

DISSERTATION

THREE ESSAYS ON THE ECONOMIC AND ENVIRONMENTAL IMPLICATIONS OF
AGRICULTURAL CONSERVATION INCENTIVES AT THE FIELD, REGIONAL, AND
GLOBAL SCALES

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ABSTRACT

THREE ESSAYS ON THE ECONOMIC AND ENVIRONMENTAL IMPLICATIONS OF AGRICULTURAL CONSERVATION INCENTIVES AT THE FIELD, REGIONAL, AND GLOBAL SCALES

Agricultural conservation policies are central to efforts to address the dual challenges of climate change mitigation and rural economic sustainability. Agriculture contributes significantly to greenhouse gas (GHG) emissions, particularly through soil-based processes, leading to the expansion of agri-environmental incentive programs aimed at encouraging the adoption of climate-smart practices. Evaluating the effectiveness of these policies requires careful consideration of economic feasibility, producer behavior, market interactions, and broader socio-economic impacts. This dissertation consists of three essays that use quantitative methods, integrating econometric models, biophysical simulations, and general equilibrium analysis, to examine these dimensions. Together, the essays underscore the importance of incorporating market feedbacks, accounting for international emissions leakage, and evaluating local labor market outcomes to design agri-environmental policies that are both environmentally effective and economically inclusive.

In the first essay (chapter 2) of this dissertation, we examine how endogenous crop prices affect estimates of greenhouse gas abatement supply on corn and soybean acres at the farm level under alternative climate change scenarios in the U.S. Corn Belt. We combine a discrete choice model of farmer behavior with a spatially explicit biogeochemical model of GHG emissions and link this model to crop demand curves to allow for price feedbacks. Producers are offered payments from the GHG reductions achieved by adopting climate-smart practices, no-till, cover crops, and reduced nitrogen application, and their adoption behavior is simulated across varying carbon price and climate scenarios. Results indicate that accounting for endogenous prices increases estimated abatement, particularly from nitrous oxide reductions, by up to 18 percent at a carbon price of \$190

t CO₂e under the extreme climate scenario and by 25 percent under the sustainability scenario, relative to estimates based on exogenous prices. Results underscore the importance of considering market interactions when constructing abatement cost functions.

In the second essay (chapter 3), we investigate emissions leakage from domestic conservation policy at the global scale by modeling the worldwide GHG emissions implications of expanding the U.S. Conservation Reserve Program (CRP). While CRP has been considered as a policy that can reduce domestic GHG emissions, our results show that it also generates significant spillover effects via global market adjustments. For an additional 4 million acres (1.6 million hectares) enrolled in CRP, approximately 236 thousand hectares of forest are converted to agriculture within the U.S., while cropland expands by 205 thousand hectares outside the U.S. due to market-driven land use changes. These spillover effects fully offset the mitigation achieved on the enrolled cropland, resulting in over 200% global emissions leakage. These findings underscore the importance of incorporating international leakage and market-mediated effects into the evaluation of land-based climate policies. The study contributes a novel framework for assessing conservation policies in a globally integrated economy and highlights the need for internationally coordinated approaches to ensure environmental effectiveness.

In the third essay (chapter 4), we assess the regional-level economic effects of agri-environmental programs by examining the employment trade-offs between land retirement and working lands programs. We use panel data and a fixed effect model to address the endogeneity of EQIP and CRP enrollment. We deploy alternative identification strategies and controls to test the robustness of our results. Findings indicate that both cropland retirement and working lands programs are associated with higher local employment levels, and that reallocating conservation dollars from temporary retirement to working lands at the state level increases overall employment in each rural county by 0.4% per million dollars, with agricultural jobs increasing faster than non-agricultural jobs. These results offer valuable insights for policymakers seeking to generate environmental benefits while supporting rural employment.

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DEDICATION

To my grandparents — the light that stayed when everything else faded.

To my son — my second degree, and I'm still earning it.

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Chapter 1

Introduction

Agriculture plays a vital role in the United States (U.S.) economy and labor market (Foster et al. 2004). In 2023, agriculture, food, and related industries contributed approximately \$1.54 trillion to U.S. Gross Domestic Product (GDP), representing 5.5% of the total economy (ERS 2025). While the direct output from farms accounted for \$222.3 billion, it also made significant contributions from food and beverage manufacturing, retail, food services, and related industries. In terms of employment, agriculture and its related sectors supported 22.1 million full- and part-time jobs in 2022, making up 10.4% of total U.S. employment (ERS 2025). Although only 2.6 million of these were on-farm jobs, the remaining 19.6 million were spread across food services, retail, and processing sectors (ERS 2025). As a foundational component of both national output and employment, agriculture remains central to discussions of economic resilience, rural development, and policy design in the face of evolving environmental and market challenges.

Despite its economic significance, U.S. agriculture is a major contributor to greenhouse gas (GHG) emissions, accounting for 9.4% of total national emissions in 2022 (EPA 2024). Among these emissions, nitrous oxide (N₂O) is of particular concern due to its high global warming potential (IPCC 2021) and is primarily released through soil management activities that increase nitrogen availability, such as fertilizer application and manure deposition (Makowski 2019). Agricultural soil management has become the largest single source of N₂O emissions in the U.S., responsible for over 75% of national totals in 2022 (EPA 2024). In addition, land management practices such as tillage, cover cropping, and land-use change significantly influence soil carbon stocks (Al-Kaisi et al. 2005; Wade et al. 2015). These soil-related emissions are especially challenging to mitigate due to their spatial variability, sensitivity to local biophysical conditions, and strong ties to crop productivity goals (Smith et al. 2007). Emissions from these sources have increased significantly over the past three decades (EPA 2024), underscoring the environmental externalities associated

with agricultural production and the pressing need for conservation practices and mitigation strategies that lower emissions while sustaining agricultural productivity.

To address the environmental externalities of agriculture, policymakers have increasingly turned to conservation incentives aimed at aligning producer behavior with environmental objectives. These efforts are implemented through federal programs that generally follow two approaches: land retirement programs—such as the Conservation Reserve Program (CRP) and Wetland Reserve Program (WRP)—and working lands programs, including the Conservation Stewardship Program (CSP), Environmental Quality Incentives Program (EQIP), and Agricultural Conservation Easement Program (ACEP). Together, the three primary programs—CRP, CSP, and EQIP—have enrolled over 132 million acres, covering approximately 15% of U.S. agricultural land (Newton 2019). As shown in Figure 1.1, more than 20 states report enrollment exceeding 20% of their farmland (Newton 2019). These programs have enabled farmers to make significant contributions to resource conservation, protecting soil and water quality while enhancing soil carbon through practices like cover cropping and no-till management.

However, land-based interventions, particularly in agriculture, have interconnected implications for climate mitigation, adaptation, food security, biodiversity, and broader environmental and economic outcomes (Köberle 2022). It is therefore essential to assess the net impact of mitigation strategies across both environmental and economic objectives. The mitigation potential of conservation agriculture and related land management practices is highly site-specific, influenced by local conditions such as climate, soil productivity, and residue management practices (Nabuurs et al. 2022). While the technical potential of these practices to reduce GHG emissions is well established (Smith et al. 2008), their economic potential, which accounts for costs, behavioral responses, and policy constraints, is considerably lower (Smith et al. 2008). These distinctions emphasize the importance of evaluating mitigation options based on their real-world feasibility under evolving market and policy conditions (Smith et al. 2007).

Although land-based climate mitigation strategies are often evaluated within domestic boundaries (Wu 2000; Wu et al. 2010; Ogle et al. 2023), agricultural land markets are globally inter-

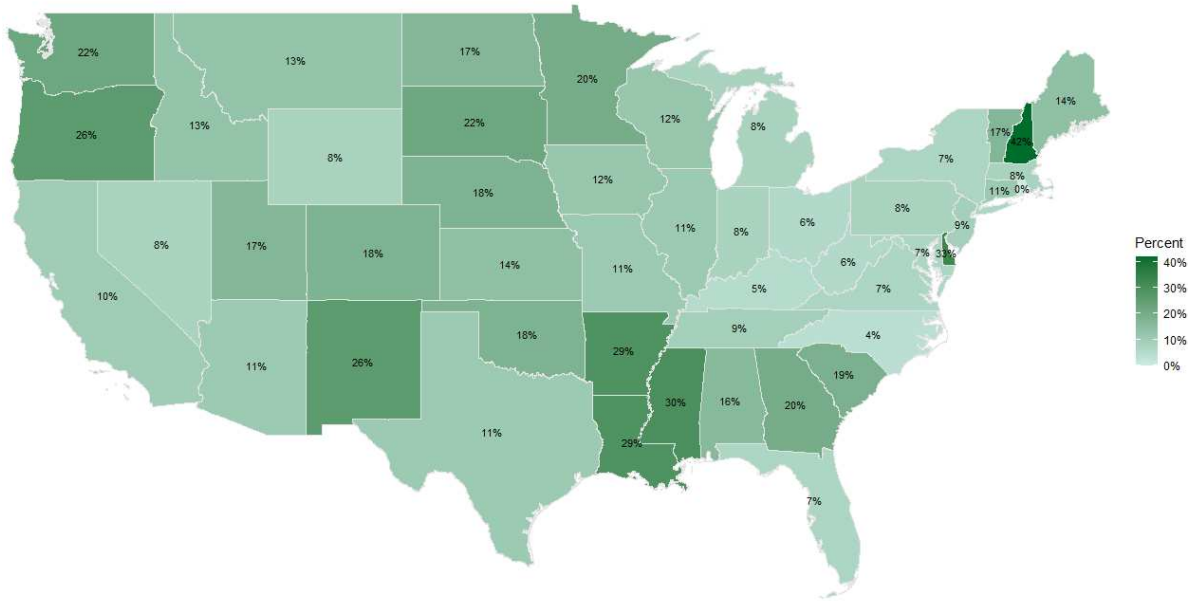


Figure 1.1: Conservation acreage as a percentage of total agricultural land

Source: Farm Bureau, 2019.

Note: This figure includes acreage under active and completed CRP, CSP, and EQIP contracts as a percent of total farmland acres.

connected, and interventions in one region can have far-reaching consequences elsewhere (Alston et al. 2007). Moreover, because GHGs are global pollutants, their climate impact is not confined to the location of emission, making international coordination critical for effective mitigation. Consequently, the effectiveness of domestic mitigation efforts must be evaluated in a global context. The interconnected nature of global agricultural markets means that domestic land-based mitigation policies can have broader implications for production, prices, and environmental outcomes beyond national borders (Hertel 2018). For example, retiring cropland in the U.S. under CRP may reduce local GHG emissions but simultaneously raise global commodity prices, encouraging agricultural expansion in regions with weaker environmental safeguards often into high-carbon landscapes such as tropical forests or peatlands (Miranda et al. 2024; Liu et al. 2021). These insights reinforce the importance of accounting for international emissions leakage effects within the global economic system when evaluating the net climate impact of domestic land-based mitigation policies.

Beyond their environmental objectives, agricultural conservation policies also play a critical role in shaping rural economic outcomes, particularly through their influence on employment (Caldeira et al. 2004). While existing studies on environmental regulation often emphasize potential job losses due to compliance costs and industrial restructuring (Walker 2011), conservation programs may function differently. Subsidies for working lands, for example, support labor-intensive practices such as nutrient management, cover cropping, and habitat restoration, activities that can stimulate demand for local conservation services and support employment in rural areas. In contrast, land retirement programs like CRP may reduce direct farm labor demand (Sullivan et al. 2004), but they have been associated with positive employment spillovers through increased recreation and tourism in rural communities (Bangsund et al. 2004; Li et al. 2023). These differing pathways highlight a central trade-off in conservation policy design. While both working lands and land retirement programs deliver environmental benefits, they may have divergent effects on the scale and structure of rural employment. Understanding these trade-offs is particularly important as policymakers continue to expand investment in land-based mitigation efforts. While specific employment effects may vary across programs and regions, evaluating the local labor market impacts of conservation subsidies provides critical insight for designing climate-smart policies that are both environmentally effective and economically inclusive.

The three essays in this dissertation contribute to a deeper understanding of the environmental and economic impacts of U.S. agricultural conservation policy. By examining field-level GHG mitigation behavior, international land-use and emissions spillovers, and rural labor market outcomes, these studies offer insights into how conservation programs can be designed to deliver both environmental and economic benefits. Together, the essays highlight the importance of accounting for global interconnections, local responses, and policy incentives when evaluating the effectiveness of land-based climate mitigation strategies.

The first chapter shows that farmers' responses to changing crop prices influence the effectiveness of agricultural conservation policies. By combining a model of land management decisions with biophysical estimates of greenhouse gas emissions (DayCent), this study examines how mar-

ket feedbacks shape mitigation outcomes. When crop prices are allowed to adjust in response to production changes, estimates of GHG abatement increase, and the composition of adopted practices shifts. Specifically, at a carbon payment of \$190 per tonne CO₂ equivalent, allowing prices to adjust increases estimated abatement by roughly 18% under the extreme climate change scenario (*FGOALS-g3* SSP3.70) and by 25% under the sustainability scenario (*FGOALS-g3* SSP1.26). Instead of switching to lower-emitting crops, farmers are more likely to reduce nitrogen inputs within existing cropping systems, resulting in greater reductions in N₂O emissions but also leading to lower yields and higher food prices. These findings reveal the importance of accounting for price responses when evaluating conservation incentives. Ignoring these market effects can lead to underestimates of mitigation potential in the Midwest U.S. and a misunderstanding of how policies affect decision-making at the field level.

The second chapter evaluates the international GHG emissions consequences of expanding the U.S. CRP. Using a global computable general equilibrium (CGE) model with spatially explicit land use detail, the analysis simulates how domestic land retirement affects global commodity markets, trade flows, land use, and associated emissions outcomes. Results show that land retirement in the U.S. leads to reduced agricultural output and higher world prices for crop commodities, which in turn incentivize agricultural expansion in other countries. This international land conversion generates additional GHG emissions that offset a significant share of the domestic mitigation gains. Under market-driven land use change, both domestic and international leakage fully offset the mitigation potential of the CRP, with domestic leakage reaching approximately 159% and total leakage, including international effects, rising to nearly 205%. This chapter underscores the need to evaluate domestic land-based mitigation efforts in the context of globally interconnected markets, where shifts in production and land use can undermine climate goals by relocating emissions across borders.

The third chapter examines how shifts in conservation funding priorities affect employment at the regional level. Using panel data from U.S. counties and fixed effects econometric methods, the study estimates the labor market effects of two major conservation program types: land

retirement (CRP) and working lands (EQIP). The analysis shows that reallocating funding from land retirement to working lands programs at the state level increases regional employment by an average of 22.8 jobs per million dollars per rural county, equivalent to a 0.4% rise in total employment. Specifically, working lands programs are associated with more employment per conservation dollar, reflecting their support for active land management and local conservation. These results highlight how conservation policy design can shape rural labor markets alongside delivering environmental benefits. The findings provide policymakers with insights into how conservation investments can be structured to support both environmental and economic objectives at the regional level.

Taken together, the three chapters in this dissertation examine how agricultural conservation policies influence GHG emissions, land use patterns, and rural labor markets. The findings show that the effectiveness of these programs is strongly influenced by how they interact with market incentives, producer behavior, and policy design across different spatial scales. This work highlights that farmers' adoption of conservation practices is influenced by output prices, which in turn affect estimated mitigation outcomes. It further demonstrates that domestic land retirement can induce land use changes abroad, diminishing the overall climate benefits. In addition, the allocation of conservation funding between land retirement and working lands programs has measurable implications for employment in rural areas.

If conservation incentives continue to expand in response to climate and sustainability goals, evaluating both environmental outcomes and economic impacts becomes increasingly important. The insights from this dissertation can support the design of conservation policies that deliver meaningful GHG reductions, promote rural economic development, and reduce unintended consequences within a globally connected agricultural system. Moving forward, research and policy should continue to integrate environmental and economic considerations to support more effective and balanced approaches to land-based pollution mitigation.

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Chapter 2

Endogenous Output Prices and Greenhouse Gas

Abatement from Corn and Soy

2.1 Introduction

Agricultural practices play an increasingly critical role in global efforts to mitigate greenhouse gas (GHG) emissions, with practices impacting soil carbon (C) sequestration and nitrous oxide (N₂O) emissions (Ogle et al. 2020). While soil carbon sequestration has received considerable attention as a climate mitigation strategy (Choi et al. 2010), N₂O's role, 265¹ times more potent than carbon dioxide (CO₂) in terms of global warming potential (GWP-100), remains underexplored in economic modeling frameworks (Ogle et al. 2020; Li et al. 2024). Agricultural N₂O emissions are projected to increase by 35–60% by 2030 (Bruinsma 2017), making it a crucial target for mitigation efforts. Crucially, reducing N₂O emissions by reducing fertilizer rates at a large scale may lead to reduced output (Brunelle et al. 2015) that impacts crop prices. This study examines how output price endogeneity affects the estimation of GHG abatement supply curves, focusing on the Cornbelt region in the United States (U.S.). We develop an integrated modeling framework that links biophysical processes, economic decisions, and market equilibrium to evaluate interactions between agricultural practices, policy incentives, and market responses.

In 2022, the U.S. Department of Agriculture (USDA) committed \$20 billion to enhance conservation programs aimed at improving soil carbon, reducing nitrogen losses, and managing CO₂, methane, or NO_x/N₂O emissions related to agricultural production.² This funding supports incentives for farmers to adopt conservation tillage practices, such as reduced or no-till farming, and implement winter cover crops, both of which play a crucial role in carbon sequestration and re-

¹IPCC AR6, 2021

²USDA Announces New Opportunities to Improve Nutrient Management

ducing soil N₂O emissions. The USDA's Natural Resources Conservation Service (NRCS) is also expanding nitrogen management efforts through initiatives like streamlined nutrient management within key programs, including the Environmental Quality Incentives Program (EQIP), EQIP Conservation Incentive Contracts, and the Conservation Stewardship Program, alongside a \$40 million nutrient management grant opportunity through the Regional Conservation Partnership Program (RCPP). However, while these conservation efforts aim to improve environmental outcomes, they also influence crop yields (Deines et al. 2023; Brunelle et al. 2015), which in turn affect market equilibrium, crop prices (Roberts et al. 2013), and overall farm profitability. These economic factors shape farmers' production decisions, ultimately affecting the efficiency of GHG mitigation strategies. Accordingly, this study evaluates how accounting for price endogeneity affects the estimation of agricultural GHG abatement supply, particularly with respect to N₂O emissions and soil carbon sequestration.

Commodity prices play a crucial role in shaping farmers' decisions regarding GHG mitigation practices and crop acreage, as market conditions—particularly input and output prices—directly impact their economic incentives and production choices (MacLeod et al. 2015). Studies such as Johansson et al. (2020) examine the relationship between GHG abatement costs, commodity prices, and land use, identifying a trade-off between higher crop prices and GHG abatement. Similarly, Roberts et al. (2013) show how yield and acreage decisions influence crop prices within the same year, highlighting the interactions between production choices and market conditions. Beyond immediate market effects, price expectations also shape agricultural decision-making. Chavas et al. (1983) show that futures and lagged prices influence acreage decisions, and Feng et al. (2010) find that anticipated price increases drive changes in crop rotation practices and encourage the expansion of acreage onto lower-quality lands. These price-driven shifts in land use can further affect agricultural productivity. For instance, Miao et al. (2016) find that rising corn prices significantly boost corn yield, suggesting that failing to account for price effects in analyses could lead to overestimations of climate change impacts, by up to 15% for soybeans and 9% for corn. Therefore,

abatement schemes should allow for changes in market prices and adopted technologies that have significant implications for opportunity costs (Tang et al. 2016).

However, few studies have considered the role of output prices in influencing the supply in farmers' practice choices, even though evidence suggests that output prices play a crucial role in affecting farmers' decisions regarding agricultural GHG mitigation practices. One study considered the endogenous crop price was conducted by Garnache et al. (2017), which evaluated the abatement efficiency of second-best agricultural GHG mitigation policies within the empirical context of field crop agriculture in California. The authors began by simulating California's abatement supply curve under an ideal GHG emission mitigation policy, initially using an exogenous crop price in their profit maximization model. They then extended the analysis to include endogenous crop prices. The results show that accounting for endogenous prices makes the marginal GHG abatement cost curve slightly more elastic, although the difference between fixed and flexible pricing was relatively small. We extend this earlier work by fully coupling the biophysical and economic models, allowing for endogenous feedback between land management decisions and environmental outcomes. This integrated framework enables us to incorporate field-level heterogeneity in GHG emissions, explicitly model nitrogen application choices, and examine how price feedbacks shape the abatement supply curve across different climate change scenarios, advancing beyond the partial linkages used in Garnache et al. (2017).

The supply curve is widely used in evaluating the economic efficiency of abatement efforts in agriculture. However, estimating the supply is complicated, as farmers' practice choices are significantly influenced by characteristics such as existing practices, soil carbon levels, and soil conditions (Dessart et al. 2019; Du et al. 2022; McCarl et al. 2001). Therefore, this study simulates the impact of price endogeneity on estimating the supply of GHG abatement from agriculture under various climate change scenarios in the American Corn Belt region by integrating a discrete choice modeling framework with a spatially explicit model of GHG emissions (Daycent (Parton et al. 1998; Del Grosso et al. 2011)). We adopt supply estimation methods similar to those used by Rad et al. (2025), while introducing endogeneity in crop prices by specifying demand curves

for each crop and enabling forward-looking simulation. Initially, we econometrically estimate utility equation parameters based on historical crop and practice choice decisions. Subsequently, we predict farmers' future practice choices and nitrogen (N) fertilizer application rates based on predicted utilities, accounting for varying climate change scenarios and crop market responses. Finally, we derive marginal GHG abatement supply curves by simulating counterfactual scenarios that impose GHG payments on CO₂ and N₂O for a net decrease in GHG emissions, relative to a no-payment baseline, under various climate change scenarios and crop market responses. We then compare the resulting supply curves for each scenario, with and without endogenous crop prices.

We first contribute to the literature by considering the price impact in estimating the supply of GHG mitigation in agriculture under various climate change scenarios. Agricultural net GHG mitigation analyses have been developed for several countries and the supply of abatement can be calculated in various ways. Vermont et al. (2010) categorize these methodologies into three broad groups: (i) supply-side, micro-economic models depict representative farmers maximizing profits under technical and economic constraints with a focus on partial equilibrium outcomes (Garnache et al. 2017). For instance, De Cara et al. (2005) evaluated the non-CO₂ mitigation costs in Europe's agricultural sector, assuming fixed prices but noted that if mitigation policy affects equilibrium output prices, the impact on marginal abatement costs is unclear; (ii) equilibrium models, incorporating endogenous pricing mechanisms. Such models illustrate the responses of a broader economic region or specific sectors to mitigation restrictions. Examples include the DICE and RICE models, covering comprehensive sectors of the worldwide economy (Nordhaus et al. 2003), the ASMGHG model, which represents the agricultural and forestry sectors in the U.S. (Schneider et al. 2007), and the CAPRI model, focusing on agriculture within Europe (Pérez Dominguez et al. 2009). While the existing equilibrium models capture economy-wide responses to mitigation policies through price adjustments, they often lack spatial explicitness and detailed representation of farm-level decisions. They operate at an aggregated regional or national scale, failing to account for spatial heterogeneity in factors like soil types, management practices, and climate conditions that influence mitigation potentials and costs. This can lead to inaccurate estimates of mitiga-

tion potential and costs, limiting their effectiveness in informing spatially-targeted policies; (iii) engineering cost approaches, which compile technical and scientific data to identify the most cost-effective mitigation options for specific emission price scenarios (Naucler et al. 2009; Eory 2015) under exogenous price assumptions.

This paper utilizes a supply-side microeconomic approach by simulating farmers' practices at the parcel level, while also incorporating the impact of crop prices in the crop markets. Our approach captures feedback effects between mitigation activities, yield changes, and resulting price adjustments in output markets. It combines the strengths of microeconomic models in representing farm-level decisions with the endogenous price mechanisms of equilibrium models, but at a finer spatial scale. By explicitly modeling spatial heterogeneity in factors affecting mitigation potential and costs, our approach provides more accurate and spatially disaggregated estimates, enabling the design of targeted mitigation policies tailored to local conditions.

Second, we contribute to the literature that develops integrated assessment modeling (Keiser et al. 2017), specifically by incorporating endogenous crop pricing mechanisms. Integrated assessment models (IAMs) have become increasingly important for natural resource management and policy analysis, and have been widely applied across domains including water resources (Manning et al. 2020), land use change (Bateman et al. 2013), fisheries management (Nielsen et al. 2018), forestry policies (Hashida et al. 2019), and greenhouse gas emission regulations (Garnache et al. 2017). Many integrated models employ programming approaches to simulate producer behavior, such as the positive mathematical programming and DayCent model used by Garnache et al. (2017) for estimating the costs of second-best GHG abatement policies, or the programming approach by Muller et al. (2009) to highlight the benefits of trading ratios in emissions trading programs. Our work builds upon and extends the existing models presented by Rad et al. (2025), by linking physical data from the biogeochemical model with producer preferences. We evaluate the impacts of policy counterfactuals in a framework that allows revealed producer behavior to interact with the grain market responses.

This study finds that incorporating endogenous crop prices into agricultural GHG policy analysis affects both the level and composition of estimated emissions reductions. Using an integrated modeling framework that links farmer decision-making with biogeochemical simulations, we compare fixed and endogenous price scenarios under different carbon payment levels. The results show that allowing prices to respond to production changes leads to higher GHG abatement, particularly through reduced N₂O emissions, than assuming fixed prices. At a carbon payment of \$190 per tonne of CO₂ equivalent, allowing prices to adjust increases estimated abatement by approximately 18% under the extreme climate change scenario (*FGOALS-g3* SSP3.70) and by 25% under the sustainability scenario (*FGOALS-g3* SSP1.26). We also find that lower carbon payments mainly encourage fertilizer reduction rather than the adoption of soil C building practices like conservation tillage or cover cropping. This occurs because, while endogenous prices reduce the incentive to switch to lower-emitting crops such as soybeans, the incentive to reduce nitrogen inputs applies across all nitrogen-using crops. In our context, the latter effect dominates, resulting in a net increase in abatement under endogenous pricing. These findings suggest that models assuming fixed prices may understate the mitigation potential of agricultural policies and overlook how farmers adjust to changing market conditions.

The next section outlines the integrated modeling framework, which combines a spatially explicit biogeochemical model (DayCent), a discrete choice model of farmer behavior, and a market equilibrium that endogenizes crop prices based on production responses. This framework is used to simulate agricultural GHG abatement across a range of carbon price scenarios. The results section presents the estimated GHG abatement supply curves and examines the underlying changes in crop acreage and management practices that drive the observed outcomes. Finally, the discussion section interprets the findings, highlights key policy implications, and concludes by emphasizing the importance of accounting for both behavioral and market responses in the design of effective agricultural climate policies.

