Three Essays in Applied and Resource Economics

by

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ABSTRACT

This dissertation includes three empirical essays in three chapter by addressing issues related to Resource Economics, Agricultural Policy, and Recreational demand. I contribute to the literature by adopting nonlinear panel estimation methods, causal inference analysis, and quantile regression to address issues of resource management, environmental resources allocation, and econometric issues.

Chapter 1 addresses the impact of the Conservation Reserve Program rental rates on program enrollment under different crop price environments using a nonlinear approach. High crop prices decrease landowners' incentives to enroll land in the Conservation Reserve Program (CRP), as returns from crop production become more favorable, relatively. We explore how CRP rental rates affect CRP land enrollment decisions under varying crop-price regimes. We use county-level data from 1986 to 2019 and employ a land-use framework estimated empirically with a Panel Smoothing Transition Regression. Our results suggest that the impact of CRP rental rate on CRP land enrollment varies depending on the level of crop prices. When crop prices are low, a 10% increase in CRP rental rates is associated with a 2.7% increase in CRP land enrollment; whereas when crop prices are high, a 10% increase in CRP rental rates causes a 1.9% increase in CRP land enrollment. We conclude that substantial carbon-sequestration and water-quality benefits are foregone under high crop price regimes.

Chapter 2 addresses the effect of the Transition Incentive Program on Beginning farmers and ranchers in the United States. This paper examines the effect of the Transition Incentive Program (TIP) on beginning farmers and ranchers (BFRs) in the midwestern agricultural region. BFRs are important for the agricultural industry in the United States as they have the potential to enhance its productivity and efficiency. The TIP is a federal program that seek to transfer near–expiring Conservation Reserve Program (CRP) lands to a beginner farmer, rancher, veteran, or socially disadvantaged farmer. We evaluate if availability of TIP affected the number of BFRs using quasi–experimental methods and pre and post implementation county–level data for the period 2002-2017. Results provide strong evidence that TIP encourages entry into agriculture that translates into more BFRs in counties with abundant CRP lands. Specifically, we find that TIP

stimulates entry by 34 more BFRs per county in the agricultural sector in the region. Similar outcomes were observed for the different subgroups of BFRs. By exploring the effects of TIP, we conclude that landowners in high-CRP counties are willing to transfer CRP lands to BFRs. Although this paper is the first to explore the effectiveness of TIP in achieving its mandate, we suggest future research to examine factors that influence this land transfer program using individual level data.

Chapter 3 addresses the issues of climate variability, socio-demographic factors, and visits to national parks. We analyze the relationship between climate variables, socio–demographic factors, and length of stay to managed natural parks in Utah. We construct an extensive dataset using recreational reservation data from the recreation.gov website to evaluate these relationships. The results provide evidence that length of stay is sensitive to extreme weather conditions. For instance, higher humidity and extremely cold weather reduces the length of stay at a national park. We realize that the socio-demographic indicators greatly influence length of stay as increasing travel cost create a greater opportunity cost for out-of-state visitors. We perform a subsample analysis where we separate the observations into warm and cold seasons and test the robustness of our results with alternative specifications of the main model. Our analysis demonstrate considerable heterogeneity in climate and socio-demographic dynamics when the analysis is conducted based on seasons.

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List of Abbreviations

BFR	Beginning farmers and Ranchers
CRP	Conservation Reserve Program
EBI	Environmental Benefits Index
FSA	Farm Service Agency
NASS	National Agricultural Statistics Service
PSTR	Panel Smoothing Transition Regression
TIP	Transition Incentive Program
USDA	United States Department of Agriculture

1. CHAPTER 1

Nonlinear Effects of Conservation Reserve Program Rental Rates on Land Enrollment under Varying Crop Price Regimes

1. INTRODUCTION

Extensive agricultural production on marginal lands threaten environmental benefits and societal welfare, generating the need for conservation programs. The United States Department of Agriculture (USDA) instituted the Conservation Reserve Program (CRP) to mitigate the undesirable effects of agriculture on marginal and sensitive croplands. The CRP is a voluntary land retirement program that was established in 1986 to remove highly erodible agricultural lands from production in exchange for monetary payments (USDA–ERS 2020). Under this program, the USDA spends over $2 billion annually to improve wildlife biodiversity, enhance soil and water quality, and reduce soil erosion (Hellerstein 2017). However, competition due to high crop prices – which increases the opportunity cost of farmers' participation in the program – threatens the long-term ability of the program to achieve its environmental objectives. In this paper, we evaluate the effect of the CRP rental rate on CRP land enrollment under time-varying crop price regimes and quantify the environmental consequences.

Prior work on the CRP covers a wide range of topics, such as identifying factors that affect land enrollment for conservation use (Plantinga et al. 2001; Isik & Yang 2004; Jang & Du 2018; Cornish et al. 2021), evaluating the impact of CRP participation on land values (Lin & Wu 2005; Lubowski et al. 2008; Berger et al. 2020), estimating effects of crop prices on CRP enrollment (Secchi & Babcock 2007; Hellerstein & Malcolm 2011), and measuring compliance in the conservation program (Secchi et al. 2008; Holland et al. 2020). Studies that evaluate the effect of the CRP rental rate on CRP enrollment have established a positive and significant relationship. For instance, Cornish et al. (2021) and Plantinga et al. (2001) show that the effect of CRP rental rate on CRP land enrollment is positive but differs in magnitude across the subregions. However, analyzing the CRP is complex due to different transition paths, regime shifts, and restriction behaviors that cause nonlinear effects. Existing studies that investigate the effect of the CRP rental rate on CRP acreage use linear models that may produce biased outcomes due to these nonlinear outcomes. In addition, it is challenging to find external instrumental variables (IVs) to resolve the simultaneity between the CRP rental rate and CRP acreage. Thus, prior studies use lagged internal variables as IVs to mitigate the endogeneity issues. However, this strategy sometimes violates the exclusion restriction and the independence assumptions (Wang & Bellemare 2019). Moreover, the CRP literature often ignores the interaction between the CRP rental rates and crop prices, although research shows that farmers may farm highly erodible lands under high crop prices (Secchi et al. 2008; Hellerstein & Malcolm 2011; Holland et al. 2020, affecting the environmental benefits generated by the program.

We examine prospective land use switches that affect CRP acreage using county-level data to address the following two objectives. First, we verify the existence of nonlinear relationships between the CRP rental rates and CRP acreage at different crop price regimes using a time-varying estimation technique. We establish the causal relationship between the CRP rental rates and CRP acreage by using a control function approach to resolve simultaneity bias. Second, we simulate how changes in CRP acreage due to high crop prices affect environmental factors including water quality and carbon sequestration. This study is timely as crop prices have been volatile since the outbreak of COVID-19 and farm exports are at a record high, circumstances under which the USDA projects an additional 2.1 million acres of cultivation of major field crops (USDA 2020). As the CRP depends on the enrollment of sensitive croplands, shocks to the agricultural sector may increase land use on the extensive margin through cultivation on sensitive cropland.

We make two contributions to the empirical literature on CRP acreage. First, our study differs from prior work as we use a flexible estimation technique that allows the incentives of CRP rental rates offered to landowners to vary as a function of crop prices and fluctuate asymmetrically, non-linearly, and over time across an unlimited number of regimes. Second, we construct a "Hausman-type instrumental variable" to mitigate the endogeneity between the CRP rental rates and CRP acreages (Hausman 1997). Lagged values of rental rates employed in past studies as IVs may not be exogenous because the variation in both the CRP acreage and CRP rental rates may be due to variations in both the land supply and cash rental rates. Thus, we adopt our constructed external instrument to address this issue.

We reject linearity for the relationship between CRP enrollment and CRP rental rates. Our estimates suggest that the impact of CRP rental rates on CRP land enrollment varies nonlinearly and depends on the crop price level. We find that when crop prices are at historically low levels, a 10% increase in CRP rental rates is associated with a 2.4% increase in CRP land enrollment.

However, the impact of CRP rental rates on the program acreage decreases when crop prices surpass 0.31 standard deviations above the historically low levels, at which point a 10% increase in CRP rental rates leads to a 1.6% increase in CRP land enrollment. The impact of the CRP rental rate on CRP enrollment remains stable regardless of how high the crop price rise above this threshold. This implies that high crop prices reduce the effectiveness of the conservation program. The environmental consequences of the lowered CRP acreage include 13 million tons of forgone carbon sequestration benefits under a high crop price regime that would have been sequestered under low crop prices. Our findings suggest that variations in crop prices have the ability to impede environmental services generated by the conservation program.

2. Empirical Approach

2.1 Base Model and Endogeneity

We adopt land rent maximization as the theoretical framework for this paper. We follow the arguments of Just and Antle (1990) and Lichtenberg (1989) and assume that a landowner allocates a parcel of land to the use with the highest net returns. Based on our framework, we hypothesize that the CRP rental rates exhibit varying effects due to the competition from agricultural crop prices. We specify a reduced-form log-log land use framework equation that captures these land use decisions as:

$$(1)\;\; lnCRP_{i,t} = \mu_i + \lambda_t + \beta_1 lnR_{i,t} + \beta_2(lnR_{i,t} \times lnCP_{i,t}) + \boldsymbol{X_{i,t}\beta_k} + \varepsilon_{i,t}$$

where the outcome variable, $CRP_{i,t}$ denotes the CRP acreage in county *i* at time *t*; $R_{i,t}$ is the CRP rental rate in county *i* at time *t*; $CP_{i,t}$ denotes the Laspeyres crop price index for eight major crops in county *i* at time *t*; and $\boldsymbol{X_{i,t}}$ is a vector of the natural logarithm of control variables that affect the CRP acreage and includes:

- $CRP_{i,t-1}$: the lagged dependent variable of the CRP acreage in county *i* at time *t*
- $PD_{i,t}$: the population density in county *i* at time *t*
- $FI_{i,t}$: the real net farm income in county *i* at time *t*
- $HI_{i,t}$: the real median household income in county *i* at time *t*
- $Temp_{i,t}$: the annual average temperature in county *i* at time *t*
- EC_{it}: a binary variable for whether county *i* is below the enrollment cap at time *t*

We include $EC_{i,t}$ to account for the CRP enrollment cap that limits CRP acreage to 25% of cropland in each county. We let μ_i and λ_t represent the county and time fixed effects to capture county-invariant and time-invariant factors that affect CRP acreage, and $\varepsilon_{i,t}$ denotes the error term. Based on this setup, the CRP rental rates have a linear heterogenous incentive effect on the program enrollment under different crop price regimes, where the incentive effect is represented as $(\beta_1 + \beta_2 \times lnCP_{i,t})$.

Estimating equation (1) may generate biased estimates for β_1 and β_2 as the CRP rental rates ($R_{i,t}$) and crop prices ($CP_{i,t}$) are endogenous, which means that they are conditionally dependent on the regression error term, $\varepsilon_{i,t}$. We use the control function technique, a two-stage residual inclusion (2SRI) strategy, to mitigate this endogeneity problem (Wooldridge, 2015). The control function estimator is chosen because it is a more efficient estimator for the nonlinear model than the commonly used two-stage least squares estimator (Guo & Small, 2016). An auxiliary regression is estimated in the first stage, and the results are used to generate residuals for the second stage regression. In the second stage, the residuals from the first stage are included as additional regressors together with the endogenous variable. In this instance, the residuals mitigate the endogeneity in the regression by serving as proxies for the factors in the error term in equation (1) that are correlated with the endogenous variables.

One source of endogeneity in the CRP literature is because the CRP rental rates offered to farmers $R_{i,t}$ and the enrolled CRP lands $CRP_{i,t}$ suffer from simultaneity issues (Miao et al., 2016; Jang & Du, 2018). First, the CRP rental rates $R_{i,t}$ is endogenous because both the payment bid $R_{i,t}$ and CRP acreage $CRP_{i,t}$ are adjusted simultaneously and thus are correlated with unobserved productivity shocks. That is, more productive farmers may bid on higher CRP rental rates per acre to compensate for higher opportunity or the forgone profits from agriculture. Another issue is that CRP participation may not be random, as farms with lower productivity may self-select and be more likely to participate. Specifically, the CRP rental rate is computed as an average for each county in a given year. Thus, the CRP acreage enters both sides of the regression equation. If the rental rate is assumed to be exogenous, then the relationship between CRP rental rate and the program enrollment will be biased (possibly downward). To resolve this simultaneity problem, we apply the widely used Hausman-type instrumental variable (Hausman, 1997). We specify that the CRP rental rate as:

$$(2)\ lnR_{ijt} = f(lnR_{-jt}, v_i)$$

where R_{ijt} is the CRP rental rate in county i in state j at time t; R_{-jt} denotes the CRP rental rate in all other counties in state j at time t, excluding the county i. We exclude the rental rates in county i from the construction of instruments to reduce the simultaneity bias caused by common county-specific enrollment shocks. We also control for county-specific effects with v_i. The main idea of the Hausman instrument is that rental rates in other counties can be employed as an instrument for rental rates in a particular county. Using neighbors' prices to instrument product prices has been widely adopted in the industrial organization literature (e.g., Hausman et al., 1997; Nevo, 2003). Identification of parameters are achieved when measurement errors in neighbors' prices and neighbors' idiosyncratic enrollment shocks are uncorrelated with those of the county instrumented. This instrument has proven to be useful when a large number of prices and short sample period make it impractical to obtain other price-related external data to serve as instruments. We adopt this strategy and specify the first stage CRP rental rate equation as $R_{ijt} = \eta_0 + \eta_1 R_{-jt} + \vartheta_{it}$ to obtain the residuals $\hat{\vartheta}_{it}$.

The second source of endogeneity is between the CRP acreage $CRP_{i,t}$ and crop prices $CP_{i,t}$ due to the slippage effect, as sensitive non-croplands may be enrolled into agricultural production due to crop price variations (Wu, 2005). We account for the endogeneity between the crop prices and the CRP acreage following Miao et al. (2016) and Bellemare (2015) by using temperature, month, and year dummies as potential instrumental variables. We include dummy variables to account for seasonal variations and to eliminate the predictability of natural disasters (Bellemare, 2015). Thus, we specify the interaction term between the crop prices and CRP rental rates as:

$$(3)\ \ lnR_{ijt} \times lnCP_{i,t} = f(lnR_{-jt}, lnT_{it}, lnR_{-jt} \times\ lnT_{it}, \rho_t, \sigma_t)$$

where CP_{it} is the crop price in county i at time t, T_{it} is the average annual temperature in county i at time t, ρ_t, and σ_t are the month and year dummies respectively at time t. We specify the first stage crop price equation as $lnR_{i,t} \times lnCP_{i,t} = \theta_0 + \theta_1 lnR_{-jt} + \theta_2 lnT_{it} + \theta_3 lnR_{-jt} \times\ lnT_{it} + \rho_t + \sigma_t + \epsilon_{it}$ to obtain the residuals $\hat{\epsilon}_{it}$.

The estimated residuals $\hat{\vartheta}_{it}$ and $\hat{\epsilon}_{it}$ from the first stage are plugged into the CRP acreage model as auxiliary variables to mitigate the endogeneity issues. The inclusion of the residuals serves as a flexible approach that is ideal to estimate a nonlinear model (Wooldridge, 2015). Therefore, after correcting the endogeneity issue, the reduced-form log-log land use framework equation (1) becomes:

$$(4)\ \ lnCRP_{i,t} = \mu_i + \lambda_t + \beta_1 lnR_{i,t} + \beta_2(lnR_{i,t} \times lnCP_{i,t}) + \boldsymbol{X_{i,t}\beta_k} + \pi_1\hat{\vartheta}_{it} + \pi_2\hat{\epsilon}_{it} + \varepsilon_{i,t}$$

2.2 Nonlinear Model Specification

To add a nonlinear structure to the CRP acreage equation to account for behavioral switches under different crop price situations, we follow Gonzalez et al. (2018) and incorporate time-varying regimes into the log-log land use framework by employing a PSTR model. The PSTR model is an extension of the Panel Threshold Regression (PTR) model developed by Hansen in 1999. At first, the PSTR model was utilized to determine the effect of capital market imperfections on investment (González et al., 2018). Researchers have since adopted the model for various studies (cf., Hurn et al., 2016; Delatte et al., 2017; Li et al., 2020; Li & Wei., 2021; Zhang et al., 2021; Wang et al., 2022). In contrast to linear models, which suffer from functional form restrictions, the PSTR model is a flexible estimation procedure that provides a nonlinear, nonmonotonic structure to the CRP acreage model that incorporates a time-varying logistic smooth transition function. We specify the model with the nonlinear structure as follows:

$$(5)\ \ lnCRP_{i,t} = \mu_i + \lambda_t + \beta_1 lnR_{i,t} + \beta_2 lnR_{i,t} \times lnCP_{i,t} g(lnCP_{it}^*; \gamma, c) + \boldsymbol{X_{i,t}\beta_k} + \boldsymbol{\hat{V}_{i,t}\pi} + \varepsilon_{i,t}$$

where $g(lnCP_{it}^*; \gamma, c) = (1 + exp\,[-\gamma \prod_1^m (lnCP_{it}^* - C)])^{-1}, \gamma > 0$

The difference between equation (4) and equation (5) comes from the term on the right-hand side of the equation, $lnR_{i,t} g(lnCP_{it}^*; \gamma, c)$, which relaxes the linear restriction on the heterogenous rental rate effect. The functional form, $g(lnCP_{it}^*; \gamma, c)$, is a smooth, nonlinear, logistic continuum of observations between two the extreme regimes and is bounded between 0 and 1; and $lnCP_{it}^*$ is the crop price transition variable. Following Li et al. (2020), the transition variable is standardized and transformed as $lnCP_{it}^* = (lnCP_{i,t} - M_i)/\sigma_i$, where M_i and σ_i are the minimum values and standard deviations of $lnCP_{i,t}$ for each county i over time. We rescale the crop price to have mean 0 and variance 1 to bring the crop price features to a common scale without distorting the differences in the range of the crop price values; γ is the speed-of-adjustment that determines how quickly the model regimes shift; c is the threshold parameter that defines the point at which farmers are likely to restrict land for conservation use and abandon conservation practices; and $\boldsymbol{\hat{V}_{i,t}}$ is the vector that includes the two residual values from the first stage regressions.

In equation (5), the model encompasses both linear and nonlinear relationships between the CRP rental rates and the CRP acreage, which are expressed as a function of the transition variable $lnCP_{it}^{*}$. When γ approaches infinity, the transition between the extreme regimes is sharp, and the PSTR model attains a panel threshold model (Hansen 1999). On the contrary, if γ approaches zero, the transition function $g(lnCP_{it}^{*};\gamma,c)$, is constant, and the model assumes a standard linear specification with a two-way fixed effect. Since the value of transition function is bounded between 0 and 1, parameters β_1 and $(\beta_1+\beta_2)$ are the CRP rental rate effects in two extreme regimes, with β_1 representing the effect in regime one and $(\beta_1+\beta_2)$ representing the effect in regime two. Regime one denotes periods with the lowest crop prices, whereas regime two is the period with the highest crop prices. Farmers and landowners make enrollment decisions with some state in between the two extremes with an infinite number of such regimes lying on that continuum and their location on the continuum expressed by the value of g.

We derive the regime-switching intervals by computing the CRP rental rate elasticity as:

$$(6)\ \ CRP\ rental\ rate\ elasticity = \frac{\partial CRP_{i,t}}{CRP_{i,t}} / \frac{\partial R_{i,t}}{R_{i,t}} = \frac{\partial \ln\,(CRP_{i,t})}{\partial \ln\,(R_{i,t})} = \beta_1 + \beta_2(lnCP_{it}^{*};\gamma,c)$$

If the switch phenomenon exists and CRP land enrollment decisions are influenced by variation in crop prices, then we expect the CRP rental rate elasticities to change over time as the crop prices index embodied in the transition variable $lnCP_{it}^{*}$ change. By doing this, we evaluate the time–varying CRP rental rate on CRP acreage under different crop price situations in equation (6). In addition, we determine the threshold point at which these land use regime–switches occur by computing the elasticity of CRP rental rate elasticity (ERRE) change with respect to the transition variable based on the transition function as:

$$(7)\ \ ERRE = \frac{\partial(\widehat{\beta_1}+\widehat{\beta_2}g(lnCP_{it}^{*};\gamma,c))}{\widehat{\beta_1}+\widehat{\beta_2}(lnCP_{it}^{*};\hat{\gamma},\hat{c})} / \frac{\partial lnCP_{it}^{*}}{lnCP_{it}^{*}} = \frac{\widehat{\beta_2}*\hat{\gamma}*e^{-\hat{\gamma}(lnCP_{it}^{*}-\hat{c})}}{(e^{-\hat{\gamma}(lnCP_{it}^{*}-\hat{c})}+1)^2} * \frac{lnCP_{it}^{*}}{(\widehat{\beta_1}+\widehat{\beta_2}(lnCP_{it}^{*};\hat{\gamma},\hat{c})}$$

The ERRE determines the threshold or the turning point that the transition and switching mechanism occurs.

A three-step strategy is used to estimate and validate the PSTR model: (1) a linearity test to determine the appropriate order of the transition function; (2) an estimation process consisting of a two-step procedure, first eliminating fixed effects, and then applying a nonlinear least square (NLS) to estimate the PSTR mode; and (3) a misspecification test to establish there is no remaining nonlinearity.

2.3 Linearity Test

The first stage requires testing the homogeneity against the PSTR alternative. This stage is important for two reasons. First, the model is not econometrically identified if the data generating process is not homogenous. Second, we conducted this test to verify the existence of the regime-switch hypothesis. Homogeneity is attained by imposing either $H_0: \gamma = 0$ or $H_0': \delta_1 = 0$. However, this procedure has unidentified nuisance parameters that render the process nonstandard under the null hypothesis. To solve this problem, we follow Gonzalez et al. (2018) and replace the transition function $g(lnCP_{it}^{*}; \gamma, c)$ by its first-order Taylor series approximation around $\gamma = 0$, which implies the following auxiliary regression:

$$(8)\ \ CRP_{i,t} = \mu_i + \lambda_t + \delta_0^{*} lnR_{i,t} + \delta_1^{*} lnR_{i,t} lnCP_{it}^{*} + \ldots + \delta_m^{*} lnR_{i,t} lnCP^{*m}_{it} + \boldsymbol{X_{i,t}\beta_k} + \boldsymbol{\widehat{V}_{i,t}\pi} + \mu_{i,t}^{*}$$

where the parameter vectors $\delta_0^{*}, \ldots \ldots, \delta_m^{*}$ are multiples of γ, and $\mu_{i,t}^{*} = \mu_{i,t} + T_m \delta_1 R_{i,t}$, where T_m is the reminder of the of the Taylor series expansion. Equation (8) is estimated, and the hypothesis is tested using a standard Lagrange multiplier test (LM_{χ^2}):

$$(9)\ \ LM_{\chi^2} = T * N \frac{(SCR_0 - SCR_1)}{SCR_0}$$

where SCR_0 is the sum of the squared residuals of a linear model with county and time fixed effects and SCR_1 is the sum of squared residuals under the auxiliary regression (8). The LM statistic follows an asymptotic χ^2 distribution with $(m * k)$ degrees of freedom, where k is the number of explanatory variables. Apart from the two important aspects of the linearity tests discussed above, the linearity test is also important in selecting the appropriate order, m, of the logistic transition variable. According to Granger and Teräsvirta (1993) and Gonzalez et al. (2018), the appropriate order of m of the logistic transition variable is performed by using the auxiliary regression (8) with $m = 3$ to test the null hypothesis $H_0^{*} = \delta_1^{*} = \delta_2^{*} = \delta_3^{*} = 0$. If the null hypothesis is rejected, we test $H_{03}^{*}: \delta_3^{*} = 0$, $H_{02}^{*}: \delta_2^{*} = 0 | \delta_3^{*} = 0$ and $\mathrm{H}_{01}: \delta_1^{*} = 0 | \delta_3^{*} = \delta_2^{*} = 0$. We select $m = 2$ if the rejection of H_{02}^{*} is the strongest; otherwise, we select $m = 1$ for the test.

