DISSERTATION

THREE ESSAYS ON THE ECONOMICS OF LAND USE AND CONSERVATION

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Mostafa Shartaj

Department of Agricultural and Resource Economics

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Doctoral Committee:

Advisor: Jordan F. Suter

Dale T. Manning
Jude Bayham
Kelly Jones

ABSTRACT

THREE ESSAYS ON THE ECONOMICS OF LAND USE AND CONSERVATION

This dissertation consists of three chapters focused on the economics of land use and conservation. The first chapter investigates the differences in groundwater use among wells irrigating State Land Board (SLB) parcels and nearby private parcels. SLB parcels represent leased parcels with limited tenure length and uncertainty of renewal. In the chapter, we demonstrate that wells irrigating SLB lands pump substantially more groundwater compared to non-SLB wells. The second chapter makes use of a novel dataset of discount rates elicited from agricultural producers across the United States to explore how estimates of discount rates for can be utilized to improve the performance of agri-environmental programs. The final paper examines camping in US Forest Service (USFS) campgrounds during the COVID-19 pandemic. Using data on campground reservations made through recreation.gov, we illustrate how camping on USFS lands was impacted by infection rates, public health restrictions and proximity to metropolitan areas and National Parks (NPs).

Imperfect property rights can lead to over-extraction of resources and provide disincentives to invest in conservation of the resource stock. In the first chapter, making use of a natural experiment, we explore the case of groundwater usage on State Land Board (SLB) parcels, relative to nearby private parcels. The SLB of Colorado leases out land to agricultural producers, with groundwater rights tied to the land leases. Leases by the SLB have tenure lengths of 10 years, where the leaseholder is allowed to renew their lease if they can match the highest bid for the next lease term. This generates uncertainty regarding access to future groundwater stocks. We contribute to the literature by demonstrating the causal impact of SLB designation on groundwater use. We show that wells irrigating SLB lands, on average, use 15 to 24 percent more groundwater compared to nearby private lands.

Adoption of conservation practices in agriculture often requires upfront costs, while the private benefits are produced in the future. As such, farmers' time preferences can play an important role in adoption decisions. In the second chapter, using elicited discount rates of farmers from 26 US states, we explore the role of farmers' discount rates in cover crop adoption, program participation, and continuation of cover cropping after the contract period. The data reveal that mean observed discount rates are lower both for farmers that adopt cover cropping and for farmers that participate in conservation programs, compared to those who do not. This suggests that time preferences play a key role in conservation adoption decisions. The empirical results are followed by a simulation analysis, which utilizes the discount rate data to explore benefits of tailoring conservation contracts based on discount rates. The simulations point out that a small increase in upfront payments can substantially increase cover cropping during the contract period, but they do little to increase continuation of cover cropping after the contract period. The simulations also reveal that tailoring the contract length and annual payment, according to the discount rate information, can allow policy makers to target higher levels of continuation, which are unattainable under the 5-year status quo contract. In the extreme case where the program administrator can observe individual discount rates, it is possible to dramatically reduce the costs of increasing continual adoption by individually tailoring the contracts.

During the COVID-19 pandemic, US public land managers faced the challenge of catering to large increases in camping demand, while maintaining social distancing guidelines. In the final chapter, we use multivariate linear regression to analyze weekly changes in reservations to US Forest Service (USFS) campgrounds between 2019 and 2020. Our sample includes 1,688 individual USFS campgrounds from across the contiguous US. The results illustrate the dramatic increases in camping on USFS land that occurred in the summer of 2020 and demonstrate that increases in local infection rates led to significant increases in camping nights reserved in the summer. The results also illustrate that the increase in camping nights reserved at USFS campgrounds was particularly dramatic for campgrounds located near large metropolitan areas and near National Parks that saw increases in overall recreational visits. These results point to the important role that public lands played during the pandemic and can help guide public land resource allocations for campground maintenance and operation.

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DEDICATION

Dedicated to Reshma Kamal for her wisdom.

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Chapter 1

State of depletion: An empirical analysis of groundwater use on State Trust Lands

1.1 Introduction

Groundwater resources, such as the Ogallala aquifer, have experienced substantial depletion in the western US (Haacker, Kendall, and Hyndman, 2016). Groundwater is a crucial input to irrigated agriculture (Lauer et al., 2018) and its availability can have substantial impacts on crop choices and agricultural rents (Hornbeck and Keskin, 2014). Given the prevalence of state trust lands and the importance of groundwater stocks across the west, it is critical to explore whether groundwater use on these lands varies considerably from privately owned land. Additionally, while groundwater use produces externalities associated with stock depletion, it remains unclear if limited property rights on public lands exacerbate the economic losses associated with over-extraction. In this paper, we utilize a natural experiment to empirically compare groundwater use on trust lands to water use on private land parcels nearby, allowing us to better understand the extent to which differences in imperfect property rights on public lands may impact common pool resource use.

Trust lands make up approximately 156 million surface acres of public land across the United States, as reported by the National Association of State Trust Lands. The State Land Board (SLB) of Colorado owns and manages 2.8 million acres of trust land in the state, 98 percent of which is leased out for agricultural uses. The revenue from these leases, as in other states, goes towards funding public schools. Leases on trust lands are often married with access to water rights owned by the SLB. The majority of these water rights are for groundwater. Leaseholders of trust lands face a limited tenure of 10 years and face an uncertain renewal mechanism. At the end of the lease tenure, the trust land goes up for auction. The current holder of the lease can match the highest bid in the auction to renew for an additional 10 years. This is referred to as the right of first refusal.

If the uncertainty of the renewal mechanism leads to poor tenure security, leaseholders may be disincentivized to conserve groundwater stocks on these lands compared to private land.

The majority of state trust lands in Colorado were uniformly allocated across space in 1875 using the US Rectangular Public Land Survey System (PLSS), acting as a natural experiment. Apart from being uniformly distributed over space, the allocation of these lands also pre-date groundwater development over the Ogallala aquifer in Colorado. In this research, we use novel information from digitalized maps of the initial 1875 allocation of state trust lands, to explore differences in annual groundwater use in recent years at SLB wells relative to privately managed wells. Groundwater wells that currently lie within these historical boundaries are more likely to be owned and managed by the SLB, and thus used by agricultural leaseholders for irrigation. Given the timing and distribution of the 1875 trust land allocation, well location relative to the historical boundary is likely to be independent of land characteristics, hydrology, and other environmental factors that may influence groundwater use today. This makes the initial allocation an ideal instrument, which we utilize to make a number of important contributions to the literature.

First, we contribute to the groundwater literature by highlighting the impact of publicly leased SLB lands on groundwater use and depletion. Groundwater represents a common pool accumulating resource, that is subject to spatial and temporal inefficiencies. Existing research has explored the influence of energy prices (Pfeiffer and Lin, 2014; Hrozencik et al., 2022a), spatial externalities (Pfeiffer and Lin, 2012), and groundwater management policies (Edwards, 2016; Smith et al., 2017; Hrozencik et al., 2017) on the extraction decisions of groundwater users. We contribute to this literature by empirically demonstrating that groundwater use by wells irrigating SLB lands is substantially higher than that of comparable privately managed lands. The magnitude of the local average treatment effect is around 15 to 24 percent of mean water use in the sample. The results also demonstrate that current levels of saturated thickness are lower for SLB wells, relative to nearby private wells. This suggests that the relative external impacts of groundwater pumping are exacerbated on SLB lands. Given our identification strategy, we are able to estimate differences in groundwater use between SLB managed wells and privately managed wells that are not confounded by observed and unobserved environmental factors that may influence groundwater use.

We also contribute to the literature exploring dynamic sources of inefficiencies in groundwater use. Despite being an accumulating resource, empirical research exploring sources of temporal inefficiencies in groundwater use and dynamic decision making by groundwater users has been scarce. Oehninger and Lawell (2021) show that, despite the disincentives to dynamic optimization by the prior appropriation doctrine, farmers using groundwater respond to expected future crop and energy prices in a way that is consistent with dynamic optimization. This is the only empirical research, to the best of our knowledge, that evaluates the influence of dynamic considerations in groundwater extraction, within an existing property right arrangement. We contribute to this literature by testing whether groundwater pumping by SLB wells is consistent with a lack of tenure security. Existing research on farmers' time preferences suggest that farmers, on average, have large and positive discount rates (Duquette, Higgins, and Horowitz, 2012; Wuepper, Henzmann, and Finger, 2023). Assuming positive discount rates and a fixed lease term, experiencing limited tenure would lead to groundwater extraction by SLB wells to increase as a function of lease year. However, given the selection of wells by the SLB is not likely to be independent of other factors driving groundwater extraction, it is difficult to isolate the influence of lease year. We again utilize the historical allocation to only look at the subset of SLB wells that lie within the boundaries of the historical allocation. This is likely to provide a set of SLB wells with comparable characteristics, other than being in different lease years. We then compare differences in groundwater use between these SLB wells associated with different lease years. The results demonstrate that, on average, groundwater use by SLB wells are an increasing function of the lease year, suggesting that low tenure security is a likely mechanism that contributes to the divergence in groundwater extraction rates between SLB and non-SLB wells. Furthermore, the results provide empirical support to the importance of dynamic decision making and inter-temporal disincentives in influencing groundwater extraction behavior.

The results also contribute to the empirical literature exploring limited property rights and resource use. Groundwater extraction can be defined as a function of inter-temporal incentives as set by the associated property rights. Early work exploring the role of property rights and resource usage theorizes that in the absence of complete property rights, resource rents will dissipate due to excessive extraction (Gordon, 1954). In practice, however, limited property rights are common for resources held in public trust, where it is common to lease out land and water to users for a limited tenure. Thus, granting resource users access without perpetually giving up control over the resource. State trust lands provide an opportunity to observe resource usage under limited property rights. Existing research has highlighted the influence of limited property rights in agricultural productivity (Banerjee, Gertler, and Ghatak, 2002), investment in irrigation technology (Ge, Edwards, and Akhundjanov, 2020), adoption of agricultural practices (Deaton, Lawley, and Nadella, 2018) and land utilization (Dippel, Frye, and Leonard, 2020). We expand this literature by demonstrating that groundwater use on limited tenure SLB lands is substantially higher from that on privately managed land. Due to the potential presence of privately rented lands in the control group, which are likely to attenuate the estimated effects, the estimates in this study provide a lower bound of actual differences in resource extraction due to tenure security.

Historically, state trust lands have been dedicated to productive uses, as state trust lands in the US have a fiduciary duty to generate revenue for funding public schools and other public beneficiaries. Davis (2008) highlights that state trust lands in the west are largely used for extractive activities. However, the differences in the intensity of extraction, between state trust lands and other public and private lands, remains unexplored. State trust lands make up three quarters of all state owned land in the US[1] (Davis, 2008). Therefore, differences in land use patterns on trust lands can have large consequences for resource depletion and the environment. Despite being germane to resource extraction, there is very little empirical research related to measuring the magnitude of resource extraction on state trust lands. Existing studies on trust lands have largely focused on technical efficiency (Bonds and Hughes, 2007), market returns (Sunderman, Spahr, and Runyan,

[1]Concentrated mostly in 18 western states

2004; Sunderman and Spahr, 2006) and revenue generation (Bonds and Pompe, 2005). In this analysis, we demonstrate the degree to which groundwater wells irrigating SLB lands exceed that of privately managed lands. The results from this analysis may help inform sustainable management of SLB trust lands.

The empirical analysis also investigates the mechanisms that lead to differences between SLB managed and privately managed wells along the intensive and extensive margin of groundwater use. We do not find conclusive evidence to suggest that the differences in groundwater use are driven by the intensive or extensive margin. Additionally, we combine satellite data on agricultural land use by the National Cropland Data Layers (NCDL) with 6 years of irrigated lands data, to explore differences in the proportion of water-intensive crop pixels on SLB irrigated parcels, relative to privately irrigated parcels. The results do not suggest differences, on average, in the proportion of water-intensive crop production between SLB and non-SLB irrigated parcels. Finally, we explore how groundwater use among SLB wells vary based on lease year, which has been discussed earlier.

The paper is organized as follows. The next section illustrates the theoretical framework for the paper. The following sections describe the historical allocation of SLB lands, description of the data and the empirical strategy used. These sections provide crucial information regarding the natural experiment and describe the process through which causal effects are estimated in this paper. The sections following that discuss the main results, mechanisms and conclusions of the paper.

1.2 Theoretical Framework

In this section, we present a 2-period common pool resource model with 2 producers designed to provide insight into the differences in behavioral incentives on SLB land compared to private land. We are interested in analyzing the difference in water use in period 1 between the two producers, within a setting of differing levels of renewable tenure related to access to a common pool resource. Let ρ represent the assurance level, as defined by the lease contract, which represents the probability that the producer will have access to the resource stock in period 2. Let us assume that each producer maximizes profit subject to a groundwater resource constraint. For simplicity, assume producers only use 1 input, which is groundwater, to produce output and the input has diminishing returns to production. Groundwater use by producer i in period j is defined as d_{ij}. The cost of extracting groundwater per unit is $c-bX_{ij}$. This cost reduces by bX_{ij}, where X_{ij} is the saturated thickness in period j. b represents the quantity by which the marginal cost of extraction declines per unit of saturated thickness. $c-bX_{ij}>0$ such that the marginal cost of extraction remains positive even at high saturated thickness levels.

The production function is assumed to be $f(d_{ij})=ad_{ij}-\frac{1}{2}sd_{ij}^2$ for producer i in period j. The 2-period maximization problem for producer 1 can then be written as:

$$\underset{\{d_{11},d_{12}\}}{\text{maximize}} \quad \pi_1 = p(ad_{11}-\frac{1}{2}sd_{11}^2)-(c-bX_{11})d_{11}+\frac{\rho[p(ad_{12}-\frac{1}{2}sd_{12}^2)-(c-bX_{12})d_{12}]}{(1+r)}$$

subject to:

$$X_{12}=X_{11}+\bar{R}-\gamma_1 d_{11}-\gamma_2 d_{21}$$

where p represents price of output, $\bar{R}$ represents the recharge rate, and γ represents the impact of water use on the groundwater stock available to producer 1, with γ_1 being the impact of water use by producer 1 and γ_2 being the impact of water use by producer 2. Both γ_1 and γ_2 are assumed to be positive. The problem can be simplified to an unconstrained optimization problem by plugging the resource constraint into the objective function. The first order conditions from the simplified problem can be expressed as:

$$\frac{\partial \pi_1}{\partial d_{11}}=p(a-sd_{11})-c+bX_{11}-\frac{b\gamma_1\rho d_{12}}{(1+r)}=0 \tag{1.1}$$

$$\frac{\partial \pi_1}{\partial d_{12}}=p(a-sd_{12})-c+bX_{11}+b\bar{R}-b\gamma_1 d_{11}-b\gamma_2 d_{21}=0 \tag{1.2}$$

To examine the difference in water use between producer 1 and 2, we need to derive the Nash equilibrium level of water use by each producer. In this analysis, we focus on an open loop Nash equilibrium, where individuals pre-commit to extraction paths and the main common pool externality is driven by increases in pumping cost that each player imposes on the other through depletion of groundwater stocks[2]. Assuming symmetry, the best response functions for d_{11} and d_{21} can be expressed as:

$$d_{11} = \frac{[ps(1+r) - b\gamma_1\rho_1][pa - c + bX_{11}] - b^2\gamma_1\rho_1\bar{R}}{(ps)^2(1+r) - (b\gamma_1)^2\rho_1} + \frac{b^2\rho_1\gamma_1\gamma_2 d_{21}}{(ps)^2(1+r) - (b\gamma_1)^2\rho_1} \tag{1.3}$$

$$d_{21} = \frac{[ps(1+r) - b\theta_1\rho_2][pa - c + bX_{21}] - b^2\theta_1\rho_2\bar{R}}{(ps)^2(1+r) - (b\theta_1)^2\rho_2} + \frac{b^2\rho_2\theta_1\theta_2 d_{11}}{(ps)^2(1+r) - (b\theta_1)^2\rho_2} \tag{1.4}$$

where X_{21} is the stock of water available to producer 2 in period 1. θ represents the impact of water use on the groundwater stock available to producer 2, with θ_1 being the impact of water use by producer 2 and θ_2 being the impact of water use by producer 1. We assume, following physical groundwater flow properties, that the impact of extraction on groundwater stocks is highest at the point of extraction and dissipates with distance. Therefore, we assume $\gamma_1 > \gamma_2$ and $\theta_1 > \theta_2$. Due to symmetry, $\theta_1 = \gamma_1$ and $\theta_2 = \gamma_2$. Additionally, ρ_1 and ρ_2 are the assurance levels of producer 1 and 2, respectively. We assume $\rho_1 < \rho_2$, such that producer 1 has a lower level of assurance for accessing the groundwater stock in period 2, as defined by their property right arrangement.

We can summarize equations 3 and 4 as:

[2] Negri (1989) explores an alternative feedback Nash equilibrium, where in addition to a pumping cost externality there is a strategic externality that arises out of competing farmers trying to capture groundwater reserves. This results in further depletion of groundwater stocks. In our analysis, we are not able to empirically estimate either the feedback solution or the open-loop solution. We rather focus on estimating differences between SLB and non-SLB lands where the potential for spillovers arising out of the common pool nature of groundwater stocks is low. Therefore, the open loop equilibrium setup is sufficient for us to demonstrate the need for controlling for spillovers with wells being nearby SLB wells.

$$d_{11} = A_1 + B_1\gamma_2 d_{21} \tag{1.5}$$

$$d_{21} = A_2 + B_2\theta_2 d_{11} \tag{1.6}$$

Both terms A and B vary as a function of ρ. The term A represents water demand for producers in the absence of CPR incentives. B represents how much producers respond to the water demand of others. Unsurprisingly, $\frac{\partial A}{\partial \rho} < 0$ if we assume $pa > c - b(X_{11} + \bar{R})$. The condition $pa > c - b(X_{11} + \bar{R})$ represents that prices need to be sufficiently large so that pa, which is the intercept of the marginal revenue curve, is greater than $c - b(X_{11} + \bar{R})$, which is the marginal cost in period 2 if there was no extraction in period 1. As tenure security improves, producers have more incentive to conserve the resource stock and so they reduce current extraction.

Interestingly, it can be shown that $\frac{\partial B}{\partial \rho} > 0$. When producers have higher assurance of access to future stocks, they respond to a greater degree to the extraction of others. However, when tenure security is low, the extraction of others weighs less on the resource extraction decisions of producers. If we assume property rights arrangements on private land provide higher assurance than public lands, water use on private lands can still be higher due to increased response to water demand by other nearby producers. The open loop Nash equilibrium can then be written as:

$$d_{11} = \frac{A_1 + B_1\gamma_2 A_2}{(1 - B_1 B_2 \gamma_2^2)} \tag{1.7}$$

As the distance between the two wells increases, we can expect the influence of each well's pumping on the other's groundwater availability to diminish. This would lead to $\gamma_2 \to 0$, which reduces the Nash equilibrium level of extraction for each farmer to:

$$d_{11} = A_1 \tag{1.8}$$

$$d_{21} = A_2 \tag{1.9}$$

and the difference between the groundwater use of each producer as:

$$\tau = d_{11} - d_{21} = A_1 - A_2 \tag{1.10}$$

When $\rho < 1$ and $\rho = 1$ for farmers 1 and 2 respectively, this difference represents the difference in groundwater use between the farmers due to differences in tenure security. If the level of tenure security on lands irrigated by SLB wells differ from privately owned ones, then we would expect the difference expressed in equation 1.10 to be greater than zero.

We can estimate the average difference in groundwater use by producers on SLB and non-SLB lands, at the well level, if we have an exogenous assignment of SLB designation. The existence of CPR effects is an important takeaway that is useful for the empirical specifications. In order to identify the impact of differences in incentives between two producers, it is important that the CPR effects between them are not large. Therefore, we focus on producers that have relatively low levels of γ_2 (or θ_2) between them. We assume that the impact that one producer's water use has on the other producer, through γ_2, diminishes with the distance between their wells. Looking at SLB and non-SLB wells that are distant from each other, can help us identify the difference in water use that is independent of γ_2.

1.3 Historical background

Historically, state trust lands represent land grants, provided by the US federal government, to the western territories upon receiving statehood by joining the Union (Pounds, 2011). The initial legislation guiding the allocation include the General Land Ordinance of 1785 and the Northwest Ordinance of 1787. To understand the initial allocation of state trust lands, we need to first describe the US Rectangular Public Land Survey System (RPLSS). The RPLSS, initially established by the General Land Ordinance, organizes all land in the US into 36 square mile grids called townships (Webster and Leib, 2011). Each township is composed of 36 one square-mile sections, arranged as shown in Figure 1.1. Initially, under the General Land Ordinance, states held section 16 of every township in trust for the state schools.

6	**5**	**4**	**3**	**2**	**1**
7	**8**	**9**	**10**	**11**	**12**
18	**17**	**16**	**15**	**14**	**13**
19	**20**	**21**	**22**	**23**	**24**
30	**29**	**28**	**27**	**26**	**25**
31	**32**	**33**	**34**	**35**	**36**

Figure 1.1: A township subdivided into 36 sections as described by the RPLSS

The Northwest Ordinance authorized Congress to pass enabling acts that allowed territories to create a constitution. Once a state constitution was agreed upon by the territory and Congress, the federal government would make an offer to the new state to join the Union. Trust lands were granted to each state as part of joining the Union. One of the big innovations in trust land allocation took place in 1875, when Congress passed the Colorado Enabling Act. Over time, Congress and the states made gradual changes to how trust lands were allocated and managed. The Colorado Enabling act of 1875 was one of the first enabling acts to explicitly mention the establishment of permanent funds for revenues derived from the trust lands. It also included conditions that set minimum prices on the sale of land and restricted the use of income from the sales.

Upon the statehood of Colorado in 1876, the SLB received sections 16 and 36 of most townships as trust lands (Bedford, 2000) from the federal government. The revenues from the use of these trust lands were to be used to fund public schools in Colorado. The state however did not receive lands in areas where the section was already occupied by Native American territories, homesteaders, reserved for parks, military bases or other federal purposes (Coloarado State Land Board, n.d.). At the time, the federal government allowed states to select "in lieu" lands from elsewhere in the public domain. Thus, the state got to pick additional lands in some counties of Colorado, which were meant to equate to the same acreage as the reserved lands.

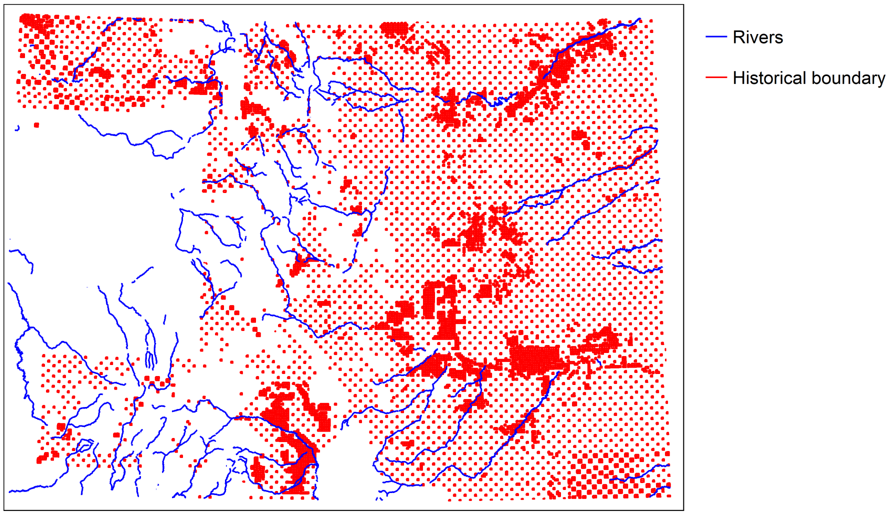


Figure 1.2: Full historical boundary of SLB lands allocated in 1876

The map in Figure 1.2 demonstrates the spatial distribution of the 1876 historical boundaries, which are represented by the red borders. As we can see, there are two distinct patterns in which trust lands were allocated. First, we can see many of the lands were allocated uniformly across space in sections 16 and 36. Second, we can see clusters of trust lands in many areas. These clusters partly reflect lands gained “in lieu", where the state had a choice in selecting the location. Some of these clusters appear to be located in riparian areas. Importantly, these allocations were made before the development of groundwater irrigation in Colorado. Therefore, we can expect these allocations to be exogenous to many of the observable and unobservable factors that may drive groundwater use today. However, due to the presence of “in lieu" lands, these historical boundaries may line up with natural features, such as nearness to rivers, that drive water use. This can pose a threat to the identification of causal impact of SLB lands classification on groundwater use. As we are able to fully observe the allocation mechanism, we can reasonably assume that the historical borders that overlap with sections 16 and 36 are exogenous to factors driving groundwater use today. Therefore, we only consider the historical boundaries related to sections 16 and 36 as our reference boundary in the empirical analysis.

1.4 Data

The study area is located within the Republican River basin in eastern Colorado. The basin overlays a substantial proportion of the Ogallala aquifer within Colorado. We combine data on agricultural leases, lease contracts, and historical boundaries, obtained from the SLB of Colorado, with data on irrigated parcels and water diversion records for the years 2008-2020, obtained from the Colorado Decision Support System (CDSS). The analysis includes SLB leases categorized as agricultural, agricultural and homesite, dry crop, grazing, and irrigation. Using spatial data on irrigated lands in 2015, and active leases in 2020, we identify which irrigated lands had an overlapping area of 80 percent or greater with SLB leased lands. SLB lands are leased for 10 years, after which they are re-leased. Therefore, we assume the spatial location of SLB lands to be fixed between 2008-2020. These overlapping irrigated parcels are identified as irrigated SLB parcels. The non-SLB irrigated parcels include irrigated parcels that have no intersections with any SLB land. Information on water rights tied to each parcel is included in the irrigated parcels data. We then utilize water rights information from irrigated parcels in 2015 to identify which wells irrigate which parcels.

It is important to note that only one year of irrigated parcels data is used to tie well-level information to SLB and non-SLB parcels. This is due to the lack of irrigated lands data available for the entire sample period. For instance, irrigated lands data for the Republican River basin, which contains most of the groundwater wells in our sample, is only available for 2010 and for 2015 to 2020. However, we have information on well-level groundwater use for 2008 to 2020. In order to utilize additional years of groundwater use data, we assume that whether a water right irrigates an SLB (or private) parcel does not vary over time. Additionally, this also assumes that the SLB lands are re-leased with the same groundwater wells every 10 years. As the sample period in the analysis has a large overlap with the active SLB lease data, this assumption is not likely to have significant impact on the results of the study. Wells that irrigate SLB parcels are considered SLB wells (or treatment wells), and wells that irrigate non-SLB parcels make up the non-SLB wells (or control wells). Wells irrigating both SLB and non-SLB parcels are removed from the sample[3]. The

[3]This resulted in dropping 6 wells from the sample.

treatment and control designations are assumed to be time invariant. SLB leased lands are rarely converted to private land, which makes this a reasonable assumption for a 12-year sample period. Wells with no water use in a year are removed for that year. This ensures we are comparing water use only across active wells. Additionally, this can also help control for years in which certain SLB lands, and their associated wells, were not successfully re-leased. We also have water rights data from the SLB of Colorado, which identify the water rights managed by the SLB for a limited number of wells. Around 97 percent of the well IDs we identify match the list of wells provided by the SLB of Colorado. The spatial location data for sections in Colorado was collected from the Colorado Geospatial Portal.

In the analysis, we firstly explore the extent to which groundwater use and saturated thickness varies between SLB and non-SLB wells. We look at both annual groundwater use and annual groundwater use as a proportion of groundwater rights appropriated, using data obtained from the CDSS. The saturated thickness represents the distance between the water table and the base of the aquifer. The saturated thickness data is described in Haacker, Kendall, and Hyndman (2016). We also explore mechanisms that drive differences in groundwater use between SLB and non-SLB wells. We make use of irrigated lands data, from the CDSS, to estimate the amount of associated acres irrigated annually by each well in the sample. Using the adjusted acres[4], we explore differences in groundwater use per acre (intensive margin) and acres irrigated (extensive margin) between SLB and non-SLB wells using the limited amount of data available on irrigated lands. Differences in the water requirement of crops planted can also lead to differences in groundwater use. We make use of rich satellite data on land covers from the National Cropland Data Layers (NCDL), retrieved from the National Agricultural and Statistics Service's (NASS) website, to explore differences in crop choices between SLB and non-SLB irrigated parcels.

NOAA U.S. Climate Gridded datasets are incorporated in the analysis to control for average maximum temperatures and average monthly precipitation during the growing season[5]. Soil type

[4]Calculation of adjusted acres are described in detail in the mechanisms section.

[5]The growing season in this study includes the months of May, June, July, August and September.

data from the USDA's gSSURGO dataset is utilized to control for the soil composition, specifically the percent sand, silt and clay for each parcel. The soil type variables are assumed to be time-invariant. We incorporate groundwater hydrology data from the US Geological Survey (USGS), which include specific yield, depth to water in 2000, and hydraulic conductivity. Additionally, we make use of data on annual groundwater volume and irrigated acres appropriated for each well from the CDSS.

We use spatial data on the 1875 historical boundaries, from the SLB of Colorado, and overlap that with spatial data on sections 16 and 36, obtained from University of Colorado's online GeoLibrary, to retain parts of the historical boundary that fall within those sections. As discussed earlier, this represents the part of the historical boundary that is most likely to be independent of factors that influence groundwater use today. We then combine this with well location data, from the CDSS, to observe which wells fall inside the historical boundary and which fall outside. The well location data is also used to control for well latitude and longitude in the regression analysis.

Non-SLB wells in close proximity to SLB wells are likely to be impacted by groundwater use at the SLB wells. In order to control for potential spillovers, we exclude non-SLB wells in close proximity to SLB wells. Figure 1.3 provides a stylized illustration of the study setting[6]. The historical SLB boundary is depicted by the inner square in the center of the figure. The dot inside the historical boundary represents a treatment well, whereas the dots outside the historical boundary represent control wells. The (outer) buffer, labeled "Bandwidth", represents a 1-mile distance from the historical SLB boundary. In the analysis, we present results that include only control wells within bandwidths of 2 miles and 1 mile, based on specification. Wells nearer to the historical boundary are likely to be similar to each other in terms of observable and unobservable characteristics that may influence water use. Therefore, limiting the sample to a certain bandwidth enables us to estimate differences in water use across comparable wells. As groundwater is a common pool resource, wells located near each other may impact each other's water use. To

[6]In the actual setting, the wells are not distributed uniformly and have imperfect compliance. However, the stylized setting is sufficient to demonstrate the concepts of well exclusion buffer and bandwidth.

reduce the impact of potential spillovers, we exclude all non-SLB wells that lie within 1 mile and 1.5 miles of any SLB wells, depending on the specification. We refer to this as the well exclusion distance, as shown by the circle around the treatment well in figure 1.3.

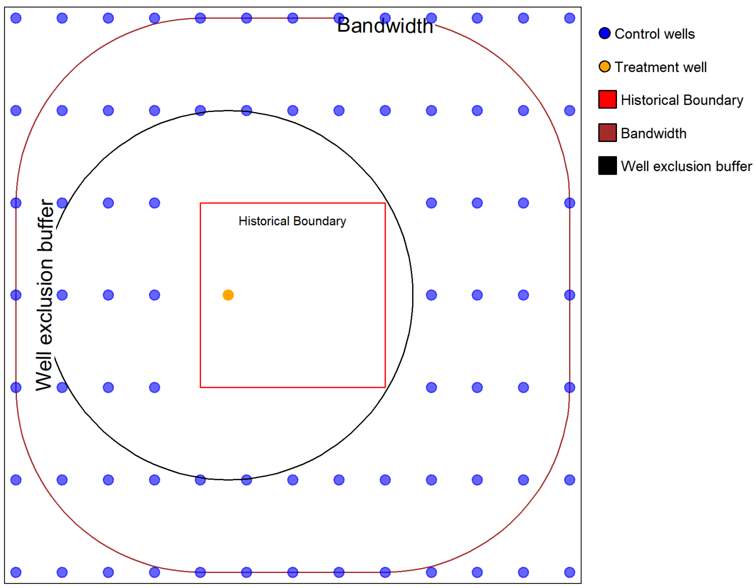
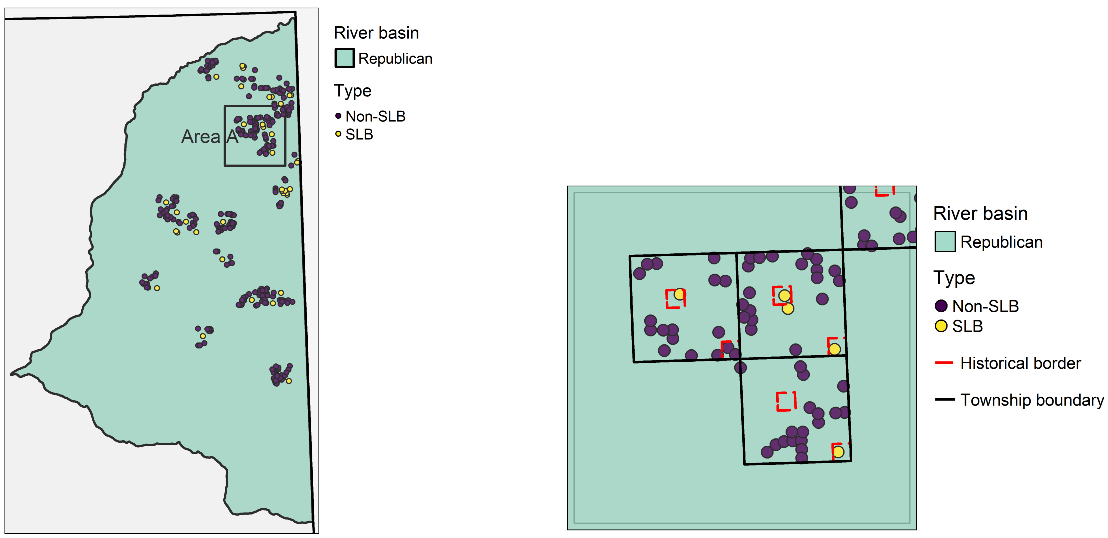


Figure 1.3: Bandwidth and Well exclusion distance

The spatial distribution of SLB and non-SLB wells, that lie within 2 miles of the historical borders and at a well-exclusion distance of 1-mile, is provided in panel (a) of figure 1.4. Panel (b) magnifies a portion of the study area and provides additional spatial information on township boundaries and the historical borders within each township.

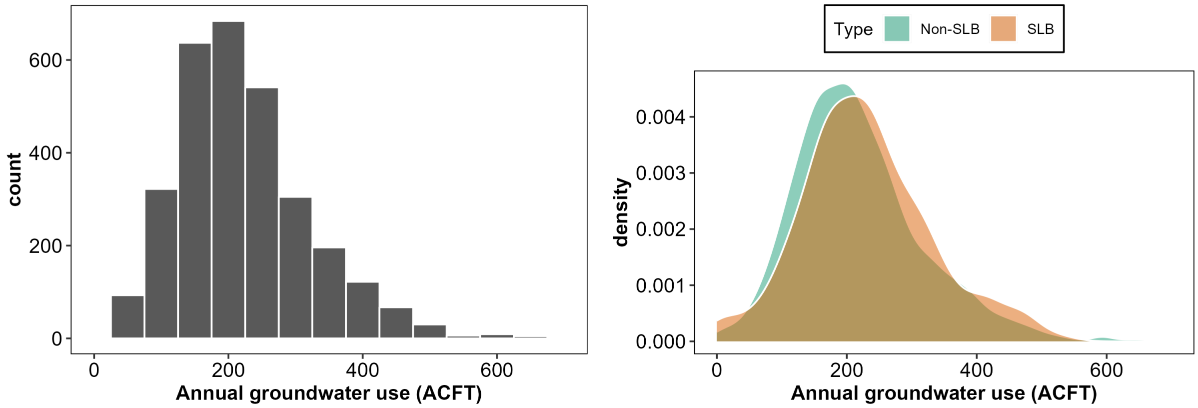


(a) Republican River basin

(b) Area A

Figure 1.4: Spatial distribution of SLB and non-SLB wells

Panel (a) of figure 1.5 presents the distribution of annual groundwater use. We see that the distribution is positively skewed, with few wells pumping more than 500 acre-feet of water annually. Panel (b) represents the density of annual groundwater use categorized by SLB designation. We see that there is a slightly higher proportion of SLB observations, relative to non-SLB observations, at higher levels of annual groundwater extraction. Additionally, the proportion of non-SLB observations is higher at lower levels of annual groundwater use.



(a) Annual groundwater use

(b) Density by treatment status

Figure 1.5: Proportion of acres and operations by management type

Table 1.1 presents differences in means between SLB and non-SLB wells with a bandwidth of 2 miles and a well-exclusion distance of 1-mile. We can think of this as the base sample and further changes in bandwidth and well-exclusion as subsets of this sample. The table shows that SLB wells use substantially more groundwater than non-SLB wells, and the difference is statistically significant.