2.2 Integrated Model

In this section, we describe how we integrate the econometric model (producer choice), climate change scenarios, the DayCent model, and the crop market equilibrium framework, as illustrated in Figure 2.1. The integrated model begins with the empirical estimation of parameters for the producer choice model using historical data. Next, the DayCent model simulates farm-level soil organic carbon (SOC) stock changes, GHG emissions, and crop yields under various crop and management practices, fertilizer application levels, and climate change scenarios. These outputs are used as inputs to predict crop, farming practices, and fertilizer application level choices within the econometric model. The predicted choices, combined with the corresponding simulated yields from DayCent, are then entered into a grain market equilibrium model to update crop prices. These crop prices will, in turn, shape expectations for the following year's producer choice decisions. Simultaneously, the predicted crop practice choices are fed back into DayCent to simulate yields, SOC stocks, and N₂O emissions for the following year. The simulation proceeds iteratively, updating crop prices, SOC, N₂O emissions, and weather conditions each year. We begin by introducing the DayCent model, as the counterfactual data needed in the econometric estimation are generated by the DayCent simulation.

2.2.1 DayCent Modeling and Climate Change Scenarios

We use the DayCent biogeochemical model (Parton et al. 1987; Parton et al. 1998; Parton et al. 1994; Del Grosso et al. 2011; Del Grosso et al. 2022) to simulate crop yields, GHG emissions, and changes in SOC stocks across our study region. DayCent models daily carbon and nitrogen dynamics and flows among the atmosphere, vegetation, and soil systems, incorporating key processes such as plant growth, nutrient cycling, organic matter decomposition, and N₂O emissions resulting from nitrification and denitrification (Zhang et al. 2014), as shown in Figure 2.2. This process-based model is widely applied to assess ecosystem responses to climatic variation and land management across croplands, forests, grasslands, and savannas (Necpálová et al. 2015; Parton et al. 2007; Hartman et al. 2009; Del Grosso et al. 2011; Del Grosso et al. 2022). In our application,

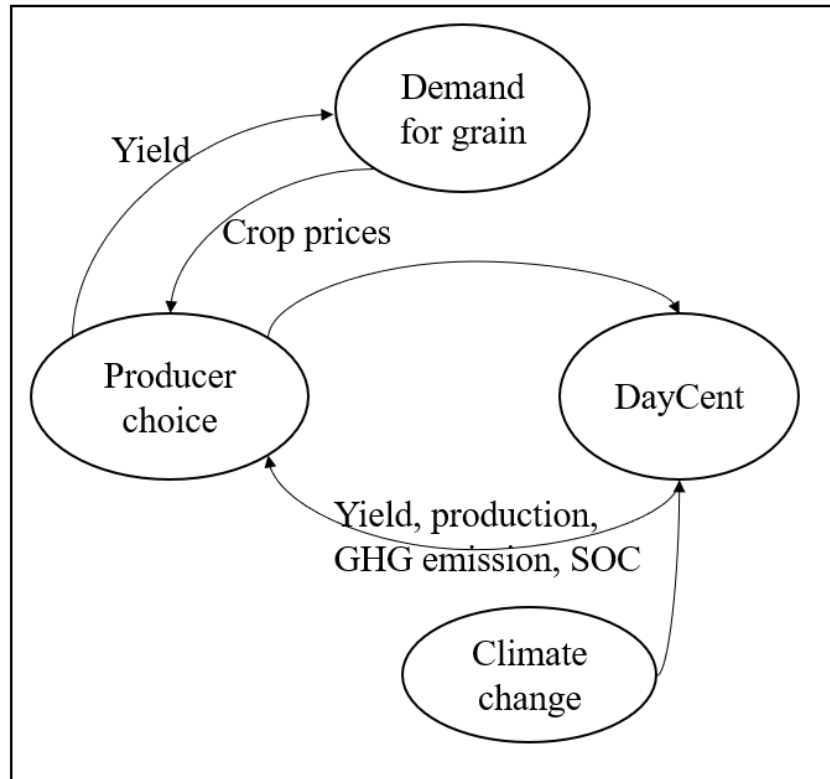


Figure 2.1: Integrated model linking producer choices, grain markets, and climate change to a biogeochemical model

DayCent generates field-level estimates of SOC changes and stock, N₂O emissions, and crop yield under varying combinations of tillage, cover cropping, and fertilizer use.

DayCent requires a suite of location-specific environmental and management inputs to operate effectively. These inputs include historical weather variables, such as daily precipitation and temperature, from the Parameter-elevation Regressions on Independent Slopes Model (PRISM); soil characteristics, including texture, bulk density, and pH from the USDA Soil Survey Geographic Database (Soil Survey Staff 2019); and crop-specific management data, such as planting dates, tillage intensity, fertilizer application rates, and the use of cover crops. As illustrated in Figure 2.2, the model integrates these inputs to simulate interactions between environmental conditions and land-use practices, enabling the estimation of crop yields, SOC changes, and GHG emissions in response to both natural variation and human-induced management (Zhang et al. 2014). DayCent is particularly effective at capturing SOC dynamics and N₂O emissions under diverse agronomic

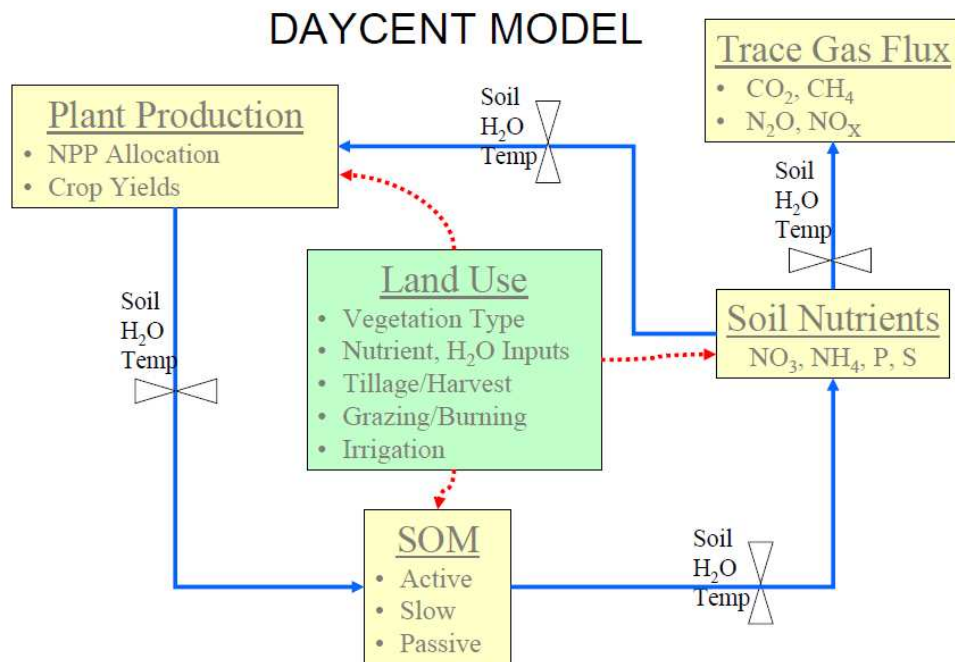


Figure 2.2: Overview of the process flow in the DayCent model

Source: Zhang et al. (2014).

conditions, producing spatially and temporally detailed estimates that can inform both economic evaluation and climate policy analysis (Del Grosso et al. 2011). Although the model does not account for all sources of yield variability, such as pest pressure or weed competition, it accurately reflects the primary biophysical drivers of productivity and soil emissions. This makes DayCent a valuable tool for assessing the trade-offs and co-benefits of climate-smart agricultural practices under current conditions and in future climate change scenarios. To assess the uncertainty in model predictions, a series of Monte Carlo simulations can be conducted to propagate error through the model analysis (Paciornik et al. 2019; Ogle et al. 2010).

To assess the effects of future climate variability on agricultural outcomes, we utilize projections from the *FGOALS-g3* global climate model, developed by the Institute of Atmospheric Physics, Chinese Academy of Sciences (Li et al. 2020). This model is part of the Coupled Model Intercomparison Project Phase 6 (CMIP6) and provides daily precipitation and temperature data that we integrate into the DayCent model to simulate crop yields, SOC, and N₂O emissions under

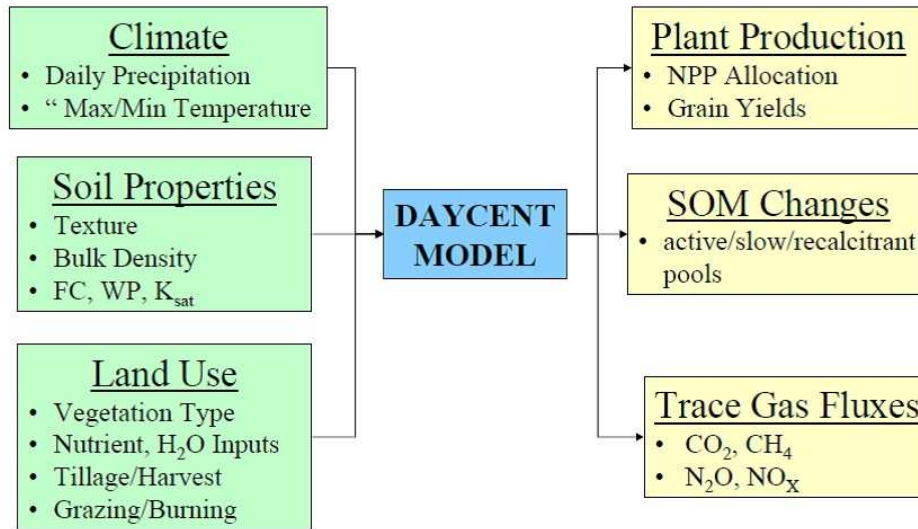


Figure 2.3: DayCent primary inputs and outputs

Source: Zhang et al. (2014).

alternative future climates. We focus on two contrasting Shared Socioeconomic Pathways (SSPs): SSP1.26, which represents a sustainable development trajectory with strong climate mitigation and low radiative forcing (2.6 W/m² by 2100), and SSP3.70, which reflects a world with regional rivalry, high population growth, weak international cooperation, and high emissions resulting in 7.0 W/m² radiative forcing by 2100 (Riahi et al. 2017).³ These scenarios enable us to evaluate how crop and practice choices respond under divergent climate futures and help assess the mitigation potential and resilience of climate-smart agricultural practices.

2.2.2 Economic Model

In this section, we first describe the producer choice model and then explain how we developed its parameterization. The model captures the endogenous relationship between crop prices and producer behavior, highlighting both the direct impact on crop profitability and the indirect influence on input decisions, including fertilizer use, tillage practices, and winter cover crop adoption.

³The SSP Scenarios

We then present the data sources, provide summary statistics, and conclude with the empirical estimation results.

Random Utility Model

First, we introduce a random utility model (RUM) (Equation 2.1) that captures the discrete choices producers make regarding crop selection and agricultural practices. We assume that the producer at each location $i = 1, \dots, N$ receives utility U_{ijt} from crop-practice combination

$$j \in \left\{ \begin{array}{l} (\text{soybeans, full-till, no cover crop}), (\text{soybeans, full-till, cover crop}), \\ (\text{soybeans, reduced-till, no cover crop}), (\text{soybeans, reduced-till, cover crop}), \\ (\text{soybeans, no-till, no cover crop}), (\text{soybeans, no-till, cover crop}), \\ (\text{corn, full-till, no cover crop}), (\text{corn, full-till, cover crop}), \\ (\text{corn, reduced-till, no cover crop}), (\text{corn, reduced-till, cover crop}), \\ (\text{corn, no-till, no cover crop}), (\text{corn, no-till, cover crop}) \end{array} \right\}$$

in year $t = 1, \dots, T$. We consider combinations of crop (2), tillage (3), and cover crop use (2) for a total of $2 \times 3 \times 2 = 12$ crop-practice choices (or “alternatives”) that can be chosen in any time period and at each National Resources Inventory (NRI) survey location. Then the utility level for a given crop-practice combination can be described as

$$U_{ijt} = \alpha_j + \beta_i R_{ijt} + \gamma_j X_{it} + \theta_j t + \lambda_j \delta_s + \varepsilon_{ijt} \quad (2.1)$$

This model incorporates alternative-specific constants, α_j , to capture time-invariant factors that are not included in the model affecting the utility of different tillage, cover crop practices common to all producers. Considering 12 alternatives, 11 constants α_j are defined, each compared against the utility of the 12th alternative, which acts as a reference. R_{ijt} represents the expected profit for each crop i and practice j , in year t . We first calculate the profit π_{ijt} , then compute a rolling average of the previous three years’ profits to obtain R_{ijt} .

In the model, X_{it} denotes a set of indicators capturing the crop grown, the cover crop planted in the previous year ($t - 1$), and the tillage practices over the past five years ($t - 5$),⁴ along with their interactions with each alternative practice. These variables account for rotational constraints (Claassen et al. 2017), and the persistence of management practices. The term θ_{jt} represents a practice-specific trend in utility, capturing temporal variations in incentives related to each tillage practice, such as subsidies or support from programs like the EQIP for adopting certain tillage practices or using winter cover crops. The δ_s term is used as a state indicator, while λ_j refers to a coefficient that is specific to each crop-practice combination, reflecting the impact of state-level policies. Lastly, ϵ_{ijt} is a random variable capturing idiosyncratic factors affecting producer utility. These are influences on decision-making processes that are not directly observable.

Then we use the estimated choice probability for alternative j' is

$$\text{Prob}(U_{ij't} > U_{ijt}) = \text{Prob}(U_{ij't} - U_{ijt} > 0), \forall j' \neq j \quad (2.2)$$

which depends only on the difference in utility, not its absolute level. When utility is decomposed into the observed and unobserved parts, Equation 2.3 expresses the choice probability as

$$\text{Prob}(U_{ij't} > U_{ijt}) = \text{Prob}(\epsilon_{ijt} - \epsilon_{ij't} < V_{ij't} - V_{ij't}), \forall j' \neq j \quad (2.3)$$

Where the observed part is

$$V_{ijt} = \alpha_j + \beta_i R_{ijt} + \gamma X_{it} + \theta_j t + \delta_{sj} \quad (2.4)$$

The mixed logit model is renowned for its exceptional flexibility, enabling it to approximate any RUM effectively (McFadden et al. 2000). In our empirical model, we utilized the mixed logit model to account for preference heterogeneity in response to changes in net revenue, which could potentially affect the population's responsiveness to net revenue changes resulting from payments

⁴Tillage data is only updated every 5 years in the imputation analysis.

for GHG abatement. Therefore, the mixed logit choice probabilities, with random parameters, can be expressed in the following form:

$$\text{Prob}(U_{ij't} > U_{ijt}) = \int \left(\frac{e^{V_{ij't}(\beta_i')}}{\sum_j e^{V_{ijt}(\beta_i)}} \right) f(\beta_i) d\beta_i \quad (2.5)$$

where $f(\beta_i)$ is the distribution of the β_i . In this case, we estimate the mean and standard deviation of the β_i across our observations.

Data

This analysis focuses on non-irrigated corn and soybean production at NRI survey points (Natural Resources Conservation Service 2018)) located within the Cornbelt Conservation Effects Assessment Project (CEAP) Region 7, which includes all or portions of Minnesota, South Dakota, Nebraska, Kansas, Oklahoma, Missouri, Iowa, Wisconsin, Illinois, Michigan, Indiana, and Ohio. These states account for the majority of U.S. corn and soybean production, and approximately 98.6% of corn and soybean acres in this region are rainfed (Rad et al. 2025). Data on crop production practices are sourced from the U.S. National Greenhouse Gas Inventory (U.S. EPA 2024), which integrates multiple datasets to produce spatially explicit estimates of crop management. While annual crop choices are directly recorded in the NRI, information on management practices, including tillage, cover cropping, irrigation, and nutrient application, is not collected. To fill this gap, the U.S. Greenhouse Gas Inventory imputes these practices using statistical and machine learning methods trained on complementary datasets, including the Agricultural Resource Management Survey (ARMS), CEAP survey data, and remote sensing products such as the Operational Tillage Information System (OpTIS). These imputed practices are available at five-year intervals and include six imputations to reflect uncertainty in the prediction process. This analysis uses one of the six imputed datasets.

Figure 2.4 shows historical trends in tillage, cover crop, and crop area shares from 1990 to 2020, based on the National Greenhouse Gas Inventory data. The left panel shows a substantial decline in the share of full tillage (FT), which decreased from over 80% to below 40%, accompanied by

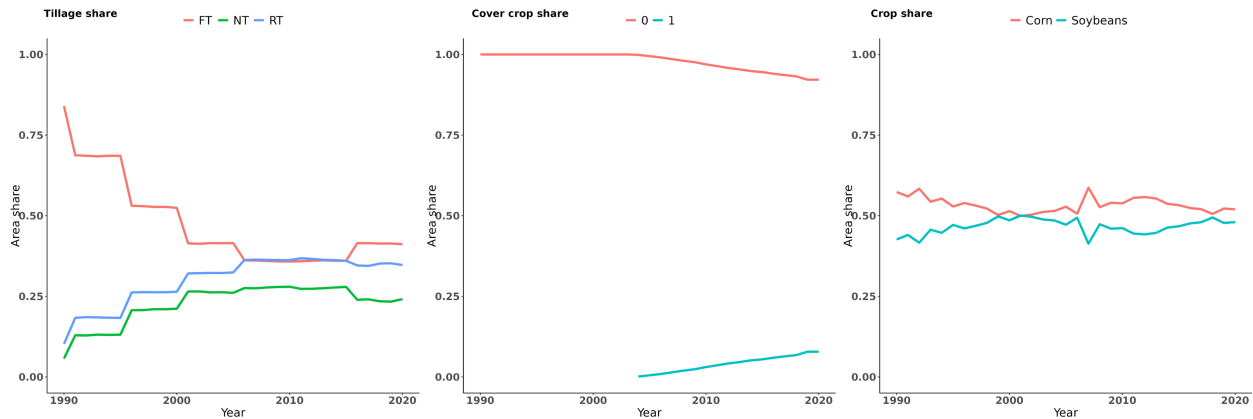


Figure 2.4: Historical trends in tillage (left), cover cropping (middle), and crop (right) area shares (1990–2020)

Note: Data are drawn from the U.S. National Greenhouse Gas Inventory. “FT” denotes full tillage, “NT” denotes no-till, and “RT” denotes reduced tillage. The cover crop variable distinguishes between winter cover crops (1) and none (0). Shares are calculated from modeled crop–practice combinations at NRI locations across years. Our analysis focuses on the pre-2015 period to avoid potential bias from recent increases in FT, likely driven by weed resistance pressures.

notable increases in no-till (NT) and reduced tillage (RT) practices. This shift reflects a broader adoption of conservation tillage over the past three decades. However, in the last five years of the sample, the share of FT shows a slight uptick, potentially driven by weed management challenges that may have prompted some farmers to revert to FT (Kumar et al. 2020; Lu et al. 2022). To avoid confounding long-term trends with this recent shift, our analysis is limited to the pre-2015 period.⁵ The middle panel shows trends in winter cover crop adoption, which remained negligible through the 1990s but steadily increased after 2003, though the overall share remains low, under 10% in 2020. The right panel displays the area shares of corn and soybeans, the two dominant crops in the region. While the relative shares have fluctuated over time, they remained relatively stable, with corn consistently occupying a slightly larger share than soybeans.

For estimation of the econometric model, the dataset is restricted to five-year intervals between 1995 and 2015, focusing on NRI point-years in which corn grain or soybeans were grown. After

⁵The RUM coefficient estimates including post-2015 data are presented in Appendix Table A2.1. Based on the profit parameter coefficients, we do not anticipate any significant differences from the pre-2015 RUM results. Given the similarity in coefficients, the GHG abatement curve would also remain similar, as it reflects farmers’ responsiveness to payments.

excluding records with missing or inconsistent information on key variables such as crop type, tillage practice, and cover crop planted, the final data sample includes 252,034 observations across 5,699 points located in 627 counties spanning 12 states. For each point, we observe binary indicators for winter cover crop use (1 = with cover crop, 0 = without cover crop) and tillage type (full, reduced, or no-till). Table 2.1 presents summary statistics for the 12 crop–practice combinations. The results show that corn is planted more frequently than soybeans, and that the majority of observations do not include a cover crop, regardless of tillage choice.

Table 2.1: Practices summary statistics

Crop	Tillage	Cover Crop	Count
Corn	FT	0	434053
Corn	FT	1	7242
Corn	NT	0	196831
Corn	NT	1	5407
Corn	RT	0	287967
Corn	RT	1	6696
Soybeans	FT	0	375371
Soybeans	FT	1	7019
Soybeans	NT	0	182018
Soybeans	NT	1	6016
Soybeans	RT	0	251972
Soybeans	RT	1	6761

Source: Author’s calculations based on the U.S. National Greenhouse Gas Inventory dataset, covering the years 1990 through 2015 for the Corn Belt CEAP Region 7.

Note: “FT” denotes full tillage, “NT” denotes no tillage, and “RT” denotes reduced tillage. The cover crop variable distinguishes between winter cover crops (1) and none (0).

To generate the set of alternatives required for the discrete choice model, we simulate crop yields using the DayCent model over the historical period from 1990 to 2015. The simulations include 18 distinct crop–practice–fertilizer combinations, each applied uniformly across the full time horizon. Each crop is combined with three tillage types (full, reduced, and no-till) and either with or without a winter cover crop. Corn is modeled using point-level nitrogen fertilizer application rates from ARMS and CEAP datasets, resulting in six combinations. For soybeans, both

unfertilized and fully fertilized scenarios are considered under each tillage and cover crop pairing, resulting in twelve combinations. These 18 counterfactuals are generated for each point and each year in the dataset.

Table 2.2: Summary statistics for revenues and costs per acre by crop and practice type

Crop	Tillage	Cover crop	Count	Yield × price (\$/ac)	Fertilizer Cost (\$/ac)	Profit (\$/ac)
Corn	FT	0	252034	476 (242.6)	40.8 (18.7)	435.2 (230.1)
Corn	FT	1	252034	476.6 (243.5)	40.8 (18.7)	435.8 (231)
Corn	NT	0	252034	448.5 (223.7)	40.8 (18.7)	407.7 (211)
Corn	NT	1	252034	442.9 (221.4)	40.8 (18.7)	402.1 (208.6)
Corn	RT	0	252034	472.1 (239.8)	40.8 (18.7)	431.3 (227.3)
Corn	RT	1	252034	472.3 (240.6)	40.8 (18.7)	431.5 (228)
Soybeans	FT	0	252034	351.3 (168.1)	15.3 (18.2)	336 (167.9)
Soybeans	FT	1	252034	352.5 (168.6)	15.4 (18.2)	337.1 (168.5)
Soybeans	NT	0	252034	340.3 (166)	14.5 (18.3)	325.8 (165)
Soybeans	NT	1	252034	328.9 (164.9)	14 (18.4)	314.9 (163.3)
Soybeans	RT	0	252034	347 (166.4)	15.1 (18.3)	331.9 (166)
Soybeans	RT	1	252034	347.2 (166.8)	15.3 (18.3)	331.9 (166.6)

Source: Author’s calculations based on simulated yield and fertilizer use from DayCent.

Note: This table reports mean values for yield revenue, fertilizer cost, and profit per acre by crop, tillage, and cover crop practice, averaged across all sites and years. Standard deviations are shown in parentheses. Profit is defined as yield revenue (yield per acre times output price) minus fertilizer cost only; it does not include other production costs such as labor, machinery, seed, or land rent.

Outputs from DayCent are converted into agronomic and economic units. Yields reported in carbon units are converted to bushels per acre using crop-specific biomass and moisture adjustment factors,⁶ and are scaled to align with USDA National Agricultural Statistics Service (NASS) yield data. Revenue per acre is calculated by multiplying the adjusted yields by annual, state-level crop prices obtained from USDA NASS. Fertilizer costs are computed using USDA Economic Research Service (ERS) state-level nutrient price indices. Phosphorus and potash application rates are inferred from nitrogen rates using decadal average nutrient ratios.

Net revenue is calculated as crop revenue minus fertilizer cost for each crop–practice–fertilizer combination. To reflect expected profitability, we take a three-year rolling average of net revenue at each location. For soybeans, we adjust fertilizer costs so that in about 25% of cases, the fully

⁶Conversion factors for translating grams of carbon per cm² to bushels per acre are 0.48 for corn and 0.38 for soybeans.

fertilized option provides higher net revenue than the unfertilized one, reflecting patterns in the Greenhouse Gas Inventory dataset. Then, for each tillage and cover crop combination, we keep only the soybean fertilizer level (with or without fertilizer) that gives the higher net revenue. This leaves six soybean alternatives, each representing a unique tillage and cover crop combination. Because the Greenhouse Gas Inventory does not provide details on fertilizer application intensity (e.g., reduced vs. no fertilizer), the fertilizer decision is made outside of the RUM, based solely on which option yields higher net revenue. Table 2.2 reports average revenue, fertilizer cost, and net returns across the 12 crop–practice combinations, aggregated over time and locations.

Table 2.3: Summary of soil carbon and N₂O emissions by crop, tillage, and cover cropping

Crop	Tillage	Cover crop	ΔSOC (CO ₂ e)	N ₂ O (CO ₂ e)	Net GHG emissions (CO ₂ e)
Corn	FT	0	-0.46	0.85	0.38
Corn	FT	1	-0.52	0.85	0.34
Corn	NT	0	-0.85	0.80	-0.06
Corn	NT	1	-0.99	0.77	-0.22
Corn	RT	0	-0.52	0.83	0.31
Corn	RT	1	-0.58	0.84	0.26
Soybeans	FT	0	-0.05	0.44	0.39
Soybeans	FT	1	-0.19	0.46	0.26
Soybeans	NT	0	-0.32	0.41	0.09
Soybeans	NT	1	-0.64	0.39	-0.26
Soybeans	RT	0	-0.09	0.43	0.35
Soybeans	RT	1	-0.27	0.45	0.18

Source: Author’s calculations based on counterfactual simulations from DayCent for the years 1995, 2000, 2005, 2010, and 2015, at locations included in the random utility model.

Note: This table presents mean values across sites and years for selected crop–practice combinations. ΔSOC values indicate changes in soil organic carbon and are negative to reflect carbon loss to the atmosphere. N₂O values represent direct emissions.

The emissions data used in this analysis include estimates of SOC and N₂O emissions associated with different crop, practice, and fertilizer application combinations. SOC is reported in metric tons of carbon per acre and converted to carbon dioxide equivalents(CO₂e) using a molecular conversion factor of 44/12. N₂O emissions are provided in metric tons per acre and converted to CO₂e using a GWP factor of 265, consistent with values from the IPCC Sixth Assessment Re-

port (AR6). These conversions allow for standardized comparisons of greenhouse gas emission reduction impacts across agricultural practices and support integration into climate-related policy evaluation. Table 2.3 summarizes the estimated changes in SOC, N₂O emissions, and total greenhouse gas emissions for each crop–practice combination.