2.4 PSTR Model Estimation

We estimate the PSTR model by using a two-step method. First, we demean the variables by subtracting the mean of each county over time and the mean for each period for all variables. Afterwards, we center the demeaned values to estimate the model by using a nonlinear least square (NLS) method. The variables are demeaned as follows:

$$(10)\ \ lnCRP_{it}^{c} = lnCRP_{it} - \overline{lnCRP_i} - \overline{lnCRP_t}$$

$$(11)\ \ lnR_{it}^{c} = lnR_{it} - \overline{lnR_i} - \overline{lnR_t}$$

$$(12)\ \ \boldsymbol{X_{it}^{c}} = \boldsymbol{X_{it}} - \boldsymbol{\overline{X_i}} - \boldsymbol{\overline{X_t}}$$

$$(13)\ \ \boldsymbol{\widehat{V}_{it}^{c}} = \boldsymbol{\widehat{V}_{i,t}} - \boldsymbol{\overline{\widehat{V}_i}} - \boldsymbol{\overline{\widehat{V}_t}}$$

$$(14)\ \ \varepsilon_{it}^{c} = \varepsilon_{it} - \overline{\varepsilon_i} - \overline{\varepsilon_t}$$

where $\overline{lnCRP_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} lnCRP_{it}$, $\overline{lnCRP_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} lnCRP_{it}$, $\overline{lnR_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} lnR_{it}$, $\overline{lnR_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} lnR_{it}$, $\overline{X_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} X_{it}$, $\overline{X_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} X_{it}$, $\boldsymbol{\overline{\widehat{V}}_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} \boldsymbol{\widehat{V}}_{it}$, $\boldsymbol{\overline{\widehat{V}}_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} \boldsymbol{\widehat{V}}_{it}$, $\overline{\varepsilon_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} \varepsilon_{it}$, $\overline{\varepsilon_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} \varepsilon_{it}$, where t is the time-period that county in which i was observed and N_t is the total number of counties observed at time t. The explanatory variables in the second regime $lnR_{i,t}g(lnCP_{it}^{*};\gamma,c)$ is transformed such that

$$(15)\ \ B_{it}^{c}(lnCP_{it}^{*};\ \gamma,c) = lnR_{it}g(lnCP_{it}^{*};\gamma,c) - \overline{B_i} - \overline{B_t}$$

where $\overline{B_i} = \frac{1}{T_i}\sum_{t=1}^{T_i} lnR_{it}g(lnCP_{it}^{*};\gamma,c)$ and $\overline{B_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} lnR_{it}g(lnCP_{it}^{*};\gamma,c)$. After demeaning the second regime equation, each row of the new centered design matrix is transformed to become $D_{it}^{c}(lnCP_{it}^{*};\gamma,c) = [lnR_{it}^{c\,\prime};\ B_{it}^{c}(lnCP_{it}^{*};\ \gamma,c)^{\prime};\boldsymbol{X_{it}^{c\,\prime}};\ \boldsymbol{\widehat{V}_{it}^{c\,\prime}}]^{\prime}$. The nonlinear least square (NLS) method is then applied to estimate the coefficients that minimize the concentrated sum of square errors:

$$(16)\ \ SSE^{c}(\gamma) = \sum_{i=1}^{N}\sum_{t=1}^{T}[lnCRP_{it}^{c} - \hat{\delta}\,(\gamma)^{\prime}D_{it}^{c}(lnCP_{it}^{*};\gamma,c)]^{2}$$

We obtain the coefficient estimators $\hat{\delta}(\gamma)$ of the second regime by using ordinary least squares (OLS) at each iteration in the nonlinear optimization. The values of γ and c in the transition function are obtained using a grid-search method in the transition function $g(lnCP_{it}^{*};\gamma,c)$. We employ a hyperparameter optimization strategy to choose the appropriate threshold and slope parameters to calibrate the transition function for our analysis. We use this method to identify the appropriate parameters that provide reliable estimates for our analysis.

2.5. No-remaining-nonlinearity test

After estimating the PSTR model, we conduct the test of no-remaining-nonlinearity to ascertain that the model specification that are chosen accounts for all the nonlinearity issues. Here, we test the assumption that there is no remaining heterogeneity and autocorrelation in the data, and that the regression estimates are consistent and unbiased. To perform this test, an additive PSTR model is considered as an alternative. We specify the test results as:

$$(17)\ lnCRP_{i,t} = \mu_i + \lambda_t + \delta_0 lnR_{i,t} + \delta_1 lnR_{i,t} g_1(lnCP^*_{it}, \gamma_1, c_1) + \delta_2 lnR_{i,t} g_2(lnCP^*_{it}, \gamma_2, c_2) + \boldsymbol{X_{i,t}\beta_k} + \boldsymbol{\widehat{V}_{i,t}\pi} + \mu_{i,t}$$

The null hypothesis of no remaining heterogeneity is formulated as $H_0\colon \gamma_2 = 0$ in equation (17). A similar null hypothesis and identification problem is solved using the abovementioned linearity test process by replacing $g_2(lnCP^*_{it}, \gamma_2, c_2)$ with a Taylor series expansion around $\gamma_2 = 0$ as:

$$(18)\ lnCRP_{i,t} = \mu_i + \lambda_t + \delta_0 lnR_{i,t} + \delta_1 lnR_{i,t} g_1(lnCP^*_{it}, \widehat{\gamma_1}, \widehat{c_1}) + \delta^*_{21} lnR_{i,t} lnCP^*_{it} + \ldots + \delta^*_{2m} lnR_{i,t} lnCP^{*m}_{it} + \boldsymbol{X_{i,t}\beta_k} + \boldsymbol{\widehat{V}_{i,t}\pi} + \mu^*_{i,t}$$

where $\widehat{\gamma_1}$ and $\widehat{c_1}$ are estimators of γ_1 and c_1 under H_0. The coefficients δ^*_{2j} for $j = 1, \ldots, m$ are multiples of γ_2. The resulting test collapses into the homogeneity test discussed in the linearity test above.

3. DATA

The model estimates are based on county-level data from 877 counties in the Lake, Corn-belt, Delta, Southern, and Plains states from 1986 to 2019.[1] Figure 1.1 shows the graphical representation of the study area. We obtained data on the CRP acreages and the CRP rental rates from the USDA–Farm Service Agency (FSA). The CRP acreage $CRP_{i,t}$ denotes the total acres of land that are enrolled in the conservation program in county i at time t. The CRP rental rate $R_{i,t}$ is the per-acre payment offered to a farmer or landowner for enrolling land into the conservation program in county i at time t. We deflate the CRP rental rates using the consumer price index to account for inflation.

[Figure 1.1]

We account for the county-level CRP enrollment cap which can limit acreage enrolled in some counties. We follow Hendricks and Er (2018) and construct a county-level total cropland

[1] The paper focused on the Southern and Midwestern regions as they have the largest concentration of CRP land acres (Cornish et al. 2021). Counties in the Atlantic and Western regions were dropped because of computational complexities arising from missing observations and zero enrollment for certain counties during the analysis. Moreover, the paper finds it worthwhile to drop those regions as a recent study by Cornish et al. (2021) indicates an insignificant relationship between CRP rental payment and CRP land acreage for the Atlantic and Western part of the United States.

variable, $Cropland_{it}$, as the sum of all planted acreage of field crops (barley, beans, canola, corn, cotton, flax seed, lentils, millet, mustard, oats, peanuts, rape seed, rice, rye, safflower, sorghum, soybeans, sugar beets, sunflower, peas, spring wheat, and winter wheat) plus harvested acreage of hay. The county-level CRP enrollment cap is computed such that counties that are at the CRP-enrollment cap of 0.25 are denoted as 0 whereas counties below the cap are denoted as 1. Around 11% of counties were at the cap over the 34-year period.

Economic and demographic factors are critical determinants of land use patterns, so we control for population density and median household income per capita. Population density is expressed as $PD_{it} = (Pop_{it}/LA_i)$; where PD_{it} is the population density in county i at time t, Pop_{it} is the number of people in county i at time t, and LA_i is the total land area in county i. We obtained data on population and land area from the Bureau of Economic Analysis (BEA) and the USDA respectively. The median household income per capita $HI_{i,t}$ consider how household income affect the conservation program. We obtained the median household income per capita $HI_{i,t}$ from the BEA. Subsequently, we account for farm profits, as net farm income has been shown to affect farmers' enrollment decisions (Chang et al. 2008). The net farm income $NFI_{i,t}$ data comprise the farm income and costs arising from the current production of either from livestock or crops in a county i at time t. The median household income per capita and net farm income variables are deflated to account for inflation.

We use county-level crop production and deflated state-level prices to construct a Laspeyres crop price index $CP_{i,t}$ for eight major agricultural commodities using 1986 as the base year (Li et al. 2019). In the year $t \in \{1986, \ldots ,2019\}$, the Laspeyres crop price index is defined as $P_{i,t}^{a} = (\sum_{l=1}^{8} Pl_{it} Ql_{i1986})/(\sum_{l=1}^{8} Pl_{i1986} Ql_{i1986})$, where Pl_{it} is the received price of crop l in state i at time t; and Ql_{i1986} is the production of crop l in state i at the base year, 1986. We obtained the crop production and price data from National Agricultural Statistics Service (NASS).

We use temperature, $Temp_{i,t}$, as a key weather variable to capture the landowner's expectation of climate conditions. Data on the average temperature were obtained from the Parameter–Elevation Relationships on Independent Slopes Model (PRISM). Table 1.1 lists the variables employed and their respective summary statistics. Figures 1.2a, 1.2b, and 1.2c are the pictorial view and spatial distribution of the CRP acreage, CRP rental rate, and crop price index variables employed in our study.

[Table 1.1]

[Figure 1.2a, 1.2b, 1.2c]

4. RESULTS AND DISCUSSION

We report the homogeneity and sequence of homogeneity test results in Tables 1.2 and 1.3. Table 1.2 contains the Heteroskedasticity-and autocorrelation-consistent (HAC) test and standard χ^2-homogeneity test with associated p-values for the test statistics when $m = 1{,}2{,}3$, where m is the order of the auxiliary regression. From the test results, we reject linearity at order levels and conclude that a regime-switch effect exists.

[Table 1.2]

Furthermore, we identify the appropriate order of m for the transition variable. This process is important because it affects the transition pattern between the extreme regimes. A first ($m = 1$) or a second ($m = 2$) order of the transition function is sufficient to ensure the necessary variations of slope coefficients suitable for estimating the model (Gonzalez, et al. 2018). Table 1.3 presents the results of the sequence of homogeneity tests for selecting order m. We conclude from Table 1.3 that order $m = 1$ is enough to construct the PSTR model.

[Table 1.3]

We examine the adequacy of the two-regime PSTR model by applying the misspecification tests of parameter constancy and of no remaining non-linearity (heterogeneity) discussed in section 2.5. Results from the wild cluster bootstrap (WCB) tests that take both heteroskedasticity and within-cluster dependence into account suggest that the p-value of the test is 0.75 (Table 1.4). This suggests that the estimated model with one transition is adequate and has no issue of remaining heterogeneity. We test the assumption of no remaining heterogeneity and autocorrelation after the estimation process to demonstrate that our results are consistent and unbiased (Table 1.4).

[Table 1.4]

We present the measures of the model estimates, test statistics, and transitional function parameters in Table 1.5. The estimate of the speed of adjustment parameter (36.95) shows that the transition function estimate is nonlinear and demonstrates a continuum of observations between the two regimes. The results suggest that, on average, the effect of the CRP rental rate on the CRP enrollment is statistically significant and positive in nature. However, when we account for the nonlinear crop price effect, the magnitude of the estimate varies significantly. Based on our estimates of β_1 and $\beta_1 + \beta_2$, we realize that a 1% increase in the CRP rental rate increases CRP acreage by about 0.27% and 0.19% when crop prices are at historically low-and-high levels, respectively. The difference in the CRP rental rate estimates confirm that farmers and landowners are sensitive to changes in crop prices and that these changes exhibit threshold effects that have diverse effects on the conservation program. In other words, to keep CRP acreage at the same level under high crop prices as it would be under low crop prices, the CRP rental rate would need to increase by a factor of 1.42.

[Table 1.5]

From Table 1.5, we show that population density, median household income, and crop price index have negative and significant effects on CRP acreage. Our results are expected and align with the findings from past studies. For instance, the population density relationship aligns with the alternative land use hypothesis that increasing population tends to increase the demand and conversion of land from agriculture to urban use (Lubowski et al. 2008). The crop price relationship illustrates that increasing crop prices reduce land enrollment for conservation use. This relationship is intuitive and conforms to intensive and extensive margin use of agriculture (Hendricks et al., 2014; Barrows et al. 2014). Furthermore, we show that farm earnings, a measure of agricultural income, affect the CRP acreage positively. This finding is tenable as empirical evidence suggest that the absence of a negative relationship between the farm earning and the CRP acreage indicates that farmers sometimes depend on government support programs to augment their farm revenue (Lambert et al., 2007). Moreover, the relationship aligns with the conservation program's mandate to improve upon the welfare of farmers (USDA–FSA, 2018).

The positive effect of the CRP rental rate on the CRP acreage is consistent with empirical studies as the CRP rental rates offered to farmers for conservation encourage land enrollment

(Cornish et al. 2021; Li et al. 2019). That is, higher CRP rental rates encourage land enrollment into the land retirement program. Our results support Holland et al. (2020), as higher crop prices encourage land use on extensive margins by converting conservation lands into croplands. Although our findings align with the abovementioned studies, we quantified the effect of CRP rental rate under both low-and-high crop price regimes on CRP lands which augments the CRP literature.

We illustrate the regime-switching impact under different crop price regimes in Figure 3 and show that it is time-variant and exhibits heterogeneity. From Figure 1.3, we notice that the effect of the CRP rental rate on CRP acreage increased from 0.19 to 0.235 when the standardized crop price index decreased from 2.68 in 1995 to 0.13 in 2002. However, the elasticity of the CRP rental rate peaked at 0.271 when the standardized crop price index reached an all-time low in 2005. But after standardized crop prices rose again after 2005, the elasticity of the CRP rental rate decreased to 0.19.

[Figure 1.3]

The heterogeneity in the CRP rental rate elasticity estimates indicates that CRP enrollment decisions differ by agricultural economic conditions. Secchi et al. (2009) and Morefield et al. (2016) support our findings, as periods of high crop prices correspond with farmers reducing land enrollment for CRP as the opportunity cost of participation increases with higher crop prices. The low-and-high crop price dynamics also affect other conservation programs (McCann & Nuñez, 2005; Claassen et al., 2008).

To explore how the CRP rental rate elasticity changes with the crop prices, we compute the elasticity of the rental rate elasticity (ERRE) to changes in the transition variable. We illustrate the results in Figure 4. We notice that the relationship between the ERRE and the standardized crop price index is nonlinear: more succinctly, L-shaped. Subsequently, we find that the sensitivity of the CRP rental rate elasticities occurs in the lower range of the standardized crop price index when crop prices are low. Figures 4a and 4b show that 0.31 standard deviations above the minimum crop price are the threshold value that switching is likely to occur. When crop prices fall below this threshold, the sensitivity of the rental rate elasticity emerges. However, when crop prices rise above this threshold, the sensitivity of the rental rate elasticity approaches zero.

[Figure 1.4a, 1.4b]

5. ENVIRONMENTAL IMPACTS

Lastly, we provide insight into how crop prices impact environmental outcomes. First, we use county-level data for the environmental benefit index (EBI) of enrolled CRP land through the general signups from 1997 to 2012. The EBI is the USDA-FSA's estimate of environmental benefits that would be generated from enrolling a parcel of land into the CRP and is comprised of five environmental factors: wildlife benefits, water quality benefits, erosion reduction benefits, enduring practices benefits, and air quality benefits. Second, we use USDA-FSA report estimates of environmental benefits generated by the CRP to evaluate how changes in the CRP rental rate would affect carbon sequestration, sedimentation, and nutrient run-off under low and high crop prices.

We simulate the impact of a 1% increase in CRP rental rates under the two crop price regimes by multiplying the 1% rental rate change times CRP acreage times our CRP rental rate elasticity coefficient to estimate the additional CRP acres that would be generated under each crop-price regime. We use CRP benefit data to estimate how this increase in CRP acreage would affect aggregate annual environmental benefits by multiplying the estimated additional acreage due to a 1% increase in CRP rental rate by the per-acre CRP environmental benefits.

We simulate the impact of a 1% increase in CRP rental rates under the two crop price regimes by multiplying the 1% rental rate change times CRP acreage times our CRP rental rate elasticity coefficient to estimate the additional CRP acreage that would be enrolled under each crop-price regime. A 1% increase in CRP rental rate would increase CRP land by 8.1 million acres under low crop prices, but only by 5.7 million acres under high crop prices – a difference of 3.4 million acres (Table 1.6a).

To simulate the impact of the 1% increase in CRP rental rate on EBI factors, we calculate the weighted average points for the overall EBI and the other five factors for each county, using the total acreage of new enrollment in each year as a weight. The weighted average EBI points are calculated using $\sum_t (a_t EBI_t)/\sum_t a_t)$, where a_t and EBI_t reported by FSA, are the CRP acreage and the average EBI points in the county in year t, respectively.

We use the product of the CRP acreage change and the average EBI points to measure the environmental impact of the 1% reduction in CRP rental rate under the low and high crop price regimes. Finally, we compute the environmental impact benefits by calculating the difference environmental impact values across low and high crop price regimes. We aggregate the calculated results for each county to determine changes in environmental benefits at the national level.

Our calculations indicate that the average EBI changes by 3.07% due to a 1% change in the CRP rental rate when crop prices are low. However, we show that the average EBI will change by 2.16% due to a 1% change in the CRP rental rate when crop prices are high. Thus, under high crop price regimes, there is a potential loss of 0.9% in EBI points that could otherwise have been accomplished under low crop price regimes. We realize that the individual environmental benefit factors incur similar magnitude of changes (Table 1.6b). From our calculations, we noticed that the air quality benefits factor is the least affected whereas water quality and wildlife factors are the most affected among the five environmental factors.

[Table 1.6]

We use CRP ecosystem service data (USDA-FSA, 2010-2017) to estimate how the increase in CRP acreage would affect aggregate annual ecosystem services by multiplying the estimated additional acreage due to a 1% increase in CRP rental rate by the per-acre CRP ecosystem service values. The increase in CRP acreage associated with a 1% increase in CRP rental rates would lead to an estimated decrease of 11.4 million metric tons of carbon sequestered under low crop prices, annually. However, this value decreases to 8.1 million metric tons under high crop prices, a 3.4 million metric ton difference (Table 1.6c). Water quality would also be affected. Our estimates suggest a 9.5 million lb increase in Phosphorus runoff, a 47.8 million lb increase in nitrogen runoff, and a 17.4-million-ton increase in sediment loss due to high crop prices.

6. CONCLUSION

We adopt a land use framework integrated with a PSTR regime-switching model to investigate how the CRP rental rates affect CRP acreages under varying crop price regimes. We find that a 10% increase in the CRP rental rates is associated with a 2.7% increase in CRP land enrollment. However, the impact of CRP rental rates on the program enrollment decreases nonlinearly as crop prices rise until crop prices reach 0.31 standard deviations above the minimum crop price, at which point a 10% increase in CRP rental rates is associated with a 1.9% increase in CRP land enrollment. We show that after this threshold, the effect of the CRP rental rate on the CRP enrollment remains stable regardless of how high the crop prices rise. These outcomes are necessary to improve and develop flexible policies in the conservation program's cost and payment structure to account for variations in the agricultural economy.

We translate our findings into ecological outcomes by determining the effect of a 1% change in the CRP rental rates due to crop price variations on various environmental benefits. We employ data from the USDA–FSA and show that a 1% increase in CRP rental rate corresponds to 2.4 million acres fewer enrolled under high crop prices relative to low crop prices. This acreage decline corresponds to 3.4 million fewer tons of carbon sequestered, 9.5 million lb of additional phosphorus runoff, 47.8 million lb of additional nitrogen runoff, and 17.4 million tons of additional sediment loss on average annually.

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6. Tables and Figures

Table 1.1: Summary Statistics

Variable	Mean	St. Dev	Min	Max
Dependent Variable				
CRP Acreage	12,294.45	21,319.68	0.1	218,483
Independent Variable				
CRP Rental Rate ($ per acre)	35.91	18.65	0.26	127.95
Population Density (population per acre)	102.06	239.39	0.43	3,234.14
Median Household Income ($ per capita)	14,365.62	3,647.81	3,839.23	54,992
Net Farm Income	14,727.82	14,692.49	5.77976	205,826
Temperature	12.39	4.38	1.06	25.2
CRP enrollment cap	0.89	0.31	0	1
Transition Variable				
Crop Price Index	109.12	27.57	28.51	235.85

Table 1.2: Homogeneity tests

	LM_x		LM_F		HAC_x		WCB
m	Test statistics	p-value	Test statistics	p-value	Test statistics	p-value	p-value
1	82.55	0.00	80.02	0.00	23.05	1.584e-06	0
2	114.3	0.00	55.41	0.00	12.71	3.027e-06	0
3	504.2	0.00	162.9	0.00	76.81	0.000e+00	0

Note: The table presents the standard L.M.–type and robust (HAC) homogeneity tests with their corresponding p-values in the panel regression of the natural log of CRP acreage and natural log of rental payments per acres (with crop price index as the transition variable) for a balanced panel for the period 1986–2019.

Table 1.3: Sequence of homogeneity tests for selecting order m of transition function.

	LM_x		LM_F		HAC_x		WCB
m	Test statistics	*p-value*	Test statistics	*p-value*	Test statistics	*p-value*	*p-value*
H_{01}	82.55	0.00e+00	80.02	0.00e+00	21.78	1.078e-06	0
H_{02}	31.88	1.64e-08	30.9	2.74e-08	14.65	1.294e-04	0
H_{03}	391.4	0.00e+00	379.4	0.00e+00	205.9	0.00e+00	0

Note: The table presents the sequence of homogeneity tests for selecting order m of transition function their corresponding p-values in the panel regression of the natural log of CRP acreage and natural log of rental payments per acres (with crop price index as the transition variable) for a balanced panel for the period 1986–2019. The listed null hypothesis have the implications H_{01}: $\delta_1^* = 0|\ \delta_2^* = \delta_3^* = 0, H_{02}$: $\delta_2^* = 0|\delta_3^* = 0,$ and H_{03}: $\delta_3^* = 0$, respectively, in the auxiliary regression (6) with $m = 3$.

