibrated to fit the real ERCOT power system.

### 4.2.3 Value Dependence: Solar Capacity, Wind Capacity and Energy Storage

Under all five scenarios, the value of type $i \in \{w, so, st\}$ capacity is (derivations are in appendix I.1):

$$V_{k_i} = \frac{\partial V}{\partial k_i} = p_1(Q_1^*)\alpha_1^i + p_2(Q_2^*)\alpha_2^i + p_3(Q_3^*)\alpha_3^i \tag{4.5}$$

The value of an additional unit of type $i$ capacity equals to the summation of its marginal revenue products across all periods, which is consistent with the results obtained in Carson and Novan (2013) and Castro (2018).

Given (4.5), the effect of capacity $j$ on the value of capacity $i$ depends on capacity $i$'s production pattern as well as the effect of capacity $j$ expansion on each period's equilibrium electricity price through its influence on total energy output in each period:

$$\begin{aligned} V_{k_i k_j} &= \alpha_1^i p_1'(.)\frac{\partial Q_1^*}{\partial k_j} + \alpha_2^i p_2'(.)\frac{\partial Q_2^*}{\partial k_j} + \alpha_3^i p_3'(.)\frac{\partial Q_3^*}{\partial k_j} \\ &= -b\alpha_1^i(\frac{\partial Q_1^*}{\partial E_1}e_1^j + \frac{\partial Q_1^*}{\partial E_2}e_2^j + \frac{\partial Q_1^*}{\partial E_3}e_3^j) \\ &\quad - b\alpha_2^i(\frac{\partial Q_2^*}{\partial E_1}e_1^j + \frac{\partial Q_2^*}{\partial E_2}e_2^j + \frac{\partial Q_2^*}{\partial E_3}e_3^j) \\ &\quad - b\alpha_3^i(\frac{\partial Q_3^*}{\partial E_1}e_1^j + \frac{\partial Q_3^*}{\partial E_2}e_2^j + \frac{\partial Q_3^*}{\partial E_3}e_3^j) \end{aligned}, \tag{4.6}$$

where the terms in the parentheses in (4.6) represent changes in period $t$ total electricity output as a response of changes in non-fossil fuel energy output ($e_t^j$) in all four periods due to type $j$ capacity expansion. In other words, the effect of type $j$ capacity on the value of type $i$ capacity is simply the weighted average of each period's price level change brought by type $j$ capacity expansion, where the weights are type $i$ capacity's capacity factors in different periods.

From (4.6), the relationship between type $i$ and type $j$ capacity depends critically on (i) how non-fossil fuel energy output in each period is affected by wind/solar/storage capacity expansion (i.e. $e_t^j$), and (ii) how total energy output in each period is affected by changes in non-fossil fuel energy supply in that period and other periods (i.e. $\frac{\partial Q_t^*}{\partial E_\tau}$, for $t, \tau \in \{1, 2, 3\}$). Detailed discussions regarding these two key factors are provided next.

#### 4.2.3.1 $e_t^j$ and $\frac{\partial Q_t^*}{\partial E_\tau}$ Under Different Scenarios

Define the effect of increasing wind/solar/storage capacity on non-fossil fuel energy output in each period as:

$$e_t^j = \frac{\partial E_t^*}{\partial k_j} = \frac{\partial \alpha_t^w k_w + \partial \alpha_t^{so} k_{so} + \partial s_t^*}{\partial k_j}. \tag{4.7}$$

Energies produced from wind and solar energy capacities are exogenous, so the key determinant of $e_t^j$ is how storage operation is changed facing wind/solar/storage capacity expansion. Table 4.1 shows the values of $e_t^j$ under different scenarios.

**Table 4.1:** Effects of Increasing Wind/Solar/Storage Capacity on $E_t$ Under Each Scenario

| | | $e_1^j$ | $e_2^j$ | $e_3^j$ |
|---|---|---|---|---|
| $L_1$ | $j = w$ | $\bar{\alpha}^w$ | $\underline{\alpha}^w$ | $\underline{\alpha}^w$ |
| | $j = so$ | 0 | $\alpha_2^{so}$ | 0 |
| | $j = s$ | -1 | 1 | 0 |
| $L_2$ | $j = w$ | $\bar{\alpha}^w$ | $\underline{\alpha}^w$ | $\underline{\alpha}^w$ |
| | $j = so$ | 0 | $\alpha_2^{so}/2$ | $\alpha_2^{so}/2$ |
| | $j = s$ | -1 | 1/2 | 1/2 |
| $L_3$ | $j = w$ | $\bar{\alpha}^w$ | $\underline{\alpha}^w$ | $\underline{\alpha}^w$ |
| | $j = so$ | 0 | $\alpha_2^{so}$ | 0 |
| | $j = s$ | -1 | 0 | 1 |
| $H$ | $j = w$ | $\bar{\alpha}^w$ | $\underline{\alpha}^w$ | $\underline{\alpha}^w$ |
| | $j = so$ | 0 | $\alpha_2^{so}$ | 0 |
| | $j = s$ | 0 | -1 | 1 |

Under scenario $L_1$, $p_1 < p_2$ and $p_2 > p_3$. The strictly positive price gap between period two and one implies that storage is fully charged in the first period and fully discharged in the second period.

When wind/solar/storage capacity is marginally increased, this price gap persists and storage still fully charges in period one and fully discharges in period two. Thus, energy supply from storage is not affected by changes in wind and solar capacities. Consequently, one unit increase in wind/solar capacity increases non-fossil fuel energy supply by its capacity factor in each period. Similarly, one unit increase in storage capacity decreases non-fossil fuel energy supply by one unit in the period when it is charging and increases that by one unit in the period when it is discharging. Similar arguments apply to scenarios $L_2$ and $H$, where storage is fully charged in one period and fully discharged in another.

However, $p_1 < p_2 = p_3$ under scenario $L_2$. Thus, storage is fully charge in period one. However, storage must be discharging in both period two and three as $p_2 = p_3$. If storage discharges in only one of these two periods, marginal profit of discharging (i.e. price) in that period must be higher than that in the other period. The non-arbitrage condition $p_2 = p_3$ solves optimal discharge amount in both periods $s_2^* = \frac{a_2 - a_3 - b\alpha_2^{so} k_{so} + bk_s}{2b}$ and $s_3^* = k_s - s_2^*$. The values in table 4.1 under scenario $L_2$ then follows.

Note that $s_2^*$ does not depend on wind capacity because wind production levels are the same in period two and three. Thus, a change in wind capacity would not lead to price imbalance between these two periods. Similarly, $s_2^*$ is also independent of fossil-fuel production[8] because $q_2^* = q_3^*$ under all *low solar* scenarios.

The next building block of this study is presented in theorem 1, which establishes the effects of increasing $E_t$ on electricity outputs in all three periods. Increasing non-fossil energy supply in one period substitutes (i.e decreases) fossil-fuel energy supply in that period. Without ramping costs, there are no dynamic linkages between any two consecutive periods. Therefore, total energy output in any other period is not affected when $E_t$ changes. However, when ramping costs present, energy output in other periods are also affected through the changes in fossil-fuel energy capacity's output.

**Theorem 1:** ***Intertemporal Electricity Generation Dependence***

*(I)* ***Own-Period Effects****: under both low and high solar scenarios, increase in non-fossil fuel*

[8]Judged by the fact that the expression of $s_2^*$ does not include any fossil-fuel energy capacity's cost parameters

*energy supply in any period decreases equilibrium fossil-fuel energy generation in that period, but increases total energy generation in that period, i.e.,* $\frac{\partial q_t^*}{\partial E_t} < 0, \frac{\partial Q_t^*}{\partial E_t} > 0$.

*(II)* ***Cross-Period Effects****:*

*(a) Low Solar Scenarios: Increase in non-fossil fuel energy supply in any period decreases equilibrium fossil-fuel and total energy generation in all other periods, i.e.,* $\frac{\partial q_t^*}{\partial E_\tau} < 0$ *and* $\frac{\partial Q_t^*}{\partial E_\tau} < 0$*, for* $t, \tau \in \{1,2,3\}, \&\ t \neq \tau$.

*(b) High Solar Scenario: Increase in* $E_2$ *(*$E_3$*) decreases equilibrium fossil-fuel and total energy supply in period three (two), but has no effect on period one, i.e.,* $\frac{\partial q_t^*}{\partial E_\tau} < 0$, $\frac{\partial Q_t^*}{\partial E_\tau} < 0$, $\frac{\partial q_1^*}{\partial E_\tau} < 0$ *and* $\frac{\partial Q_1^*}{\partial E_\tau} < 0$ *for* $t, \tau \in \{2,3\} \&\ t \neq \tau$.

*(III)* ***Cross-Period Attenuation****:* $|\frac{\partial Q_{t-1}^*}{\partial E_t}| \cdots > |\frac{\partial Q_{t-m}^*}{\partial E_t}|$, *and* $|\frac{\partial Q_{t+1}^*}{\partial E_t}| \cdots > |\frac{\partial Q_{t+m}^*}{\partial E_t}|$ *under all scenarios.*

*(IV)* ***Symmetry****:* $\frac{\partial Q_t^*}{\partial E_\tau} = \frac{\partial Q_\tau^*}{\partial E_t}$ *for* $t, \tau \in \{1,2,3\}$ *under all scenarios.*

*(V)* ***Total Generation Neutrality****: Under both low and high solar scenarios, the effect of an increase in non-fossil fuel energy output in any period on total electricity generations summed over all three periods are the same, i.e.,* $\frac{\partial [Q_1^* + Q_2^* + Q_3^*]}{\partial E_t} \equiv M$ *for* $t \in \{1,2,3\}$*, where* $M = \frac{C_P''}{b + C_P''} > 0$.

*(VI)* ***Middle-Period Effects Comparison****:*

*(a) The own-period effect for period two is higher under low solar scenarios than under the high solar scenario, i.e.,* $\frac{\partial Q_2^{*L}}{\partial E_2} > \frac{\partial Q_2^{*H}}{\partial E_2}$.

*(b) Under low solar scenarios,* $|\frac{\partial Q_1^{*L}}{\partial E_2}| < |\frac{\partial Q_3^{*L}}{\partial E_2}|$.

In what follows, I illustrate the intuition of the theorem. Formal derivations of the quantities shown in the theorem is moved to appendix I.2.

First, an increase in $E_t$ reduces residual demand facing fossil-fuel energy generators in period $t$, pushing $q_t^*$ downward. But total energy output $Q_t^*$ is increased because increase in $E_t$ raises total period $t$ supply.

Second, upward ramping is costly but downward ramping is costless. When $q_t^* > q_{t-1}^*$, decreasing $q_{t-1}$ raises the marginal cost of production in period $t$ through increased ramping. As $E_{t-1}$ expansion reduces $q_{t-1}^*$, $q_t^*$ is also reduced. Similarly, decreasing $q_t$ increases the opportunity cost to keep period $t-1$ power generation high to avoid upward ramping cost. As $E_t$ expansion reduces $q_t^*$, $q_{t-1}^*$ is also reduced. This argument only applies to the transition from period two to period three under the *high solar* scenario because only this transition represents an upward ramping process. Under *low solar* scenarios, a upward ramping from period one to period two also presents, so the argument above also follows for this transition. Although $q_2^{*L} = q_3^{*L}$ (i.e. no upward ramping presents), this equality would not be would not be violated by marginally changing $q_2^*$.[9] As increasing $E_2(E_3)$ decreases $q_2^*(q_3^*)$, $q_3^*(q_2^*)$ would also be decreased.

Going from fossil-fuel electricity generation ($q_t$) to total electricity generation ($Q_t$) is straightforward since $E_\tau$ only affects $Q_t^*$ for $t \neq \tau$ through affecting fossil-fuel electricity generation in period $t$.

Third, "cross-period attenuation" emerges because $E_t$ only has direct effect on its own period and the periods next to/prior to period $t$. Intuitively, each period is a "buffer" for the next/previous period with respect to a change in $E_t$.

Fourth, "symmetry" and "total generation neutrality" emerges due to the assumption that the marginal ramping cost function $C_r'(\cdot)$ depends solely on fossil-fuel energy generation difference in consecutive periods (i.e. $q_{t+1} - q_t$). One implication of the "total generation neutrality" property is that the positive own-period effect dominates the summation of all (or every single) negative cross-period effects.

Fifth, decrease in $q_2$ (i.e. $E_2$ expansion) only increases the marginal cost of increasing $q_3$ under the *high solar* scenario. However, under *low solar* scenarios, this will increase explicit/implicit cost of production in both period one and three: $q_2$ decline increases the opportunity cost to keep period one power generation high. Meanwhile, since $q_2^* = q_3^*$ still holds when $q_2^*$ is marginally changed, decreasing $q_2^*$ will also decrease $q_3^*$, which decreases period three profit.[10] This is an implicit cost

[9]For more details on this point, please refer to the discussion of (I.2) in appendix I.1

[10]This argument is a direct implication of I.2 in appendix I.1

of reducing $q_2$. Since reduction in $q_2$ affects more periods under the *low solar* scenarios, one unit increase in $E_2$ would lead to less $q_2$ reduction under these scenarios, which means the increase in total electricity output in period two is larger.