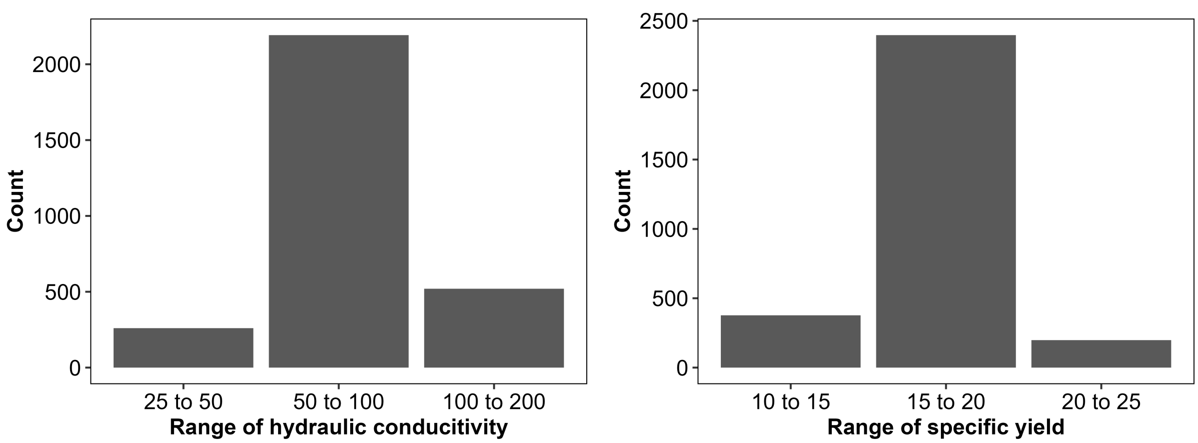
Existing research shows that imperfect property rights can lead to reduced adoption of irrigation technology (Ge, Edwards, and Akhundjanov, 2020). In such a case it may be difficult to isolate differences in extraction, that are not influenced by differences in investment, both of which are impacted by dynamic considerations faced by farmers. Table 1.1 shows that the uptake of sprinkler irrigation is very high for both SLB and non-SLB wells, and the difference between them is not statistically significant. Thus, any differences in groundwater use is not likely to be driven by systematic differences in irrigation technology in this analysis.

When focusing on hydrology, water access, and water rights, we see minimal differences between SLB and non-SLB wells. However, SLB wells exhibit lower depth to water and higher specific yield, compared to non-SLB wells and these differences are statistically significant[7]. A

[7]Specific yield is the ratio of the volume of water a saturated soil or rock will yield by gravity to the volume of the rock (Cederstrand and Becker, 1998; Johnson, 1967).

lower depth to water may indicate that SLB wells face lower pumping costs, relative to non-SLB wells.

Panel (a) of figure 1.6 shows the distribution of hydraulic conductivity by discrete categories measured in feet per day. We see that only a small portion of the observations fall into the 25 to 50 category. Therefore, we combine the two lower categories to generate a 25 to 100 category in the analysis. As presented in panel (b) of figure 1.6, wells in the sample fall into specific yield ranges of 10 to 15, 15 to 20, and 20 to 25, with the 20 to 25 category including a small proportion of observations. We consolidate the two upper categories to generate a dummy for specific yield ranges between 15 to 25 in the analysis. Table 1.1 reports the lower bound of specific yield for SLB and non-SLB wells. It is also important to note that none of the wells in the sample irrigate parcels that have surface water rights.



(a) Distribution of hydraulic conductivity

(b) Distribution of specific yield

Figure 1.6: Distribution of hydraulic conductivity and specific yield

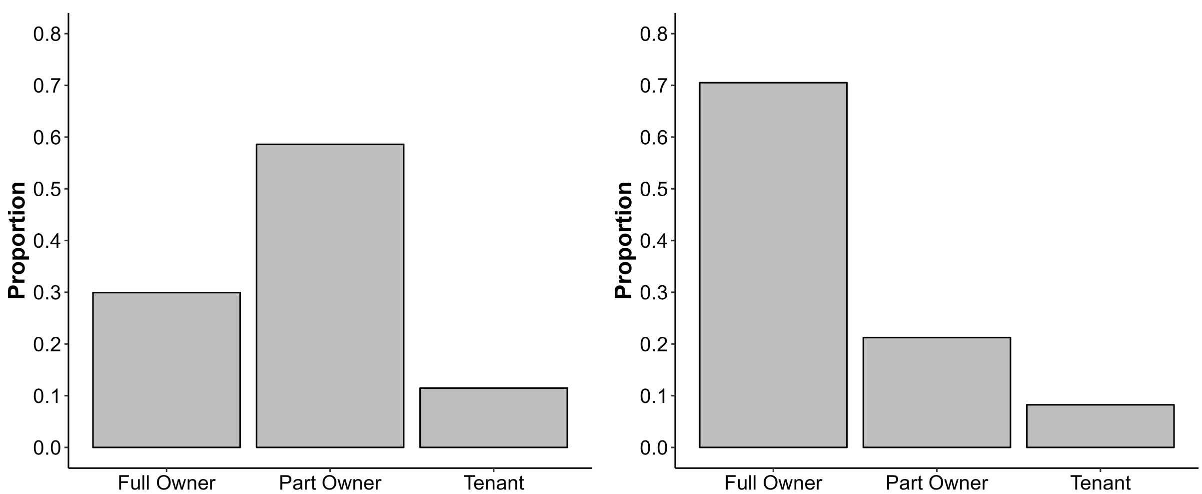
Table 1.1 also reflects that the number of SLB wells in the sample is substantially lower than the non-SLB wells. Additionally, we see that the number of neighboring SLB wells within 1 mile and 1.5 miles is higher for SLB wells, relative to non-SLB wells. However, this is partly driven by our design choice of excluding non-SLB wells that fall within 1 mile of an SLB well. Finally, the table highlights that there are statistically significant differences in soil composition of parcels being irrigated, between SLB wells and non-SLB wells. SLB wells tend to irrigate parcels with lighter, sandier soil.

Table 1.1: Test of mean differences between SLB and Non-SLB parcels

	SLB	Non-SLB	Difference (SLB - Non-SLB)	p-value
Time-varying variables				
Annual groundwater use (ACFT)	230.71	220.29	10.42*	0.0522
Average Precipitation (mm)	60.19	60.35	−0.16	0.8514
Average Max Temperature (°C)	28.86	28.88	−0.02	0.7490
Proportion of sprinkler acres	0.95	0.94	0.01	0.8842
Time-invariant variables				
Hydrology, water access and water rights				
Depth to water in 2000 (feet)	144.06	165.70	−21.64**	0.0288
Hydraulic conductivity (feet/day)	106.98	114.16	−7.18	0.1982
Specific yield (%)	20.23	19.62	0.61*	0.0568
Saturated thickness in 1935 (m)	48.04	43.56	4.48	0.2873
Well capacity (Gal/min)	802.91	778.12	24.79	0.6400
Groundwater appropriated (ACFT)	403.41	424.03	−20.62	0.2900
Irrigated acres appropriated	168.63	178.63	−10.00	0.3900
Additional groundwater rights	0.14	0.19	−0.05	0.3594
Surface water rights	0.00	0.00	0.00	-
Average distance to nearest river (miles)	14.69	14.78	−0.09	0.9439
Number of wells	43.00	279.00	−236.00	-
Number of neighboring wells (any) within:				
1 mile	8.16	7.96	0.21	0.7923
1.5 miles	15.95	15.08	0.87	0.5370
2 miles	23.19	23.28	−0.09	0.9640
Number of neighboring SLB wells within:				
1 mile	1.26	0.00	1.26***	0.0000
1.5 miles	1.67	0.66	1.01***	0.0038
2 miles	1.81	1.30	0.51	0.1243
Soil composition				
Percent clay	16.77	20.26	−3.49*	0.0532
Percent sand	56.53	44.95	11.59**	0.0200
Percent silt	27.05	34.39	−7.34**	0.0287

Significance levels are defined as *$p<0.1$; **$p<0.05$; ***$p<0.01$.

In the analysis, we compare wells irrigating SLB parcels to wells irrigating nearby private land. In order to identify impacts related to tenure security on SLB lands, ideally we would compare SLB lands to only private owner operated lands or to privately leased lands. However, characteristics of the operator are unobservable for non-SLB parcels. Figure 1.7 represents the proportion of acres farmed and number of farming operations by management type for the counties in the sample based on the 2017 US Census of Agriculture[8]. In the Census, tenure type is categorized as full owner, part owner and tenant. Full owner and tenant categories represent operators that only own land and rent, respectively. Part owners represent operators that both own land and rent land. Looking at the distribution of tenure types, it is likely that some of the wells in the control group are rented. Therefore, it is important to note that the estimated effects represent a lower bound of actual differences between SLB and owner operated private lands due to differences in tenure security.



(a) Proportion of acres operated

(b) Proportion of farm operations

Figure 1.7: Proportion of acres and operations by management type

[8]The figure was constructed from using 2017 Agricultural Census data. It can be retreived from: https://quickstats.nass.usda.gov/

1.5 Identification Strategy and Specifications

In order to estimate the impact of SLB designation on groundwater use, we would require an exogenous assignment of SLB lands that is independent of environmental, farmer specific, farm specific or other factors that may influence water use. In practice the existing allocation of SLB lands are partly a function of decisions made by the SLB. Over time, the SLB has bought and sold lands potentially with the objective of benefiting the trust. This makes it unlikely that the current distribution of SLB lands is independent of other factors that may influence groundwater demand. Fortunately, part of the initial allocation of SLB lands in 1876, related to sections 16 and 36, were made uniformly across space in Colorado. Whereas, part of the historical boundary, related to the "in lieu" lands, are subject to selection bias due to the state being able to choose the location of those lands. The historical boundary used in the analysis excludes boundaries related to the "in lieu" lands. Apart from being uniformly located across space, the historical boundary of sections 16 and 36 was allocated before the development on the Ogallala aquifer. These factors make it likely that the historical boundaries of sections 16 and 36 are independent of individual or environmental factors that may dictate the present groundwater demand. This initial allocation acts as a natural experiment that we use to estimate the causal impact of SLB lands classification on groundwater use.

Due to both purchase and sales of SLB parcels, there is imperfect compliance of SLB well location and the historical border. As a result, we may find SLB wells outside the historical boundaries, as well as non-SLB wells inside the boundary. We make use of instrumental variable (IV) methods to identify the causal impact of SLB classification on groundwater use. The IV models accommodate imperfect compliance while estimating local average treatment effects. We use information on whether a well is located inside the historical SLB boundary or outside as the instrument in the IV model.

Using a two stage least squares (2SLS) approach, we estimate the impact of SLB designation on annual groundwater use. The second stage of the IV is specified as:

$$Y_{it} = \alpha_0 + \beta_s S\hat{L}B_i + \mathbf{\Theta X_{it}} + \delta_t + \gamma_c + \epsilon_{it} \tag{1.11}$$

and the first stage is specified as:

$$SLB_i = a_0 + \beta_b B_i + \mathbf{\Gamma X_{it}} + d_t + g_c + v_{it} \tag{1.12}$$

where Y_{it} is the dependent variable associated with well i in year t, SLB_i is a dummy variable for whether the well i irrigates an SLB parcel and B_i is a dummy for being located within the historical SLB boundary. The first and second stage include the same set of conditioning variables (X_{it}), which control for parcel and well-specific features. Well-level estimates of parcel features represent average levels of the variables experienced by the parcels being irrigated by well i. These features include average maximum temperature, average precipitation, percent sand and silt, and average distance to the nearest river. The well-specific controls include latitude and longitude of well i, depth to water in 2000, dummy variables for specific yield ranges of 15 to 25, dummy variables for hydraulic conductivity ranges of 100 to 200, and saturated thickness in 1935. a_0 and α_0 represent intercept terms, g_c and γ_c represent township fixed effects, d_t and δ_t represent year fixed effects, and v_{it} and ϵ_{it} represent the error term in the first and second stage, respectively. The standard errors are clustered at the well-level in all well-level specifications.

1.6 Results

We estimate parameters for the IV model in equation 1.11 and 1.12 with 4 different combinations of well-exclusion and distance from historical boundary restrictions. In specifications 1 and 2, we include wells that lie within 2 miles of the historical boundary, which roughly covers a township when measured from the central section (section 16). Increasing the well-exclusion distance reduces the influence of potential spillovers, by dropping non-SLB wells that lie nearby SLB wells, but it also reduces the sample size. Specifications 1 and 2 present results at well-exclusion distances of 1 and 1.5 miles, respectively. Wells that are closer to the historical boundary are more likely to experience similar environmental factors. Therefore, specifications 3 and 4 estimate the models as described by specifications 1 and 2, but with only including wells that lie within 1 mile of the historical boundary.

The estimates of β_s are referred to as the treatment effect in the regression tables and they represent the difference in the dependent variable, on average, due to SLB designation. First, we explore the following dependent variables: (1) Annual groundwater use; (2) Groundwater use as a proportion of groundwater appropriated; (3) Changes in saturated thickness. These inform the extent to which groundwater usage and depletion levels differ between SLB and privately managed wells. Models exploring depletion of saturated thickness only use a cross-section of wells. Thus, we exclude year fixed effects in models exploring saturated thickness.

We then explore potential mechanisms which lead to differences in groundwater use between SLB and non-SLB wells. First, we explore differences between SLB and non-SLB wells in groundwater use per acre (intensive margin), and associated irrigated acres (extensive margin). Second, we explore differences in crops planted between SLB and non-SLB irrigated parcels. Third, taking the sample of only SLB wells, we inspect whether groundwater use by SLB leaseholders vary systematically by lease year. Finally, we explore the influence of spillover effects by varying the well-exclusion restriction between 0 to 2 miles.

1.6.1 Annual groundwater use per well

Table 1.2 presents estimates of the average treatment effect of SLB designation on annual groundwater use. The estimates reveal that SLB wells use substantially more groundwater relative to non-SLB wells. Focusing on the specifications with statistically significant estimates, SLB wells use between 33 to 55 acre-feet more of groundwater, relative to non-SLB wells. The majority of estimates reflect that the difference in groundwater use is statistically significant, with the magnitude of average treatment effects fall between 15 to 24 percent of mean annual groundwater use in their respective samples.

Table 1.2: Regression results: Differences in groundwater use

Dependent Variable:	Annual groundwater use per well (ACFT)			
Model:	(1)	(2)	(3)	(4)
Independent variables				
Treatment effect	22.63	33.07*	55.79***	47.95*
	(20.50)	(19.35)	(20.99)	(24.87)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,972	1,597	1,032	846
Distance from HB (miles)	2	2	1	1
Well-exclusion distance (miles)	1	1.5	1	1.5
Dependent variable mean	220.97	216.37	226.85	222.40
R^2	0.34	0.41	0.48	0.48
Adjusted R^2	0.33	0.39	0.46	0.46
F-test (1st stage), Treatment effect	5,323.09	2,219.86	1,962.81	1,365.52

Clustered (Well-level) standard-errors in parentheses
*Significance levels are represented as ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.*
Controls: *well latitude, well longitude, average maximum temperature, average precipitation, parcel proportion sand, parcel proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

1.6.2 Groundwater use as a proportion of groundwater appropriated

Groundwater use in Colorado is constrained by water rights. These water rights define volumetric limits on groundwater use, which were set when permits were initially allocated. Due to current improvements in irrigation technology, these limits are largely non-binding (Hrozencik et al., 2022b). In regions or in time periods when water is scarce, these constraints, however, may influence groundwater use. As demonstrated in table 1.1, on average, the groundwater appropriated does not vary between SLB and non-SLB wells. Thus, if a substantial chunk of wells faced binding constraints, it would be difficult to detect differences in groundwater use between SLB and non-SLB wells. Figure 1.8 represents the distribution of the proportion of appropriated groundwater used. We see that the limits on usage were binding for a small portion of the observations. We also notice that for a small proportion of the data, groundwater use exceeds the volumetric limits set by the water right. The point estimates of the treatment effect provided in 1.3 have the expected positive signs, however, the estimates are not statistically significant.

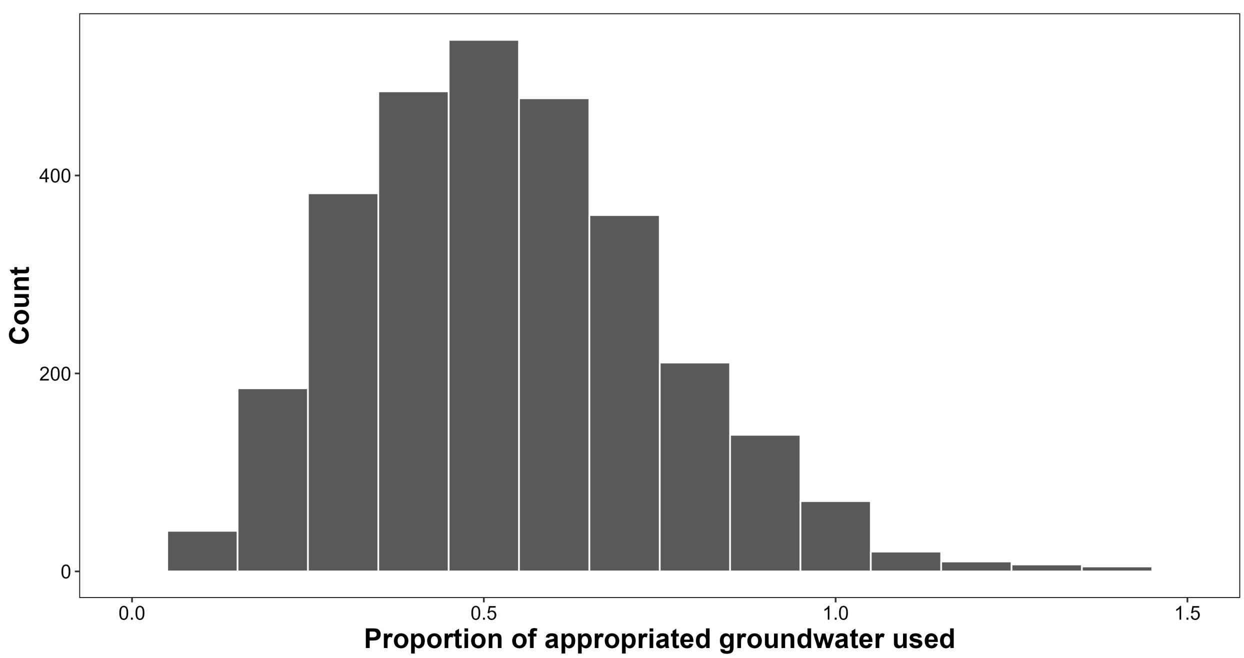


Figure 1.8: Distribution of groundwater used as a proportion of appropriated

Table 1.3: Regression results: Differences in proportion of appropriated groundwater used (full sample)

Dependent Variable:	Proportion of appropriated groundwater used			
Model:	(1)	(2)	(3)	(4)
Independent variables				
Treatment effect	0.0665	0.0507	0.1010	0.0359
	(0.0698)	(0.0546)	(0.0639)	(0.0404)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,972	1,597	1,032	846
Distance from HB (miles)	2	2	1	1
Well-exclusion distance (miles)	1	1.5	1	1.5
Dependent variable mean	0.54	0.53	0.56	0.52
R^2	0.25	0.29	0.32	0.28
Adjusted R^2	0.23	0.27	0.29	0.24
F-test (1st stage), Treatment effect	5,323.09	2,219.86	1,962.81	1,365.52

Clustered (Well-level) standard-errors in parentheses
Significance levels are represented as $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.
Controls: *well latitude, well longitude, average maximum temperature, average precipitation, parcel proportion sand, parcel proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

1.6.3 Impact on Saturated thickness

Persistent differences in groundwater extraction between SLB and non-SLB parcels can lead to differences in saturated thickness over time. We incorporate hydrological data modeled in Haacker, Kendall, and Hyndman (2016), to explore the extent to which groundwater depletion has varied between SLB and non-SLB wells. The data provides estimated saturated thickness levels at a resolution of 250 by 250 m (0.16 by 0.16 mile) grids. Figure 1.9 shows differences in saturated thickness, in meters, between 2000 and 2016. The red squares represent treatment sections. As we can see, a lot of the treated sections are in areas that have faced substantial depletion.

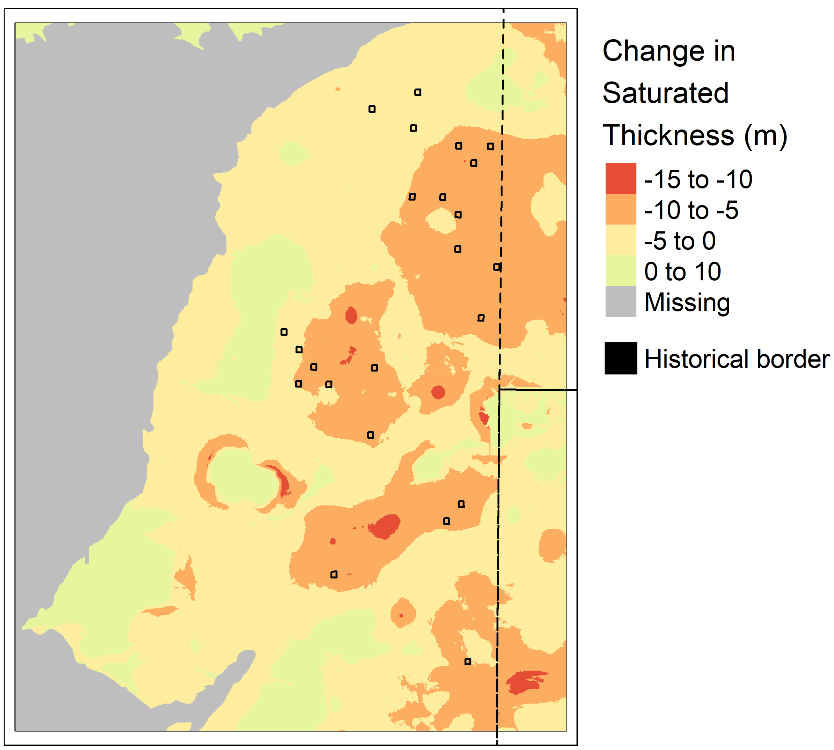


Figure 1.9: Changes in Saturated Thickness between 2000 and 2016

We calculate the difference in saturated thickness between the years 2016 and 2000 for each well in the sample. This is the dependent variable in the regression models presented in table 1.4, which reflects the level of depletion experienced by each well. It is important to note that this reduces the data to a single cross-section of SLB and non-SLB wells. The time varying controls of average maximum temperature and precipitation are replaced by long run average maximum temperature and precipitation over the period 2000 to 2016 in the regression model. Given the limited number of observations, a township fixed effect may be too restrictive to estimate differences between SLB and non-SLB wells. Thus, we estimate models using county fixed instead in the main paper.

The results from table 1.4 show that SLB wells experienced substantially higher levels of depletion of groundwater stocks, relative to non-SLB wells. The estimate from specifications 3 and 4 is statistically significant, and the magnitude of the difference is greater than 20 percent of the mean depletion experienced in the sample. We also estimate models using township fixed effects, which are included in the appendix. Including township fixed effects reduces the statistical significance of the estimates, but the results remain qualitatively similar to those in table 1.4.

Overall, these results suggest that SLB wells use considerably more groundwater compared to similar private wells. Moreover, the excess extraction (over private levels) of groundwater contribute to the exacerbation of groundwater stock depletion.

Table 1.4: Regression results: Change in saturated thickness (2016 - 2000)

Dependent Variable:	Change in saturated thickness (2016 - 2000)			
Model:	(1)	(2)	(3)	(4)
Independent variables				
Treatment effect	-0.5774	-0.4728	-1.369**	-1.218*
	(0.4109)	(0.5345)	(0.5549)	(0.6550)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Fit statistics				
Observations	305	163	107	86
Distance from HB (miles)	2	2	1	1
Well-exclusion distance (miles)	1	1.5	1	1.5
Dependent variable mean	-5.89	-5.61	-5.55	-5.34
R^2	0.57	0.61	0.59	0.63
Adjusted R^2	0.54	0.56	0.52	0.55
F-test (1st stage), Treatment effect	490.74	184.82	151.38	119.65

Clustered (Well-level) standard-errors in parentheses
*Significance levels are represented as ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.*
***Controls:** well latitude, well longitude, difference in average maximum temperature, difference in average precipitation, parcel proportion sand, parcel proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

1.7 Mechanisms

1.7.1 Intensive and extensive margin effects

In order to understand the margin along which SLB classification impacts groundwater use, we inspect the impact of SLB designation on groundwater use per acre, representing the intensive margin, and associated irrigated acres per well, representing the extensive margin. Irrigated acreage data is only available for a few years, which reduces the sample size. Multiple wells may irrigate the same parcel, which makes it difficult to find the precise number of acres irrigated by each well. Additionally, a well may irrigate multiple parcels. For all wells tied to a parcel, we assume that each well irrigates an equal share of the parcel. Under this assumption, we divide the total acres of each irrigated parcel by the number of associated wells to calculate well-level number of irrigated acres for each year. Groundwater use per acre is then calculated by dividing the annual groundwater use for each well by the total number of irrigated acres.

The coefficient estimates in table 1.5 reflect the impact of SLB designation on groundwater use per acre. We see that the point estimates are positive for all specifications, but none of the estimates are statistically significant. Table 1.6 reflects the difference in acres irrigated between SLB and non-SLB wells. Similar to the intensive margin results, we see positive coefficient estimates that are not statistically significant. Given the challenges with measuring irrigated acres, along with the limited sample size, we are unable to examine differences in the intensive and extensive margin of groundwater use between SLB and non-SLB wells with precision.

Table 1.5: Regression results: Differences in groundwater use per acre

Dependent Variable:	Water use per adjusted acre (ACFT/Acre)			
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment effect	0.0240	0.0822	0.0289	0.0206
	(0.0813)	(0.0920)	(0.1097)	(0.1169)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,780	953	616	502
Distance from HB (miles)	2	2	1	1
Well-exclusion distance (miles)	1	1.5	1	1.5
Dependent variable mean	1.27	1.25	1.27	1.27
R^2	0.34	0.36	0.40	0.46
Adjusted R^2	0.33	0.34	0.36	0.42
F-test (1st stage), Treatment effect	3,049.18	1,246.12	1,045.85	752.03

Clustered (Well-level) standard-errors in parentheses
Significance levels are represented as ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Controls: *well latitude, well longitude, average maximum temperature, average precipitation, parcel proportion sand, parcel proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

Table 1.6: Regression results: Differences in acres irrigated

Dependent Variable:	Adjusted acres irrigated			
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment effect	8.356	8.480	33.52	29.99
	(19.28)	(20.71)	(22.18)	(23.77)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,780	953	616	502
Distance from HB (miles)	2	2	1	1
Well-exclusion distance (miles)	1	1.5	1	1.5
Dependent variable mean	173.85	173.43	178.49	176.29
R^2	0.20	0.31	0.37	0.45
Adjusted R^2	0.18	0.28	0.33	0.41
F-test (1st stage), Treatment effect	3,049.18	1,246.12	1,045.85	752.03

Clustered (Well-level) standard-errors in parentheses
Significance levels are represented as ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Controls: *well latitude, well longitude, average maximum temperature, average precipitation, parcel proportion sand, parcel proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

1.7.2 Crop type

Groundwater use by SLB wells can be driven by farmers' choice of more water intensive land use, such as planting corn, or alfalfa. We use the irrigated lands data to identify irrigated parcels tied to the SLB and non-SLB wells, and categorize them as SLB and non-SLB parcels, respectively. We then make use of the rich National Cropland Data Layers (NCDL) dataset to explore differences in cropping patterns between the irrigated SLB and non-SLB parcels. The NCDL data provides rasters of annual land use classifications, at a 30 m resolultion, that identifies cropping patterns in the contiguous US (Lark, Schelly, and Gibbs, 2021). Using this dataset, we extract the fraction of area by land use category for each irrigated parcel for the years 2015 to 2020 for each SLB and non-SLB parcel.

Figure 1.10 reports the total proportion of area in SLB and non-SLB irrigated lands, averaged over the sample period, for the most common land use categories. We see that land use on irrigated lands is largely dedicated to growing corn, with both SLB and non-SLB lands growing a similar proportion. The figure also reveals that a larger proportion of SLB irrigated lands, on average, are dedicated to growing alfalfa, which is a water-intensive crop. Finally, we see that a relatively smaller proportion of SLB irrigated lands grow winter wheat, a crop with a low water requirement.

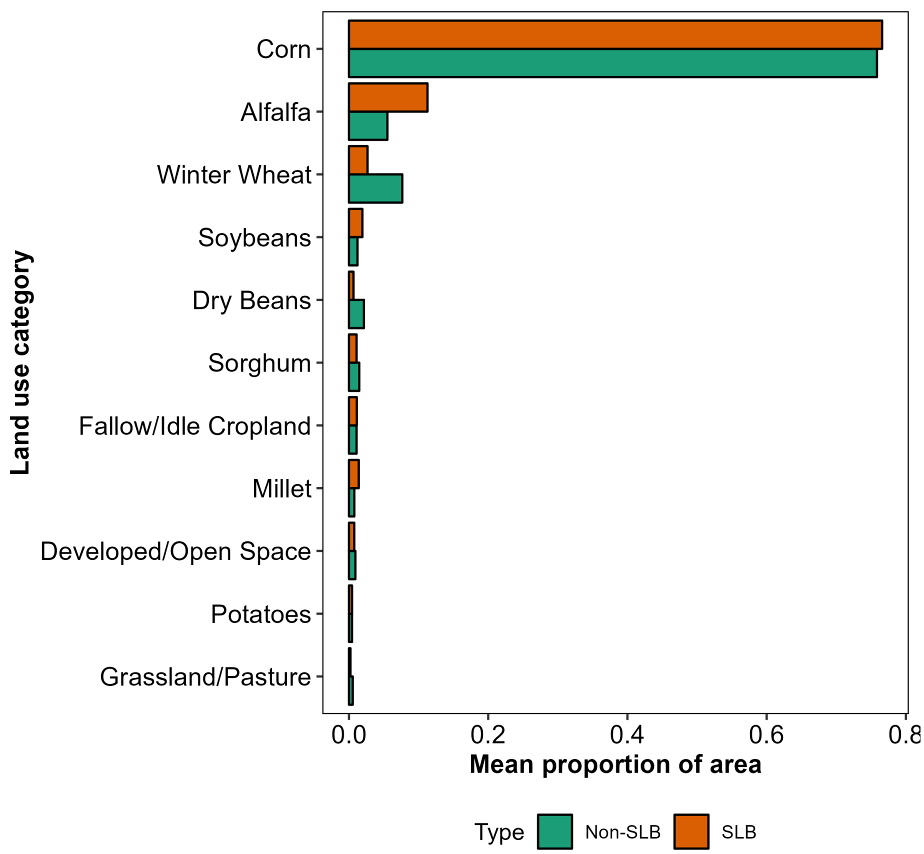


Figure 1.10: Land use by SLB and non-SLB sections

In the regression analysis, we use the 2SLS approach to formally test for difference in the planting of water-intensive crops between SLB and non-SLB parcels using the irrigated land parcels as the unit of analysis. A dummy for whether a parcel intersects the historical boundary is used as the instrument. We define a water-intensive category as pixels that are categorized as corn, alfalfa, or soybeans, and calculate the proportion of water-intensive area for each irrigated parcel. This is used as the dependent variable in the regression analysis.

All data sources are similar to that used for the well level analysis. For the regression analysis, we use parcel-level data on average maximum temperature, average precipitation, parcel centroid longitude and latitude, and parcel distance to nearest river. Additionally, we use parcel-level averages of well-level data for soil characteristics and hydrology variables. These parcel-level and well-level characteristics are included in the regression as control variables. Finally, we include township and year fixed effects. The regressions are similar to that in equation 1.11 and 1.12, with all the variables being at the parcel-level. A dummy for SLB irrigated parcels, as defined earlier, is the treatment variable of interest[9].

The regression analysis includes 4 specifications that mirror the well-level analysis[10]. Table 1.7 presents estimates of the average differences in the proportion of water-intensive land use by SLB and non-SLB irrigated lands. The sign of the coefficient estimates are not robust across specifications and the estimates are not statistically significant. The point estimates are also small, suggesting that, on average, the difference in water-intensive cropping between SLB and non-SLB irrigated parcels is not substantial after controlling for groundwater and soil characteristics.

[9]Spatial shape of parcels can vary from year to year, but parcels within the same location are identified with a Master ID in the CDSS data. We cluster standard errors using this Master ID.

[10]Specifically, specifications 1, 2, 3, and 4, include irrigated parcels that are associated with the wells included in specifications 1, 2, 3, and 4 in the well-level analysis, respectively.

Table 1.7: Regression results: Differences in land use

Dependent Variable:	Water-intensive crops as a proportion of irrigated land			
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment effect	0.0051	0.0190	0.0519	-0.0179
	(0.0399)	(0.0498)	(0.0561)	(0.0723)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Statistics and sample description				
Observations	3,711	1,976	1,302	1,025
Dependent variable mean	0.71	0.70	0.71	0.71
R^2	0.11	0.14	0.11	0.13
Adjusted R^2	0.10	0.13	0.09	0.10
F-test (1st stage), Treatment effect	5,845.94	2,774.74	1,644.38	1,224.29

Clustered (Parcel-level) standard-errors in parentheses
Significance levels are represented as $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.
Controls: *parcel centroid latitude, parcel centroid longitude, average maximum temperature, average precipitation, parcel proportion sand, proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

1.7.3 Heterogeneity by lease year

If farmers operating on SLB lands are dynamic decision makers and if they face poor tenure security, ceteris paribus, then we would expect groundwater use by SLB wells to systematically vary based on the time left till the end of the lease. If farmers face high uncertainty regarding renewal, then the remaining years in the lease represents the periods that will receive more weight in driving resource use decisions, as farmers still need to conserve sufficient groundwater to use during the lease period. Given a fixed lease term of 10 years, with each passing lease year that time horizon gets shorter, which in turn reduces the incentive to conserve. Assuming a positive discount rate, we can then expect groundwater use to increase as a function of the lease year. However, if there was a high degree of certainty regarding renewal, then the end of the lease period would not be pertinent to defining the time horizon over which farmers leasing SLB lands make resource use decisions. In such a case, we would expect to find differences in groundwater use among SLB leaseholders' that are in different years of their existing lease.

In order to explore how groundwater by SLB wells varies by lease year, we make use of the combined well-level lease contract data and subset the sample to only include SLB wells that fall within the historical borders. The current set of wells managed by the SLB is not a random sample, and maybe be selected by the SLB due to factors that may also influence groundwater use. In order to identify a set of SLB wells that are likely to be independent of this selection process, we limit the SLB wells to only include those that fall within the historical boundaries. We define lease year as the number of years since the start of the lease. The distribution of observations with different lease years is given by figure 1.11. We see that there are relatively few observations with a lease year greater than 5.

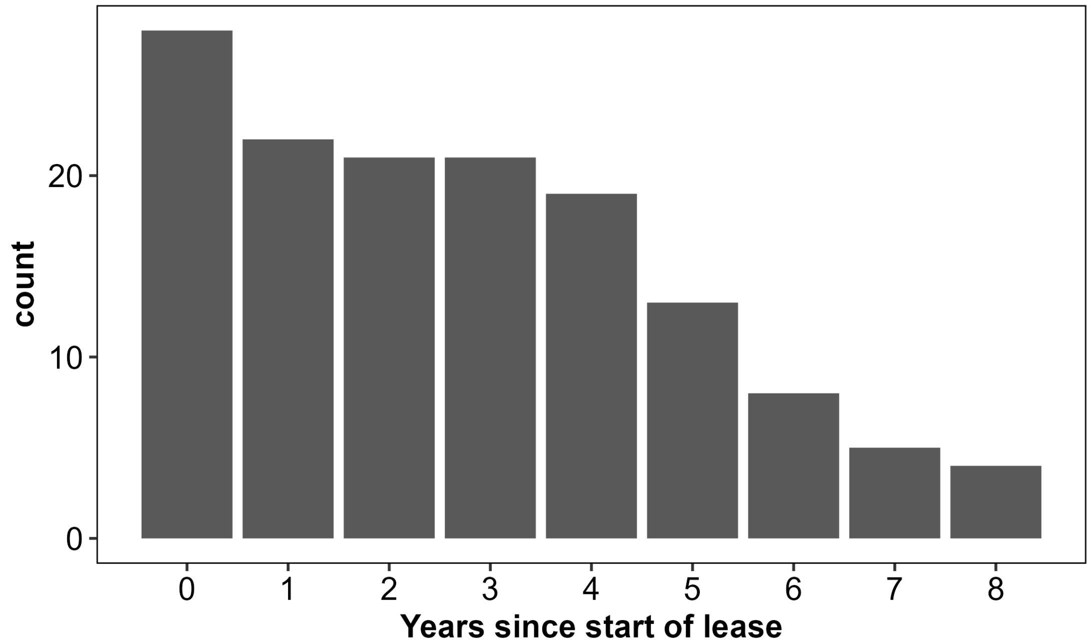


Figure 1.11: Distribution of observations by lease year

To estimate the impact of lease term on groundwater extraction by SLB wells, the regression model is specified as:

$$Y_{it} = \alpha_0 + \sum_{k=1}^{8} \beta_k L_{itk} + \mathbf{\Theta X_{it}} + \delta_t + \gamma_{county} + \epsilon_{it} \tag{1.13}$$

where Y_{it} is annual groundwater use by well i in year t. L_{itk} is a set of k lease year dummies, where year 0 is the reference period. X_{it} includes the same set of control variables as in the main well-level analysis presented in table 1.2, but with only SLB wells that lie within the historical border. Many of the townships of the sample include only 1 SLB well, making township fixed effects no longer viable. Therefore, we include county fixed effects, γ_{county}, instead to control for time invariant factors. Finally, δ_t represents year fixed effects and ϵ_{it} represents the error term. We use OLS to estimate the model parameters and the standard errors are clustered at the well-level.