Table 1.4: Misspecification tests for no autocorrelation and no remaining heterogeneity

m	LM_{χ} Test Statistics	LM_{χ} *p–value*	LM_F Test Statistics	LM_F *p–value*	HAC_X Test Statistics	HAC_X *p–value*	WCB *p–value*
No autocorrelation							
$m = 1$	375.4	0	33.07	0	123.0	0	0.75
No remaining non-linearity (heterogeneity)							
$m = 1$	4353	0	383.4	0	342.3	0	0.25

Note: The table presents the misspecification tests in a PSTR model for the natural log of CRP acreage and natural log of rental payments per acres (with crop price index as the transition variable) for a balanced panel for the period 1986–2019.

Table 1.5. Parameter estimation of the PSTR model[2].

Parameters	Regime–Switching Variables	Coefficient estimates
β_1	CRP rental rate elasticity under the low crop prices	0.2716*** (0.0709)
β_2	CRP rental rate elasticity difference between low and high prices	-0.08*** (0.0105)
$\beta_1 + \beta_2$	CRP rental rate elasticity under high crop prices	0.1916*** (0.0668)
	Control Variables	
β_3	Crop price elasticity	-1.402*** (0.4778)
β_4	Farm earnings elasticity	0.0337*** (0.0062)
β_5	Median household income elasticity	-0.5883*** (0.0502)
β_6	Population density elasticity	-0.5046*** (0.0833)
β_7	Lagged–CRP acreage elasticity	0.5542*** (0.0105)
β_8	Temperature elasticity	0.0621*** (0.0836)
β_9	CRP enrollment cap elasticity	-0.1779*** (0.0199)
	Model specifications	
c	Transition function threshold parameter	0.1399 (0.0091)
γ	Speed of adjustment of transition function (Slope parameter)	36.95 (10.76)
Observations		**29,818**

Note: The standard errors in the parenthesis are cluster-robust and heteroskedastic-consistent covariance estimators in nature and allow for error dependence within counties. $* p < 0.1$; $** p < 0.05$: $*** p < 0.01$

β_1 denotes the payment effect when the observations are within the linear regime (when the transition function equals 0) and depicts periods when the crop prices are below the historical average (low crop price regime). $\beta_1 + \beta_2$ denotes payment effect when observations are in the nonlinear regime (when the transition function is greater than 0 but does not exceed 1) and depicts periods when the crop prices are above the historical average (high crop price regime).

Table 1.6: Effect of a 1% increase in CRP rental rate on CRP acreage, the environmental benefit index, and ecosystem services under low vs. high crop prices, 2016-2017 annual average

	Low Crop Prices	High Crop Prices	Difference
	(a) CRP Acreage		
Additional CRP Acres (million)	8.1	5.7	2.4
	(b) Environmental Benefits Index		
Environmental Benefits Index	3.07	2.16	0.9
Wildlife factor	0.83	0.59	0.24
Water quality benefit factor	0.75	0.53	0.22
Erosion factor	0.65	0.46	0.19
Enduring benefit factor	0.22	0.15	0.06
Air quality benefit factor	0.13	0.09	0.04
	(c) Ecosystem Services		
CO_2 sequestration (million metric tons)	11.4	8.1	3.4
Phosphorus (million lb)	32.3	22.8	9.5
Nitrogen (million lb)	162.4	114.6	47.8
Sediment (million tons)	59.0	41.6	17.4

Note: This table presents the impact of the 1% increase in CRP rental rates under the low and high crop price regimes.

Figure 1.1. Geographic coverage of the study area.

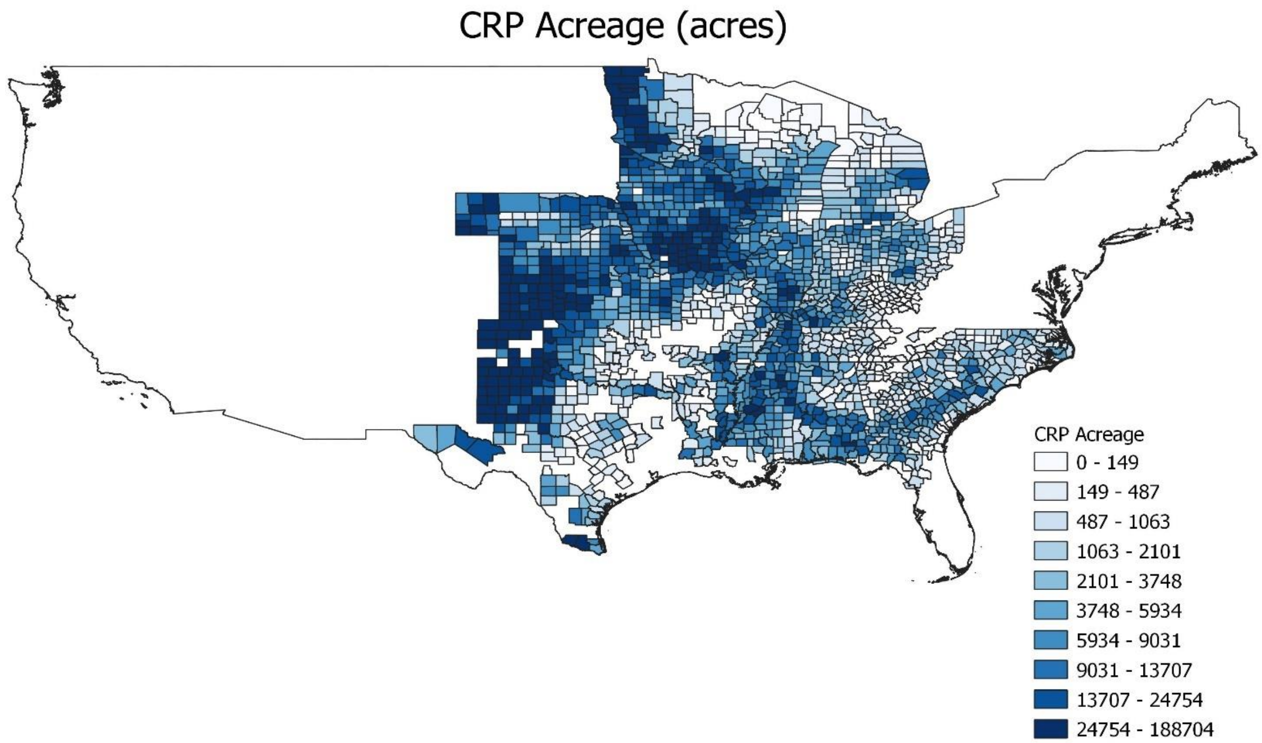


Figure 1.2a. Conservation Reserve Program (CRP) acreage over 1986–2019

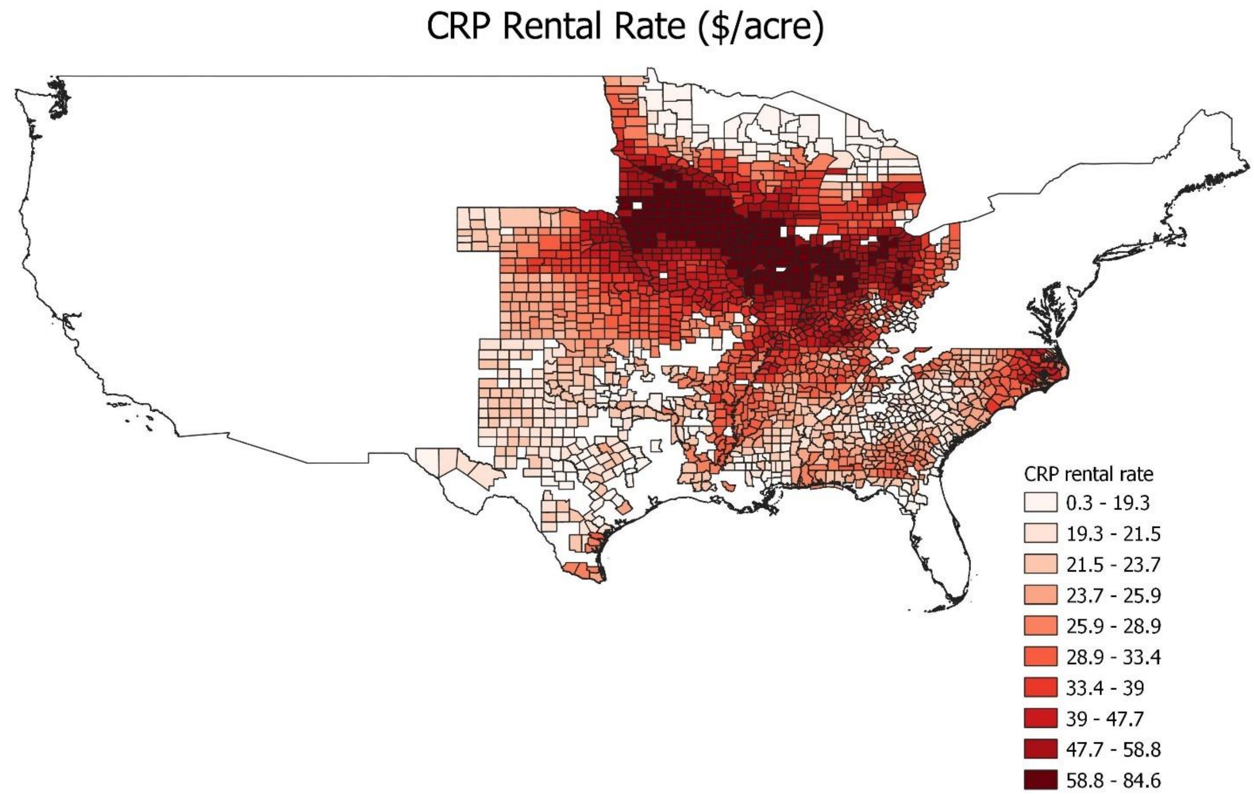
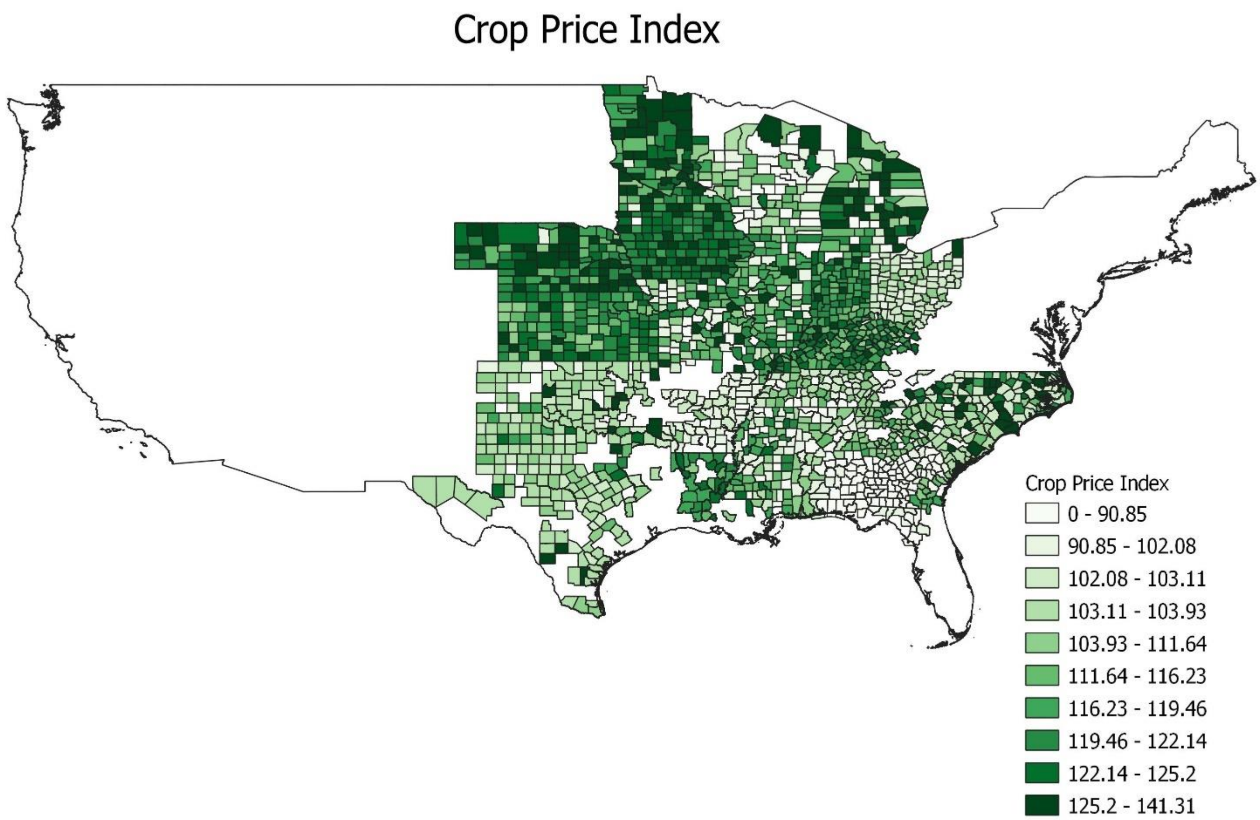


Figure 1.2b. CRP rental rate over 1986–2019



Figures 1.2c. Crop Price Index over 1986 – 2019

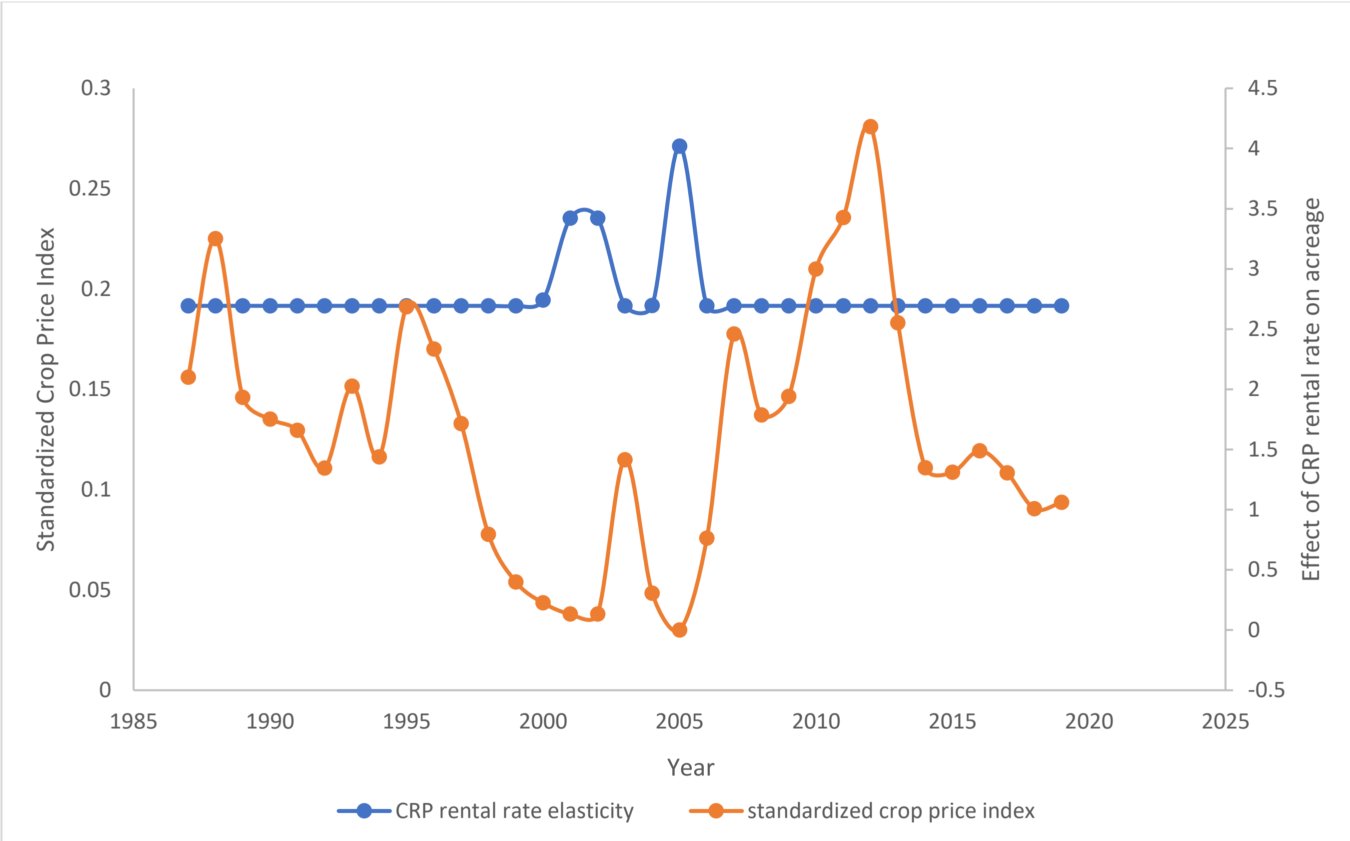


Figure 1.3. CRP rental rate elasticities and standardized crop price index against Year

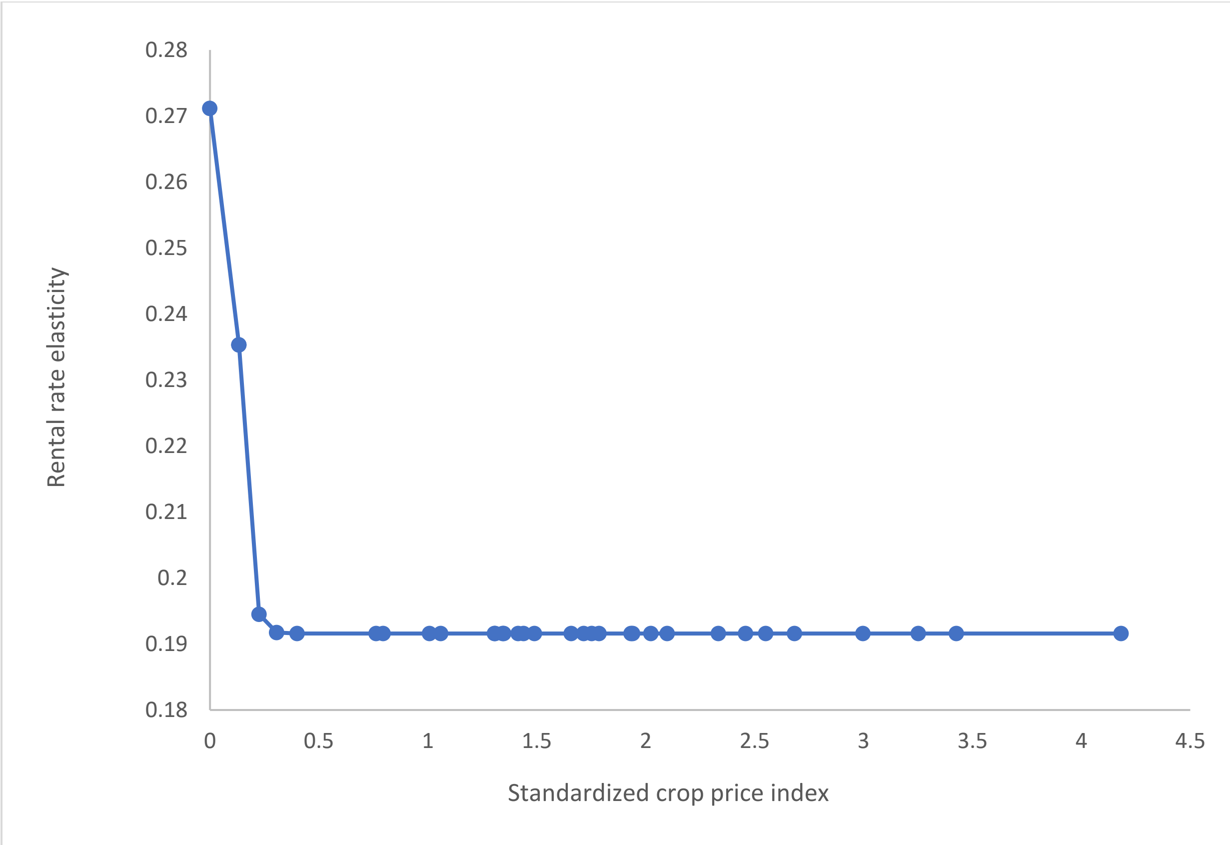


Figure 1.4a. CRP rental rate elasticity and the standardized crop price variable.

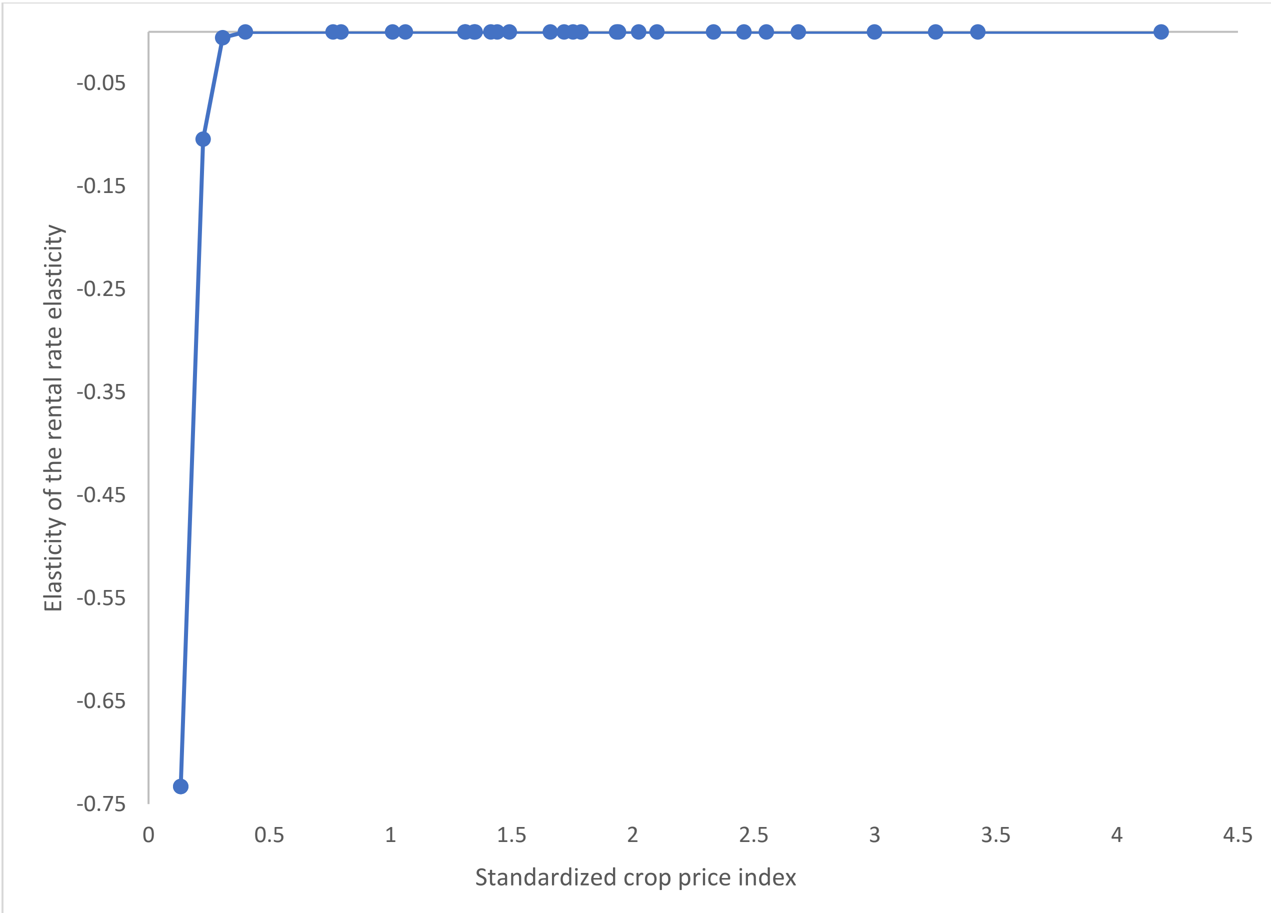


Figure 1.4b. CRP elasticity of rental rate elasticity and the standardized crop price variable.