Econometric Estimates

In this section, we present the coefficient estimates for our discrete choice model. Based on the comparison of distributions in Rad et al. (2025),⁷ we adopt the distribution of β_i as “log normal,” allowing for heterogeneity in the response across decision-makers while constraining all individual-level responses to be non-negative. The coefficient estimate results are shown in Table 2.4. The model includes controls for state fixed effects, a linear year trend, and lagged indicators for crop type, tillage, and winter cover crop adoption. Alternative-specific constants (ASCs) are included to account for fixed, unobserved utility associated with each crop–practice option relative to the omitted category.

The estimated mean of the log-transformed net revenue coefficient is statistically significant and negative (-7.780), implying a positive average response to net revenue when transformed back to level form. Specifically, the mean marginal effect of net revenue on utility is approximately $e^{(-7.780 + \frac{1.665^2}{2})} = 0.00167$, indicating that increases in expected profitability raise the likelihood of choosing a given crop–practice combination. The estimated standard deviation of the log-transformed coefficient (1.665) is also highly significant, providing evidence of considerable heterogeneity in producers’ responses to net returns. The implied standard deviation of the marginal utility is calculated as $\left(\left(e^{1.665^2} - 1 \right) \cdot e^{2 \times (-7.780) + 1.665^2} \right)^{0.5} \approx 0.00647$, suggesting that while the average response is positive, some producers may exhibit stronger or weaker sensitivity to net revenue due to unobserved factors such as risk preferences.

⁷In their study, they compare standard logit models with and without controls, mixed logit models with normal distribution, truncated normal distribution, and log normal distribution. The results indicate that the mixed logit model, which assumes β_i is distributed as log normal, achieves the highest likelihood.

Table 2.4: Coefficient estimates for discrete choice model

	Logged response	Level of the variable
Net revenue (mean)	-7.780*** (0.098)	0.00167*** -
Net revenue (SD)	1.665*** (0.052)	0.00647*** -
ASC	X	-
state FE	X	-
year	annual trend	-
lag crop	X	-
lag tillage	X	-
lag cover crop	X	-
first year	1995	-
Observations	252,034	-
R ²	0.559	-
Log Likelihood	-204,713.400	-
LR Test	519,478.000*** (df = 189)	-

*p<0.1; **p<0.05; ***p<0.01

Note: “ASC” is alternative specific constants (ASCs), with is the alternative crop practices in this study; we control for state fixed effects, year trend, and lag crop, lag tillage, and lag cover crop in the random utility model. Level estimates represent the mean and standard deviation of the original (unlogged) response, derived from the mean and standard deviation of its log-transformed values.

Table 2.5 presents the own- and cross-price elasticities of crop-practice selection with respect to net revenue for each of the 12 alternatives in the mixed logit model with a log-normal distribution of the profit coefficient. These elasticities are computed at each point-year by perturbing the net revenue of each alternative and tracking the resulting change in the choice probabilities across all options (Rad et al. 2025). The values are then scaled by the ratio of baseline net revenue to baseline choice probability and averaged across observations.

Own-elasticities, shown along the diagonal, are all positive, with values ranging from 0.523 to 1.596 for corn combinations and from 0.365 to 0.536 for soybean combinations. This suggests that, on average, producers are more responsive to changes in expected profitability when choosing among corn practices compared to soybeans. For instance, the highest elasticity is observed for “Corn_FT_1” (1.596), indicating a highly elastic response to profitability under full tillage

Table 2.5: Elasticity of crop selection with respect to net revenues

	Corn_FT_0	Corn_FT_1	Corn_NT_0	Corn_NT_1
Corn_FT_0	1.088	-0.509	-0.155	-0.149
Corn_FT_1	-0.017	1.596	-0.003	-0.003
Corn_NT_0	-0.3	-0.305	0.523	-0.107
Corn_NT_1	-0.008	-0.009	-0.003	0.609
Corn_RT_0	-0.418	-0.424	-0.126	-0.12
Corn_RT_1	-0.013	-0.014	-0.003	-0.003
Soybeans_FT_0	-0.118	-0.119	-0.092	-0.091
Soybeans_FT_1	-0.002	-0.002	-0.002	-0.002
Soybeans_NT_0	-0.108	-0.11	-0.063	-0.061
Soybeans_NT_1	-0.004	-0.004	-0.002	-0.002
Soybeans_RT_0	-0.097	-0.097	-0.072	-0.07
Soybeans_RT_1	-0.003	-0.003	-0.002	-0.002
	Corn_RT_0	Corn_RT_1	Soybeans_FT_0	Soybeans_FT_1
Corn_FT_0	-0.332	-0.336	-0.097	-0.098
Corn_FT_1	-0.009	-0.01	-0.002	-0.002
Corn_NT_0	-0.251	-0.254	-0.059	-0.06
Corn_NT_1	-0.007	-0.007	-0.002	-0.002
Corn_RT_0	0.914	-0.29	-0.075	-0.076
Corn_RT_1	-0.009	1.205	-0.002	-0.002
Soybeans_FT_0	-0.112	-0.113	0.407	-0.117
Soybeans_FT_1	-0.002	-0.002	-0.004	0.536
Soybeans_NT_0	-0.095	-0.096	-0.076	-0.08
Soybeans_NT_1	-0.004	-0.003	-0.003	-0.003
Soybeans_RT_0	-0.09	-0.09	-0.084	-0.09
Soybeans_RT_1	-0.003	-0.003	-0.003	-0.004
	Soybeans_NT_0	Soybeans_NT_1	Soybeans_RT_0	Soybeans_RT_1
Corn_FT_0	-0.086	-0.079	-0.093	-0.093
Corn_FT_1	-0.002	-0.002	-0.002	-0.002
Corn_NT_0	-0.053	-0.048	-0.057	-0.057
Corn_NT_1	-0.002	-0.001	-0.002	-0.002
Corn_RT_0	-0.067	-0.062	-0.072	-0.073
Corn_RT_1	-0.002	-0.002	-0.002	-0.002
Soybeans_FT_0	-0.085	-0.076	-0.097	-0.1
Soybeans_FT_1	-0.002	-0.002	-0.002	-0.005
Soybeans_NT_0	0.365	-0.049	-0.069	-0.071
Soybeans_NT_1	-0.002	0.38	-0.002	-0.003
Soybeans_RT_0	-0.063	-0.057	0.401	-0.076
Soybeans_RT_1	-0.002	-0.002	-0.002	0.482

Source: Author's calculations based on the RUM coefficient estimation results.

Note: 0 and 1 are binary indicators representing the absence or presence of cover crops. Elasticity captures how responsive farmers are to changes in net revenue for each crop–practice combination; the higher the elasticity, the greater the responsiveness. 29

with cover crops. In contrast, the elasticity for “Soybeans_FT_1” is 0.536, and several soybean combinations have elasticities below 0.4.

All cross-price elasticities are negative, consistent with economic theory, and reflect substitution effects. When the profitability of one alternative increases, the probability of selecting competing options declines. These substitution effects are generally stronger within crops than across crops, suggesting that producers are more likely to adjust tillage or cover crop practices within a crop rather than switch between corn and soybeans in response to profitability changes. Overall, these elasticities reflect economically meaningful substitution and responsiveness to profitability, consistent with forward-looking and adaptive behavior among producers.

2.2.3 Grain Market Equilibrium

In the grain market equilibrium, supply equals demand, allowing us to endogenize crop prices through constant demand elasticity for each crop. This study utilizes demand elasticity values from Roberts et al. (2013) research, which estimates supply and demand elasticities for U.S. agricultural commodities. Their methodology simplifies the commodity market into a unified caloric metric, applying storage theory to analyze price dynamics and the impact of exogenous shocks. Specifically, we adopt their findings on corn’s own-price demand elasticity, which is -0.287, and an own-price demand elasticity of -0.236 for soybeans, under the symmetry cross-price elasticity assumption.

We represent the demand function as $Q_d(P) = AP^e$, where $Q_d(P)$ denotes quantity demanded at price P , e is the elasticity, and A is a crop-specific scale parameter. At equilibrium, quantity supplied equals quantity demanded, as shown in Equation 2.6:

$$Q_s(P) = Q_d(P) = AP^e \tag{2.6}$$

To calibrate A , we use the formula $A = Q/P^e$, where Q and P are the average historical production and price, respectively, and e is the elasticity. Because our simulation locations do not match historical production exactly, some locations may not grow corn or soybeans every year, we use

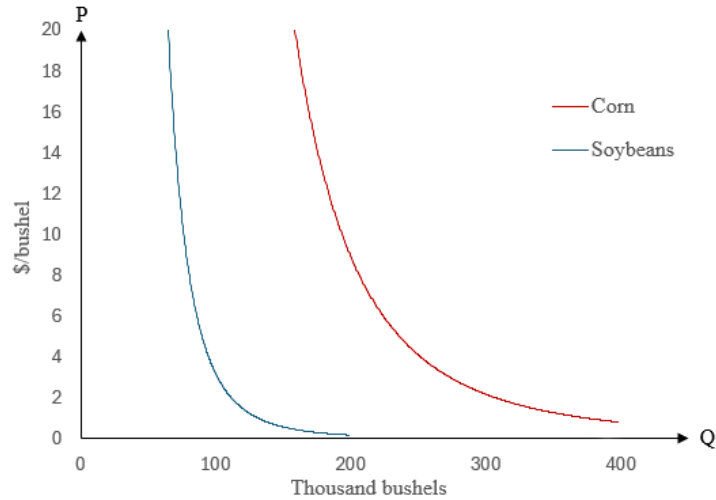


Figure 2.5: Constant elasticity demand curves of corn and soybeans in the U.S.

Source: Author's calculation.

average production across years rather than total quantities to maintain consistency. Based on this approach, we estimate $A = 374070$ for corn and $A = 131102$ for soybeans. These values are then used to derive separate demand curves for corn and soybeans, parameterized by their respective elasticities.

Figure 2.5 illustrates the parameterized demand curves for corn and soybeans based on estimated A and historical production data. From the demand curves, it is evident that both corn and soybeans exhibit considerable elasticity, but the parameterization is inelastic, suggesting that quantity changes could lead to price changes. This highlights the importance of endogenous pricing within our integrated model. After obtaining yield outputs from the DayCent model, represented as Q , we can then determine the price P using the formula $P = \left(\frac{Q}{A}\right)^{\frac{1}{\epsilon}}$.

2.2.4 Simulation

We employ a simulation-based approach to quantify the GHG abatement cost function associated with rainfed corn and soybean production. The simulation spans a 40-year horizon from 2021 to 2060 and compares crop choices, fertilizer application, tillage practices, and cover crop adoption under a no-policy baseline and a range of carbon price scenarios. The total farmland area

is held constant throughout the simulation, meaning land does not enter or exit production over time. By evaluating changes in net GHG emissions across these scenarios, we construct marginal GHG abatement supply curves.

As shown in Figure 2.6, the simulation process begins with DayCent running all counterfactual scenarios (j,f) for each location i , based on the crop–practice combination applied in 2020. In each simulation year, farmers are assumed to select the fertilizer level that maximizes expected profitability. For corn, the options include full fertilization and a 10% reduction; for soybeans, the options are full fertilization or no fertilization. Each crop–tillage–cover crop combination (j) is paired with both fertilizer regimes (f), yielding 24 distinct crop–practice–fertilizer combinations (j,f) per location per year. For each climate change scenario, we begin by running the DayCent baseline simulation incorporating crop variety selection to optimize production as an adaptation to climate change (Etten et al. 2019). From each simulation, we extract outputs including nitrogen fertilizer application rates, crop yield, SOC, and N_2O emissions for each of the 24 counterfactuals. Using these data, we compute net revenue for each combination at each location.

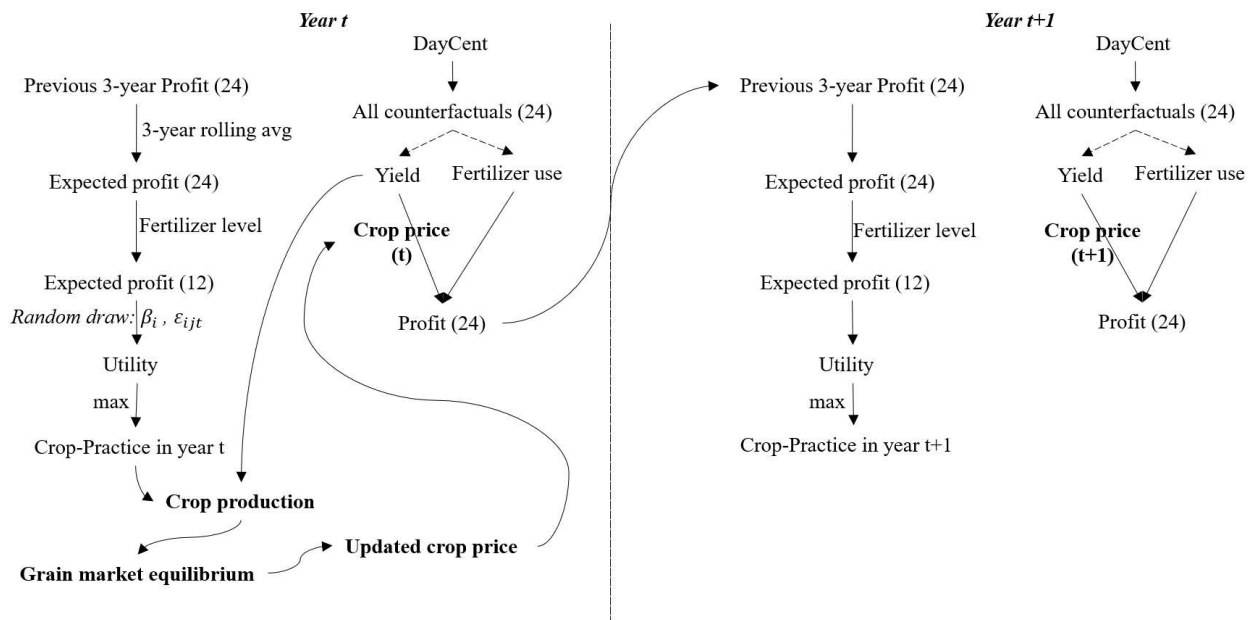


Figure 2.6: Simulation flow from 2021 to 2060

Fertilizer prices are held constant over the 40-year simulation period, based on average prices from 2011 to 2020. Fertilizer costs are estimated by multiplying total fertilizer use by price. Nitrogen application is obtained directly from DayCent outputs, while phosphate and potash use are imputed using fixed ratios relative to nitrogen application, based on 2011–2020 state-level crop averages. Total fertilizer cost is calculated as the sum of the cost of nitrogen, phosphate, and potash. For soybeans, we apply a point-specific markup to the reduced fertilizer cost of full fertilization to reflect historical application patterns,⁸ calibrated using 2021–2060 DayCent simulations under no climate change. The markup is set to ensure that approximately 25% of soybean observations select full fertilization, and is held constant across all simulation scenarios.

Yields are derived from the DayCent output variable representing carbon content in harvested grain. These values are first converted to dry yield using crop-specific dry matter content, and then converted to bushels per acre. To ensure consistency with observed data, we scale simulated yields by the average ratio of state-level NASS yields to DayCent-simulated yields between 2011 and 2020. We distinguish between two pricing scenarios. Under the exogenous price scenario, crop prices are fixed at their 2011–2020 average values throughout the simulation period. Under the endogenous price scenario, the crop price in year t is based on the realized price from year $t-1$. The procedure for updating prices annually in the endogenous scenario is detailed in the following paragraph.

To reflect farmers' adaptive expectations, expected profit for each crop–practice–fertilizer combination (jf) in year t is calculated as the rolling average of realized profits from years $t-3$ to $t-1$. We assume that producers first decide on the fertilizer level. For each crop–tillage–cover crop combination (j), the fertilizer level (f) that yields the higher expected profit is chosen, as shown in Equation 2.7. In cases where profits are equal between fertilizer levels for the same j , we

⁸Soybeans are legumes and can fix atmospheric nitrogen through symbiosis with rhizobia, reducing their reliance on synthetic nitrogen fertilizer. As a result, fertilizer application rates for soybeans are generally low. However, some farmers still apply nitrogen fertilizer, typically at modest levels, to support early-season growth.

assume that full fertilization ($f = 100$) is applied.

$$R_{ijt} = \max_{f \in \mathcal{F}_{ij}} \left\{ \frac{\tilde{\pi}_{ijft-1} + \tilde{\pi}_{ijft-2} + \tilde{\pi}_{ijft-3}}{3} \right\} \quad (2.7)$$

where the fertilizer choice set \mathcal{F}_{ij} is defined as:

$$\mathcal{F}_{ij} = \begin{cases} \{90\%, 100\% \} & \text{if crop is corn} \\ \{0\%, 100\% \} & \text{if crop is soybeans} \end{cases}$$

After the fertilizer level is selected, each location is left with 12 crop–practice alternatives (j), each paired with a selected fertilizer level (f). Using the estimated parameters from the RUM (Equation 2.1), we compute the utility associated with each alternative. In the mixed multinomial logit framework, a location-specific coefficient on net revenue, β_i , is drawn randomly based on the estimated mean and standard deviation from the RUM results. Next, we calculate the deterministic (observed) component of utility for each alternative using Equation 2.4, incorporating predicted net revenue, state fixed effects, and lagged crop, tillage, and cover crop indicators. To isolate structural effects and avoid confounding with secular trends, we fix the time index to 2021 in all utility calculations. The random draw of β_i for each location is held constant across all scenarios and simulation years to ensure internal consistency and comparability across scenarios.

For the stochastic (unobserved) component of utility, a random error term ε_{ijt} is drawn from a Type II extreme value (Gumbel) distribution for each location, alternative, and year. To maintain consistency across scenarios, the random error term is drawn once and held fixed across all simulations and scenarios. We also conduct uncertainty tests using multiple random draws to evaluate the robustness of predicted outcomes. Finally, the alternative j that yields the highest total utility (i.e., the sum of the observed and unobserved components) is selected as the predicted choice for that location and year. This chosen practice is then assigned as the input to DayCent as the base year to simulate all counterfactuals in the subsequent year.

Under the endogenous crop price scenario, crop choices at each location in year t determine the average production of corn and soybeans based on simulated yields from DayCent. These production quantities feed into the grain market equilibrium model, which solves for the updated market-clearing crop prices. The resulting equilibrium prices are then used as the revealed crop prices in year t to calculate profits for all 24 crop–practice–fertilizer counterfactuals. In this way, crop prices are updated annually in response to simulated supply. Expected profits for year $t + 1$ are computed as a three-year rolling average of realized profits from years $t - 3$ to $t - 1$, thereby incorporating crop prices from years $t - 3$ to $t - 1$.

To evaluate the impact of carbon pricing on GHG emissions from agriculture, we simulate a policy scenario in which farmers receive payments for environmental benefits arising from changes in SOC and N₂O emissions. These payments are made when simulated outcomes under alternative crop and practice decisions lead to either an increase in SOC stocks or a reduction in N₂O emissions relative to a no-policy baseline. Payments are based on the change in net emissions,⁹ measured in CO₂e, as defined in Equation 2.8. Avoided N₂O emissions are assumed to be permanent and thus compensated at the full carbon price. In contrast, SOC storage is considered temporary and is compensated using a rental approach that reflects the present value of delaying emissions over a 10-year period (Rad et al. 2025). The rental value is discounted using a producer discount rate of 0.07,¹⁰ while the carbon price is discounted using a social rate of 0.05¹¹. The total payment is

⁹Under the assumption of fixed total farmland acreage, a carbon tax on higher emissions is equivalent to a subsidy for reduced emissions. For example, the profit under a subsidy scheme (π_i^s) is given by $\pi_i^s = \pi_i + P(e_0 - e_i)$, where π_i is the profit before payment, P is the carbon price, e_0 is the baseline emission level, and e_i is the emission under the subsidy scenario. Similarly, the profit under a carbon tax (π_i^t) is $\pi_i^t = \pi_i - P(e_i - e_0)$, which is equivalent to π_i^s . However, when farmland acreage is allowed to adjust, this equivalence breaks down. Subsidies lower average production costs and may incentivize land expansion to increase payment eligibility, potentially undermining environmental gains. In contrast, a carbon tax imposes additional production costs, discouraging expansion and prompting farmers to reduce costs through operational adjustments. In the context of conservation program adoption, yield losses are expected. Under a tax, farmers may respond by optimizing input use or adjusting fixed costs to mitigate revenue loss, leading to more abatement. As a result, achieving the same abatement target typically requires higher total payments under a subsidy than under a tax.

¹⁰The Office of Management and Budget recommends a discount rate of roughly 7% when assessing before-tax returns from private investment activities (Gruber 2007).

¹¹This aligns with the Interagency Working Group’s reinstated rates of 2.5-5% that prioritize intergenerational equity considerations, with sensitivity testing at higher rates (7%) left for future work.

calculated as:

$$E_{ijft} = P \times \left(\Delta N_2O + \Delta SOC \times \frac{\delta}{1 + \delta} \sum_{s=0}^9 \frac{1}{(1 + \rho)^s} \right) \quad (2.8)$$

Where E_{ijft} denotes the total payment for counterfactual jf at location i in year t , P is the carbon price, ρ is the discount rate for the carbon price, and δ is the producer's discount rate for SOC. In our baseline specification, we set $\rho = 0.05$ and $\delta = 0.07$, which implies that the present value of storing one tonne of SOC over 10 years is approximately $0.53P$. The total payment for emissions abatement is calculated as:

$$E_{ijt}(P) = \max \{P(0.53 \times \Delta SOC + \Delta N_2O), 0\}$$

where payments are set to zero if net emissions exceed those in the baseline. This payment is then added to the profit term and directly affects the utility U_{ijt} . Consequently, the expected profit used in choice prediction also incorporates a three-year average of carbon payments, meaning that the expected payment in year t reflects the average payments received in years $t-3$ to $t-1$. Since fertilizer is associated with the N_2O emission, this approach introduces flexibility in both practice choice and input use as pathways for emissions abatement and enables estimation of cost-effective responses under alternative carbon pricing policies.

We calculate the total cumulative GHG abatement at each NRI survey location for each carbon price by comparing SOC stocks and N_2O emissions to the baseline. Cumulative abatement represents the difference in CO_2e in the atmosphere at the end of our simulation. We aggregate impacts to our study area to estimate total abatement and calculate the average annual abatement. Plotting abatement against carbon price produces the marginal GHG abatement supply curve.

2.3 Results

In this section, we first present results from the baseline scenarios without carbon payments, both with and without endogenous crop prices under two climate change scenarios. We begin by examining trends in crop adoption under different climate change scenarios. Next, we present the

GHG abatement supply curves, emphasizing how incorporating endogenous crop prices alters the estimated mitigation potential. Finally, to better understand the underlying drivers of these effects, we examine how endogenous prices influence the adoption of reduced fertilizer use, conservation tillage, and overall production.

2.3.1 Baseline Simulation

This section examines the impact of endogenous crop pricing on GHG emissions over time, compared to a fixed-price scenario. To explore these effects, we compare emissions outcomes, crop adoption trends, and projected crop prices under a baseline climate change scenario. The analysis includes a more extreme climate change mitigation pathway represented by the *FGOALS-g3* SSP3.70 scenario and a more optimistic socioeconomic pathway represented by *FGOALS-g3* SSP1.26, both generated using the same climate model.

From the baseline perspective, total GHG emissions over the simulation period are approximately 1,820.77 million tonnes of CO₂e under SSP1.26 and 1,964.64 million tonnes under SSP3.70 with endogenous crop prices, compared to 1,823.93 million tonnes under SSP1.26 and 1,985.12 million tonnes under SSP3.70 with fixed prices. This difference suggests that holding prices constant leads to an overestimation of emissions by approximately 3.16 and 20.49 million tonnes of CO₂e over 40 years, equivalent to roughly 79 and 512 thousand tonnes per year, under SSP1.26 and SSP3.70, respectively. These results show that the gap between endogenous and fixed price scenarios widens under more severe climate conditions. In hotter and drier environments, yield-driven price changes have a stronger influence on land use decisions and resulting emissions. As a result, models that ignore these market responses risk producing biased estimates of both baseline emissions and the effectiveness of climate policies.