Figure 1.12 presents the influence of lease year on groundwater use. The results reveal that, on average, annual groundwater extraction by SLB wells increases with the year of the lease. We see a monotonic increase in the magnitude of the point estimates as a function of the lease year. The estimates are also statistically significant, implying that the level of extraction is statistically different from the initial lease year. These patterns suggest that time preferences and dynamic decision making play an important role in determining groundwater extraction by SLB wells. Additionally, if SLB wells had strong tenure security, we would not expect groundwater use to be systematically related to the lease year. Thus, the results also suggest the current renewal mechanism for SLB leases may not provide considerable tenure security to leaseholders.

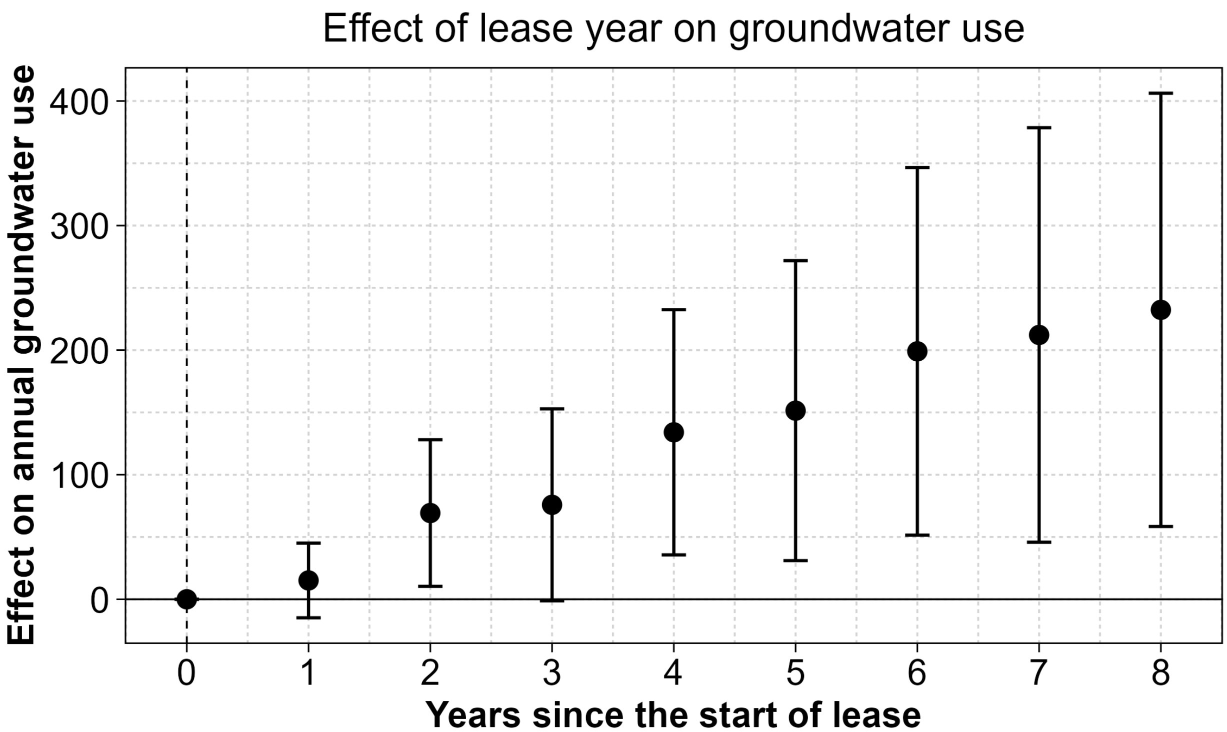


Figure 1.12: Groundwater use as a function of lease year

1.7.4 Spillover effects

In the main analysis, we included specifications that exclude control group wells within 1 mile and 1.5 miles. In order to understand how spillover effects influence the estimate of the treatment effect, we expand the exclusion restriction. The 4 specifications in this analysis include: (1) an exclusion restriction of 0 miles that retains all the control group wells; (2) an exclusion restriction of 1 mile; (3) an exclusion restriction of 1.5 miles; (3) an exclusion restriction of 2 miles. In all specifications, we only include wells that fall within 2 miles of the historical boundaries. This is to ensure that we retain a sufficient number of control group wells at a 2-mile exclusion restriction.

Groundwater represents a shared resource, so when faced with neighbors with high groundwater usage, a farmer may have less incentive to conserve. In such a case, we can expect control wells nearby SLB wells to increase their extraction in response to the high groundwater extraction rate by the SLB wells. Alternatively, the high extraction of groundwater at SLB wells can lower saturated thickness nearby, which increase the pumping cost of the neighbors. As a result, private wells in close proximity to SLB wells may reduce groundwater extraction. In the first case, increasing the well-exclusion restriction should increase the magnitude of estimated treatment effect, whereas in the latter case, we should expect the estimated effects to get smaller as we increase the well-exclusion restriction.

Table 1.8 illustrates how the estimated treatment effect varies by changing the exclusion restriction. The results reveal that the size of the point estimates increase as we increase the exclusion restriction, which implies that SLB wells have a positive spillover effect on nearby non-SLB wells.

Table 1.8: Regression results: Differences in groundwater use by spillover definition

Dependent Variable:	Annual groundwater use per well (ACFT)			
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment effect	15.30	20.92	33.51*	49.56*
	(19.15)	(20.07)	(19.35)	(25.14)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Statistics and sample description				
Observations	5,004	3,021	1,630	654
Distance from HB (miles)	2	2	2	2
Well-exclusion distance (miles)	-	1	1.5	2
Dependent variable mean	224.89	221.15	217.58	207.16
R^2	0.31	0.34	0.41	0.54
Adjusted R^2	0.30	0.33	0.39	0.51
F-test (1st stage), Treatment effect	8,494.25	5,550.83	2,338.10	1,086.48

Clustered (Well-level) standard-errors in parentheses
Significance levels are represented as ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Controls: *well latitude, well longitude, average maximum temperature, average precipitation, parcel proportion sand, parcel proportion silt, average parcel distance to nearest river, saturated thickness in 1935, specific well-yield, hydraulic conductivity, and depth to water.*

1.8 Conclusion

The results of this study highlight the substantially higher groundwater use by SLB wells, relative to comparable non-SLB wells, with the excess extraction making up around 15 to 24 percent of mean annual groundwater use. These differences imply that existing agricultural use of state trust land may impact long term sustainability of sensitive groundwater resources, such as the Ogallala aquifer. On the other hand, agricultural leases bring in large amounts of funding for public schools in Colorado. These results bring attention to the need for sustainable management practices and policies regarding the use of state trust lands.

Existing research on state trust lands largely focuses on exploring revenue generation. However, in order to understand the inter-temporal trade-offs faced by states, research focused on evaluating long run economic costs of excess extraction of resource stocks is necessary. Given the scarcity of groundwater resources, achieving sustainable groundwater use on trust lands is crucial. Trust Lands provide us with a setting where revenues from natural capital extraction are invested in human capital generation. Thus, understanding the extent to which natural capital is being diminished is critical for evaluating the sustainability of trust land management.

The results also suggest that limited property rights on SLB land exacerbate the existing externalities associated with groundwater use and lead to further depletion of groundwater stocks. This contributes to the literature on the impact of limited property rights on public lands, and dynamic decision making on extraction of common pool resources. Due to the potential presence of privately rented land in the control group, the estimates only provide a lower bound of actual differences driven by differences in tenure security between SLB and privately managed land. Furthermore, we provide additional evidence that groundwater extraction on SLB lands is influenced by dynamic considerations. Given a fixed lease period of 10 years, if SLB leases provided adequate tenure security, we would expect groundwater extraction to be independent of the lease year. The results demonstrate that groundwater extraction by SLB wells is an increasing function of the lease year, which suggests that the current renewal mechanism by the SLB is not likely to provide sufficient tenure security to SLB leaseholders. These patterns of extraction are also consistent with the hypothesis that groundwater users are dynamic decision makers.

The results of the study are also likely to contribute to the existing policy discussion related to conservation within the state of Colorado. The Republican River basin is an area facing a number competing demands for groundwater. The river basin overlies a major portion of the Ogallala aquifer within Colorado, making it an important region that influences depletion of an interstate groundwater resource. The economy of the counties surrounding the Republican River basin, within Colorado, is predominantly agricultural and the region hosts around 600,000 acres irrigated by groundwater sources (Republican River Compact Administration, n.d.). Agriculture in the region is also influenced by an interstate compact between Colorado, Nebraska, and Kansas, known as the Republican River Compact. In 2004, the state of Colorado formed the Republican River Water Conservation District (RRWCD) to manage local efforts of compliance with the Republican River Compact (Republican River Water Conservation District, n.d.). The District, utilizing funding from existing federal programs, encourages voluntary participation in water conservation among farmers in the region. Failure to meet existing compliance goals could result in the existential threat to shut down all irrigation wells in the region. In such a scenario, it is important to consider whether the current high groundwater extraction levels on SLB managed wells align with the long-term goals of the state of Colorado. One of the largest conservation programs in the region involves permanent retirement of water rights and conservation of associated land for 15 years by providing annual payments to farmers. Given the existing demands on groundwater rights in the region, a substantially high groundwater use by wells managed by the SLB may be counterproductive to the existing efforts for conservation within the state. The retirement of SLB wells for a payment may present an opportunity that serves both the revenue generation purposes of the SLB along with the water conservation goals of the RRWCD.

We are unable to find conclusive evidence regarding differences in groundwater use between SLB wells and non-SLB wells along the intensive margin and extensive margins. We also explore whether parcels being irrigated by SLB wells are used for growing more water-intensive crops. We do not find evidence to suggest that parcels being irrigated by SLB wells grow more water-intensive crops compared to parcels irrigated by privately managed wells.

It is important to mention that trust lands have a range of uses in Colorado beyond grazing and agriculture. State trust lands are also used for recreation, renewable energy generation, oil and gas development, and land conservation. Research on the costs and benefits of transitioning to different land uses can be an important area of exploration that can inform sustainable management of state trust lands. Trust lands can also be enrolled in conservation programs. If the benefits of enrolling trust lands is higher than that of private land, decision makers should consider encouraging participation in conservation programs amongst SLB wells.

The results also highlight the heterogeneity in the estimated treatment effects by exclusion of control wells nearby treated wells. This suggests that it is important to control for potential spatial spillover effects when analyzing differences in extraction of a common pool resource, such as groundwater. Additionally, the results imply that proximity to SLB wells has a positive impact on the groundwater use by non-SLB wells. However, we are unable to explore the mechanism of the spillovers to identify how much of the spillover is driven by differences in expected pumping costs vs strategic competition for limited groundwater resources.

This research, although highlighting important impacts of state trust lands, is not without limitations. Due to a lack of data, we were unable to explore farmer characteristics in this study. If farmers that only operate on private lands have systematic and large differences in preference regarding sustainability, environment, and time, compared to farmers on SLB lands, then this would represent another mechanism through which SLB designation can impact water use. As decisions related to groundwater extraction is likely to be driven largely by economic value, we do not expect groundwater use to systematically vary by preferences for SLB participation.

Chapter 2

Discount rates under cover: An exploration on the role of discount rates in conservation adoption

2.1 Introduction

Adoption of conservation practices in agriculture can provide a host of private and social benefits and is crucial for sustainable agriculture. Practices such as cover cropping can improve soil health, water quality, and carbon sequestration (Snapp et al., 2005; Kaye and Quemada, 2017). The private benefits from conservation practices may take multiple years of implementation to be realized, whereas the costs of adoption are often immediate. Government financed conservation programs and agri-environmental schemes often encourage adoption of specific conservation practices by offering incentive payments to farmers. Given the intertemporal nature of costs and benefits of both conservation practices and programs, we can expect farmers' time preferences to be pertinent to adoption behavior. Yet there is very little existing literature that explores the role of discount rates in conservation program and practice adoption. In this paper, we highlight the significance of farmers' time preferences on conservation practice adoption and conservation program participation. We make use of elicited discount rate data from a national field experiment of farmers across the US, to demonstrate the potential cover crop adoption among farmers with heterogeneous discount rates. Using simulation analysis, we then explore how the temporal features of conservation contracts can influence changes in program participation, temporary cover crop adoption, and perpetual cover crop adoption.

We focus on working land conservation programs, that are typically 5-year contracts[11] and are not renewable. Payments from the conservation program may not result in continued adoption of

[11] This is true for the major federal working land programs. Environmental Quality Incentives Program (EQIP) contracts can be less than 5 years but cannot exceed that threshold. The contract period for the Conservation Stewardship Program (CSP) is 5 years.

an agricultural practice after the contract period, especially if the long run benefits do not catch up to the costs of continuing the practice. This can lead to one-shot adoption and subsequent dis-adotpion of the practice. Farmers with high discount rates are less likely to be incentivized by long-run benefits, whereas the short term payments from working land programs can encourage them to participate during the contract period. As a result, farmers with high discount rates might be prone to only engage in cover cropping during the contract period. Adoption beyond the contract period of 5-years can be important if the targeted social benefits take time develop and are maximized through long periods of adoption. Research suggests that this is the case for building up soil organic carbon (SOC) stocks derived from cover cropping (Blanco-Canqui, 2022; Poeplau and Don, 2015). Existing research also points to concerns regarding dis-adoption of conservation programs (Sawadgo and Plastina, 2022). Therefore, encouraging continuation of cover cropping beyond the contract period can be crucial to maximizing social benefits derived from cover cropping. We explore how changing aspects of program design, such as payment timing and contract length, impact both adoption of cover cropping during the contract period and continuation of the practice afterwards.

The distribution of experimentally elicited discount rates reveal substantial heterogeneity among farmers, with many farmers having high discount rates. We observe that farmers that have reported to participate in conservation programs have lower mean discount rates compared to non-participating farmers. Moreover, the mean discount rates of farmers that adopted cover cropping and precision agriculture were lower than farmers that did not. This provides suggestive evidence that discount rates may play an important role in program participation and conservation practice adoption.

The temporal features of conservation contracts can impact adoption of cover cropping. We combine data on elicited farmer discount rates and benefits and costs of cover cropping to simulate conservation outcomes for the sample of farmers. In the simulation analysis, we demonstrate that upfront payments can greatly increase participation in the conservation program, but they do not impact cover cropping decisions after the contract period. The contract length of working land programs can play an important role in both farmers' adoption and continuation decisions, and thus impact the degree of social benefits engendered by the conservation programs. Ando and Chen (2011), using dynamic environmental benefit functions, show that longer contracts are optimal when parcels are less likely to be re-enrolled into conservation programs. This makes longer contract lengths pertinent to working land programs, such as EQIP, which cannot be renewed. We contribute to this literature by demonstrating the impact of tailoring contract length, based on heterogeneous discount rates, on conservation outcomes for working land programs. In the simulation analysis, we explore tailoring the contract length and annual payment for both individualized contracts and common contracts based on discount rate information. The results reveal that common contracts that utilize discount rate information to set the contract length and annual payment are able to achieve higher levels of continuation, which are unattainable under the status quo contract length of 5 years. Additionally, individualized contracts that utilize discount rate information result in cost savings, when compared to the status quo 5-year contract and contracts that are common to all producers. The cost savings from the individualized contracts represent the upper bound of cost reduction benefits that can be gained from utilizing discount rate information. In practice, individualized contracts may not be a feasible policy option due to both the cost associated with uncovering discount rate information and the challenge of implementing differentiated contracts. Policy makers might find it more feasible to tailor a common contract using an underlying sample of discount rates. Overall, the results illustrate the potential benefits of utilizing farmers' time preferences when designing conservation contracts.

In the next section, we discuss the existing literature related to cover cropping adoption, working land programs, and discount rate elicitation. In the section, we also describe the data on benefits and costs of cover cropping, existing structure of conservation programs, and the elicited discount rate data. In section 2.3, we provide the conceptual framework for the analysis. In section 2.4, we parameterize the model presented and present the results of the simulation. In the last section, we end with concluding thoughts on the benefits of incorporating discount rate information in the design of conservation contracts.

2.2 Background and Data

There is an extensive literature that explores the impact of factors that influence conservation practice adoption in agriculture, a subset of which focuses on the role of farmer attitudes and preferences. Prokopy et al. (2019) presents a comprehensive review of empirical studies, from 1982 to 2017, that explore consistent determinants of the adoption of conservation practices in US agriculture. The authors highlight the importance of attitudes related to environmental beliefs, farmer identity, climate perceptions, attitude towards conservation programs, risk preferences and attitude toward government regulation. However, time preferences are not investigated in their review.

2.2.1 Cover cropping

In this paper, we focus on cover cropping as the agricultural conservation practice. Cover cropping yields a number of long-term benefits, but requires upfront costs. Thus, time preferences can play a notable role in cover crop adoption. Research on cover crop adoption often uses a cash flow analysis that focuses on the private costs and benefits of adoption overtime without explicit use of discount rates (Singh et al., 2021; Chahal et al., 2020). These studies essentially assume that farmers use an implied discount rate of 0 when evaluating future costs and benefits of cover cropping. In a comprehensive review, Bergtold et al. (2019) outline the importance of direct and indirect costs and benefits of cover cropping, but the role of discount rates remain unexplored. DeVincentis et al. (2020) presents the only exception in this literature, where the authors use a discount rate of 2.6 percent when evaluating cover crop adoption decisions in California. Recent literature on farmer discount rates suggest that a discount rate of 2.6 percent is considerably below the mean discount rate (Duquette, Higgins, and Horowitz, 2012), and thus the predictions from such cash-flow models may overestimate the net potential gains from cover cropping to the average farmer. In this study, we incorporate experimentally elicited discount rates to explore their role in cover crop adoption and continuation behavior.

Estimates of the costs and benefits of cover cropping overtime vary in the literature, however, most research agrees that the private net benefits are initially negative, and it takes a number of years for the returns to become non-negative (Cai et al., 2019; Plastina et al., 2020; Thompson et al., 2020). There is also evidence of the long term private benefits of cover cropping, such as increases in soil organic carbon, which take time to build up (Ding et al., 2006; Crystal-Ornelas, Thapa, and Tully, 2021). The benefits and costs of cover cropping can vary based on local soil, climate, type of cover crop and management practices (Wallander et al., 2021; Boyer et al., 2018; Bergtold et al., 2019). As a result, there can be substantial regional heterogeneity in net benefits of cover cropping.

We use cash flow estimates of cover cropping from Myers, Weber, and Tellatin (2019), which makes use of 5 years of data from the National Cover Crop Survey. The survey collected information on cover cropping annually for years between 2012 to 2016 (inclusive) and included responses from about 2,000 farmers. Although based on self-reported numbers, the survey reflects farmers' perceptions about cover cropping benefits, which we believe to be pertinent to farmers' adoption decisions. The net benefits from the survey data are generally smaller than cover cropping returns produced by controlled field experiments, such as in Cai et al. (2019). Therefore, they provide a more conservative estimate of the private net benefits provided by cover cropping.

Myers, Weber, and Tellatin (2019) provides estimates of private direct net benefit estimates for years one, three and five. We average years one and three to estimate direct net benefits in year two, and average years three and five to estimate direct net benefits in year four. Table 2.1 represents the direct costs and benefits of cover cropping. The changes in benefits and costs from the table reflect that cover cropping has upfront costs, and that it takes a few years for direct benefits to exceed those costs.

The savings on inputs are driven by savings from fertilizer costs, weed control and erosion repair. Farmers that used cover crops on some fields but not on others, with the fields being somewhat similarly managed, were asked to report yields. The survey also included questions on consecutive years of cover crop planting. Yield estimates as a function of continuous years of cover cropping were then estimated using simple linear regression. The income from the extra yield reported in table 2.1 is based on a base of 200 bushels of corn times, the yield estimates, and a price of $\$3.50$ per bushel. The cost of seeding cover crops can vary based on available machinery and method of seeding. The costs of seeding in table 2.1 reflect the median cost from the survey, which is driven by the cost of seed purchase, seeding, and annual termination of the cover crop.

It is important to note that these direct costs do not fully reflect all costs associated with planting the cover crop. Indirect costs can include reduced soil water for the following cash crop and the opportunity cost of time and effort spent in cover cropping (Bergtold et al., 2019). Therefore, the net benefits in table 2.1 should be interpreted as direct net benefits.

Table 2.1: Costs and benefits of cover cropping

Year	Savings on inputs ($)	Income from extra yield ($)	Cost of seed and seeding ($)	Direct Net Benefits: base ($)
1	2.00	3.64	37	-31.36
2	14.05	7.98	37	-14.97
3	26.10	12.32	37	1.42
4	30.00	16.66	37	9.66
5	33.9	21.00	37	17.90

Note: The estimates of savings on inputs, income from extra yeild, cost of seeding and net benefits for years 1, 3 and 5 are taken from Myers, Weber, and Tellatin (2019). Year 2 estimates are averages of years 1 and 3 and year 4 estimates are averages of years 3 and 5.

2.2.2 Working land conservation programs

Agricultural working land conservation programs have gained popularity in recent years (Reimer, 2013). These programs focus on incentivizing conservation practices that do not require agricultural land be taken out of production. The two major Federal working land programs include the Environmental Quality Enhancement Program (EQIP) and the Conservation Stewardship Program (CSP). EQIP considers cover cropping as an annual practice and farmers are able to recieve compensation through EQIP for cover cropping on the same field for up to 5 years (maximum) (Wallander et al., 2021). The majority of these programs offer a fixed annual payment to farmers. Existing research demonstrates the efficacy of these programs in improving the adoption of conservation practices (Claassen, Duquette, and Smith, 2018; Reimer, Denny, and Stuart, 2018). In the last 14 years, EQIP has seen a large increase in USDA funding, alongside experiencing increases in acres enrolled and payments per acre provided. Existing research has shown that increases in overall EQIP payments correlate with increases in county-level cover crop adoption (Park et al., 2022). It is important to distinguish between additional EQIP participation and additionality in cover crop adoption. Some farmers that participate in EQIP may have cover cropped without conservation payments, whereas others may discontinue the practice after the contract period (Wallander et al., 2021). The long-term private benefits from cover cropping are worth more to farmers with relatively low discount rates. Understanding the distribution of farmer discount rates can help improve conservation outcomes by informing temporal aspects of the EQIP program, such adjustments to payment timing and contract length. This presents an additional margin along which conservation adoption can be increased.

In the analysis, we focus on EQIP as the conservation program when exploring program participation and conservation practice adoption under heterogeneous discount rates. We use EQIP contract payment data from the US Forest Service Research Data Archive (Basche et al., 2020). Payment per acre for each contract is derived using data on planned acres and total payments made. We then subset the dataset to only look at payment per acre in 2018 for the 26 states included in the discount rate experiment, which is discussed in the next section. Figure 2.1 shows the distribution of EQIP payments for cover cropping in 2018. We see that there is considerable variation in the per acre payment and the mean payment is around $\$55$ per acre.

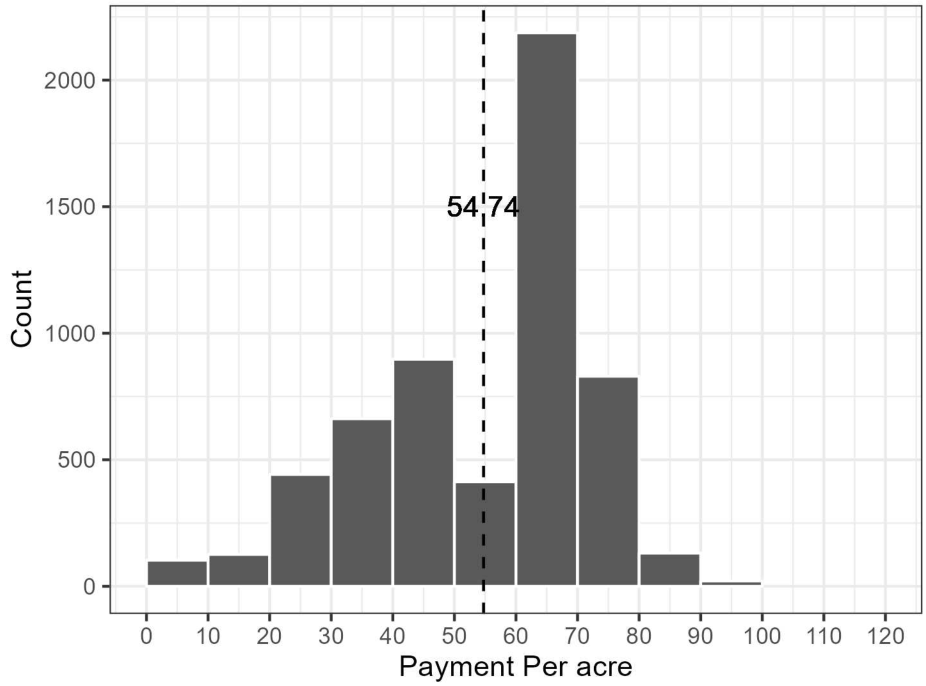


Figure 2.1: Histogram of EQIP payments per acre for cover cropping in 2018

2.2.3 Social benefits, perpetual adoption and dis-adoption

Cover cropping provides a number of social benefits, which may be under-provided at privately optimum levels of adoption. Cover cropping can reduce soil erosion, reduce water pollution, reduce N leaching and increase soil organic carbon (SOC) (Bergtold et al., 2019; Blanco-Canqui, 2022). Benefits, such of reduced water pollution and erosion, can extend to neighboring farmers and the community in each year of cover cropping. Other benefits, such as carbon storage through build up of increased SOC stocks, can take many years to build up.

Blanco-Canqui (2022), in a systematic review of 77 studies comparing cover cropping impacts on SOC stocks, revealed that around 53 percent of medium term studies (5 to 10 years) and 54 percent of long term studies (greater than 10 years) had reported significantly higher SOC stocks on cover cropped lands, whereas only 14 percent of short term studies (less than 5 years) found any meaningful differences. This indicates that some social benefits, such as carbon sequestration, are more likely to be achieved if cover crops are adopted for long periods. Moreover, existing research shows that time since introduction of cover crop has a statistically significant influence on SOC stock changes and the effects continue to grow for long time horizons (Poeplau and Don, 2015).

If the existing design of working land programs only incentivize adoption during the contract period, they may not be able to capture the long-run social benefits of cover cropping. Continuation of cover cropping after the contract period is a relevant concern and can substantially limit the amount of cover cropped acres in the US (Sawadgo and Plastina, 2022). Farmers' with high discount rates, who may be motivated to participate due to conservation payments, may not continue after the contract period. In this analysis, we highlight the impact of incorporating discount rate information in contract design to increase adoption of cover cropping during the contract period and continuation of cover cropping after the contract ends.

2.2.4 Discount rate elicitation

The literature on experimentally elicited farmer discount rates imply that discount rates are likely to be substantially higher than the rates used in current cover crop adoption studies. Duquette, Higgins, and Horowitz (2012), using experimental data on US producers, reported average discount rates of 34 percent. The elicited farmer discount rates that are used in this study reveal substantial heterogeneity. Unsurprisingly, existing research highlights that farmers with high discount rates are less likely to accept contracts with delayed payments (Fischer and Wollni, 2018) and adopt green technology (Mao et al., 2021). Evidence from existing literature also suggests that time preferences influence adoption decisions of perennial energy crops, which require upfront costs and can take between one to five years to yield benefits (Khanna, Louviere, and Yang, 2017).

Despite the importance of discount rates to adoption, their impact on program participation and conservation practice adoption largely remains unexplored. We extend this literature by exploring how elicited discount rates can be applied to inform the design of conservation programs. We make use of farmer discount rates elicited by Feldman et al. (unpublished) using convex time budgets (CTB). In experiments involving the CTB method, subjects are asked to allocate tokens to sooner and later payments, with a delay of k weeks in between. Tokens in the sooner payments are worth less than tokens in the later payments. The implied annual rate of interest between the sooner and later payment increases monotonically between each decision. Subjects, through their allocation, adjust along an intertemporal budget line, which allows for identification of the curvature of the utility function and discount rates. The interest rates and payment dates are varied orthogonally, which allows disentangling of the curvature of the utility function and the discount rate. The curvature of the utility function represents the level of risk aversion in this model. One of the major advantages of CTB, compared to other methods, is that the discount rate estimates are not biased in situations where individuals may have different risk parameters when facing intemporal and atemporal decisions (Grijalva et al., 2018).

The experiment elicits discount rates using responses from 380 famrers from 26 US states[12]. The experiment is the only of its kind to elicit farmer discount rates with a national-level sample. Additionally, the magnitude of the payments provided ranged from $ 0 to $1,500 for each choice the farmers made. Using such large stakes to estimate the discount rate makes the experiment novel to the current discount rate elicitation literature that is focused on farmers. The experiment was carried out through an online survey of farmers in 2018. Figure 2.2 reflects that the farmers in the study are from a geographically wide range of states. This is likely to make the sample of farmers representative of agricultural producers across the US.

[12]The initial sample included 393 farmers. Discount rates for 11 farmers could not be elicited from the data. Additionally, 2 farmers with discount rates greater than 30 (3000%) were removed from the sample. All these exclusions led to dropping around 3.31 percent of the original sample.

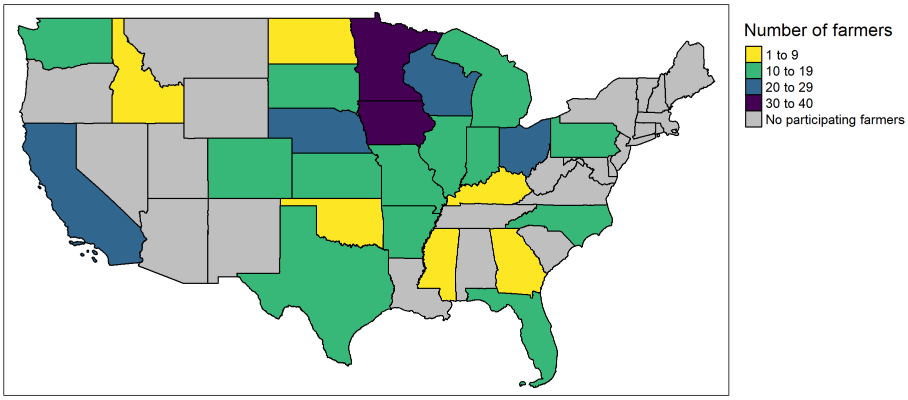


Figure 2.2: Distribution of farmers participating by state

Table 2.2 provides a summary of the demographics of the participating farmers. We see that the farmers were on average 58 years old, with annual gross farm incomes of around $\$560,000$, largely male and the majority of them were not retired at the time of the survey. We also see that majority of the farmers in the sample grow some amount of corn and soybeans.

Table 2.2: Summary statistics of survey responses

Details	Mean	SD	N
Age	58.58	12.26	380
Gross farm income	568,773	1,522,476	380
Proportion male	0.86	0.35	380
Proportion retired	0.13	0.34	380
Proportion producing corn	0.78	0.41	380
Proportion producing soy	0.71	0.45	380
Proportion producing wheat	0.43	0.50	380
Proportion producing hay	0.60	0.49	380
Proportion participating in EQIP	0.32	0.47	380
Proportion participating in CSP	0.22	0.42	380
Proportion participating in CRP	0.46	0.50	380
Proportion participating in Easements	0.18	0.38	380
Proportion planting cover crops	0.47	0.50	380
Proportion practicing precision agriculture	0.49	0.50	380
Proportion practicing no-till	0.65	0.48	380

Figure 2.3 reveals the distribution of experimentally elicited discount rates. The histogram reveals noticeable heterogeneity in individual discount rates. The mean discount rate is around 41 percent, while the median discount rate is around 10 percent. The high mean, median and positive skew of the distribution reflect that current discount rates incorporated in cover crop adoption studies are likely to be too low. This also implies that cash flow analysis of cover crop adoption, using zero or low discount rates, may overestimate the likelihood of cover crop adoption by farmers. Interestingly, there are also a number of farmers with negative discount rates. In cases when the long-run benefits exceed cover cropping costs, these farmers would be likely to participate without conservation payments.

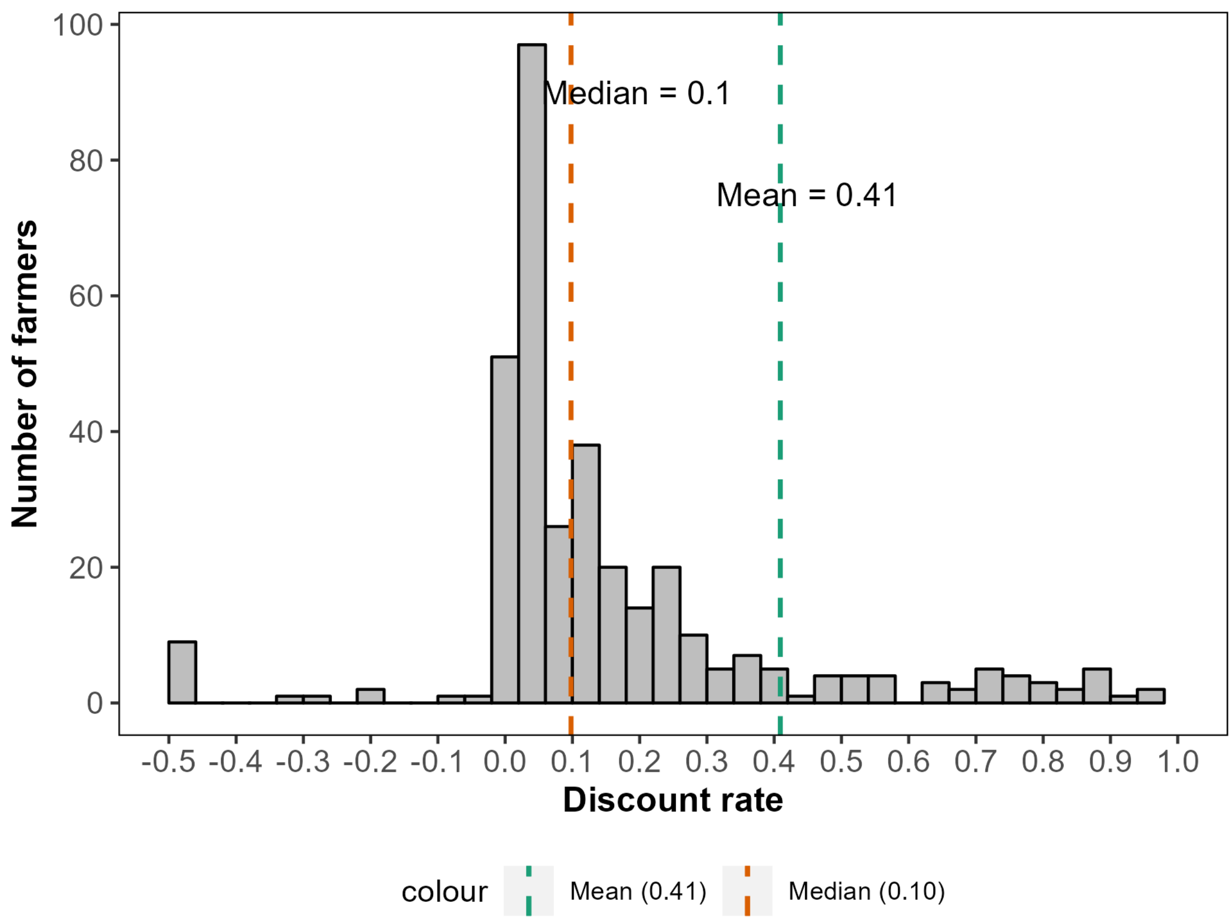


Figure 2.3: Distribution of Farmers' elicited annual discount rates

Note: The distribution above represents 92 percent of the data, as there are a few observations that fall outside the range of discount rates presented.

Structural estimation of discount rates require assumptions about the curvature of the utility function. Research by Andreoni and Sprenger (2012a) point out that the curvature of the utility function may differ in situations when individuals make risky decisions within a period, compared to making decisions that are intertemporal. When the application is focused on time preferences, it would be appropriate to measure both the curvature of the utility function and time parameters, with experimental tasks involving intertemporal decisions.