Finally, reduction in $q_2^{*L}$ leads to an increase in the opportunity cost of keeping $q_1^L$ high, which shifts period one fossil-fuel energy capacity's marginal cost curve to the left. As the cost function (i.e. production cost+ramping cost) is concave, one unit increase in marginal cost function results in less than one unit decrease in $q_1^{*L}$. In contrast, $q_2^{*L} = q_3^{*L}$ still holds by marginally changing $E_2$, as discussed earlier. Thus, one unit reduction in $q_2^{*L}$ results in one unit reduction in $q_3^{*L}$. Part (b) in theorem 1 (IV) then follows.

Given theorem 1, I analyze wind-solar, solar-storage, and wind-storage relationships in sequence. Specifically, I show that the these relationships are different under the *low solar* and *high solar* scenarios.

#### 4.2.3.2 Relationship Between Wind and Solar Energy Capacities

The relationship between wind and solar energy capacities is characterized by $V_{k_w k_{so}}$, i.e., the effect of increasing solar energy capacity on the value of wind energy capacity. Given $e_t^{so}$ in table 4.1, $V_{k_w k_{so}}$ under scenarios $L_1, L_3$ and $H$ becomes:

$$\begin{aligned} V^n_{k_w k_{so}} &= -b\bar{\alpha}^w(\frac{\partial Q_1^{*n}}{\partial E_2}\alpha_2^{so}) - b\underline{\alpha}^w(\frac{\partial Q_2^{*n}}{\partial E_2}\alpha_2^{so}) - b\underline{\alpha}^w(\frac{\partial Q_3^{*n}}{\partial E_2}\alpha_2^{so}) \\ &= -b\bar{\alpha}^w\alpha_2^{so}\frac{\partial Q_1^{*n}}{\partial E_2} - b\underline{\alpha}^w\alpha_2^{so}\left[\frac{\partial Q_2^{*n}}{\partial E_2} + \frac{\partial Q_3^{*n}}{\partial E_2}\right] \\ &= -b\bar{\alpha}^w\alpha_2^{so}\underbrace{\frac{\partial Q_1^{*n}}{\partial E_2}}_{L:(-);H:(0)} - b\underline{\alpha}^w\alpha_2^{so}\underbrace{\left[M - \frac{\partial Q_1^{*n}}{\partial E_2}\right]}_{(+)}, \quad \text{for } n \in \{L_1, L_3, H\}, \end{aligned} \tag{4.8}$$

where $\alpha_1^w = \bar{\alpha}^w > \underline{\alpha}^w = \alpha_2^w = \alpha_3^w$.

Increasing solar capacity increases non-fossil fuel energy supply in period two. Thus, total electricity output in period two increases due to the "own-period effect". Meanwhile, total electricity output in period three is reduced due to the "cross-period effect" under all three scenarios. Consequently, period two price decreases and period three price increases.

Since the positive own-period effects dominates the summation of all (or every single) negative cross-period effects (an implication of "total generation neutrality" property), the overall price (output) change in period two and three is negative (positive). As wind energy output are the same in these period two and three, the net effect of solar expansion on wind energy production in these two periods is negative.

Under the *high solar* scenario ($H$), solar expansion in period two has no effect on output(price) in period one (i.e. $\frac{\partial Q_1^{*s}}{\partial E_2} = 0$). Thus, the overall effect of solar capacity on the value of wind capacity is negative, which means solar and wind energy capacities are substitutes.

However, solar expansion raises period one price and thus the value of wind energy output in that period under scenarios $L_1$ and $L_3$ due to the "cross-period effect". Although the summation of price (output) changes across all three periods is negative (positive), the fact that wind energy production is higher in period one than in the other two periods makes the sign of (4.8) undetermined.

The value of $V_{k_w k_{so}}$ under scenario $L_2$ is exactly the same as those under scenarios $L_1$ and $L_3$. Note that $V_{k_w k_{so}}$ is exactly the same as $V_{k_{so} k_w}$, the influence of wind capacity on the value of solar. According to table 4.1, increasing wind capacity would not affect storage energy supply under all *low solar* scenarios (i.e. $L_1, L_2, L_3$). Thus, the effects of wind energy capacity on the value of solar energy capacity are the same under all three *low solar* scenarios.

Finally, it could also be shown that wind and solar energy capacities substitute each other under the *medium solar* scenario ($M$). The derivation is similar to the derivations above, so it is omitted in this chapter to save space. The relationship between wind and solar capacities in summarized in proposition 1:

**Proposition 1:** *Wind energy capacity and solar energy capacity are likely to be complements under low solar scenarios, but they become substitutes for sure under medium solar and high solar scenarios.*

Intuitively, wind energy and solar energy production overlaps in certain periods across a day. In this sense, wind and solar are substitutes. One the other hand, wind energy and solar energy production are volatile (i.e., intermittent), but their production patterns always complement each other. Therefore, combining these two energy sources in the electricity grid would smooth out renewable energy production across a day, which reduces fossil-fuel energy sources' ramping (i.e., output changes). This smoothing effect is valuable when fossil-fuel energy capacity is ramping up because upward-ramping is costly. In this sense, wind and solar are complements. The degree of complementarity depends on the duration of upward-ramping. When solar capacity is low, the duration of upward-ramping is three, which drops to two when solar energy is high. Thus, as solar energy increases, the degree of complementarity drops but the degree of substitution keeps constant. Finally, wind and solar energies become absolute substitutes at high levels of solar energy capacity.

Also note that if ramping is costless, the value of renewable energy smoothing disappears. In such case, wind and solar energies are always substitutes under all possible scenarios. The degree of substitution between wind and solar would also be overestimated due to the loss of the complementarity effect.

#### 4.2.3.3 Relationship Between Solar Energy Capacity and Energy Storage

The relationship between solar energy and energy storage capacities is characterized by $V_{k_{so}k_s}$, i.e., the effect of increasing storage capacity on the value of solar energy capacity. Under the *low-low solar* scenario, storage is fully charged in period one and fully discharged in period two. With this operation pattern, $V_{k_{so}k_s}$ under the *low-low solar* scenario becomes:

$$V^{L_1}_{k_{so}k_s} = -b\alpha_2^{so} \underbrace{\left[ -\frac{\partial Q_2^{*L}}{\partial E_1} + \frac{\partial Q_2^{*L}}{\partial E_2} \right]}_{(+)} < 0, \tag{4.9}$$

Storage capacity expansion increases storage discharging (thus non-fossil fuel energy supply) in period two, which increases period two total energy output through the "own-period effect".

Storage charging in period one is also increased, which equivalent to a reduction in period one non-fossil fuel energy supply, which increases period two total energy output through the "cross-period effect". Since both forces raise period two total energy output, period two price decreases and the value of solar energy capacity is reduced as solar energy is only produced in period two. Thus, solar and storage are substitutes under the *low-low solar* scenario.

Under the *low-medium solar* scenario, storage charges fully in period one, but discharge a portion of stored energy in period two and the remaining energy in period three. $V_{k_{so}k_s}$ becomes:

$$
\begin{aligned}
V^{L_2}_{k_{so}k_s} &= -b\alpha_2^{so}\left[\underbrace{-\frac{\partial Q_2^{*L}}{\partial E_1}}_{(+)} + \frac{1}{2}\underbrace{\frac{\partial Q_2^{*L}}{\partial E_2}}_{(+)} + \underbrace{\frac{1}{2}\frac{\partial Q_2^{*L}}{\partial E_3}}_{(-)}\right] = -b\alpha_2^{so}\left[-\frac{\partial Q_2^{*L}}{\partial E_1} + \frac{1}{2}\left(\frac{\partial Q_2^{*L}}{\partial E_2} + \frac{\partial Q_3^{*L}}{\partial E_2}\right)\right] \\
&= -b\alpha_2^{so}\left[-\frac{\partial Q_2^{*L}}{\partial E_1} + \frac{1}{2}\left(M - \frac{\partial Q_1^{*L}}{\partial E_2}\right)\right] < 0,
\end{aligned}
\tag{4.10}
$$

where the second equality follows the "symmetry" property (theorem 1 (IV)). Similar to scenario $L_1$, increased charging in period one increases (decreases) period two total energy output (price). However, the additional one unit charging is evenly spread to period two and three, which increases and decreases period two total energy output, respectively. But own-period effects dominate the cross-period effect according to theorem 1 (V). Thus, increased discharging brought by storage expansion increases period two total energy output. Combining the influence of additional charging and discharging, period two electricity price falls and the value of solar energy capacity declines.

Under the *low-high solar* scenario, storage charges fully in period one, and is fully discharged in period three. $V_{k_{so}k_s}$ becomes:

$$
V^{L_3}_{k_{so}k_s} = -b\alpha_2^{so}\left[-\frac{\partial Q_2^{*L}}{\partial E_1} + \frac{\partial Q_2^{*L}}{\partial E_3}\right] = -b\alpha_2^{so}\underbrace{\left[-\frac{\partial Q_2^{*L}}{\partial E_1} + \frac{\partial Q_3^{*L}}{\partial E_2}\right]}_{(-)} > 0,
\tag{4.11}
$$

The additional discharging in period three now decreases period two total electricity output. According to theorem 1 (IV) and (VI) (b), this decrease dominates the output increase brought by additional charging in period one. Therefore, price in period two increases and storage complements solar capacity under this scenario.

Under the *high solar* scenario, storage is fully charged in period two and fully discharged in period three. With this operation pattern, $V_{k_{so}k_s}$ under the *high solar* scenario becomes:

$$V^H_{k_{so}k_s} = -b\alpha_2^{so} \underbrace{\left[ -\frac{\partial Q_2^{*H}}{\partial E_2} + \frac{\partial Q_2^{*H}}{\partial E_3} \right]}_{(-)} > 0 \tag{4.12}$$

Both the additional charging in period two and additional discharging in period three decrease price level in period two. The resulting increase in period two electricity price raises the value of solar energy under this scenario.

Finally, solar energy and energy storage capacities also complement each other under the *medium solar* scenario ($M$). Again, the derivation is similar to the derivations above and is omitted to save space.

The relationship between solar energy and energy storage is summarized in proposition 2:

**Proposition 2:** *Solar energy and energy storage are substitutes when the amount of solar capacity is low and become complements as solar capacity keeps increasing.*

The argument in the last section also applies here to help understand the intuition behind the change in the relationship between solar energy and storage. When solar capacity is very low, energy supply patterns of storage and solar energy are very similar, are overlapped and do not smooth each other. Thus, solar and storage are substitutes. As solar capacity increases, solar and storage energy supplies become less overlapped and starts to smooth each other's variation. Thus, the two energy sources gradually become complements.

#### 4.2.3.4 Relationship Between Wind Energy and Storage

The relationship between wind energy and energy storage capacities is characterized by $V_{k_wk_s}$, i.e., the effect of increasing storage capacity on the value of wind energy capacity.

Increasing storage capacity by one unit results in both a one-unit decrease and a one-unit increase in non-fossil fuel energy supply through the charging and discharging cycle, although the increase and decrease happen in different periods. Due to the "total generation neutrality" property, storage expansion would not change the summation of total electricity output across all three periods.

Under all *low solar* scenarios, storage is fully charged in period one. The only difference among the three *low solar* scenarios is the period in which the storage discharges, which then affects $e_t^s$. In general, $V_{k_w k_s}$ under all *low solar* scenarios shares the same form:

$$\begin{aligned} V^n_{k_w k_s} &= -b\bar{\alpha}^w\left[-\frac{\partial Q_1^{*L}}{\partial E_1}+\frac{\partial Q_1^{*L}}{\partial E_2}\right]-b\underline{\alpha}^w\left[-\frac{\partial Q_2^{*L}}{\partial E_1}*e_1^{sn}+\frac{\partial Q_2^{*L}}{\partial E_2}*e_2^{sn}+\frac{\partial Q_2^{*L}}{\partial E_3}*e_3^{sn}\right] \\ &\quad -b\underline{\alpha}^w\left[-\frac{\partial Q_3^{*L}}{\partial E_1}*e_1^{sn}+\frac{\partial Q_3^{*L}}{\partial E_2}*e_2^{sn}+\frac{\partial Q_3^{*L}}{\partial E_3}*e_3^{sn}\right] \\ &= -b\bar{\alpha}^w\underbrace{\left[-\frac{\partial Q_1^{*L}}{\partial E_1}+\frac{\partial Q_1^{*L}}{\partial E_2}\right]}_{(-)}-b\underline{\alpha}^w\left[\frac{\partial Q_1^{*L}}{\partial E_1}-\frac{\partial Q_1^{*L}}{\partial E_2}\right]>0, n\in\{L_1,L_2,L_3\} \end{aligned}, \quad (4.13)$$

Both the additional charging in period one and additional discharging in the other periods decreases period one total electricity output. Thus, price level in period one increases.