2. CHAPTER 2

Evaluating the effect of Transition Incentive Program on Beginning Framers' and Ranchers

1. Introduction

Beginning farmers and ranchers (BFRs) face significant challenges when starting agricultural operations. One such challenge is land availability (Ahearn, 2011; C-FARE, 2017; Figueroa & Penniman, 2020). Land access is difficult for BFRs, whether they seek rental, crop-share, or purchase arrangement and whether they come from a multi-generational farm family or are first-generation (Carolan, 2018). This situation occurs due to established farmers' competitive advantage over BFRs and other factors, such as farmland price hikes (Burns et al., 2018). For instance, the 2021 National Agricultural Statistical Survey (NASS) report suggests that farm real estate values averaged $3,380 per acre for 2021, a 7% increase from 2020. Subsequently, the value of croplands, rangelands, and pasturelands have increased by 8%, 6%, and 8%, respectively, compared to previous years. The tight supply is reflected in the projections showing that only 4% of the 897 million acres of farmland is available to sell to non-relatives and other farmers (Bigelow, 2016; USDA, 2015). The Transition Incentive Program (TIP) was introduced to address the shortage of farmland for BFRs, and we offer evidence about its effect on the population of BFR.

We investigate to what extent TIP helps by evaluating its impact on the increase in BFRs in the Midwestern agricultural region by focusing on the following states: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Wisconsin. This study is important as little attention is paid to the federal program that seeks to transfer lands to BFRs. Valliant et al. (2021) is the only study that evaluates the effect of the Land Access Policy Incentive (LAPI) on BFRs and shows that about 75% of farmers in the Midwest and Plain regions are willing to transfer farmlands to BFRs. We contribute to the literature by providing interpretable and direct estimates on how the introduction of TIP has influenced entry dynamics and growth in the size of BFRs. We achieve this objective by developing an instrument that captures the dynamics of acres enrolled in the Conservation Reserve Program (CRP) over the total cropland acres, as the TIP primarily depends on the availability of conservation lands. Subsequently, we focus our analysis on the Midwest and Plain regions due to their large share of CRP lands and intensive agricultural activities (Cornish et al., 2021).

Prior studies have evaluated different factors that affect BFRs under various scenarios. For instance, government policies that seek to solve BFR financial issues have been studied (Kropp & Katchova, 2011; Kaufmann, 2013; Katchova & Dinterman, 2018; Griffin et al., 2020; Hartarska & Nadolynak, 2021). Past studies have also explored how socioeconomic factors and climate variability contribute to BFRs' productivity (Nadolynak et al., 2019; Katchova & Dinterman, 2017). The entry and exit dynamics of BFRs have also been investigated (Hoppe & Korb, 2006; Mishra et al., 2010; Kuehne, 2012; Ahearn, 2013; Katchova & Ahearn, 2017; Griffin et al., 2019). Researchers have also evaluated how some government support programs influence BFRs (Weiss, 1999; Goetz & David, 2001; Key & Roberts, 2006; Kropp & Katchova, 2011). Interestingly, none of these studies addresses the federal land program that seeks to make more farmland available to BFRs, even if it was introduced in 2008. Given the importance of land in agriculture and the need to facilitate its acquisition for farming activities, we investigate the impact of TIP on different categories of BFRs. Understanding the impact of the federal transition program will enable policymakers to develop appropriate strategies to alleviate BFR land acquisition problems.

We contribute to the literature in the following ways. First, we adopt a matched-pair control group approach as our empirical strategy with county-level data from 2002–2017 at 5-year intervals. Second, we construct an instrument representing the TIP-based share of acres enrolled in CRP over the total cropland acres. We create treatment groups (high-CRP counties) and control groups (low-CRP counties). We employ matching techniques to reduce selection biases as CRP enrollments are not randomly assigned, and landowners may enroll in lands with lower opportunity costs (Jisang et al., 2022; Wu, 2005).

First, we use the regression – adjusted (RA) propensity score estimation method to determine the impact of TIP on BFRs and show that principal BFRs, BFRs with 5–9 years of farming experience, BFRs with <5yrs farming experience, and BFRs with <3yrs farming experience increased by 34, 23, 11, and 3 in high–CRP counties, respectively. We turn our attention to the inverse probability weighting (IPW) method and highlight that principal BFRs, BFRs with 5–9 years of farming experience, BFRs with <5yrs farming experience, and BFRs with <3yrs farming experience increased by 39, 32, 11, and 4 for high–CRP counties, respectively. Thus, we show that (1) the number of BFRs increased in counties that are active participants in CRP, and (2) the effect is more substantial for BFRs increase in experience. In summary, the federal land transfer program that seeks to mitigate the land acquisition challenges encountered by BFRs is effective as it encourages entry into the agricultural sector. We argue that the effects are possibly due to (i) the relative abundance of CRP lands in high – CRP counties that makes it easy to access land for farming purposes or (ii) high – CRP counties are predominantly agricultural hubs, thus providing enough farm support for BFRs to thrive. We conduct robustness tests using inverse Kernel nearest neighbor matching (KNN) and nearest neighbor matching (NNM) methods and obtain similar outcomes.

The remainder of this study proceeds as follows. In the next section, we provide a brief background of the conservation reserve program, the transition incentive program, and the linkage between the two programs. We describe the empirical model in section three and the data construction in section four. We present the empirical results in section five. The final section provides concluding remarks.

2. Background of the Transition Incentive Program

The Transition Incentive Program is a federal program that seeks to transfer near-expiring Conservation Reserve Program (CRP) lands from an original landowner to a beginning, veteran, socially disadvantaged farmer or rancher who is not a family member (USDA–FSA, 2019a). The program was established to alleviate the land acquisition issues faced by BFRs under the 2008 Farm Bill. Initially, the federal program provided $25 million over five years, and the mandatory funding level increased to $33 million over the next five years (National Sustainable Agriculture Coalition., 2014). Subsequently, the 2018 Farm Bill further increased funding to $50 million through 2023 (USDA–FSA, 2019a). Although the program fund keeps increasing under various Farm Bills, it has experienced some changes. For instance, the 2014 Farm Bill modified the program eligibility to include veterans and socially disadvantaged farmers, while the 2018 Farm Bill has expanded the eligibility of the program to all CRP contract holders and allowed farmers to count the last two years of their expiring CRP contract towards the three years required for organic certification (Calo & Peterson-Rockney, 2018).

The CRP is the most extensive private land retirement program in the United States. Under this program, landowners are offered 10–15-year contracts and are paid an annual rental payment in exchange for enrolling their sensitive cropland for conservation use to improve environmental health (USDA, 2018). Objectives of the CRP are to reduce soil erosion, enhance biodiversity, improve air and water quality, decrease surplus production of agricultural commodities, and provide income support for landowners enrolled in the program (Ribaudo et al., 2001). Initially, the CRP started with about 8 million acres in 1986 but has increased to about 23.4 million acres in 2020 with a per acre rental payment ranging from \$60 – \$150 (USDA, 2020). The CRP uses a cap and environmental benefits index system to control the acreages and type of croplands enlisted into the program. This strategy controls the program's land supply and ensures that highly productive agricultural lands are not enrolled for conservation purposes. Initially, each county could enroll up to 25% of the total croplands into the program (U.S. Congress, 1990). The 25% allotted land policy had to be cropped for 2–5 years preceding enrollment and had to be environmentally sensitive. However, the cropping criteria of 2–5 years was modified to 4–6 years under the Farm Security and Rural Investment Act of 2002 (USDA, 2020).

According to the 2023 Farm Service Agency report, TIP creates an opportunity to return conservation lands for agricultural use while preserving established conservation practices. Subsequently, the program allows underserved farmers to expand their farming activities while ensuring sustainable agricultural practices. TIP requires that landowners sell, enter into a long-term lease (at least five years), or a lease with an option to purchase some or all of the land covered by CRP to a BFR or socially disadvantaged farmer who is not a family member. As part of the agreement, the landowners gain additional benefits and rental payments from CRP enrollment (USDA–FSA, 2023). Conversely, the program mandates that the BFR, socially disadvantaged farmers, or veterans implement conservation plans on the land. This agreement allows the recipient to own lands for sustainable agricultural use. While TIP participation fluctuates with the number of acres expiring from CRP in any given year, the program has proven useful across regions with high CRP enrollments. Since the program was first created, over 3,200 producers have used TIP to transfer more than 500,000 acres of land to underserved farmers (Valliant & Freedgood, 2020).

Access to farmland remains one of the challenges new farmers face when entering into agriculture. However, the federal land transfer program, which encourages landowners to sell or lease long-term to new and underserved farmers, is poorly patronized and unpopular in certain parts of the country (USDA-FSA, 2019a). For instance, states like Georgia, Alabama, Mississippi, and Louisiana have not utilized TIP funds. However, it is popular in the Midwest and Plain agricultural regions. For instance, Minnesota has demonstrated high demand and efficient usage of the program and managed to obligate $2.2 million to farmers who transferred CRP lands to BFRs. This land transfer translates into about 19,528 acres of Minnesota farmland for the next generation of farmers (Valliant & Freedgood, 2020). The TIP has also proven popular in states such as North Dakota and Nebraska, as evidence shows the use of TIP funds (Valliant & Freedgood, 2020).

3. Empirical Approach

3.1 Conceptual Framework

Ideally, we would like to have data on the actual TIP usage to determine if it is associated with an increase in the BFR numbers, but unfortunately such data are not available. As the use of TIP should be closely linked to the available CRP acreage, we create two groups of counties: high–CRP and low(no)–CRP, following the concept used in Brown et al. (2019).[3] We identify these groups based on the share of acres enrolled in CRP over the total cropland acres. The underlying assumption is that there is no opportunity for BFRs to participate in TIP if there are no or very few acres enrolled in CRP. We classify such counties as a "control" group. The "treated" counties are those that have more than 25% of their total cropland acres enrolled in CRP because TIP participation is likely in high CRP participation.[4] Matching the control and treatment counties based on their characteristics described below allows isolating the impact of the TIP on the BFR numbers.

There are specific identification issues that need to be addressed. First, CRP acreages are not random, as landowners self–select into the program (Jang & Du, 2018). Second, government agencies that regulate the CRP attempt to restore the ecological value of highly erodible agricultural lands by considering several factors, including enrollment caps, selection procedures, and the overall suitability of the land to qualify for the CRP (USDA, 2021). Thus, we expect

[3] Brown et al. (2019) apply the same approach to determine the effect of the conservation reserve program on rural economies: deriving a statistical verdict from a null finding. They assume that counties with low–CRP lands serve as control and counties with high–CRP lands serve as the treatment.

[4] While the CRP mandates a cap of 25% of total cropland, the majority of counties with non-negligible shares of CRP acres exceed it. The distribution of CRP enrollment on county level is highly bi-modal. We consider this 25% enrollment cap in our analysis because some counties reach and exceed this cap because of the opportunity to enroll in continuous sign-up after the general sign-up (Hellerstein, 2017). Moreover, the 25% cap requirement at the county–level is not strictly enforced in that "the Secretary [of Agriculture] determines that such action would not adversely affect the local economy of such counties" (Food Security Act of 1985, P.L. 99–198, p. 1509).

landowners to enroll lands with lower opportunity cost.[5] These issues are primarily resolved by using matching techniques to eliminate the non-randomness by comparing high-CRP counties to as similar as possible low–CRP counties using observable confounders that are correlated with CRP enrollment. This strategy controls for various factors that affect BFRs and also attenuates the selection biases and endogeneity. Another concern is the suitability of the CRP lands to support BFR farm activities. Since the CRP contracts last for about 10–15 years, we assume that the acres enrolled in the CRP might have improved sufficiently in quality, as evidence shows that CRP tends to improve soil health and water quality as well as reduce erosion (Allen & Mark, 2012).

3.2 Econometric Specification

3.2.1 Propensity Score Matching

Propensity score matching (PSM) helps overcome the endogenous treatment selection biases inherent in observational studies. To estimate the effect of the TIP on the number of BFRs we first follow Rubin (1974), defining the average treatment effect on the treated (ATT):

$$ATT = E[Y_1 - Y_0|Z,\ D = 1] = E[Y_1|Z, D = 1] - E[Y_0|Z, D = 1] \qquad (1)$$

where Y_1 and Y_0 are the (potential) outcomes with the treatment and control, and D indicates whether the county is treated (1) or not treated (0). In this context of this study, high – CRP counties and low – CRP counties denote the treatment and control groups respectively. Vector Z is a set of covariates that affect both high-CRP counties and low-CRP counties.

The ATT is estimated using a matching algorithm that utilizes propensity score estimates that characterize a unit's attributes in Z. Since an observation can only be classified as treated or control, a matching by propensity score procedure provides a counterfactual estimate of the potential outcome of an untreated unit if it were treated conditional on Z $E[Y_0|Z, D = 1]$. The propensity score is the probability treatment (selection into a treatment group) conditional on the covariates in Z:

$$P(Z) = \Pr\,(D = 1|Z) \qquad (2)$$

We estimate the propensity score using a logit model where the variable of interest, TIP, is zero if the share of acres enrolled in CRP over the total cropland acres is zero or negligible and one if the

[5] There may be exceptions to this case as landowner enrollment decisions may depend on the state of the agricultural economy and other macroeconomic factors (Henricks and Er, 2018).

share of acres enrolled in CRP over the total cropland acres is greater or equal to 0.25. Combining the expression for the ATT with the propensity score, we express ATT as:

$$ATT = E[Y_1 - Y_0|P(Z),\ T = 1] = E[Y_1|P(Z), T = 1] - E[Y_0|P(Z), T = 1] \quad (3)$$

The ATT obtained using propensity scores may be interpreted as causal if the outcome satisfies the exchangeability assumption (Rubin, 1974). Exchangeability implies that if the two groups exhibit similar characteristics and potential outcomes, there are no measurement errors that may likely imbalance the groups. As this assumption is unrealistic in observational research, we control for counties' known characteristics, which allows us to achieve conditional exchangeability (Cole and Hernán, 2008). When there is a disbalance, propensity score matching is useful to eliminate the selection bias by balancing covariates between the treatment and control groups to provide causal inference (Imbens and Wooldridge 2009; Ferraro and Miranda 2017).

The propensity score matching algorithm (kernel, nearest neighbor or alternative) matches units from treatment and control groups by their propensity (balancing) scores as they summarize the set of covariates used in the scores' estimation. Treatment and control counties that have (almost) the same propensity scores exhibit similar characteristics (Rosenbaum and Rubin, 1983). The covariates used for matching are based on previous literature and include population density, average farm size, per capita median household income, crop price index, phosphorus and nitrogen on-farm fertilizer application, temperature (GDD 10 – 29^{0}C), precipitation, total agricultural sales, government support payments, farmland prices, net farm income, operators age between 35–64, and operators age above 64 years.

The reduced–form regression features a full set of location and time effects after matching treated and untreated counties is:

$$BFR_{it} = \beta_0 + \beta_1 TIP_{it} + \boldsymbol{X'_{it}}\beta_n + \eta_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where $\boldsymbol{BFR_{it}}$ is the number of BFRs in county *i* at time *t*; $\boldsymbol{TIP_{it}}$ is the policy variable, which is the interactive dummy that equals one if the year is 2012 or 2017 (after TIP) and the county is high-CRP (treated) and zero otherwise; $\boldsymbol{X'_{it}}$ is a vector of county attributes; $\boldsymbol{\beta_j}, j \epsilon \{1, \dots, n\}$, are coefficients to be estimated[6]. We control for time-constant land attributes such as soil quality,

[6] TIP_{it} is the interaction between two variables. First, we generate a time dummy variable to denote the pre-and-post transition policy implementation. We denote pre policy implementation periods as 0 and post policy implementation period as 1. Second, we construct a dummy variable to denote the treatment and control counties as already discussed where treatment counties are 1while control counties are 0. We interact the two variables to obtain our policy instrument so that our analysis captures the effect of post–TIP establishment.

climate, etc., through the fixed effects $\boldsymbol{\eta_i}$. The effects of common macroeconomic shocks, such as changes in commodity prices and region-specific unobservable are absorbed through the time effects $\boldsymbol{\lambda_t}$; $\boldsymbol{\varepsilon_{it}}$ is the idiosyncratic error term. Estimation of this linear model requires two important assumptions that ensure no significant bias in models with fixed effects: that counties respond homogeneously to economy-wide or regional shocks and that the treatment effect is additive homogenous so that it does not depend on counties' characteristics. We report the estimated $\widehat{\boldsymbol{\beta}}$ via the fixed effects estimation and compare with the estimated $ATTs$.

4. Data and Variables

To determine the impact of the TIP on BFRs, we use county-level data from 2002 through 2017 with 5-year intervals from multiple sources. CRP practices differ by location and environmental objectives. For instance, landowners in the southeast U.S. adopt tree-planting measures (Assogba and Zhang, 2022) while landowners in the Midwest and the Plains adopt various tillage practices, which makes accessing CRP land much less expensive (Holland et al., 2020; Zuber et al., 2017; Behnke et al., 2018).[7] We focus our analysis on 15 states – Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, and Wisconsin – which together account for a vast majority of CRP acreage and are active participants in the TIP program (Dickinson et al., 2020; Sustainable Agriculture Coalition, 2015). Figure 1.1 shows the map of the study area.

For the dependent variables, we use four subgroups of BFRs by their farming experience: BFRs with <3yrs, <5yrs, and 5–9 years of farming experience, as well as BFRs principal operators. Most of the data come from the Census of Agriculture and National Agricultural Statistics Service (USDA–NASS) website.[8] The binary treatment variable is the share of acres enrolled in CRP over the total cropland acres. Counties with shares of cropland in CRP greater or equal to 0.25 are considered "treated groups", while counties with zero or infinitesimal values are considered "control groups"[9]. The CRP acreage data (total acres of land enrolled for conservation purposes)

[7] Holland et al. (2020) find evidence of switching conservation lands for continuous cropping in the wake of high crop prices.
[8] Data source, detailed explanation, and related definitions are attached the appendix section of this paper.
[9] We focused our analysis on these two groups and omit counties in between from the study. This decision is motivated by past studies and reports (Sullivan et al., 2004; Brown et al., 2019) that utilize low–CRP counties and high–CRP in their analysis.

comes from the USDA-FSA (FSA, 2019). The cropland data represents the total amount of cropland in each county and is obtained from the USDA (USDA – NASS, 2019).[10]

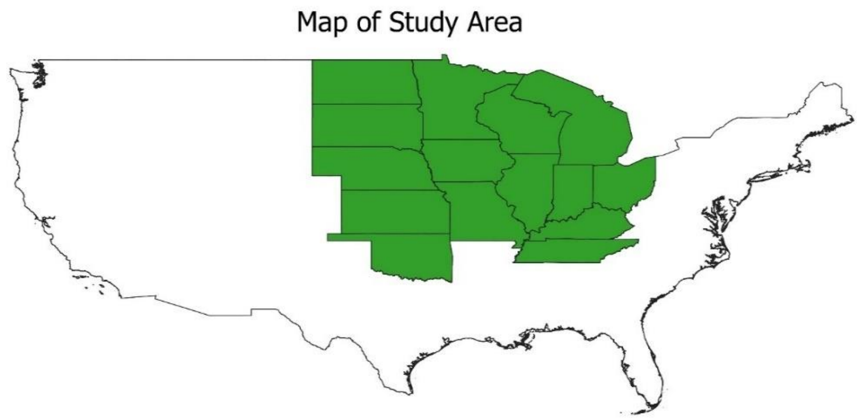


Figure 2.1: Map of study area

A number of control variables are used in the propensity score and fixed effects estimations. County-level crop production and deflated state-level prices are used to construct a Laspeyres' crop price index for nine agricultural commodities (Li et al., 2019).[11] The index is computed as $(\sum_{l=1}^{9} Pl_{it} Ql_{i2002})/(\sum_{l=1}^{9} Pl_{i2002} Ql_{i2002})$, where Pl_{it} is the received price of crop l in state i at time t and Ql_{i2002} is the production of crop l in state i at the base year, 2002. Farmland price controls for agricultural land value. County-level average farm size is computed as the total cropland area operated divided by the number of farm operations (Hartarska et al., 2022). On-farm nitrogen and phosphorus fertilizer application data come from Brakebill and Gronberg (2017). We include the monetary value of the total agricultural sales in each county in the analysis. This variable measures the total value of production that comprise of both crop sales and livestock sales. Thus, we are able to capture the cropland and pastureland production value. We follow Schlenker and Roberts (2009) and include climatic variables such as growing degree days (GDD) as a

[10] The total cropland acres include idle cropland, which include CRP acreages.
[11] The nine crops are barley, corn, oats, peanuts, rice, rye, sorghum, soybeans, and wheat.

measure of temperature and precipitation in our study. Growing degree days are defined as the accumulated degrees that fall into the range that is favorable for crop production. We adopt the range of between 10 and 32 degrees Celsius. Similarly, we include precipitation in our analysis. The climate data are obtained from Schlenker and Robert (2009) where they build the dataset based on the Parameter-elevation Regressions on Independent Slopes Model (PRISM) weather dataset.

Additional control variables include population density, average net farm income, median household income per capita, government payments received, and operator's age (Hartarska et al., 2022, Stevens et al., 2022). Population density is defined as $PD = (Pop/LA)$ where Pop is county's population and LA is the total land area in count. Data on population density, median household income, farm earnings, and government support payments are obtained from the Bureau of Economic Analysis (BEA). To control for operators' characteristics, we include the number of farm operators aged 35 to 64 and above 64 years old from USDA–NASS to capture both active and retiring farmer participation. All income and prices are in 2017-dollar value computed using the consumer and producer price indices. Table 1 displays the summary statistics for the full sample, and for the treatment and control groups. The full sample consists of 1144 county-by-year combinations while the treatment and control groups before matching have 334 and 810 observations respectively. On average, there are more BFRs in the control counties. Population density is much smaller while average farm size and farm income are much larger in the treatment group. Curiously, the treatment counties seem to have more fertilizer applications and government payments, although the standard deviations indicate large outliers. The treatment group has a majority of farm operators aged between 35–64 years whereas the control has a majority of farm operators above 64 years. There is not much of a difference between the treatment and control group with respect to the crop price index.