CTB methods jointly estimate both of these parameters using the same experimental task[13]. It is a common outcome in CTB experiments that most individuals have lower curvature of utility compared to the curvature derived using static risk experiments (Andreoni and Sprenger, 2012a; Andreoni, Kuhn, and Sprenger, 2015). This implies that individuals are likely to be more risk tolerant in intertemporal decisions, relative to atemporal decisions. Andreoni and Sprenger (2012b) had hypothesized that their results were explained by a preference for certainty in outcomes close to the present. However, Cheung (2015) demonstrate that the findings in Andreoni and Sprenger (2012b) are sensitive to the experimental instrument used and the effect is halved when the CTB involves use of a single lottery, instead of two independent lotteries. This provides some evidence that the results in Andreoni and Sprenger (2012b) are, at least partially, driven by intertemporal diversification. Miao and Zhong (2015), using an enriched experimental setting, show that the findings of Andreoni and Sprenger (2012b) are explained by a separation between risk attitude and intertemporal substitution.

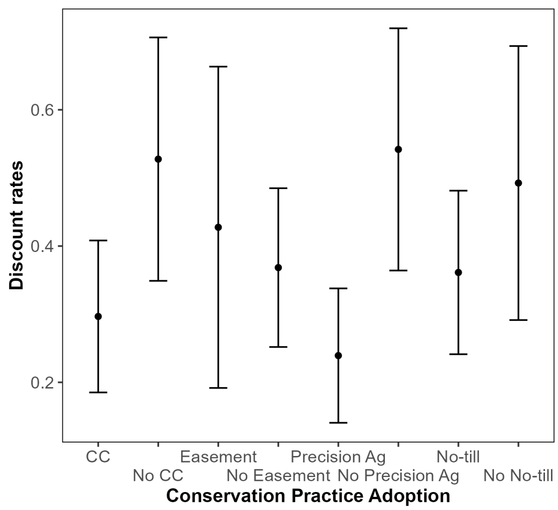
One criticism of comparisons of utility function curvature between atemporal and intertemporal tasks, is that the experimental settings under which they are estimated may not be comparable to each other. The experiments of curvature estimation vary in type of experimental instrument used, type of choices (binary choice vs CTB type task), and type of decision (atemporal vs intertemporal). Therefore, observed differences in utility curvature may be due to the features of the experimental design, such as the instrument used or type of choice, rather than differences in temporal features. Cheung (2020) revisits estimating the utility curvature using a modified Holt

[13]Detailed description of the CTB method is provided in the appendix.

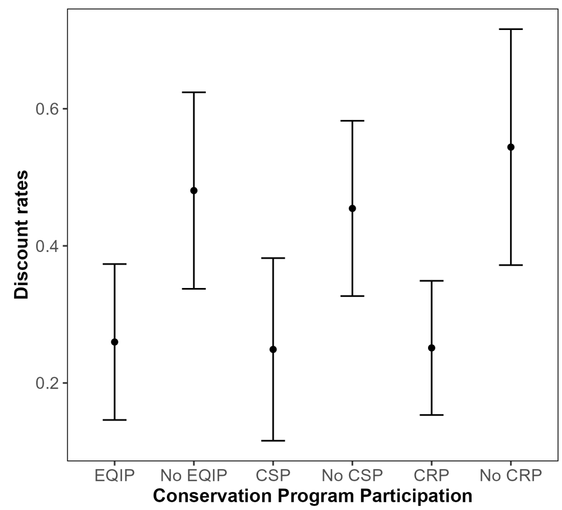
and Laury (2002) risk elicitation procedure, where the method is extended to time-dated payoffs. The author also estimates utility curvatures for risk and time using a unified design and estimation framework, which allows more comparable estimates of utility curvature. The results of the study show that utility curvature elicited overtime, although concave, is much closer to linear compared to utility elicited with atemporal decisions, and that the effect of adjusting discount rates are marginal compared to assuming linearity. These results provide further evidence of the difference between utility curvature, and the implied risk associated with atemporal and intertemporal decisions.

In this paper, we use the estimates of Feldman et al. (unpublished), who estimate the utility curvature and discount rates using non-linear least squares. Given that around 90 percent of the sample are found to have risk preferences (alpha) between 0.8 to 1, we assume risk neutrality for farmers in the simulation.

The online survey also asked farmers whether they used certain conservation practices or participated in conservation programs in the last 3 years. The conservation practices mentioned include cover cropping, easements, precision agriculture and no-till farming. The conservation programs that were asked about include EQIP, CSP and CRP.



(a) Conservation practice



(b) Program participation

Figure 2.4: Discount rates by conservation practice adoption and program participation

Note: The difference in mean discount rates between participating and non-participating farmers are statistically significant for EQIP, CSP and CRP. For conservation practices, difference in mean discount rates are statistically significant for cover cropping and precision agriculture. Around 12 farmers did not report their conservation practice history, and so they were not included in the estimation of mean values presented in panel (b). The error bars represent 95 percent confidence intervals.

Panel (a) of figure 2.4 compare mean discount rates between farmers that adopted certain conservation practices, in the last 3 years, to those that did not. We see that the mean discount rates are statistically larger for non-adopters, relative to adopters, for cover cropping and precision agriculture. This provides suggestive evidence that discount rates, on average, inversely correlate with the likelihood of adopting cover cropping and precision agriculture. We do not see similar differences for easements and no-till agriculture.

For all conservation programs in the survey, which include EQIP, CSP and CRP, panel (b) reveals that participating farmers have a considerably lower mean discount rate, compared to farmers that do not participate. Using a two-tailed t-test of mean differences for each program, we find that the differences between participating and non-participating farmers are statistically significant at a 5 percent significance level. This may indicate that existing working land programs may not be attracting farmers with high discount rates.

2.3 Conceptual Framework

We the explore adoption decisions of farmers under logistic growth of benefits. Under logistic growth, the increase in benefits due to continuing to cover crop decreases overtime. The benefits associated with cover cropping include savings on inputs and income from extra yield as described in table 2.1. Under a logistic growth process, benefits can be defined as:

$$B_{t+1} = B_t + gB_t(1 - B_t/K) \tag{2.1}$$

where B_t is the benefit of cover cropping in period t, g is the logistic growth rate, and K represents the maximum value that benefits can grow to. The growth of benefits decrease as the benefits approach K. In the simulations, we assume $K = 80$ and then estimate the value of g using regression analysis. The value of K is important in determining long run net benefits such that, before discounting, the net benefits are negative in initial years of cover cropping but later become positive. The net present value of cover cropping from period 1 to period T for each farmer i can be represented as:

$$NPV_{i1T} = \sum_{t=1}^{T} \frac{(B_t - DC - IC)}{(1 + r_i)^t} \tag{2.2}$$

The sum above does not have a convenient closed form solution as $T \longrightarrow \infty$. Given that the growth in net benefits is limited by K overtime, with $r > 0$ we can expect NPV_{iT} to converge to a finite number as T gets sufficiently large. In this section, we simulate the above expression for $T = 1000$, which is sufficiently large to ensure the NPV_{iT} for each farmer i converges. Incorporating conservation payments into our model, farmers' NPV of cover cropping until period T is given by:

$$NPV_{i1T} = \sum_{t=1}^{T} \frac{(B_t - DC - IC)}{(1 + r_i)^t} + \sum_{t=1}^{l} \frac{P}{(1 + r_i)^t} \tag{2.3}$$

where P is the annual payment and l is the contract length. For farmers that have not participated in the conservation program, the decision to participate can be expressed as:

$$a_i(P, l; r) = \begin{cases} 1, & \text{if } max(NPV_{i1l}(P, l; r), NPV_{i1T}(P, l; r)) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.4}$$

where a_i represents whether a farmer initially cover crops and participates in the conservation program. Farmers are assumed to continue to cover crop at the end of the contract period, if the net present value of cover cropping from that point is positive. This can be expressed as:

$$h_{i;r}(l) = \begin{cases} 1, & \text{if } NPV_{i(l+1)T}(l; r) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.5}$$

$NPV_{i(l+1)T}$ represents the net present value of net benefits minus indirect costs from the period immediately after period l to period T. It is important to note that this is the net present value evaluated in period l, which is the last year of the contract period. The number of farmers that will participate in the conservation program and continue to cover crop afterwards is given by $\sum_{i=1}^{H} a_i h_i$, where H is the total number of farmers in the analysis. It is important to note that the decision of farmers in this model is reduced to only whether they cover crop or not, given the contract length, payment offered, and the net benefits of cover cropping. In reality, farmers may make optimal cover cropping choices both over time and space or choose to cover crop a certain proportion of their acres. In this model, we abstract away from those details for simplicity and focus on farmers' cover cropping decisions, initial participation in the conservation program, and continuation of cover cropping in the year following the end of the contract.

In our model, we assume that the program administrator has a target participation level that they want to achieve at minimum cost. Assuming a social discount rate of 0, We define the administrators' problem as[14]:

[14]Future analysis should evaluate situations where the social discount rate is greater than zero.

$$\min_{\{P,\, l\}} C = \sum_{i=1}^{H} a_i(P, l; r_i)Pl$$

subject to:

$$\sum_{i=1}^{H} a_i(P, l; r_i)h_i(l; r_i) = D \tag{2.6}$$

$$P \geq 0$$

$$l \geq 0$$

where D is the target level of farmers that will continue cover cropping after the end of the contract. Additionally, we also impose constraints that the annual payment (P) and contract length (l) offered to farmers is non-negative and we assume that the contract length is discrete.

2.4 Simulations

In this section, we use simulations to explore different contract structures under heterogeneous discount rates. Given the data on the benefits of cover cropping provided earlier, we estimate values for the growth rate of benefits, which are then used to parameterize the optimization model described in section 2.3. Combining the estimated net benefits with the elicited discount rate data, we first explore how upfront payments may influence adoption and continuation of the conservation practice. Then, assuming equal payments in each period, we explore the benefit of tailoring contract length and annual payment magnitude for a group of farmers with heterogeneous discount rates. We compare the minimum cost required for farmers to adopt and continue cover cropping under individualized contracts, common contracts, and the status quo contract. Finally, we explore how benefits from the various contracts change if the underlying distribution of discount rates were different.

2.4.1 Deriving the value of g

We can modify equation 2.1 to write down the following first difference model:

$$\Delta B_t = gS + \epsilon \tag{2.7}$$

where $\Delta B_t = B_{t+1} - B_t$, g is the growth factor, $S = \left(B_t - \dfrac{(B_t)^2}{K} \right)$, and ϵ is the error term. We add up savings on inputs and income from extra yield, provided earlier in table 2.1, to calculate benefits. We then calculate the lagged value of benefits and deduct it from current benefits to get ΔB_t. This is the dependent variable in the regression model. Assuming a value for K, we are able to calculate S. Once we have S, we can estimate g through linear regression without a constant term. The results of the regression model for the various assumed values of K are provided in the Appendix table A.16.

For the simulation analysis, we pick $K = 80$ and $g = 0.671$, based on the model that best fits the data. We then use the estimated value of g, the assumed value of K, and the value of benefits in the initial year, B_1, as provided in table 2.1 to simulate the time path of cover cropping benefits, as shown in figure 2.5.

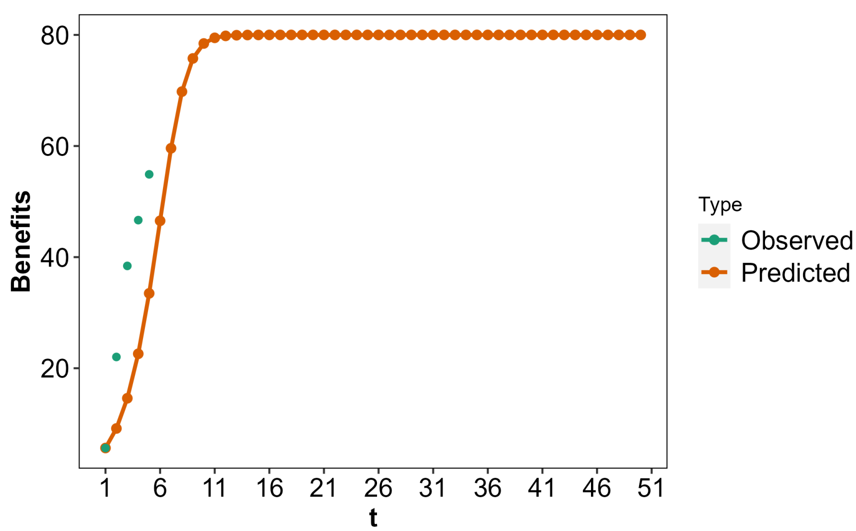


Figure 2.5: Cover cropping benefits under logistic growth

In the simulation analysis, we assume the value of IC such that annual net benefits are negative in the initial years and positive in later years. This helps us qualitatively connect to conservation practices that follow a similar pattern of change in net benefits overtime. In order to calculate net benefits, we deduct the sum of direct and indirect costs. Figure 2.6 shows the time path of net benefits with heterogeneous discount rates. Given the stream of net benefits overtime, individuals with a discount rate lower than 0.023 find it profitable to always cover crop. In order to compare the additionality of the different program design options, we exclude these farmers from the analysis[15].

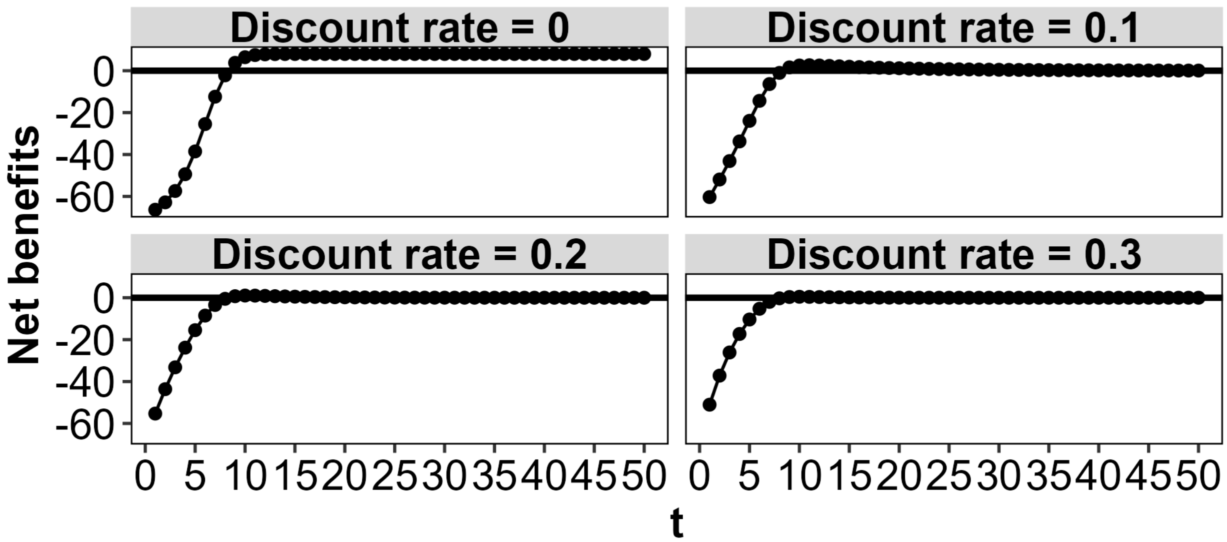


Figure 2.6: Net benefits by discount rate

We combine the simulated stream of net benefits with the elicited discount rate data to calculate the level of adoption and continuation associated with the status quo contract. Using information on EQIP contracts for cover cropping, we assume a contract length of 5 years and an annual payment of \$55 per acre for the status quo contract[16]. Under the status quo contract, around 50 percent of farmers in the sample are predicted to adopt cover cropping. It is important to note that, for working land programs, the actual participation rate observed in the sample ranges between 22 to 32 percent, which is lower than what is predicted here by the status quo. The predicted adoption associated with the status quo contract also highlights the limited ability of the status quo

[15]These excluded farmers represented approximately 18 percent of the sample.

[16]The payment of \$55 represents the average payment made for EQIP contracts in 2018.

to generate participation without incorporating discount rate information. Additionally, everyone that is predicted to participate using the status quo contract is also predicted to continue cover cropping at the end of the contract. This indicates that the distribution of discount rates, along with the simulated net benefits of cover cropping, do not predict large levels of dis-adoption associated with the status quo contract.

2.4.2 Influence of upfront payments on adoption

In this section we explore the impact of upfront payments on adoption of conservation practices. Upfront payments shift a larger portion of the total payment to earlier periods, which therefore provide higher discounted net benefits to farmers with positive discount rates, which should increase their likelihood of program participation. However, upfront payments do not influence the incentives to continue to cover cropping at the end of the contract period. As a result, they have limited potential to increase the number of producers that continuously adopt.

In order to analyze the efficacy of upfront payments, we simulate a payment structure, with a fixed contract length of 5 years, where the payment in the first year is given by wP_{total}. P_{total} is the sum of all payments that will be made over the contract period and w is the portion of that payment that will be paid in the first year. For the remaining 4 years the payment is equally divided, with farmers receiving $\frac{P_{total}(1-w)}{4}$ in each of the remaining years. We set $P_{total} = \$275$ based on the status quo payment of $\$55$ and contract length of 5 years. We then simulate the proportion of adopting and continuing farmers at various levels of 1st year payments.

Figure 2.7 illustrates the impact of upfront payments on conservation practice adoption and continuation. A 0.2 proportion of payment in the first year represents equal payments made in each of the 5 years. Proportions above 0.2 represent upfront payments and proportions below 0.2 represents back-ended payments, where individuals receive a lower proportion of total payments in the 1st year. We see that back-ended payments reduce adoption and continuation among farmers, compared to both equal payments and upfront payments. Additionally, a small increase in upfront payments has a high impact on adoption, suggesting that conservation programs can substantially increase program participation by moving from equal payments to upfront payments. It is interesting to see that upfront payments do increase the proportion of farmers that adopt and continue cover cropping after the program period, but only for a small proportion of farmers. These are likely to be farmers with marginally higher discount rates, than those that adopt with equal payments. Finally, the simulation suggests that the majority of the gains from participation and continuation from upfront payments can be derived from a small increase, around 10 percentage points, in 1st year payments.

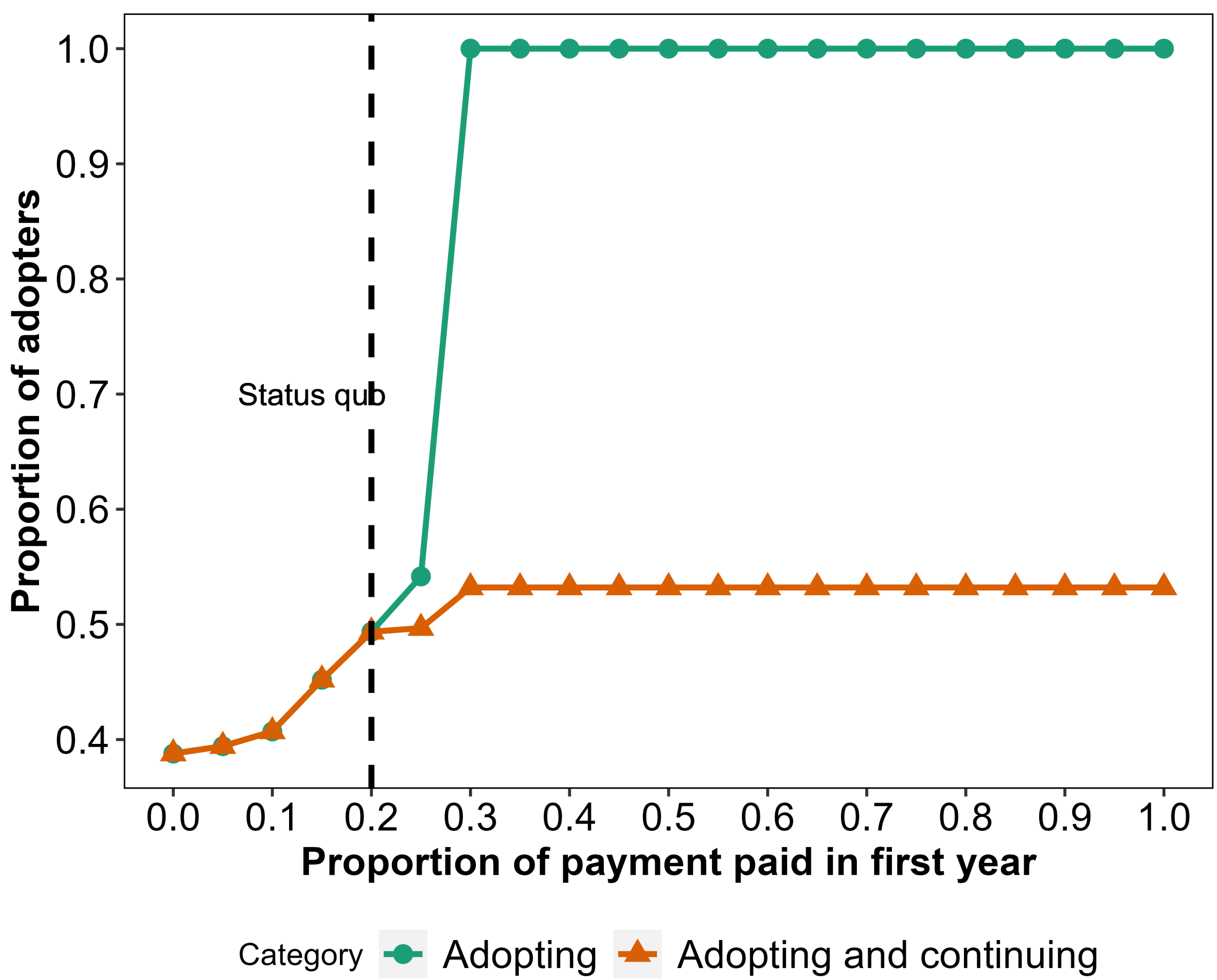


Figure 2.7: Impact of upfront payments on adoption and continuation

2.4.3 Optimal P and l under heterogeneous discount rates

We utilize optimization models to compare the minimum cost required to achieve target levels of continuation for both individualized contracts, and common contracts. We use a grid search method to solve the optimization problem stated in equation 2.5, using the individual discount rates from the experimental data described in the data section. Similar to the one farmer problem, we estimate the value of total cost (C) and proportion of continuing farmers (D) at discrete values of annual contract payment and length. We use the values of g and K as described in section 2.4.1.

In the first case, we optimize assuming each individual can be provided an individualized contract based on their discount rate. This provides us the case where contracts can be tailored to match individual time preferences and helps illustrate the upper bound of cost reductions or gains in participation that can result from identifying differences in discount rates among individuals. In the second case, we optimize assuming that we know the individual discount rates, but we can only provide one common contract to all farmers. Even without individualized contracts, the 5-year status quo contract length may not be the minimum cost contract. A 5-year contract may also be limited in it's ability to attain certain continuation targets. Thus, the common contract case helps to illustrate the benefits of tailoring a common contract to the existing distribution of discount rates. We calculate the cost required to achieve target levels of farmer participation and continuation under a status quo contract length of 5 years. The status quo contract can be thought of as a special case of the common contract, when the contract length is also constrained[17].

The cost minimizing contract length and annual payment for a given continuation target is the same for both individualized and common contract. Figures 2.8 and 2.9 compare the marginal contract length of common and individualized contracts to the status quo of 5 years. The marginal contract length is defined as the contract length offered to obtain an additional continuing adopter. We see that the cost minimizing contract length is increasing as we aim to target a higher proportion of continuing farmers. Given that farmers have positive discount rates, it is preferable to the

[17] Unlike the status quo contract in subsections 2.4.1 and 2.4.2, we allow the annual payment to vary, instead of fixing it at $55. This allows us to compare other contracts to the status quo over a wider range of continuous adoption targets

producer to have payments made over a shorter period of time[18]. However, longer contracts allow more time for the net benefits of cover cropping to grow, increasing the likelihood of a positive net present value from cover cropping at the end of the contract period. Thus, the contract length has to increase as we target a higher proportion of continuing adoption. The cost minimizing contract length is lower than the status quo when targeting a small proportion of continuing adopters (rates below 35 percent). As we aim to increase the proportion of continuing adopters, between ranges of around 0.35 to 0.54, the status quo contract length of 5 years coincides with the cost minimizing contract length. The line describing the status quo contract length ends at 0.54, as increasing the proportion of continuing adopters beyond 0.54 is not possible without increasing the contract length from 5 years. The contract length required when targeting a higher proportion of continuing adopters is greater than 5 years.

The annual payment for the status quo is lower over the range where status quo contract length is higher than the optimal contract length, and then it overlaps with the annual payment for common and individualized contracts. Similar to the marginal contract length, the marginal annual payment for the status quo ends at 0.54, beyond which no changes in annual payment can attain an increase in the proportion of continued adopters without increasing the contract length. The optimal annual payment is increasing over the ranges of continued adoption where the optimal contract length does not vary. The least cost solution, within those ranges, is associated with paying a higher annual payment rather than an increase in contract length. Once the target level of continued adoption increases beyond that point, an increase in contract length is required to support additional continued adoption of cover cropping.

[18] Assuming a social discount rate of 0.

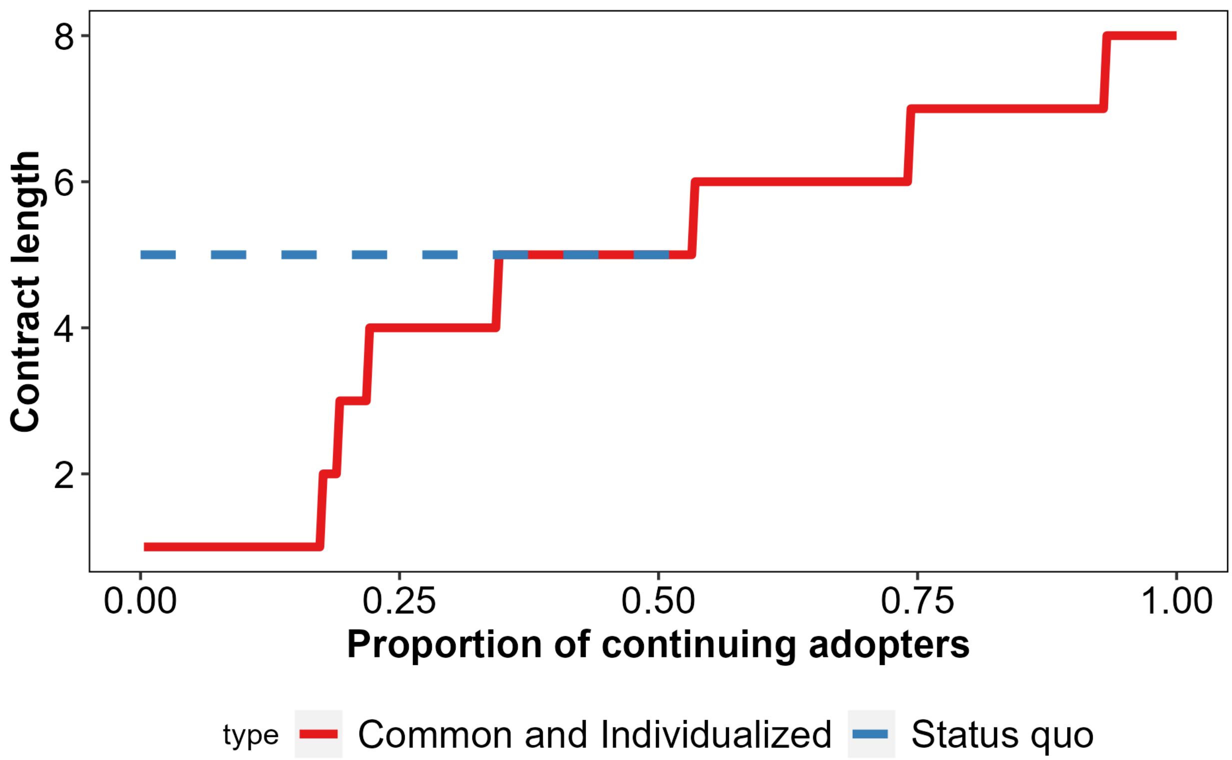


Figure 2.8: Cost minimizing marginal contract length

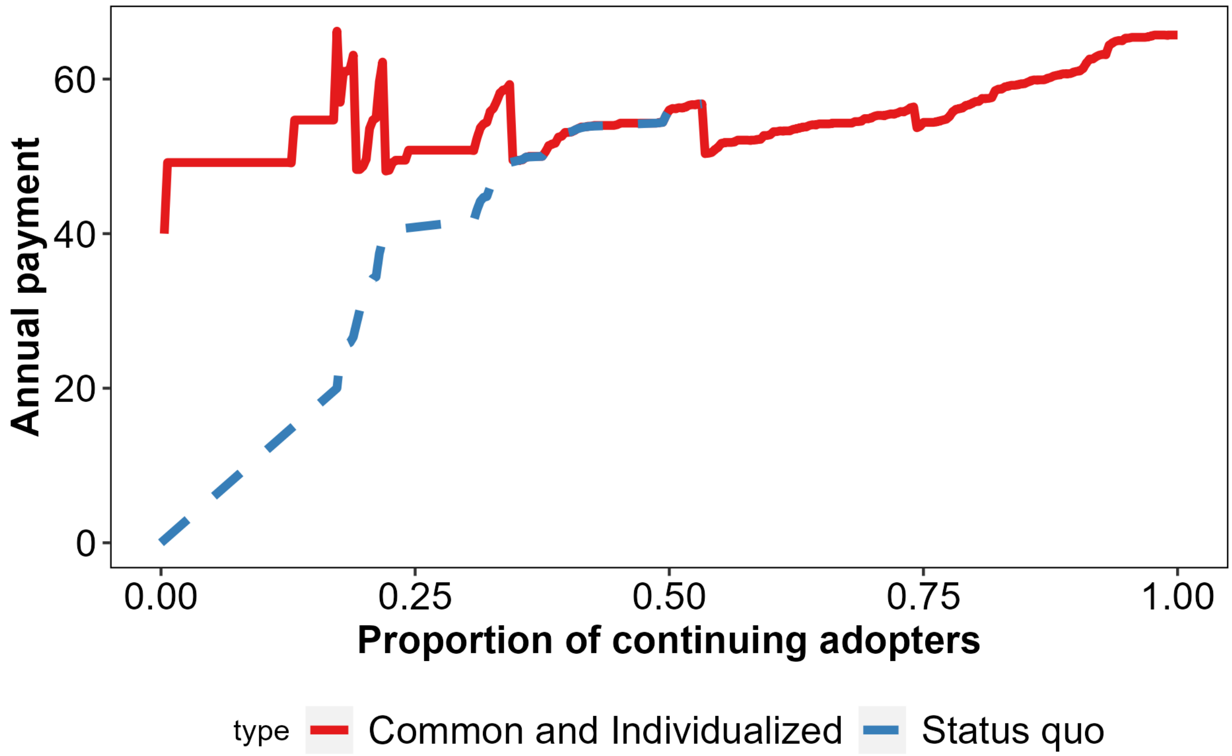


Figure 2.9: Cost minimizing annual payment

Figure 2.10 illustrates the minimum total cost required to achieve a target proportion of adoption and continuation, given by different contract types. As described earlier, the cost minimizing marginal annual payment and contract length for both common and individual contracts are the same. However, individualized contracts can provide differentiated contracts to each individual, whereas the common contract has to provide everyone with the marginal contract length. This results in higher cost for common contracts. We see that individualized contracts result in lower costs than both common contracts and the status quo 5-year contract. Additionally, cost savings grow when targeting a higher proportion of continuing adopters. Thus, there are large potential gains associated with targeting individuals that may have different discount rate distributions. The common contract also achieves levels of participation at a lower cost compared to the status quo. For instance, the aggregate minimum cost required to achieve continued adoption of 0.25 is $\$528$ less for the common contract compared to the status quo contract. This difference represents approximately 2 percent of the cost of required by the status quo to achieve continued adoption of 0.25. Given the distribution of discount rates, a 5-year contract is not sufficient to increase the proportion of continuing farmers beyond 0.54. Thus, common contracts that make use of discount rate information can target higher levels of continuing adopters compared to 5-year contracts.

Overall, the results of the analysis highlight that there are substantial benefits to incorporating discount rate information when designing individualized contracts and common contracts.

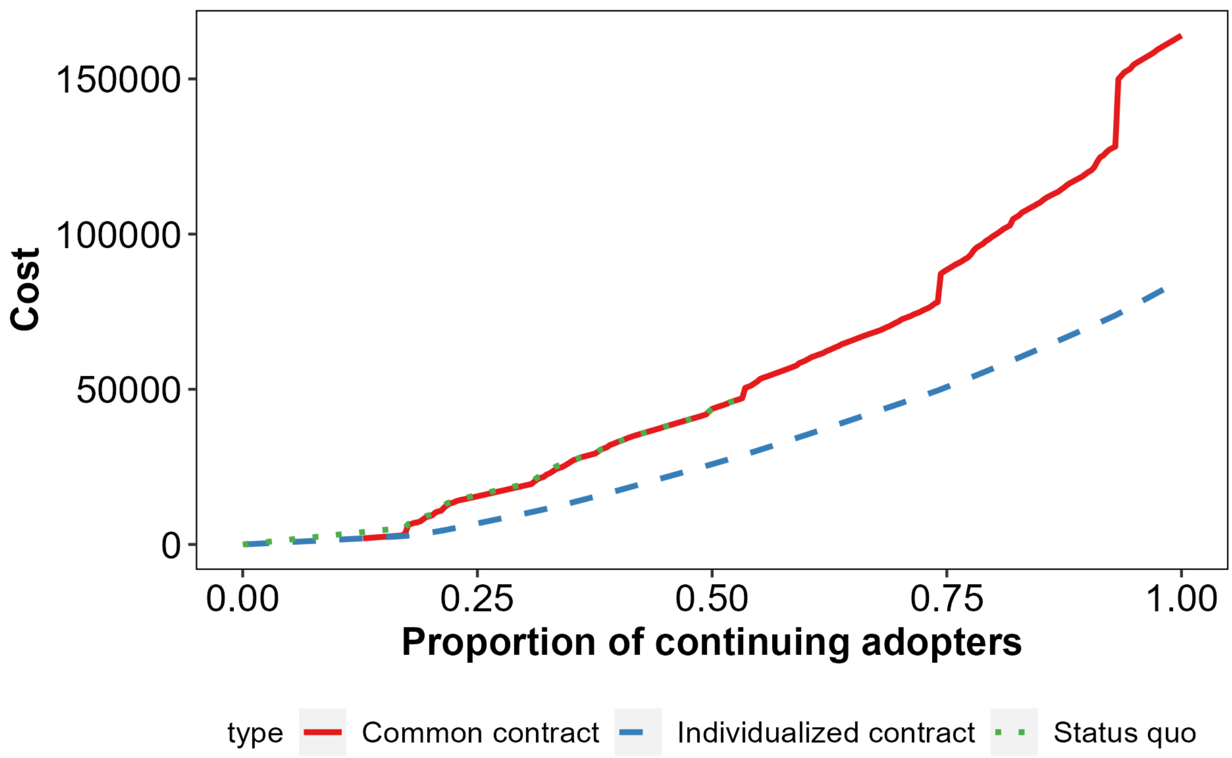


Figure 2.10: Minimum total cost to a achieve a given level of continuous adoption required

2.4.4 Optimal payment and contract length by distribution parameters

In this section, we explore how program costs and benefits from the individualized contract change if the distribution of discount rates were different. The underlying distribution of discount rate of farmers targeted by a conservation program may vary from that observed in our sample. Additionally, the discount rate distribution of farmers may vary across regions, age, or other observable characteristics. This analysis helps us understand whether the main results of the simulation analysis, related to minimum cost and contract length for common and individualized contracts, vary under different distributions of discount rates.

In order to explore the relationship between the distribution of discount rates and the cost minimizing contract structure, we firstly fit a beta distribution to the existing discount rate data to estimate parameters with which the distribution of discount rates can be described. Specifically, we estimate the alpha and beta parameters of the beta distribution. The beta distribution was chosen in order to accommodate the positive skewness observed in the underlying discount rate data. Then, using the estimated parameter values, we randomly draw 312 observations from a beta distribution to generate distribution 2, which is presented in table 2.3 along with the 3 other generated distributions of discount rates. The mean of the beta distribution is given by $\frac{\alpha}{(\alpha+\beta)}$. We can change the value of α to generate different positively skewed distributions with varying means, which represent different regions with different discount rate distributions. When $\alpha < \beta$, and holding β fixed at 2.39, reducing the value of α leads to a higher proportion of lower discount rates in the generated distribution of discount rates. We then reduce the value of $alpha$ and randomly draw 312 observations to generate distribution 1 which has a lower mean and median than the base distribution. This case helps to demonstrate how the minimum cost, proportion of continuing adopters, and associated contract length changes in response to having a higher proportion low discount rate individuals, compared to the base case. Distributions 3 and 4 are generated by using higher values of α, compared to the base case, resulting in cases where we have a higher proportion of farmers with high discount rates.

Table 2.3: Alternative distributions of generated discount rates

Item	α	Mean	Median
Distribution 1	0.3796	0.1370	0.0639
Distribution 2 (base)	0.6296	0.2233	0.1735
Distribution 3	1.1296	0.3235	0.2936
Distribution 4	1.6296	0.3914	0.3665

It is important to note that as the value of α increases, the distribution of discount rates also become less skewed. Figure 2.11 illustrates the distribution of the 4 sets of discount rates.