Figure 2.7 shows the baseline emissions from soil carbon sequestration and N₂O, both expressed in CO₂e. Soil carbon is reported as a negative emission because it represents carbon being removed from the atmosphere and stored in the soil. Soil carbon sequestration appears relatively stable across the two scenarios, with both lines closely overlapping and exhibiting minor fluctua-

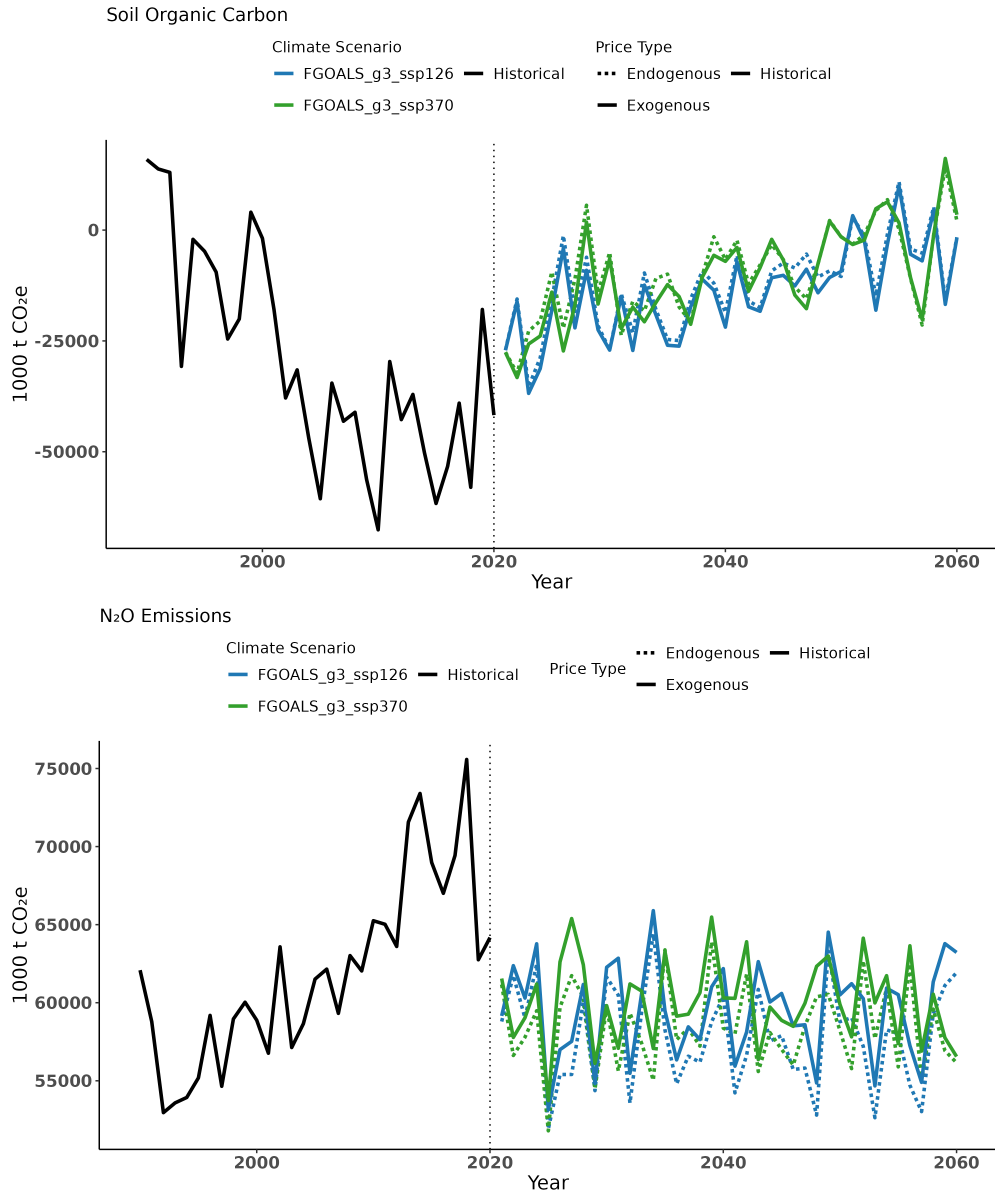


Figure 2.7: Baseline emissions from soil carbon sequestered (top), and N₂O emissions (bottom)

Note: All values are reported in CO₂-equivalent units. Historical trends are also presented for reference. SOC is reported as a negative emission because it represents carbon being removed from the atmosphere and stored in the soil.

tions. This reflects the fact that practices affecting soil carbon, such as tillage and cover cropping, tend to change gradually and are less sensitive to short-term market price feedback. In contrast, N₂O emissions are consistently lower when crop prices respond endogenously to production decisions. This reduction is primarily due to a shift in planting decisions: producers allocate more land to soybeans (Figure 2.8), which require less nitrogen fertilizer than corn. As fertilizer use declines, so do associated N₂O emissions. Figure 2.8 also shows that crop shares are relatively stable under fixed prices, whereas they fluctuate more under endogenous pricing. Under SSP3.70, the fluctuations in crop shares are slightly larger than those observed under SSP1.26. This highlights that farmers adjust cropping decisions in response to market price signals.

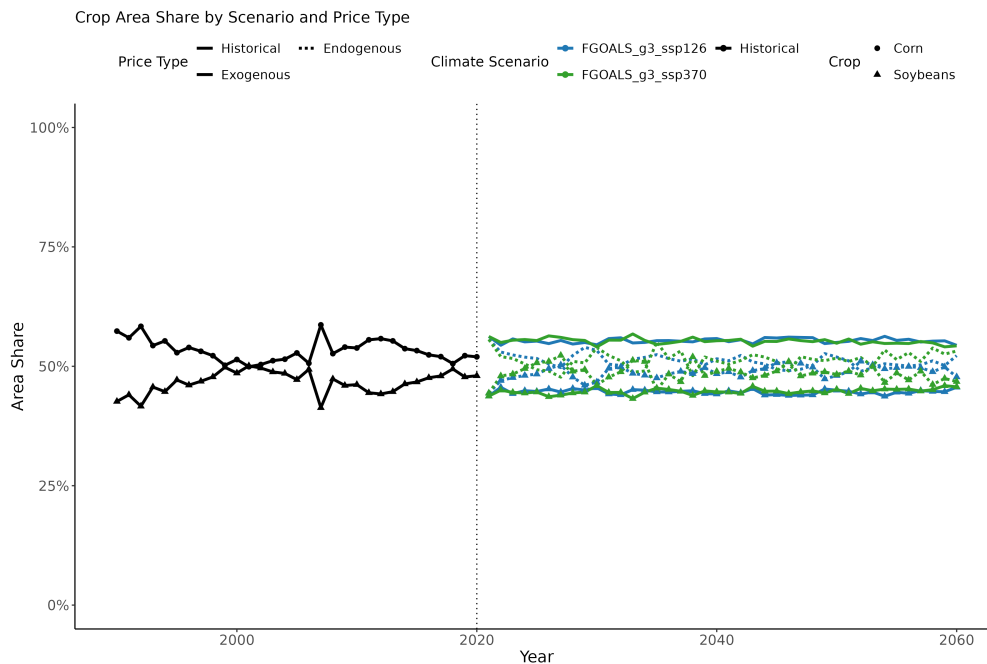


Figure 2.8: Corn and soybeans area proportions under the historical period and baseline simulation from 2021 to 2060.

Note: Historical trends are shown for reference. Crop shares remain relatively stable under fixed prices but exhibit greater variability under endogenous pricing across both climate change scenarios. Under *FGOALS-g3* SSP3.70, the fluctuations in crop shares are slightly larger than those observed under *FGOALS-g3* SSP1.26.

We observe a discontinuity in both N₂O emissions and soil carbon sequestration at the transition from the historical period to the simulation baseline. Several factors contribute to this shift. First,

as shown in Figure 2.4, there is a slight increase in full tillage adoption during the last five years of the historical period; however, this trend is not captured in the RUM model fitting. Second, the simulation baseline allows for fertilizer rate reductions, which are not incorporated in the historical data, particularly for corn. For example, under the SSP3.70 climate change scenario, 23.6% of corn production in the fixed-price (exogenous) baseline and 26.6% in the endogenous baseline adopt a reduced fertilizer rate of 10%. For soybeans, approximately 13.4% of production under the endogenous scenario and 16.6% under the exogenous scenario receive fertilizer applications, diverging from the historical period.

2.3.2 GHG Abatement Supply Curve

In this section, we compare the impact of endogenous crop prices under a range of carbon payment incentive scenarios. Specifically, we simulate carbon payments of \$100, \$190, and \$300 per tonne of CO₂e abated and construct the corresponding GHG abatement supply curves under two climate change scenarios. The \$190 per tonne payment reflects the U.S. EPA's 2020 estimate of the social cost of carbon,¹² serving as a policy-relevant benchmark for evaluating the efficiency of agricultural mitigation strategies. The inclusion of \$100 and \$300 payment levels allows us to assess the sensitivity of endogenous price effects to the stringency of carbon incentives and to better understand how market feedbacks scale with different policy interventions.

We begin by presenting the GHG abatement supply curves to illustrate how incorporating grain market responses influences the estimated supply of abatement under different climate change scenarios. We then examine the composition of abatement by breaking down emissions reductions into soil carbon sequestration and N₂O mitigation. To further understand the sources of these reductions, we explore changes in the area under crops, reduced fertilizer use, conservation tillage, and cover crop adoption across the different carbon price scenarios. Finally, we assess changes in crop production, which serve as a direct driver of crop prices and help explain the feedback effects captured under endogenous pricing.

¹²Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances

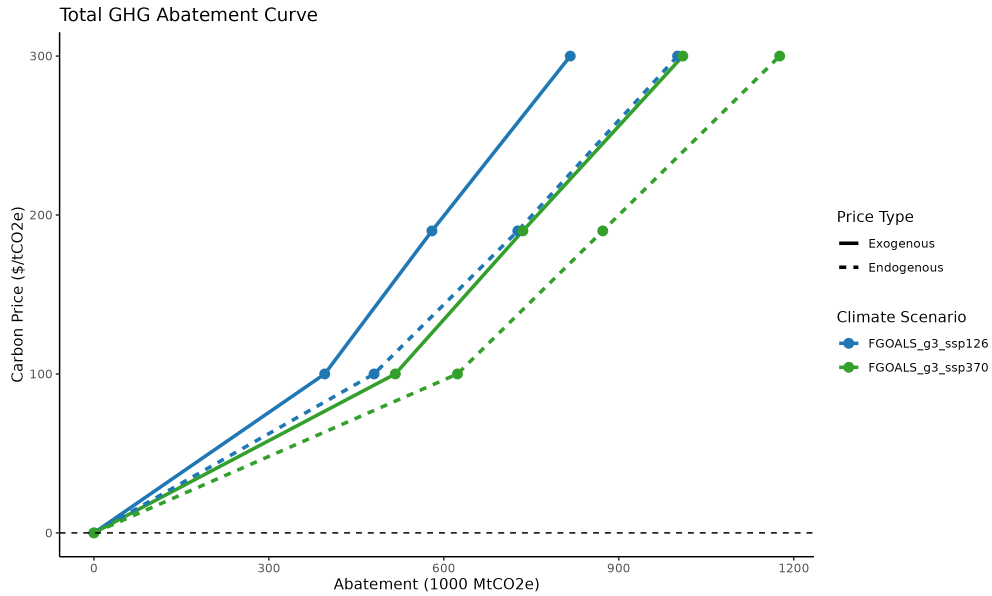


Figure 2.9: GHG abatement supply curve comparing exogenous and endogenous crop prices.

Note: Abatement values represent GHG reductions relative to the no-carbon payment baseline scenario. Dashed lines indicate the GHG abatement supply curve under endogenous crop prices, while solid lines represent the supply curve under fixed crop price assumptions.

Figure 2.9 presents GHG abatement levels under various carbon price scenarios. The solid line illustrates the abatement supply curve assuming fixed crop prices, while the dashed line represents the curve when crop prices are allowed to adjust endogenously. To enable consistent comparison across scenarios, cumulative GHG abatement is annualized by dividing by the 40-year simulation period. The findings show that allowing crop prices to respond to market forces results in a more elastic abatement supply curve under both climate change scenarios. In other words, for a given carbon price, greater GHG abatement is achieved when farmers adapt their land use and management practices in response to price signals. Specifically, at a carbon price of \$190 per tonne of CO₂e, the endogenous price scenario achieves 137,019 more tonnes of annual GHG abatement than the fixed price scenario under the extreme climate change scenario (SSP3.70), representing an 18% increase. Under the sustainability climate change scenario (SSP1.26), the endogenous price scenario results in 147,219 more tons of CO₂e abatement compared to the fixed price case, corresponding to a 25% increase. However, despite the larger relative gain under SSP1.26, the ab-

solute level of GHG abatement is lower than under SSP3.70. This is likely due to higher baseline emissions and greater mitigation potential in the hotter and drier climate associated with SSP3.70.

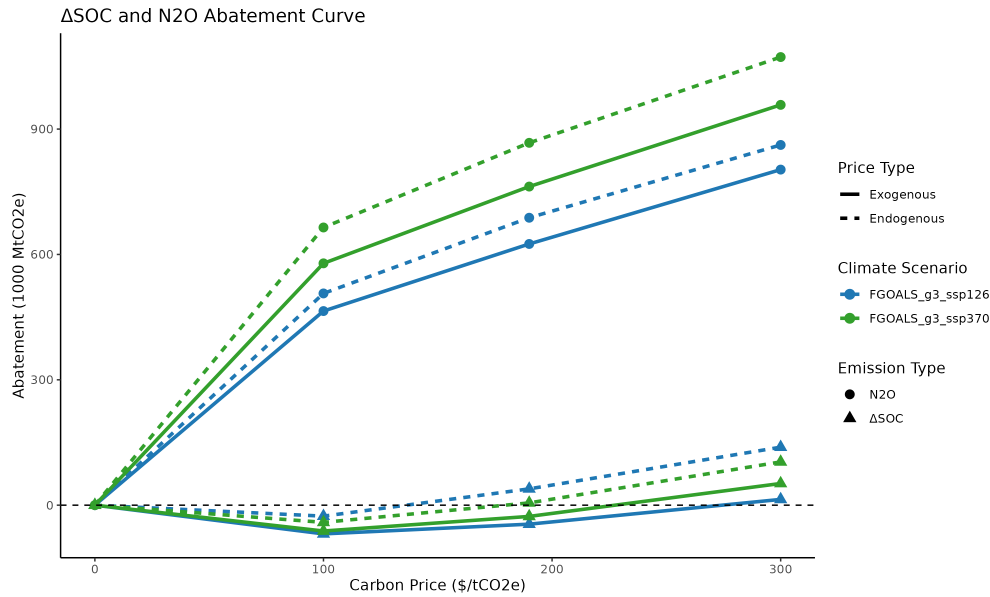


Figure 2.10: GHG abatement by emission source: SOC and N₂O under different carbon prices

Note: Abatement values represent GHG reductions relative to the no-carbon payment baseline scenario. Dashed lines indicate the GHG abatement supply curve under endogenous crop prices, while solid lines represent the supply curve under fixed crop price assumptions.

Figure 2.10 presents the contributions of N₂O abatement and soil carbon sequestration to total GHG reductions across carbon price levels, climate change scenarios, and crop price assumptions. The results show that most of the emissions reductions are driven by avoided N₂O emissions under both climate change scenarios, consistent with findings by Garnache et al. (2017) and Rad et al. (2025). When crop prices adjust endogenously, both N₂O abatement and soil carbon sequestration increase across all carbon payment levels compared with the fixed crop price scenario, contributing to greater total GHG reductions under endogenous crop price scenarios. While the extreme climate change scenario results in higher N₂O abatement, the sustainability scenario shows a larger difference in ΔSOC between endogenous and exogenous price settings. This suggests that under more favorable climate conditions, market-driven adjustments, particularly in practices that enhance SOC, respond more sensitively to price signals. One likely reason is that milder temper-

atures and higher soil moisture under SSP1.26 create more favorable biophysical conditions for SOC accumulation, making the adoption of practices like reduced tillage or cover cropping more effective and economically attractive when incentivized by carbon payments. In contrast, under hotter and drier conditions (SSP3.70), the biophysical limits to SOC gains reduce the responsiveness of farmers to market signals aimed at increasing SOC sequestration.

However, soil carbon behaves differently at low carbon prices. In these cases, soil carbon sequestration is negative relative to the baseline. One possible explanation is that the payment level is too low to motivate widespread adoption of SOC-enhancing practices such as no-till or cover crops. Instead, farmers may shift toward soybeans, which require less fertilizer and emit less N₂O to get the abatement payment, but also return less residue to the soil. Since corn typically contributes more C input through residues to SOC than soybeans (Wu et al. 2025), a decline in corn acreage can reduce overall soil carbon, while still abating GHGs through a reduction in N₂O. Additionally, reduced fertilizer use will also reduce soil carbon sequestration (Garnache et al. 2017). Therefore, if conservation practices are not adopted at a scale sufficient to offset the decline from crop switching and reduced fertilizer use, soil carbon stocks fall. As carbon prices rise, the incentives become strong enough to encourage greater adoption of SOC-building practices, like cover crop (Jian et al. 2020) and conservation tillage (Liu et al. 2023), eventually leading to net sequestration gains.

To support our hypothesis regarding soil carbon losses at lower carbon payment levels and the mechanisms driving higher abatement under endogenous price scenarios, we examine changes in crop area, fertilizer use, and conservation practices under both climate change scenarios. Figure 2.11 shows changes in crop area (top) and fertilizer reduction (bottom), measured in 1,000 hectares (ha). Across all scenarios, carbon payments lead to a shift from corn to soybeans, with a larger shift observed under SSP3.70. This occurs because soybeans require less fertilizer and emit less N₂O, making them more responsive to abatement incentives. However, this crop shift may result in a net loss of SOC due to the lower SOC contribution of soybeans relative to corn (Wu et al. 2025). As shown in Figure 2.12, the top panel illustrates changes in conservation tillage area,

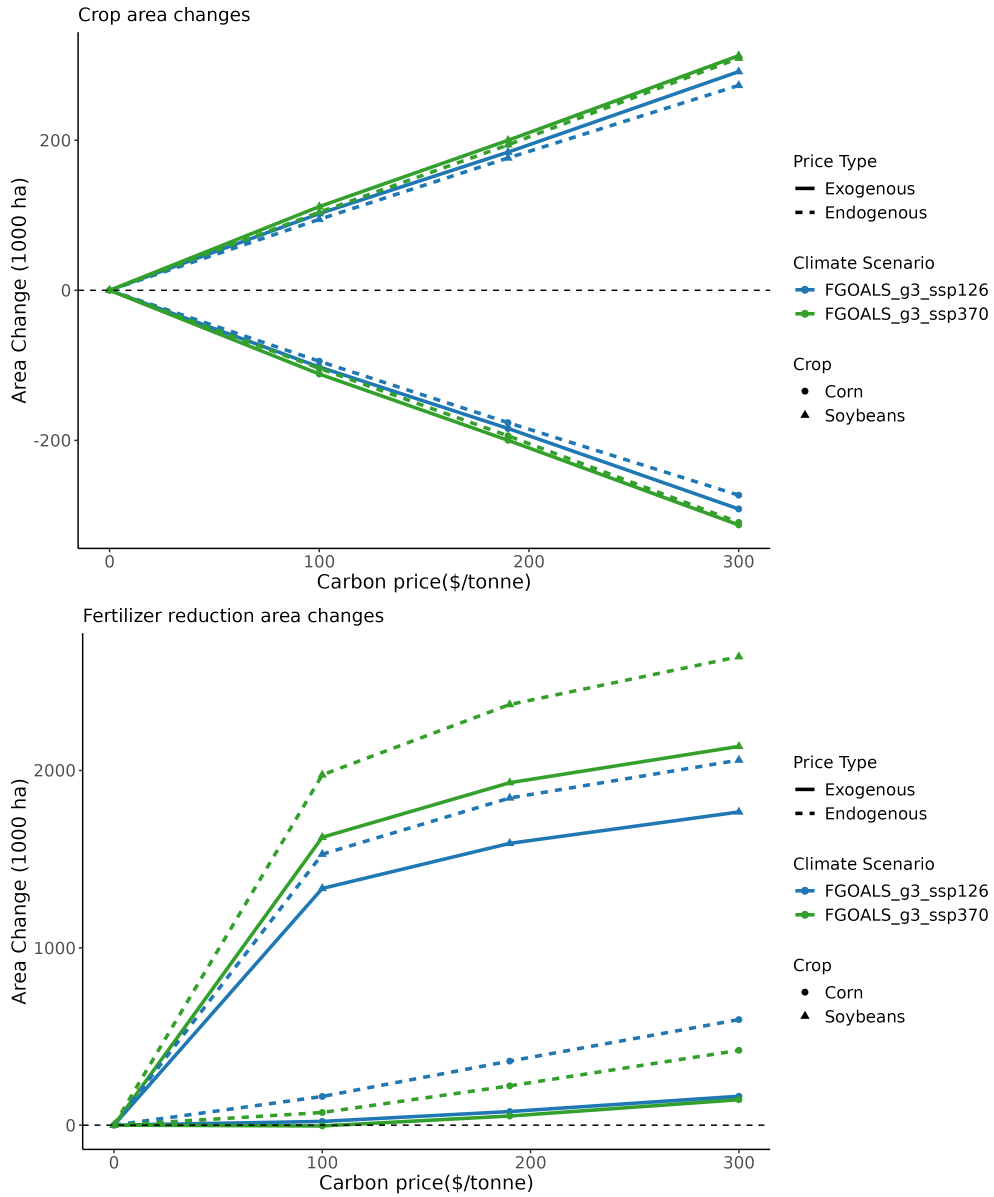


Figure 2.11: Average annual changes in crop area (top) and fertilizer reduction (bottom) across carbon price scenarios.

Note: Area changes are measured relative to the no-carbon payment baseline scenario. Dashed lines indicate the GHG abatement supply curve under endogenous crop prices, while solid lines represent the supply curve under fixed crop price assumptions.

including reduced and no-tillage, while the bottom panel displays changes in winter cover crop adoption. Although both practices see increased adoption at low carbon payment levels (69,100 ha for conservation tillage and 102,000 ha for cover crops under SSP3.70, and 66,100 ha and 99,000 ha, respectively, under SSP1.26), these gains may not be sufficient to offset the reduction in corn area. Under a carbon payment of \$100 per tonne, corn area declines by 111,000 ha under SSP3.70 and 102,000 ha under SSP1.26. Although conservation practices can enhance SOC over time, their effects tend to materialize more slowly and may be smaller in magnitude than the immediate SOC loss from crop switching. As a result, total SOC under low carbon payments may still fall below baseline levels.

When crop prices adjust endogenously, two offsetting effects shape the abatement outcome. First, endogenous pricing diminishes the incentive to switch from corn to soybeans, as shown in the top panel of Figure 2.11. As soybean acreage expands, market prices decline, reducing the relative profitability of further switching. This limits the extent of N₂O abatement that would otherwise occur through crop substitution. However, by maintaining more corn acreage, this effect helps preserve SOC. Figure 2.10 confirms that SOC losses at lower carbon payment levels are smaller under the endogenous price scenario compared to the fixed price case. Second, endogenous pricing strengthens the incentive to reduce nitrogen fertilizer use across both corn and soybeans, as illustrated in the bottom panel of Figure 2.11. Fertilizer decisions are made prior to the RUM and are based solely on the expected net revenue difference between full and reduced fertilizer application, holding crop, tillage, and cover crop choices constant. These decisions rely on a three-year rolling average of predicted profits, which in turn are calculated using crop prices from the preceding three years. Because crop prices fluctuate annually, the use of lagged prices may introduce a delayed response in fertilizer choices. However, our results suggest that this price response makes fertilizer reduction more economically attractive and results in broader adoption of input-reduction strategies. While the net impact of these opposing mechanisms is theoretically ambiguous, our results indicate that the incentive to reduce nitrogen inputs dominates. Overall, we

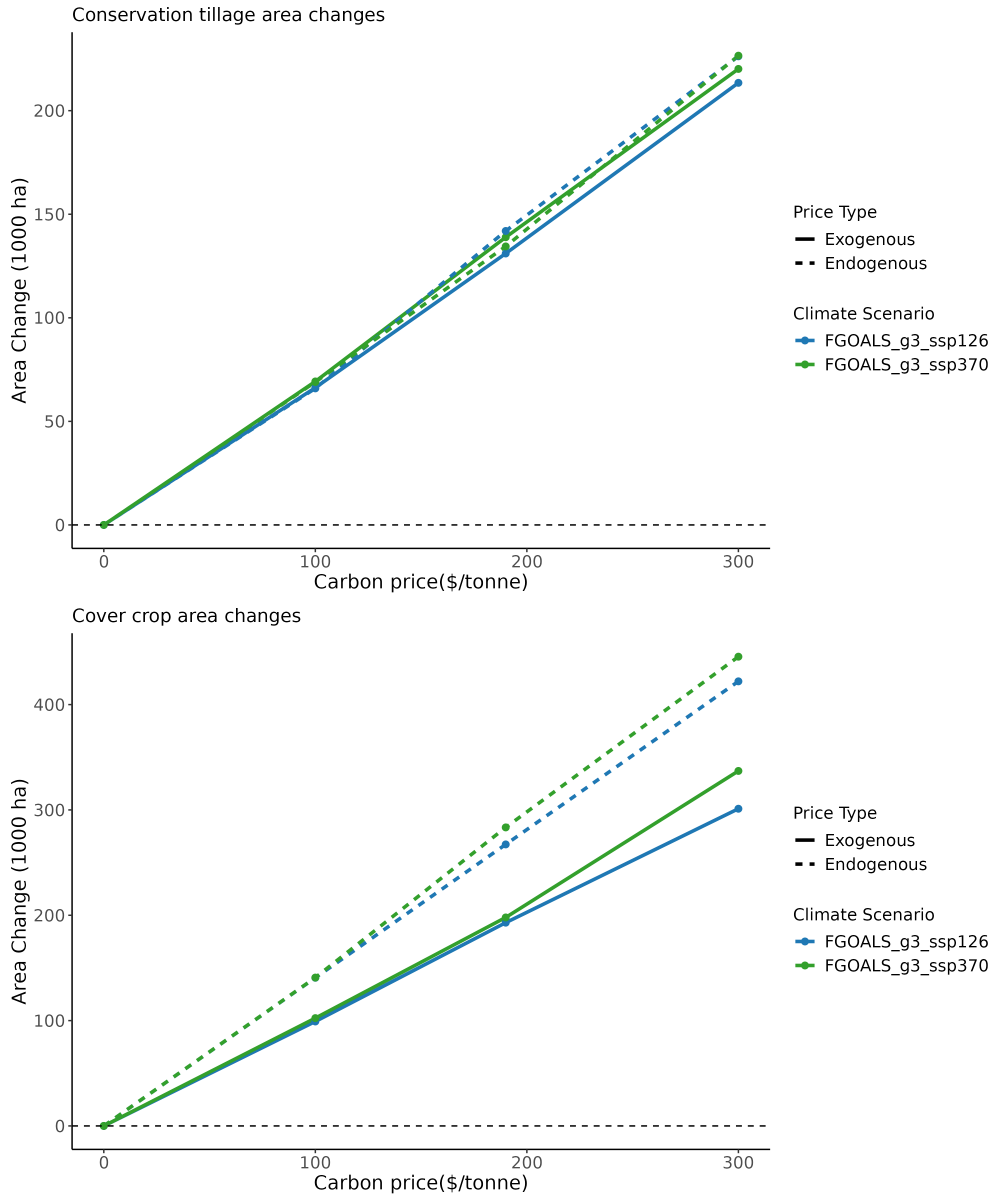


Figure 2.12: Average annual changes in the area under conservation tillage (top) and cover crop (bottom) adoption across carbon price scenarios.

Note: Area changes are measured relative to the no-carbon payment baseline scenario. Dashed lines indicate the GHG abatement supply curve under endogenous crop prices, while solid lines represent the supply curve under fixed crop price assumptions.

observe greater reductions in fertilizer use and higher total GHG abatement when crop prices are allowed to adjust endogenously.

Under endogenous pricing, the adoption of cover crops increases significantly, particularly in soybean production. As shown in Appendix Table A2.2, cover cropping continues to result in a slight yield penalty for soybeans, with yields declining by approximately 0.0434 to 0.0440 t/ha under endogenous pricing in the SSP3.70 climate scenario. However, Appendix Figure A2.1, which presents changes in practice area under SSP3.70, shows that as the carbon price increases, soybean area under the combination of cover crops, reduced fertilizer use, and conservation tillage (NT/RT) expands significantly, especially under endogenous pricing. This pattern suggests that producers adopt cover crops not because they avoid yield loss (Tonitto et al. 2006), but because cover crops make nitrogen fertilizer reductions more feasible and less costly. By improving nitrogen retention and cycling, cover crops reduce the negative yield impact of cutting fertilizer, which helps producers meet N₂O abatement goals at a lower marginal cost. Under endogenous pricing, where supply contractions (due to lower yields or land shifts) lead to higher crop prices, the value of every unit of production increases. This makes yield-preserving mitigation strategies more attractive, even if those strategies involve a small yield penalty, because the economic return per unit of emissions abated is higher.