Table 2.1: Summary Statistics

A. All groups				
Variables	Mean	Std. dev.	Min	Max
Dependent variables				
BFRs experience <3yrs	31.86	31.63	1	251
BFRs experience <5yrs	80.67	72.8	2	588
BFRs experience 5 – 9yrs	111.5	86.13	1	539
BFRs experience <10yrs	192.82	153.13	8	1015
Independent variables				
Population density	155.09	430.83	0.34	3259.41
Median household income	14642.02	3560.58	7972.57	37395.2
Crop price index	142.36	33.07	39.21	250.82
Farm earnings	3878.82	9309.86	-7299.46	161876
Farmland price	3066.38	1465.35	599.51	8000
Average farm size	382.52	625.26	7.45	7735.87
Nitrogen application	2054709	2847882	0	22000000
Phosphorus application	315775.5	433251.6	0	3400000
Operators age between 35 – 64 years	455.75	319.66	8	2256
Operators age > 64 years	234.14	171.92	3	1321
Precipitation	79.96	22.68	19.71	146.92
Temperature (GDD 10–29^{0}C)	1899.21	338.27	1059.47	2560.29
Total agricultural sales	60700000	99400000	33000	1140000000
Government payment	2520.33	3525.53	0	23077
Observations			**1144**	

B. Type of group	**Treatment group**		**Unmatched Control group**	
Variables	Mean	Std. dev	Mean	Std. dev
Dependent Variable				
BFRs experience <3yrs	25.26	16.73	34.59	35.67
BFRs experience <5yrs	65.55	38.81	86.91	82.06
BFRs experience 5 – 9yrs	103.19	57.71	114.93	95.24
BFRs experience <10yrs	168.74	92.94	202.74	170.98
Independent Variable				
Population density	17.87	20.42	211.67	501.1
Median household income	15121.68	3361.79	14444.24	3622.94
Crop price index	144.75	28.2	141.38	34.85
Farm earnings	7908.06	12142.49	2217.38	7231.98
Farmland price	2754.65	1932.32	3194.92	1200.07
Average farm size	720.74	639.32	243.05	563.39
Nitrogen application	4,486,480	3,135,087	1,051,978	1,991,235
Phosphorus application	670,870	478,830	169,354	311,935
Operators age between 35 – 64 years	436.23	224.67	231.52	192.79
Operators age > 64 years	240.51	105.37	463.79	351.24
Precipitation	62.88	24.33	87	17.69
Temperature (GDD 10–29^{0}C)	1809.32	329.98	1936.26	334.87
Total agricultural sales	113000000	134000000	39300000	70600000
Government payment	6467.15	3390.71	892.87	1935.3
Observations	**334**		**810**	

5. Results

5.1 Logit Results

Table 2.2 contains the results for a logit model where the dependent variable is whether a county is in the treatment (high CRP share can utilize the TIP) or in the control group. The model estimates propensity scores used in the PSM algorithm. The results show a good model (Pseudo R^2 about 75%) fits with intuitive interpretations.

Population density is negative (0.09), consistent with the land use literature indicating that increasing population puts pressure to convert alternative land use types for development purposes (Adjei et al., 2023; Lubowski et al., 2008). We realize that household income and net farm income have no significant association with counties with high CRP lands. We find that CRP enrollment decrease average farm size and increase farmland prices in counties with high CRP land. This is an expected outcome and consistent with the farmland demand-supply theory (Konyar & Osborn, 1990). Government payments increase the probability of being a high-CRP county, likely because they support farm production activities and in line with the findings of Key et al. (2005) that government payments positively correlate with the decision to participate in conservation programs.

We control for the potential BFRs by including the number of operators aged 35 to 64 years and find a negative effect but a positive effect for operators older than 64 years, which is intuitive as retirement age farm operators are more likely to engage in conservation programs compared to younger farm operators (Lambert et al. 2007). We find that total agricultural lands is positively associated with high-CRP counties. This is an expected result as the majority of enrolled CRP lands are located in areas with large acres of agricultural lands (Cornish et al., 2021). Turning to the climate variables, we find significant outcomes associated with high–CRP lands. This is an expected association as climate variables affect farmland decision making.

Table 2.2: Logit Results for Higher-CRP Counties, coefficients, and marginal effect

Variable	Coefficient	Marginal effects
Population density	-0.0222***	-0.0009***
	(0.0059)	(0.0002)
Median household income	-0.0001	-0.0004
	(0.0001)	(0.0003)
Crop price index	0.0086*	0.0004*
	(0.0047)	(0.0002)
Farm earnings	-0.0001	-0.0002
	(0.00004)	(0.0002)
Farmland price	0.0007***	0.00003***
	(0.0001)	(5.86e-06)
Average farm size	-0.0021***	-0.0001***
	(0.0004)	(0.00002)
Nitrogen application	-0.0006***	-0.0003***
	(0.0002)	(0.0001)
Phosphorus application	-0.0004**	-0.0002**
	(0.0002)	(0.0001)
Operators age between 35–64 years	-0.0062***	-0.0003***
	(0.0013)	(0.0001)
Operators age > 65 years	0.0086***	0.0004***
	(0.0022)	(0.0001)
Government payment	0.0007***	0.00003***
	(0.0001)	(4.46e-06)
Temperature (GDD 10–29^{0}C)	0.001***	0.00004***
	(0.0003)	(0.00001)
Precipitation	-0.1667***	-0.007***
	(0.0519)	(0.0022)
Total agricultural sales	-0.0001***	-0.00004***
	(0.00003)	(0.00001)
Total agricultural land	0.0001***	2.52e-04***
	(6.87e-05)	(2.51e-05)
Observations	1,144	1,144
Log likelihood	-170.605	
Pseudo R^2	0.7531	

Notes: Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. The coefficient standard errors are robust in nature. The marginal effect errors are obtained using the Delta method.

5.2 Matching and Balancing

We use the nearest neighbor propensity-score matching estimator to match the “treatment” (high CRP enrolment) to the “control” counties based on the estimated propensity score values to estimate the ATT for the regression adjusted model. The algorithm matched 283 treatment and 660 control observations out of 1144, with the average standardized mean difference of approximately

5.5 indicating a satisfactory balance as desired in the quasi-experimental framework. Table 2.3 reports the covariate balancing results.

Table 2.3: Covariate Balance for propensity score matching (Regression Adjustment)

Variable	High-CRP counties	Low-CRP counties	| Standardized Difference |	p>|t|
Population density	15.16	15.081	0.00	0.954
Median household income	0.004	0.05	5.7	0.484
Crop price index	145.19	147.07	5.8	0.5
Farm earnings	0.031	0.004	3.2	0.702
Farmland price	0.004	0.002	0.2	0.98
Average farm size	0.063	0.003	7.1	0.389
Nitrogen application	0.074	0.003	9.3	0.264
Phosphorus application	0.091	0.004	11.3	0.19
Operators age between 35 – 64 years	0.0228	0.001	2.6	0.761
Operators age > 64 years	0.015	0.002	2.1	0.795
Government payment	0.003	0.165	19.4	0.081
Temperature	0.663	0.626	5.7	0.488
Precipitation	0.004	0.052	6.8	0.398
Total agricultural sales	0.003	0.013	2.0	0.812
Total agricultural land	0.003	0.015	1.4	0.87
Observations (counties)	286	636		

***Note*:** We transformed and normalized our covariates to bring the features to a common scale without distorting the differences in the range of the values. The standard difference is calculated as $100 * (X_T - X_M)/\sqrt{(S_T^2 + S_R^2/2)}$ where X_T and X_M are the means across matched with high-CRP counties and low-CRP counties respectively. S_T and S_R denote the standard deviations in the matched with high-CRP counties and low-CRP counties respectively. Rosenbaum and Rubin (1985) suggest that the bias is problematic when a standardized difference exceeds 20.

5.3 Treatment Effect Results

We estimate the effect of TIP on four types of BFRs. We first determine the ATT by comparing high–CRP counties and low–CRP counties in the matched and balanced samples. The main result comes from estimating the ATT by a regression adjustment (RA) model. The regression adjusted model offers the opportunity to control for additional covariates to improve the estimated average treatment effect ATE (Lin, 2013; Negia & Wooldridge, 2021). The estimated ATT coefficients from all the estimation strategies present the averages of the individual treatment effect for BFRs in the treated group.[12]

Table 2.4: Average Treatment Effect on the Treated (ATT)

	Regression Adjusted (RA)			
	BFRs <10yrs	BFRs 5 – 9yrs	BFRs <5yrs	BFRs <3yrs
ATT	34.1863***	23.6498***	11.1609***	3.7213***
	(9.3032)	(6.0721)	(4.0984)	(1.7941)
95% confidence interval	(15.9282, 52.4444)	(11.7329, 35.5667)	(3.1176, 19.2043)	(0.2002, 7.2425)

Notes: Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are bootstrapped based on 200 bootstrap draws. The 95% confidence intervals (bias–corrected) for the propensity score model is based on 200 bootstrap draws. All results are based on 2 nearest neighbors matched. All covariates (including county dummies) are included in the regression adjusted model. The bootstrapped standard errors and 95% confidence interval (normal-based) for the regression adjusted models are based on 200 bootstrap draws.

We estimate, as presented in Table 2.4 that the increase in the number of in principal BFRs in high-CRP counties is at an average of around 34. Additionally, we report that BFRs with 5-9 years of farming practice experience an increase of around 23 in high-CRP counties. Lastly, we find that the average number of BFRs with <5yrs- and 3-yrs farming experience in high–CRP counties is approximately 11and 3 respectively. Our findings show that the increase in BFRs with <3yrs of agricultural experience increases with each next group as expected.

Similarly, we perform an inverse probability weighting (IPW) mechanism to estimate the effect of TIP on the four types of BFRs. The IPW is a beneficial method as it doubly robust in nature. That is, if either the propensity score model or the outcome model is correctly specified, the estimated effect of interest will be unbiased (Stevens & Teal, 2023; Funk et al., 2011). The IPW uses a quasi–maximum likelihood method to estimate the parameters of the conditional probability model (Melstrom, 2020). Since we are interested in the ATT, we follow Wigger et al. (2019) and adopt the normalized treatment-adjusted inverse-probability weights method. Again, we follow Imai and Ratkovic (2014) and conduct a test to check whether the propensity score is correctly specified and balanced for the IPW model. From the test, we reject the null hypothesis

[12] From this study, our ATT simply denotes the absolute difference between BFRs in high–CRP counties and low–CRP counties through the propensity scores. We say that, conditional on the propensity scores, the outcome and treatment are independent. This is equivalent to saying that high–CRP counties and low–CRP counties with the same propensity scores differ in treatment only for random reasons when they share the same covariates.

$\boldsymbol{chi2(16) = 20.4529}$; $\boldsymbol{Prob > chi2 = 0.2005}$ and conclude that the covariates are balanced. Table 2.5 reports the covariate balancing results for IPW.

Table 2.5: Covariate Balance for inverse probability weighting (IPW)

Variable	Raw	Weighted
Population density	-0.5621	-0.0725
Median household income	0.6224	-0.0478
Crop price index	0.1011	-0.0456
Farm earnings	-0.0694	0.0081
Farmland price	0.0691	-0.0373
Average farm size	0.6738	0.0255
Nitrogen application	0.5799	0.0341
Phosphorus application	0.5809	0.0548
Operators age between 35 – 64 years	-0.0231	0.0019
Operators age > 65 years	0.0494	-0.0344
Government payment	0.0585	-0.0067
Temperature	-0.7072	-0.0137
Precipitation	-0.1007	0.0391
Total agricultural sales	0.6195	-0.0266
Total agricultural land	-0.5391	0.0448
Observations	922	922
Treatment counties	286	474
Control counties	636	447

Note: This table presents the covariate balance for the IPW.

After ascertaining the certainty of our covariate balance, we estimate the ATT for the IPW model and present the results in Table 2.6. We find that TIP has a positive association with the different types of BFRs. In particular, we observe an increase in the number of in principal BFRs in high-CRP counties at an average of around 39. Moreover, we report that BFRs with 5-9 years of farming practice experience an increase of around 32 in high-CRP counties. Lastly, we find that the average number of BFRs with <5yrs- and 3-yrs farming experience in high–CRP counties is approximately 11and 4 respectively. Our findings show that the increase in BFRs with <3yrs of agricultural experience increases with each next group as expected and consistent with the RA estimates.

Table 2.6: Average Treatment Effect on the Treated (ATT)

	Inverse Probability Weighting			
	BFRs <10yrs	BFRs 5–9yrs	BFRs <5yrs	BFRs <3yrs
ATT	39.6355***	32.1762***	11.6858***	4.0705***
	(8.7996)	(5.4059)	(3.7878)	(1.6265)
95% C. I.	(22.3885 56.8825)	(21.5807 42.7717)	(4.2618 19.1098)	(0.8825 7.2585)

Notes: Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.4 Robustness checks

We conduct a series of robustness checks to probe the sensitivity of our results to the characteristics of the research design. We adopt two matching methods to test the robustness of our results. First, we adopt the kernel Nearest Neighbor (KNN) matching method to determine the effect of TIP on BFRs. Following Rosenbaum and Rubin (1985), we apply two approaches to assessing matching quality: (1) the Standardized Percentage Bias method, which calculates the percentage bias reduction after matching; (2) the Two-sample *t-test* method to test whether there is still a significant difference in covariates between high–CRP counties and low CRP–counties.

The matching quality test for KNN is $(n = 2)$ as we select matches that minimize the "Mahalanobis distances" between the two groups. The Mahalanobis distance measures the similarity between observations based on a set of key characteristics-the smaller the distance, the more similar the matching, based on the characteristics being examined. From Table 2.7, the two-sample t-test results show that all variables are statistically insignificant between the high–CRP counties and low CRP–counties group after KNN matching. The results from the KNN indicate an increase in the number of in principal BFRs in high-CRP counties at an average of around 49. Moreover, we report that BFRs with 5-9 years of farming practice experience an increase of around 38 in high-CRP counties. Lastly, we find that the average number of BFRs with <5yrs- and 3-yrs farming experience in high–CRP counties is approximately 14 and 5 respectively. The results are presented in Table 2.8.

Table 2.7: Covariate Balance for Kernel Nearest Neighbor Propensity Score Matching

Variable	High-CRP counties	Low-CRP counties	| Standardized Difference |	p>|t|
Population density	15.396	22.226	1.8	0.310
Median household income	0.007	0.043	4.3	0.609
Crop price index	144.85	146.88	6.3	0.456
Farm earnings	0.002	0.016	2.2	0.798
Farmland price	0.008	0.035	3.2	0.698
Average farm size	0.011	0.012	2.8	0.739
Nitrogen application	0.001	0.011	1.2	0.886
Phosphorus application	0.001	0.037	4.3	0.619
Operators age between 35 – 64 years	0.008	0.002	1.2	0.892
Operators age > 65 years	0.003	0.027	2.9	0.730
Government payment	0.004	0.008	0.6	0.945
Temperature	0.003	0.006	1.2	0.885
Precipitation	0.670	0.641	4.3	0.604
Total agricultural sales	0.006	0.047	5.0	0.557
Total agricultural land	0.002	0.023	2.5	0.771
Observations	286	636		

Table 2.8: Average Treatment Effect on the Treated (ATT)

	Kernel Nearest Neighbor Matching (KNN)			
ATT	49.0229***	38.7325***	15.6485***	6.0625***
	(14.1691)	(6.7654)	(5.1431)	(2.6371)
95% C. I.	(21.252, 76.7937)	(25.4724, 51.992)	(5.5681, 25.729)	(0.8938 11.231)

Notes: Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are bootstrapped based on 200 bootstrap draws. The 95% confidence intervals (bias–corrected) for the propensity score model is based on 200 bootstrap draws. All results based on 2 nearest neighbors matched sample.

We employ the nearest neighbor matching NNM approach as an alternative sensitivity test method. We present the covariate balancing results for NNM methods in Table 2.9 and the estimated ATT in Table 2.10. We find a similar satisfactory covariate balance test. Again, we notice that TIP has a significant effect on increasing the number of BFRs in high–CRP counties. For instance, principal BFRs numbers increase by 55 in high – CRP counties. Also, BFRs with 5-9 years of farming practice experience had an increase of around 38 in high-CRP counties. Lastly, we find that the average number of BFRs with <5yrs- and 3-yrs farming experience in high–CRP counties is approximately 18 and 6 respectively.

Table 2.9: Covariate Balance for Nearest Neighbor Propensity Score Matching

Variable	High-CRP counties	Low-CRP counties	| Standardized Difference |	p>|t|
Population density	15.39	15.31	0.00	0.954
Median household income	0.007	0.055	5.7	0.49
Crop price index	144.85	146.31	4.5	0.604
Farm earnings	0.0022	0.038	4.4	0.606
Farmland price	0.008	0.003	1.3	0.875
Average farm size	0.0114	0.069	7.0	0.405
Nitrogen application	0.001	0.068	8.2	0.335
Phosphorus application	0.002	0.074	8.7	0.313
Operators age between 35 – 64 years	0.008	0.012	0.6	0.948
Operators age > 65 years	0.003	0.009	1.5	0.857
Government payment	0.004	0.156	18.2	0.082
Temperature	0.669	0.637	4.9	0.55
Precipitation	0.003	0.054	6.0	0.461
Total agricultural sales	0.005	0.014	2.4	0.782
Total agricultural land	0.002	0.01	1.5	0.858
Observations (counties)	281	636		

Note: The Mahalanobis distance metric takes the form $d^2(X_T, X_C) = (X_T - X_c)'\Sigma^{-1}(X_T - X_C)$, where X is the vector of selection variables, T is the treatment (i.e. high-CRP) county, C is a control county, d is the Mahalanobis distance between the two vectors, and Σ is the variance-covariance matrix of possible control counties. Rosenbaum and Rubin (1985) suggest that the bias is problematic when a standardized difference exceeds 20.

Table 2.10: Average Treatment Effect on the Treated (ATT)

	BFRs <10yrs	BFRs 5–9yrs	BFRs <5yrs	BFRs <3yrs
ATT	55.2941***	38.8541***	18.5938***	6.938***
	(12.3877)	(7.2122)	(7.9964)	(2.6309)
95% C. I.	(31.0146 79.5736)	(24.7183 52.9898)	(2.921 34.2665)	(1.7814 12.0946)

Notes: Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses are obtained using the Delta method.

6. Discussion and Policy Implications

The objective of this research is to determine how the federal transition incentive program that seek to transfer CRP lands from an original landowners to a BFR has encouraged entry and also increased the number of BFRs into the agricultural sector. Given that the CRP acreage that supports the TIP is unevenly distributed across the country, could the program exhibit varying effect based on the availability of CRP lands in the counties? How might the distribution of these CRP acreages influence the growth rate of BFRs? To achieve our research objectives, we instrument the federal transition program by using the share of acres enrolled in CRP over the total cropland acres as a local measure to differentiate between high–CRP counties and low–CRP counties. Afterwards, we analyze the impact of the program on the number of BFRs using different estimation strategies.

Our first set of analysis adopts a logistic regression to determine how socio-economic factors, agricultural attributes, and commodity prices affect high–CRP counties relative to low–CRP counties. Our findings demonstrate statistical significance with intuitive interpretations. For instance, we find that operators age above 64 years has positive and significant association with high–CRP counties. This is intuitive as retiring farmers prioritize exiting agriculture and enrolling their croplands in conservation programs in exchange for rental benefits. A study by Valliant et al. (2021) show that about 75% of retiring farmers in the Midwest and Plain regions showed interest in transferring their farmlands to fund their retirements. Demographic factors are often used to explain land use patterns, so we determine the effect of population density and find a negative effect on high – CRP counties. Our outcome aligns with previous studies on land use patterns as population density captures opposing effect on CRP enrollment (Plantinga et al., 2001). In addition, we realize that the climate variables showing opposite and significant effect as the accumulated temperature for growing degree days 10 – 29^0C is positive whereas precipitation is negative. We expect these significant outcomes as temperature and precipitation affect crop yield, thereby affecting returns from farming which invariably influence CRP enrollment decisions (Cornish et al., 2021). We realize that the government support payments have a positive association with CRP enrollment. This is because rental payments from CRP participation serve as additional income to offset farm labor cost to improve the overall economic well–being of households (Chang et al., 2008). Moreover, government payments have a positive effect on high–CRP counties as these regions are characterized as agricultural hubs. The government has a support program through crop insurance and other programs that ensure that farmers have sufficient income to support their agricultural activities.

From our analysis, we find that the federal transition program has been effective by increasing the number of BFRs in high–CRP counties. The increase in BFR numbers is laudable as the prospect of the federal transition program has the potential to improve upon the number and drive entry of beginning farmers into agriculture. Apart from the higher rates of BFRs, the TIP ensures the adoption of sustainable agricultural practices as the program mandates BFRs to continue with the environmental practices already adopted on the land (USDA–FSA, 2019b). The positive outcome of the TIP in improving upon the number of BFRs could represent, to an extent, the support established farmers are willing to offer young farmers through land transfer. We compare our study with a similar policy, Land Access Policy Incentive (LAPI), that seeks to facilitate the transfer of farmlands to BFR. Original landowners who are engaged in the LAPI benefit by earning a refundable state tax credit equal in value to a portion of the income earned through the land access agreement. However, this policy differs from the TIP as landowners under the TIP earn two years of additional CRP payment. Valliant et al. (2022) indicated that landowners in the Midwest and the Plain regions are willing to transfer farmland to BFRs. Interestingly, their outcome suggest that about 97% of the respondents expressed interest in transferring farmlands to BFRs who are not relatives whereas 75% expect intra-familial succession under the LAPI. These findings align with our results as we observe a significant increase in BFRs under the TIP in the Midwest and Plain regions.

7. Conclusion

We examined the impact of the federal transition incentive program on BFRs in the Midwest and Plain states with county-level data. We focus on these regions as these are areas of intensive agricultural production and are active participants in the federal transition program. The preferred model, which controls for a wide range of potential confounding factors by combining a matching design with additional covariates, indicates that the transition program has successfully increased the number of BFRs in counties with large amounts of CRP lands. In particular, the analysis suggests that the number of BFRs increased in counties with high-CRP acreage relative to counties with low CRP acreages.

These results have important policy implications. We encourage attempts to enhance the transition program in non-participating counties to improve BFR entry into the agricultural sector. Improving the number of BFRs can translate into agricultural productivity to bridge the gap between beginning and established farmers. We are aware that the county-level estimates may mask heterogeneity as some counties may be more directly affected by the CRP–TIP than others in the county, depending on the distribution of the CRP acreage. In any case, the evidence of this article indicates that BFRs located in counties with high-CRP lands improve in number compared to their counterparts in counties with low-CRP lands.