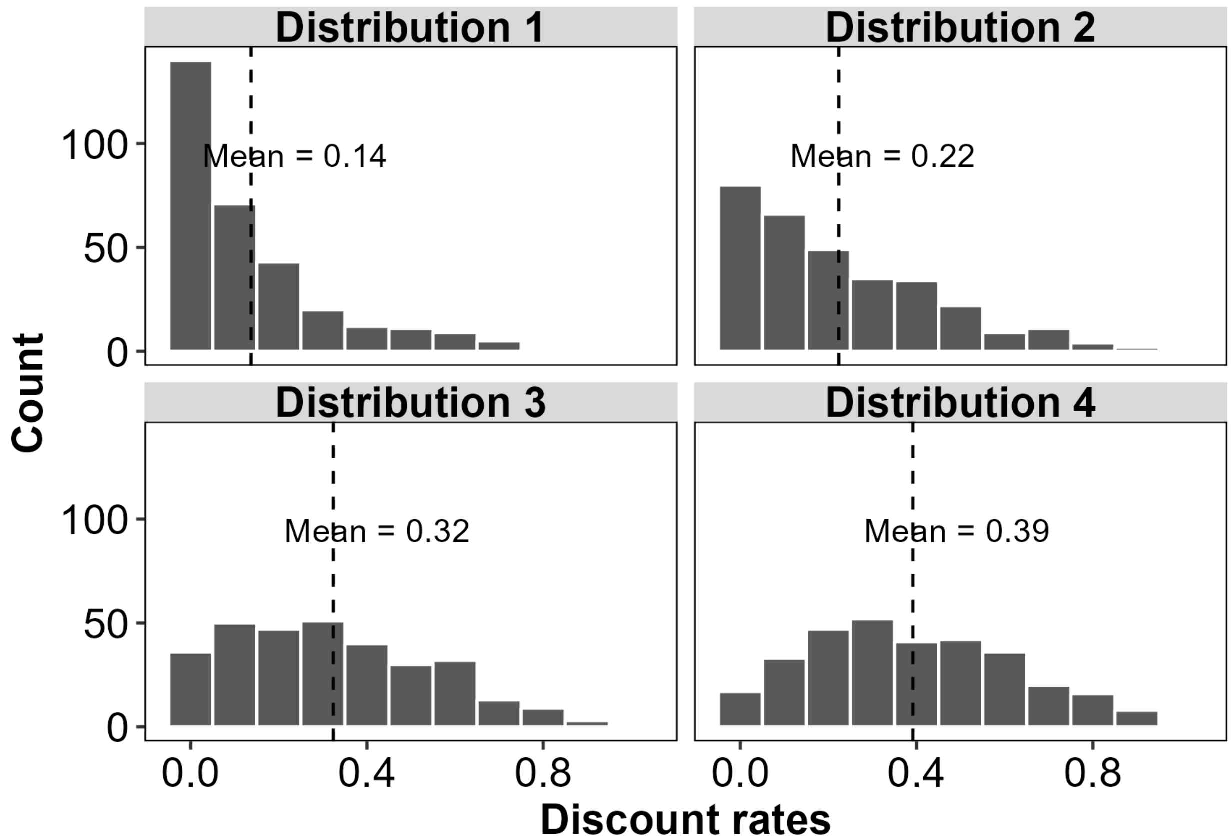
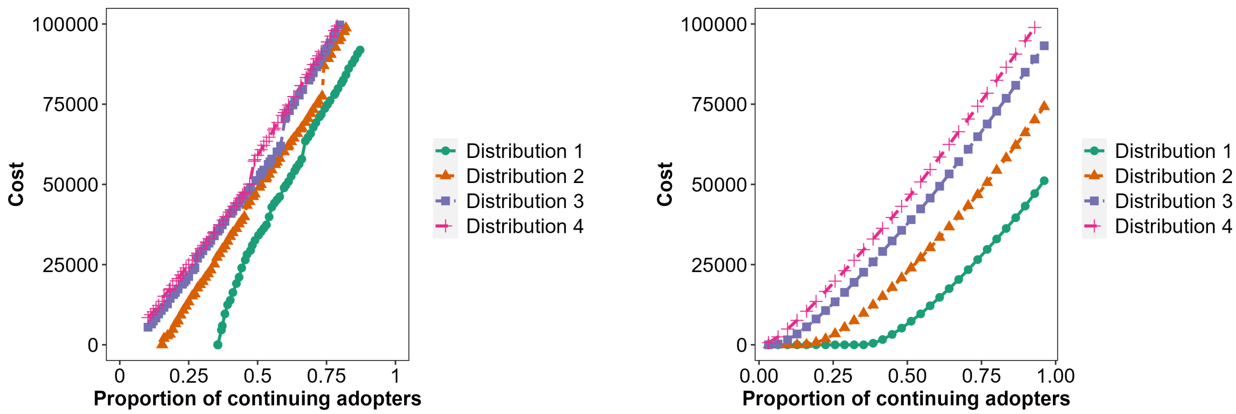


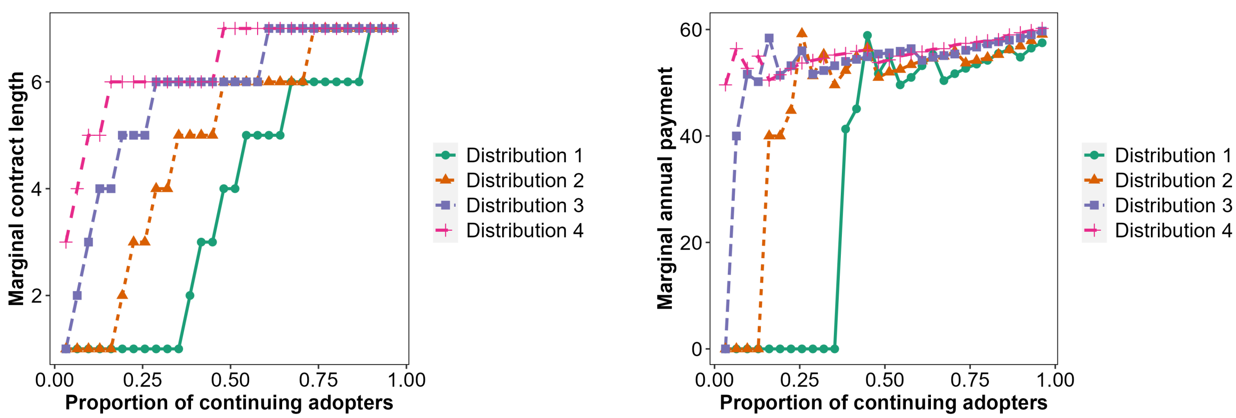
Figure 2.11: Randomly drawn sets of discount rates

Panels (a) and (b) of figure 2.12 represent the total cost required to achieve a target level of continuing adopters for common and individualized contracts, respectively. We see that cost increases as a higher proportion of farmers have higher discount rates for both types of contracts. The difference in cost between the distributions are higher for individualized contracts, compared to common contracts. As discussed earlier, the cost minimizing annual payment and contract length does not vary between individualized and common contracts. Panel (a) of figure 2.13 reveals that the associated marginal contract lengths for individualized and common contracts systematically increase as the proportion of farmers with high discount rates increase. Panel (b) of figure 2.13 reveals that the annual payment also systematically increases with a higher proportion of farmers with high discount rates.



(a) Common contract　　**(b)** Individualized contract

Figure 2.12: Cost by discount rate distribution



(a) Contract length　　**(b)** Annual payment

Figure 2.13: Marginal annual payment and contract length by discount rate distribution

Figure 2.14 compares the cost minimum required for varying levels of continuation between the individualized contract and the common contract. We see that the benefit of the individualized contract, relative to the common contract gets smaller as we move from distribution 1 to distribution 4. This is evidenced by a narrowing gap between the two curves as the mean discount rate in the distribution increases. The result is likely to be driven by the reduced skewness in the distribution of discount rates as we move from distribution 1 to 4.

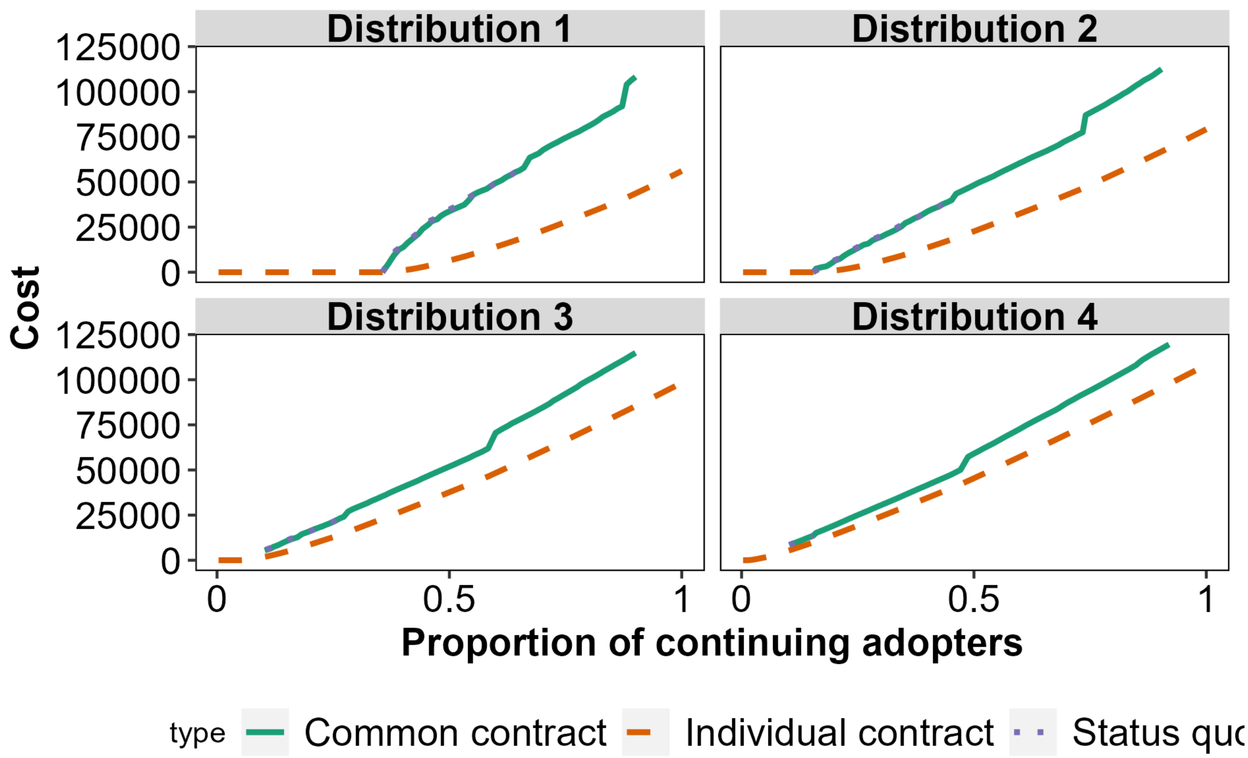


Figure 2.14: Comparisons of total costs by distribution

These results suggest that the gains to tailoring contracts to discount rate information hold under different distributional assumptions of farmer discount rates. Additionally, the difference in costs between the common contract and the individualized contract reduce when a higher proportion of farmers have high discount rates. It is important to note that individual discount rate information is generally not observed and can be costly to uncover. Additionally, it is not clear which observable characteristics are likely to systematically vary with discount rates. Given these considerations, common contracts that make use of discount rate information may provide a more feasible policy option. Under common contracts, the benefit to tailoring the contract length, based on discount rate information, is that it allows the policy maker to achieve higher levels of post program adoption, which is not possible when holding the contract length at 5 years.

In addition to the benefits of incorporating discount rate information, there are costs to tailoring contracts to an incorrect distribution of discount rates. For instance, let us assume that a program administrator believes that distribution 4 correctly represents the distribution of discount rates among the population of interest, where a high proportion of farmers have large discount rates. Let us also assume that the actual distribution of discount rates is provided by distribution 1, which has a lower proportion of farmers with high discount rates compared to distribution 4. If the program administrator has an objective of a 0.5 proportion of continuing farmers, the marginal contract length they will choose is 7 years, which is 3 more years than the least cost contract length associated with distribution 1 for a target of 0.5. Suppose the program administrator can adjust the annual payment to achieve the target level of 0.5 with a 7 year contract. As the contract length is higher than the least cost contract, the total program cost will increase. This excess cost can be attributed to choosing the distribution of discount rates where the proportion of farmers with large discount rates is higher than the actual, leading to offering a longer contract length. Figure 2.15 highlights the excess cost, when the assumed distribution of discount rates (distribution 4) deviates from the actual (distribution 1), for a target proportion of continuing adopters. We see that there is a considerable increase in cost due to incorrectly specifying the discount rate distribution. The excess cost makes up around 6 to 8 percent of the actual total cost incurred by choosing the longer contract. Thus, information that helps to accurately identify the distribution of discount rates is likely to increase cost savings for the conservation program.

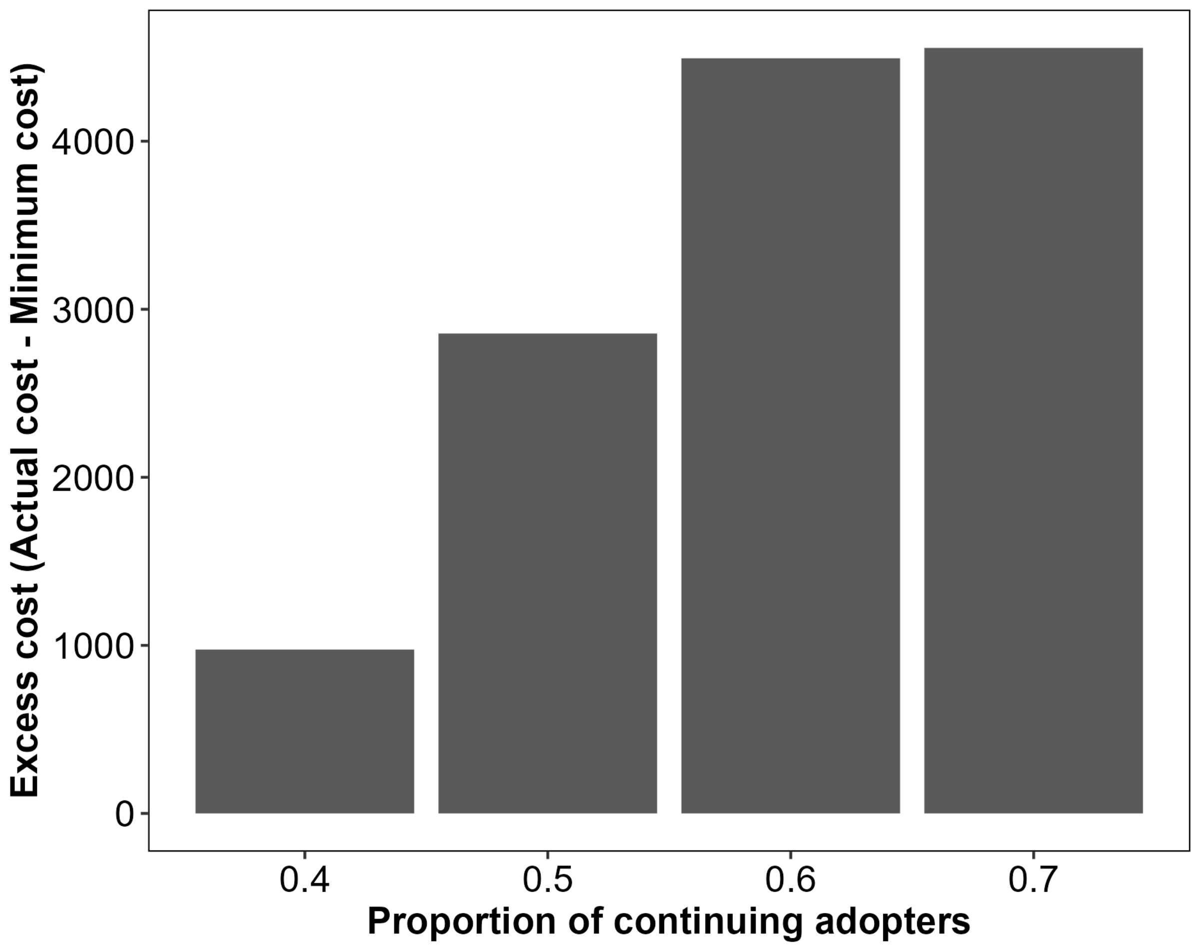


Figure 2.15: Cost due to the assumed distribution (distribution 4) deviating from the actual (distribution 1)

2.5 Conclusion

In this paper, we explore conservation program participation, cover crop adoption and continuation under heterogeneous discount rates. The discount rates in the study reveal substantial heterogeneity in time preferences of farmers. Exploring the mean discount rates by conservation practices reveals that farmers who had adopted cover crops and precision agricultural practices, in the last 3 years, had a statistically smaller mean discount rate, compared to non-adopters. Moreover, farmers that participated in a conservation program, which included EQIP, CSP and CRP, had a lower mean discount rate, relative to farmers that did not participate. This provides suggestive evidence that discount rates play a crucial role in conservation adoption and program participation decisions.

We also conduct simulation analysis to explore how discount rate information can be incorporated in the design of conservation contracts. In the simulation analysis, we first explore the role of upfront payments. Given the data on the distribution of discount rates, we demonstrate that a slight increase in upfront payments can lead to considerable increases in the proportion of farmers adopting the conservation practice during the contract period. We also demonstrate that upfront payments have little to no effect on the proportion of farmers that continue the conservation practice after the end of the contract period. The results from the simulations also demonstrate that continued adoption of cover cropping may require longer contract lengths. Common contracts that tailor contract length and annual payment based on the underlying distribution of discount rates are able to achieve higher levels of continuation, which are unattainable under the status quo contract length of 5 years. Additionally, individualized contracts based on discount rate information can result in cost savings, when compared to the status quo 5-year contract. However, offering individualized contracts may not be feasible due to the cost of acquiring discount rate information and challenges with targeting and offering individualized contracts.

The study provides important analytical and simulated results regarding the role of discount rates in adoption and continuation decisions of conservation practices. However, the study is not without its limitations. Due to a lack of data on dis-adoption and long-term conservation adoption outcomes, we are limited to only exploring the implied or simulated outcomes, rather than actual outcomes, and their relation to discount rates. Despite this pitfall, the results demonstrated in this study reveal the potential gains from incorporating heterogeneous discount rate information when designing conservation contracts. Another limitation in the study is the lack of information on state-level conservation programs. Due to a lack of data, differences in mean discount rates between participating and non-participating farmers could not be assessed for state-level conservation programs. However, the simulated results are based on the dynamics of the costs and benefits of cover cropping, and the nature of the program payments. Therefore, they should still be applicable to state-level programs that provide per-acre payments for cover cropping practices. A final limitation of the study, is the absence of social benefits and costs associated with cover cropping.

Due to the lack of information on the dynamics of cover cropping social benefits, we are unable to specify models that maximize social benefits. Instead we focus on the least cost contract designs that can improve adoption and continuation of cover cropping among farmers. Therefore, the findings of the paper can better inform maximization of social benefits, when those benefits strongly coincide with long periods of adoption.

Chapter 3

Summer crowds: An analysis of USFS campground reservations during the COVID-19 pandemic

3.1 Introduction

Over the last two decades, there has been a sustained increase in demand for outdoor recreation on public lands in the United States. At the same time, the budgets for operating and maintaining recreation sites on public lands have stagnated, resulting in widespread deferred maintenance backlogs (Blahna et al., 2020; Jenkins, Dougher, and Garlick, 2020). Within this context, the COVID-19 pandemic has precipitated an additional set of challenges for public land managers. Over the course of 2020, outdoor recreation emerged as one of the few accessible leisure activities generally deemed to be safe, and recent research points to increases in the values for nature-based recreation brought on by the pandemic (Morse et al., 2020). Between March 1 and May 31 of 2020, the pandemic spurred mandatory stay-at-home orders for all residents in 36 states, with the remaining 14 states imposing orders for persons at increased risk or stay-at-home advisories (Moreland et al., 2020). In addition, many local, state, and national outdoor recreation sites were restricted or shuttered during the spring (Kupfer et al., 2021; Volenec et al., 2021). The result was a documented decrease in household visits to public land recreation areas in the early stages of the pandemic (Landry et al., 2020). The easing of public health restrictions in May and June of 2020, however, led to dramatic changes in recreation visits to public lands across the country. In this research, we document changes in demand for recreation on public land during the COVID-19 pandemic by analyzing data on reservations for USFS campgrounds.

The analysis makes use of a sample that includes weekly campground reservation data for 1,688 individual USFS campgrounds for 2019 and 2020. The rich dataset of campground reservations allows us to evaluate camping demand at a fine temporal scale for the entire contiguous US. We focus exclusively on USFS campgrounds to reduce the administrative heterogeneity that might exist if the analysis were to include campgrounds managed by other federal agencies (e.g., NPS, Bureau of Land Management) and because the USFS accounts for the vast majority of federally managed campgrounds that can be reserved. Conceptually, the focus of the analysis is to infer how demand for camping responded to direct and indirect COVID-19 induced changes experienced during 2020. Specifically, we employ a multivariate linear regression with weekly fixed effects to investigate how COVID-related variables impacted the change in weekly campground nights reserved between 2019 and 2020.

The first set of regression models that we estimate analyze the direct impact of changes in the local COVID infection rate and public health restrictions on camping demand. The dependent variable in these models is the change in weekly camping reservations between 2019 and 2020 for each campground in each week. By evaluating the change in reservations from one year to the next, the models control for time invariant characteristics of the campgrounds, like their size and location. We expect that higher local infection rates caused individuals to substitute away from leisure activities with a higher risk of infection, such as dining at restaurants, to leisure activities, such as camping, that allowed for more social distancing. A conceptual framework that illustrates how infection risk may cause individuals to substitute between leisure activities is provided in the Appendix. The models also evaluate how public stay-at-home orders and advisories, which varied across space over the course of 2020, impacted campground reservations.

The second set of models that we estimate add additional independent variables that account for the indirect impacts of COVID, which we label spatial spillovers, on camping demand. In particular, we investigate how proximity to urban areas and NP boundaries impacted the change in camping reservations in 2020 relative to 2019. Given the relative lack of leisure activities with adequate social distancing in cities, travel restrictions, and the large populations, we expect increases in camping demand in 2020 to be particularly large at campgrounds near urban areas. Similarly, since many campgrounds in NPs were closed or operating at reduced capacity in 2020, we expect USFS campgrounds near those NPs to see larger increases in demand, as households substituted

USFS camping for NP camping. The regression models also control for occurrences of nearby wildfire activity, which we expect to depress camping demand.

This research makes three primary contributions. First, we show that following a decline in campground reservations in the spring of 2020, there was a dramatic increase in reservations in the summer months relative to the reservations made in 2019. Previous studies investigating the impact of COVID-19 induced changes on visitation to public lands have generally not included summer months and instead focused on the first COVID-19 wave (Landry et al., 2020; Rice and Pan, 2020; Geng et al., 2021). As the largest proportion of individuals recreate during the summer, the studies miss out on the dramatic changes that occurred after the spring of 2020. Second, we exploit local variation in COVID infection rates and public health policy directives over time and across space, to assess the impact they had on camping demand. Third, we illustrate how key spatial variables led to differential changes in demand for camping reservations. Craig (Craig, 2020), using a survey of 2,685 US respondents, reveals that individuals reported to be more likely to camp in closer proximity to their home due to COVID. We contribute to the literature by using reservations data to demonstrate that this preference for local camping led to the largest increases in reservations occurring near population centers. In addition, while most USFS campgrounds were fully open during the summer, many campgrounds in US NPs remained partially or fully closed. The resulting demand spillovers generated particularly large increases in reservations for USFS campsites in close proximity to NPs. There is a dearth of research that focuses on spillover effects of management decisions between the National Park Service (NPS) and the USFS. This study contributes to the literature by demonstrating spillover effects, which suggest the potential for benefits associated with a more coordinated response by the agencies. Overall, our results highlight the critical role that public lands played in providing recreational opportunities and a refuge from the challenges households faced during the pandemic year of 2020.

Understanding the impact of public policies, perceived risk of infection, and spatial demand spillovers can inform the USFS in understanding where they may beneficially allocate more resources. Moreover, many of the COVID-19 related impacts observed in 2020 are likely to persist, as the US struggles to keep COVID infections low. Over the course of the pandemic, markets for many goods and services, including protective equipment, medicine and hygiene products, have faced COVID-19 induced shortages (Ranney, Griffeth, and Jha, 2020; Romano et al., 2021). We add to the literature of COVID-19 induced impacts by demonstrating how the changes impacted camping in public lands.

This paper is organized into three major sections. The first section focuses on the direct impact of COVID-19 infection rates and public health restrictions on total nights reserved at USFS campgrounds. The second section demonstrates the indirect impacts of COVID by evaluating the role of spatial spillovers, controlling for infection rates and public health restrictions. Each of these sections begins with a data description, followed by model specification and results. The final section provides concluding thoughts and policy implications of this research.

3.2 USFS reservations and COVID-19 infection rates

The empirical analysis evaluates the factors that impact reservations at USFS campgrounds in 2020 relative to 2019. Specifically, we use data on campground reservations made through recreation.gov in 2019 and 2020, made available by the USFS. The dataset has information on the final record of daily campground reservations, after excluding cancellations, voids and full refunds. In other words, in the data we observe only the camping reservations that were not canceled. We expect campsite reservations to be slightly different from actual visitation given that we do not observe whether individuals that reserved campsites actually showed up for the duration of their reservation. We also do not observe any walk-up camping that may have occurred from campers that did not make a reservation. Therefore, the results of the study reflect how COVID-19 induced changes impacted households' intention to camp in 2020, relative to 2019.

The reservation data is combined with time invariant location data from the Recreation Information Database (RIDB) to get campground locations. The sample of campgrounds are limited to those in the contiguous United States. The sample of reservations only includes overnight camping reservations that do not include a discount pass, for which the total payment to reserve is greater than 0, have less then 11 occupants and the reservation length is between 0 and 11 days (exclusive). In general, campground reservations to USFS campgrounds can be made up to 6 months in advance. The analysis only includes reservations that have been reserved less than 201 days in advance. These filters help ensure that the analysis focuses on individual household campground visitation. After applying all filters, we retain 81.3 percent of all overnight reservations made to USFS campgrounds in the contiguous US.

For each campground we calculate the difference in total nights reserved for every week in 2020 compared to the same week in 2019. Only campgrounds with at least one reservation in both 2019 and 2020 are included in the analysis. This helps ensure a zero reservation in any week is not due to that campground no longer being operational. This criterion results in dropping less than 2 percent of reservations in 2019 and 2020. Thus, the exclusion is unlikely to impact our results. We then proceed with merging the data for weekly total nights reserved with data on campground capacity utilization, county-level infection rates, public health restrictions and the spatial variables of interest to create our final dataset. This process leads to 8 additional campgrounds dropping out. Thus, the final dataset includes total nights reserved at 1,688 campgrounds across the contiguous US, from week 7 to week 37 for both 2019 and 2020. To provide a reference, week 7 begins in early February and week 37 ends near mid-September. Campgrounds may have zero reservations during the off season for a given campground. To control for that, we exclude weeks for which a campground has zero reservations for both 2019 and 2020.

Fig 3.1 shows the difference in reservations for the average campground by week in 2020 compared to 2019 by USFS region. USFS regions faced two distinct trends in the change in camping in 2020, relative to 2019. Following the WHO announcement of COVID-19 as a global pandemic on March 11 of 2020, we see a decline in USFS camping reservations compared to 2019. This decrease is likely driven by both policies at the state level and risk avoidance behavior by individuals. Then we see a gradual increase in relative camping nights reserved, starting from the week preceding Memorial day up until Labor day. In the analysis, summer is defined as the period between the week of Memorial day to the week of Labor day (inclusive). The dependent variable in the analysis is the change in weekly nights reserved between 2019 to 2020 for each campground.

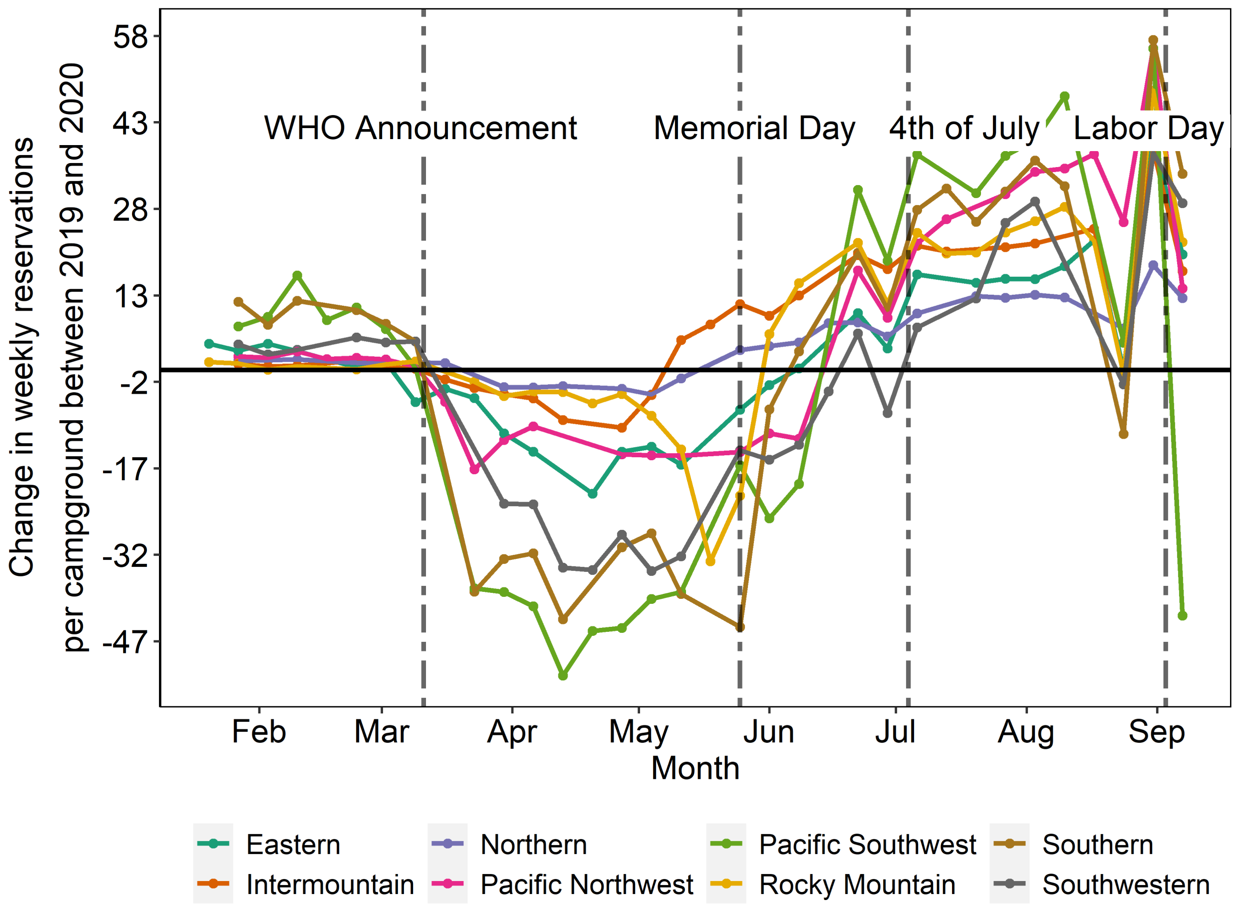


Figure 3.1: Change in weekly reservations per campground between 2020 and 2019 by USFS Region.

The empirical analysis employs data on reservations and campground closures, provided by the USFS, which are used to estimate capacity utilization in 2019 and the number of days that a campground was closed in each week of 2020. Campgrounds that had high capacity utilization in 2019 have less availability to expand reservations, therefore we expect the 2019 capacity utilization to be negatively correlated with the change in camping reservations between 2019 and 2020. Daily capacity utilization is defined as the proportion of available campsites that are reserved on a given day at a given campground. We then calculate average capacity utilization for each campground for every week in 2019. Similarly, we calculate the daily proportion closed variable as the number of closed campsites divided by the number of campsites in inventory for each campground. Campgrounds only appeared in our closures data if they were available in the season. When a campground is off-season, we assume that all campsites for that specific campground were closed. If the proportion of closed sites for a given campground is greater than 0.85, then that campground is categorized as closed on that day. We then calculate the number of days each campground was closed for each week of 2020.

Table 3.1: Summary statistics for USFS campground reservations in 2019 and 2020.

Description	2019	2020	Difference	Percentage Change (%)
Mean days in advance	64.417	47.305	-17.112***	-26.564
Mean reservation length	3.283	3.179	-0.104***	-3.168
Mean number of occupants	3.967	3.971	0.004	0.101
Mean price per night	18.708	18.731	0.023	0.123
Mean nights reserved per week	39.251	50.346	11.095***	28.267

Note: The asterisks indicate p-values from unpaired t-tests on the difference in means; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. The statistics presented in the table are estimated from the 1,688 campgrounds in our sample.

As shown in Table 3.1, the average number of nights reserved at a campground per week increased by nearly 28 percent in 2020. Additionally, there is a considerable decline in the average days in advance for each reservation and a slight decline in reservation length in 2020. Table 3.1 also reflects that the number of occupants per reservation and prices per night reserved remained more or less unchanged.

3.2.1 COVID infection rate and public policies

We use confirmed case data from USA Facts to calculate the county-level COVID-19 infection rate for every week (USA FACTS, 2020, 2021). This dataset has been used in previous studies tracking and analyzing COVID-19 cases and deaths (Oster et al., 2020; Sarah et al., 2020; Andersen et al., 2021). An increase in local COVID infection rates can result in higher perceived risk for all activities outside the home, which could lower demand for outdoor recreation. However, camping can be considered a relatively low risk activity compared to other forms of leisure, such as dining out. As a result, individuals may substitute to camping and away from riskier leisure activities as described in the conceptual model presented in the Appendix. Thus, how local infection rates impact camping demand becomes an empirical question. In this paper, the weekly infection rate is calculated as:

$$r_{iw} = \frac{New\,Cases_{iw}}{Population_i} \times 100\,, \tag{3.1}$$

where r_{iw} is the county-level infection rate at campground i in week w, $New\,Cases_{iw}$ is the number of new cases in week w in the county of campground i and $Population_i$ is the population of the county of campground i. We assume that the county-level infection rate is not affected by the number of nights reserved at a campground. Given that camping is a relatively secluded form of recreation and documented infections lag exposure, it is reasonable to assume the nights reserved at an individual campground in a week do not have a significant impact on the county-level infection rate experienced in that week. The empirical model uses the 3-week moving average of the infection rate, which is calculated as:

$$X_{1iw} = \frac{r_{iw} + r_{i(w-1)} + r_{i(w-2)}}{3}\,, \tag{3.2}$$

where X_{1iw} is the 3-week moving average of the infection rate, and $r_{i(w-1)}$ and $r_{i(w-2)}$ are the lagged values of the infection rate. Along with the 3-week moving average, we have also tried modeling the infection rate with just the current and 2-week moving average infection rates. These results are presented in the Appendix. The results are not qualitatively different for these alternative specifications, therefore, we choose to focus on the 3-week moving average.