As the summation of total electricity output across all three periods is unchanged, the summation of total electricity output in period two and three increases by the same amount as the decrease in period one output. Thus, price summation across period two and three decreases by the same amount as the increase in period one price. Because wind energy output is higher in period one than in the other periods, the overall value of wind energy capacity increases and storage complements wind under *low solar* scenarios.

In contrast, the effects of energy storage on the value of wind energy under the *high solar* scenario is:

$$\begin{aligned} V^H_{k_w k_s} &= -b\underline{\alpha}^w\left[-\frac{\partial Q_2^{*H}}{\partial E_2}+\frac{\partial Q_2^{*H}}{\partial E_3}\right]-b\underline{\alpha}^w\left[-\frac{\partial Q_3^{*H}}{\partial E_2}+\frac{\partial Q_3^{*H}}{\partial E_3}\right] \\ &= -b\underline{\alpha}^w\left[-\frac{\partial Q_2^{*H}}{\partial E_2}+\frac{\partial Q_2^{*H}}{\partial E_3}\right]-b\underline{\alpha}^w\left[\frac{\partial Q_2^{*H}}{\partial E_2}-\frac{\partial Q_2^{*H}}{\partial E_3}\right]=0 \end{aligned}, \quad (4.14)$$

Storage now fully charges in period two and fully discharges in period three. Neither the charging nor discharging affect prices in period one because the fossil-fuel energy output is ramping down from period one to period two.

Again, storage expansion would not change the summation of total energy output in period two and three, which implies that the increase in period two price is the same as the decrease in period three price. As wind energy outputs are the same in period two and three, the overall value of wind energy capacity would not change as storage capacity changes.

Finally, wind energy and energy storage capacities also complement each other under the *medium solar* scenario ($M$). Again, the derivation is similar to the derivations above and is omitted to save space. The relationship between wind energy and energy storage is summarized in proposition 3:

**Proposition 3:** *Wind energy and energy storage complement each other under a wide range of renewable energy capacity levels. They only become independent after solar energy capacity increases to a very high level.*

#### 4.2.3.5 The Critical Turning Points

In the previous section, I show that the relationships between the values of wind energy, solar energy and energy storage vary depending on which scenario happens in equilibrium, which is heavily affected by the level of solar capacity. The varying relationships are summarized in table 4.2.

**Table 4.2:** Analytical Results Summary

| | $L_1$ | $L_2$ | $L_3$ | $M$ | $H$ |
|---|---|---|---|---|---|
| Wind-Solar | (+) | (+) | (+) | (-) | (-) |
| Solar-Storage | (-) | (-) | (+) | (+) | (+) |
| Wind-Storage | (+) | (+) | (+) | (+) | 0 |

Indeed, not only solar capacity, but also wind and storage capacities, affect which scenario happens in equilibrium. Figure 4.2 shows two critical solar capacity levels as functions of wind capacity and storage capacity.

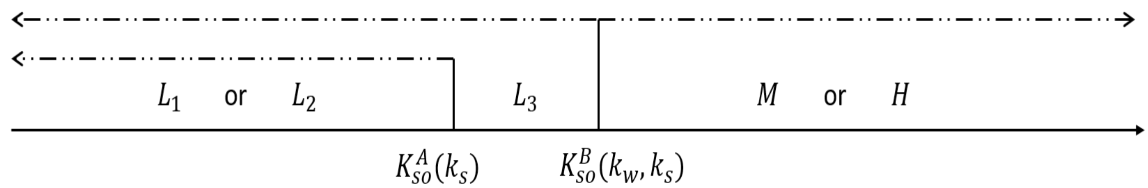



Figure 4.2: Scenario Boundaries

The first critical level, $K^A_{so}$, separates scenarios $L_1/L_2$ from scenarios $L_3/M/H$. It also represents the minimum level of solar capacity required for solar capacity to complement storage capacity. I show in appendix I.3 that $k^A_{so}(k_s)$ increases as storage capacity goes up. With increased discharging in period three under $L_3$, $p_3$ tends to be lower. Thus, more solar capacity is needed to push $p_2$ below $p_3$ if we still want to stay under at least the *low-high solar* scenario ($L_3$) rather than switching to the other two *low solar scenarios* (i.e. $L_1$ and $L_2$).

The second critical level, $K^B_{so}$, separates scenarios $L_1/L_2/L_3$ from scenarios $M/H$. This is also the maximum level of solar capacity required for solar capacity to complement wind capacity. Specifically, $k^B_{so}(k_w, k_s)$ is increasing in the capacity of wind, but is decreasing in the capacity of storage. $q^*_1$ tends to be lower when wind capacity is higher because wind energy production is more active in period one. Even with more solar capacity, $q^*_2 > q^*_1$ still holds and we are still under *low solar* scenarios (i.e. $L_1, L_2, L_3$). Increasing storage capacity increases charging in period one under scenario $L_3$, which increases $q^*_1$. Thus, less solar capacity could be accommodated to keep $q^*_2 > q^*_1$ if we still want to stay in scenario $L_3$ rather than switching to *medium and high solar* scenarios.

**Proposition 4:** *Wind capacity, solar capacity and storage capacity all affect which scenario occurs in equilibrium, which in turn affects the equilibrium relationships between wind, solar and energy storage. Specifically,*

*(I) Low solar scenarios, under which wind and solar energies are complements, are more likely to happen when the level of wind capacity is high and the level of storage capacity is low.*

*(II) Among all low solar scenarios, the low-low and low-medium solar scenarios, where solar energy and storage are substitutes, are more likely to happen when the level of storage capacity is low.*

## 4.3 Empirical Simulation Model

In this section, I first describe the simulation model that is used to obtain the value function associated with the social planner's optimal operation decisions, under given capacity levels of wind, solar and storage. This value function serves as the basis of empirically quantify the value dependence between wind, solar and storage capacities. It also serves as the building block of the social planner's optimal capacity choice problem, which is used to empirically quantify the effect of solar capacity cost decline on renewable energy penetration. The investment simulation model is presented following the operation model.

The setup of the simulation model is similar to those in Cullen and Reynolds (2017) and Reynolds (2018), with certain modifications. Compared to the analytical model, the simulation model includes more fossil-fuel power generators. In addition, the abstract output adjustment costs is represented by startup costs and minimum generation levels.

Startup costs, as the name suggests, are incurred when a fossil-fuel power generator is started up from inactive status. Once started up, it must be producing at a level higher than its minimum generation. The existence of startup costs and minimum generation levels makes the intertemporal cost structure of a fossil-fuel generator similar to the one specified in the analytical model. Therefore, insights obtained in the analytical model also apply to analyze results obtained from the simulation model.

### 4.3.1 Social Planner's Operation Problem

Consistent with the notations used in the analytical model, wind and solar capacity levels are denoted as $k_w$ and $k_{so}$, with capacity factors in hour $t$ being $\alpha_t^w$ and $\alpha_t^{so}$, respectively. Moreover, let $k_s$ still be the total capacity of energy storage, whose energy supply in hour $t$ is $h_t$.

Unlike in the analytical model, there are four types ($J = 4$) of fossil-fuel power generation technologies in the grid: coal, combined cycle, gas steam and gas turbine. Total amount of type $j$ generation capacity summed over all type $j$ firms is $k_j$. Thus, total electricity supply in hour $t$ becomes $Q_t = \sum_{j=1}^{J} q_{jt} + \alpha_t^w k_w + \alpha_t^{so} k_{so} + h_t$. Electricity suppliers are atomistic price taking firms. Each firm operates one unit (arbitrarily small) of energy generation capacity (i.e. generator). Therefore, I will use "firm" and "generator" interchangeably the in rest of this paper.

Fossil-fuel power generators are subject to start-up costs and minimum generation. Startup cost $g_j$ is incurred if a type $j$ generator switches from "off" status (i.e. not producing anything) to "on" status in a given hour. Once it is turned on, it must be producing at a level in $[m_j, 1]$. It is assumed that $g_j$ and $m_j$ are homogeneous within each technology type. Moreover, startups takes one hour to be effective. That is, the amount of new capacities turned on in hour $t$ could only be utilized to produce electricity from hour $t + 1$.

Finally, production cost needs to be defined. Each fossil-fuel energy generator has a constant marginal production cost over its production range, but different generators with the same technology type are allowed to have different marginal production costs, following Reynolds (2018). I assume that marginal production costs of type $j$ generators fall into $n_j$ classes, with $c_1 < c_2 < \cdots < c_{n_j}$. Let $x_{ijt} \in [0, k_{ij}]$ be the amount of type $j$ capacities with production cost $c_{ij}$ that are kept on at the beginning of hour $t$. For a given level of aggregate production $q_{jt} = \sum_i^{n_j} q_{ijt}$ for type $j$ generators (where $q_{ijt} \in [m_{ij}x_{ijt}, x_{ijt}]$), the cost function is defined as:

$$C(q_{jt}; x_{jt}) = \min_{q_{ijt}} \sum_i^{n_j} c_{ij} q_{ijt} \tag{4.15}$$

As firms' startup costs and minimum generation levels within each technology type are homogeneous, only generators with the lowest production costs will be kept "on" given a feasible production level $q_j$. A direct implication of this result is that the aggregate production cost of type $j$ firms, $C(q_{jt}; x_{jt})$, is continuous and convex in $q_{jt}$ for given $x_{jt}$ (Reynolds, 2018). For more discussion on the properties of $C(q_{jt}; x_{jt})$, please refer to Reynolds (2018). The construction of this total production function is shown in appendix J. Due to a lack of carbon policy in the study region, carbon emission costs are not included to construct $C(q_{jt}; x_{jt})$. This conforms to the current reality that carbon costs are not taken into consideration when the grid manager arranges hourly electricity generation everyday.

The existence of minimum generation level and discrete startup decision (i.e. a generator is either "on" or "off") render non-convexity to generator-level production possibility sets. However, by assuming that firms are measure zero, Cullen and Reynolds (2017) and Reynolds (2018) show that the ***aggregate*** production possibility set is convex for each technology type. I modify their aggregate production possibility sets by adding storage:

$$PT(k) = \{0 \leq y_j \leq x_j, 0 \leq z_j \leq k_j - x_j, m_j x_j \leq q_j \leq x_j, \tilde{k}_s - k_s \leq h \leq \tilde{k}_s, \tilde{k}_s \leq k_s; j = 1, \ldots, J\}. \tag{4.16}$$

where $x = \{x_1, \ldots, x_J\}$ is a vector of the amount of "on" capacities at the beginning of each hour. $y_j$ is the amount of "on" capacities that type $j$ firms decide to carry on to the next hour. $z_j$ is the amount of new capacities that firms decide to turn on. $\tilde{k}_s$ is the amount of electricity stored in the energy storage equipment. $PT(k)$ is compact for any vector of $k = \{k_s, k_w, k_{so}, k_f\}$, where $k_f = \{k_1, k_2, k_3, k_4\}$. Finally, the transitions of state variables satisfy:

$$\begin{cases} x_{t+1} = y_t + z_t \\ \tilde{k}_{st+1} = \tilde{k}_{st} - h_t \end{cases} . \tag{4.17}$$

The first equation in (4.17) states that the amount of "on" fossil-fuel power capacities in the next hour is the amount of current "on" capacities that is kept on to the next hour plus the amount of new capacity started. This specification allows one hour lag between the startup decision and when the new start-up capacities could produce energy. The second equation states that the amount of power stored in the next hour equals to the amount currently stored minus the amount of energy discharged (sold) in the current hour.

Similar to Reynolds (2018), the aggregate (aggregated over each technology type) electricity production technology is convex due to the compactness of $PT(x)$ and linearity in the transition rules[11]. Given market demand, market supply and capacity vector $k$, hourly payoff for the whole

[11] I do not introduce energy storage's round-trip efficiency because it will render non-linearity in $\tilde{k}_s$'s transition rule

electricity grid is:

$$H(q_t, z_t, x_t, h_t; k) = B(\sum_{j=1}^{J} q_{jt} + \alpha_t^w k_w + \alpha_t^{so} k_{so} + h_t) - \sum_{j=1}^{J} C(q_{jt}; x_{jt}) - \sum_{j=1}^{J} g_j z_{jt}, \qquad (4.18)$$

where $q_t = \{q_{1t}, q_{2t}, q_{3t}, q_{4t}\}$, $z_t = \{z_{1t}, z_{2t}, z_{3t}, z_{4t}\}$ and $x_t = \{x_{1t}, x_{2t}, x_{3t}, x_{4t}\}$. The social planner's operation problem is to choose the sequence of $\{q_t, z_t, x_t\}$ to maximize the sum of hourly payoffs (4.18) across the planning horizon $T$, subject to the aggregate production possibility set $PT(x)$ specified in (4.16) and state transition rules specified in (4.17). The value function associated with the social planner's optimal operation decisions is denoted as:

$$V(k) = max_{q,z,x,h \in PT(k)} \sum_{t=1}^{T} H(q_t, z_t, x_t; k), \qquad (4.19)$$

Planning horizon $T$ in (4.19) needs to be selected to solve the social planner's operation problem. As quantifying $V_{k_i k_j}, i, j \in \{w, so, s\}$ for different renewable and storage capacity combinations is one of this study's focus, the social planner's operation problem needs to be solved for many times. Setting $T$ to be very large or infinity, as in Cullen and Reynolds (2017) and Reynolds (2018), is infeasible for this purpose due to the heavy computational burden caused by the large set of choice/state variables and the extremely small time step (1 hour).