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APPENDIX

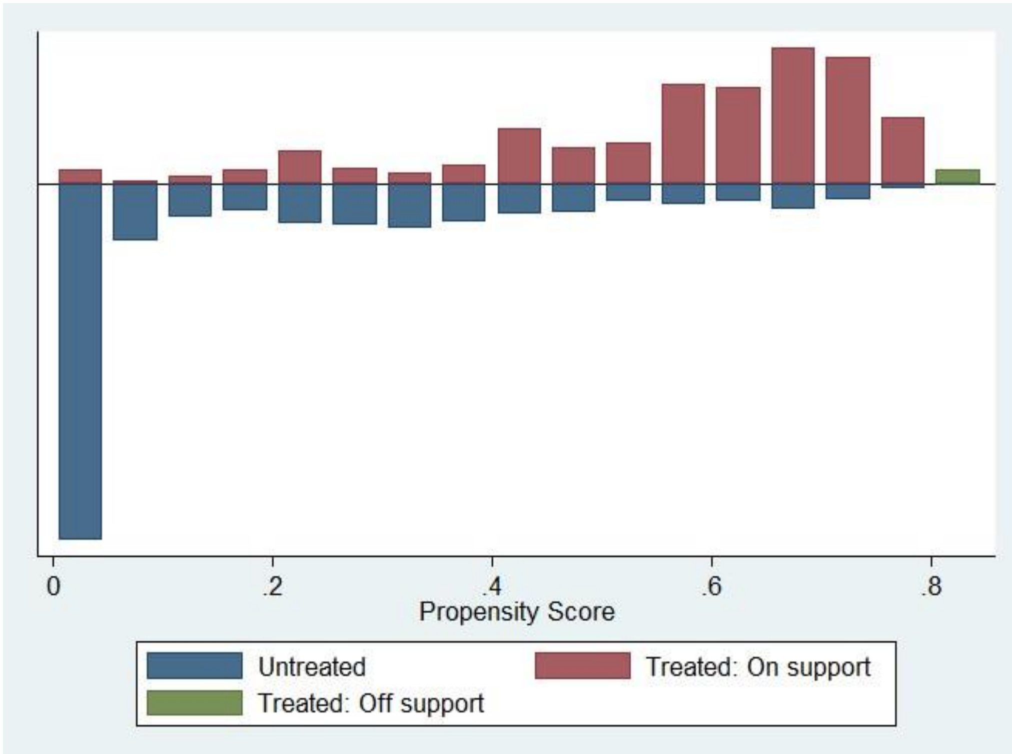

Figure 2: Covariate Balancing Test

Table 2.11: Variables and definitions

Variables	Definitions	Source
BFRs experience <10yrs	This variable denote anyone who has operated a farm for less than ten years	Census of Agriculture
BFRs experience 5 – 9 years	This variable denote anyone who has operated a farm for between 5 – 9 years	Census of Agriculture
BFRs experience <5yrs	This variable denote anyone who has operated a farm for less than five years	Census of Agriculture
BFRs experience <3yrs	This variable denote anyone who has operated a farm for less than three years	Census of Agriculture
Crop price index	This is a Laspeyres crop index constructed from county-level crop production and deflated state-level prices for 10 major agricultural commodities with 2002 as the base year.	Authors' computations from the USDA – NASS
Farmland price	This variable denotes the county – level average price of agricultural land.	USDA-NASS
Operators age between 35 – 64 years	This variable represents the number of farm operator's with ages between 35 – 64 years	Census of Agriculture
Operators age > 64 years	This variable represents the number of farm operator's with ages above 65 years	Census of Agriculture
Real farm earnings	This variable comprise of the net income of sole proprietors, partners, and hired laborers arising directly from the current production of agricultural commodities, either livestock or crops. It includes net farm proprietors' income and the wages and salaries, pay-in-kind, and other labor income of hired farm laborers; but specifically excludes the income of farm corporations	Bureau of Economic Analysis
Average farm size	The average farm size is defined as the cropland area operated divided by the number of farm operations.	Census of Agriculture
Population density	The number of individuals who reside in a given area	Bureau of Economic Analysis
Real median household income	The median household income of a given area divided by the resident population of the area	Bureau of Economic Analysis
Government payments	Federal government payments to farm operators consist of deficiency payments under price support programs for specific commodities,	Bureau of Economic Analysis (BEA)

	disaster payments, conservation payments, and direct payments to farmers under federal appropriations legislation.	
On-farm nitrogen and phosphorus fertilizer application	Nitrogen and phosphorus application is the on-farm fertilizer application data from the Association of American Plant Food Control Officials (AAPFCO) commercial fertilizer sales where state-level estimates are allocated to the county level using fertilizer expenditure from the Census of Agriculture (COA) as county weights for farm fertilizer.	Brakebill and Gronberg (2017)
Precipitation	The precipitation variable is the accumulated rainfall or snow over the growing season for each year.	Schlenker and Robert, (2006) [PRISM weather data]
Temperature	Growing degree days are defined as the accumulated degrees that fall into the range that is favorable for crop production. We adopt the range of between 10 and 32 degrees Celsius.	Schlenker and Robert, (2006) [PRISM weather data]
Total agricultural sales	The sum of the animal and crop sales	Computed using NASS – USDA data

3. CHAPTER 3

Climate Variability, Socio-Demographic, and Visitation to Natural Parks

1. Introduction

The National Park Service indicates that visits to managed national parks for recreational use generate over \$28.6 billion to the nation's economy and supports about 234,000 jobs (National Park Service, 2020). Furthermore, about 237 million visitors spend approximately \$14.5 billion in communities that are within 60 miles of a national park. Of the 234,000 jobs, about 194,400 are in communities located within 60 miles of a park. Moreover, the hotels and restaurants generate about \$5 billion and \$3 billion in economic output nationally from the recreational use of national parks. Visitors' spending supports more than 43,100 jobs in lodging and 45,900 jobs in restaurants, indicating the significance of recreation on local economies (Rosenberger et al., 2017; White et al., 2016). However, visitation to managed natural areas is highly dependent upon climate and weather apart from travel cost and other socio-economic factors (Smith et al., 2018) as many tourists select their destinations based on expected climatic conditions (Hamilton & Lau, 2006) while many regional tourists and local visitors plan their trips to areas where the near-term weather forecasts project desirable conditions (Patrolia et al., 2017; Rutty & Andrey, 2014). Often, tourists adjust their trip timing and their length of stay or the outdoor recreation activities they participate in, based on the weather (Becken & Wilson, 2013). Thus, it is possible that weather changes may threaten economic benefits from outdoor recreation due to extreme variations in temperature and exacerbating precipitation patterns.

Various factors such as financial constraints, availability of leisure time, and weather and climate are drivers of recreational demand (Gössling et al., 2012). Moreover, institutional schedules (e.g., national, religious, and school holidays) are influential; nevertheless, the overall demand patterns across managed national facilities consistently relate to regional climate patterns (Albano et al., 2013), and more specifically to direct and indirect effects of temperature (Rosselló-Nadal, 2014). The relationship between climate and recreational demand has been analyzed at different spatial scales ranging from specific national parks (Richardson & Loomis, 2004; Scott et al., 2007), to regional tourism systems (Coombes et al., 2009; Smith et al., 2016), to national (Fisichelli et al., 2015; Liu, 2016) and international (Barrios & Ibanez, 2015) networks of tourism destinations. These studies correlate past visitation rates with a select set of climate variables, among which temperature is mostly adopted (Gossling & Hall, 2006; Lise & Tol, 2002). However, these studies evaluate the climate–recreation relationship by focusing on average point estimates. Although understanding how climate variations affect recreation is important, it is no less critical to examine the impacts of climate and other determinants on the lower and upper tails of utility derived from recreation. Although variations in weather patterns have the potential to alter recreational utility, we expand on the existing literature by exploring how climate impacts on length of stay to federally managed natural parks in Utah via quantiles.

In this paper, we examine the reduced-form relationship between weather variables, socio-economic factors and length of stay to federally managed national parks in Utah by addressing the aforementioned research gaps. To determine how climate variables affect recreation, past studies often identify a single climate variable (e.g., mean temperature) that is significantly related to recreation. Often these studies lack destination-specific data that can be utilized to determine if a wider spectrum of climatic variables (e.g., humidity, vapor pressure, etc.) are also related to these demands. Exploring how a broad set of climate variables affect length of stay will improve our understanding of which climate variables are most predictive of duration of stay apart from the socio-economic factors. To ensure that the estimates are robust, we employ a quantile regression model that accounts for potential outliers in the utility measure.

Quantile regression is gaining popularity in explaining economic phenomenon in the education, labor, and health fields (Koenker & Hallock, 2001). Although quantile regression is useful in explaining underlying distributional heterogeneity in comparison to the regular conditional-mean models, the method has not gained sufficient recognition in tourism studies. Quantile regression is relevant in assessing recreation as it will provide a description of the estimates at different distributions and also evaluate point estimates at different levels of recreational benefits. Since utility from recreation exhibits varying responses due to changing weather patterns and socio-demographic characteristics (Scott et al., 2007; Scott & Lemieux, 2010; Scott et al., 2008; Smith et al., 2019), this study creates an opportunity to explore the unexploited benefits of investigating the climate–recreation as well as the socio-demographic–recreation link via quantile analysis.

1.1 Related Literature

A variation in climate has the potential to significantly alter recreational benefits, as outdoor recreationists are sensitive to unpredictable weather patterns. For instance, warming temperatures may decrease the length of skiing days (Dawson et al., 2013; Rutty et al., 2015; Scott et al., 2008) as research shows a direct relationship between weather conditions and the closure of ski areas (Beaudin & Huang, 2014). These findings illustrate how climate change can alter recreation. Although there is much research on the impacts of climate on winter outdoor recreation, changes in summer weather influence recreational demand (Denstadli et al., 2011; Falk, 2015). Studies have investigated the potential impact of climate change on future national park visits (Fisichelli et al., 2015; Liu, 2016; Scott et al., 2007). Scott et al. (2007) modeled future visitation to Waterton Lakes National Park by comparing past monthly visitation data to monthly temperature and precipitation. Similarly, Liu (2016) used temperature and precipitation to model visits to Taiwan's national parks and found precipitation as a stronger predictor of visitation. Again, Richardson and Loomis (2004) modeled future visits to Rocky Mountain National Park (USA), using minimum and maximum temperature, precipitation, and snow depth. We recognize the importance of these past studies and expand on the literature by employing length of stay data to explore the heterogeneity weather patterns are influencing of stay at five national parks in Utah.

Researchers usually adopt four central climate variables: temperature (minimum, maximum, and mean), precipitation, wind, and sunshine (Hewer et al., 2015; Steiger et al., 2016). Tourists' perceptions of the importance of these variables depend on the destination's location and the geophysical characteristics of its landscape (Rutty & Scott, 2010; Scott et al., 2008). Surveys of tourists suggest that beach tourists tend to rate sunshine and precipitation as the highest importance (Moreno & Amelung, 2009; Scott et al., 2008), while mountain tourists perceive precipitation to be most influential (Scott et al., 2008; Steiger et al., 2016), while urban tourists are most sensitive to temperature (Scott et al., 2008). Additionally, perceptions of acceptable conditions tend to vary by individual based on their home location, their expectations and experiences of the destination's climate, and their planned recreational activities (Gossling et al., 2016; Rutty & Scott, 2016; Scott et al., 2008). This has led researchers in dissimilar geographies to reach different conclusions about the impact of climate and weather on tourists. We expand on these studies and include other climatic variables (e.g., vapor pressure deficit, and dew point temperature) and account for other socio-economic factors.

While a variety of different climate and weather variables have been used in previous research, the effects of those variables have been inconsistent, appearing to be dependent on the geographic location, dominant activity type at the destination, and spatial scale of analysis. Studies at the national or international scale tend to only focus on the importance of temperature, while more site-specific variables are often disregarded (Berrittella et al., 2006; Serquet & Rebetez, 2011). However, studies at smaller spatial scales often find other variables, besides temperature, to be meaningful predictors of visits (Førland et al., 2013; Koberl et al., 2016; Yu et al., 2009). Thus, we investigate the impact of numerous climate variables on length of stay and account for how these determinants affect the upper and lower tails of length of stay, considering demographic characteristics, visitor's distance to park, nearest of the park to major cities, and holiday weeks.

2. Study Area

We focus our analysis on a regional network of national parks located in southern Utah. The parks (Arches National Park, Bryce Canyon National Park, Canyonlands National Park, Capitol Reef National Park, and Zion National Park) are under the management of the National Park Services. Arches, Canyonlands, and Capitol Reef national parks are located within the Colorado Plateau whereas Bryce Canyon and Zion national parks are located in the southern extent of the southern Wasatch mountains. The difference in ecoregions affect the types of recreational opportunities that are offered within each park. For instance, Bryce Canyon and Zion national parks offer more trails in canyons with some vegetative covers.

Arches national park is the most eastern park in Utah and sits northeast of Moab. Being part of the Colorado Plateau, the climate is characterized as arid, with hot summers and cold winters, and large daily temperature fluctuations that often span a range of 20^0C. The park is described by protruding sandstone formations amongst a relatively flat desert floor covered by low-growing vegetation. The difference between elevations is about 516m. Bryce Canyon is located in southcentral Utah and has the highest elevation of amongst all of Utah's managed national parks. It is characterized by lower temperatures, more vegetation, and more snow accumulation. Bryce Canyon is the only national park that offers snow-based recreational activities in Utah. Bryce Canyon usually receives over 45mm of precipitation monthly in the fall and averages 30mm of precipitation in the winter months, most of which falls as snow. Much of Bryce

Canyon's upper elevations are covered by conifer forests, but as areas of the park descend into lower elevations the vegetation changes into ponderosa pine forest, and then further down it transitions into pinyon and juniper.

Canyonlands national park is located west of Moab. The Canyonlands is in the heart of the Colorado Plateau, giving it many of the similar climatic and vegetative characteristics as Arches and Bryce Canyon national parks. Summer temperatures in the park often exceed 30^0C. The canyons were created by the Green and Colorado rivers, which enter the northern end of the park, converge in the middle, and flow out of the southern end. Many visitors are attracted to Canyonlands due to its kayaking and rafting opportunities. Subsequently, the Capitol Reef national park is located in south-central Utah and is characterized by brightly colored canyons, cliffs, monoliths, and buttes. Maximum daily temperatures often exceed 30^0C in the summer months. The park is centrally located in the Colorado Plateau and its landscape is high arid desert with several slot canyons cut in by the Fremont River. Lastly, Zion national park is the most southwestern park in Utah and is located at the junction of the Colorado Plateau, the Great Basin, and the Mojave Desert. The largest feature in the park is Zion Canyon, which is 15 miles long, and up to half a mile deep. The park's canyons, along with dense vegetative cover in their bottoms, shade and cool many of the most heavily used trails within the park. Shade and cooler temperatures are often a relief, as daily maximum temperatures can often exceed 33^0C in the summer months. Zion offers the largest vertical relief, spanning 1550m.

3. Theoretical Framework and Empirical Specification

We follow past studies (Guimaraes et al.; Rosselló-Nadal, 2014) and consider a discrete choice modeling approach embedded within the framework of revealed preferences as the primary theoretical model. We aim to answer why an individual or a group chooses to visit a particular recreational destination relative to other recreational sites. Recreational choices are quantitative and qualitative consumption. However, we adopt a quantitative unit of tourism consumption which we denote as the length of stay per day at a park as the measure of utility. As different recreational destinations provide different units or bundles of characteristics in the form of utility, there is a possibility that visitors recreational preferences might differ across the destination sites. Thus, attractions are characteristics and is dependent on the destination's climate, natural and historical attributes, and on other features such as the recreational facility distance from a major city center.

Taking the utility theory into account within the context of recreational decisions, we follow Morley (1992), and allow for the consideration of different perspectives of tourism decisions, together with a larger set of explanatory variables that influence recreational decision making. Analytically, we consider the utility U_{ijt} that an individual i derives from choosing to visit recreational facility j at time t to take the form:

$$\boldsymbol{U_{ijt}} = \boldsymbol{X'_{jt}\beta} + \boldsymbol{Z'_{ijt}}\gamma + \varepsilon_{ijt} \tag{1}$$

where U_{ijt} is the utility of visiting park j at time t to individual i; $\boldsymbol{X'_{ijt}}$ is a vector of various climatic factors that affect the utility; $\boldsymbol{Z'_{ijt}}$ is a vector of socio-demographic factors that affect the recreational utility; $\boldsymbol{\varepsilon_{ijt}}$ is the error term. As individuals are assumed to visit the recreational facility that yields the greatest utility, the probability π_{ijt} of a visitor opting for recreational facility i is:

$$\pi_{ijt} = \Pr\left(\boldsymbol{X'_{ijt}\beta} + \boldsymbol{Z'_{ijt}}\gamma + \varepsilon_{ijt} > \boldsymbol{X'_{ikt}\beta} + \boldsymbol{Z'_{ikt}}\gamma + \varepsilon_{ikt}\right) \forall j \neq k \tag{2}$$

Thus, we assume that individuals with similar socioeconomic and demographic characteristics might choose very different destinations. However, the decision to visit a particular recreational facility is not an independent decision, but the final decision of a set of choices. Thus, once a decision has been made to visit a recreational facility based on certain socio-economic and climatic condition, individuals chose a recreational facility conditional on their preference and attribute characterizing the alternative in the choice set (Eugenio-Martín, 2003). Importantly, we extend this assumption and estimate the random utility model in the context of a quantile regression. This method is beneficial as it is flexible and accommodates the heterogeneity in the conditional distributions that characterizes utility from naturally managed national parks. We model the reduced-form random utility model between climate conditions, socioeconomic factors, visitor demographics factors, and length of stay at different quantiles conditional on the latter. We specify our quantile regression as follows:

$$LOS_{ijt} = \beta_0 + \boldsymbol{X'_{jt}}\beta_q + \boldsymbol{\omega'_{ijt}}\vartheta_q + \varepsilon_{ijt} \tag{3}$$

where LOS_{ijt} is the length of stay of individual i at park j at time t; $\boldsymbol{X'_{jt}}$ is a vector of weather conditions associated with park j at time t; $\boldsymbol{\omega'_{ijt}}$ is a vector of socio-economic and other variables that influence the length of stay of individual i at park j at time t; the coefficients β_0 is the intercept; β_q is the vector of unknown parameters associated with the q^{th} quantile. $\boldsymbol{\omega'_i}$ is a vector of socio-economic and other variables that affect length of stay. ϑ_q is the vector of unknown parameters associated with the q^{th} quantile that is associated with the socio-demographic. ε_{ijt} is the error term.[13]

The quantile regression minimizes $\sum_{ijt} q|\varepsilon_{iji}| + \sum_{ijt}(1-q)|\varepsilon_{ijt}|$, a sum that gives the asymmetric penalties $q|\varepsilon_{ijt}|$ for underprediction and $(1-q)|\varepsilon_{ijt}|$ for overprediction. The q^{th} quantile regression estimator $\widehat{\beta_q}$ minimizes over β_q the objective function: $Q(\beta_q) = \sum_{ijt=LOS_{ijt}\geq\psi'_{ijt}\theta}^{N} q|LOS_{ijt} - \beta_0 - \boldsymbol{\psi'_{ijt}\theta_q}| + \sum_{ijt=LOS_{ijt}<\psi'_{ijt}\theta}^{N}(1-q)|LOS_{ijt} - \beta_0 - \boldsymbol{\psi'_{ijt}\theta_q}$; where $0 < q < 1$. We estimate β_q instead of β to make clear that different choices of q estimate for different values of β. We specify the standard conditional quantile regression as: $Q_q(LOS_{ijt}|\boldsymbol{\psi'_{ijt}}) = \boldsymbol{\psi'_{ijt}\theta_q}$ for each of the covariates embedded in the vector $\boldsymbol{\psi'_{ijt}}$ regressors. We specify the marginal effect of the coefficient for the q^{th} quantile as: $\partial Q_q(LOS|\boldsymbol{\psi})/\partial\psi_j = \theta_{qj}$; where ψ_j are the individual independent variables embedded in the vector $\boldsymbol{\psi'_{ijt}}$. The estimate θ_{qj} estimates the change in a specified quantile $\boldsymbol{q}$ of the length of stay LOS_{ijt} produced by a one-unit change in the independent variables $\boldsymbol{\psi_{ijt}}$. The marginal effects are for infinitesimal changes in the regressors, assuming that the independent variables remain in the same quantile.

We also analyze recreational length of stay benefit via a generalized linear method approach. From past recreational literature, conditional logit or Poisson models are usually adopted as appropriate strategies to estimate random utility models (Guimaraes et al., 2003; Melstrom & Vasarhelyi, 2019). We follow the approach of Melstrom & Vasarhelyi (2019) and specify our Poisson utility model as:

$$U_{ijt} = exp(\beta_0 + \boldsymbol{X'_{jt}\beta} + \boldsymbol{Z'_{ijt}}\gamma)\varepsilon_{ijt} \tag{4}$$

where U_{ijt} is the utility (length of stay) of visiting park j at time t to individual i; $\boldsymbol{X'_{ijt}}$ is a vector of various climatic factors that affect the utility; $\boldsymbol{Z'_{ijt}}$ is a vector of socio-demographic factors that affect the recreational utility; $\boldsymbol{\varepsilon_{ijt}}$ is the error term. The equation (4) is transformed as $logU_{ijt} = \beta_0 + \boldsymbol{X'_{jt}\beta} + \boldsymbol{Z'_{ijt}}\gamma + log\varepsilon_{ijt}$. This model is synonymous with taking a logarithm of the utility measure (length of stay) and estimating with an OLS approach.

[13] For the sake of simplicity, we classify the vector of covariates X'_{jt} , ω'_{ijt} as ψ_{ijt} for easy understanding. However, we are aware that the weather conditions affect each individual i equally so note that the X'_{jt} implicitly holds in ψ_{ijt}.

4. DATA

We estimate the recreational utility response changes by constructing a dataset of more than 310,000 visitors between January 2007 to December 2018 from the Recreation.gov website (Rec.gov, 2021). A recreation visit is a unique entrance into a park to participate in outdoor recreation. We adopt length of stay as our utility measure as it is a good indicator for determining utility from tourism consumption and is positively related to the aggregate earnings obtained from tourist activities (Alegre et al., 2011; Barros et al., 2010). To determine how weather and other socio-demographic factors affect length of stay, we obtain the visitor's arrival and departure date to compute the length of stay at the recreational facility.

Besides the weather factors usually employed (Fisichelli et al., 2015; Parthum & Christensen, 2022), we account for other weather variables to mitigate potential omitted variable bias in the study. We include dew point temperature and maximum vapor pressure deficit as these variables are usually omitted in most tourism studies. Again, we employ both the minimum and maximum temperatures instead of the popular mean temperature in the analysis. Thus, our climate indicators comprise five weather variables: maximum temperature, minimum temperature, precipitation, dew point temperature, and maximum vapor pressure deficit. We obtain the weather data from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). The PRISM climate data comprises single-event gridded data from 15-25 nearby weather station locations surrounding that grid cell. PRISM bases the influence of each weather station on its distance from the grid cell, its physiographic and climatic similarity to the grid cell, and, where applicable, how similar its radar-derived precipitation value is to that of the grid cell (Daly et al., 1994; 2002; 2008).

We employ temperature as studies show that it influences recreational decision-making (Smith et al., 2017). We define *temperature* as the daily minimum and maximum temperature observed at a park. Again, we follow the tourism literature and include the precipitation, which is the measure of the total amount of rain and melted snow, as precipitation impacts recreation (Steiger et al., 2016; Yu et al., 2009). To account for the effect of humidity, we include the maximum vapor pressure deficit and the mean dew point temperature. Vapor pressure deficit is the difference between the amount of air moisture and how much moisture the air can hold when saturated. The dew point is the temperature the air needs to cool to achieve relative humidity (NOAA, 2023). Maximum vapor pressure deficit and the mean dew point temperature are important weather indicators as they directly affect how “comfortable” it feels outside. As most recreational activities occur in the open, including such variables are essential.