Figure 2.13 shows the percentage change in corn and soybean production relative to the baseline across different carbon payment levels and climate change scenarios. Although production changes remain within 2%, the results suggest that endogenous crop prices still influence GHG abatement outcomes in meaningful ways. Specifically, soybean production increases are smaller under endogenous pricing under both SSP1.26 and SSP3.70 climate change scenarios, reflecting how market feedbacks temper large changes in crop acreage. These price-induced adjustments help stabilize production, reduce the risk of supply disruptions, and illustrate how farmers weigh economic returns against environmental incentives. Even modest shifts in national crop output can have broader implications for market balance, food security, and the overall efficiency of climate policy.

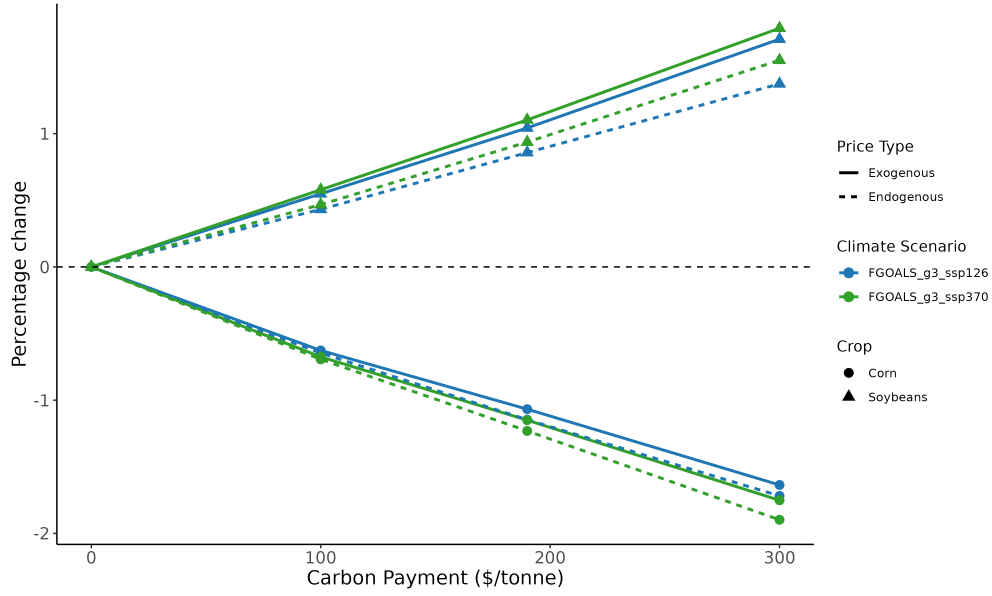


Figure 2.13: Changes in crop production across carbon price scenarios.

2.4 Discussion and Conclusion

This study emphasizes the potential role of agriculture in global GHG mitigation efforts, particularly through practices that influence soil carbon sequestration and N₂O emissions. While the agricultural sector is a major source of emissions, it also offers substantial mitigation potential if climate-smart practices are adopted at scale. While numerous policies seek to incentivize climate-friendly practices, their effectiveness depends not only on technical mitigation potential but also on how farmers respond to economic signals. A clear understanding of the economic and environmental trade-offs associated with policy interventions is critical for developing effective and well-informed climate strategies.

We develop an integrated modeling framework that links empirically estimated farmer behaviors with biogeochemical process simulations of soil carbon sequestration and N₂O emissions. The behavioral model captures how expected net returns shape land use and management decisions, while the biogeochemical model quantifies the consequences of those decisions under different climate change scenarios. A key contribution of this framework is the inclusion of endogenous crop prices, allowing prices to adjust in response to aggregate production decisions, thereby capturing critical feedbacks between producer behavior, market responses, and environmental outcomes.

We begin by estimating the empirical relationship between expected net revenues and farmers' land management decisions. This relationship serves as the foundation of a producer choice model that captures how economic incentives influence the adoption of conservation practices. The estimation results provide clear evidence that producers are responsive to changes in net returns, reinforcing the relevance of policy instruments such as carbon payments. Yet these decisions occur within broader market environments. As farmers also respond to changing market conditions, such as shifts in crop prices driven by aggregate supply responses, it is essential to account for this endogenous feedback.

We then link this behavioral model with a biogeochemical simulation to assess the integrated effects of climate change, grain markets, and carbon payment policies on agricultural emissions. In the baseline simulation, we find that farmers' responses to expected net revenues lead to differences in land management choices when crop prices are allowed to adjust endogenously. In particular, the inclusion of price feedbacks results in a shift toward lower-input practices, such as increased soybean acreage and reduced fertilizer use, which contributes to lower N₂O emissions over time. In contrast, soil carbon sequestration remains relatively consistent across scenarios, likely reflecting the slower adoption of tillage and cover crop practices. This comparison underscores the risk of overestimating GHG emissions under fixed-price assumptions. Notably, even in the absence of explicit policy incentives, endogenous market responses can yield meaningful environmental co-benefits that static models would fail to capture.

Using these integrated simulations, we construct GHG abatement supply curves under carbon prices of \$100, \$190, and \$300 across two climate change scenarios, offering insights into the marginal policy cost of mitigation in the agricultural sector. In this study, we define the marginal policy cost as the supply curve for GHG mitigation in agriculture. This marginal policy cost does not reflect the true social marginal cost under a second-best policy, as it does not account for additional societal costs relative to a first-best policy framework. The estimated abatement supply curves show that policy evaluations based on fixed crop prices likely understate the mitigation potential of carbon pricing in agriculture. Across all simulated carbon payment levels and cli-

mate scenarios, allowing crop prices to adjust endogenously yields greater GHG abatement. This result underscores the sensitivity of land use and management decisions to expected profitability and highlights the risk of designing policies that overlook these behavioral responses, potentially leading to inefficient or overly conservative mitigation strategies.

Our findings diverge from Garnache et al. (2017) in the elasticity of the GHG abatement supply curve under endogenous crop pricing, primarily due to differences in how crop prices are endogenized and how producer behavior is modeled. While their model imposes regional residual demand functions with crop-specific constant elasticities to calibrate price responses, our approach allows prices to adjust endogenously through the interaction between aggregate supply shifts, driven by producer land and management choices, and a national crop market equilibrium. As a result, our model captures feedback effects where rising crop prices, especially for soybeans, reduce the relative incentive to apply nitrogen fertilizer, leading to greater emissions abatement at a given carbon price. This mechanism makes our marginal abatement cost curve more elastic under endogenous prices, in contrast to their findings, where endogenizing prices modestly increase mitigation costs. These differences highlight the importance of modeling supply-side behavioral responses and market feedback jointly when assessing the cost-effectiveness of climate mitigation policies in agriculture.

While this study emphasizes the critical role of endogenous pricing in shaping agricultural GHG mitigation strategies, it is important to acknowledge several limitations. First, our analysis focuses on price effects prior to considering potential emissions leakage. That is, we do not account for the possibility that GHG emissions may shift to other regions or sectors as a result of the implemented policies. As such, our estimates may overstate the actual mitigation achieved if emissions are displaced beyond the boundaries of the modeled system. Second, the structure of our model may overemphasize the effectiveness of N₂O abatement incentives. By assigning relatively high returns to fertilizer reduction strategies, such as shifting to soybeans, our framework may inadvertently under-incentivize the adoption of SOC-building practices like conservation tillage or cover cropping. This could lead to an imbalance in practice adoption that does not fully reflect

real-world trade-offs or constraints. Additionally, while the model captures producer responsiveness to carbon prices, it does not endogenize fertilizer prices. This simplification may also lead to an overstatement of N₂O abatement potential, as widespread fertilizer reductions would likely reduce demand and depress fertilizer prices, thereby affecting both adoption decisions and abatement costs. Future work should incorporate fertilizer market feedbacks to better capture these interactions.

A further limitation lies in the structure of the decision-making process. The model assumes a two-stage framework in which fertilizer intensity is selected first based solely on maximum expected profit, and the remaining practices (crop, tillage, and cover cropping) are chosen within an RUM that allows for non-monetary influences. While this sequential approach reduces computational burden, it imposes the assumption that fertilizer use is driven only by profitability, excluding behavioral, informational, or agronomic factors that may also shape fertilizer decisions. This may overstate responsiveness to carbon incentives and limit the model's ability to capture cross-practice interactions. A unified RUM with all 24 combinations of practices would allow for more realistic trade-offs and behavioral consistency but would introduce significant complexity. Future research could explore the feasibility of jointly modeling fertilizer decisions alongside other conservation practices within a unified choice framework.

The model's use of simplified gross and net revenue calculations also introduces limitations. While we capture practice profits based on differences in yields, fertilizer cost, and carbon payments, the model does not account for fixed or capital costs associated with adopting certain conservation practices. For instance, practices like cover cropping or transitioning to no-till may involve machinery investments, learning curves, or longer-term maintenance requirements that are not reflected in annual revenue differences. As a result, the model may overestimate the profitability, and thus the adoption likelihood, of practices with high upfront costs but modest annual returns. In the RUM framework, unobserved, time-invariant factors affecting adoption are partially captured by alternative-specific constants. These constants may reflect non-monetary considerations such as risk aversion, learning costs, or social norms, as well as structural barriers like access to equipment

or agronomic suitability. However, because they are inferred from historical adoption patterns and not directly linked to observable variables, they limit our ability to explicitly evaluate the impact of changing policies or conditions on adoption behavior.

The current choice model accounts for rotational dynamics by controlling for the crop planted in the previous year, effectively capturing the influence of crop rotation on current decisions. As shown in Appendix Table A2.3, the coefficients on the lagged indicator for soybeans as the previous crop are positive for corn choices and negative for soybean choices. But and the long-term benefits of conservation practices like cover cropping and reduced tillage. These practices may entail short-term costs but offer future soil health and productivity benefits that influence behavior over multiple years. Expanding the model to incorporate intertemporal decision-making and rotation constraints would provide a more realistic depiction of practice adoption under climate policy. Finally, our estimates of grain market equilibrium depend heavily on assumed price elasticities of supply and demand. While these parameters are informed by existing literature, further robustness checks using alternative elasticity values are necessary to assess the sensitivity of our results. Despite these limitations, the integrated framework developed in this study provides valuable insights into how market feedbacks shape the environmental and economic outcomes of climate policies in agriculture. By highlighting the importance of endogenous pricing and behavioral responses, this work contributes to the design of more realistic and effective mitigation strategies for the agricultural sector.

Building on these insights, ongoing work aims to broaden the model's scope and improve its robustness. We are testing alternative assumptions about producer price expectations, such as adaptive learning and forward-looking behavior, to better reflect decision-making under uncertainty. To account for parameter uncertainty, we plan to conduct Monte Carlo simulations using probabilistic distributions for key model components, including the random utility model's net revenue coefficients and point-specific error terms for each crop, practice, and year. In addition, further analysis through decomposition and sensitivity testing will help more precisely identify the key drivers of GHG abatement, such as fertilizer intensity, crop switching, and tillage practices. Together, these

extensions will support a deeper understanding of mitigation pathways and inform the design of more effective, resilient, and targeted agricultural climate policies under future climate and market uncertainty.

Taken together, our results underscore the importance of integrating behavioral responses and market feedbacks into the design and evaluation of agricultural climate policies. By explicitly modeling how farmers adjust land use and management practices in response to carbon incentives and evolving market conditions, this study offers a more realistic assessment of mitigation potential than conventional approaches that assume fixed crop prices. In doing so, we highlight how endogenous price adjustments not only influence the scale of emissions reductions but also shape the pathways through which they are achieved, whether through fertilizer reduction, crop switching, or conservation practice adoption. This integrated perspective is essential for capturing the complexity of agricultural systems and for avoiding policy missteps that could arise from static or partial equilibrium assumptions. Assuming climate policy efforts increasingly turn to agriculture for cost-effective solutions, our framework provides a foundation for designing more efficient, adaptive, and evidence-based interventions that align environmental goals with producer incentives.

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Chapter 3

International Leakage and the Effectiveness of Agricultural Land Retirement as Greenhouse Gas Mitigation

3.1 Introduction

Agricultural production significantly contributes to global environmental challenges, accounting for nearly 12% of global anthropogenic greenhouse gas (GHG) emissions (Linqvist et al. 2012). To address these environmental impacts, agri-environmental policies have been developed to encourage farmers to adopt sustainable agricultural practices (Claassen et al. 2001). In the United States (U.S.), the Department of Agriculture (USDA) leads numerous conservation initiatives that have implications for GHG emissions. The Conservation Reserve Program (CRP), established in 1985 and administered by the USDA's Farm Service Agency (FSA), is the largest U.S. land conservation initiative in terms of total payments made to participants (Pratt 2024). While extensive research has assessed the domestic environmental benefits of CRP on GHG mitigation (Swan et al. 2018; Ogle et al. 2023), its global effects, particularly the potential for international emissions leakage and associated land-use changes, remain relatively understudied.

CRP is a voluntary initiative that compensates landowners for generating environmental benefits by temporarily removing cropland and pastureland from production. Research shows that converting cropland to CRP land increases soil organic carbon (SOC) sequestration and reduces nitrous oxide (N₂O) emissions (Swan et al. 2018). However, retiring cropland under CRP can lead to the conversion of non-cropland into cropland elsewhere in the U.S., thereby undermining overall emission mitigation efforts (Wu 2000). Furthermore, international trade introduces additional emissions leakage, as reduced domestic agricultural production can shift pressures to other countries' agricultural sectors (Liu et al. 2024). Since land retirement programs limit available

agricultural land and influence land rental rates, it is likely to induce leakage effects in global agricultural markets. Therefore, when evaluating the effectiveness of domestic conservation policies, especially with respect to global pollutants like GHGs, it is crucial to consider both the direct on-site GHG abatement and the indirect leakage effects that may occur domestically and internationally.

To study the impacts of land retirement through CRP in the U.S. on global agricultural production, trade, welfare, land use change, and GHG emissions, we employ a Computable General Equilibrium (CGE) model (Tabeau et al. 2006; Boyd et al. 1992; Uri et al. 1996). CGE models have been widely applied in the study of climate change mitigation policies at the national, regional, and global levels (Babatunde et al. 2017), as they account for interactions among sectors, regions, and global markets. This modeling framework enables an integrated assessment of CRP-induced changes across production, consumption, and government transfers, and effectively simulates how U.S. land retirement affects global commodity prices, trade patterns, economic welfare, land use, and GHG emissions. This is essential for capturing the full range of CRP's spillover effects, both domestically and internationally.

In fiscal year 2022, CRP enrolled approximately 22 million acres of cropland and pastureland, supported by an annual budget nearing \$1.8 billion. In 2021, the USDA announced plans to expand CRP by enrolling up to 4 million additional acres and offering higher payments to farmers for setting aside their land, with the goal of mitigating an additional 3 million metric tons (Mt) of carbon dioxide equivalent (CO₂e) (USDA Press 2021). The expansion is expected to be facilitated through increased rental rates. As of 2021, the CRP acreage cap stands at 25 million acres, with 20.8 million acres currently enrolled.¹³ Therefore, our research contributes to understanding how these proposed increases to CRP enrollment are likely to influence land use decisions, agricultural production, and associated environmental and economic outcomes. In particular, we assess whether the program can achieve its stated mitigation goals when accounting for potential leakage effects.

¹³The CRP acreage cap is set to gradually increase, reaching 27 million acres by 2023

U.S. domestic policies exert substantial influence on global agricultural production and food security (Josling et al. 2007; Bruce et al. 2012). As a major agricultural exporter (Beckman et al. 2017), U.S. domestic policies significantly impact global agricultural production, trade flows (Rossmiller et al. 1991), and commodity price stability (Mayrand et al. 2003; Gilbert 2012). For example, domestic support within the U.S. can shift production costs to farm households in developing nations (Alston et al. 2007), highlighting the far-reaching implications of U.S. agricultural policy. While extensive literature has explored the global consequences of U.S. farm bills on specific commodities such as cotton (Gillson et al. 2009), corn (Spittler et al. 2011; Shetty et al. 2015), and biofuels (Westhoff et al. 2008), the broader effects of agri-environmental conservation policies, which have become more prevalent in recent years, remain less studied. Moreover, existing studies on conservation policy impacts primarily focus on domestic outcomes within the U.S. (Prokopy et al. 2019). Therefore, this paper adds to the literature by evaluating the global implications of U.S. conservation policies on agricultural markets, land use changes, and GHG mitigation, while covering multiple agricultural commodities.

The domestic GHG mitigation effects of CRP have been extensively studied. Johnson et al. (2016) estimated potential reductions in GHG emissions by varying the acres enrolled in the program, while assuming a 20% leakage. USDA Press (2021) stated that the acres enrolled in CRP as of 2021 mitigate more than 12 million metric tons of CO₂e. De et al. (2020) estimated that approximately 9.5 million ha of U.S. cropland enrolled in CRP as of 2017 could potentially sequester around 4×10^6 Mg of C per year at a 15 cm soil depth. While Ogle et al. (2023) simulated the impact of CRP on SOC stocks in the U.S. and found that the impact declined over time, with the largest increase of 2.4 ± 1.8 Mt C occurring in 1996 and falling to a low of 1.1 ± 1.6 Mt C by 2015. These differing findings suggest that while CRP land has the capacity to enhance SOC and contribute to climate mitigation, actual outcomes are likely to vary depending on site-specific conditions, management practices, and temporal factors. However, these estimates primarily reflect on-site land use changes and do not account for indirect leakage effects, such as land conversion or increased input use elsewhere. In addition to climate-related impacts, other environmental benefits

of CRP have been well studied, including improvements in water quality (Rao et al. 2010; Yin et al. 2021), reductions in soil erosion (Karlen et al. 1998; Sullivan et al. 2004), and enhancements in biodiversity (Chen et al. 2022).

The land spillover effects of the CRP have been identified in several studies. Wu (2000) finds that for every 100 acres of cropland retired under CRP, an additional 20 acres of non-cropland are converted into cropland in the U.S., offsetting 9% and 14% of CRP water and wind erosion reduction benefits, respectively. However, the reliability of Wu's empirical findings has been challenged by Roberts et al. (2005), who present evidence questioning the magnitude of this land conversion. In response, Wu (2005) offers additional empirical support to reinforce his original conclusions. Extending the analysis, Tabeau et al. (2006) applied a general equilibrium framework combined with econometric methods to demonstrate that the CRP significantly affects land markets, raising land prices by up to 10.6%, inducing an 18.9% land slippage effect, and increasing fertilizer use on remaining farmland. These studies provide evidence of the domestic slippage effect of CRP; however, the potential spillover effects of CRP beyond U.S. borders remain largely unexplored in the existing literature. Pfaff et al. (2017) highlight the importance of recognizing spillovers, both positive and negative, that extend beyond the geographic boundaries of conservation interventions. They identify five key channels through which such effects can occur: input reallocation, market prices, learning, nonpecuniary motivations, and ecological-physical links. Our study builds on this work by examining how CRP may generate not only domestic but also international spillovers through changes in land use and commodity markets, offering new insights into the broader spillover effects of land retirement policies.

The regional economic spillovers of CRP have also been extensively studied. Sullivan et al. (2004) raise concerns that CRP enrollment may unintentionally contribute to rural population decline and economic downturns by reducing demand for local goods and services, intensifying competition in land markets, and limiting access to productive farmland for beginning and expanding farmers, particularly in agriculturally dependent communities with high enrollment levels. Young et al. (1990) find that with the implementation of CRP, agricultural production is projected to de-

crease by 3%, accompanied by a 2% decline in agricultural input industries and marginal decreases in household sector income, total gross output, employment, and agricultural processing. Wu et al. (2010) demonstrate that CRP can boost average farmland values by 2% to 14%, varying by location within the U.S. Li et al. (2023) find enrollment in CRP significantly reduces employment in agricultural sectors. However, there remains a research gap in understanding the spillover effects of CRP on global agricultural market, trade, welfare, land use, and GHG emissions.

In this study, we extend the Global Trade Analysis Project (GTAP) model with Agro-Ecological Zones (AEZs) to create the GTAP-CRP model, incorporating the CRP as a new sector where land across various AEZs is the sole input. Our simulation results show that enrolling an additional 4 million acres into the CRP in the U.S. would lead to a decrease in agricultural output and exports, leading to price increases for most agricultural commodities. While the U.S. experiences welfare gains, some other regions face welfare losses due to reduced resource allocation efficiency. We also estimate the slippage effect of the U.S. land retirement. The result shows that with a 4 million acres (\approx 1.6 million hectares) land retired from cropland and pastureland, 236 thousand hectares of forest and 140 thousand hectares of unmanaged land will be transferred into agricultural land within the U.S. When assessing the GHG implications of these land use changes, we find that the mitigation potential of CRP is entirely offset once spillover effects are accounted for, resulting in emission leakage of approximately 159% domestically and nearly 205% when international leakage is included.

This study contributes to the literature on agri-environmental policy by providing one of the first evaluations of the global spillover effects of a U.S. land conservation program. While previous studies have extensively studied the domestic environmental and economic outcomes of CRP, relatively little attention has been paid to how large-scale land retirement policies in the U.S. influence global agricultural markets, land use changes, and GHG emissions. Previous studies have provided evidence of domestic slippage associated with CRP, with estimates ranging from 4% to 20% of the land enrolled in the program being offset by new agricultural conversion elsewhere (Wu 2000; Fleming-Muñoz 2010). The robustness of these estimates has been questioned due to

data limitations and unobservable confounding factors (Roberts et al. 2005). Our study addresses these challenges by utilizing a modified GTAP-AEZ model, which allows for a more integrated analysis of CRP-induced shifts in land use, trade, and emissions at both domestic and international scales. This approach allows us to assess whether the program’s intended GHG mitigation benefits hold once potential leakage effects are taken into account, offering new insights into the overall effectiveness of conservation policies in addressing climate change—particularly with respect to globally dispersed pollutants such as greenhouse gases.

This paper is organized as follows. The next section describes the CRP market mechanism and the theoretical framework for analyzing the domestic and international economic impacts of CRP. Section 3 describes the GTAP modeling approach, including the modifications made to the standard model and the design of the simulation scenarios. Section 4 presents the data and key summary statistics. Section 5 reports the primary results from our general equilibrium simulations. The final section offers a discussion of the results and concludes the paper.

3.2 Background of CRP

3.2.1 CRP History and Allocation Rules

CRP was established in 1985 and initially designed to preserve soil quality (Mausbach 1996). Since then, CRP has expanded its focus to improve water and air quality, while also enhancing wildlife habitats (Hammerson et al. 2012). Under CRP contracts, enrolled land is removed from agricultural production for the duration of the contract, typically spanning 10 to 15 years. Before 2000, CRP accounted for more than 90% of conservation-related expenditures in the U.S. Farm Bill. Although its share of conservation funding decreased after the 2008 Farm Bill, CRP remained the largest federal conservation program in terms of funding (Coppess 2023). The program was initially designed to retire 40-45 million acres of land to address environmental concerns. Since then, it has seen fluctuating enrollment caps over time, ranging from 25 to 45 million acres. Initially, CRP enrollment was generally limited to 25 percent of the cropland within each county to avoid economic loss in farm-dependent communities. However, this cap essentially never binds

(Aspelund et al. 2024). As illustrated in Figure 3.1, which shows CRP enrollment by county in 2017, enrollment rates remained below 5 percent in most counties.

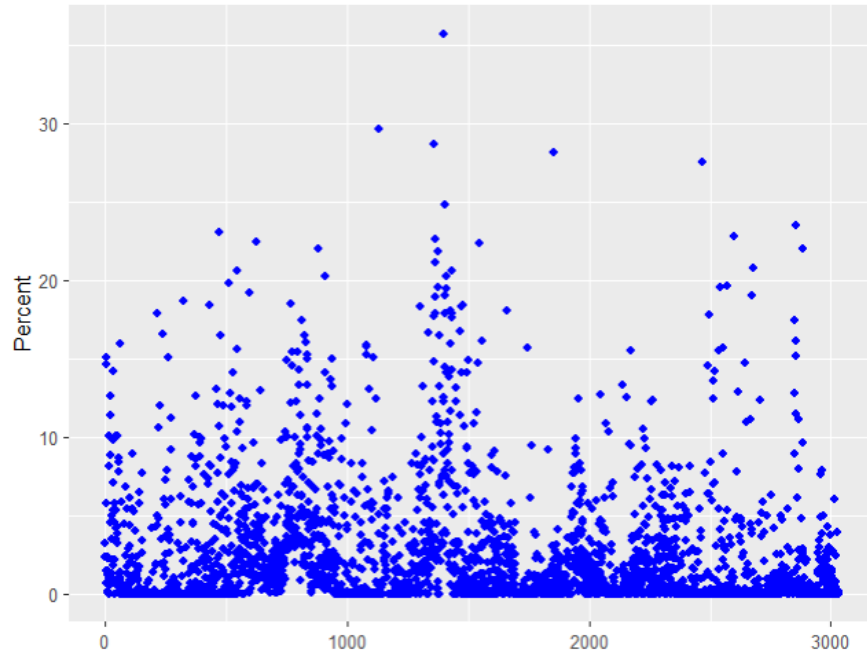


Figure 3.1: Percentage of CRP land relative to cropland and pastureland in each county

Note: The figure presents data from 2017. CRP data are sourced from the USDA FSA; county cropland and pastureland data come from NASS Quick Stats. Each point on the figure represents an individual county.

The national CRP acreage cap has also varied over time. It was set at 38 million acres in 1992, reduced to 36.4 million acres by 1996, and then increased to 39.2 million acres in 2002. The cap was subsequently lowered to 32 million acres in 2009. The 2014 Farm Bill imposed a further reduction, limiting enrollment to no more than 25 million acres beginning in 2016. The 2018 Farm Bill later permitted a gradual increase, allowing the cap to rise to 27 million acres by 2023 (ERS 2020). Figure 3.2 displays cumulative CRP enrollment and the corresponding acreage caps from 1986 to 2022, highlighting that these national caps, like the county-level caps, have seldom been binding.