Instead, I choose $T$ to be 48 hours in two days. The two days are exactly the same in terms of hourly energy demand and hourly renewable energy output. That is, I construct a representative day and replicate it twice. The construction of the representative day is detailed in section 4.4. The initial "on" capacities for all fossil-fuel technology types at the beginning of the first day are set to 0 (i.e. $x_j = 0, j \in \{1, 2, 3, 4\}$). I then use only the second day to calculate $V(k)$ because the second day is less affected by the initial adjustment of "on" capacities from 0. In a model with long planning horizon, the initial adjustment periods' effect on the final simulation results is very small compared to the sum of the rest periods. As the model is only simulated for two days, incorporating adjustment periods in calculating $V(k)$ will overshoot the importance of this period. Indeed, the duration of the initial adjustment periods is relatively short – hourly fossil-fuel energy generation looks very similar on the two days after 4:00am. As an robustness check, I also extend $T$ to be 72 hours in three consecutive representative days. Hourly operations in the second and third days are almost the same.

Note that the formulation of social planner's problem assumes away uncertainty – the social planner knows perfectly wind generation, solar generation and demand shocks in each hour in the future. This assumption is not too restrictive because the chosen $T$ is relatively small.

### 4.3.2 Social Planner's Investment Problem

Knowing $V(k_w, k_{so}, k_s, k_f)$ for all $k$, the social planner's investment problem is to maximize:

$$\max_{k_w, k_{so}, k_s} W(k_w, k_{so}, k_s, k_f) = \sum_{\tau=0}^{30} \beta^{\tau} 365 * V(k_w, k_{so}, k_s, k_f) - \theta_w k_w - \theta_{so} k_{so} - \theta_s k_s \quad (4.20)$$

where $\theta_w, \theta_{so}$ and $\theta_s$ are the per megawatt capacity costs of wind turbine, solar PV and energy storage, respectively. Since $V(k_w, k_{so}, k_s, k_f)$ is the value function from optimal capacity operation in a single representative day, it is multiplied by 365 to obtain the annual value function. On average, wind turbine and solar PV last for thirty years.[12] Thus, the present value of the operation value function in thirty years is calculated to be the benefit from capacity investment.

Through varying $\theta_{so}$, the maximization problem (4.20) delivers optimal $k_w, k_{so}$ and $k_s$ under each level of solar capacity cost, based on which renewable energy penetration is calculated. Since the focus of this study is the effects of solar cost decline on wind/storage investment and renewable energy penetration, the levels of different fossil-fuel energy capacities are set to be fixed.

Given the optimal capacities $k_w^*, k_{so}^*$ and $k_s^*$, the private surplus from renewable energy capacity investment is defined as:

$$W(k_w^*, k_{so}^*, k_s^*, k_f) - W(0, 0, k_f) \quad (4.21)$$

Note that the surplus is private surplus, not social welfare, as the social damage caused by carbon emissions are not taken into consideration when making investment decisions due to the lack of carbon policies in the study region. As will be shown later in section 4.6, this is exactly the reason why declining solar capacity costs might lead to social welfare loss.

[12]Data Source: NREL Energy Analysis: https://www.nrel.gov/analysis/tech-footprint.html

## 4.4 ERCOT Data and Parameter Calibration

The Electric Reliability Council of Texas (ERCOT) is an independent system operator for an electricity grid that covers most of Texas. ERCOT serves about 90 percent of the state's electricity demand and is largely unconnected with the other U.S. electricity grids. Therefore, electricity demand in ERCOT region is almost solely supplied by energy generation capacities located inside its serving area.

Historically, fossil-fuel generation capacities such as natural gas and coal power generators dominate energy supply in ERCOT. Up to 2015, total fossil-fuel generation capacity reaches $70,791$ MW. All coal, combined cycle, natural gas steam and natural gas turbine energy generators located in ERCOT with a nameplate capacity greater than 10MW are utilized to calibrate fossil-fuel capacity cost parameters. The total capacities of these generators adds up to 65,622MW, which accounts for 93% of total generation capacities in ERCOT in 2015. Table 4.3 summarizes information on different fossil-fuel technology types used in the study.

**Table 4.3:** ERCOT Generation Technology Parameters (2015)

| **Generation Technology** | **Capacity** (MW) | **Minimum Generation** $m_j$ (% of Cap) | **Startup Cost** $g_j$ ($/MW Cap) |
|---|---|---|---|
| Coal | 18,771 | 0.53 | 105 |
| Combined Cycle | 30,648 | 0.51 | 79 |
| Gas Steam | 11,923 | 0.33 | 75 |
| Gas Turbine | 4,340 | 0.64 | 32 |
| Total | 65,622 | | |

Startup costs of different generation technologies are calibrated from Kumar et al. (2012). I obtain minimum generation level per unit of capacity for all generators in ERCOT market from EIA form 860. Minimum generation for each type of generation technology is calculated as the capacity-weighted average minimum generation level of power generators within this type. In general, coal power generator is the most inflexible technology characterized by a high startup cost and relatively high minimum generation level, while generators using gas as fuel are more flexible.

Information on generation capacities are drawn from EIA form 860. I use summer capacity instead of nameplate capacity to calculate total capacities as the former is a more realistic measure of the maximum hourly generation rate a power generator could achieve. The grid is dominated primarily by combined cycle and coal generation capacities, with a small amount of natural gas turbine capacities primarily utilized during peak hours.

Construction of the aggregate production cost function $C(q_{jt}; x_{jt})$ for each type of generation technology is more complex. The procedure is described in appendix J. In general, production cost is lowest for coal power generators, followed by combined cycle generators, then by gas steam generators and finally by gas turbine generators.

A representative day is constructed using hourly renewable generation data and electricity quantity demanded (load) data in 2015. Hourly electricity demanded and electricity price in the representative day are also constructed by averaging the observed hourly demand and prices across all days in 2015. Given the linear demand function $P(Q_t, \theta_t) = \theta_t - bQ_t$, the slope parameter $b$ is calibrated by setting elasticity of demand calculated at the pair of daily average price and daily average load to be -0.05, following Cullen and Reynolds (2017). Subsequently, each $\theta_t$, for $t \in \{1, 2, \ldots, 24\}$, is fixed by solving the inverse demand function using the calibrated slope parameter. Wind and solar energy output in each hour in the representative day are obtained in the same fashion. Starting from the early 2000s, renewable energy capacities, especial wind capacity, keep increasing rapidly. By the end of 2015, the amount of wind capacity reaches $14,683$ MW. Although the level of solar capacity is relatively low in 2015 ($1,101$ MW), it is expected to increase rapidly in the future due to the constantly declining capacity costs.

Figure 4.3 plots ERCOT's hourly average wind and solar generation capacity factors as well as hourly average realized electricity demand in 2015. Consistent with the analytical model, wind energy production peaks in the morning and late night but decreases during daytime.

Finally, parameters regarding capacity costs are calibrated. According to NREL renewable energy capacity cost projection (Augustin et al., 2018), average capacity costs of wind stays relatively unchanged from 2016 to 2050, at roughly about \$1600/kW. However, average solar capacity costs will drop rapidly from \$1778/kW in 2016 to around \$700/kw in 2050. Consistent

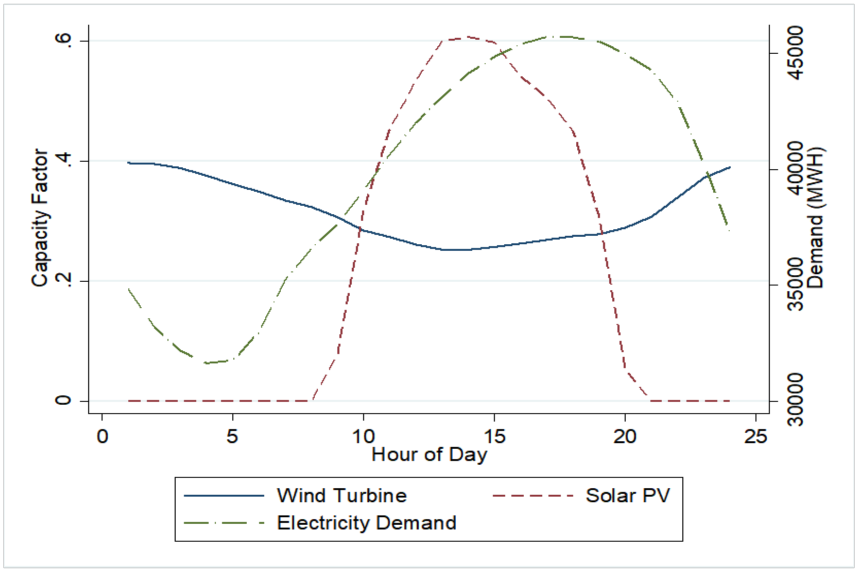


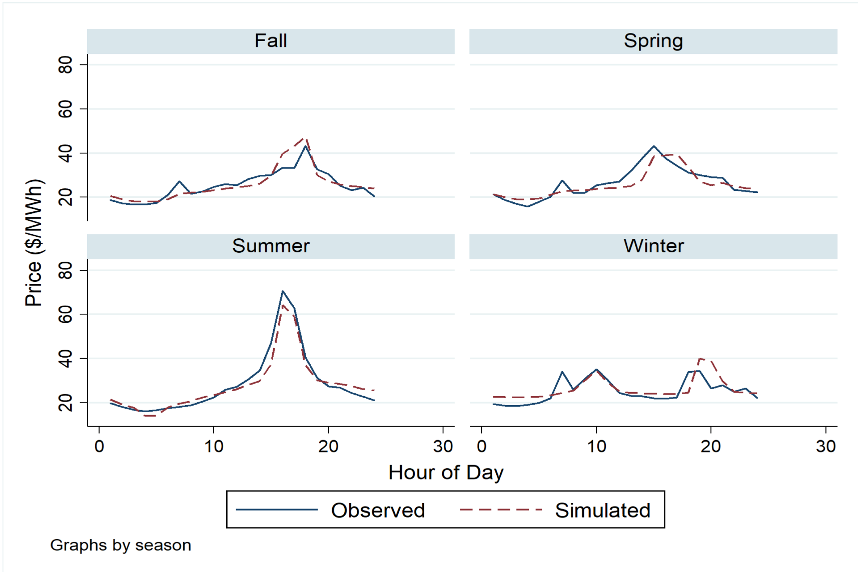

Figure 4.3: Average Renewable Energy Generation Pattern and Average Demand Pattern

with this projection I set $\theta_w = \$1600/\text{kW}$ and $\theta_{so} \in \$(700, 1200)/\text{kW}$, with increments of \$10/kW,[13] Currently, both wind and solar capacity expansions are subsidized in the U.S. The Renewable Electricity Production Tax Credit (PTC) offers \$24/MWh for wind energy production in the first ten years after initial investment, while solar investment is subject to a 30% Investment Tax Credit (ITC). I adjust the capacity costs accordingly by deducing these tax credits from the initial capacity costs in the simulation. Finally, capacity cost of storage ($\theta_s$) is fixed at \$1500/kW, its 2018 level (U.S. EIA, 2018).

## 4.5 Simulation Implementation and Model Validation

Before turning to the formal analysis, I test model validity by replicating observed hourly average price patterns. For validation purpose, I obtain hourly average demand and renewable generation for each season (i.e. spring, summer, fall and winter). This exercise gives four representative days and the model is executed for four times, one for each season. The simulation is performed using Artelys Knitro nonlinear optimization toolbox in Matlab.

[13]Shown by the simulation results latter, solar capacity is never developed when $\theta_{so} > \$1090/\text{kW}$. Thus, I adjust the upper bound of $\theta_{so}$ down from \$1244/kW to \$1200/kW for the neatness of figures in the next section. This adjustment will not affect the conclusions from the simulation exercises because optimal investment decisions are the same for $\theta_{so}$ between \$1200/kW and \$1788/kW.




*Note: average daily startups are 335MW in spring, 1739MW in summer, 641MW in Fall, and 19 MW in winter.*

Figure 4.4: Observed and Simulated Hourly Average prices for Four Seasons

Figure 4.4 plots these validation results. Daily capacities started up is also reported for each season below the figure. The simulation model predicts the observed hourly average price patterns for the four seasons quite well. In particular, the summer price spike is caused by the relatively large amount of peak hour startups during peak hours, showing the importance of modeling startup costs explicitly.

For the ease of explaining results later in the paper, I still use the annual representative day constructed in section 4.4, rather than the four seasonal representative days, in the formal simulation. Results obtained by using the annual representative day and the seasonal representative days are very similar.

## 4.6 Results And Discussions

This section presents the simulation results and discusses their implications. First, the empirical simulation model in section 4.3 is executed with different values of wind, solar and energy storage capacities in order to determine whether wind energy, solar energy and energy storage are complements or substitutes in ERCOT. Then, based on the results in the first step, the effects of solar capacity cost decline on the investment of other renewable resources and renewable energy penetration are presented.