We employ data from different sources to determine how socio-demographic determinants impact length of stay. First, we determine how the park fees influence length of stay. The 'park fee,' comprises of the facility use fee, discounts, and transaction fee. This variable captures the monetary value the visitor pays to access the recreational facility. We obtain the total amount of money paid from the recreation.gov website. This variable is essential as it measures the association between length of stay and park revenue. Subsequently, we include daily gasoline prices in our analysis to account for transportation costs. Past studies (Boyer et al., 2017; Melstrom et al., 2015) recognize the importance of gasoline prices in random utility estimation. The gasoline data is the daily US national gasoline price obtained from the Energy Information Administration (EIA) website. Again, we determine the effect of travel costs in this study. We calculate the variable travel cost using information on the travel distance, travel time, facility use fee, and the value for travel time. We use the centroid of the visitor's home zip code to estimate the travel distance and travel time based on the visitor's georeferenced coordinates recorded at the national park. We follow Melstrom et al. (2015) to derive the driving cost, which constitutes the average national fuel price plus the marginal depreciation and cost maintenance. To compute the travel time, we adopt one-third of the wage rate commonly utilized in recreation demand studies (Vesterinen et al., 2010). We calculate the wage rate as the visitor's zip code median household income divided by 2000, which is assumed to be the total amount of working hours in a year to proxy the opportunity cost of travel time (Parsons, 2017). Finally, we derive the travel cost as round-trip distance in miles times per mile fuel, maintenance, depreciation costs plus the opportunity cost of travel plus the total amount of money paid.

We control for other factors that can influence length of stay by using covariates such as the visitor's zip code median household income, the visitor's distance to the national park, and the distance of a national park to the closest city. We expect the median household income variable to positively affect length of stay as increasing household income makes recreation affordable. We obtained the income data from the Internal Revenue Service (IRS). We matched the visitor's home zip code reported during visit to the park to the IRS-reported zip code level household income to obtain the median income data. In addition, we include the visitor's distance to the national park as a proxy for the substitution effect. We derive the visitor's distance to a park from the visitor’s home zip code to the visitor's camping site coordinate at the park.[14] Equally, we account for the distance of the closest city to the park in our analysis.[15]

We introduce dummy variables to eliminate endogeneity through omitted variable bias to prevent biased outcomes in our analysis.[16] For instance, the variable visitor's state is a dummy variable that determines whether the visitor is from in-state or out-of-state. The dummy variable visitor's state equals one if the visitor is from Utah and 0 if the visitor is not from Utah. Subsequently, we control for overnight stays at the park. Again, we use a dummy variable to capture holiday effects. The dummy variable holiday week equals one if the day of the visit to the park is a holiday and 0 otherwise. The analysis accounts for seasonality, time, and park effects through dummies. We present the summary statistics in Table 3.1.

Table 3.1: Summary Statistics of the data

Variables	Mean	St. dev	Min	Max
DEPENDENT VARIABLES				
Length of stay (days)	1.72	1.59	0	27
INDEPENDENT VARIABLES				
Total price ($)	32.86	33.96	0	1400
Travel cost	66.25	37.64	8.21	2274
Precipitation (mm)	0.92	3.31	0	50.31
Minimum temperature (^{0}C)	10.45	6.25	-13.8	27.1
Maximum temperature (^{0}C)	25.96	7.49	-4.1	42.1
Dew point temperature (^{0}C)	-0.52	6.61	-21.1	17.1
Maximum vapor pressure deficit (PHa)	30.66	14.63	0.02	77.48
Price of gasoline ($)	2.94	0.61	1.64	4.05
Visitor's distance to park (miles)	642.01	570.01	1.5	2881.5
Distance of closest cities to park (miles)	3.73	4.37	1.45	27.8
Median HH income ($1000)	47.11	22.3	0.41	3428.1
Holiday week (dummy variable)	0.95	0.21	0	1
Visitor's state (dummy variable)	0.19	0.39	0	1
Season (dummy variable)	2.23	0.81	1	4
Observations	**310,507**			

[14] Since most national parks have different campsite, various recreational facilities, and offer different activities, visitors are likely to opt for different locations based on their preferred activities and choice. In the dataset, we observe that visitors in a national park have different georeferenced coordinate systems (longitude and latitude) that are linked to various campsites, facilities in the national park, and recreational activities. We use these coordinates together with the visitor's home zip code to estimate the distance from visitor from this home to the national park.

[15] Likewise, we calculate the distance of the park to the closest city by using the visitor's georeferenced coordinates and the centroid of the closest city coordinates.

[16] Due to incidental parameter problem, we do not include the dummy variables in the main quantile regression. However, we account for them in the OLS regression and the Poisson regression.

5.0 RESULTS AND DISCUSSION

5.1 Descriptive statistics

Table 3.1 presents the descriptive statistics. Table 3.1 shows that the average length of stay is about a day and some hours. According to the National Park Service (NPS) annual reports from 2018 to 2021, the average number of hours a visitor spends at a National Park is approximately 7.4 hours. Furthermore, we show that a recreational facility fee is about $32, with minimum and maximum fees of $0 and $1440, respectively. From Table 3.1, the average travel cost is $66 and ranges from $8 to $2274. The average visitor's distance to the recreational facility is 642 miles, with the minimum value at 1.5 miles and the maximum at 2882 miles. We calculate the proportion of visitors from outside Utah and notice that they constitute about 80% of the total observations, whereas in-state visitors are about 20%. Subsequently, we notice that about 19% of the visitors stay overnight, whereas 81% vacate the recreational facility effectses after their visit. As expected, we realize that about 88% of out–of–state visitors do not stay overnight in camps or other housing facilities in the recreational areas as they prefer to spend the night elsewhere. [17] We also observe that the closest city to a national park is about 4 miles, with a minimum distance of 1.5 and a maximum distance of almost 28 miles. Regarding the weather variables, the average precipitation, minimum temperature, maximum temperature, dew point temperature, and vapor pressure deficit are 0.92mm, 10.450C, 25.960C, -0.520C, and 30.66Pha.

Again, we expand on visits to the national parks in Figure 1. From the figure, we realize that Zion National Park is the most visited National Park in Utah, receiving an average of nearly 57000 visits based on reservation bookings from the recreation.gov website (rec.gov, 2022).[18] Our description is consistent with Smith et al. (2017) which indicate that the Zion National Park (NP) is the most visited recreational site in Utah. The second most visited park is the Arches NP. However, the park with the least number of visits is the Capitol Reef NP with an average of approximately 870 reservation. We present the average number of visitors to each park in Table 3.2.

[17] Overnight stay refers to visitors that usually camp or set up tents at the National Parks to spend the night.
[18] Our estimates are based on the ticket reservation that are purchased and recorded. It is possible that the total number can be larger as visitors walk-in into the various parks without reserving tickets.

Table 3.2: Average number of visitors to each national park

National Park	Average number of visitors
Arches NP	13,289
Bryce Canyon NP	5,284
Canyonland NP	904
Capitol Reef NP	870
Zion NP	57,017

To illustrate how seasonality affects the visitors, we graphically present how visitations to the various national parks differ monthly. We show that visits to the parks peak during the summer months (April–September) and decline during the winter months (November–February). As part of the study, we determined how climate conditions differ at the various parks and present the results in the appendix. We notice heterogeneity among the different weather variables for all the five parks. This indicates that the various parks exhibit differences in weather conditions which is likely to influence visitors recreational decisions.

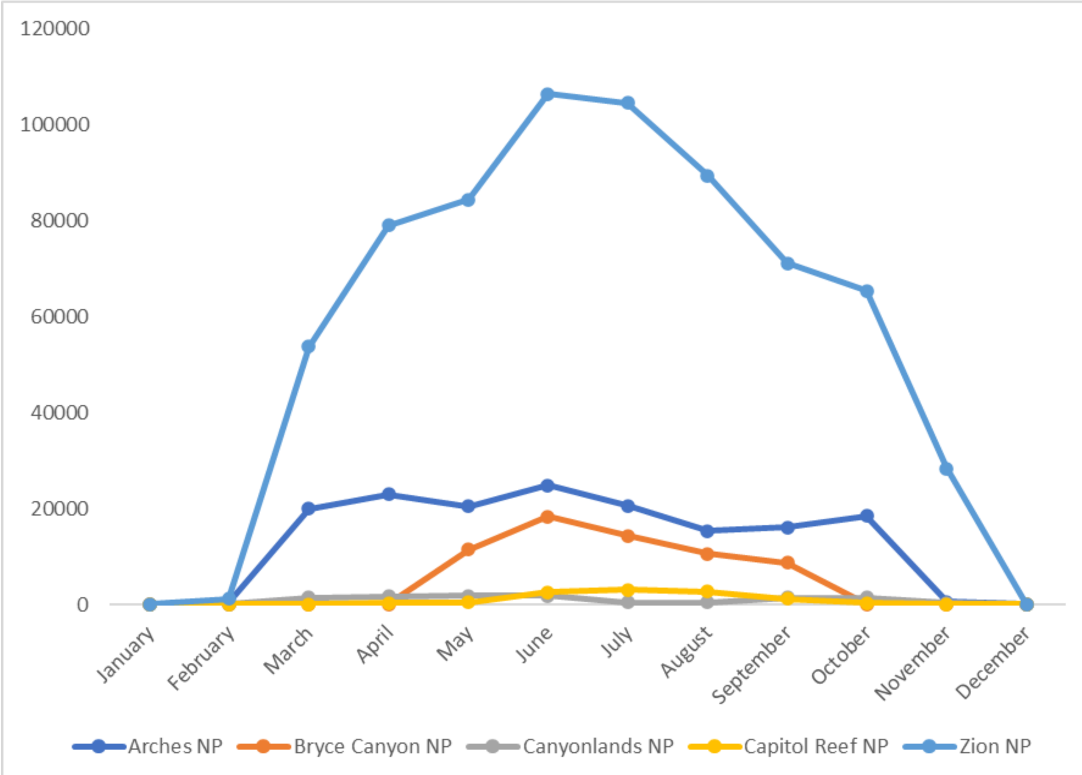

Figure 3.1: Average daily visitation for the study parks (2007–2018). Source: Authors.

Turning to the weather variables, we realize that the average precipitation ranges from 0.68mm (Canyonland NP) to 1.32mm (Capitol Reef NP), indicating more precipitation in the Capitol Reef NP relative to the other parks. Subsequently, we compute the minimum temperatures among the parks and notice that it ranges from 0.83^{0}C (Bryce Canyonland NP) to 7.13^{0}C (Zion NP). Small temperature values are observed in the Bryce Canyon NP as it is the only park that offer snow–related recreational activities (Smith et al., 2018). However, the temperature values do not differ much across the other parks. We observe that dew point temperature, a measure of the air needed to cool to achieve relative humidity, is lowest in the Bryce Canyon with an average value of -6.13^{0}C whereas it is largest in the Canyonland NP with an average value of -2.4^{0}C. Lastly, we observe a lower maximum vapor pressure deficit value (1.5PHa) in the Bryce Canyons NP relative to Zion NP (5.3PHa). The other national parks (Arches NP, Canyonland NP, and Capitol Reef NP) have an average vapor pressure deficit of 4.5PHa. We present the weather statistics in Table 3.3.

Table 3.3: Average weather statistics

National Park	Precipitation	Minimum temperature	Maximum temperature	Dew point temperature	Vapor pressure deficit
Arches NP	0.88	6.02	20.26	-2.76	4.95
Bryce canyon NP	1.29	0.83	15.31	-6.13	1.57
Canyonlands NP	0.68	5.85	21.98	-2.48	4.21
Capitol Reef NP	1.31	7.07	18.83	-2.91	4.5
Zion NP	0.89	7.13	21.08	-3.28	5.39

5.2 Empirical Specification Results

Table 3.4 presents the quantile regression estimates for the length of stay recreational demand model. As part of the regression, we present the OLS results in Table 3.5. We observe that the model has the expected signs and aligns with a prior expectation of past studies (Smith et al., 2018; Smith et al., 2019). First, we examine the association between park fees and the length of stay and notice a positive and significant association. This is an expected results and consistent with the tourism literature as length of stay has positive implication on park revenue (Alegre & Pou, 2007). Extended stays at a park translates into additional park fees that increase the revenue for park management. The decision to extend the length of stay may be due to the aesthetic value of the park, as most tourists value on the park's amenities, services, and natural attractions and are willing to pay.

We demonstrate that increasing travel costs tend to decrease the length of stay. Possibly, the opportunity cost of an extended stay is greater than the utility from the park. Moreover, we find similar results for the quantile regression, but the magnitude of the coefficients differs across each quantile. This highlights that travel costs can prevent potential visitors from assessing parks amenities as they perceive the trip to be unaffordable. We examine the effect of precipitation on the length of stay and reveal that the relationship is not different from zero as we realize precipitation is a poor predictor of length of stay via quantiles. This outcome is consistent with the findings of Smith et al. (2018), which reveal that precipitation does not influence recreation in Utah. However, precipitation–length of stay relationship is nonlinear as low precipitation positive affect length of stay but contribute adversely when the precipitation rises as observe in the OLS estimates. We examine the effect of minimum temperature on length of stay and the relationship is negative with varying significant levels at the quantiles. The geographical location of Utah can explain this outcome, as it is an arid state with a lot of sunshine. Thus, most visitors are likely to patronize recreational services during the sunny seasons. We focus on the maximum temperature and find an alternate response as, on average, the maximum temperature tends to impact length of stay positively. We observe a negative relationship between dew point temperature and length of stay. We analyze the association between length of stay and maximum vapor pressure deficit and notice a nonlinear relationship. The effect of vapor pressure deficit on length of stay is negative at its maximum. However, when the maximum vapor pressure deficit declines, it encourages length of stay. This highlights that dry and arid weather conditions discourage outdoor recreation, but cool atmospheric conditions creates a conducive opportunity for outdoor recreational activities.

We evaluate how gasoline prices affect length of stay and reveal a positive and significant outcome. However, our estimates are inconsistent with past studies that indicate that increasing gasoline prices cause a decline in recreational demand (Boyer et al., 2017). As expected, we show that visitors' home distance negatively and significantly affects length of stay. We expect this outcome as longer travel time may increase recreational and opportunity cost. We turn our attention to evaluating how holidays affect length of stay. The outcome is negative and significant on average but with some heterogeneity at the seasonal level. We realize that holidays are drivers of winter recreation. Furthermore, our results indicate that in-state visitors are more likely to visit recreational facilities within their states than out-of-state visitors.

Table 3.4: Quantile regression estimation model (Full Model)

Variables	Quantile regression at 0.25th quantile	Quantile regression at 0.5th quantile	Quantile regression at 0.75th quantile	Quantile regression at 0.9th quantile
Park fees ($)	0.02482***	0.0535***	0.0923***	0.1282***
	(0.001)	(0.0008)	(0.0025)	(0.0044)
Travel cost	-0.0014***	-.01245***	-0.0524***	-0.0924***
	(0.001)	(0.0008)	(0.0025)	(0.0045)
Precipitation (mm)	0.0003	-0.0003	0.0028	0.0097**
	(0.0011)	(0.0009)	(0.0027)	(0.0048)
Precipitation squared (mm)	-0.00002	0.00001	-0.0000	-0.0001
	(0.00004)	(0.0000)	(0.0001)	(0.0002)
Min. temp. (^{0}C)	-0.0036***	-0.0024**	-0.0051	0.0115**
	(0.0012)	(0.001)	(0.0031)	(0.0055)
Min. temp squared (^{0}C)	-0.0001	-0.0005***	-0.0006***	-0.0005**
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Max. temp. (^{0}C)	0.0014	0.0005***	0.0194***	0.0306*
	(0.0024)	(0.0021)	(0.0062)	(0.011)
Max. temp squared (^{0}C)	0.0002***	0.0008***	0.0005**	-0.0014***
	(0.0001)	(0.0001)	(0.0002)	(0.0004)
Dew point temp. (^{0}C)	-0.0013	-0.0055***	-0.0064***	-0.0044
	(0.0009)	(0.0008)	(0.0023)	(0.0042)
Dew point temp. squared (^{0}C)	-0.0001**	-0.0002***	-0.0007***	-0.0008***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Max. vapor pressure deficit (PHa)	-0.0063***	-0.0221***	-0.0288***	0.0066
	(0.0024)	(0.002)	(0.0061)	(0.0108)
Max. vapor pressure deficit	0.0000	0.0000***	0.0001***	-0.0014***
squared (PHa)	(0.0000)	(0.0000)	(0.0000)	(0.0004)
Gasoline price ($)	0.0361***	0.1321***	0.1875***	0.1512***
	(0.0027)	(0.0022)	(0.0067)	(0.0119)
Visitor's distance to park (miles)	-0.0000***	-0.0001***	-0.0002***	-0.0004***
	(2.72e-06)	(2.28e-06)	(6.77e-06)	(0.0000)
Closest city to park (miles)	-0.0035***	-0.0089***	-0.0089***	-0.0131***
	(0.0003)	(0.0003)	(0.0008)	(0.0014)
Median HH income ($1,000)	0.0007	0.0075***	0.0333***	0.0596***
	(0.0006)	(0.0005)	(0.0016)	(0.0029)
Constant	0.5522***	0.4083***	0.9642***	2.4153***
	(0.0243)	(0.0204)	(0.0606)	(0.1081)
R–squared	0.1084	0.2703	0.2463	0.1919
Observations	251,197	251,197	251,197	251,197

Notes: ***, ** and * indicate significance levels 1%, 5% and 10% respectively. Standard errors for coefficients in parentheses

Table 3.5: OLS estimation model

Variables	Full Sample	Warm Season	Cold Season
Park fees ($)	0.0516*** (0.0017)	0.06*** (0.0019)	0.0342***(0.0032)
Travel cost	-0.0308*** (0.0018)	-0.0395*** (0.0021)	-0.0124***(0.0035)
Precipitation (mm)	0.0063*** (0.0018)	0.0059*** (0.0022)	0.0039***(0.0056)
Precipitation squared (mm)	-0.0002*** (0.0001)	-0.0002*** (0.0001)	0.0002 (0.0004)
Min. temp. (^{0}C)	-0.0043* (0.0023)	-0.005 (0.0032)	-0.0048 (0.0038)
Min. temp squared (^{0}C)	-0.0003*** (0.0001)	-0.0002*** (0.0001)	0.0000 (0.0002)
Max. temp. (^{0}C)	0.0104*** (0.0047)	0.0244*** (0.0066)	-0.0053 (0.011)
Max. temp squared (^{0}C)	-0.0001 (0.0002)	-0.0005*** (0.0002)	0.0007* (0.0004)
Dew point temp. (^{0}C)	-0.0029* (0.0016)	-0.0011 (0.0017)	-0.0115***(0.0048)
Dew point temp. squared (^{0}C)	-0.0003*** (0.0001)	-0.0004*** (0.0001)	-0.0006***(0.0002)
Max. vapor pressure deficit (PHa)	-0.0054***(0.0041)	-0.0041 (0.0046)	-0.0134 (0.012)
Max. vapor pressure deficit squared (PHa)	0.00004* (0.00002)	0.0001*** (0.0000)	-0.0001 (0.0001)
Gasoline price ($)	0.0621*** (0.016)	0.1011*** (0.0201)	-0.0894**(0.0413)
Visitor’s distance to park (miles)	-0.0001***(4.55e-06)	-0.00013*** (5.16e-06)	-0.0002***(9.40e-06)
Closest city to park (miles)	-0.6022*** (0.0675)	-0.5626*** (0.0652)	-0.7571*** (0.2506)
Median HH income ($1,000)	0.0197*** (0.0012)	0.0256*** (0.0013)	0.0074*** (0.0023)
Holiday week (Yes)	0.0067 (0.0122)	-0.0236*** (0.0137)	0.0948***(0.0255)
Visitor’s state (Yes)	-0.0121 (0.0087)	-0.0108 (0.0111)	-0.0177 (0.0142)
Bryce Canyon NP	-6.5681*** (0.7299)	-6.1263*** (0.7053)	-8.2773*** (2.7089)
Canyonlands NP	7.833*** (0.9351)	7.3724*** (0.9051)	9.8534*** (3.4656)
Capitol Reef NP	-5.3332*** (0.3653)	-5.1028*** (0.3822)	-6.1225*** (1.2016)
Zion NP	-7.3926*** (0.843)	-6.8824*** (0.8145)	-5.1542*** (1.7095)
Winter	-0.2098*** (0.0772)		
Spring	-0.0815*** (0.0083)		
Summer	-0.1572*** (0.0086)		
Constant	9.9741*** (0.9448)	9.1987*** (0.9145)	12.5519*** (3.5041)
Day dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
R–squared	0.2525	0.2554	0.2525
Observations	169,594	169,594	169,594

Notes: ***, ** and * indicate significance levels 1%, 5% and 10% respectively. Standard errors for coefficients in parentheses

5.2.1 Seasonal Analysis

We conduct a seasonal analysis to determine how the climate and other variables influence the length of stay. We separate the data into cold and warm observations, where the warm seasons consist of summer and autumn months while the cold seasons consist of winter and spring months. Tables 3.6 and 3.7 present the results and test statistics. Our results indicate good model fitness and are significant with intuitive interpretations.

From the seasonal analysis, we observe considerable differences among the models regarding the climate variables. For instance, we notice that the climate variables are not good predictors of length of stay to recreational facilities when the length of stay is short. The climate variables influencing the stay duration in warm seasons are highly related to air moisture and relative humidity, not the regular temperature variables, as observed in Table 6. Regarding the demographic characteristics, we observe no differences in the estimated models. For instance, we notice that the visitor's distance to the recreational facility is inversely related to the length of stay. However, for the OLS estimates (Table 3.5), gasoline prices show an inverse association with stay duration during the cold seasons. The median household income effect is positive across both seasons.

We observe heterogeneity in the climate effect for the seasonal analysis as climatic factors tends to influence stay durations at national parks differently depending on the season. For instance, the main climatic driver of length of stay in the warm season are higher levels of the vapor pressure deficit. This is an indication that cooling temperatures at arid recreational facility improve visitor's recreational experience. Generally, we realize that the weather patterns during the cold season are not good predictors of determining recreational demand except the socio-demographic factors.