We also employ a dataset that provides county-level stay-at-home orders from the US Centers for Disease Control and Prevention (CDC). Fig 3.2 shows the number of states adopting different

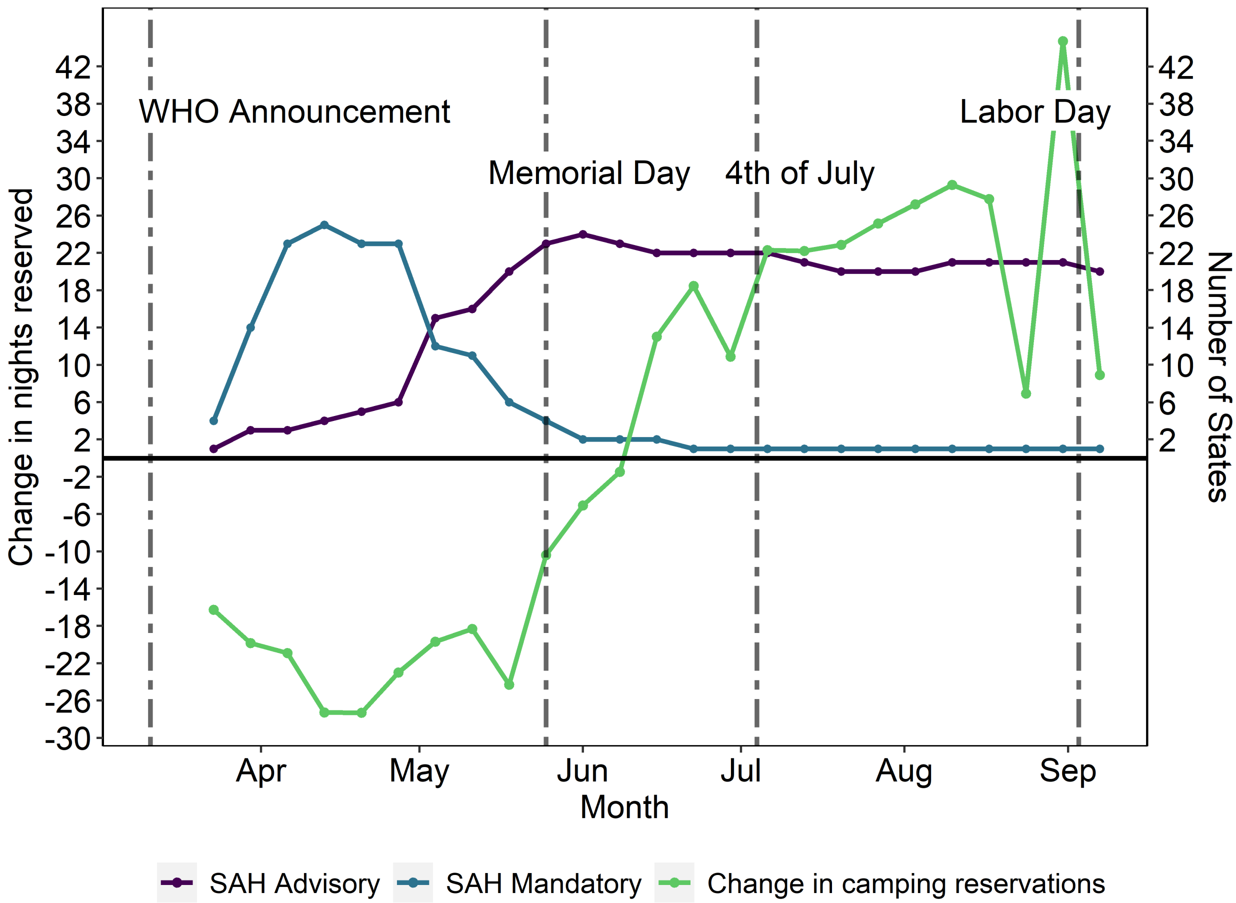


Figure 3.2: Average change in weekly camping nights reserved by campground between 2020 and 2019 and Stay-at-Home Orders (SAH).

stay-at-home orders in weeks following the World Health Organization's (WHO) announcement of COVID- 19 as a global pandemic. We see that a majority of the states issued mandatory stay-at-home orders, while fewer states issued less restrictive stay-at-home advisories. However, there is a relatively rapid decline in states keeping the mandatory stay-at-home orders in place in April and early May. Moreover, even among the states with mandatory stay-at-home orders, camping was still permitted in some states either initially or later on during the year. We also see an increase in the number of stay-at-home advisories as states reduced mandatory restrictions. The restrictions posed by stay-at-home advisories can vary by state but in general they are more lenient than mandatory stay-at-home orders.

The variation in policies enables us to identify how camping demand responded to mandatory stay-at-home orders or advisories, relative to having a more lenient or no stay-at-home order in place. In the majority of the cases, stay-at-home orders do not vary within a state. However, there are a few instances where counties might have a different stay-at-home policy than the one issued at the state level. We use county-level stay-at-home orders, whether issued by the county or by the state, to capture the impact of such heterogeneity. Partially restrictive orders, such as, stay-at-home orders for high risk individuals and only for certain areas, are less restrictive than mandatory stay-at-home orders for all individuals. While understanding the impact of these partial restrictions would be interesting, there is insufficient variation in the number of states that enacted these orders and therefore they are not included in the empirical analysis.

3.2.2 Model Specification: Infection rate and public health restrictions

The dependent variable in this paper represents the difference between total nights reserved for a specific week in 2020, relative to 2019, for each campground.

$$\Delta Y_{iw} = Y_{iw2020} - Y_{iw2019} \, ,$$

where Y_{iw} is the the total nights reserved at campground i at week w. Camping demand and campground availability is seasonal. In order to ensure the change in camping reservations are comparable, we take the difference in total nights reserved on the same week across 2019 and 2020 for each campground. Differencing also helps remove potential time invariant unobservable characteristics at campgrounds that may confound our estimates. The regression model in this section is specified as

$$\Delta Y_{iw} = \sum_{k=1}^{5} \beta_k X_{kiw} + \sum_{k=1}^{5} \gamma_k X_{kiw} S_w + \delta_w + \epsilon_{iw} \tag{3.3}$$

where δ_w represents weekly fixed effects, which control for shocks common to all campgrounds over time and also help control for weeks that may be non-comparable across years. For instance, Labor Day in 2019 and 2020 fall in different weeks. X_{1iw} is the three week moving average of the county-level infection rate (including the current week), X_{2iw} is a dummy variable for mandatory stay-at-home orders, X_{3iw} is a dummy variable for stay-at-home advisory orders, X_{4iw} represents the number of days that campground i was closed in week w in 2020. Campgrounds already near full capacity in 2019 are less likely to experience substantial increases in reservations, compared to campgrounds that were not utilized as much. We therefore include the average capacity utilization in percentage points at the campground in 2019, labeled as X_{5iw}. S_w is a dummy variable for summer that is interacted with each variable and ϵ_{iw} is the idiosyncratic error term. Interacting each variable with the summer dummy allows us to observe the heterogeneity in impacts of each independent variable between the spring and summer of 2020.

From equation 3, we can derive the marginal effects for each variable, which can be represented as:

$$\frac{\partial[\Delta Y_{iw}]}{\partial X_{kiw}} = \begin{cases} \beta_k & \text{if } \ S_w = 0 \\ \beta_k + \gamma_k & \text{if } \ S_w = 1 \end{cases} \tag{3.4}$$

For simplicity, Table 3.2 only reports the marginal effects demonstrated in equation 4. The marginal effects when $S_w = 0$ are reported under Spring and the marginal effects when $S_w = 1$ are reported under Summer.

3.2.3 Econometric Results: Infection rate and public health restrictions

As shown in Table 3.2, specification 1 provides the marginal effects from equation 4. Specification 2 is similar to 1 but excludes the number of days campgrounds were closed in 2020. Specification 3 is also similar to 1, but it uses a USFS region-by-week fixed effect instead of a weekly fixed effect. This is done to ensure that potential time variant changes due to differing USFS regional policies are controlled for. The full regression tables for each specification can be found in the Appendix. We see that the lagged 3-week average infection rate has robust signs across specifications for the summer. In the summer, an increase in the 3-week average infection rate led to between 24.73 to 26.36 more nights reserved per week at a typical campground in 2020, after controlling for the

Table 3.2: Marginal Effects from Direct Effects Model.

	Dependent Variable: Change in nights reserved					
	(1)		(2)		(3)	
	Spring	Summer	Spring	Summer	Spring	Summer
3-week avg infection rate	-20.180	26.364*	-26.374	20.012+	32.401	24.726*
	(19.030)	(10.406)	(18.764)	(11.127)	(20.796)	(10.778)
Mandatory SAH	-16.420***	2.339	-18.538***	1.809	-4.006	1.788
	(3.024)	(2.574)	(3.023)	(2.703)	(4.972)	(3.883)
Advisory SAH	-9.096**	0.345	-10.920***	2.449	-12.388**	0.644
	(3.234)	(1.690)	(3.268)	(1.751)	(3.803)	(1.802)
Days closed in 2020	-1.813***	-6.311***			-1.329*	-6.058***
	(0.512)	(0.343)			(0.578)	(0.360)
Capacity utilization in 2019	-0.046+	-0.216***	-0.071*	-0.303***	-0.101**	-0.207***
	(0.027)	(0.022)	(0.030)	(0.023)	(0.032)	(0.024)
Observations	29,619		29,619		29,619	
Fixed effects	Weekly		Weekly		Region-by-week	
Clustered Standard Errors	Campground level		Campground level		Campground level	
R^2	0.223		0.159		0.260	
Adjusted R^2	0.222		0.157		0.253	
Residual Std. Error	44.936(df = 29578)		46.753(df = 29580)		44.011(df = 29361)	
F statistic	211.9***(df = 40; 29578)		146.7***(df = 38; 29580)		310.8***(df = 10; 29361)	

Notes: +p<0.1; *p<0.05; **p<0.01; ***p<0.001 two-tailed;
The standard errors are clustered by campground and provided in parenthesis.

number of closed campground days. Given that the mean camping nights reserved in 2020 was 50.35, a 1 percentage point change in the 3-week moving average infection rate has a considerable impact on camping nights reserved. To put this in perspective, the mean 3-week avg infection rate in of the sample was 0.04 percentage points with a standard deviation of 0.067 percentage points. Thus, a 1 standard deviation increase in the infection rate led to an estimated 3.29 percent increase of the mean camping nights reserved in 2020. As the perceived risk of outside activity increased, the demand for less risky (more remote) outdoor activity led to increased camping demand. The magnitude of this coefficient decreases when we do not control for days closed. Counties that saw more infection rates are likely to have closed more of their sites, which decreased camping reservations. However, after controlling for the number of days a campground was closed, we see that the USFS campgrounds that remained open saw an increase in camping demand.

The mandatory SAH orders have a negative impact on the change in camping reservations in the spring weeks although the significance drops when the model includes region-by-week fixed effects. The mandatory SAH orders do not have a significant impact during the summer, although there were very few states that had mandatory SAH orders in the summer months, so the results are likely to be driven by only a few counties. The results for SAH advisory orders are similar, however the coefficient for the SAH advisory orders remains significant even after controlling for region-by-week differences for the spring weeks. The findings of camping demand being depressed in the Spring are in line with existing literature (Landry et al., 2020). Not surprisingly, the number of days a campground is closed has a significant and negative impact on camping reservations. Additionally, looking at the capacity utilization of campgrounds in 2019, we see that campgrounds that had higher utilization rates for a given week in 2019 experience a significantly smaller change in camping reservations in 2020, as expected.

3.3 Spillover effects: National Parks, Metros and Wildfire

In this section, we explore how changes in campground nights reserved were impacted by a shift in risk attitudes and increased preferences for more remote activities during the COVID-19 pandemic. These spillovers represent the indirect impacts of COVID-19 induced changes on camping nights reserved. The spillover effects that we explore include spillovers from a campground's proximity to (1) NPs; (2) metropolitan areas; and (3) wildfires. As shown in Fig 3.3, NP campgrounds experienced substantial closures throughout 2020, relative to USFS campgrounds. Despite the campground closures, most NPs remained opened for some level of day-use visitation. As a result, individuals who preferred to visit the NPs are likely to camp at nearby USFS campgrounds. Thus, we would expect the largest spillovers from NPs that experienced considerable recreation visits. The empirical model estimates this heterogeneous impact of NPs spillovers on USFS campground demand. Additionally, traveling during 2020 was either restricted or discouraged in most states. Furthermore, most metros also experienced non-essential business closures and provided reduced opportunities for other leisure activities. As a result, we expect to see the largest increases in reservations near high population metro areas in 2020, relative to 2019. Finally, we expect spillovers that reduce USFS camping demand nearby wildfire activity. Wildfires result in both increased risks and reduced air quality at campgrounds nearby. Given that many forests saw wildfire activity in 2020, we expect proximity to wildfire to reduce camping reservations in USFS campgrounds.

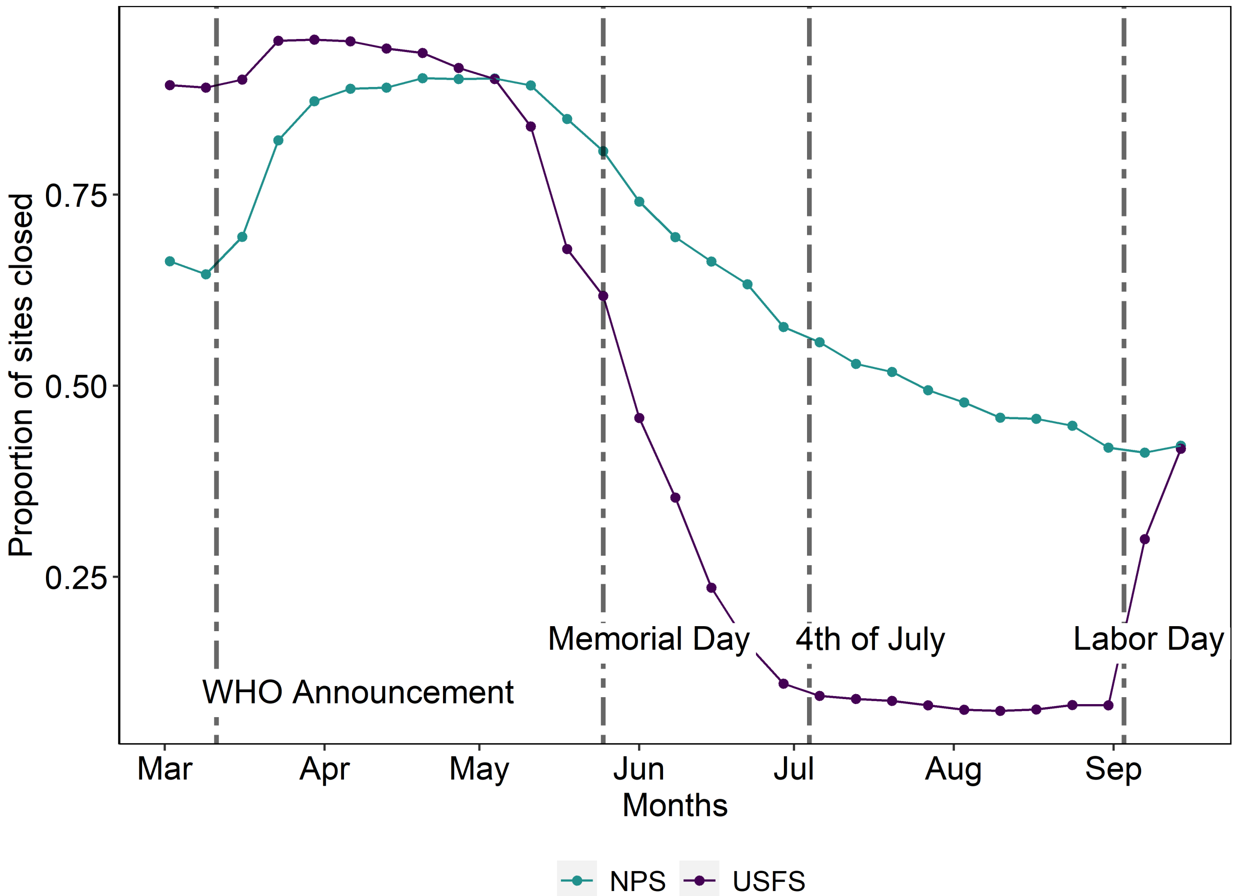


Fig 3.3: Proportion of USFS and NP campgrounds closed by week in 2020.

3.3.1 National Parks

We use NP boundary data from the NPS to identify USFS campgrounds near NPs. We also employ NPS visitor use statistics to estimate heterogeneous treatment effects of being near a NP (National Park Service, 2020). We make use of campground closure data from recreation.gov to investigate the differences in closures between NP campgrounds and USFS campgrounds. Fig 3.4 displays the spatial distribution of campgrounds and NPs in the western US, as well as the total change in annual camping reservations between 2019 and 2020. The difference in annual nights reserved in Fig 3.4 is estimated by summing up total nights reserved from week 4 to week 37 for each year and then taking the difference. In order to identify potential spillover effects from NPs on nearby USFS campgrounds, we identify which USFS campgrounds fall within 50 miles of each NP. As initial campground locations are exogenous to changes experienced between 2019 and 2020, we are able to estimate the potential spillover effects from NPs on camping reservations in USFS campgrounds. We estimate the spillover effect on USFS camping reservations due to a campground being within 50 miles of a NP, relative to being further than 50 miles of a NP boundary.

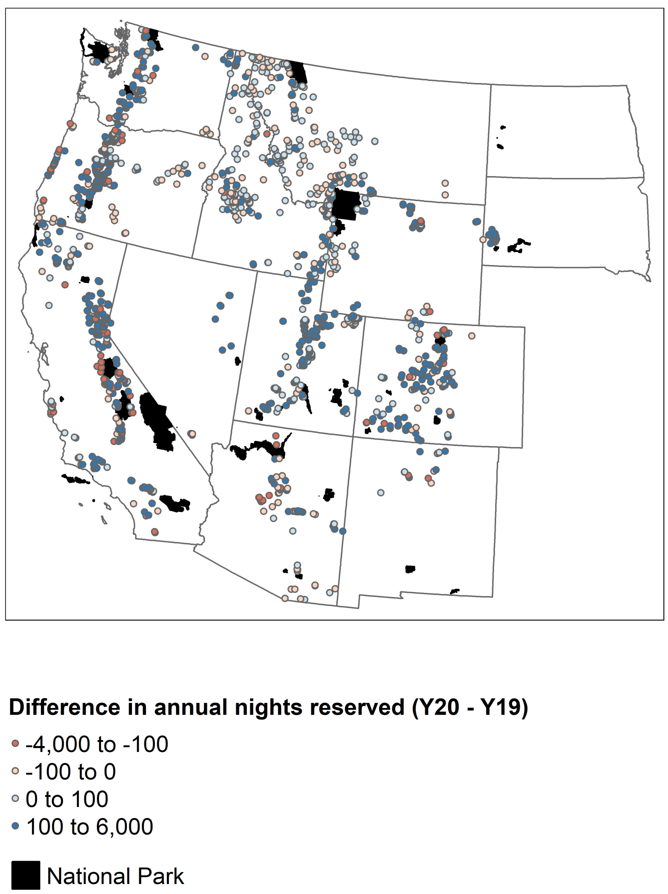


Figure 3.4: Difference in annual campground reservations between 2019 and 2020 at each campground.

We also explore the mechanism through which NP spillovers may impact nights reserved at USFS campgrounds. Individuals engaged in other forms of recreation at the NP may choose to camp at nearby USFS campgrounds. We demonstrate the impact of being near NPs as a function of the change in recreation visits to the NP between the months of 2019 and 2020. Each dot in Fig 3.5 represents the proportional change in NP visitation in a month of 2020, relative to 2019. Each dot represents a unique NP. As the figure shows, many NPs experienced large declines in visitation in March, April, and May. Some of the NPs experienced increased recreational visitation in the summer months in 2020 compared to 2019. We assign this monthly visitation data to the corresponding weeks and then assign dummy variables that indicate whether a USFS campground was near at least one NP, in a given week, that experienced an increase (above the zero line) in recreational visits in 2020.

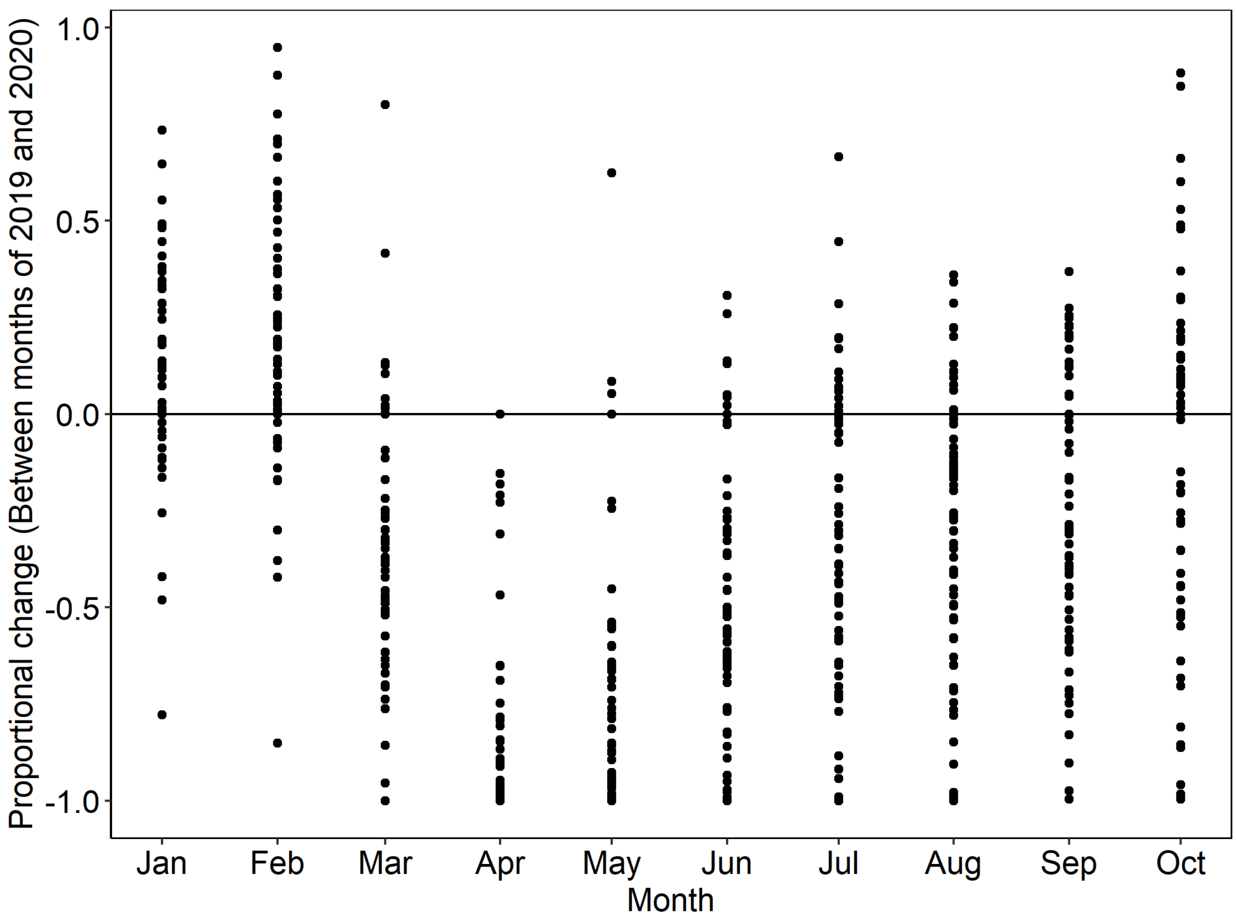


Figure 3.5: Proportional change in all recreation visits to NPs between 2019 and 2020.

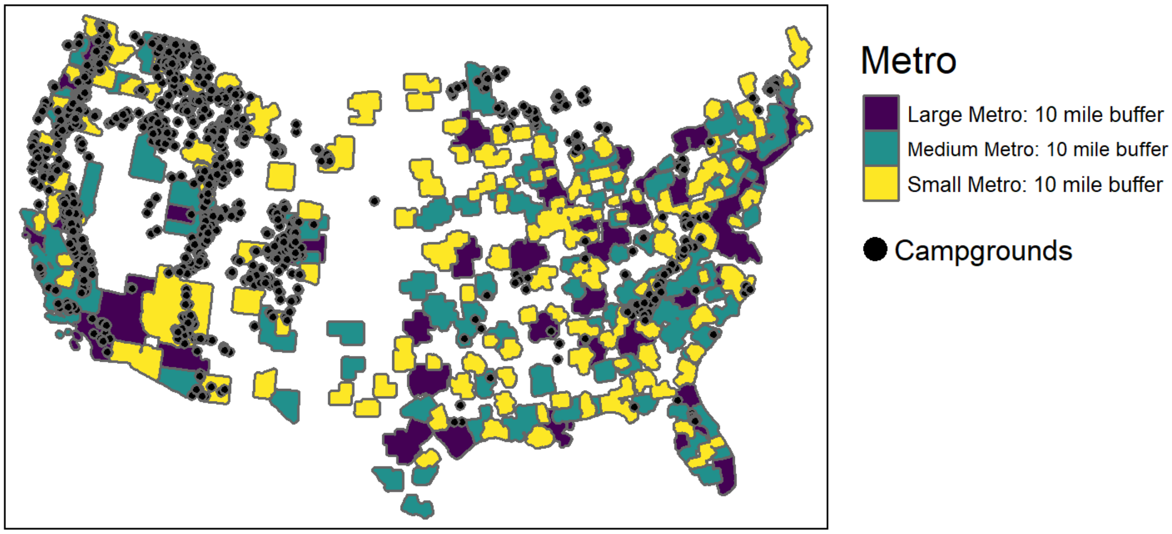


Figure 3.6: Map of metropolitan areas and campgrounds.

To evaluate the relationship between USFS reservations and proximity to population centers, we make use of data on the location of metropolitan counties using the Rural Urban codes 2013 dataset from the Economic Research Service (ERS). During 2020, most states had some form of travel restriction in place in an effort to reduce COVID transmission rates. Moreover, households were likely to avoid travel to reduce their risk exposure to the virus. Therefore, we expect increases in preferences for camping locally. The implication of an increase in demand for local camping is that we expect USFS campgrounds located near higher population density counties to experience a relative increase in reservations compared to campgrounds that are far from population centers. We investigate the extent to which changes in camping reservations were influenced by the campground location being within 10 miles of a metropolitan area boundary. We generate 10-mile buffers around the county shapes for each metropolitan area using R, with the "simple features" (sf) package. We then identify which campgrounds were located within these buffer areas. The metropolitan areas are categorized as metropolitan areas with less than 250,000 population, labeled as small metropolitan area, metropolitan areas with populations of 250,000 to 1 million, labeled medium metropolitan area, and finally metropolitan areas with more than 1 million population, labeled as large metropolitan area. These classifications are analogous to how the official Office of Management and Budget (OMB) defines metropolitan areas in the US. Fig 3.6 shows the geographical distribution of these metropolitan areas with a 10 mile buffer.

3.3.2 Wildfire

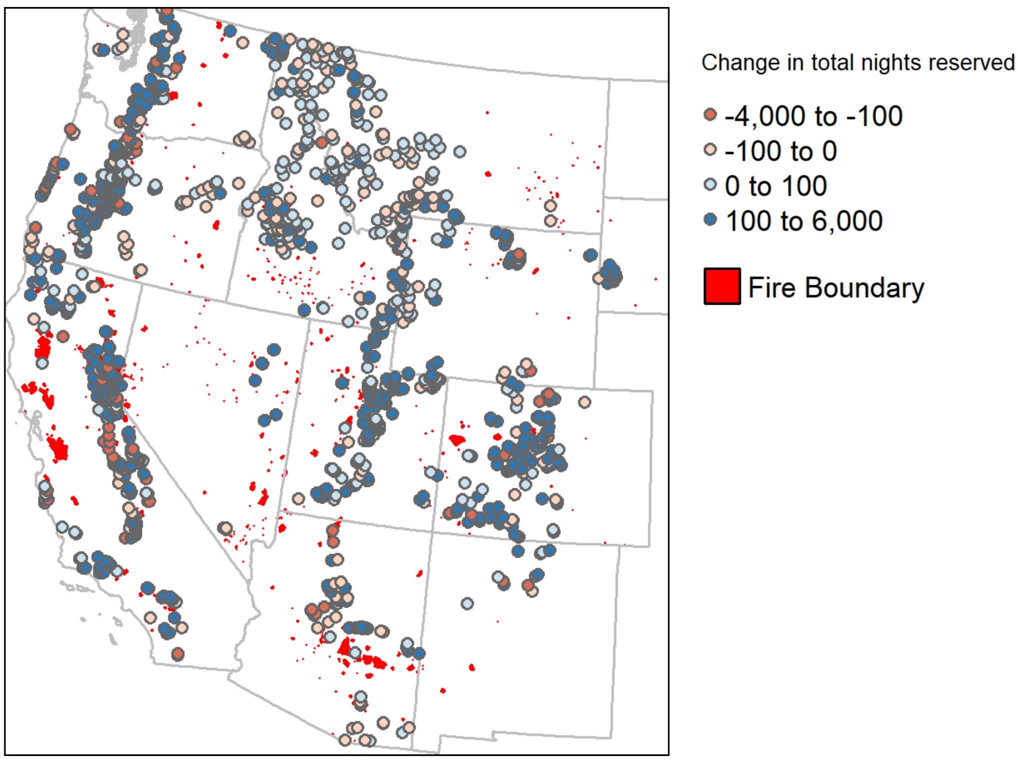


Figure 3.7: Wildfire perimeters in the western US in 2020.

In 2020, the US experienced considerable wildfire activity, with over 10 million acres burned according to National Interagency Fire Center (NIFC) estimates (National Interagency Fire Center, 2021a). Existing research demonstrates that wildfire can result in a decrease in campground usage (Gellman et al., 2021). Wildfire also has the potential to cause NP closures and population movement that could influence COVID infection rates. This makes wildfire both an important control and a variable of interest, when looking at changes in camping demand in 2020. Fig 3.7 represents the wildfire boundaries experienced in the western US in 2020. To understand the impact of wildfire on demand for USFS campground reservations, we use the 2020 Perimeters to Date dataset from the NIFC (National Interagency Fire Center, 2021b). It is important to note that some of the largest fires of 2020, including California's August Fire, Arizona's Cow Canyon Fire and Colorado's Cameron Peak Fire, occurred after the study period. We also only look at fire activity within the contiguous US, due to focusing on camping only in those regions. In order to estimate the impact of wildfire on camping demand, we identify campgrounds located within 10 miles from a fire boundary and between 10 to 20 miles of a fire boundary in a given week. This does not count the small number of campgrounds within the fire boundary itself. Their inclusion does not meaningfully impact the results. These campground classifications are time variant due to fire boundaries changing over time. We expect campgrounds nearby fire boundaries to experience reduced reservations, due to increased risk and reduced air quality in those areas. The two distance buffers are included in the model to evaluate the extent to which the impact of wildfire on reservations dissipates with distance from the fire.

3.3.3 Model Specification: Spatial spillovers

The empirical model that we estimate to evaluate the impact of spillovers is specified as:

$$\Delta Y_{iw} = \sum_{k=1}^{12} \alpha_k X_{kiw} + \sum_{k=1}^{12} \rho_k X_{kiw} S_w + \delta_w + \epsilon_{iw} \tag{3.5}$$

where δ_w again represents weekly fixed effects and ϵ_{iw} is the idiosyncratic error term. The definitions of the dependent variable along with the independent variables X_{1iw}, X_{2iw}, X_{3iw}, X_{4iw} and X_{5iw} are the same as that defined in equation (3). X_{6i} is a time invariant dummy variable for campground i being in the 50 mile buffer of a NP boundary. We also test alternative specifications using different mutually exclusive buffer distances around NP boundaries. The results for these alternative specifications can be found in the Appendix and they show that alternative buffer distances do not qualitatively impact the results. The X_{7iw} variable is a dummy for campgrounds that fall within 50 miles of at least one NP that saw an increase in recreation visits in week w of 2020, relative to 2019. X_{8i}, X_{9i} and X_{10i} represent dummy variables for campgrounds within 10 miles of small, moderate and large metropolitan areas respectively. X_{11iw} is a dummy variable that indicates if campground i was within 10 miles of the boundary of a wildfire in week w. X_{12iw} is a dummy variable that indicates if campground i was between 10 and 20 miles of a wildfire boundary. Similar to equation (3), the model includes the summer dummy variable interacted with each independent variable.

From equation 5, we can derive the marginal effects for each variable, which can be represented as:

$$\frac{\partial[\Delta Y_{iw}]}{\partial X_{kiw}} = \begin{cases} \alpha_k & \text{if } S_w = 0 \\ \alpha_k + \rho_k & \text{if } S_w = 1 \end{cases} \tag{3.6}$$

Table 4 only reports the marginal effects demonstrated in equation 6. The marginal effects when $S_w = 0$ are reported under Spring and the marginal effects when $S_w = 1$ are reported under Summer.

3.3.4 Results: Spatial spillovers

The results from Table 3.3 for infection rates and mandatory stay-at-home orders are qualitatively similar to those observed in Table 3.2. The full regression results with interaction terms for Models 1, 2 and 3 of Table 3.3 are provided in the Appendix. The results show that having an advisory SAH, relative to having no SAH, resulted in reduced reservations for camping both in the summer and non-summer weeks after including the spatial variables as controls.

The results from Table 3.3 also reveal that USFS campgrounds near a NP that experienced increased visitation in 2020, relative to 2019, saw a considerable increase in reservations in the summer. The magnitude of the increase is approximately 13 percent of the mean value of campground nights reserved in 2020. The sign and significance of the effect is robust across all specifications. This result demonstrates a mechanism through which USFS campgrounds nearby NPs experienced spillovers during the pandemic. We see a reversal in the sign of the marginal effects for the Medium and Large metropolitan areas. Being near highly populated metros generally resulted in decreased camping in the spring. However, during the summer months campgrounds near populated metros experienced large increases in reservations, relative to other campgrounds. These marginal effects can be attributed to increased preferences for more remote activities, such as camping, amongst urban residents. The results illustrate that during the summer, USFS campgrounds within 10 miles of a large metropolitan area experienced around 13 to 15 more camping nights reserved, compared to campgrounds located further away. The magnitudes are of considerable size as they represent about 27 to 31 percent of the mean of camping nights reserved in 2020, respectively. The estimates from Table 3.3 also reflect that being near a fire boundary significantly reduced camping in the summer weeks. The magnitudes of the reductions are around 25 percent of the mean value of camping nights reserved in 2020. Finally, we see results similar to Table 3.2 for the campground closures and 2019 capacity utilization variables.

Table 3.3: Marginal effects for full model with spatial spillovers

	Dependent variable: Change in nights reserved					
	(4)		(5)		(6)	
	Spring	Summer	Spring	Summer	Spring	Summer
3-week moving avg infection rate	-14.660	16.445	-19.230	11.096	33.878^{+}	17.812^{+}
	(17.754)	(10.363)	(17.360)	(11.059)	(19.988)	(10.532)
Mandatory SAH	-13.362***	-1.083	-15.272***	-1.420	-2.421	1.131
	(2.802)	(2.559)	(2.798)	(2.679)	(4.648)	(4.026)
Advisory SAH	-8.295*	-2.817^{+}	-10.046**	-0.765	-11.262**	-2.417
	(3.306)	(1.664)	(3.333)	(1.706)	(4.011)	(1.809)
Within 50 miles of NP	-4.940^{+}	1.695	-5.384*	1.773	-4.029	1.725
	(2.550)	(1.838)	(2.566)	(1.898)	(2.492)	(1.882)
Increase in NP visits	4.557	7.665**	5.294^{+}	8.531**	4.971^{+}	6.671**
	(2.826)	(2.528)	(2.834)	(2.610)	(2.568)	(2.472)
Small metropolitan area	-2.256	1.213	-2.938	-0.359	1.712	-1.303
	(2.150)	(1.812)	(2.151)	(1.904)	(2.277)	(2.079)
Medium metropolitan area	-10.580***	3.527	-10.759***	3.307	-4.676	2.489
	(3.121)	(2.169)	(3.131)	(2.278)	(3.387)	(2.338)
Large metropolitan area	-11.427**	15.700***	-11.857**	14.223***	-6.817	13.642***
	(4.149)	(2.888)	(4.194)	(3.056)	(4.424)	(3.119)
Wildfire 10	-9.178	-12.726***	-6.049	-17.663***	-25.539	-12.900***
	(16.006)	(2.779)	(15.366)	(3.092)	(16.398)	(2.820)
Wildfire 20	-15.461	-8.960***	-13.825	-8.383**	-25.749*	-9.650***
	(14.810)	(2.709)	(15.058)	(2.861)	(13.045)	(2.713)
Days closed in 2020	-1.709***	-6.336***			-1.354*	-6.001***
	(0.509)	(0.350)			(0.568)	(0.361)
Capacity utilization in 2019	-0.073*	-0.208***	-0.098**	-0.296***	-0.096**	-0.207***
	(0.030)	(0.021)	(0.032)	(0.022)	(0.031)	(0.023)
Observations	29,619		29,619		29,619	
Fixed effects	Weekly		Weekly		Weekly	
Clustered SEs	Campground level		Campground level		Campground level	
R^2	0.239		0.175		0.270	
Adjusted R^2	0.237		0.173		0.264	
Residual Std. Error	44.482(df = 29564)		46.315(df = 29566)		43.708(df = 29347)	
F statistic	177.1***(df = 24; 29564)		120.3***(df = 52; 29566)		40.13***(df = 271; 29347)	

Note: $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001 two tailed;
The standard errors are clustered by campground and provided in parentheses.

3.4 Conclusion

In this research we demonstrate how COVID-19 infection rates, public health restrictions, and spillovers from proximity to NPs, metropolitan areas and wildfire, contributed to changes in USFS campground reservation demand in 2020, relative to 2019. A primary strength of the analysis is the use of national-level data on daily reservations at individual campgrounds. The results exemplify that increased local infection rates contributed to the increases in demand during 2020. As camping is a relatively socially distanced activity, it is sensible that camping was perceived as a preferable leisure activity when local infection rates were increasing. The findings also demonstrate that nearness to NPs and metropolitan areas resulted in increased demand, which can inform the USFS on where to expect large increases in visitation. The research also shows that proximity to NPs with increased recreational visits resulted in increased USFS campground reservations. The results are indicative of the fact that individuals that are recreating in a NP are likely to reserve USFS campgrounds nearby.