Specifically, 10000 combinations of wind, solar and energy storage capacities are randomly drawn to run the dynamic operation simulation model. I limit the range of wind capacity to be between 15000MW and 75000MW, the range of solar capacity to be between 300MW and 35000MW, and the range of energy storage capacity to be between 300MW and 15000MW. The lower bounds of wind and solar energy capacities are set according to the 2015 installed capacities of wind and solar. The lower bound of storage capacity is set according to the 2020 energy storage capacity projection.[14] The upper bounds of the capacities are set high enough to enclose a variety of possible renewable energy penetration levels in the future. With 75000MW of wind capacity, 35000MW of solar capacity and 15000MW of energy storage, renewable energy could serve up to 85% of ERCOT electricity demand on average across a whole day.[15]

A third order polynomial regression of the optimized $V(k_w, k_{so}, k_s)$ is fitted with respect to wind capacity, solar capacity and energy storage. The partial derivative of the fitted $V(k_w, k_{so}, k_s)$ with respect to wind (solar/storage) capacity represents the value of wind (solar/storage) energy ($V_{k_i}, i \in \{w, so, s\}$).[16] The regression results are omitted here but the overall fitting of the regression is exceptional, with $R^2 = 0.9999$.

After each $V_{k_i}$ for $i \in \{w, so, s\}$ is obtained, the relationships between one type of capacity and the other types of capacities are characterized by comparing the value of $V_{k_i}$ at different levels of $k_j, j \neq i$. If $V_{k_i}$ increases as $k_j$ increases, type $i$ and type $j$ capacities are complements. Otherwise, they are substitutes.

[14]There were almost no storage capacity in ERCOT by the end of 2015.

[15]With theses levels of renewable/storage capacities, the hourly percentage of electricity demand met by renewable energies and energy storage ranges from 70% to 100%.

[16]Ideally, for each of the 10000 capacity combinations, I could calculate the value of one specific renewable energy through increasing its capacity level by a small amount. The difference between the initial optimized social value and the new value is the value of that energy source. However, this will greatly increase the computational burden. As there are three renewable sources, $3 \times 2 \times 10000 = 60000$ simulations are needed, comparing to only 10000 runs for the selected method.

### 4.6.1 Values of Wind, Solar and Energy Storage

Before showing the results related to value dependence, the simulated values of wind, solar and storage are compared with the estimates found in the literature as another round of robustness check. Based on ERCOT energy generation capacity levels in 2015, the simulated values of wind, solar and storage are \$23.7/MWh, \$25.4/MWh, and \$20/MWh, respectively.[17]

Callaway, Fowlie, and McCormick (2018) estimates that the avoided operation cost associated with wind energy production is \$30/MWh in ERCOT.[18] In a simulation model that does not consider startup cost, Castro (2018) estimates that the value of wind is \$59/MWh in ERCOT in 2015, considering both avoided operation cost and the benefit of offsetting carbon emissions. In the literature, the value of carbon offsetting associated with wind energy production in ERCOT ranges from \$19/MWh-\$25/MWh (Callaway, Fowlie, and McCormick, 2018; Cullen, 2013). Subtracting the value of carbon offset, the value of avoided operation cost associated with wind energy production becomes \$35/MWh-\$40/MWh in Castro (2018).

Wind energy's value obtained in this study is lower than those obtained in Callaway, Fowlie, and McCormick (2018) and Castro (2018). Part of the reason is that startup costs are ignored in these studies. Because fossil-fuel energy capacities' output adjustments incurs high startup costs, ignoring startup costs tends to overestimate the value of wind energy.

Callaway, Fowlie, and McCormick (2018) estimates that the value of solar energy is \$41/MWh during 2010-2012. Solar energy is only produced during daytime. Under current solar capacity levels, daytime hours are periods when more expensive natural gas generators set price. During 2010-2012, average natural gas price is 1.5 times that in 2015. Thus, the value of solar energy estimated in Callaway, Fowlie, and McCormick (2018) is approximately equivalent to $\$41 MWh/1.5 = \$27.3$/MWh in 2015, which is similar to the estimate in this study.

Finally, the value of storage (without considering social cost of carbon) is estimated to be

[17]The initial unit of $V_{k_i}$ is \$/MW-day. It is converted to \$/MWh though dividing $V_{k_i}$ by resource $i$'s total energy production during the representative day.

[18]Only the values associated with avoided operation cost in other studies are considered here because these are the values that are directly related to investment decisions without any carbon policies. The values associated with carbon emission offsets are re-added later in this section to calculate the full social surplus from renewable energy investment.

$42/MWh in ERCOT during 2007 to 2009 in Carson and Novan (2013). The value of storage largely depends on arbitraging price difference between low-price and high-price periods, which is again largely driven by natural gas price. During 2007-2009, average natural gas price is about 2.4 times higher than that in 2015. Thus, the private value of energy storage estimated in Carson and Novan (2013) is approximately equivalent to $42MWh/2.4=$17.5/MWh in 2015, which is also similar to the estimate in this study.

### 4.6.2 Relationships Between Wind Energy, Solar Energy and Energy Storage Capacities

Figure 4.5 plots the value of wind energy capacity against different levels of solar energy capacities. For each level of solar capacity, wind capacity is set to be either 20000MW (low) or 50000MW (high). Similarly, storage capacity is set to be either 300MW (low) or 10000MW (high). As solar

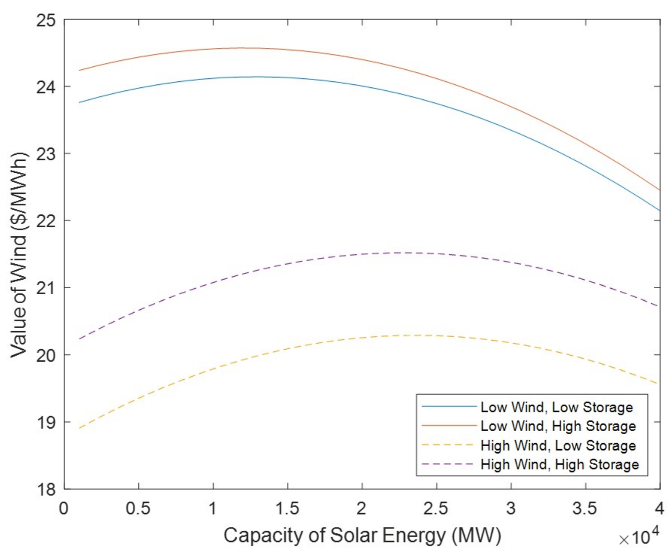



Figure 4.5: Effect of Solar Energy On the Value of Wind Energy

energy capacity increases, the value of wind energy capacity first increases and then decreases under all combinations of wind and storage capacities. Thus, wind energy and solar energy are complements when the level of solar capacity is relatively low, and gradually become substitutes as the level of solar capacity increases. This result is consistent with proposition 1. Moreover, wind and solar complement each over over a wider range of solar capacity levels when the level of wind capacity is high. This observation is consistent with proposition 4, which predicts that the threshold of solar capacity above with solar starts to substitute wind is higher when more wind capacity presents in the grid.

The complementary/substitution relationship between wind energy and energy storage is also illustrated by figure 4.5 through comparing the two solid lines (or the two dashed lines). Holding wind and solar capacities constant, the value of wind is always higher when more storage capacity presents, which is consistent with the prediction in proposition 3 that wind energy and storage are never substitutes.

Figure 4.6 plots the value of energy storage capacity against different levels of solar energy capacities. Again, wind capacity is set to be either 20000MW (low) or 50000MW (high), and storage capacity is set to be either 500MW (low) or 10000MW (high).

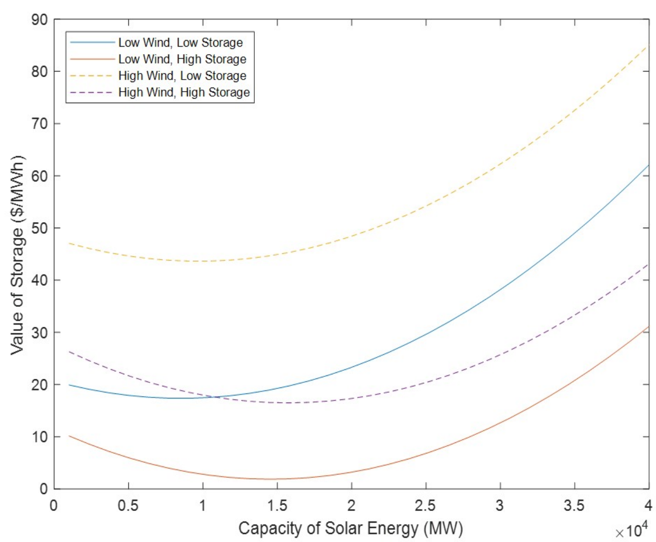
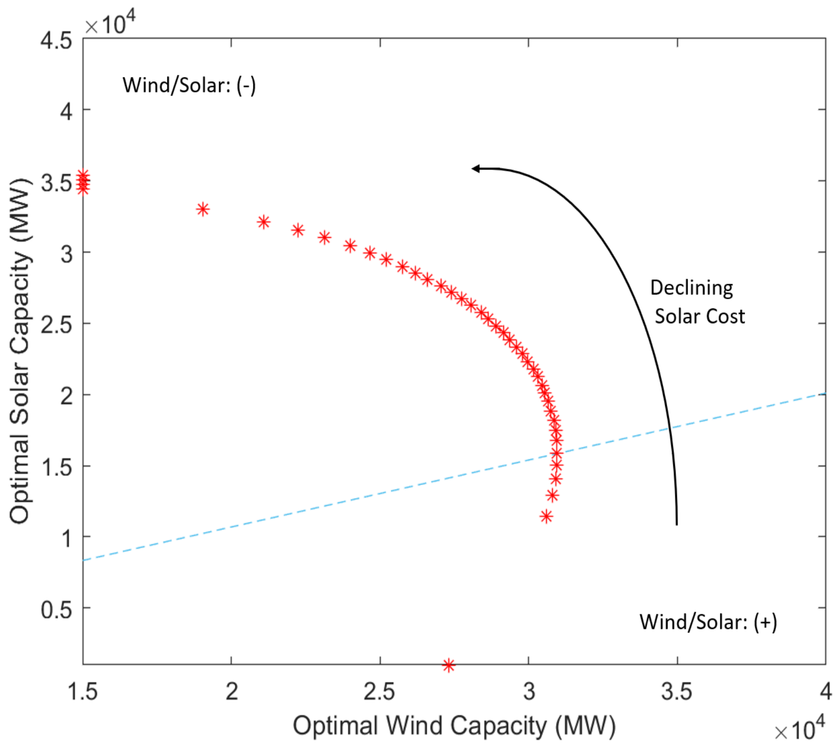



Figure 4.6: Effect of Solar Energy On the Value of Energy Storage

Consistent with proposition 2, the value of energy storage first decreases and then increases as solar capacity continues increasing. This relationship holds under all wind/storage capacity combinations being considered.

### 4.6.3 Declining Solar Capacity Costs, Increasing Renewable Penetration?

Given the social planner's investment problem defined in (4.20) as well as investment cost parameters assumed in section 4.4, optimal wind and solar capacity levels are solved out over the range of solar capacity costs. The results are plotted in figure 4.7.




*Note: when solving the investment problem, wind capacity is constrained to be no lower than 15000MW, its observed 2015 level. Wind turbines could last for a long time period (30 years). Once built, it is almost irrational for wind capacity to exit due to the extremely low production cost. Similarly, solar capacity is constraint to be no lower than its observed 2015 level (1101MW).*

Figure 4.7: Optimal Wind and Solar Capacities Under Different Solar Capacity Cost

In the figure, each star marker represents a combination of optimal wind capacity and optimal solar capacity under a specific level of solar capacity cost. The solid long arrow signifies the direction of solar cost change. The figure also includes a dashed line that represents the boundary above which wind and solar capacities become substitutes. Consistent with proposition 4, the boundary line is higher when the level of wind capacity is higher.

When the capacity costs of solar are very high, it is not optimal for investors to develop solar capacity, representing an "all wind" solution. As solar costs gradually decrease, more solar is added. At first, the increase in solar capacity also drives up wind capacity because solar complements wind when solar capacity is relatively low. However, as solar costs keep decreasing, optimal wind and solar capacity combination passes the dashed boundary line and solar starts to substitute wind. This happens when pre-subsidy solar capacity costs drop roughly to \$1040/kW, about \$200/kW higher than the 2030 projection. As a result, solar cost decline not only pushes up optimal solar capacity, but also drives down optimal wind capacity. At the projected 2050 pre-subsidy solar capacity costs, it is optimal to invest only in solar capacity, reaching an "all solar" solution. Further, due to the high capacity costs and relatively low per megawatt value, storage capacity is never deployed in equilibrium under all solar cost scenarios.