One of the key developments in the history of CRP was the introduction of the Environmental Benefits Index (EBI) in the early 1990s. The EBI is a scoring system used to evaluate and rank

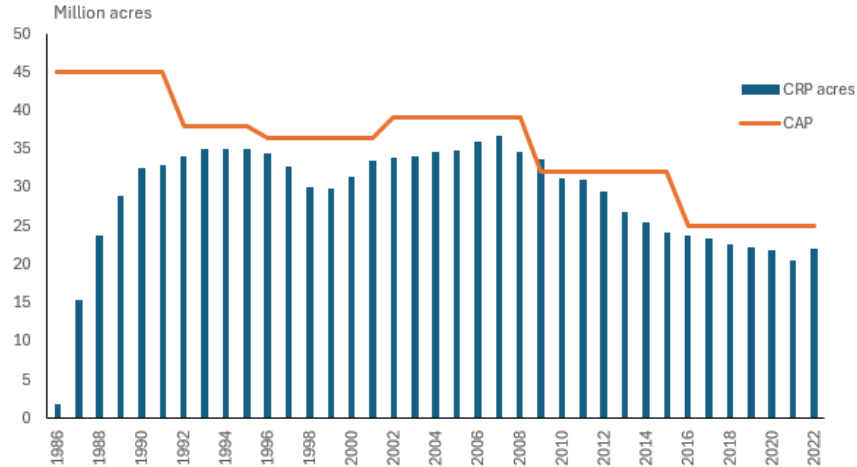


Figure 3.2: Cumulative CRP acres and the CRP cap

Note: The cumulative CRP data are sourced from the USDA FSA, and the cap data are summarized from ERS (2020).

the environmental benefits of land parcels offered for enrollment. Initially, all bids with acceptable rental rates were accepted, leading to the enrollment of only low-productivity lands. The development of the EBI scores enabled the USDA to enroll environmentally sensitive yet highly productive lands into the program (Sullivan et al. 2004). The EBI awards points based on multiple indicators of environmental value, enabling the USDA to prioritize offers that align with broader conservation goals. Over time, the EBI has been expanded to incorporate criteria such as wildlife habitat, water and air quality, and long-term environmental benefits. Beginning with the 13th sign-up in 1995, the index was further refined to account for the cost to the government of accepting each bid (Ribaud et al. 2001). In the 26th sign-up in 2003, carbon sequestration was explicitly included as a subcomponent under the air quality category, with a weight of 30 out of the total 415 points in the EBI scoring system.

The enrollment process for CRP utilizes an auction-based mechanism, strategically designed to optimize environmental benefits while ensuring fair compensation for landowners (Aspelund et al. 2024). In this auction, landowners submit sealed bids specifying both the annual rental payment and the conservation practices they are willing to implement. Bids are ranked using the EBI, which incorporates measures of environmental benefit and program cost. Rather than

operating under a fixed budget, CRP sets an approximate acreage target for enrollment. Each parcel is subject to a maximum allowable bid, known as the Soil Rental Rate (SRR), which is disclosed to landowners before bidding (Hellerstein et al. 2015). Additionally, CRP enrollment in any given county is limited to 25 percent of the county's total cropland. The auction consists of a single binding round, but general signups are held periodically, usually annually, allowing rejected offers to be revised and resubmitted. CRP uses a discriminatory pricing rule, paying landowners their bid amount if accepted. Since the total number of bidders is unknown prior to each auction, landowners must weigh the trade-off between asking for higher rental payments against the risk of their offer being rejected. There is an ongoing debate over the auction design of CRP. Some proposed that landowners tend to bid at or near the SRR cap, even when their actual opportunity cost is lower (Hellerstein 2017), while others suggest that bids reflect landowners' marginal costs (Aspelund et al. 2024).

Understanding the incentives that motivate farmers to participate is a key factor in analyzing the CRP market. For farm operators seeking to exit active farming—whether through retirement or by pursuing alternative livelihoods—CRP offers a reliable source of income with minimal labor requirements, while allowing them to retain ownership of their land. These operators often aim to enroll as much land as possible to support this transition, maintaining ties to the land either as a homestead or an investment (Sullivan et al. 2004). The auction should theoretically reveal farmers' marginal willingness to accept to participate in the program (Aspelund et al. 2024), but whether this occurs in practice has been questioned (Hellerstein 2017). According to the report by Sullivan et al. (2004), a significant portion of farm operator participants in CRP can be classified as either retirement or residential farm operators. Retirement farms are those managed by individuals who identify as “retired”, whereas residential farms are managed by individuals who primarily identify with occupations outside of farming. These two farm categories also account for a significant portion of CRP acres and receive the majority of payments. The method for modeling an increase in enrollment will be discussed in the scenario design section (Section 3.4.3).

Table 3.1: CRP acceptance rates

Signup	Offers		Acres		Acceptance Rates		Payments	
	Received	Accepted	Received	Accepted	Offers	Acres	Total(\$/Year)	Per Acre
2022	22919	19981	2290000	2069638	87.2%	90.4%	106,659,056	51.54
2016	26,279	4,842	1860000	407116	18.4%	21.9%	2,548,2767	62.59
2013	27,821	24,213	1900000	1680000	87.0%	88.4%	108,253,928	64.44
2012	47,934	42,010	4500000	3900000	87.6%	86.7%	198,595,184	50.92
2011	38,715	29,878	3750000	2830000	77.2%	75.5%	136,201,438	48.13
2010	50,094	45,000	4840000	4340000	89.8%	89.7%	200,164,926	46.12

Note: Data from USDA FSA. The USDA published only these six signups.

Table 3.1 displays CRP acceptance rates for several sign-ups after 2010, revealing that the acceptance rates typically range from 75 percent to 90 percent, with the notable exception of an unusually low acceptance rate in 2016. This may be attributed to the 25 million acre cap implemented in 2016. For instance, in 2022, the USDA received 22,919 offers covering 2.29 million acres, of which 87.2 percent were accepted, resulting in an average rental payment of \$51.54 per acre. Offers may be rejected due to exceeding national or local acreage caps, or because the bid provides relatively lower environmental benefits based on EBI scores. CRP is implemented at the county level, thereby exhibiting a lot of heterogeneity across counties due to varying local environmental needs, land use practices, and conservation priorities. When studying the impact of CRP on global agricultural markets, it is necessary to aggregate CRP data to the sub-national (AEZs) level and assume that this aggregated data accurately represents the majority of farmers' behaviors.

3.2.2 Global Implications of CRP

Figure 3.3 presents a conceptual framework illustrating the direct and indirect pathways through which CRP affects GHG emissions at both domestic and international scales. The framework begins with CRP payments, which incentivize landowners to retire cropland or pastureland from active production. This land retirement directly reduces GHG emissions by curbing emissions-intensive agricultural activities on environmentally sensitive lands. However, the reduction in

agricultural output and input demand affects market prices, which subsequently influence land use and production decisions elsewhere (Tabeau et al. 2006). In addition, CRP payments increase landowners' income, which may also affect market behavior and price. These price changes are transmitted through international trade, potentially inducing shifts in production and land use beyond U.S. borders (Sumner 2003). As a result, the net emissions impact of CRP depends not only on direct domestic effects but also on indirect, market-driven responses both within and beyond U.S. borders.

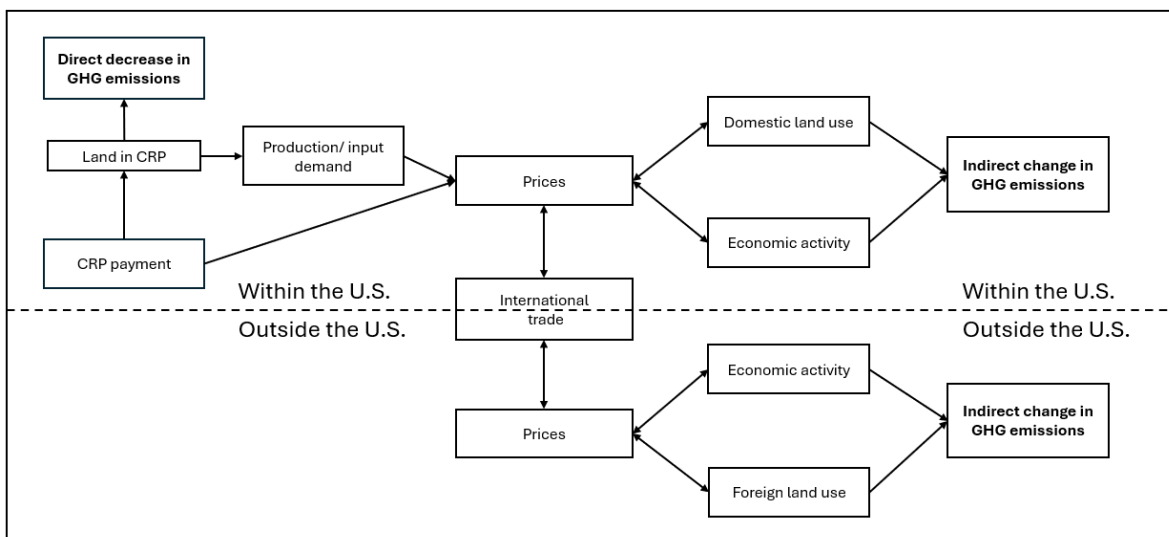


Figure 3.3: Conceptual model illustrating the global economic impact of CRP

Domestically, higher agricultural prices resulting from CRP-induced supply reductions may encourage the cultivation of additional land or increased input use, potentially leading to indirect increases in GHG emissions. Internationally, other countries may respond to price increases in global agricultural markets by expanding their own agricultural production, which can involve converting non-agricultural land, such as forests or grasslands, into cropland, thereby contributing to emissions leakage. This framework underscores that although CRP achieves its intended environmental benefits through direct emissions reductions, it may also generate unintended spillover

effects that partially offset these gains through indirect land use changes and associated emissions at both domestic and international levels.

3.3 GTAP-CRP Model

To study the impacts of CRP in the U.S. on global agricultural production, trade, land use, and emissions, we build on the Global Trade Analysis Project (GTAP) model. We follow the approach of incorporating AEZs into the GTAP model, as introduced by Lee (2005), to account for the spatial heterogeneity in agricultural production. The AEZ approach allows for a more accurate representation of the differences in land productivity and the suitability of land for various crops across different regions. We then modify GTAP-AEZ to create a new model, GTAP-CRP, to specifically analyze the impacts of expanding CRP.

3.3.1 Structure of GTAP model and Land Use Data

The standard GTAP model (Hertel 1997; Corong et al. 2017) is a widely used, comparative static, multi-region, multi-sector CGE model developed to analyze international trade and environmental policy issues. It provides a consistent analytical structure for global economic modeling by linking economic agents—households, firms, and governments—across countries and sectors. At its core, the GTAP model assumes perfect competition and constant returns to scale across all sectors. Production is modeled using nested Constant Elasticity of Substitution (CES) functions, combining primary factors—land, labor, capital, and natural resources—with intermediate inputs to generate output. The model incorporates region-specific households that allocate income among private consumption, government spending, and savings, typically using Cobb-Douglas or non-homothetic demand systems. International trade is modeled through the Armington assumption (Armington 1969), distinguishing goods by region of origin to account for product differentiation in global markets. The model's equilibrium is characterized by market clearance, zero economic profits for firms, and balanced regional household budgets. Additionally, global savings and investment are equalized, and the model enforces a neutral global trade balance. Over time, the

GTAP model has been extended to accommodate a wide range of applications, including welfare analysis, climate mitigation, and sector-specific policy simulations.

In the standard GTAP model, land serves as a sluggish endowment, reallocated in response to changes in relative land rents. However, the suitability of various crops within a country varies geographically, limited by local adaptability. Most crops can only grow under specific conditions of temperature, moisture, soil type, and landform (Lee 2005). This principle extends to land use in the livestock and forestry sectors as well. Therefore, to address this issue, Lee (2005) developed the land endowment representation in the standard GTAP by dividing national land into 18 AEZs, following the classification by the United Nations Food and Agricultural Organization (FAO) (FAO and IIASA 2000). This classification provides a globally consistent framework for characterizing land across crop, livestock, and forestry, taking into account key biophysical factors that determine agricultural potential.

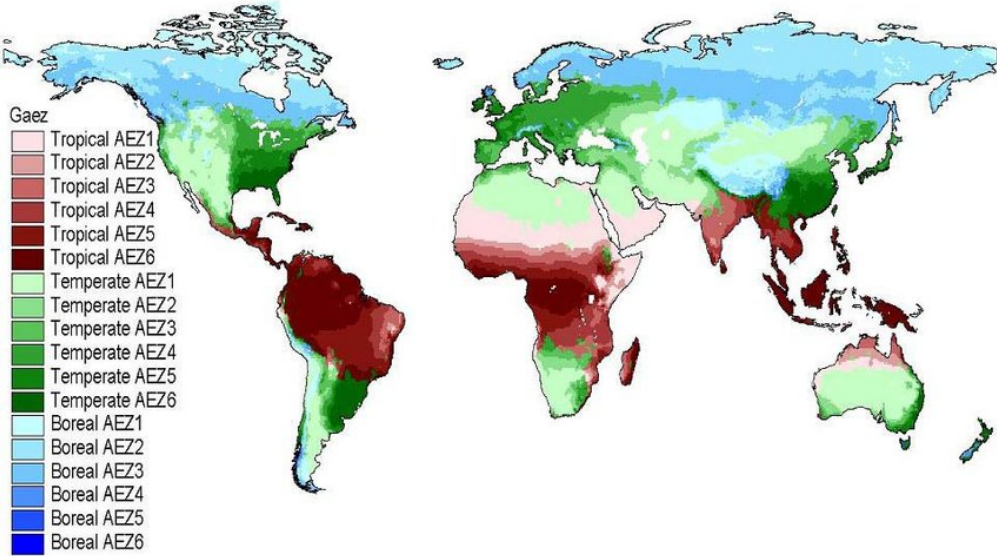


Figure 3.4: The sage global map of the 18 AEZs

Source: Lee et al. (2005)

AEZs classify land based on biophysical characteristics such as precipitation, temperature, soil type, and terrain. This zoning approach divides land into units that share similar constraints

and potential for agricultural use. In the GTAP-AEZ framework, AEZs are primarily defined by their “length of growing period” (LGP), a key determinant of crop suitability. For instance, AEZ 1 includes areas with up to 60 days of growing conditions annually, while AEZ 6 covers regions with an LGP of 270 to 360 days. The GTAP-AEZ database includes 18 AEZs, which span six LGP categories across three major climatic zones: tropical, temperate, and boreal. This classification supports a more refined allocation of land-based activities, such as crop production, livestock grazing, and forestry, based on both climate and soil conditions. Figure 3.4, adapted from Lee (2005), illustrates the global distribution of AEZs at a 0.5-degree resolution. Color gradients represent LGP length, with lighter shades indicating shorter growing seasons and darker shades (e.g., AEZ6, AEZ12, and AEZ18) representing longer ones. Climatic zones are distinguished by color: red for tropical, green for temperate, and blue for boreal. Additional details on the GTAP-AEZ model structure and data sources are provided in Lee (2005).

3.3.2 Structure of GTAP-AEZ

Over the past decades, the standard GTAP model and its associated database have been regularly updated and extended to support a wide range of policy applications. The GTAP-AEZ model (Hertel et al. 2008) is a modified version of the standard GTAP model that is specifically developed to facilitate a more detailed structural analysis of land use by incorporating opportunity costs and accounting for spatial heterogeneity in land quality and suitability. A central feature of the GTAP-AEZ model is its integration of AEZ-specific land use data. In contrast to the standard GTAP model, which assumes land is perfectly substitutable across agricultural and forestry uses, the GTAP-AEZ model introduces constraints on land mobility through a nested Constant Elasticity of Transformation (CET) structure. This structure reflects the reality that land cannot easily shift between alternative uses due to climatic, soil, and other biophysical limitations.

As illustrated in Figure 3.5, in the GTAP-AEZ model, landowners allocate land among broad categories such as forest, cropland, and pasture based on relative returns, subject to transformation elasticities. Each land-using sector within an AEZ operates under a unique production function,

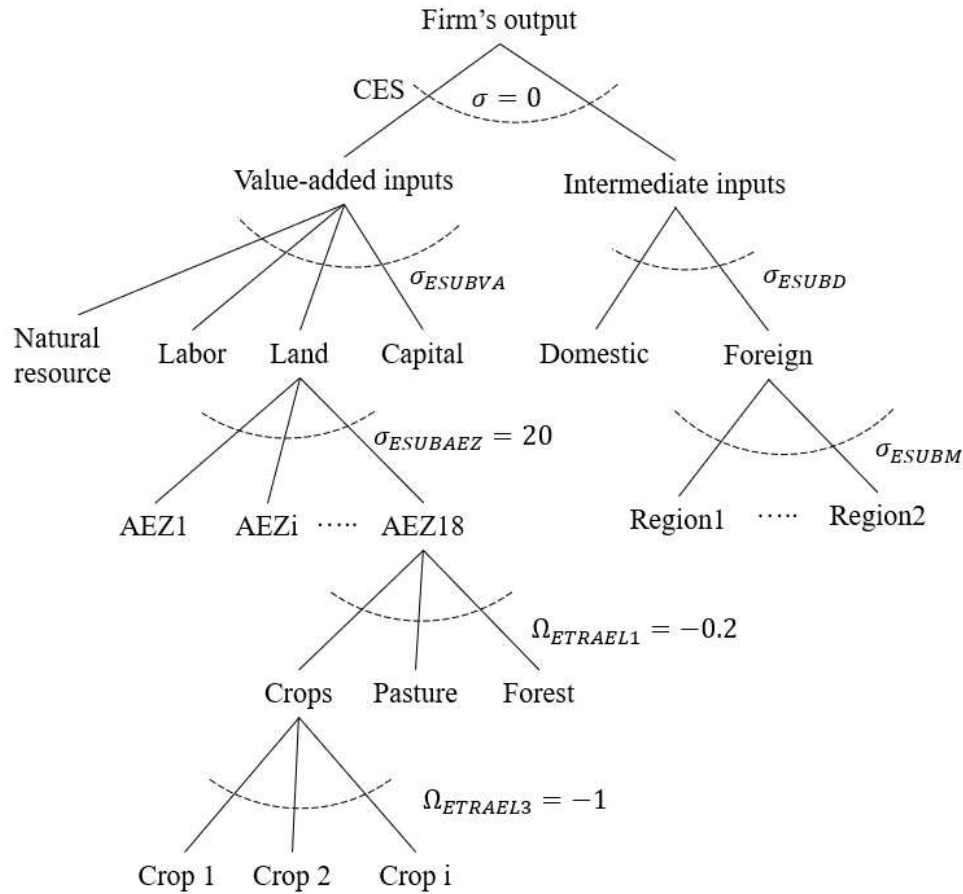


Figure 3.5: Production structure of GTAP-AEZ model

allowing for variation in land productivity across zones. For example, the production function for the paddy rice sector in AEZ 1 varies significantly from that in AEZ 6, reflecting differences in land productivity. Despite this spatial differentiation in production, sectors such as paddy rice across different AEZs are treated as producing a homogeneous commodity for market transactions. This detailed spatial structure enhances the model’s capacity to capture land competition among sectors and better represent the environmental and economic trade-offs associated with land use policies (Hertel et al. 2008).

3.3.3 GTAP-CRP Modelling Framework

This research extends the GTAP-AEZ model by developing the GTAP-CRP model to simulate the effects of expanding the U.S. CRP on global agricultural markets, land use, and emissions.

The standard GTAP and GTAP-AEZ models do not include CRP land as a distinct use in the U.S., making this extension necessary for evaluating its broader economic and environmental spillover effects. A previous study by Birur (2010) treated CRP land as cropland in their analysis of the global impact of biofuels on agriculture, trade, and the environment. In that framework, CRP land competed for returns in the land market, and total CRP payments were modeled as a reduction in capital endowment. Birur (2010) explored the implications of fixed CRP acreage under biofuel policy scenarios, comparing them to alternatives with fixed CRP rents. Building on this foundation, we update both the land supply structure and data sources. We develop a three-tier nested CET land supply model, allowing for land transitions not only between crops and pasture but also into CRP.¹⁴ In addition, we update the GTAP and CRP databases to ensure that enrollment acres and payment values correspond to the GTAP reference year of 2017.

In the GTAP-CRP model, CRP is introduced as a new sector in which land across AEZs is the sole input. As shown in Equation 3.1, Q_{CRP} is the output of CRP sector, and AEZ_i denotes land within a specific AEZ. All CRP output is consumed by the government, with no involvement in international trade or private household demand. Landowners receive income from land enrolled in CRP, and CRP payments are reflected as the supply price of CRP in the GTAP-CRP model.

$$Q_{CRP} = f(AEZ_i) \quad (3.1)$$

Given the fixed total land supply within each AEZ, land allocated to CRP competes directly with land allocated to agricultural production. To better capture land competition, we extend the two-tier CET land allocation structure from Hertel et al. (2008) into a three-tier framework. As illustrated in Figure 3.6, landowners first choose between allocating land to agriculture or forestry. In the second tier, agricultural land is allocated among cropland, pasture¹⁵, and CRP. In the bottom tier, cropland is allocated among individual crop types.

¹⁴Grassland CRP has become increasingly important since its reauthorization under the 2018 Farm Bill.

¹⁵The Grassland CRP, under the broader CRP, engages farmers to transition environmentally sensitive land from ranching to conservation (USDA FSA, Grassland CRP).

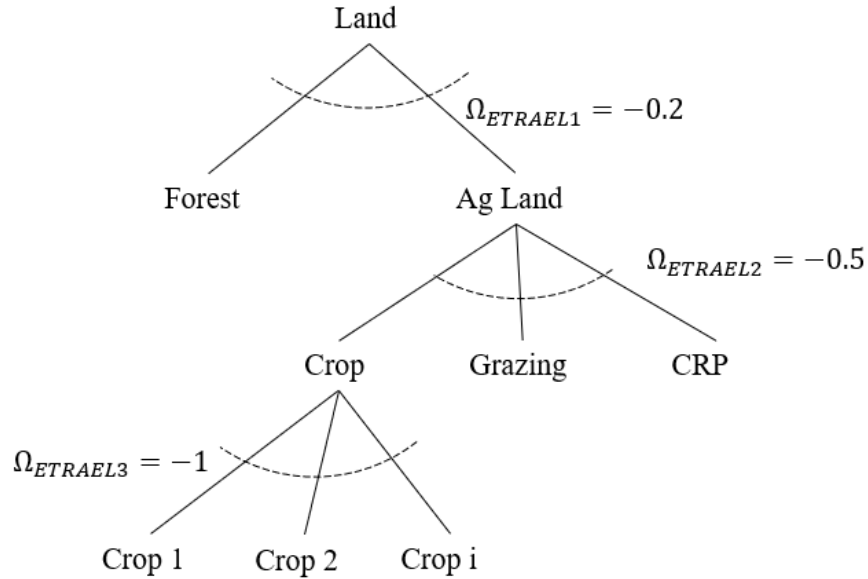


Figure 3.6: Land supply in the GTAP-CRP model

Note: $\Omega_{ETRAEL1}$ and $\Omega_{ETRAEL3}$ are adopted from the standard GTAP-AEZ model, while $\Omega_{ETRAEL2}$ is adopted from Birur (2010).

We adopt transformation elasticities in line with the GTAP-AEZ model as outlined by Hertel et al. (2008) to reflect varying degrees of land-use flexibility across different decision levels. At the top tier, the elasticity of transformation between forest and agricultural land ($\Omega_{ETRAEL1}$) is set to -0.2 , reflecting a relatively low mobility due to natural constraints. At the bottom tier, which allocates cropland among specific crops, we apply an elasticity of -1 ($\Omega_{ETRAEL3}$) from the standard GTAP model. This value is informed by econometric evidence from U.S. land supply to crop sectors and indicates greater substitutability among crops. For the intermediate tier ($\Omega_{ETRAEL2}$), which governs the allocation of agricultural land among cropland, pastureland, and CRP, we set the elasticity of transformation at -0.5 , following Birur (2010). The inclusion of CRP in this nest allows us to capture the increasing enrollment of pastureland in CRP under the expanding Grassland CRP initiative following the 2018 Farm Bill. The transformation elasticity reflects a moderate degree of land mobility that is more flexible than between forest and agriculture, but more constrained than among individual crops. To assess the robustness of our results, we also conduct

a Systematic Sensitivity Analysis (SSA) by increasing or decreasing this elasticity by 50%. The resulting impacts on land use change and emissions are reported in Appendix Table A3.1.

3.4 Data and Simulation

In this section, we first describe the process of integrating CRP data into the GTAP land use database. We then describe the emissions data embedded in the GTAP-CRP framework. Following the data integration, we present the simulation scenario used to evaluate the spillover effects of U.S. CRP expansion.

3.4.1 GTAP-CRP Data

This study employs the GTAP-AEZ model and the GTAP version 11c database (Aguilar et al. 2019), with 2017 as the reference year. The model collapses 65 sectors into 14 sector aggregates and 160 regions into 9 modeled regions as detailed in Appendix Table A3.2 and Appendix Table A3.3, with aggregation based on land use and agricultural trade. To incorporate the CRP into the GTAP database, we first separate the CRP sector from the Livestock, raw milk, wool sector.¹⁶ Next, we aggregate 2017 cumulative county-level CRP enrollment data from the USDA FSA¹⁷ to the AEZ level. We then incorporate government consumption, firms' endowment purchases, and CRP land cover into the GTAP-CRP database. Finally, we use the GTAPAdjust model to rebalance the database to ensure internal consistency.

CRP payments are classified in the Organisation for Economic Co-operation and Development (OECD) Producer Support Estimate (PSE) data as either Group Commodity Transfers (GCT) or Other Transfers to Producers (OTP). As shown in Table 3.2, CRP payments in the GCT category began in 2014 and accounted for less than 5% of the total CRP payments. It is clearly stated that agricultural domestic support in the GTAP database, derived from the OECD's Producer Support

¹⁶The specific sector from which CRP is split is arbitrary, as the CRP sector is assigned a zero weight in the initial step. This is necessary because the database structure does not permit the creation of entirely new sectors; it only allows splits from existing ones.

¹⁷Conservation Reserve Program Statistics

Estimates (Wang et al. 2023), includes GCT payments as input subsidies. However, the majority of CRP payments are categorized as OTP, which are not included in the standard GTAP framework. These OTP payments correspond to land retirement compensation and must be explicitly added to ensure an accurate representation of CRP's scale and implication. Thus, while GCT payments remain unchanged, CRP payments classified under OTP are incorporated as a distinct land-based subsidy in the GTAP-CRP model.

Table 3.2: CRP payment in OECD database in U.S. million dollars

Year	Group Commodity Transfers (GCT)		Other Transfers to Producers (OTP)	
	CRP payment	Share of total CRP payment	CRP payment	Share of total CRP payment
2014	65.00	3.4%	1,841.00	96.6%
2015	31.00	1.7%	1,804.00	98.3%
2016	65.73	3.5%	1,830.57	96.5%
2017	94.91	4.8%	1,881.89	95.2%

Note: Only Group Commodity Transfers (GCT) are included in the standard GTAP database.

Source: Authors' calculations based on CRP data from the OECD PSE database and guidance from the GTAP Resource Paper "Chapter 10.A: Agricultural Domestic Support" (Huang et al. 2019).