There are several policy implications based on the empirical results of the analysis. The first is that public health concerns and policies can drive rapid changes in recreation demand on public lands. In general, there is limited ability to quickly alter the infrastructure that supports public land recreation (e.g., campgrounds, trailheads, etc.). As a result, rapid changes in demand for recreational activities with particular attributes can create significant challenges for public land managers. Second, the results imply that USFS camping demand is impacted by changes in NP visitation. Thus, there is a potential benefit to coordination among agencies when facing national-level challenges. Third, the locational characteristics of particular campgrounds are critical for understanding the changes in demand that have occurred due to the pandemic. Campgrounds near urban areas and NPs have seen considerably larger increases in demand as a result of COVID-related factors. As recreation managers consider staffing decisions and investments in infrastructure, additional resources should be allocated to these campgrounds in close proximity to cities and NPs. Finally, it is likely that rapid increases in demand for campgrounds in 2020 caused many campgrounds to reach their capacity. This likely fueled an increase in dispersed camping, outside of established campgrounds, near these locations. Public land managers should consider the implications of these localized increases in dispersed camping on ecosystem health.

One weakness of the research is that we only observe campground reservations for overnight stays and thus we do not take into account walk up visitation to campgrounds. Given the increased uncertainty, whether walk up camping increased or decreased as a result of the pandemic remains an open empirical question. Additionally, the analysis only focuses on final reservations, as we only observe the record of the final disposition of the campground reservation. During times of increased demand, individuals may choose to reserve campgrounds ahead of time only to cancel them later on. Although, we see the mean days in advance reservations are made significantly decrease for the final reservations in 2020 (Table 3.1), it would be interesting to see whether that is due to a large number of cancellations made earlier.

Metropolitan areas generally faced greater COVID-related restrictions, which are the likely drivers for the increased reservations. However, we are unable to separate the heterogeneous impacts between population and specific restrictions, such as travel restrictions and business closures, on campground reservation demand. Additionally, we look at public health restrictions enacted largely at the state-level and do not investigate impacts of local policies, such as lockdowns. Recent research (Goodman-Bacon and Marcus, 2020) points out that local policies to control infections, such as lockdowns, are often packaged with many other restrictions taking place at the same time. This makes it difficult to isolate the causal impact of the policy. Therefore, we focus on the impact of state-level packaged restrictions with varying degrees of leniency in this paper. Public health restrictions in one state are likely to impact reservations at out of state campgrounds that are relatively close to state borders. The potential impact of inter-state spillovers stemming from public health restrictions are not explored in this paper, but would make a fruitful area for future research.

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Appendix A

A.1 Additional tables for chapter 1

Full table for annual groundwater use is provided below.

Table A.1: Regression results: Differences in groundwater use

Dependent Variable:	Annual groundwater use per well (ACFT)			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-2,420.6	-23,335.8**	-50,133.7***	-43,389.1***
	(8,541.3)	(10,627.8)	(15,660.3)	(14,857.0)
Treatment effect	22.63	33.07*	55.79***	47.95*
	(20.50)	(19.35)	(20.99)	(24.87)
Well longitude	-0.0016	0.0014	-0.0015	-0.0012
	(0.0021)	(0.0024)	(0.0033)	(0.0035)
Well latitude	0.0008	0.0049**	0.0114***	0.0098***
	(0.0020)	(0.0024)	(0.0035)	(0.0035)
Average max temperature	9.043	7.995	14.61	6.880
	(10.74)	(15.90)	(26.26)	(28.68)
Average precipitation	-0.9124***	-0.9249***	-0.9713**	-1.164**
	(0.2234)	(0.3395)	(0.4805)	(0.5440)
Percent sand	1.014	6.019***	7.230***	10.60***
	(1.486)	(1.909)	(2.273)	(2.377)
Percent silt	1.478	9.013***	11.46***	16.65***
	(2.345)	(3.042)	(3.727)	(3.820)
Distance to nearest river	0.1219	5.699	-4.782	-1.141
	(3.410)	(4.650)	(5.549)	(6.951)
Depth to water in 2000	-0.1027	0.3143	0.4658	0.2388
	(0.2724)	(0.3255)	(0.4379)	(0.4682)
Hydraulic conductivity (100 to 200)	-20.75	-20.58	10.80	-11.58
	(17.83)	(22.07)	(29.97)	(32.91)
Specific yield (15 to 25)	0.3960	13.38	-19.71	-1.590
	(18.05)	(23.61)	(31.28)	(34.73)
Saturated thickness in 1935	1.464**	-0.7103	-0.3577	-1.508
	(0.6374)	(0.8901)	(1.138)	(1.441)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,972	1,597	1,032	846
Dependent variable mean	220.97	216.37	226.85	222.40
R^2	0.34	0.41	0.48	0.48
Adjusted R^2	0.33	0.39	0.46	0.46
F-test (1st stage), Treatment effect	5,323.09	2,219.86	1,962.81	1,365.52

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for groundwater use as a proportion of groundwater appropriated with the full sample is provided below.

Table A.2: Regression results: Differences in proportion of groundwater used

Dependent Variable:	Proportion of appropriated groundwater used			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-15.27	-30.51	-83.15**	-86.73***
	(21.68)	(28.53)	(32.37)	(23.83)
Treatment effect	0.0665	0.0507	0.1010	0.0359
	(0.0698)	(0.0546)	(0.0639)	(0.0404)
Well longitude	1.01×10^{-6}	1.14×10^{-6}	-9.85×10^{-7}	-2.1×10^{-6}
	(5.66×10^{-6})	(7.5×10^{-6})	(9.94×10^{-6})	(8.48×10^{-6})
Well latitude	3.35×10^{-6}	6.7×10^{-6}	1.89×10^{-5}**	2.01×10^{-5}***
	(5.19×10^{-6})	(6.47×10^{-6})	(7.68×10^{-6})	(5.36×10^{-6})
Average max temperature	-0.0024	-0.0139	-0.0240	-0.0507
	(0.0488)	(0.0752)	(0.1294)	(0.1421)
Average precipitation	-0.0026***	-0.0027*	-0.0032	-0.0038
	(0.0009)	(0.0014)	(0.0023)	(0.0026)
Percent sand	0.0037	0.0107***	0.0112**	0.0152***
	(0.0025)	(0.0032)	(0.0050)	(0.0035)
Percent silt	0.0038	0.0133***	0.0161*	0.0239***
	(0.0038)	(0.0047)	(0.0083)	(0.0059)
Distance to nearest river	-0.0036	-0.0082	-0.0258	0.0004
	(0.0134)	(0.0184)	(0.0192)	(0.0111)
Depth to water in 2000	0.0003	0.0005	0.0008	0.0004
	(0.0008)	(0.0011)	(0.0016)	(0.0016)
Hydraulic conductivity (100 to 200)	0.0605*	0.0728*	0.1323**	0.1307**
	(0.0318)	(0.0401)	(0.0523)	(0.0525)
Specific yield (15 to 25)	0.0060	0.0105	-0.0284	-0.0112
	(0.0325)	(0.0430)	(0.0621)	(0.0495)
Saturated thickness in 1935	0.0022	0.0017	0.0044	-0.0014
	(0.0023)	(0.0026)	(0.0036)	(0.0024)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,972	1,597	1,032	846
Dependent variable mean	0.54	0.53	0.56	0.52
R^2	0.25	0.29	0.32	0.28
Adjusted R^2	0.23	0.27	0.29	0.24
F-test (1st stage), Treatment effect	5,323.09	2,219.86	1,962.81	1,365.52

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for saturated thickness with township fixed effects is provided below.

Table A.3: Regression results: Change in saturated thickness (2016 - 2000)

Dependent Variable:	diff2016_2000			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	640.1***	447.1	900.0**	761.4
	(216.3)	(396.9)	(438.5)	(558.2)
Treatment effect	-0.6198**	-0.5425	-0.3038	-0.0373
	(0.3057)	(0.4493)	(0.4071)	(0.6217)
Well longitude	0.0001**	0.0001	0.0003***	0.0004***
	(4.39×10^{-5})	(9.69×10^{-5})	(8.65×10^{-5})	(0.0001)
Well latitude	$-8.12 \times 10^{-5**}$	-3.87×10^{-5}	-8.38×10^{-5}	-4.11×10^{-5}
	(4×10^{-5})	(6.85×10^{-5})	(7.65×10^{-5})	(9.35×10^{-5})
Average maximum temperature (2000 to 2016)	-9.538***	-7.500	-13.23**	-12.87*
	(2.993)	(4.942)	(5.427)	(7.270)
Average precipitaiton (2000 to 2016)	-1.486**	-2.597	-6.251***	-8.134***
	(0.6292)	(1.645)	(1.197)	(1.863)
Percent sand	0.0161	-0.0095	0.0201	-0.0182
	(0.0121)	(0.0276)	(0.0294)	(0.0281)
Percent silt	0.0338*	-0.0056	0.0206	-0.0380
	(0.0185)	(0.0437)	(0.0478)	(0.0468)
Distance to nearest river	0.0166	-0.0824	0.0756	0.0769
	(0.0744)	(0.1123)	(0.0975)	(0.1417)
Depth to water in 2000	0.0011	0.0101	-0.0046	-0.0032
	(0.0043)	(0.0064)	(0.0079)	(0.0114)
Hydraulic conductivity (100 to 200)	-0.5370	-0.4751	-1.813***	-1.816***
	(0.4671)	(0.5670)	(0.6292)	(0.6290)
Specific yield (15 to 25)	-0.5922	-0.7162	-0.4572	-0.9048
	(0.3737)	(0.5163)	(0.6148)	(0.6760)
Saturated thickness in 1935	-0.0238**	-0.0101	-0.0194	-0.0148
	(0.0093)	(0.0142)	(0.0141)	(0.0225)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Fit statistics				
Observations	305	163	107	86
Dependent variable mean	-5.89	-5.61	-5.55	-5.34
R^2	0.81	0.79	0.85	0.83
Adjusted R^2	0.77	0.73	0.78	0.75
F-test (1st stage), Treatment effect	435.15	148.43	116.06	83.12

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for saturated thickness with county fixed effects is provided below.

Table A.4: Regression results: Change in saturated thickness (2016 - 2000)

Dependent Variable:	diff2016_2000			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	50.33	-143.3	149.2	208.8
	(120.3)	(139.2)	(184.5)	(189.6)
Treatment effect	-0.5774	-0.4728	-1.369**	-1.218*
	(0.4109)	(0.5345)	(0.5549)	(0.6550)
Well longitude	$-4.23 \times 10^{-5*}$	-3.32×10^{-5}	-4.92×10^{-5}	2.25×10^{-5}
	(2.36×10^{-5})	(3.66×10^{-5})	(4.04×10^{-5})	(4.89×10^{-5})
Well latitude	1.87×10^{-5}	$4.44 \times 10^{-5**}$	3.94×10^{-6}	3.36×10^{-6}
	(1.57×10^{-5})	(1.81×10^{-5})	(2.36×10^{-5})	(2.3×10^{-5})
Average maximum temperature (2000 to 2016)	-4.813***	-2.318	-5.611**	-7.050**
	(1.722)	(2.215)	(2.772)	(3.393)
Average precipitaiton (2000 to 2016)	0.4857	0.5867	0.4419	-0.6638
	(0.4409)	(0.6961)	(0.8401)	(0.9646)
Percent sand	0.0353**	0.0098	0.0031	-0.0040
	(0.0177)	(0.0319)	(0.0286)	(0.0391)
Percent silt	0.0376	-0.0045	-0.0046	-0.0310
	(0.0261)	(0.0483)	(0.0445)	(0.0602)
Distance to nearest river	-0.0387*	-0.0823***	-0.0583	-0.0361
	(0.0198)	(0.0298)	(0.0407)	(0.0434)
Depth to water in 2000	0.0022	0.0066	0.0019	0.0029
	(0.0039)	(0.0057)	(0.0067)	(0.0074)
Hydraulic conductivity (100 to 200)	-0.5676	-0.4535	-0.9801	-0.9368
	(0.4910)	(0.5344)	(0.6243)	(0.6142)
Specific yield (15 to 25)	0.2646	0.1832	0.4453	0.4459
	(0.2739)	(0.4190)	(0.4822)	(0.5464)
Saturated thickness in 1935	-0.0065	-0.0091	0.0016	0.0074
	(0.0084)	(0.0101)	(0.0121)	(0.0135)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Fit statistics				
Observations	305	163	107	86
Dependent variable mean	-5.89	-5.61	-5.55	-5.34
R^2	0.57	0.61	0.59	0.63
Adjusted R^2	0.54	0.56	0.52	0.55
F-test (1st stage), Treatment effect	490.74	184.82	151.38	119.65

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for groundwater use per adjusted acre is provided below.

Table A.5: Regression results: Differences in groundwater use per acre

Dependent Variable:	Water use per adjusted acre (ACFT/Acre)			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	25.12	28.84	-17.57	46.52
	(33.85)	(51.82)	(65.62)	(65.68)
Treatment effect	0.0240	0.0822	0.0289	0.0206
	(0.0813)	(0.0920)	(0.1097)	(0.1169)
Well longitude	6.11×10^{-6}	-1.99×10^{-7}	1.85×10^{-5}	2.05×10^{-5}
	(9.4×10^{-6})	(1.17×10^{-5})	(1.83×10^{-5})	(1.72×10^{-5})
Well latitude	-6.52×10^{-6}	-7.1×10^{-6}	2.3×10^{-7}	-1.49×10^{-5}
	(7.9×10^{-6})	(1.17×10^{-5})	(1.54×10^{-5})	(1.54×10^{-5})
Average max temperature	0.0342	0.1214*	0.0609	0.0708
	(0.0474)	(0.0689)	(0.0790)	(0.0870)
Average precipitation	-0.0048***	-0.0022	-0.0051**	-0.0048*
	(0.0013)	(0.0020)	(0.0021)	(0.0025)
Percent sand	0.0027	0.0082	0.0246***	0.0351***
	(0.0042)	(0.0068)	(0.0074)	(0.0087)
Percent silt	3.65×10^{-5}	0.0140	0.0414***	0.0633***
	(0.0067)	(0.0112)	(0.0134)	(0.0151)
Distance to nearest river	0.0014	-0.0122	0.0186	0.0077
	(0.0147)	(0.0206)	(0.0255)	(0.0249)
Depth to water in 2000	-0.0008	0.0004	0.0052**	0.0053***
	(0.0010)	(0.0014)	(0.0020)	(0.0019)
Hydraulic conductivity (100 to 200)	0.0919	0.1607*	0.3268**	0.3237**
	(0.0620)	(0.0873)	(0.1303)	(0.1285)
Specific yield (15 to 25)	-0.0402	-0.1767	-0.0948	-0.2601*
	(0.0847)	(0.1097)	(0.1366)	(0.1462)
Saturated thickness in 1935	0.0042	0.0060	0.0075	0.0104*
	(0.0027)	(0.0037)	(0.0053)	(0.0056)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,780	953	616	502
Dependent variable mean	1.27	1.25	1.27	1.27
R^2	0.34	0.36	0.40	0.46
Adjusted R^2	0.33	0.34	0.36	0.42
F-test (1st stage), Treatment effect	3,049.18	1,246.12	1,045.85	752.03

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for adjusted acres irrigated is provided below.

Table A.6: Regression results: Differences in associated acres irrigated

Dependent Variable:	Adjusted acres irrigated			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-8,588.7	-26,168.3**	-41,832.7***	-47,598.1***
	(7,552.2)	(11,363.5)	(14,399.6)	(14,494.9)
Treatment effect	8.356	8.480	33.52	29.99
	(19.28)	(20.71)	(22.18)	(23.77)
Well longitude	8.58×10^{-5}	0.0038*	-0.0023	-0.0012
	(0.0018)	(0.0022)	(0.0033)	(0.0031)
Well latitude	0.0019	0.0053**	0.0097***	0.0109***
	(0.0018)	(0.0026)	(0.0034)	(0.0034)
Average max temperature	4.551	-8.002	18.31**	7.006
	(6.417)	(7.612)	(8.363)	(8.112)
Average precipitation	0.1507	-0.2148	0.3697	0.0980
	(0.1558)	(0.2171)	(0.2475)	(0.2915)
Percent sand	0.0540	2.362**	1.772	2.342
	(0.6959)	(0.9892)	(1.172)	(1.651)
Percent silt	0.8353	3.348**	2.823	2.918
	(1.114)	(1.581)	(2.150)	(2.814)
Distance to nearest river	0.9033	5.634	-6.680	-3.093
	(2.854)	(4.296)	(5.807)	(6.363)
Depth to water in 2000	0.2070	0.4318	-0.0996	-0.2291
	(0.2252)	(0.2655)	(0.3488)	(0.3484)
Hydraulic conductivity (100 to 200)	-30.49*	-40.15**	-38.44	-51.78*
	(16.03)	(17.89)	(28.44)	(27.34)
Specific yield (15 to 25)	-0.3945	36.60**	-6.203	32.38
	(12.48)	(16.22)	(22.25)	(22.49)
Saturated thickness in 1935	0.0544	-1.938**	-1.710	-2.979**
	(0.4891)	(0.7504)	(1.052)	(1.141)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,780	953	616	502
Dependent variable mean	173.85	173.43	178.49	176.29
R^2	0.20	0.31	0.37	0.45
Adjusted R^2	0.18	0.28	0.33	0.41
F-test (1st stage), Treatment effect	3,049.18	1,246.12	1,045.85	752.03

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for irrigated acres in water-intensive crops is provided below.

Table A.7: Regression results: Differences in land use

Dependent Variable:	Water-intensive crops as a proportion of irrigated land			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	5.639	-19.81	18.87	-25.59
	(22.84)	(38.84)	(51.95)	(67.53)
Treatment effect	0.0051	0.0190	0.0519	-0.0179
	(0.0399)	(0.0498)	(0.0561)	(0.0723)
Parcel centroid longitude	-3.29×10^{-6}	4.01×10^{-6}	7.92×10^{-6}	1.22×10^{-5}
	(5.38×10^{-6})	(8.21×10^{-6})	(1.05×10^{-5})	(1.26×10^{-5})
Parcel centroid latitude	-3.87×10^{-6}	-1.47×10^{-6}	-5.61×10^{-6}	-3.68×10^{-7}
	(4.32×10^{-6})	(7.08×10^{-6})	(9.81×10^{-6})	(1.21×10^{-5})
Average max temperature	0.4380*	0.7967*	-0.0340	0.5446
	(0.2592)	(0.4321)	(0.5721)	(0.7901)
Average precipitation	0.0243	0.0157	0.0190	0.0333
	(0.0275)	(0.0421)	(0.0473)	(0.0584)
Percent sand	0.0014	-0.0008	0.0033	0.0098
	(0.0019)	(0.0035)	(0.0039)	(0.0066)
Percent silt	0.0002	-0.0031	0.0050	0.0162
	(0.0030)	(0.0056)	(0.0071)	(0.0111)
Distance to nearest river	-0.0019	0.0070	0.0011	0.0163
	(0.0066)	(0.0117)	(0.0136)	(0.0167)
Depth to water in 2000	0.0003	0.0017*	0.0017	0.0021
	(0.0006)	(0.0010)	(0.0013)	(0.0014)
Hydraulic conductivity (100 to 200)	-0.0097	0.0527	0.1244*	0.1254*
	(0.0443)	(0.0528)	(0.0699)	(0.0759)
Specific yield (15 to 25)	-0.0149	0.0142	-0.0491	0.0598
	(0.0308)	(0.0472)	(0.0696)	(0.0934)
Saturated thickness in 1935	0.0050***	0.0023	0.0074***	0.0044
	(0.0013)	(0.0020)	(0.0025)	(0.0029)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,711	1,976	1,302	1,025
Dependent variable mean	0.71	0.70	0.71	0.71
R^2	0.11	0.14	0.11	0.13
Adjusted R^2	0.10	0.13	0.09	0.10
F-test (1st stage), Treatment effect	5,845.94	2,774.74	1,644.38	1,224.29

Clustered (MASTER_ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table containing lease-year regressions is provided below.

Table A.8: Regression results: Differences in groundwater use by lease year

Dependent Variable:	Annual groundwater use per well (ACFT)
Model:	(1)
Variables	
Constant	7,333.4
	(9,544.0)
Lease year = 1	15.13
	(14.61)
Lease year = 2	69.25**
	(28.69)
Lease year = 3	75.82*
	(37.56)
Lease year = 4	134.0***
	(47.95)
Lease year = 5	151.4**
	(58.68)
Lease year = 6	199.0**
	(71.92)
Lease year = 7	212.2**
	(81.08)
Lease year = 8	232.3**
	(84.75)
Well longitude	6.76×10^{-5}
	(0.0041)
Well latitude	-0.0014
	(0.0016)
Average max temperature	-19.33
	(25.87)
Average precipitation	-0.7167
	(0.7484)
Percent sand	5.573**
	(2.677)
Percent silt	5.979
	(4.315)
Distance to nearest river	12.43**
	(5.582)
Depth to water in 2000	-1.662
	(1.489)
Hydraulic conductivity (100 to 200)	-58.81
	(185.2)
Specific yield (15 to 25)	-179.2**
	(71.76)
Saturated thickness in 1935	-3.176
	(2.003)
Fixed-effects	
County	Yes
Year	Yes
Fit statistics	
Observations	141
Dependent variable mean	234.28
R^2	0.51
Adjusted R^2	0.37

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Full table for spillover specifications is provided below.

Table A.9: Regression results: Differences in groundwater use by spillover definition

Dependent Variable:	Annual groundwater use per well (ACFT)			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-7,465.3	-4,034.3	-26,957.1**	-37,072.5***
	(7,246.4)	(8,469.2)	(10,737.7)	(12,918.7)
Treatment effect	15.30	20.92	33.51*	49.56*
	(19.15)	(20.07)	(19.35)	(25.14)
Well longitude	-0.0003	-0.0008	0.0022	0.0047
	(0.0017)	(0.0021)	(0.0023)	(0.0032)
Well latitude	0.0016	0.0010	0.0056**	0.0077***
	(0.0016)	(0.0019)	(0.0025)	(0.0028)
Average max temperature	16.53**	9.703	8.996	-14.64
	(7.855)	(10.69)	(15.77)	(27.71)
Average precipitation	-0.6750***	-0.8958***	-0.8946***	-1.375**
	(0.1713)	(0.2209)	(0.3345)	(0.6110)
Percent sand	1.038	1.370	5.173***	2.984*
	(1.017)	(1.346)	(1.503)	(1.757)
Percent silt	1.652	1.933	7.614***	4.662*
	(1.611)	(2.142)	(2.378)	(2.706)
Distance to nearest river	1.103	1.015	6.761	2.242
	(2.627)	(3.386)	(4.638)	(5.744)
Depth to water in 2000	0.0018	-0.0128	0.4074	0.2400
	(0.2284)	(0.2721)	(0.3269)	(0.4236)
Hydraulic conductivity (100 to 200)	-8.360	-24.64	-20.38	-28.34
	(14.07)	(18.10)	(21.90)	(29.53)
Specific yield (15 to 25)	6.230	1.462	13.29	62.58*
	(12.75)	(17.97)	(24.28)	(36.30)
Saturated thickness in 1935	1.192**	1.530**	-0.6591	-0.6650
	(0.5184)	(0.6413)	(0.8955)	(1.287)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,004	3,021	1,630	654
Dependent variable mean	224.89	221.15	217.58	207.16
R^2	0.31	0.34	0.41	0.54
Adjusted R^2	0.30	0.33	0.39	0.51
F-test (1st stage), Treatment effect	8,494.25	5,550.83	2,338.10	1,086.48

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2 Additional first stage models for chapter 1

The first stage models for all the IV models are provided below.

Table A.10: First stage for groundwater use models and proportion of use models

Dependent Variable:	Treatment effect			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	20.53	29.80	72.87	68.38
	(18.32)	(33.97)	(47.48)	(51.53)
Inside historical boundary	0.8311***	0.7965***	0.7978***	0.7671***
	(0.0592)	(0.0747)	(0.0823)	(0.0974)
Well longitude	8.9×10^{-6}*	1.02×10^{-5}	4.33×10^{-6}	8.77×10^{-6}
	(5.17×10^{-6})	(9.61×10^{-6})	(8.53×10^{-6})	(1.09×10^{-5})
Well latitude	-5.96×10^{-6}	-8.23×10^{-6}	-1.69×10^{-5}	-1.67×10^{-5}
	(4.42×10^{-6})	(7.77×10^{-6})	(1.11×10^{-5})	(1.24×10^{-5})
Average max temperature	-0.0209**	-0.0378**	-0.0386**	-0.0454***
	(0.0099)	(0.0162)	(0.0163)	(0.0164)
Average precipitation	-0.0002	-0.0003	-0.0005**	-0.0003
	(0.0001)	(0.0003)	(0.0003)	(0.0002)
Percent sand	-0.0003	0.0012	-0.0029	0.0031
	(0.0015)	(0.0038)	(0.0053)	(0.0064)
Percent silt	0.0010	0.0034	-0.0015	0.0072
	(0.0019)	(0.0057)	(0.0088)	(0.0104)
Distance to nearest river	0.0187**	0.0239*	0.0320*	0.0502**
	(0.0079)	(0.0139)	(0.0180)	(0.0231)
Depth to water in 2000	0.0007	0.0002	-0.0005	-0.0008
	(0.0005)	(0.0010)	(0.0013)	(0.0014)
Hydraulic conductivity (100 to 200)	-0.0047	-0.0092	-0.0717	-0.1073
	(0.0589)	(0.0836)	(0.1215)	(0.1287)
Specific yield (15 to 25)	0.0617*	0.1289***	0.1674**	0.2729***
	(0.0333)	(0.0493)	(0.0645)	(0.0889)
Saturated thickness in 1935	-3.96×10^{-5}	0.0023	0.0046	0.0015
	(0.0025)	(0.0040)	(0.0036)	(0.0046)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,972	1,597	1,032	846
Dependent variable mean	0.13	0.21	0.27	0.27
R^2	0.74	0.73	0.81	0.80
Adjusted R^2	0.73	0.72	0.80	0.79
F-test (1st stage)	5,323.09	2,219.86	1,962.81	1,365.52

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.11: First stage of Change in saturated thickness (2016 - 2000)

Dependent Variable:	Treatment effect			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	58.48**	96.83**	177.6**	222.8***
	(26.56)	(43.79)	(83.86)	(76.11)
Inside historical boundary	0.8257***	0.7344***	0.7552***	0.6942***
	(0.0642)	(0.0860)	(0.1004)	(0.1207)
Well longitude	1.23×10^{-5}	-1.06×10^{-5}	-7.36×10^{-7}	-2.17×10^{-6}
	(8.61×10^{-6})	(1.74×10^{-5})	(1.78×10^{-5})	(1.98×10^{-5})
Well latitude	$-1.05 \times 10^{-5**}$	$-1.79 \times 10^{-5**}$	$-3.06 \times 10^{-5**}$	$-3.61 \times 10^{-5***}$
	(5.07×10^{-6})	(8.42×10^{-6})	(1.39×10^{-5})	(1.31×10^{-5})
Average maximum temperature (2000 to 2016)	-0.7062*	-1.360**	-1.875*	-3.128***
	(0.3702)	(0.5640)	(1.098)	(1.034)
Average precipitaiton (2000 to 2016)	-0.0029	0.5023**	0.2235	0.5044
	(0.1054)	(0.2540)	(0.3400)	(0.3925)
Percent sand	-0.0007	0.0003	-0.0057	-0.0029
	(0.0016)	(0.0040)	(0.0060)	(0.0063)
Percent silt	0.0010	0.0024	-0.0054	-0.0029
	(0.0021)	(0.0060)	(0.0100)	(0.0102)
Distance to nearest river	0.0182**	0.0294**	0.0327*	0.0552**
	(0.0082)	(0.0148)	(0.0189)	(0.0227)
Depth to water in 2000	0.0002	-0.0017	-0.0022	-0.0037**
	(0.0005)	(0.0012)	(0.0016)	(0.0015)
Hydraulic conductivity (100 to 200)	-0.0169	0.0010	-0.0477	-0.0678
	(0.0602)	(0.0828)	(0.1120)	(0.1054)
Specific yield (15 to 25)	0.0428	0.1514***	0.0738	0.2150**
	(0.0353)	(0.0563)	(0.0852)	(0.1021)
Saturated thickness in 1935	-0.0004	-0.0008	0.0044	-0.0002
	(0.0027)	(0.0046)	(0.0044)	(0.0053)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Fit statistics				
Observations	305	163	107	86
Dependent variable mean	0.12	0.21	0.27	0.27
R^2	0.73	0.75	0.81	0.84
Adjusted R^2	0.68	0.67	0.73	0.76
F-test (1st stage)	435.15	148.43	116.06	83.12

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.12: First stage of Change in saturated thickness (2016 - 2000)

Dependent Variable:	Treatment effect			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-4.748	10.82	-4.240	10.00
	(10.90)	(16.70)	(24.95)	(25.55)
Inside historical boundary	0.8259***	0.7780***	0.7694***	0.7704***
	(0.0598)	(0.0738)	(0.0778)	(0.0850)
Well longitude	-5.99×10^{-7}	-1.75×10^{-6}	-5.96×10^{-6}	-4.04×10^{-6}
	(2.61×10^{-6})	(5.93×10^{-6})	(5.3×10^{-6})	(9.32×10^{-6})
Well latitude	9.2×10^{-7}	-5.96×10^{-8}	2.36×10^{-6}	2.57×10^{-6}
	(1.35×10^{-6})	(2.09×10^{-6})	(3.2×10^{-6})	(3.09×10^{-6})
Average maximum temperature (2000 to 2016)	-0.0579	-0.5059	-0.3060	-0.8473*
	(0.1694)	(0.3085)	(0.4077)	(0.4968)
Average precipitaiton (2000 to 2016)	0.0488	0.0911	0.1229	0.1098
	(0.0379)	(0.0907)	(0.0892)	(0.1374)
Percent sand	0.0002	0.0009	0.0002	0.0016
	(0.0017)	(0.0043)	(0.0047)	(0.0067)
Percent silt	0.0006	0.0019	0.0031	0.0046
	(0.0023)	(0.0065)	(0.0073)	(0.0103)
Distance to nearest river	-0.0062**	-0.0073	-0.0050	-0.0019
	(0.0031)	(0.0054)	(0.0077)	(0.0085)
Depth to water in 2000	-0.0008*	-0.0021**	-0.0024**	-0.0034**
	(0.0004)	(0.0009)	(0.0011)	(0.0013)
Hydraulic conductivity (100 to 200)	0.0353	0.0465	-0.0161	-0.0871
	(0.0518)	(0.0754)	(0.1036)	(0.1201)
Specific yield (15 to 25)	0.0495**	0.1353**	0.1209	0.1626*
	(0.0212)	(0.0519)	(0.0776)	(0.0841)
Saturated thickness in 1935	1.68×10^{-5}	0.0002	-0.0014	-0.0027
	(0.0007)	(0.0016)	(0.0016)	(0.0022)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Fit statistics				
Observations	305	163	107	86
Dependent variable mean	0.12	0.21	0.27	0.27
R^2	0.67	0.65	0.72	0.74
Adjusted R^2	0.65	0.61	0.67	0.68
F-test (1st stage)	490.74	184.82	151.38	119.65

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.13: First stage for intensive and extensive margin models

Dependent Variable:	Treatment effect			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	23.74	33.56	86.07*	73.09
	(19.75)	(35.85)	(50.90)	(53.58)
Inside historical boundary	0.8279***	0.7885***	0.7888***	0.7603***
	(0.0602)	(0.0775)	(0.0877)	(0.1051)
Well longitude	8.68×10^{-6}*	9.75×10^{-6}	2.65×10^{-6}	8.48×10^{-6}
	(5.24×10^{-6})	(9.95×10^{-6})	(9.03×10^{-6})	(1.16×10^{-5})
Well latitude	-6.6×10^{-6}	-8.84×10^{-6}	-1.95×10^{-5}	-1.76×10^{-5}
	(4.74×10^{-6})	(8.2×10^{-6})	(1.19×10^{-5})	(1.29×10^{-5})
Average max temperature	-0.0285**	-0.0599**	-0.0586**	-0.0730***
	(0.0134)	(0.0254)	(0.0243)	(0.0243)
Average precipitation	-0.0005*	-0.0011*	-0.0013**	-0.0014***
	(0.0003)	(0.0006)	(0.0005)	(0.0005)
Percent sand	-0.0004	0.0009	-0.0036	0.0047
	(0.0016)	(0.0044)	(0.0062)	(0.0083)
Percent silt	0.0011	0.0034	-0.0021	0.0101
	(0.0020)	(0.0064)	(0.0103)	(0.0133)
Distance to nearest river	0.0192**	0.0250*	0.0333*	0.0517**
	(0.0080)	(0.0142)	(0.0189)	(0.0236)
Depth to water in 2000	0.0007	0.0002	-0.0006	-0.0007
	(0.0005)	(0.0010)	(0.0014)	(0.0015)
Hydraulic conductivity (100 to 200)	-0.0049	-0.0077	-0.0735	-0.1065
	(0.0592)	(0.0842)	(0.1233)	(0.1315)
Specific yield (15 to 25)	0.0650*	0.1333**	0.1837***	0.2745***
	(0.0346)	(0.0512)	(0.0684)	(0.0911)
Saturated thickness in 1935	7.46×10^{-6}	0.0023	0.0047	0.0018
	(0.0026)	(0.0041)	(0.0037)	(0.0047)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,762	935	598	484
Dependent variable mean	0.12	0.22	0.28	0.28
R^2	0.73	0.73	0.80	0.80
Adjusted R^2	0.72	0.71	0.79	0.78
F-test (1st stage)	3,023.49	1,218.55	1,022.72	706.31

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.14: Regression results: Differences in land use

Dependent Variable:	Treatment effect			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	48.24^{***}	100.0^{***}	190.6^{***}	291.9^{***}
	(15.56)	(33.76)	(54.26)	(65.20)
Inside historical boundary	0.7150^{***}	0.7283^{***}	0.6495^{***}	0.6343^{***}
	(0.0476)	(0.0564)	(0.0582)	(0.0683)
Parcel centroid longitude	4.54×10^{-6}	4.63×10^{-6}	-3.96×10^{-7}	1.98×10^{-5}
	(3.95×10^{-6})	(7.79×10^{-6})	(1.04×10^{-5})	(1.23×10^{-5})
Parcel centroid latitude	$-9.35 \times 10^{-6***}$	$-1.6 \times 10^{-5***}$	$-3.76 \times 10^{-5***}$	$-5.15 \times 10^{-5***}$
	(2.96×10^{-6})	(5.81×10^{-6})	(9.36×10^{-6})	(1.11×10^{-5})
Average max temperature	-0.4115	-1.207^{**}	-0.8793	-2.661^{***}
	(0.2507)	(0.4795)	(0.6741)	(0.8207)
Average precipitation	0.0309	0.0419	0.0393	-0.0204
	(0.0243)	(0.0413)	(0.0515)	(0.0629)
Percent sand	0.0001	0.0007	-0.0039	0.0043
	(0.0012)	(0.0030)	(0.0047)	(0.0047)
Percent silt	0.0018	0.0036	-0.0024	0.0095
	(0.0014)	(0.0042)	(0.0075)	(0.0078)
Distance to nearest river	0.0101^{**}	0.0157^{*}	0.0194	0.0551^{***}
	(0.0049)	(0.0095)	(0.0146)	(0.0164)
Depth to water in 2000	-0.0003	-0.0017^{**}	-0.0014	-0.0023^{**}
	(0.0004)	(0.0008)	(0.0011)	(0.0011)
Hydraulic conductivity (100 to 200)	-0.0289	-0.0516	-0.1080	-0.1703^{**}
	(0.0401)	(0.0556)	(0.0786)	(0.0716)
Specific yield (15 to 25)	0.0663^{**}	0.0972^{**}	0.1977^{***}	0.2711^{***}
	(0.0274)	(0.0397)	(0.0696)	(0.0850)
Saturated thickness in 1935	6.78×10^{-5}	-0.0005	-4.57×10^{-6}	-0.0015
	(0.0022)	(0.0035)	(0.0036)	(0.0036)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,711	1,976	1,302	1,025
Dependent variable mean	0.10	0.18	0.22	0.24
R^2	0.69	0.75	0.76	0.79
Adjusted R^2	0.69	0.74	0.75	0.79
F-test (1st stage)	5,845.94	2,774.74	1,644.38	1,224.29

Clustered (MASTER_ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.15: First stage: Differences in groundwater use by spillover definition

Dependent Variable:	Treatment effect			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	8.525	20.17	30.07	-73.27
	(10.97)	(17.99)	(32.85)	(44.04)
Inside historical boundary	0.8189***	0.8347***	0.8005***	0.9751***
	(0.0558)	(0.0578)	(0.0727)	(0.1356)
Well longitude	4.11×10^{-6}	8.96×10^{-6}*	9.95×10^{-6}	1.69×10^{-5}
	(2.96×10^{-6})	(5.1×10^{-6})	(9.16×10^{-6})	(1.25×10^{-5})
Well latitude	-2.47×10^{-6}	-5.9×10^{-6}	-8.24×10^{-6}	1.35×10^{-5}
	(2.65×10^{-6})	(4.35×10^{-6})	(7.51×10^{-6})	(1.04×10^{-5})
Average max temperature	-0.0173**	-0.0209**	-0.0377**	-0.0259**
	(0.0072)	(0.0099)	(0.0163)	(0.0121)
Average precipitation	-0.0002**	-0.0002	-0.0004	-0.0002
	(9.99×10^{-5})	(0.0001)	(0.0003)	(0.0002)
Percent sand	-5.94×10^{-5}	-0.0001	0.0006	0.0053
	(0.0009)	(0.0012)	(0.0023)	(0.0039)
Percent silt	0.0008	0.0011	0.0024	0.0100
	(0.0012)	(0.0016)	(0.0035)	(0.0067)
Distance to nearest river	0.0121**	0.0182**	0.0227*	0.0469**
	(0.0051)	(0.0078)	(0.0136)	(0.0192)
Depth to water in 2000	0.0003	0.0007	0.0002	0.0029*
	(0.0004)	(0.0005)	(0.0009)	(0.0015)
Hydraulic conductivity (100 to 200)	-0.0216	-0.0041	-0.0067	0.0709
	(0.0314)	(0.0578)	(0.0800)	(0.1074)
Specific yield (15 to 25)	0.0162	0.0616*	0.1276***	-0.0064
	(0.0161)	(0.0332)	(0.0489)	(0.0551)
Saturated thickness in 1935	-0.0009	7.33×10^{-6}	0.0025	0.0069
	(0.0014)	(0.0025)	(0.0040)	(0.0044)
Fixed-effects				
Township	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,004	3,021	1,630	654
Dependent variable mean	0.08	0.13	0.21	0.28
R^2	0.70	0.74	0.73	0.83
Adjusted R^2	0.69	0.74	0.73	0.82
F-test (1st stage)	8,494.25	5,550.83	2,338.10	1,086.48

Clustered (WDID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.3 Placebo testing for chapter 1

We present a placebo analysis to examine if our results are just picking up any systematic differences across sections, that may not be driven by SLB designation. In this analysis, we randomly pick two sections, other than 16 and 36, as placebo sections without replacement. We remove all SLB wells from the sample and apply all same restrictions as in the main analysis. The bandwidth is based on distance to the nearest border of the placebo sections, and the well-exclusion is based on the proximity of control wells to the placebo wells. We then estimate coefficients for the 4 specifications described in the main analysis, with the placebo wells being treated as treatment wells. In this setting, there is no imperfect compliance, so we estimate model parameters using Ordinary Least Squares (OLS). We then repeat this process 4 more times, such that we have a total of 5 estimates from 5 random draws of the two sections for each specification. The estimated placebo treatment for each specification is given in the figures provided below. The estimates provided in the figures provide limited evidence of statistically significant differences in groundwater use between the placebo wells and control group wells. This suggests that the estimates of the difference in groundwater use between SLB and non-SLB wells, in the main analysis, is not likely to be driven by systematic differences across sections in the study area.