Figure 4.8 plots the effects of such wind/solar mixture changes on renewable energy penetration and total carbon emissions. The star shaped markers represent renewable energy penetrations under different solar cost levels, and the triangle shaped markers represent the corresponding annual carbon emissions.

As solar capacity costs gradually decrease (from right to the left in the figure), both solar capacity and wind capacity increase first, driving up renewable energy penetration. Since renewable energy production is carbon-free, carbon emissions also drop correspondingly. When solar capacity costs drop below the point where wind and solar become substitutes, renewable energy penetration still increases for a while because the drop in wind energies is more than offset by the increase in solar energies (see figure 4.7). However, when solar costs drop below \$880/kW, just a little bit higher than the 2030 projection, renewable energy penetration starts to decrease and carbon emissions start to increase due to the fast decline in wind capacity (again, see figure 4.7). After solar costs drop to low enough and "all solar" solution emerges, further decline in solar costs then drives up renewable penetration through increasing solar capacity, but the range of solar costs when such changes happen is small.

To summarize, renewable energy penetration first goes up from 22% to 36% when solar costs decline from the 2016 projection to the 2030 projection, and then goes down to 30% as solar costs

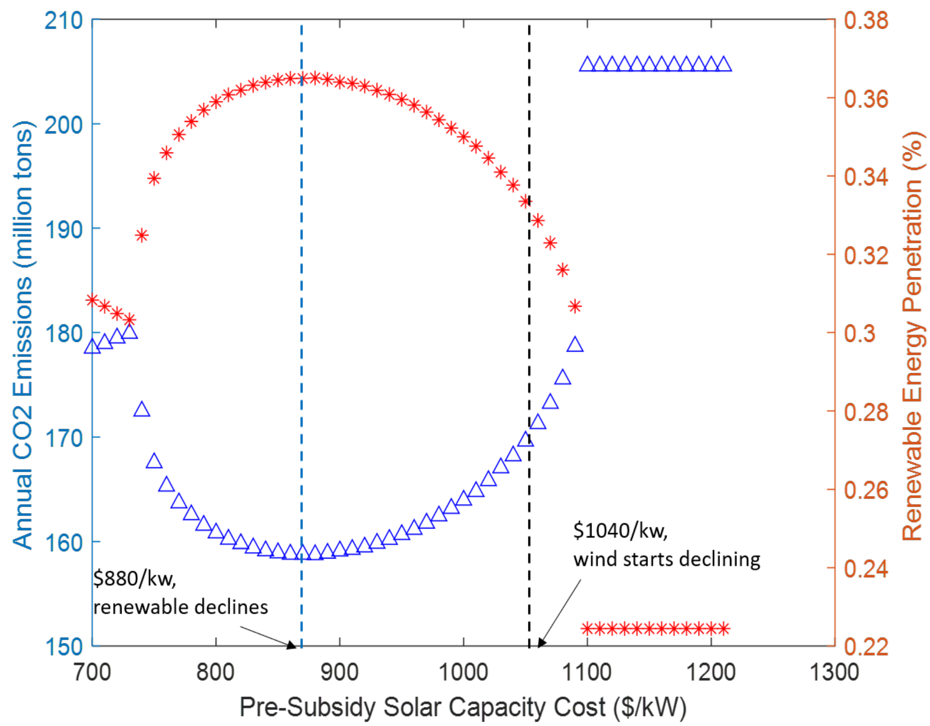



Figure 4.8: Response of Renewable Energy Penetration And Annual Carbon Emissions to Solar Capacity Cost Decline

keep declining to its the 2050 projection. Correspondingly, carbon emissions first decrease by 22%, but then increase by 12.9% from the minimum point.

Changes in renewable energy penetration and carbon emissions due to solar capacity cost decline translate directly into changes in social welfare from renewable energy investment, which is the private surplus from renewable investment defined by (4.21), net of social damage caused by carbon emissions. Figure 4.9 plots this change, assuming a social cost of $38/ton of $CO_2$ (Callaway, Fowlie, and McCormick, 2018; U.S. Interagency Working Group on Social Cost of Carbon, 2014).

Consistent with the changes in carbon emissions (figure 4.8), social welfare from renewable energy investment first increases, then decreases, and then increases as the capacity costs of solar decline. The highest social welfare is reached when solar capacity costs decline to around $820/kW, the 2030 projection. Social welfare from renewable energy investment drops by as high as 17.2%, or $0.57 billion/year in dollars, when solar capacity costs decrease from the 2030 projection to the 2050 projection. This represents an unexpected consequence associated with solar capacity cost

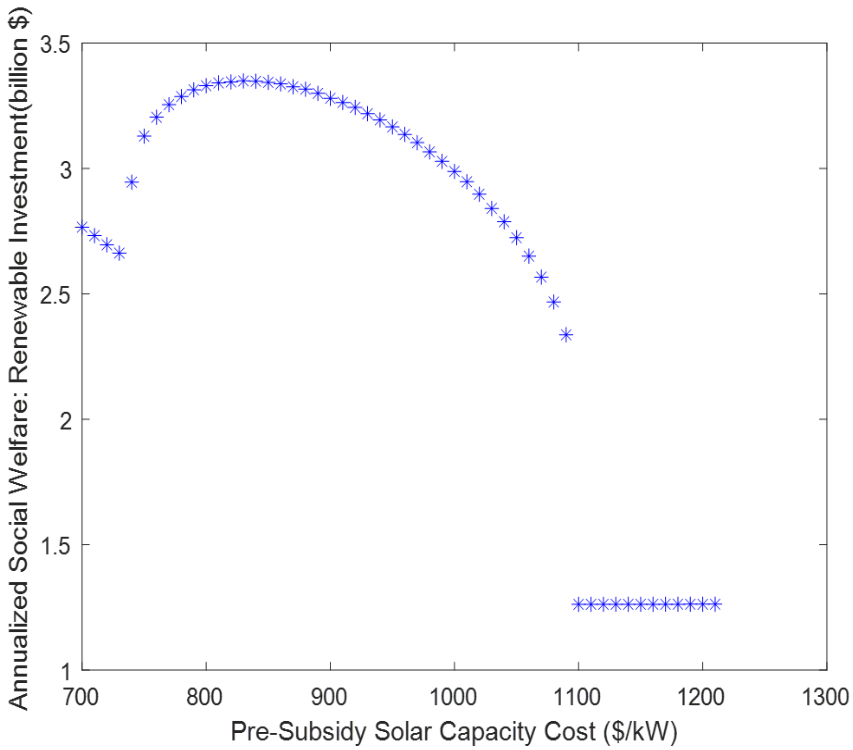



Figure 4.9: Changes in Social Welfare Gain From Renewable Energy Investment Due to Solar Capacity Cost Decline

decline due to the interaction of solar capacity and wind capacity.

An ideal policy to counter this bad unexpected consequence is to impose a carbon tax that is equal to the social cost of carbon to internalize the environmental externalities when making renewable energy investment decisions. Without a carbon tax, setting stricter RPS renewable energy penetration thresholds could serve as a second-best policy. For example, when it is required that renewable energy penetration could not drop below 36%, the highest penetration level achievable shown in figure 4.8, social welfare from renewable energy investment could increase by 27%, or $0.77 billion/year in dollars when the capacity costs of solar drop to the 2050 projection.

### 4.6.4 Effect Of Solar Capacity Cost Decline on The Value of Energy Storage

Although it is not optimal to invest in energy storage due to its high investment costs, the value of energy storage does increase at a fast rate in general as solar capacity costs decline (figure 4.10).

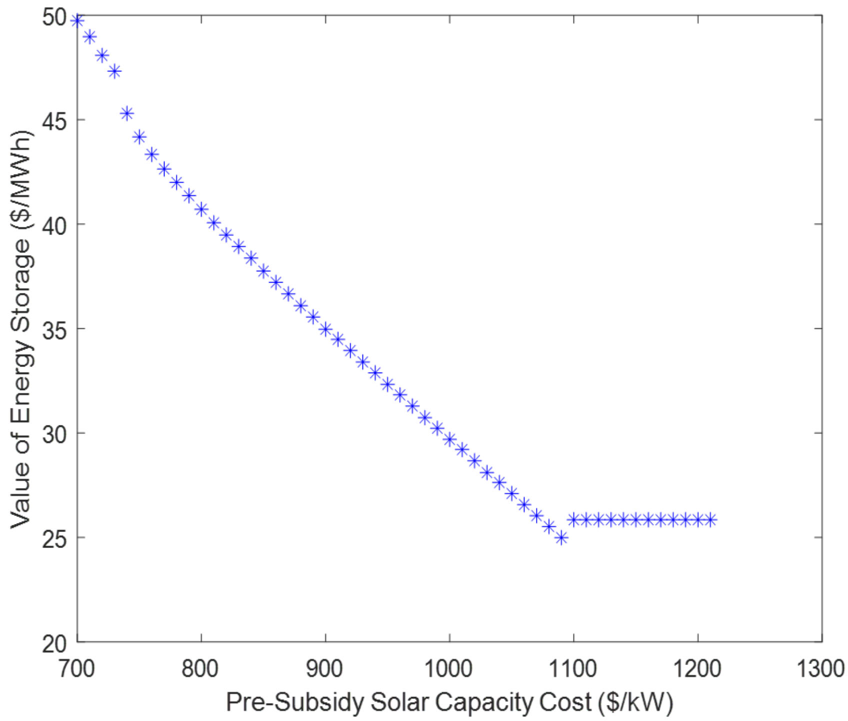



Figure 4.10: Response of Energy Storage's Value With Respect To Solar Capacity Cost Decline

When solar costs decline, there is a slight decrease in the value of energy storage when the costs are still high. According to proposition 2 and figure 4.6, solar substitutes storage at low solar capacity levels. Thus, an increase in solar capacity caused by solar cost decline decreases the value of storage when solar costs are high. However, solar starts to complement storage and the value of storage continues going up as more and more solar capacity is added due to solar cost decline. When pre-subsidy solar capacity costs decrease from $1200/kW to around $700/kW (the 2050 projection), the private value of energy storage (evaluated at 324MW, the projected level in 2020) increases by $23.9/MWh, representing a 92.5% increase.

Therefore, it is reasonable to expect that more storage capacity would be added to the grid if solar capacity cost decline continuous after 2050, and if storage capacity costs could be driven down due to future technological improvements. As storage complements solar at high solar capacity levels, the presence of storage capacity by the time when solar capacity costs are very low is very likely to increase renewable penetration and to drive carbon emissions down.

## 4.7 Conclusions and Future Directions

Development of clean renewable energies such as wind and solar is partly limited by their high capacity costs. A recent report by the National Renewable Energy Laboratory (NREL), however, projects that solar capacity costs will drop dramatically in the next thirty years. This chapter investigates how this cost decline affects renewable energy penetration and social welfare.

Changes in renewable energy penetration depends on how the capacities of wind, solar and storage are adjusted facing sharp solar cost decline, which in turn depends on whether these resources complement or substitute each other. I show that wind and solar substitute each other on the one hand because energies produced from different resources are perfect substitutes and so compete with each other. On the other hand, mixing wind and solar resources helps smoothing aggregate renewable energy output and reducing fossil-fuel energy generators' startup costs. I show in an analytical model that the complementarity effect is stronger than the substitution effect if the level of solar capacity is relatively low, but the strengths of the two effects reverse and solar starts to substitute wind as solar capacity gradually increases. Moreover, while storage never substitutes wind, it only complements solar at high solar capacity levels.

Two simulation models are then combined to empirically determine the effects of solar cost decline on renewable energy penetration and social welfare in the ERCOT electricity grid. The first is a dynamic grid-level power plant operation simulation model that takes fossil-fuel energy capacities' startup costs into consideration, and the second is a stylized renewable energy investment model. Because wind and solar switches from being complements to being substitutes as solar capacity increases, simulation results show that the decline in solar capacity costs first increases renewable energy penetration through increasing both solar and wind capacities, but then decreases the penetration through decreasing wind capacities when solar capacity increases. Specifically, renewable energy penetration first goes up from 22% to 36% when solar costs decline from the 2016 level to the 2030 projection, and then goes down to 30% as solar costs keep declining to the 2050 projection. Correspondingly, carbon emissions first decrease by 22% but then increase by 12.9% from the minimum point.

Due to the lack of carbon policies, social welfare from renewable energy investment drops by \$0.57 billion/year when solar costs decrease from the 2030 projection to the 2050 projection. Thus, a decline in solar cost does not necessarily imply an increase in renewable penetration and social welfare. I show that a policy that requires a minimum renewable energy penetration level would lead to large increases in social welfare when solar costs are low.

As storage complements solar at high solar capacity levels, the presence of storage capacity by the time when solar capacity costs are very low has the potential to further increase renewable penetration and is likely to drive carbon emissions down. Even though it is not optimal to invest in storage currently, the value of storage increases at a fast rate as solar costs decline. A 93% increase in the value of storage is observed as solar costs decrease from the 2016 level to the 2050 projection. Therefore, it is reasonable to expect storage to become competitive if solar capacity cost decline continuous after 2050, and if storage capacity costs could be driven down in the future.