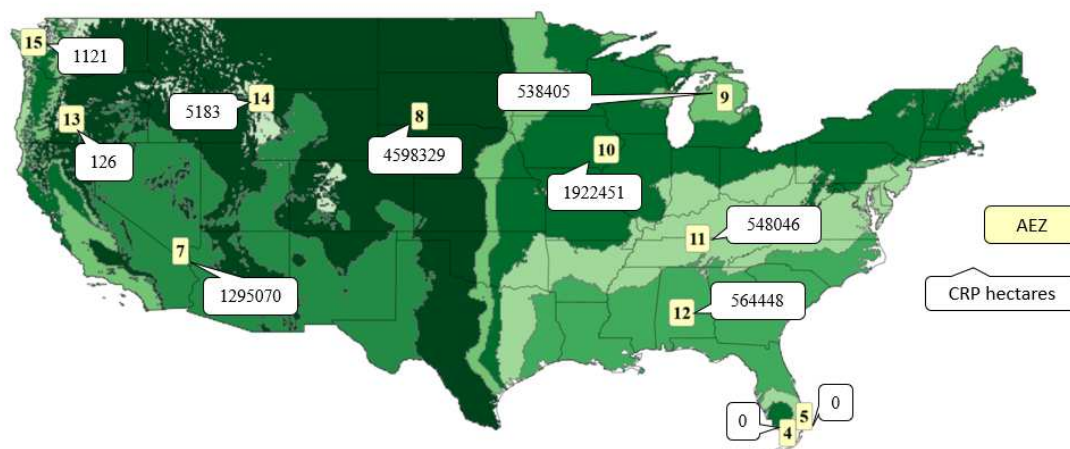


Figure 3.7: The distribution of CRP hectares across AEZs

Note: This figure displays the distribution of total CRP hectares across AEZs in 2017.

Figure 3.7 presents the spatial distribution of CRP hectares across AEZs¹⁸ in the continental U.S. Alaska and Hawaii are excluded from the figure due to limited data availability, although CRP participation exists in both states. In the map, bold numbers in yellow shapes indicate AEZ identifiers, and numbers in white shapes show the total CRP hectares within each AEZ. Darker green shades represent higher levels of CRP enrollment. AEZ8 shows the highest enrollment, reflecting substantial conservation efforts in the central U.S. AEZ10 and AEZ7 also show substantial CRP enrollment, with 1,922,451 and 1,295,070 hectares, respectively. In contrast, AEZ13 has less than 1,000 CRP hectares, indicating minimal enrollment. Notably, AEZ4 and 5 are present in the U.S. but have no CRP hectares enrolled.

3.4.2 Emission Data

The emission factors (EFs) employed in the GTAP-CRP model are derived from the Agro-Ecological Zone Emission Factor (AEZ-EF) framework (Plevin et al. 2014), which estimates net GHG fluxes associated with land-use transitions at the AEZ-by-region level. Each EF, expressed in metric tons of CO₂e per hectare, reflects the total emissions or sequestration assumed to occur instantaneously at the time of land conversion, and is then amortized evenly over a 30-year period, consistent with the static equilibrium framework of the GTAP-AEZ model. These EFs are calculated following the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2006) GHG inventory approach, incorporating six key components: (1) changes in carbon stocks in above- and below-ground biomass, (2) carbon retained in harvested wood products, (3) emissions from land clearing by fire (CO₂, CH₄, N₂O), (4) soil organic carbon losses and related N₂O emissions, (5) carbon released through the decay of biomass, and (6) foregone carbon sequestration from the loss of potential future growth.

¹⁸For counties that span multiple AEZs, allocation will be made to the AEZ that contains the majority of the county's area.

In this study, emissions from land-use change are calculated by multiplying the area of land converted (ΔLUC) by the relevant emission factor:

$$\text{Emissions}_{i,r,e} = \Delta LUC_{i,j,r} \times EF_{i,r,e} \quad (3.2)$$

where $\Delta LUC_{i,j,r}$ is the change in land cover of type j in AEZ i and region r , and $EF_{i,r,e}$ is the emission factor for the corresponding land-use transition. The EFs are specific to each type of land conversion, with distinct values reflecting the biophysical and management characteristics of the AEZ and region. Table 3.3 summarizes the carbon flow changes associated with different transitions. For example, converting cropland to pasture typically yields negative EFs due to gains in above- and below-ground biomass and soil related GHG emissions, while forest-to-cropland conversion accounts for biomass loss, soil-related GHG emissions, foregone soil carbon sequestration¹⁹, and harvested wood products (HWP). The methodology and data sources for EF calculations are detailed in Plevin et al. (2014).

Table 3.3: Biomass, SOC, foregone sequestration, and HWP by land transition

	Biomass	Soil GHGs	Foregone Sequestration	HWP
Forest-Crop	Yes	Yes	Yes	Yes
Forest-Pasture	Yes	Yes	Yes	-
Pasture-Crop	Yes	Yes	-	-
Pasture-Forest	Yes	-	-	-
Crop-Forest	Yes	Yes	Yes	Yes
Crop-Pasture	Yes	Yes	-	-
Crop-CRP	Yes	Yes	-	-
Pasture-CRP	-	-	-	-
Unmanaged-Crop	Yes	Yes	-	-

Note: Land transition between cropland, pastureland, forest, and CRP are sourced from Plevin et al. (2014).

¹⁹Foregone soil carbon sequestration refers to the carbon the soil would have continued to store if the land had remained undisturbed.

The GTAP-CRP model incorporates new land-use categories such as CRP land by explicitly defining new transitions (e.g., cropland to CRP, pasture to CRP, CRP to cropland, and CRP to pastureland) and assigning them their respective emission factors. Based on the national survey of CRP land conducted by Allen et al. (2003), the dominant vegetation cover on CRP lands consists of native grasses (55%), introduced grasses (31%), and trees (14%). Given this composition, we approximate CRP land as functionally equivalent to pastureland for the purposes of this study and adapt the corresponding emission factors from the standard AEZ-EF model, as calibrated values for CRP land are not available. As a result, the EF for cropland to CRP transitions is set equal to that of cropland to pasture, and the EF for pasture to CRP transitions is assumed to be zero, as shown in Table 3.3.

We also consider spillover effects on unmanaged land. Unmanaged land refers to land that is not currently used for economic production and does not generate market returns. In the GTAP Land Use and Land Cover (LULC) database (Baldos 2017), non-productive land categories include SavnGrasland, Shrubland, BuiltUpLand, and OtherLand. In this study, we define unmanaged land specifically as the SavnGrasland category, which represents savannas, natural grasslands, and other non-commercial open landscapes. Because unmanaged land is not associated with any economic activity, it lacks an assigned price in the GTAP model.²⁰ So we manually include it as a residual land pool that can be drawn into agricultural use when needed. To incorporate emission leakage effects into the GTAP-CRP model, we assume a minimum of 20% domestic leakage rate from CRP enrollment, meaning that for every 100 acres added to CRP, up to 20 acres of cropland or pastureland can be offset by the conversion of non-agricultural land (Wu 2005). Because forest land²¹ can adjust freely to relative land price changes under a constant transformation elasticity, we impose the substitution assumption only on unmanaged land. For example, in AEZ7, if forest loss exceeds 20% of the CRP land increase, no unmanaged land is assumed to move into agricultural use. However, if forest loss is less than 20% of enrolled CRP acres, then unmanaged land supplies

²⁰In practice, savannas and natural grasslands may be used for livestock grazing and could therefore have some economic value.

²¹In the GTAP dataset, the forest sector is defined as “forestry and logging products.”

the remaining land needed to reach 20% leakage within the US. Finally, similar to the standard GTAP-AEZ model where the total area of productive land (forest, cropland, and pastureland) is fixed, we hold the total area of forest, cropland, pastureland, CRP land, and unmanaged land constant within each AEZ. When calculating emissions, we assign the same emission factors used for pastureland to unmanaged land. As a result, emissions from unmanaged land converted to pastureland are set to zero, and emissions from unmanaged land converted to cropland are treated as equivalent to those from pastureland converted to cropland.

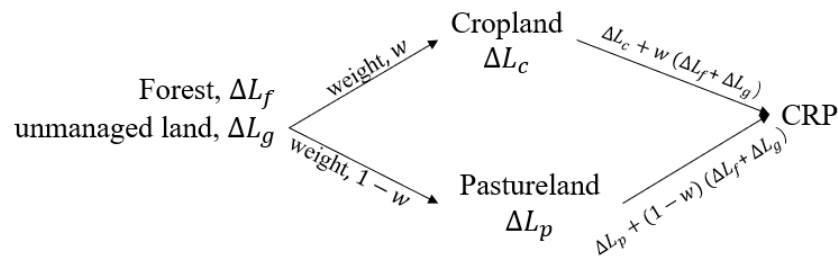


Figure 3.8: Land cover changes for emission calculation in the US.

Note: w is calculated based on the proportion of cropland and pastureland within each AEZ.

CRP enrollment is restricted to cropland or pastureland in practice, and the GTAP-CRP model is a static comparative model, meaning it computes a new equilibrium in one step relative to the baseline, rather than modeling a sequence of transitions over time. As a result, we cannot directly trace land cover changes within the simulation. Although we cannot explicitly prevent land from transitioning from forest to CRP within the nested CET land supply structure of the GTAP-CRP model, we approximate this constraint by manually adjusting the CRP land quantity function so that CRP land is sourced only from cropland and pastureland. Specifically, we compare the price of CRP land with those of cropland and pastureland, allowing CRP to draw land directly from these two sources rather than competing within the broader agricultural land bundle. In this way, we effectively limit CRP expansion to cropland and pastureland.

The model maintains land-use balance, meaning the total net change in land area is zero. As a result, the change in cropland and pastureland may not equal the total area enrolled in CRP. This

discrepancy arises from endogenous shifts of land from forest into cropland and pastureland to offset land enrolled in CRP. Since these forest to agriculture transitions are not directly observable, we impose an assumption for calculating emissions in the GTAP-CRP model for the U.S.,²² as illustrated in Figure 3.8. As shown in Figure 3.9, the total amount of cropland and pastureland enrolled in CRP includes both the observed reduction in cropland and pastureland area and the portion backfilled by land converted from forest and unmanaged land. We assume that forest and unmanaged land are converted into cropland and pastureland based on the existing area shares within each AEZ, cropland (w) and pastureland ($1 - w$).

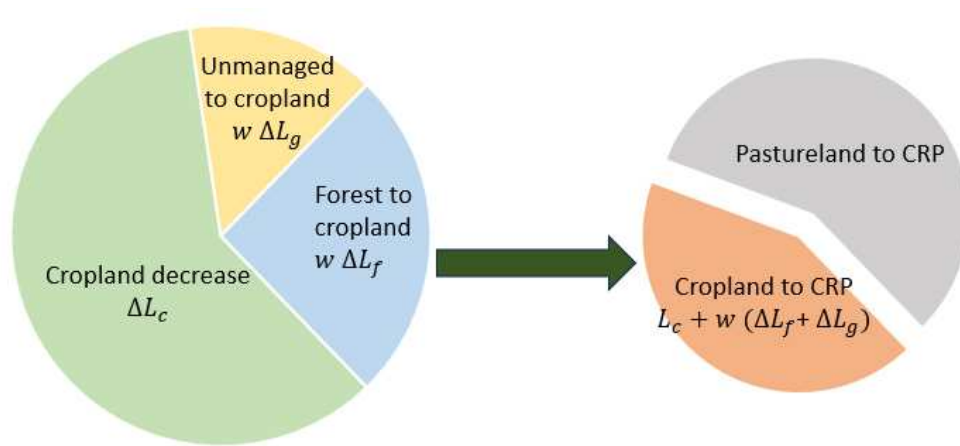


Figure 3.9: Composition of CRP land converted from cropland.

Note: The shares in the chart are illustrative only and do not represent actual values.

3.4.3 Scenario Design

We begin our analysis by simulating the policy announced by USDA to expand CRP enrollment by an additional 4 million acres in 2021 (USDA Press 2021). In 2021, CRP was capped at 25 million acres, with 20.8 million acres enrolled. Then the cap was set to increase to 27 million acres by 2023 (USDA Press 2021). Therefore, on the national level, the acreage cap will not be a binding constraint. However, enrollment in CRP is not guaranteed upon application. Landowners

²²There is no CRP land outside the United States, so emission calculations in other regions follow the standard GTAP-AEZ approach.

must submit offers, which are evaluated using the EBI score, and only those that provide sufficient environmental benefits at an acceptable cost are selected. As a result, expanding total enrollment requires offering payments to landowners who were previously unwilling to participate at existing compensation levels or be rejected due to a higher cost. So to bring additional land into the program, payments must be raised to attract landowners with higher opportunity costs, resulting in an increase in the average rental rate.

Figure 3.10 illustrates the mechanism used to simulate CRP expansion. The baseline enrollment level Q_0 corresponds to an upward-sloping supply curve $S(Q)$, which reflects the opportunity cost of diverting land from other productive uses, conditional on prices and costs across the economy. To reach the expanded enrollment target Q_1 , the program must draw in additional parcels that offer higher returns in alternative uses and therefore require greater compensation. Because sectors such as crop and pasture production exhibit diminishing marginal productivity of land, reallocating land to CRP increases its marginal opportunity cost, giving rise to an upward-sloping supply curve.

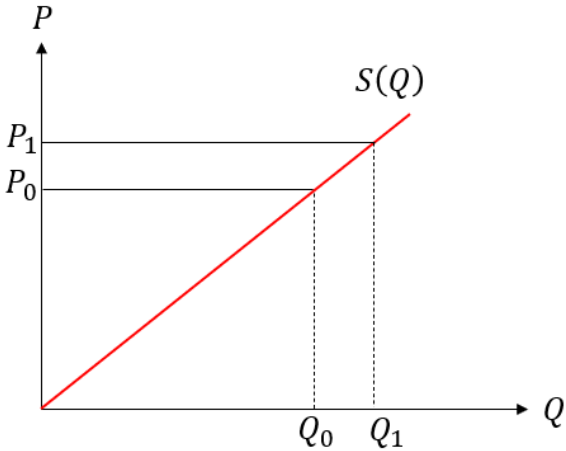


Figure 3.10: Simulation of CRP expansion in the U.S.

In the GTAP-CRP model, this policy is simulated by exogenously increasing CRP demand in the U.S. and allowing endogenous reallocation of land from other land types to CRP within each AEZ to achieve the targeted expansion. Enrolling an additional 4 million acres in the CRP repre-

sents approximately a 17% increase in demand for CRP land in the U.S., relative to the baseline level of 23.4 million acres in 2017. The simulation causes shifts in sectoral output, prices, bilateral trade, and overall welfare. These changes result in land-use reallocation both within the U.S. and internationally, which cause changes in emissions from land-use change.

3.5 Results

This section presents the primary results from our general equilibrium simulations. We begin with the GHG emissions outcomes associated with CRP enrollment, as emissions reduction is a central objective of the program. We then examine the underlying land use changes, both within the U.S. and internationally that drive these emissions outcomes. To better understand the mechanisms underlying these slippage effects, we then focus on the U.S. case, highlighting changes in land rental rates across different land uses. Finally, we analyze the broader economic impacts, including changes in commodity prices, agricultural output, international trade patterns, and regional welfare.

3.5.1 Impact on GHG Emissions

We simulate the emissions associated with land use changes resulting from CRP expansion. As shown in Table 3.4, the addition of 4 million acres of CRP land mitigates approximately 1.93 million tonnes of CO₂e per year from cropland. However, these results indicate that the USDA's goal of achieving a 3-million-tonne annual reduction may not be feasible if CRP enrollment is endogenously allocated between cropland and pastureland based on market land prices. This is because land enrolled from pastureland does not contribute to emission reductions, although it may provide other environmental benefits. The overall mitigation effect in the U.S. is negative. Emissions from forest and unmanaged land conversion fully offset the gains from enrolling cropland in CRP. According to Appendix Table A3.4, the emission factors associated with converting forest to cropland or pastureland are much higher than those for shifts between cropland and pastureland. As a result, even limited forest conversion can offset much of the mitigation gains from CRP expansion.

On average, CRP enrollment results in a net mitigation of 1.19 tonnes of CO₂e per hectare per year from cropland enrollment. This estimate is slightly higher than previous findings but remains within the reported range, which includes mitigation rates ranging from 0.77 tonnes CO₂e per hectare per year in 1996 to 0.62 tonnes CO₂e per hectare per year in 2015 (Ogle et al. 2023), and 1.54 tonnes CO₂e per hectare per year as of 2017 (De et al. 2020). Assuming a 20% leakage rate in each AEZ, the conversion of unmanaged land is estimated to generate approximately 98 million tonnes of CO₂e emissions per year, diminishing the mitigation impact of CRP expansion within the U.S. Overall, the leakage effects associated with forest and unmanaged land conversion reduce the program’s emission mitigation benefits by roughly 159%.

Table 3.4: Emissions from land cover changes in the U.S. in 1000 tCO₂e per year

	Crop-Forest	Crop-Pasture	Forest-Crop	Forest-Pasture	Pasture-Crop	Pasture-Forest	Crop-CRP	Pasture-CRP	Unmanaged-Crop	Total
AEZ 7	-2.31	0	0	0	0	-30.63	-27.16	0	0	-60.10
AEZ 8	0	0	46.12	169.68	0	0	-298.04	0	89.43	7.19
AEZ 9	0	0	58.86	81.46	0	0	-102.22	0	15.63	53.73
AEZ 10	0	0	712.36	220.05	0	0	-1081.08	0	0	-148.67
AEZ 11	0	0	526.66	163.75	0	0	-272.98	0	0	417.43
AEZ 12	0	0	614.07	387.25	0	0	-144.39	0	0	856.93
AEZ 13	0	0	0.04	1.42	0	0	-0.01	0	0	1.45
AEZ 14	0	0	0.73	12.61	0	0	-0.16	0	0	13.18
AEZ 15	0	0	0.59	1.72	0	0	-0.17	0	0	2.14
Total	-2.31	0	1959.43	1037.95	0	-30.63	-1926.22	0	105.07	1143.29

Source: Authors’ simulation.

Note: This table includes only U.S. AEZs with land transitions; the full version is provided in Appendix Table A3.6.

These international land use shifts further increase emissions outside the U.S., contributing an additional 886 thousand tonnes of CO₂e per year. In total, expanding CRP by 4 million acres results in a global net increase of approximately 2.03 million tonnes of CO₂e annually. As shown in Table 3.5, the policy induces approximately 444 thousand tonnes of CO₂e emissions per year in Europe and 339 thousand tonnes in the rest of North America. Based on the cost of enrolling an additional 4 million acres at \$295 million, the implied cost of GHG abatement through CRP on the enrolled land is approximately \$153 per tonne of CO₂e, which is close to the estimated social cost of carbon at \$185 per tonne of CO₂e, as reported by Rennert et al. (2022). However, this cost-effectiveness estimate assumes that the enrolled land generates net emission reductions. When domestic and international emissions leakage are taken into account, the program instead contributes

to a global increase in emissions. These findings underscore the need to consider international land use feedbacks when evaluating the global climate effectiveness of domestic conservation policies.

Table 3.5: Emissions leakage across regions (1000 tCO₂e yr⁻¹)

	US	RNA	China	Europe	CS Africa	SE Asia	R Asia Oceana	MENA	CS America	Total
Crop-Forest	-2.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-2.31
Crop-Pasture	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Forest-Crop	1959.43	177.00	0.00	177.39	0.00	5.47	106.75	2.91	2.91	2431.86
Forest-Pasture	1037.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	1038.30
Pasture-Crop	0.00	181.38	13.25	268.03	65.44	7.08	73.48	26.17	193.59	828.44
Pasture-Forest	-30.63	-19.44	-90.64	-1.27	-62.56	-0.17	-14.94	-4.14	-221.66	-445.46
Crop-CRP	-1926.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1926.22
Pasture-CRP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Unmanaged-Crop	105.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	105.07
Total	1143.29	338.94	-77.39	444.14	2.88	12.39	165.29	24.95	-24.82	2029.68

Note: In this table, "US" stands for the United States, while "RNA" represents the Rest of North America. "CS Africa" is shorthand for Central and Southern Africa. "SE Asia" denotes Southeast Asia, and "R Asia & Oceana" refers to the remaining countries in Asia and the Oceania region; "MENA" is used for the Middle East and North Africa, "CS America" covers all countries in Central and South America. Source: Authors' simulation.

3.5.2 International Slippage Effects on Land Cover

Table 3.6 presents the simulated results of land cover changes across various regions and at the global level following a 4-million-acre (1.6 million hectares) expansion of CRP enrollment in the U.S. The results are reported in thousand hectares, with slippage rates, defined as the percentage of the U.S. CRP land increase offset by land cover changes, shown in parentheses. Because the model does not allow a direct shock to CRP land area, we simulate the expansion by increasing demand for the CRP commodity. As a result, the actual increase in CRP land is not exactly 1,618,000 hectares but is very close, at approximately 1,621,000 hectares. From Table 3.6, we conclude that enrolling an additional 1.6 million hectares in the U.S. CRP leads to net reductions of 421.1 thousand hectares of cropland and 823.5 thousand hectares of pastureland within the U.S., along with a loss of 236.3 thousand hectares of forest and the conversion of 140.7 thousand hectares of unmanaged land into agricultural production. Outside the U.S., the model simulates a reduction of 6,440 hectares of forest and 199.5 thousand hectares of pastureland, alongside an increase of 206 thousand hectares of cropland. These results indicate that although cropland declines in the

U.S., cropland expansion occurs in other regions, providing clear evidence of international land use leakage.

As shown in Table 3.6, the slippage rates quantify the extent of these offsetting effects. For every 100 hectares of cropland and pastureland enrolled in CRP, approximately 14.57 hectares of forest and 8.67 hectares of unmanaged land within the U.S. are converted into agricultural use. Outside the U.S., every 100 hectares enrolled in CRP corresponds to an additional 12.7 hectares of cropland expansion, 12.3 hectares of pastureland loss, and 0.4 hectares of forestland loss. Due to the imposed 20% minimum leakage constraint in each AEZ (Wu 2000), the overall observed leakage exceeds this threshold domestically. In some AEZs, forestland loss alone surpasses 20% of the total CRP enrollment. Detailed land cover changes by AEZ in the U.S. are provided in Appendix Table A3.5.

Table 3.6: Land cover changes across regions and globally

	US	RNA	China	Europe	CS Africa	SE Asia	R Asia& Oceana	MENA	CS America	Global	Outside US
Forest	-236.33 (-14.57%)	-10.54 (-0.65%)	7.23 (0.45%)	-14.53 (-0.90%)	4.40 (0.27%)	-0.27 (-0.02%)	-4.25 (-0.26%)	0.14 (0.01%)	11.39 (0.70%)	-242.78 (-14.97%)	-6.44 (-0.40%)
Cropland	-421.10 (-25.97%)	36.96 (2.28%)	4.13 (0.25%)	56.44 (3.48%)	18.83 (1.16%)	2.54 (0.16%)	31.73 (1.96%)	9.80 (0.60%)	45.55 (2.81%)	-215.14 (-13.27%)	205.96 (12.70%)
Pastureland	-823.51 (-50.80%)	-26.42 (-1.60%)	-11.35 (-0.70%)	-41.90 (-2.60%)	-23.23 (-1.40%)	-2.27 (-0.10%)	-27.48 (-1.70%)	-9.93 (-0.60%)	-56.94 (-3.50%)	-1023.03 (-63.10%)	-199.52 (-12.30%)
Unmanaged	-140.70 (-8.67%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	-140.70 (-8.67%)	0.00 (0.00%)

Note: The data are shown in million acres with the slippage as a percentage of the US CRP land increase in parentheses. In this table, "US" stands for the United States, while "RNA" represents the Rest of North America. "CS Africa" is shorthand for Central and Southern Africa. "SE Asia" denotes Southeast Asia, and "R Asia & Oceana" refers to the remaining countries in Asia and the Oceania region; "MENA" is used for the Middle East and North Africa, "CS America" covers all countries in Central and South America.

Source: Authors' simulation.

In the GTAP-CRP model, land cover changes are driven by variations in land prices across AEZs for specific land types, moderated by the elasticity of transformation. Land use allocation is modeled through a nested constant elasticity of transformation CET supply tree structure. At the top nest, forestland and agricultural land compete based on the aggregate endowment land price within each AEZ. For example, if the price of forestland in AEZ8 increases less than the average endowment land price, the area of forestland in that AEZ declines. At the second nest, cropland and pastureland compete relative to the average agricultural land price: if cropland prices rise more rapidly than the average agricultural land price, cropland expands at the expense of pastureland.

CRP enrollment draws land directly from cropland and pastureland; thus, CRP land competes directly with cropland and pastureland within the land market. Changes in land prices across activities are determined by shifts in supply prices and demand for different land uses. Table 3.7 reports the changes in land supply prices across land types in the U.S., offering insight into the observed reductions in cropland, forestland, and pastureland areas following CRP expansion.

Table 3.7: The impact of CRP on land prices for different land covers in U.S.

AEZs	U.S. total	Forestland	Agricultural	Cropland	Pastureland	CRPland
AEZ 5	1.79	1.79	1.79	1.80	1.56	1.79
AEZ 6	1.85	1.85	1.85	1.86	1.57	1.85
AEZ 7	3.63	0.68	3.87	1.80	1.61	20.30
AEZ 8	3.34	0.68	3.50	1.76	1.60	20.28
AEZ 9	2.22	0.66	2.31	1.76	1.58	20.21
AEZ 10	2.23	0.66	2.77	1.75	1.58	20.23
AEZ 11	1.62	0.66	1.91	1.65	1.56	20.19
AEZ 12	1.17	0.65	1.95	1.63	1.56	20.18
AEZ 13	0.67	0.65	1.74	1.72	1.55	20.16
AEZ 14	0.83	0.65	2.13	1.72	1.56	20.18
AEZ 15	1.51	0.66	2.59	1.71	1.57	20.21
AEZ 16	0.65	0.65	1.55	1.19	1.55	1.19

Note: All values are expressed in percent changes. This table includes only U.S. AEZs with land price changes; the full version is provided in Appendix Table A3.7.

Source: Authors' simulation.

In Table 3.7, the column “U.S. total” reports overall changes in land prices across the U.S. The largest increases are observed in AEZs 7 (3.63%), 8 (3.34%), 10 (2.23%), and 9 (2.22%), corresponding to the Mountain, Southern Plains, and Northern Plains regions, respectively, as shown in Figure 3.7. These results are consistent with Wu et al. (2010), who found that CRP had the greatest impact on farmland values in these regions, increasing land prices by 5% to 14% in the Mountain region, 4% to 6% in the Southern Plains, and 2% to 5% in the Northern Plains. The magnitude of land price changes in our results is somewhat smaller. Since our model allows CRP land to be drawn from both cropland and pastureland, whereas Wu and Lin consider only cropland. This distinction also reflects the evolution of CRP enrollment policies over time, which

increasingly allow pastureland to participate. Since pastureland typically has a more elastic supply than cropland, its inclusion flattens the effective land supply curve, resulting in a more moderate price response. Nonetheless, we still observe the largest price increases in AEZs corresponding to the Mountain, Southern Plains, and Northern Plains regions, consistent with high CRP enrollment shares and relatively high CRP rental payments compared to agricultural returns in those areas (Wu et al. 2010).