Table 3.6: Quantile regression estimation model (Warm Season)

Variables	Quantile regression at 0.25th quantile	Quantile regression at 0.5th quantile	Quantile regression at 0.75th quantile	Quantile regression at 0.9th quantile
Park fees ($)	0.022***	0.0597***	0.101***	0.1488***
	(0.0029)	(0.001)	(0.0028)	(0.0056)
Travel cost	-0.0016	-0.0191***	-0.0609***	-0.113***
	(0.003)	(0.0011)	(0.0028)	(0.0056)
Precipitation (mm)	0.0006	0.0014	0.0028***	0.0102*
	(0.0032)	(0.0011)	(0.0031)	(0.006)
Precipitation squared (mm)	-0.00002	-0.00004	-0.00001	-0.0002
	(0.0001)	(0.00003)	(0.0001)	(0.0001)
Min. temp. (^{0}C)	-0.0049	-0.0081***	-0.0147***	0.0054
	(0.0044)	(0.0015)	(0.0042)	(0.0082)
Min. temp squared (^{0}C)	-0.00001	-0.0003***	-0.0003*	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Max. temp. (^{0}C)	0.0028	0.0014	0.02508***	0.0472***
	(0.0087)	(0.0031)	(0.0083)	(0.0164)
Max. temp squared (^{0}C)	0.0001	0.0005***	-0.0001	-0.0023***
	(0.0003)	(0.0001)	(0.0002)	(0.0005)
Dew point temp. (^{0}C)	-0.0005	-0.0021**	-0.0011	0.0027
	(0.0026)	(0.0009)	(0.0025)	(0.0049)
Dew point temp. squared (^{0}C)	-0.0001	-0.0004***	-0.0008***	-0.001***
	(0.0001)	(0.0000)	(0.0001)	(0.0002)
Max. vapor pressure deficit (PHa)	-0.0047	-0.0161***	-0.0197***	0.0165
	(0.0068)	(0.0024)	(0.0065)	(0.0129)
Max. vapor pressure deficit squared (PHa)	0.0000	0.00004***	0.0001***	0.0001
	(0.0000)	(0.00001)	(0.00003)	(0.0001)
Gasoline price ($)	0.0297***	0.1366***	0.185***	0.1715***
	(0.0082)	(0.0029)	(0.0079)	(0.0155)
Visitor's distance to park (miles)	-8.92e-06	-0.0001***	-0.0001***	-0.0003***
	(7.77e-06)	(2.78e-06)	(7.42e-06)	(0.0000)
Closest city to park (miles)	-0.0036	-0.0078***	-0.0091***	-0.0137***
	(0.0009)	(0.0003)	(0.0009)	(0.0018)
Median HH income ($1,000)	0.0009	0.012***	0.0389***	0.0732***
	(0.0019)	(0.0007)	(0.0018)	(0.0037)
Constant	0.6214***	0.4699***	1.0497***	2.3385***
	(0.0874)	(0.0313)	(0.0835)	(0.1646)
Pseudo R–squared	0.0931	0.2703	0.2549	0.1997
Observations	169,594	169,594	169,594	169,594

Notes: ***, ** and * indicate significance levels 1%, 5% and 10% respectively. Standard errors for coefficients in parentheses

Table 3.7: Quantile regression estimation model (Cold Season)

Variables	Quantile regression at 0.25th quantile	Quantile regression at 0.5th quantile	Quantile regression at 0.75th quantile	Quantile regression at 0.9th quantile
Park fees ($)	0.0269***	0.0461***	0.065***	0.0642***
	(0.0027)	(0.0014)	(0.0047)	(0.0079)
Travel cost	0.0002	-0.0035***	-0.0245***	-0.0289***
	(0.0027)	(0.0014)	(0.0048)	(0.008)
Precipitation (mm)	0.0035	0.0056**	0.0043	0.0121
	(0.0044)	(0.0022)	(0.0078)	(0.0131)
Precipitation squared (mm)	-0.0001	-0.0002	0.0003	-0.00004
	(0.0002)	(0.0001)	(0.0004)	(0.0008)
Min. temp. (^{0}C)	-0.0052*	-0.0043***	-0.0046	0.0079
	(0.0029)	(0.0014)	(0.0051)	(0.0086)
Min. temp squared (^{0}C)	0.0004*	0.0003***	-0.0003	-0.0004
	(0.0002)	(0.0001)	(0.0004)	(0.0006)
Max. temp. (^{0}C)	0.002	0.0122***	0.0097	-0.029
	(0.0088)	(0.0044)	(0.0155)	(0.0259)
Max. temp squared (^{0}C)	0.0002	0.0001	0.0006	0.0004
	(0.0004)	(0.0001)	(0.0006)	(0.001)
Dew point temp. (^{0}C)	-0.0034	-0.0045**	-0.0042	-0.0013
	(0.0039)	(0.0019)	(0.0068)	(0.0115)
Dew point temp. squared (^{0}C)	-0.0001	-0.00001	0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0004)
Max. vapor pressure deficit (PHa)	-0.0046	-0.0141***	-0.0272	-0.029
	(0.0101)	(0.0051)	(0.0175)	(0.0259)
Max. vapor pressure deficit squared (PHa)	-0.00001	0.0001**	0.0001	-0.0004*
	(0.0001)	(0.0000)	(0.0001)	(0.0002)
Gasoline price ($)	0.0558***	0.1435***	0.1912***	0.0781***
	(0.0068)	(0.0034)	(0.0119)	(0.0199)
Visitor’s distance to park (miles)	-0.00002***	-0.0001***	-0.0002***	-0.0005***
	(7.85e-06)	(3.97e-06)	(0.00001)	(0.0000)
Closest city to park (miles)	-0.0014**	-0.01***	-0.0076***	-0.0085***
	(0.0007)	(0.0004)	(0.0014)	(0.0023)
Median HH income ($1,000)	-0.0004	0.0017**	0.0151***	0.0177***
	(0.0018)	(0.0009)	(0.0031)	(0.0053)
Constant	0.3891***	0.1379***	0.8461***	2.7672***
	(0.0619)	(0.0313)	(0.1084)	(0.1814)
Pseudo R–squared	0.1399	0.2735	0.2549	0.1997
Observations	169,594	169,594	169,594	169,594

Notes: ***, ** and * indicate significance levels 1%, 5% and 10% respectively. Standard errors for coefficients in parentheses

5.3 Robustness Checks: Alternative specifications results

We present the results of the robustness checks using the alternative empirical specifications in Table 3.8. We realize that the Poisson model show low explanator power as the R-squared values are relatively small compared to the main models (Tables 3.4–3.7). However, the results are all generally consistent with those from our main model specifications in Tables 3.4 and 3.5 except for some deviations. The impact of park fees on length of stay is still positive (and primarily statistically significant). Similarly, we notice that the effect of travel cost is consistent with the results from the primary model, as increasing travel cost decreases the length of stay at a national park in Utah. We notice that the climate variables are consistent for all the model specifications except the dew point temperature and vapor pressure deficit, which exhibit conflicting effects for the estimated models (Tables 3.7 and 3.8). We indicate that humidity and air moisture level are essential weather indicators for recreational activities in Utah. The dry nature of Utah's weather explains the sensitivity of these two climate variables. Surprisingly, precipitation tends to have a positive and significant effect on length of stay.

Table 3.8: Poisson estimation model

Variables	Full Sample	Warm Season	Cold Season
Park fees ($)	0.0355*** (0.0016)	0.0384*** (0.0014)	0.02845*** (0.0028)
Travel cost	-0.03123*** (0.0018)	-0.0338*** (0.0015)	-0.02445*** (0.0032)
Precipitation (mm)	0.0037*** (0.0009)	0.0034*** (0.0011)	0.0035 (0.0026)
Precipitation squared (mm)	-0.00011*** (0.0000)	-0.0001*** (0.0000)	-0.00003 (0.0001)
Min. temp. (^{0}C)	-0.0022* (0.0012)	-0.0008 (0.0018)	-0.0035** (0.0018)
Min. temp squared (^{0}C)	-0.0001** (0.0005)	-0.0002*** (0.0001)	0.0001 (0.0001)
Max. temp. (^{0}C)	0.0051** (0.0023)	0.0099*** (0.0034)	0.0053 (0.0059)
Max. temp squared (^{0}C)	-0.0001 (0.0001)	-0.0002** (0.0001)	0.00001 (0.0003)
Dew point temp. (^{0}C)	-0.0018** (0.0009)	-0.0009 (0.001)	-0.0061** (0.0024)
Dew point temp. squared (^{0}C)	-0.0001** (0.0000)	-0.0002* (0.0001)	-0.0003*** (0.0001)
Max. vapor pressure deficit (PHa)	-0.0022 (0.0023)	-0.0018 (0.0026)	-0.0069 (0.0061)
Max. vapor pressure deficit squared (PHa)	0.0000 (0.0000)	0.00002* (0.0000)	0.00004 (0.0001)
Gasoline price ($)	0.0358*** (0.0085)	0.0631*** (0.0111)	-0.0702*** (0.0205)
Visitor’s distance to park (miles)	-0.0001*** (2.97e-06)	-0.0001*** (3.72e-06)	-0.00001*** (5.42e-06)
Closest city to park (miles)	-0.5614*** (0.0433)	-0.5262*** (0.0485)	-0.8454*** (0.0922)
Median HH income ($1,000)	0.0202*** (0.0011)	0.022*** (0.001)	0.0156*** (0.0021)
Holiday week (Yes)	-0.0003 (0.0075)	-0.0169 (0.0105)	0.0458*** (0.012)
Visitor’s state (Yes)	-0.0032 (0.0043)	-0.0032 (0.0058)	-0.0071 (0.0066)
Bryce Canyon NP	-6.131*** (0.4686)	-5.735*** (0.5248)	-9.2398*** (0.997)
Canyonlands NP	7.5368*** (0.597)	7.0269*** (0.6741)	11.477*** (1.2731)
Capitol Reef NP	-3.2629*** (0.2181)	-3.1348*** (0.2465)	-4.5744*** (0.4424)
Zion NP	-6.9462*** (0.5416)	-6.4975*** (0.6063)	-10.5064*** (1.1516)
Winter	-0.0835*** (0.0371)		
Spring	-0.0385*** (0.0043)		
Summer	-0.0791*** (0.0047)		
Constant	8.5379*** (0.6039)	7.9021*** (0.6782)	12.8002*** (1.2887)
Day dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Pseudo R–squared	0.0473	0.0507	0.089
Observations	251,197	251,197	251,197

Notes: ***, ** and * indicate significance levels 1%, 5% and 10% respectively. Standard errors for coefficients in parentheses

6. Conclusion

We analyze the impact of weather and socio-demographic characteristics on length of stay for Utah's national parks. We achieve our research objective using reservation data from five National Parks in Utah. We adopt quantile and ordinary least square estimation strategies for our analysis. As part of the study, we conduct a of robustness checks to ascertain the validity of our results with a Poisson model. Before conducting the regression, we performed some descriptive statistics and presented our results using figures and tables. From our figures, we realize that summer is the optimal time for most recreationists patronizing Utah's naturally managed national parks. However, the winter season is the least favorable time to visit Utah. Regarding climate statistics, we realize that the various national parks have varying climate conditions but with some similarities, except for the Bryce Canyon NP.

Overall, our findings demonstrate the importance of accounting for visitors' demographic characteristics as they contribute to recreational decision–making as we realize that variables such as the median household income, the visitor's distance from home, and travel costs are good predictors of visiting a national park for recreational use. For instance, the relationship between travel cost and recreational demand outcomes can be attributed to opportunity cost, as long-distance trips can affect productive working hours. We observe a similar explanation for the relationship between visitors' home distance and recreational demand.

We find that varying weather and climate variables affect recreational demand as our analysis suggests precipitation does not affect recreation as Utah is arid and "desert-like" with low rainfall and snowfall However, we observed considerable heterogeneity in temperature as the maximum temperature is a key driver of recreational demand in Utah. However, we experience the opposite relationship for minimum temperature. Again, we notice that visitors exhibit negative reaction towards lower humidity and extremely dry weather pattern. By exploring the consequences of climate variability on recreational demand, we demonstrate that different climates affect visitation to managed natural areas differently. The climate-recreation nexus emanates from the geophysical characteristics and recreational opportunities available at specific destinations. As the quantile estimates demonstrate, the climate variables are related to recreational demand patterns. However, how and why it relates to recreational demand patterns is a product of many factors.

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APPENDIX

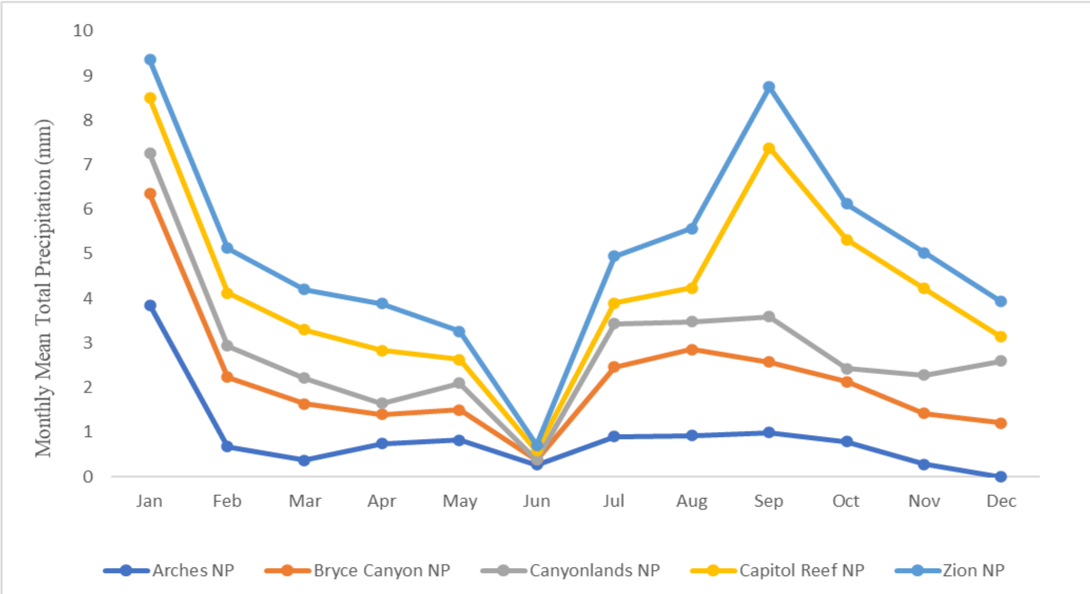

Figure 3.2: Monthly Precipitation for the National Parks

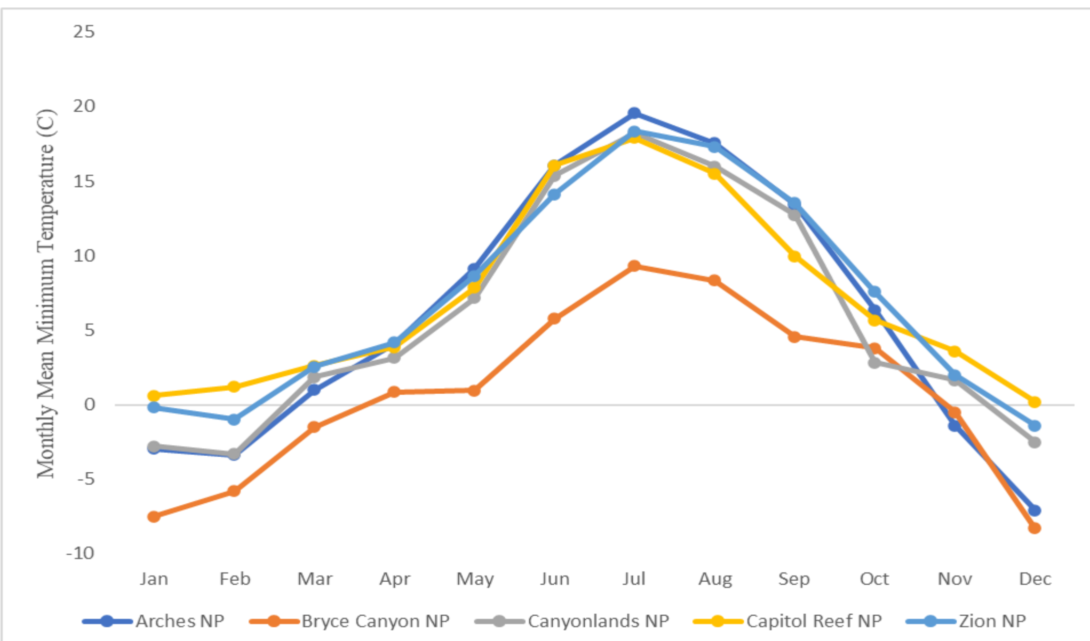

Figure 3.3: Monthly Minimum Temperature for the National Parks

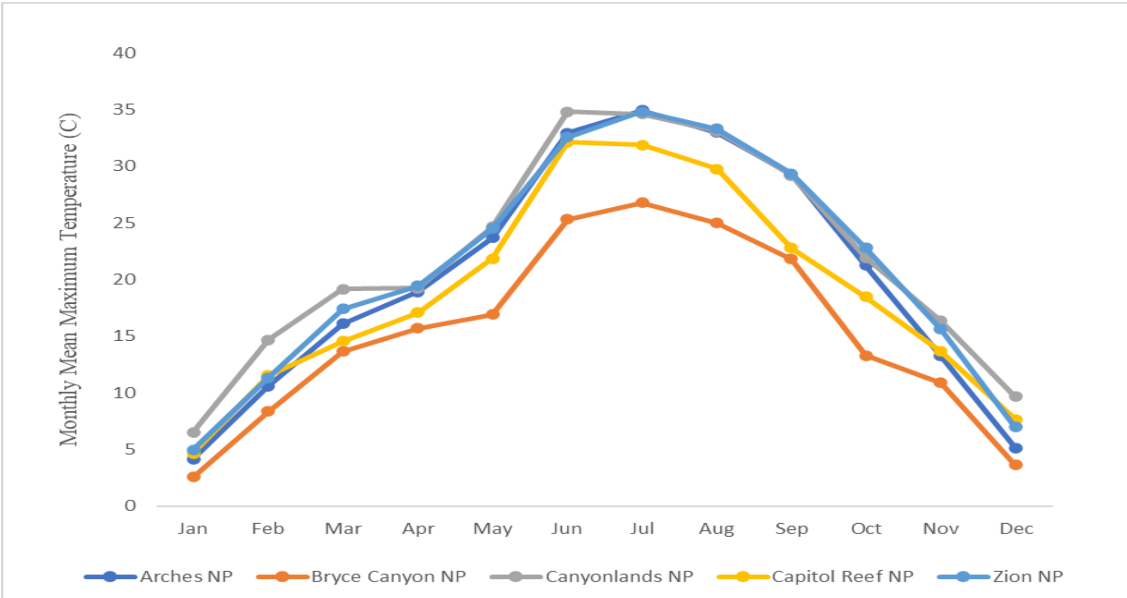

Figure 3.4: Monthly Maximum Temperature for the National Parks

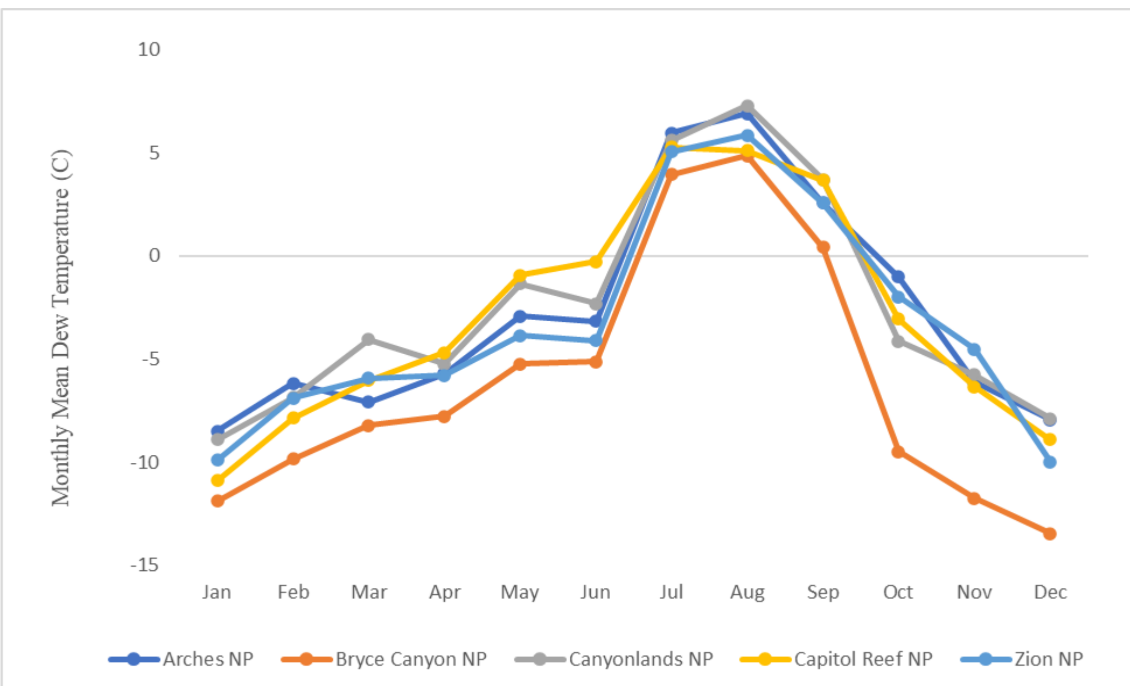

Figure 3.5: Monthly Dew Point Temperature for the National Parks

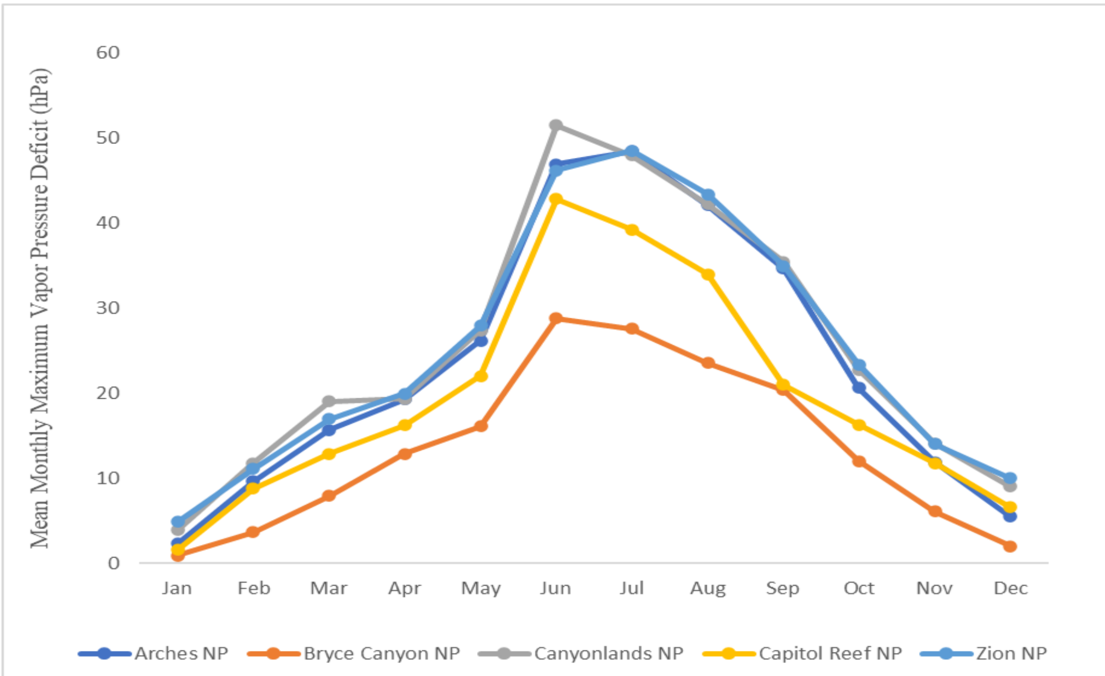

Figure 3.6: Monthly Maximum Vapor Pressure Deficit for the National Parks