There are several directions to extend the analyses in this chapter. First, fossil-fuel capacity would also vary in the long run in response to renewable energy capacities' relative cost advantages. A model that also takes fossil-fuel energy generators' enter/exit decisions into consideration will be a useful step in the future. Second, the investment decisions are also dynamic in nature. Real-world renewable resource developments are characterized by slow year-by-year adjustments: both project approval and site construction take considerable time. Further, investors update their expectations of future capacity costs by observing current and past cost realizations. Therefore, a dynamic investment model, rather than the static one used here, that takes full consideration of these dynamic and uncertainty factors would provide more insights into how different renewable energy resources gradually adjust their capacities (as well as how renewable penetration gradually changes) overtime facing solar cost decline.

# APPENDICES

# APPENDIX I

# DERIVATION DETAILS IN THE ANALYTICAL MODEL

## I.1 Derivation – Value of Renewable Energies and Energy Storage

**Low Solar Scenarios ($q_1^* < q_2^* = q_3^*$)**

Given the ordering of optimal fossil-fuel energy generation $q_1^* < q_2^* = q_3^*$, as well as social planner's problem defined in (4.3) and (4.4), the first order conditions (FOCs) with respect to $q_1$ is:

$$p_1(Q_1^*) - C_P'(q_1^*) + C_r'(q_2^* - q_1^*) = 0 \tag{I.1}$$

The necessary conditions for $q_2$ and $q_3$ are different from that for $q_1$ due to the kink in output adjustment function $\tilde{C}_r(q_3 - q_2)$ at $q_3 - q_2 = 0$. Specifically, the necessary condition for period 3 fossil-fuel energy generation is:

$$0 < p_3(Q_3 | q_3 = q_2^*) - C_P'(q_3 = q_2^*) < C_r'(0). \tag{I.2}$$

(I.2) has two implications: (i) it is profitable to increase $q_3$ when there is no ramping cost. Otherwise, downward ramping of fossil-fuel energy production would be observed since downward-ramping is costless. (ii) marginal cost of ramping up fossil-fuel power production in period 3 must be higher than its marginal benefit, evaluated at the point where no ramping happens.

Due to the continuity of $p_t(\cdot)$ and $C_P'(\cdot)$, the inequalities above still hold if $q_2^*$ is marginally changed and $q_3$ is set equal to the new $q_2^*$. Thus, for all $q_2$ in the neighborhood of $q_2^*$, optimal $q_3$ is always equal to $q_2$ (i.e. $\hat{q}_3^* = q_2$, where $\hat{q}_3^*$ is optimal period 3 fossil-fuel power production if fossil-fuel power production in period 2 is set to $q_2$). Therefore, $\tilde{C}_r(\hat{q}_3^* - q_2) = 0$ for all $q_2$ in the neighborhood of $q_2^*$, which implies that $\tilde{C}_r'(\hat{q}_3^* - q_2^*) = 0$ in this neighborhood. Consequently, the FOC associated with $q_2$ is:

$$p_2(Q_2^*) + p_3(Q_3 | q_3^* = q_2^*) - 2C_P'(q_2^*) - C_r'(q_2^* - q_1^*) = 0 \tag{I.3}$$

Plug $q_1^*, q_2^*$ and $q_3^*$ into (4.3), we get the optimized value function $V(k_w, k_{so}, k_s)$. Take partial derivative of $V(k_w, k_{so}, k_s)$ with respect to $k_i$ and denote $e_t^i = \frac{\partial E_t^*}{\partial k_i} = \frac{\partial \alpha_t^w k_w + \partial \alpha_t^{so} k_{so} + \partial s_t^*}{\partial k_i}$, the value of type $i \in \{w, so, s\}$ capacity is:

$$\begin{aligned}
V_{k_i} &= \sum_{t=1}^{3}[p_t(Q_t^*)(e_t^i + \frac{\partial q_t^*}{\partial k_i}) - C_P'(q_t^*)\frac{\partial q_t^*}{\partial k_i}] - \frac{\partial \tilde{C}_r(q_2^* - q_1^*)}{\partial k_i} - \frac{\partial \tilde{C}_r(q_3^* - q_2^*)}{\partial k_i} \\
&= \sum_{t=1}^{3}[p_t(Q_t^*)(e_t^i + \frac{\partial q_t^*}{\partial k_i}) - C_P'(q_t^*)\frac{\partial q_t^*}{\partial k_i}] - \frac{\partial C_r(q_2^* - q_1^*)}{\partial k_i} \\
&= \sum_{t=1}^{3}[p_t(Q_t^*)(e_t^i + \frac{\partial q_t^*}{\partial k_i}) - C_P'(q_t^*)\frac{\partial q_t^*}{\partial k_i}] + C_r'(q_2^* - q_1^*)\frac{\partial q_1^*}{\partial k_i} - C_r'(q_2^* - q_1^*)\frac{\partial q_2^*}{\partial k_i} \\
&= p_1(Q_1^*)e_1^i + p_2(Q_2^*)e_2^i + p_3(Q_3^*)e_3^i
\end{aligned} \quad . \tag{I.4}$$

Again, marginally changing $k_i$ will only deliver a new optimal $q_2$ in the neighborhood of $q_2^*$. Thus, the inequalities in (I.2) would not be violated and $\tilde{C}_r(\hat{q}_3^* - q_2) = 0$ still holds for each $q_2$ in the neighborhood of $q_2^*$. Therefore, $\frac{\partial \tilde{C}_r(q_3^* - q_2^*)}{\partial k_i} = 0$ in the second line. Finally, the last line is obtained by plugging (I.1) and (I.3) into $V_{k_i}$.

The values of $e_t^i$ depends critically on how storage operation changes when $k_i$ is increased. Since wind and solar energy production are exogenous, $\frac{\partial \alpha_t^w k_w}{\partial k_i}$ and $\frac{\partial \alpha_t^{so} k_{so}}{\partial k_i}$ are constants. However, $\frac{\partial s_t^*}{\partial k_i}$ may vary across different scenarios because storage production is also a control variable of the social planner. The optimal $s_t$ is shown in table I.1.

**Table I.1:** Optimal Energy Storage Production Under Each Scenario

| | $s_1^*$ | $s_2^*$ | $s_3^*$ |
|---|---|---|---|
| $L_1$ | $-k_s$ | $k_s$ | 0 |
| $L_2$ | $-k_s$ | $\frac{a_2 - a_3 - b\alpha_2^{so} k_{so} + bk_s}{2b}$ | $\frac{a_3 - a_2 + b\alpha_2^{so} k_{so} + bk_s}{2b}$ |
| $L_3$ | $-k_s$ | 0 | $k_s$ |
| $H$ | 0 | $-k_s$ | $k_s$ |

Under scenario $L_2$, storage discharge spreads to two periods (period two and three) since $p_2 = p_3$, which translates into the following optimality condition for storage production: $a_2 -$

$b(q_2^* + \alpha_2^w k_w + \alpha^{so} k_{so} + s_2^*) = a_3 - b(q_3^* + \alpha_3^w k_w - s_2^*)$, which delivers the value of $\alpha_2^{s*}$ shown in table I.1 by imposing $\alpha_2^w = \alpha_3^w$.

Finally, plug $s_t^*$ in table I.1 into (I.4) and impose $p_2(Q_2^*) = p_3(Q_3^*)$ for scenario $L_2$, the expression of $V_{k_i}$ for $i \in \{k, so, s\}$ under all *low solar* scenarios could be re-written as:

$$V_{k_i} = p_1(Q_1^*)\alpha_1^i + p_2(Q_2^*)\alpha_2^i + p_3(Q_3^*)\alpha_3^i \tag{I.5}$$

where $\alpha_t^s = \dfrac{\partial s_t^*}{\partial k_s}$ is defined as the capacity factor of storage in period $t$.

The derivation under the *medium solar* scenario (omitted here) is similar to that under the *low-medium solar* scenario (i.e. $L_2$). $V_{k_i}$ under this scenario is exactly the same as that in (I.4).

**High Solar Scenario ($q_1^* > q_2^* < q_3^*$)**

Given this ordering of optimal fossil-fuel energy generation ($q_1^* > q_2^* < q_3^*$), the first order conditions (FOCs) with respect to $q_1, q_2$ and $q_3$ are:

$$\begin{cases} p_1(Q_1^*) - C_P'(q_1^*) = 0 \\ p_2(Q_2^*) - C_P'(q_2^*) + C_r'(q_3^* - q_2^*) = 0 \\ p_3(Q_3^*) - C_P'(q_3^*) - C_r'(q_3^* - q_2^*) = 0 \end{cases} \tag{I.6}$$

Similar to the *low solar* scenarios above, the value of type $i \in \{w, so, s\}$ capacity is:

$$\begin{aligned} V_{k_i} &= \sum_{t=1}^{3}[p_t(Q_t^*)(\alpha_t^i + \frac{\partial q_t^*}{\partial k_i}) - C_P'(q_t^*)\frac{\partial q_t^*}{\partial k_i}] - \frac{\partial C_r(q_3^* - q_2^*)}{\partial k_i} \\ &= \sum_{t=1}^{3}[p_t(Q_t^*)(\alpha_t^i + \frac{\partial q_t^*}{\partial k_i}) - C_P'(q_t^*)\frac{\partial q_t^*}{\partial k_i}] + C_r'(q_3^* - q_2^*)\frac{\partial q_2^*}{\partial k_i} - C_r'(q_3^* - q_2^*)\frac{\partial q_3^*}{\partial k_i}. \\ &= p_1(Q_1^*)\alpha_1^i + p_2(Q_2^*)\alpha_2^i + p_3(Q_3^*)\alpha_3^i \end{aligned} \tag{I.7}$$

## I.2 Derivation: Theorem 1

**Low Solar Scenarios ($q_1^* < q_2^* = q_3^*$)**

Totally differentiating the FOCs specified by (I.1) and (I.3) with respect to $q_1^{*L}$, $q_2^{*L}$ and $E_t$, we get:

$$\begin{bmatrix} -b - C_P'' - C_r'' & C_r'' \\ C_r'' & -2b - 2C_P'' - C_r'' \end{bmatrix} \begin{bmatrix} \frac{dq_1^{*L}}{dE_t} \\ \frac{dq_2^{*L}}{dE_t} \end{bmatrix} = e_t^L \tag{I.8}$$

where $e_1^L = [b \quad 0]'$, $e_2^L = [0 \quad b]'$ and $e_3^L = [0 \quad b]'$. Solving the equation system above by Cramer's Rule for each $t = 1, 2, 3$ delivers the upper panel of table I.2. Note that due to the property of Case I discussed in section I.1, $\frac{dq_2^{*L}}{dE_t} = \frac{dq_3^{*L}}{dE_t}$ for all $t = 1, 2, 3$.

**Table I.2:** Effect of Changing Exogenous Energy Supply in One Period On Electricity Output Changes in All Periods

(a) Low Solar Scenarios

| | $dq_1^{*L}$ | $dq_2^{*L}$ | $dq_3^{*L}$ |
|---|---|---|---|
| $dE_1$ | $\frac{-b(2b+2C_P''+C_r'')}{(b+C_P'')(2b+2C_P''+3C_r'')}$ | $\frac{-bC_r''}{(b+C_P'')(2b+2C_P''+3C_r'')}$ | $\frac{-bC_r''}{(b+C_P'')(2b+2C_P''+3C_r'')}$ |
| $dE_2$ | $\frac{-bC_r''}{(b+C_P'')(2b+2C_P''+3C_r'')}$ | $\frac{-b(b+C_P''+C_r'')}{(b+C_P'')(2b+2C_P''+3C_r'')}$ | $\frac{-b(b+C_P''+C_r'')}{(b+C_P'')(2b+2C_P''+3C_r'')}$ |
| $dE_3$ | $\frac{-bC_r''}{(b+C_P'')(2b+2C_P''+3C_r'')}$ | $\frac{-b(b+C_P''+C_r'')}{(b+C_P'')(2b+2C_P''+3C_r'')}$ | $\frac{-b(b+C_P''+C_r'')}{(b+C_P'')(2b+2C_P''+3C_r'')}$ |

(b) High Solar Scenario

| | $dq_1^{*H}$ | $dq_2^{*H}$ | $dq_3^{*H}$ |
|---|---|---|---|
| $dE_1$ | $\frac{C_P''}{b+C_P''}$ | 0 | 0 |
| $dE_2$ | 0 | $\frac{-b(b+C_P''+C_r'')}{(b+C_P'')(b+C_P''+2C_r'')}$ | $\frac{-bC_r''}{(b+C_P'')(b+C_P''+2C_r'')}$ |
| $dE_3$ | 0 | $\frac{-bC_r''}{(b+C_P'')(b+C_P''+2C_r'')}$ | $\frac{-b(b+C_P''+C_r'')}{(b+C_P'')(b+C_P''+2C_r'')}$ |

*Note: the "L" and "H" subscripts index low solar and high solar scenarios.*

**High Solar Scenario** ($q_1^* > q_2^* < q_3^*$)

Totally differentiating the FOCs specified by (I.6) with respect to $q_1^{*H}$, $q_2^{*H}$, $q_3^{*H}$ and $E_t$,

$t \in \{1,2,3\}$:

$$\begin{bmatrix} -b - C_P'' & 0 & 0 \\ 0 & -b - C_P'' - C_r'' & C_r'' \\ 0 & C_r'' & -b - C_P'' - C_r'' \end{bmatrix} \begin{bmatrix} \frac{dq_1^{*H}}{dE_t} \\ \frac{dq_2^{*H}}{dE_t} \\ \frac{dq_3^{*H}}{dE_t} \end{bmatrix} = e_t^H \tag{I.9}$$

where $e_1^H = [b \quad 0 \quad 0]'$, $e_2^H = [0 \quad b \quad 0]'$ and $e_3^H = [0 \quad 0 \quad b]'$. Solving the equation system above for each $t \in \{1,2,3\}$ delivers the lower panel of table I.2.