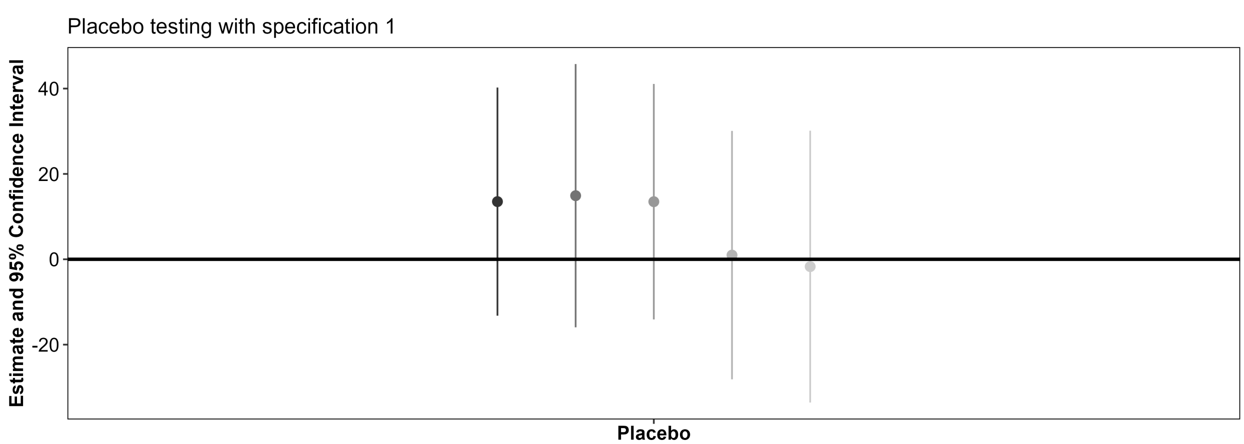

Figure A.1: Placebo testing with bandwidth of 2 miles and well-exclusion of 1 mile

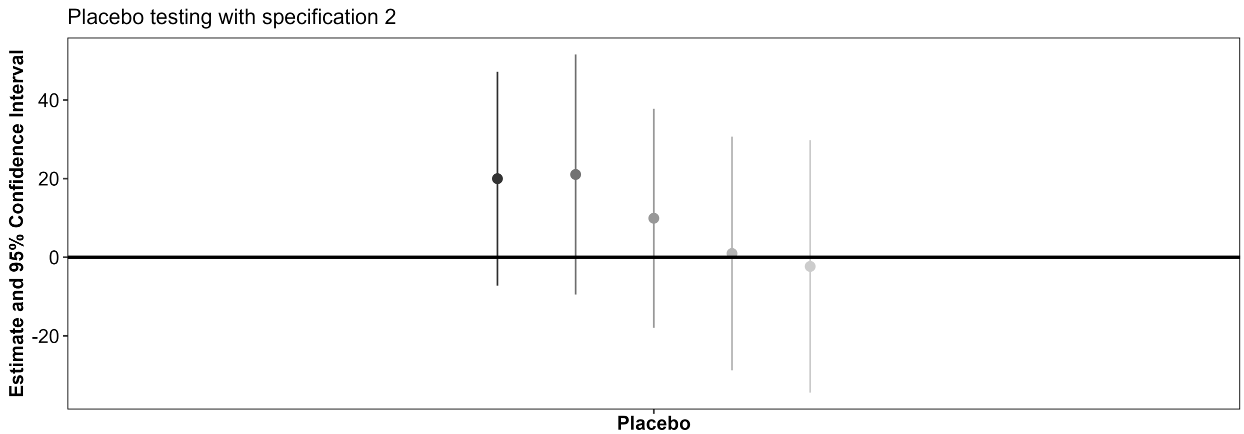

Figure A.2: Placebo testing with bandwidth of 2 miles and well-exclusion of 1.5 miles

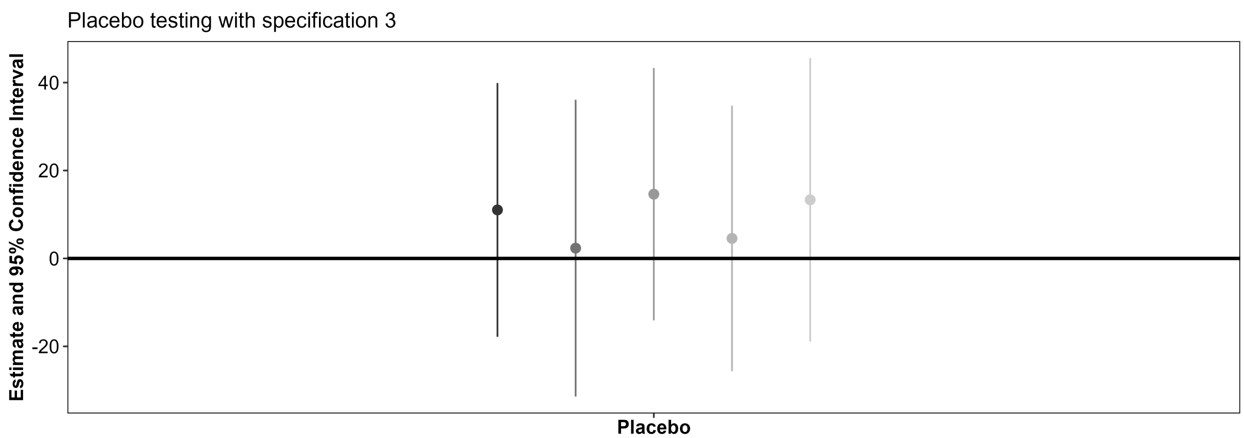

Figure A.3: Placebo testing with bandwidth of 1 mile and well-exclusion of 1 mile

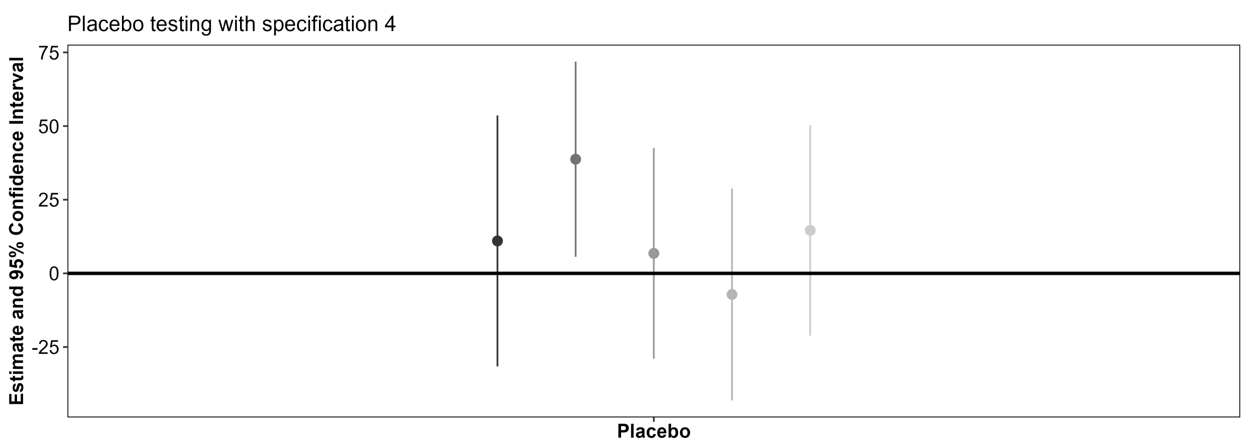

Figure A.4: Placebo testing with bandwidth of 1 mile and well-exclusion of 1.5 miles

A.4 CTB method of discount rate elicitation for chapter 2

In this study, the utility curvature parameter is estimated from the intertemporal CTB task. The assumed utility function that is used to derive estimates of alpha and the discount rate is expressed as:

$$U(c_t, c_{t+k}) = \frac{(c_t - w_1)^\alpha}{\alpha} + \frac{\beta\delta^k(c_{t+k} - w_2)}{\alpha} \tag{A.1}$$

where c_t and c_{t+k} represent the two experimental rewards with a delay of k periods, δ is the discount factor, β is the present bias factor, and α is the utility function curvature parameter (alpha). w_1 and w_2 are variables representing consumption when income is 0. They can be interpreted as minimum consumption requirements, that are commonly included in Stone-Geary utility functions (Andreoni and Sprenger, 2012a).

The functional form represents a CRRA utility function, with an absolute risk aversion of $\frac{1-\alpha}{W}$ and a relative risk aversion parameter of $1-\alpha$, where W is wealth, which is $c_t - w_1$ in period t and $c_{t+k} - w_2$ in period $t+k$. We see that an alpha of 1 corresponds to risk-neutrality, an alpha less than 1 corresponds to risk-aversion and an alpha greater than 1 corresponds to being risk-loving. All the payment choices were provided with a front end delay of at least 25 weeks, with the average delay being 103 weeks. Therefore, the present bias parameter is assumed to be 1, since it reflects absence of present bias due to experimental design. This reduces the above equation to:

$$U(c_t, c_{t+k}) = \frac{(c_t - w_1)^\alpha}{\alpha} + \frac{\beta\delta^k(c_{t+k} - w_2)^\alpha}{\alpha} \tag{A.2}$$

We can then maximize utility subject to the budget constraint:

$$(1+r)c_t + c_{t+k} = m \tag{A.3}$$

Solving the optimization problem, we can derive the tangency condition as:

$$\frac{c_t - w_1}{c_{t+k} - w_2} = (\delta^k(1+r))^{\frac{1}{\alpha-1}} \tag{A.4}$$

The tangency condition is further simplified by assuming background consumption of the income derived from the experiment to be 0 for both periods, such that:

$$\frac{c_t}{c_{t+k}} = (\delta^k(1+r))^{\frac{1}{\alpha-1}} \tag{A.5}$$

The equation above can further be simplified by plugging in the budget constraint, such that we get the expression:

$$c_t = \frac{(\delta^k(1+r))^{\frac{1}{\alpha-1}}}{(1+(\delta^k(1+r))^{\frac{1}{\alpha-1}})} m \tag{A.6}$$

The parameters α and δ can be estimated from the above equation using non-linear least squares, assuming r, k and m are exogenous. We can also estimate the parameters using OLS if we log linearize equation A.5. The equation then can be expressed as:

$$ln\left(\frac{c_t}{c_{t+k}}\right) = \left(\frac{ln(\delta)}{\alpha-1}\right) k + \left(\frac{1}{\alpha-1}\right) ln(1+r) \tag{A.7}$$

Assuming additive error structure the above equation can be written as:

$$lnY = \gamma_1 k + \gamma_2 ln(1+r) + Constant + \epsilon \tag{A.8}$$

where $Y = \dfrac{c_t}{c_{t+k}}$, $\gamma_1 = \dfrac{ln(\delta)}{\alpha-1}$ and $\gamma_2 = \dfrac{1}{\alpha-1}$. Once we have γ_1 and γ_2, we can calculate α, which is the utility curvature parameter, and δ, which is the discount factor. The annualized discount rate is then derived using the discount factor.

A.5 Estimates of g for assumed values of K for chapter 2

The table below provides estimates of g for the assumed values of K. The results reveal that the point estimate decreases for higher values of K. The estimates from the first specification, where $K = 80$, was used to calculate the time path of benefits from cover cropping.

Table A.16: Estimating the growth rate

	Dependent variable:		
	ΔB_t		
	(1)	(2)	(3)
Estimates of g	0.671**	0.577**	0.517**
	(0.137)	(0.138)	(0.136)
Observations	4	4	4
R^2	0.888	0.853	0.828
Adjusted R^2	0.851	0.804	0.770
K	80	90	100
$K - DC - IC$	8	18	28
Note:	*p<0.1; **p<0.05; ***p<0.01		

A.6 Additional conceptual model for chapter 3

In this section, we use a utility maximization framework to illustrate how the demand for one good (good B) changes in response to changes in the relative risk associated with another good (good A). Assume that goods A and B that are net substitutes. Good A requires individuals to participate in activities that might be associated with increased COVID infection risk, for example dining at a restaurant. If an individual is infected, they potentially incur health costs, hospital costs, and other costs due to physical and mental stress. Let the total cost of being infected be represented by i. Let π_A represent the probability of being infected when consuming A and π_B be the probability of being infected when consuming B. Let us also assume that $\pi_A > \pi_B$. Additionally, assume $\pi_B = 0$, that is individuals perceive B to have no infection risk. We can think of B representing goods such as camping that have minimal infection risk.

Let us assume individuals maximize utility from the consumption of these two goods. Let p_A and p_B represent prices for good A and B respectively, while X_A and X_B represents the units of consumption for each good. Let the income of the individual be represented by I and that consumers have the utility function, $U(X_A, X_B)$, which is quasi-concave, continuous, strictly increasing in X_A and X_B and differentiable. The consumer's probability of incurring cost $(p_A + i)$ per unit of good A is π_A and the probability of incurring a cost of p_A is $(1 - \pi_A)$. That is if infected, the consumer faces an additional cost of i along with the price of the good. This results in the consumer's expected budget constraint $I = \pi_A(p_A + i)X_A + (1 - \pi_A)p_A X_A + p_B X_B$, which simplifies to $I = (p_A + \pi_A i)X_A + p_B X_B$. Writing $\pi_A i = \theta_A$, the budget constraint becomes $I = (p_A + \theta_A)X_A + p_B X_B$, where θ is increasing in p_A and i. The consumer's utility maximization problem then becomes:

$$\begin{aligned} \underset{\{X_A, X_B\}}{\text{maximize}} \quad & U(X_A, X_B) \\ \text{subject to} \quad & I = (p_A + \theta_A)X_A + p_B X_B \end{aligned}$$

Given the assumptions, the demand functions derived from this optimization problem satisfy the general Slutsky equation (Jehle and Reny, 2011). The Slutsky equation for cross price effects for good B can be written as:

$$\frac{\partial X_B}{\partial \theta_A} = \frac{\partial h_B}{\partial \theta_A} - X_A \frac{\partial X_B}{\partial I}, \tag{A.9}$$

where h_B is the Hicksian demand for good B. As good A and B are net substitutes $\frac{\partial h_B}{\partial \theta_A} > 0$. This term represents the substitution effect between the two goods. The second term represents the income effect. There is empirical support to suggest the relationship between camping demand and income is negative (Brox and Kumar, 1997; Shartaj and Suter, 2020). We simply assume that the income effect is smaller than the substitution effect. Given these assumptions, we can see that $\frac{\partial X_B}{\partial \theta_A} > 0$. As θ_A is increasing in infection risk for good A, we can then deduce that increases in the perceived risk of good A will lead consumers to substitute to good B, causing an increase in the market demand for B. The market demand is simply the sum of all individual demand curves (represented in Fig 8 as D1). In the short run, we expect the supply and price of campsites within each campground to be fixed, which results in the campgrounds either facing excess demand or excess supply.

As the perceived risk of good A increases, the Marshallian demand for good B will shift outwards moving from D1 to D2, as shown in Fig 8. Campgrounds that are facing excess supply experience an increase in nights reserved from 2 to 4. For campgrounds facing excess demand, nights reserved would remain the same. This illustrates the importance of controlling for baseline capacity utilization. High capacity utilization campgrounds, represent sites that are already facing excess demand and thus have no room for growth, whereas, low capacity utilization campgrounds represent sites facing excess supply, and thus having room for experiencing growth in nights reserved.

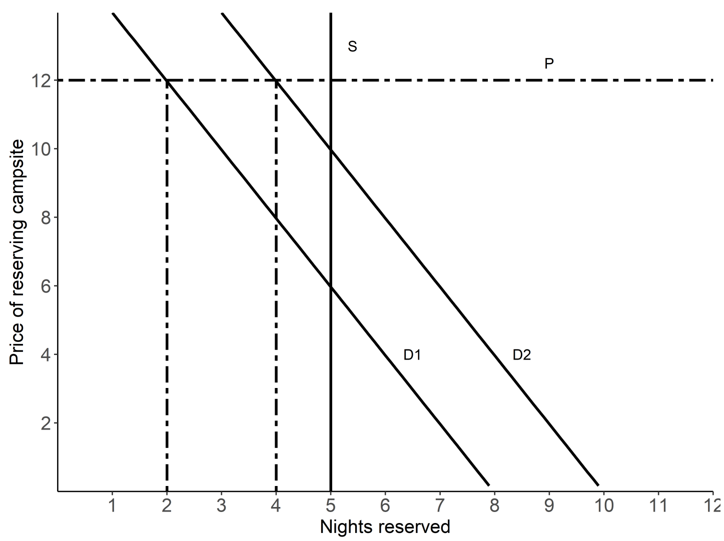

Fig 8. Graphical exposition of changes in campground demand.

Infection risk can be moderated by the level of public health restrictions. Therefore, we control for public health restrictions in the analysis when estimating changes in the infection rates on camping reservation demand. This captures the direct impacts on camping nights reserved due to COVID-19.

A.7 Additional regression tables for chapter 3

Table A.17: Full regression with interaction terms for Model 1 of the infection rate section

	Dependent variable: Change in nights reserved
	Estimate [95 % CI low, 95 % CI high]
3-week moving avg infection rate	−20.180 [−57.477, 17.118]
	p = 0.289
3-week moving avg infection rate x Summer	46.544* [6.574, 86.513]
	p = 0.023
Mandatory SAH	−16.420*** [−22.347, −10.492]
	p = 0.00000
Mandatory SAH x Summer	18.759*** [11.734, 25.783]
	p = 0.00000
Advisory SAH	−9.096** [−15.434, −2.758]
	p = 0.005
Advisory SAH x Summer	9.441** []2.743, 16.140]
	p = 0.006
Days closed in 2020	−1.813*** [−2.817, −0.809]
	p = 0.0005
Days closed in 2020 x Summer	−4.499*** [−5.573, −3.425]
	p = 0.000
Capacity utilization in 2019	−0.046+ [−0.099, 0.007]
	p = 0.091
Capacity utilization in 2019 x Summer	−0.171*** [−0.233, −0.108]
	p = 0.00000
Observations	29,619
Fixed effects	Weekly
Clustered SEs	Campground level
R^2	0.223
Adjusted R^2	0.222
Residual Std. Error	44.936 (df = 29578)
F statistic	211.9*** (df = 40 ; 29578)
Note:	+p<0.10 ;*p<0.05; **p<0.01; ***p<0.001 two tailed;
	The standard errors used to estimate the confidence intervals are clustered by campground.

Table A.18: Full regression with interaction terms for Model 2 of the infection rate section

	Dependent variable: Change in nights reserved
	Estimate [95 % CI low, 95 % CI high]
3-week moving avg infection rate	−26.374 [−63.151, 10.403]
	p = 0.160
3-week moving avg infection rate x Summer	46.386* [5.442, 87.329]
	p = 0.027
Mandatory SAH	−18.538*** [−24.463, −12.613]
	p = 0.000
Mandatory SAH x Summer	20.347*** [13.319, 27.375]
	p = 0.000
Advisory SAH	−10.920*** [−17.324, −4.516]
	p = 0.0008
Advisory SAH x Summer	13.369*** [6.574, 20.164]
	p = 0.0002
Capacity utilization in 2019	−0.071* [−0.129, −0.014]
	p = 0.016
Capacity utilization in 2019 x Summer	−0.232*** [−0.297, −0.167]
	p = 0.000
Observations	29,619
Fixed effects	Weekly
Clustered SEs	Campground level
R^2	0.159
Adjusted R^2	0.157
Residual Std. Error	46.753 (df = 29580)
F statistic	146.7*** (df = 38 ; 29580)
Note:	+p<0.10 ;*p<0.05; **p<0.01; ***p<0.001 two tailed;

The standard errors used to estimate the confidence intervals are clustered by campground.

Table A.19: Full regression with interaction terms for Model 3 of the infection rate section

	Dependent variable: Change in nights reserved
	Estimate [95 % CI low, 95 % CI high]
3-week moving avg infection rate	32.401 [−8.359, 73.161]
	p = 0.120
3-week moving avg infection rate x Summer	−7.675 [−52.418, 37.068]
	p = 0.737
Mandatory SAH	−4.006 [−13.751, 5.739]
	p = 0.421
Mandatory SAH x Summer	5.795 [−5.674, 17.263]
	p = 0.323
Advisory SAH	−12.388** [−19.841, −4.935]
	p = 0.002
Advisory SAH x Summer	13.032** [5.044, 21.020]
	p = 0.002
Days closed in 2020	−1.329* [−2.461, −0.197]
	p = 0.022
Days closed in 2020 x Summer	−4.729*** [−5.927, −3.531]
	p = 0.000
Capacity utilization in 2019	−0.101** [−0.163, −0.039]
	p = 0.002
Capacity utilization in 2019 x Summer	−0.106** [−0.180, −0.032]
	p = 0.005
Observations	29,619
R^2	0.260
Adjusted R^2	0.253
Residual Std. Error	44.011 (df = 29361)
F statistic	310.8*** (df = 10 ; 29361)
Note:	$^{+}$p<0.10 ;*p<0.05; **p<0.01; ***p<0.001 two tailed;

The standard errors used to estimate the confidence intervals are clustered by campground.

Table A.20: Full regression with interaction terms for Model 1 of spatial spillovers section

	Dependent variable: Change in nights reserved
	Estimate [95 % CI low, 95 % CI high]
3-week moving avg infection rate	-14.660 [-49.458, 20.138] p = 0.409
3-week moving avg infection rate x Summer	31.105 [-6.188, 68.398] p = 0.103
Mandatory SAH	-13.362^{***} [-18.854, -7.869] p = 0.00001
Mandatory SAH x Summer	12.278^{***} [5.707, 18.849] p = 0.0003
Advisory SAH	-8.295^{*} [-14.774, -1.815] p = 0.013
Advisory SAH x Summer	5.478 [-1.468, 12.423] p = 0.123
Within 50 miles of NP	-4.940^{+} [-9.938, 0.058] p = 0.053
Within 50 miles of NP x Summer	6.635^{*} [0.722, 12.548] p = 0.028
Increase in NP visits	4.557 [-0.981, 10.095] p = 0.107
Increase in NP visits x Summer	3.108 [-3.380, 9.597] p = 0.348
Small metropolitan area	-2.256 [-6.470, 1.958] p = 0.295
Small metropolitan area x Summer	3.468 [-1.760, 8.696] p = 0.194
Medium metropolitan area	-10.580^{***} [-16.696, -4.464] p = 0.0006
Medium metropolitan area x Summer	14.107^{***} [6.565, 21.650] p = 0.0003
Large metropolitan area	-11.427^{**} [-19.559, -3.295] p = 0.006
Large metropolitan area x Summer	27.127^{***} [17.347, 36.907] p = 0.00000
Wildfire 10	-9.178 [-40.549, 22.192] p = 0.567
Wildfire 10 x Summer	-3.548 [-35.373, 28.277] p = 0.828
Wildfire 20	-15.461 [-44.488, 13.566] p = 0.297

Wildfire 20 x Summer	6.501 [−20.420, 33.421]
	p = 0.637
Days closed in 2020	-1.709^{***} [−2.706, −0.712]
	p = 0.00078
Days closed in 2020 x Summer	-4.628^{***} [−5.705, −3.550]
	p = 0.000
Capacity utilization in 2019	-0.073^{*} [−0.133, −0.014]
	p = 0.016
Capacity utilization in 2019 x Summer	-0.135^{***} [−0.201, −0.068]
	p = 0.0001
Observations	29,619
Fixed effects	Weekly
Clustered SEs	Campground level
R^2	0.239
Adjusted R^2	0.237
Residual Std. Error	44.482 (df = 29564)
F statistic	177.1^{***} (df = 24 ; 29564)

Note: $^{+}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$ two tailed;
The standard errors used to estimate the confidence intervals are clustered by campground.

Table A.21: Full regression with interaction terms for Model 2 of spatial spillovers section

	Dependent variable: Change in nights reserved
	Estimate [95 % CI low, 95 % CI high]
3-week moving avg infection rate	-19.230 [-53.254, 14.795] p = 0.268
3-week moving avg infection rate x Summer	30.326 [-7.721, 68.372] p = 0.119
Mandatory SAH	-15.272^{***} [-20.756, -9.788] p = 0.00000
Mandatory SAH x Summer	13.852^{***} [7.222, 20.482] p = 0.00005
Advisory SAH	-10.046^{**} [-16.578, -3.514] p = 0.003
Advisory SAH x Summer	9.281^{*} [2.253, 16.308] p = 0.010
Within 50 miles of NP	-5.384^{*} [-10.412, -0.355] p = 0.036
Within 50 miles of NP x Summer	7.157^{*} [1.096, 13.219] p = 0.021
Increase in NP visits	5.294^{+} [-0.260, 10.848] p = 0.062
Increase in NP visits x Summer	3.237 [-3.424, 9.897] p = 0.341
Small metropolitan area	-2.938 [-7.154, 1.279] p = 0.173
Small metropolitan area x Summer	2.579 [-2.748, 7.906] p = 0.343
Medium metropolitan area	-10.759^{***} [-16.896, -4.623] p = 0.00056
Medium metropolitan area x Summer	14.066^{***} [6.332, 21.800] p = 0.0004
Large metropolitan area	-11.857^{**} [-20.077, -3.637] p = 0.005
Large metropolitan area x Summer	26.080^{***} [15.833, 36.327] p = 0.00000
Wildfire 10	-6.049 [-36.167, 24.068] p = 0.694
Wildfire 10 x Summer	-11.614 [-42.581, 19.353] p = 0.463
Wildfire 20	-13.825 [-43.338, 15.689]

Capacity utilization in 2019	-0.098^{**} [-0.161, -0.035]
	p = 0.003
Capacity utilization in 2019 x Summer	-0.198^{***} [-0.267, -0.128]
	p = 0.00000
Observations	29,619
Fixed effects	Weekly
Clustered SEs	Campground level
R^2	0.175
Adjusted R^2	0.173
Residual Std. Error	46.315 (df = 29566)
F statistic	120.3^{***} (df = 52 ; 29566)
Note:	$^{+}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$ two tailed;

The standard errors used to estimate the confidence intervals are clustered by campground.

Table A.22: Full regression with interaction terms for Model 3 of spatial spillovers section

	Dependent variable: Change in nights reserved
	Estimate [95 % CI low, 95 % CI high]
3-week moving avg infection rate	33.878^{+} [−5.297, 73.053] p = 0.091
3-week moving avg infection rate x Summer	−16.065 [−58.735, 26.604] p = 0.461
Mandatory SAH	−2.421 [−11.531, 6.690] p = 0.603
Mandatory SAH x Summer	3.552 [−7.862, 14.965] p = 0.542
Advisory SAH	-11.262^{**} [−19.123, −3.402] p = 0.005
Advisory SAH x Summer	8.845^{*} [0.270, 17.421] p = 0.044
Within 50 miles of NP	−4.029 [−8.912, 0.854] p = 0.106
Within 50 miles of NP x Summer	5.754^{+} [−0.134, 11.642] p = 0.056
Increase in NP visits	4.971^{+} [−0.061, 10.004] p = 0.053
Increase in NP visits x Summer	1.700 [−4.250, 7.650] p = 0.576
Small metropolitan area	1.712 [−2.751, 6.175] p = 0.453
Small metropolitan area x Summer	−3.016 [−8.770, 2.739] p = 0.305
Medium metropolitan area	−4.676 [−11.315, 1.962] p = 0.168
Medium metropolitan area x Summer	7.165^{+} [−0.703, 15.033] p = 0.075
Large metropolitan area	−6.817 [−15.488, 1.854] p = 0.124
Large metropolitan area x Summer	20.459^{***} [10.042, 30.876] p = 0.0002
Wildfire 10	−25.539 [−57.679, 6.601] p = 0.120
Wildfire 10 x Summer	12.639 [−19.524, 44.802] p = 0.442
Wildfire 20	-25.749^{*} [−51.317, −0.181] p = 0.049
Wildfire 20 x Summer	16.099 [−7.294, 39.491] p = 0.178

Days closed in 2020	-1.354^{*} [-2.467, -0.240]
	p = 0.018
Days closed in 2020 x Summer	-4.647^{***} [-5.835, -3.459]
	p = 0.000
Capacity utilization in 2019	-0.096^{**} [-0.156, -0.035]
	p = 0.003
Capacity utilization in 2019 x Summer	-0.112^{**} [-0.183, -0.041]
	p = 0.003
Observations	29,619
Fixed effects	Region by week
Clustered SEs	Campground level
R^2	0.270
Adjusted R^2	0.264
Residual Std. Error	43.708 (df = 29347)
F statistic	40.13^{***} (df = 271 ; 29347)

Note: $^{+}p<0.10$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$ two tailed;

The standard errors used to estimate the confidence intervals are clustered by campground.

A.8 Additional robustness testing for chapter 3

The majority of USFS campgrounds are located in the western US, therefore we estimate the model described in equation (4), but with only including campgrounds from western states. The results are presented in specification (1) of Table C1. We see the results are similar to previous estimates using the entire sample. In specification (2), we estimate the model described in equation (4) but exclude the increase in NP visits variable and instead include two alternative distances. The variables 'Within 75 of NP' and 'Within 100 of NP' represent dummy variables for campgrounds between 50 to 75 miles and between 75 to 100 miles of a NP, respectively. We see that campgrounds that lie within 50 miles of a NP experienced increases in campground reservations in 2020, relative to campgrounds further away. Moreover, the magnitude and significance falls as we include campgrounds that lie further than 50 miles of a NP, as represented by the coefficient estimates of 'Within 50 miles of NP' and 'Within 100 miles of NP'.

Table A.23: Marginal effects for alternative models.

	Dependent variable: Change in nights reserved			
	(1)		(2)	
	Spring	Summer	Spring	Summer
3-week moving moving avg infection rate	-50.703*	20.103+	-12.000	16.243
	(22.097)	(11.151)	(17.780)	(10.370)
Mandatory SAH	-18.608***	-2.249	-13.347***	-1.865
	(3.290)	(2.706)	(2.798)	(2.640)
Advisory SAH	-8.866**	-2.465	-8.245*	-3.114+
	(2.827)	(1.763)	(3.350)	(1.704)
Within 50 miles of NP	-3.977	1.515	-4.176	4.783*
	(2.420)	(1.908)	(2.598)	(2.122)
Within 75 miles of NP			-1.978	1.139
			(3.085)	(2.162)
Within 100 miles of NP			1.891	-0.598
			(2.638)	(2.380)
Increase in NP visits	4.944+	8.228**		
	(2.695)	(2.541)		
Small metropolitan area	-2.496	1.725	-2.557	1.091
	(2.104)	(1.952)	(2.121)	(1.814)
Medium metropolitan area	-6.541*	5.027*	-10.950***	3.597
	(3.021)	(2.365)	(3.158)	(2.184)
Large metropolitan area	-15.059***	15.572***	-11.480**	15.535***
	(3.967)	(2.994)	(4.135)	(2.920)
Wildfire 10	-14.238	-12.210***	-9.498	-13.092***
	(16.627)	(2.782)	(15.981)	(2.817)
Wildfire 20	-19.034	-9.197***	-15.722	-8.994**
	(14.395)	(2.729)	(14.758)	(2.734)
Days closed in 2020	-1.229**	-6.700***	-1.755***	-6.351***
	(0.473)	(0.395)	(0.512)	(0.350)
Capacity utilization in 2019	-0.075*	-0.230***	-0.070*	-0.208***
	(0.032)	(0.025)	(0.030)	(0.021)
West only	Yes		No	
Observations	24,469		29,619	
Fixed effects	Weekly		Weekly	
Clustered SEs	Campground level		Campground level	
R^2	0.243		0.237	
Adjusted R^2	0.242		0.236	
Residual Std. Error	44.19(df = 24414)		44.53(df = 29562)	
F statistic	145.5***(df = 54; 24414)		164.2***(df = 56; 29562)	
Note:	+p<0.1; *p<0.05; **p<0.01; ***p<0.001 two-tailed; *The standard errors are clustered by campground and provided in parentheses.*			

Table C2 presents the impact of alternative definitions used for the infection rate. The marginal effects from the table reflect that the sign and significance of the infection rate is robust to the different definitions used. Additionally, increasing the average number of weeks in the infection rate slightly increases both the magnitude of the marginal effect and the standard error.

Table A.24: Marginal effects for alternative infection rate definitions.

	Dependent variable: Change in nights reserved			
	(1)		(2)	
	Spring	Summer	Spring	Summer
Weekly avg infection rate	0.470	13.444^{+}		
	13.944	8.161		
2-week avg infection rate			-9.367	15.747^{+}
			15.963	9.558
Mandatory SAH	-13.426***	-1.055	-13.433***	-1.081
	2.799	2.558	2.803	2.557
Advisory SAH	-8.013*	-2.843^{+}	-8.227*	-2.822^{+}
	3.290	1.663	3.303	1.664
Within 50 miles of NP	-4.950*	1.788	-4.899^{+}	1.726
	2.460	1.826	2.524	1.833
Increase in NP visits	5.015^{+}	7.574**	4.655	7.613**
	2.804	2.527	2.869	2.527
Small metropolitan area	-2.132	1.252	-2.182	1.224
	2.024	1.809	2.088	1.811
Medium metropolitan area	-9.469**	3.548	-10.001***	3.523
	2.904	2.175	3.009	2.172
Large metropolitan area	-10.272**	15.739***	-10.919**	15.708***
	3.894	2.889	4.037	2.888
Wildfire 10	-9.233	-12.687***	-9.222	-12.699***
	16.024	2.776	16.017	2.778
Wildfire 20	-15.965	-8.895**	-15.694	-8.914***
	14.771	2.709	14.790	2.708
Days closed in 2020	-1.693***	-6.332***	-1.703***	-6.335***
	0.502	0.350	0.505	0.350
Capacity utilization in 2019	-0.071*	-0.208***	-0.071*	-0.208***
	0.028	0.021	0.029	0.021
Observations	30,007		29,814	
Fixed effects	Weekly		Weekly	
Clustered SEs	Campground level		Campground level	
R^2	0.238		0.239	
Adjusted R^2	0.237		0.237	
Residual Std. Error	44.22(df = 29950)		44.35(df = 29758)	
F statistic	167.5***(df = 56; 29950)		169.6***(df = 55; 29758)	

Note: $^{+}$p<0.1; *p<0.05; **p<0.01;***p<0.001 two-tailed;
The standard errors are clustered by campground and provided in parentheses.