## I.3 Derivation – Boundaries of Scenarios $L_2/L_3$ and $L_3/M$

From table 4.2, it is clear that the left boundary of scenario $L_3$ defines the boundary between scenarios $L_2$ and $L_3$, and its right boundary defines the boundary between scenarios $L_3$ and $M$. Therefore, finding out the boundaries defining scenario $L_3$ is enough to define the two turning points that we are interested in. The inequalities that defines scenario $L_3$ are:

$$\begin{cases} p_3(Q_3^{*L_3}) > p_2(Q_2^{*L_3}) \\ p_2(Q_2^{*L_3}) > p_1(Q_1^{*L_3}) \\ q_2^{*L_3} > q_1^{*L_3} \end{cases} \tag{I.10}$$

From the FOCs defined in (I.1) and (I.3), $q_1^{*L_3}$ and $q_2^{*L_3}$ could be solved out as functions of wind/solar/storage capacities, cost parameters as well as demand parameters. Plug $q_1^{*L_3}$ and $q_2^{*L_3}$ into the inequalities above, (I.10) is reformulated as:

$$\begin{cases} k_{so} > \frac{a_2 - a_3}{b} + k_s = k_{so}^A \\ k_{so} < \frac{(a_2-a_3)b+(a_2-a_1)(4c_2+6\gamma_2)+3b\gamma_1}{4bc_2+6b\gamma_2+b^2} - \frac{4bc_2+6b\gamma_2-b^2}{4bc_2+6b\gamma_2+b^2}k_s + \frac{(\bar{\alpha}^w - \underline{\alpha}^w)}{4bc_2+6b\gamma_2+b^2}k_w = k_{so}^{B_2} \\ k_{so} < \frac{a_2+a_3-2a_1-3\gamma_1}{b} - 3k_s + 2k_w(\bar{\alpha}^w - \underline{\alpha}_w) = k_{so}^{B_1} \end{cases} \tag{I.11}$$

Define $k_{so}^B = \min(k_{so}^{B_1}, k_{so}^{B_2})$. Scenario $L_1$ or $L_2$ emerges if $k_{so} \in [0,\ k_{so}^A]$. Scenario $L_3$ emerges if $k_{so} \in [k_{so}^A,\ k_{so}^B]$. Finally, scenario $M$ or $H$ emerges if $k_{so} \in [k_{so}^B,\ \infty]$.

Further, it is straightforward to show that $k_{so}^{A}$ is increasing in $k_s$. Assuming $4c_2 + 6\gamma_2 > b$, both $k_{so}^{B_1}$ and $k_{so}^{B_2}$ are increasing in $k_w$ and decreasing in $k_s$. Thus, $K_{so}^{B}$ is also increasing in $k_w$ and decreasing in $k_s$.

## APPENDIX J

## AGGREGATE PRODUCTION COST CURVE FOR EACH GENERATION TECHNOLOGY

In this section, I show how to construct $C(q_{jt}; x_{jt})$ for type $j$ generation capacities from each generator's marginal production cost. I calibrate generator level marginal production cost as:

$$C_{ij} = P_{fij} * HR_{ij} + P_{SO2} * SO2Rate_{ij} + P_{NOX} * NOXRate_{ij} + VOM_j,$$

where $HR_i$ is heat rate of generator $i$, which is the amount of heat input (measured in mmbtu) required to generate 1 MW of electricity. I obtain generator level heat rate from EGRID database. $P_{fij}$ is fuel price measured in $\$/mmbtu$, which is obtained from EIA. $SO2Rate_{ij}$ and $NOXRate_{ij}$ SO2 and NOX emission per MW of electricity generated, measured in tons. This information is also obtained from EGRID. Finally, $VOM_j$ is technology-specific Variable Operations and Maintenance cost calibrated from Cullen and Reynolds (2017).

The difficulty of constructing aggregate production cost function for each generation technology comes from its dependence on the amount of capacities being kept on at the beginning of year $t$, $x_{jt}$. It is straightforward to show that the aggregate production cost when aggregate output is at the minimum generation level of "on" capacities, $C(m_j x_{jt}; x_{jt})$, is piecewise linear and convex in $m_j x_{jt}$. The slope of this curve increases at the points of $m_j x_1, m_j(x_1 + x_2), \ldots, m_j(x_1 + x_2 + \cdots + x_{n_j})$. This is a direct implication of the result mentioned in the main text that only the least-cost generators within a generation type would be kept on.

For a given level of $x_{jt}$, $C(q_{jt} > m_j x_{jt}; x_{jt})$ is also piecewise linear and convex in $q_{jt}$. The slope of this curve increases at points where the closest lower-cost generation capacities are exhausted.

To make the argument concrete, consider a simple case where the marginal production costs for type $j$ generation technology fall into three classes ($n_j$=3): $c_1 < c_2 < c_3$. The total capacities of generators within each class are $k_1 = 200, k_2 = 60$ and $k_3 = 100$. Further, the minimum generation level per unit of capacity is $m_j = 0.5$.

Figure J.1 plots the aggregate production cost function with different levels of “on" capacities. The line with arrows represents production cost when producing at the aggregate minimum generation level of “on" capacities. The bold solid lines are production cost when producing above the aggregate minimum generation level.

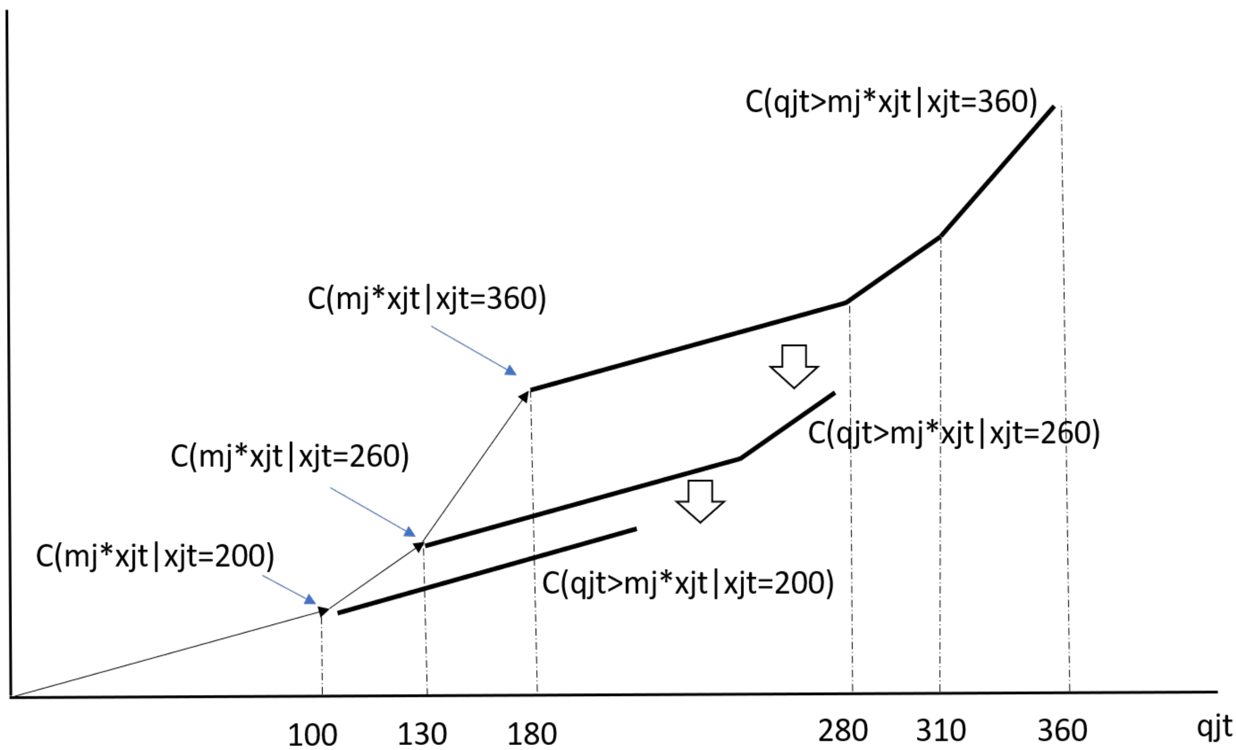



Figure J.1: Aggregate Production Cost in the Simple Example

In practice, I fit quadratic regression lines to $C(q_{jt} > m_j x_{jt}; x_{jt} = k_j)$ curve (i.e. the uppermost curve in the figure) and $C(m_j x_{jt}; x_{jt})$ curve. To adjust “on" capacity level, I adjust estimated $C(q_{jt} > m_j x_{ijt}; x_{jt} = k_j)$ along the esimated $C(m_j x_{ijt}; x_{ijt})$ curve. The resulting aggregate production cost curve $C(q_{jt}; x_{ijt})$ is convex in $x_{jt}$ and $q_{jt}$.

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# CHAPTER 5

# CONCLUSIONS

New technologies in the sectors of food, water and energy are cited as mitigation and adaptation strategies facing climate change. However, the use of these new technologies may not lead to the expected consequences that these technologies are designed to deliver. In food and water sectors, I find that the use of more efficient irrigation technologies in Kansas HPA increases, rather decreases, groundwater extraction. In the energy sector, further decline in solar capacity costs decreases wind energy capacity investment when solar cost is already low due to the complex value dependence of wind and solar capacities. As a result, renewable energy penetration decreases and $CO_2$ emissions increases. Somewhat surprisingly, cheaper renewable energy costs not always lead to a cleaner grid.

Economists have long recognized the limitations of purely technological solutions to environmental problems, and argued that resilient and effective institutions and policies can be effective adaptation strategies. Combining the use of new technologies with properly-designed environmental policies and institutions, thereby, might lead to significant social welfare increase. For example, the rebound effects following efficient irrigation technology adoption are found to be greater for farmers with larger water rights. Reducing water rights by 10% is found to be able to reduce the rebound effects by 15.4%. After rebound effects are controlled, an insurance policy which subsidizes farmers when the new technology' annual profit gain is lower than a minimum level would reduce farmers' uncertainty and increase adoption rate. Such an insurance policy is found to be more cost-effective than the more commonly used cost share subsidies.

As for the renewable energy example, a policy that mandates a 36% renewable energy penetration when solar capacity costs are low increases wind capacity investment, compared with the no-policy scenario. Consequently, social welfare increases by \$0.77 billion/year due to an increase in renewable energy penetration and a corresponding decrease in $CO_2$ emissions.

Most analyses in this dissertation take partial-equilibrium approaches such that policy/technology interactions are studied separately for each sector (except in chapter two). Therefore, the results in this dissertation are best interpreted as "own-sector" welfare effects of policy/technology interactions in the food-energy-water nexus. Indeed, food, water and energy sectors are closely related to each other. Therefore, I also provide a brief discussion below on the connections among different sectors to guide future researches on food-energy-water nexus.

Shown in chapter two, a part of LEPA irrigation's rebound effects comes from switching to more water-intensive crops such as corn. From the perspective of food-water nexus, policies or technology adoptions in food and agricultural sectors that reduce water use by corn growers could also help ameliorate the rebound effects of LEPA. Moreover, LEPA adoption might also reduce energy usage because the energy requirements of LEPA irrigation are much lower than those of traditional irrigation technologies. Therefore, policies that promote LEPA adoption are also likely to reduce energy use.

Renewable energy development is another bridge between energy and water sectors. Unlike fossil-fuel energy generators, renewable energy resources such as wind and solar energy generators not only emit zero air pollutants, but also requires much less water for cooling. As renewable energy capacity costs continue declining, energies produced from renewable resources would gradually replace those from fossil-fuel energy generators, which reduces water use in the energy sector. Besides bridging energy and water sectors, renewable energy development also connects energy and food sectors. Land requirements for wind and solar power plants are much larger than those for fossil-fuel energy generators. A large share of these land requirements is met by converting farmland into solar/wind farms, which reduces food production. Policies aiming at increasing renewable energy penetration would thus also influence both regional water balance and food production structures.

Future researches should aim to quantify these cross-sector effects of environmental policies and institutions. These results, combined with the own-sector effects obtained in this dissertation, would be able to provide comprehensive empirical support for the design of effective environmental policies and institutions that complement technology improvements in the food-energy-water nexus.