3.5.3 Impact on Food Market and Welfare

The conceptual model shown in Figure 3.3 states that policy changes in U.S. land use incentives can cause land use and emission leakages abroad, primarily through international trade responses. So to better understand the international leakage effects, we look at commodity prices, bilateral trade, and welfare across regions. Appendix Table A3.5 illustrates the expansion of CRP by 4 million acres results in significant cropland reallocation from production to conservation, primarily in AEZs 10, 8, 11, and 9. These regions are major production zones for key crops, which directly contribute to the observed sectoral output reductions in Table 3.8. For example, AEZ 10 contributes significantly to national soybean and corn output. Since soybeans make up over 90% of U.S. oilseed production, cropland reductions in AEZ 10 account for the 0.32% decline in oilseed output (equivalent to a loss of 183 thousand hectares). Corn production in the same region also contracts, contributing to the 0.06% drop in grain output (–84 thousand hectares). Wheat output falls by 0.39% (–101 thousand hectares), largely due to land retirement in AEZ 8, a leading wheat-producing zone. Vegetable and fruit output declines by 0.27% (–29 thousand hectares), reflecting cropland losses in AEZs 9, 10, and 11, which together represent a significant share of national vegetable production. In addition, AEZs 8, 9, and 10, located in the Midwest U.S., are key livestock-producing regions, particularly for cattle. The contraction of pastureland in these zones, especially the significant reduction in AEZ 8 (–505 thousand hectares), contributes to the 0.05% decline in national livestock output.

Outside the U.S., the expansion of CRP induces output increases in many regions with existing comparative advantages in agricultural production. For instance, wheat production rises in Rest of North America (0.25%), Rest of Asia and Oceania (0.12%), and EU (0.04%). These regions, particularly Canada, Australia, and parts of the EU, are already major wheat exporters, and their output gains suggest a substitution effect as they fill the supply gap left by the U.S. Oilseed output also rises in Rest of North America (0.23%), China (0.06%), and Central and South America (0.10%), reflecting adaptive capacity in major soybean-producing regions like Brazil, Argentina, China, and Canada. There is also an increase in output in the manufacturing and service sectors within the U.S., which aligns with prior findings that CRP reallocates labor and other resources toward non-agricultural sectors (Li et al. 2023; Sullivan et al. 2004). In contrast, the small but negative responses in processed food, manufacturing, and services across most regions indicate resource reallocation from non-agricultural sectors, amplifying the agricultural response to U.S. land policy shocks.

Table 3.8: The impact of CRP on sector outputs

	US	RNA	China	Europe	CS Africa	SE Asia	R Asia&Oceana	MENA	CS America
Rice	-0.0756	0.0886	-0.0016	0.0097	-0.0024	-0.0051	-0.0019	-0.0003	0.0177
Wheat	-0.3851	0.2490	0.0045	0.0379	0.0552	0.1199	0.0415	0.0162	0.0174
Grain	-0.0557	0.0134	0.0022	0.0120	0.0006	-0.0016	0.0195	-0.0002	0.0202
Veg and Fruit	-0.2731	0.0774	0.0037	0.0180	0.0064	0.0138	0.0098	0.0189	0.0340
Oil Seeds	-0.3178	0.2282	0.0600	0.0485	0.0233	0.0195	0.0371	0.0340	0.0963
Cane and Beet	-0.0271	-0.0050	-0.0010	0.0030	0.0004	-0.0048	-0.0022	-0.0054	-0.0044
Fibre Crops	-0.2272	0.0091	0.0088	0.0142	0.0512	0.0652	0.0264	0.0328	0.0558
Other Crops	-0.5347	-0.0197	0.0402	0.0597	0.0346	0.0315	0.0335	0.0568	0.0018
Livestock	-0.0459	-0.0021	-0.0002	0.0016	-0.0007	-0.0009	-0.0016	-0.0037	-0.0035
Forest	-0.1344	-0.0096	0.0063	-0.0034	0.0008	0.0030	0.0035	-0.0085	-0.0110
Processed Food	-0.0317	-0.0065	-0.0011	0.0024	0.0016	-0.0054	-0.0019	-0.0023	-0.0042
Manufacturing	0.0080	-0.0052	-0.0005	-0.0019	-0.0058	-0.0006	-0.0017	-0.0006	-0.0080
Services	0.0010	-0.0002	-0.0003	-0.0001	-0.0003	-0.0003	-0.0003	-0.0003	0.0002

Note: All values are expressed in percent changes. The region descriptions are the same as those in Table 3.5.

Source: Authors' simulation.

In the U.S., prices for most agricultural commodities increase, with “cane&beet” experiencing the largest increase at 0.43%. These price increases are likely driven by the reduced domestic supply of these commodities due to the reallocation of land to CRP. For example, most sugar beets

are planted in AEZ 8, one of the regions with the highest number of CRP acres, which includes states such as Minnesota and North Dakota (*Sugar Beet Production by State 2015*). Outside the U.S., agricultural prices also increase across regions. For example, wheat prices rise by 0.12% in Southeast Asia and 0.04% in the Rest of Asia and Oceania. Oilseed prices increase by 0.04% to 0.10% in China, Europe, and Latin America, regions with significant soybean production. These price increases occur even where output expands. In Southeast Asia, for instance, oilseed and wheat outputs grow by 0.02% and 0.12%, respectively. Similar patterns are observed for other staple commodities, including vegetables and fruits. Overall, global price responses reflect that the reduction in U.S. supply is not fully offset by increased production elsewhere.

Table 3.9: The impact of CRP on commodity output prices

	US	RNA	China	Europe	CS Africa	SE Asia	R Asia&Oceania	MENA	CS America
Rice	0.170	0.116	0.020	0.020	0.030	0.030	0.021	0.049	0.063
Wheat	0.166	0.031	0.022	0.035	0.034	0.019	0.036	0.029	0.064
Grain	0.166	0.082	0.021	0.026	0.028	0.033	0.031	0.035	0.045
Veg and Fruit	0.289	0.114	0.022	0.037	0.028	0.034	0.033	0.026	0.060
Oil Seeds	0.221	0.023	0.036	0.029	0.033	0.037	0.041	0.035	0.049
Cane and Beet	0.427	0.132	0.020	0.020	0.019	0.027	0.029	0.050	0.050
Fibre Crops	0.166	0.083	0.020	0.039	0.038	0.058	0.036	0.028	0.037
Other Crops	0.278	0.081	0.031	0.025	0.039	0.036	0.037	0.029	0.058
Livestock	0.091	0.037	0.006	0.014	0.014	0.008	0.015	0.014	0.023
Forest	0.268	0.093	0.032	0.044	0.032	0.036	0.038	0.042	0.063
Processed Food	0.029	0.016	0.007	0.004	0.004	0.012	0.008	0.008	0.013
Manufacturing	-0.005	-0.002	-0.002	-0.001	-0.000	-0.002	-0.001	-0.002	0.001
Services	-0.007	-0.001	-0.002	-0.001	0.000	-0.003	-0.002	-0.001	0.001

Note: All values are expressed in percent changes. The region descriptions are the same as those in Table 3.5. In the GTAP-CRP model, we exogenize crop demand by swapping it with the output tax, which renders the output price of CRP meaningless; therefore, we do not report it in this table.

Source: Authors' simulation.

The impact of enrolling an additional 4 million acres in the U.S. CRP on international trade is presented in Table 3.10. The results indicate a decline in U.S. exports across most agricultural commodities. For example, U.S. rice, wheat, and oilseeds exports fall by 0.45%, 0.82%, and 0.60%, respectively. Similar declines for vegetables and fruits (-0.59%), feed grains (-0.16%), and other crops (-1.23%). These reductions reflect decreased agricultural output due to land retirement under CRP expansion. In contrast, many other regions increase their agricultural exports in response to

the contraction in U.S. supply, suggesting a redistribution of trade flows in the global agricultural market. Southeast Asia and the Rest of Asia and Oceania, for example, expand their wheat exports by 0.36% and 0.19%, respectively, and their oilseed exports by 0.23% and 0.14%. The EU and the Rest of North America also increase their wheat exports. However, since Canada, Russia, and Ukraine are already among the world's top five wheat exporters, the percentage increases in these regions remain relatively modest. The EU also shows small increases in oilseed (0.11%) and vegetable and fruit (0.04%) exports. These export increases in non-U.S. regions suggest that as U.S. exports decline, other countries partially offset the reduction by increasing their own agricultural production and trade. This substitution effect is most evident in staple commodities such as wheat, rice, and oilseeds, which are especially sensitive to global supply shifts.

Table 3.10: The impact of CRP on commodity exports in FOB weights

	US	RNA	China	Europe	CS Africa	SE Asia	R Asia&Oceana	MENA	CS America
Rice	-0.4469	-0.7325	0.0519	0.2241	0.0373	-0.0027	0.0526	0.1063	0.4204
Wheat	-0.8246	0.2767	0.2631	0.0731	0.1553	0.3564	0.1890	0.1567	0.0108
Grain	-0.1566	-0.0149	0.1595	0.0267	0.0594	0.0448	0.0682	0.0633	0.0364
Veg and Fruit	-0.5883	0.0672	0.1094	0.0434	0.0860	0.1019	0.0927	0.0899	0.1151
Oil Seeds	-0.5984	0.2768	0.1643	0.1105	0.1861	0.2303	0.1370	0.1408	0.1553
Cane and Beet	-0.9043	0.0196	0.0565	0.0145	0.1734	0.0913	0.0356	-0.0417	0.2647
Fibre Crops	-0.4042	-0.0342	0.3062	0.1229	0.1499	0.0730	0.1777	0.1534	0.1994
Other Crops	-1.2269	-0.0635	0.1260	0.0939	0.0545	0.0898	0.0991	0.1248	-0.0001
Livestock	-0.2392	0.0215	0.0640	0.0163	0.0092	0.0419	0.0134	0.0058	0.0237
Forest	-0.9021	-0.1148	0.1622	0.0237	0.0801	0.0831	0.0636	0.0675	0.0010
Processed Food	-0.0746	-0.0152	0.0157	0.0105	0.0123	-0.0101	0.0061	0.0005	-0.0130
Manufacturing	0.0210	-0.0058	-0.0014	-0.0028	-0.0095	-0.0007	-0.0029	-0.0010	-0.0203
Services	0.0193	-0.0072	-0.0005	-0.0029	-0.0083	-0.0001	-0.0032	-0.0041	-0.0131

Note: All values are expressed in percent changes. The region descriptions are the same as those in Table 3.5.

Source: Authors' simulation.

The corresponding welfare effects, measured by equivalent variation (EV), are shown in Figure 3.11. The U.S. shows a modest welfare gain of approximately \$199 million, while changes in EV for other regions remain limited. To better understand the drivers of these changes, a decomposition analysis (Table 3.11) identifies increased endowment use and improvements in international trade as the primary sources of the U.S. welfare gain. A 17% increase in CRP demand results in a substantial reallocation of endowments toward the CRP sector, contributing positively to welfare.

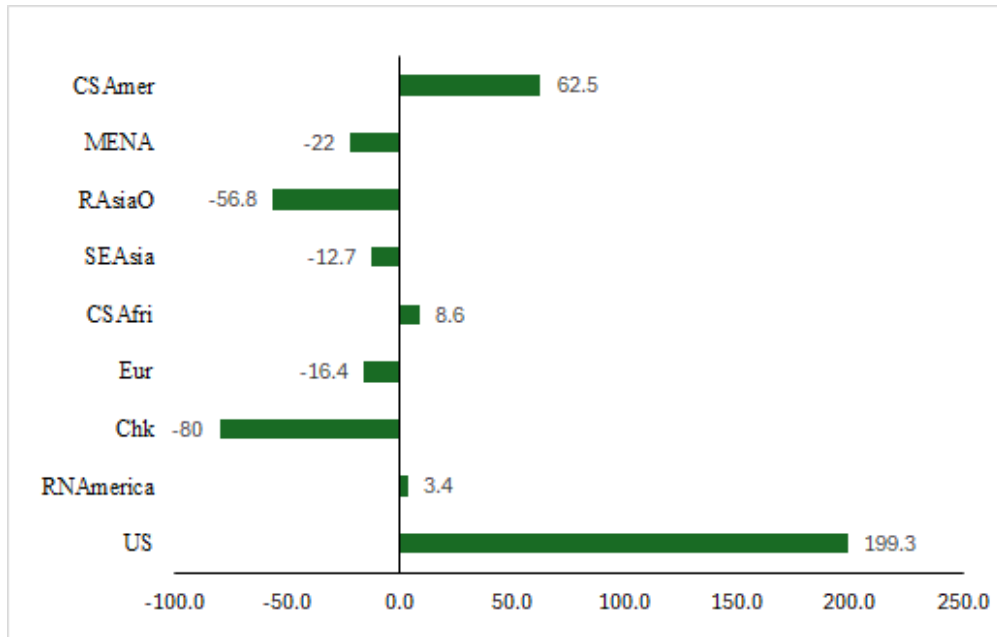


Figure 3.11: Changes in welfare valued in millions of US dollars.

Note: The region descriptions are the same as those in Table 3.5.

In the model, welfare changes from endowment reallocation are calculated as the sum of each endowment's supply change multiplied by its marginal value across all activities and regions. These marginal values reflect the after-tax contribution of each endowment, accounting for policy distortions such as subsidies and taxes. In this scenario, land reallocated to the CRP from several AEZs generates the largest positive contribution, due to both sizable increases in supply and relatively high marginal values. Sectors such as wheat and fibres crops make modest positive contributions, while most conventional agricultural sectors, including vegetables and fruits, other crops, and livestock, contribute negatively, reflecting reductions in land use under the CRP expansion.

In contrast, regions outside the U.S. experience losses in resource allocation efficiency. A closer look at the decomposition of allocative efficiency reveals that nearly all non-U.S. regions incur losses due to endowment taxes on labor and capital. As agricultural production increases, labor and capital are reallocated away from highly taxed sectors such as manufacturing and services toward lower-taxed sectors like farming and grazing (Huff et al. 2000). China, the EU, and the Rest

Table 3.11: Welfare decomposition

	Alloc(A1)	Endw(B1)	Tech(C1)	Pop(D1)	Tot(E1)	IS(F1)	Pref(G1)	Total
US	6.10	162.03	0	0	67.01	-35.86	0	199.27
RNAmerica	-5.70	0	0	0	8.19	0.86	0	3.35
China	-21.85	0	0	0	-71.42	13.24	0	-80.03
Europe	-18.62	0	0	0	-10.59	12.81	0	-16.39
CS Africa	-0.88	0	0	0	9.12	0.35	0	8.59
SE Asia	-4.09	0	0	0	-10.72	2.09	0	-12.73
R Asia&Oceana	-30.90	0	0	0	-30.14	4.21	0	-56.83
MENA	-0.54	0	0	0	-23.02	1.52	0	-22.03
CS America	0.19	0	0	0	61.56	0.77	0	62.52
Total	-76.29	162.03	0	0	0	-0	0	85.74

Note: All values are expressed in million dollars. The region descriptions are the same as those in Table 3.5. "alloc (A1)" is allocative efficiency effect; "endw (B1)" is endowment effect; "tech (C1)" is technological change effect; "pop (D1)" is population effect; "tot (E1)" is terms of trade effect; "IS (F1)" is investment-savings effect; "pref (G1)" is consumer preference effect.

Source: Authors' simulation.

of Asia and Oceania face losses from domestic tax effects, primarily driven by increased production in their subsidized crop sectors.²³

3.6 Conclusion and Discussion

This study examines the global implications of expanding the U.S. CRP, revealing how a nationally targeted land retirement policy can generate far-reaching environmental and economic consequences through global market channels. Using a global computable general equilibrium model with detailed land use and emissions data, our findings show that while conservation policies like CRP deliver significant local environmental improvements on enrolled land, they also induce significant emission spillovers, both domestically and internationally. The findings underscore the need to evaluate domestic conservation policies within a broader global context, especially when considering a global pollutant like GHGs.

From an emissions perspective, expanding CRP enrollment leads to significant GHG reductions on retired cropland. However, these gains are fully offset by increased emissions from the

²³Beginning in 2004, China launched a countrywide farm subsidy initiative that serves as a key policy mechanism to motivate agricultural households in grain production activities (Zhang et al. 2024).

conversion of forest and unmanaged land to agriculture within the U.S., resulting in an estimated domestic leakage of 159%. When accounting for international land use spillovers, total leakage rises to approximately 205%. In the GTAP-CRP model, land use transitions are governed by a constant elasticity of transformation, making the elasticity parameter a key driver of outcomes. To test the robustness of the results, we conduct a systematic sensitivity analysis by varying the elasticity of transformation by 50%. As shown in Appendix Table A3.1, although the magnitude of emissions varies with elasticity, the pattern of increased emissions both domestically and globally remains consistent. This suggests that in a market-driven land reallocation scenario, CRP expansion does not deliver net GHG benefits to society. Although CRP expansion on cropland provides significant site-level mitigation, enrolling pastureland in CRP does not directly reduce emissions. Instead, it influences land markets, triggering indirect land use changes that cause both domestic and international leakage. These findings underscore the need to account for cross-border spillovers when assessing the climate effectiveness of regional conservation policies especially as the USDA's FSA has increasingly allocated funding to the Grassland CRP in recent years.

From a land use perspective, the expansion of CRP land in the U.S. leads to reductions in forest area and the conversion of unmanaged land into agricultural use. These shifts are primarily driven by changes in land rental rates. As demand for CRP enrollment rises, the associated rental payments increase, raising the average price of agricultural land. This creates market incentives for forestland and unmanaged land to be reallocated toward crop and pasture production. At the same time, as cropland and pastureland are retired into CRP, the effective supply of land available for agricultural production contracts, placing upward pressure on commodity prices. Notably, output declines in major crop-producing AEZs trigger global supply shortfalls that are only partially offset by production increases in other regions. The resulting supply shock contributes to rising agricultural prices both in the U.S. and internationally, with staple commodities such as wheat, oilseeds, and vegetables facing modest but broad-based increases. These price movements, in turn, drive shifts in global trade patterns, reducing U.S. exports while inducing modest export gains in

regions with comparative advantages in crop production such as Canada and Central and South America.

This paper contributes to the understanding of land-based climate policies by providing a quantitative assessment of how the expansion of the U.S. land retirement program affects global land use, GHG emissions, international trade, and welfare. Moving beyond previous literature that has primarily focused on domestic outcomes or site-based measurements of SOC changes on CRP land, this study integrates land use emissions with commodity market responses by modeling CRP as a distinct “commodity” that is consumed solely by the U.S. government. In doing so, the analysis endogenizes land retirement within the global economic system, allowing spillover effects to emerge naturally through price shocks and trade reallocation. This framework captures how policy interventions targeting land use within the U.S. reshape global market conditions, induce land use changes abroad, and redistribute welfare across regions. By linking land, emissions, and trade within a global general equilibrium framework, this study enriches the methodological treatment of land-based mitigation policies and highlights the importance of evaluating their effectiveness not only through site-specific carbon outcomes but also through their broader global spillovers.

It is important to acknowledge the limitations of this study. First, land enrollment in CRP varies significantly by land quality, region, and land use history. However, the GTAP-CRP model does not simulate the program’s actual enrollment mechanism, which is based on an EBI and bid-based auction system that allows for price discrimination among participants. Instead, land is allocated to the CRP sector based on average land rents and regional land availability, without accounting for policy-driven targeting. This simplification may lead to an underestimation of site-specific environmental benefits, as real world CRP enrollment tends to concentrate on environmentally sensitive and marginal lands. Second, the GTAP framework assumes frictionless international trade, enabling relatively efficient adjustment in global supply chains in response to U.S. output reductions. In practice, infrastructure constraints, trade barriers, and policy interventions can limit this adjustment, leading to potentially larger price increases or slower supply responses. As a result, the model may overstate the capacity of other regions to substitute for lost U.S. exports, particularly

for bulk commodities like grains and oilseeds. Third, the model assumes that CRP land is completely retired from economic production, with no grazing, haying, or biomass harvesting. This assumption may be increasingly unrealistic given recent policy changes, particularly the growth of Grassland CRP, which functions more like a working lands program by allowing managed grazing. By excluding these economic activities, the model may overstate the opportunity cost of CRP enrollment, especially in regions where livestock production plays a central role. Additionally, the emissions are calculated relying on net changes in land cover, which may underestimate total emissions impacts. For instance, if deforestation occurs simultaneously with reforestation elsewhere, the net land use change could appear negligible, even though the emissions released during forest clearing occur much more rapidly than carbon sequestration through biomass growth (Plevin et al. 2014). Thus, even in the absence of large net land cover changes, there may be additional CO₂ in the atmosphere. Finally, we introduce additional land use leakage by bringing unmanaged land into production. However, because unmanaged land is not associated with any economic activity in the GTAP model, its baseline value is assumed to be zero. This may lead to an overstatement of the marginal value of CRP in the welfare calculation. A useful robustness check for future work would be to relax the assumption that additional unmanaged land is available for conversion, or to assume that income increases only by the change in rental rate as unmanaged land comes into production. Despite these limitations, this study still provides useful insights that highlight the balance between pursuing environmental conservation objectives and addressing the economic consequences for stakeholders at both local and global levels. It underscores the importance of thorough policy analysis and international collaboration in the development of environmental and agricultural policies.

One potential improvement for future analysis is to design scenarios in which CRP enrollment is limited to either cropland or pastureland. In the current model, land enters CRP from both sources through market-driven reallocations, which may overstate emission leakage. For ex-

ample, we estimate that 51% to 74% of CRP land in the model originates from pastureland.²⁴ Because GHG mitigation outcomes are driven by price-induced land shifts in a competitive market framework, enrollment decisions reflect relative land rents rather than policy targeting. Modeling separate cropland-only and pastureland-only enrollment scenarios would help clarify how the source of land affects leakage, especially given the recent expansion of Grassland CRP. We would expect leakage to decrease with greater cropland enrollment and increase with higher pastureland enrollment, though not proportionally, due to potential land use shifts between cropland and pastureland.

In summary, this study provides a quantitative evaluation of how domestic land retirement policies interact with global land use, emissions, and trade systems. While the expansion of CRP can deliver substantial local environmental benefits, such as reduced land degradation and lower emissions on retired land, it also reveals critical limitations when evaluated through a global lens. Specifically, conservation policies that reduce agricultural land use within national borders can unintentionally shift production and emissions abroad, diminishing their net climate effectiveness through land use and emissions leakage. As conservation and climate strategies increasingly seek to balance food security, rural livelihoods, and environmental stewardship, it becomes critical to design policies that minimize leakage, enhance carbon additionality, and align domestic incentives with global sustainability goals. Future policy design should integrate strategies that not only target local environmental improvements but also minimize unintended cross-border effects, potentially through mechanisms such as international agreements, coordinated conservation efforts, or incentives for sustainable land use practices globally. In a world where markets, ecosystems, and emissions are tightly interlinked, truly effective land-based mitigation strategies will require both national action and global collaboration.

Future work should improve the representation of land heterogeneity by incorporating variations in land quality and productivity across and within AEZs. This would allow for a more realistic

²⁴Assuming no forest or unmanaged land offsets pasture loss, 51% of CRP land comes from pasture (lower bound); assuming full offset, the share rises to 74% (upper bound).

assessment of which types of land are likely to be enrolled in CRP and how they affect production and emissions outcomes. In addition, incorporating features of the CRP enrollment process, such as bid selection, payment differentiation, and evolving program rules (e.g., Grassland CRP's allowance for managed grazing), would help bridge the gap between modeled assumptions and real world implementation. Accounting for partial economic uses of CRP land could also provide a more accurate estimate of its opportunity cost and environmental effectiveness. Finally, future studies could explore policy interactions, such as how CRP expansion aligns or conflicts with biofuel mandates, crop insurance incentives, or international land use policies, to identify cost-effective and coordinated approaches for reducing land-based emissions without compromising food production or rural income.

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Chapter 4

Agri-environmental Policies and Rural Employment

4.1 Introduction

Agricultural and natural resource-based sectors are an important source of economic activity and employment, particularly in rural economies (Foster et al. 2004). In 2022, agriculture, food, and related industries provided 22.1 million full- and part-time jobs in the U.S., accounting for 10.4 percent of total employment. Of these jobs, about 2.6 million were direct on-farm employment, representing 1.3 percent of total U.S. employment.²⁵ In addition to farm jobs, agricultural production contributes to employment and income in other sectors linked through supply chains and household expenditure (Hornbeck et al. 2015). Yet, agriculture also produces significant environmental externalities (Zilberman et al. 1993; Stoyanova et al. 2019; Paudel et al. 2021; Sumner et al. 1996). To address agri-environmental challenges over the past several decades, the United States Department of Agriculture (USDA) has used voluntary incentive programs that encourage agricultural producers and landowners to undertake conservation on agricultural lands. These agri-environmental policies have largely followed one of two approaches: “retirement,” which incentivizes temporary land retirement from production (e.g., the Conservation Reserve Program (CRP)) and “working lands,” which provides financial support for conservation practice adoption on working lands (e.g., the Environmental Quality Incentive Program (EQIP)).

Agri-environmental programs, or conservation programs, have raised concerns about their effects on rural labor outcomes (Kaldor 1957), especially when land is removed from production (Mortensen et al. 1989). Li et al. (2023) investigate the employment impacts of land retirement through the CRP, but research has yet to examine the labor trade-offs from allocating conservation dollars from land retirement to working lands programs. While in theory this reallocation could

²⁵USDA, Economic Research Service, Ag and Food Sectors and the Economy, <https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/ag-and-food-sectors-and-the-economy>

allow more local jobs and resources to remain in agricultural production, this hypothesis has not been tested empirically. This research gap grows more significant as working lands programs claim an increasing share of conservation spending—from less than 10% in 1996 to over 50% in 2018.²⁶

In this paper, we quantify the impacts of EQIP, a working lands program, and CRP, a land retirement program, on rural employment in the U.S. Specifically, we ask how state-level EQIP and CRP payments (defined as the number of program dollars in a state divided by total farmland²⁷ acres in a state) affect local level²⁸ total employment, agricultural employment, non-agricultural employment, and the unemployment rate. Then, we use our econometric estimates to describe the employment trade-offs from reallocating conservation funding to working lands from retirement.

Examining the labor market impacts of reallocating conservation dollars to working lands programs informs policy impacts as working lands programs comprise an ever-larger share of federal conservation dollars (Figure 4.1). For example, the 2018 Farm Act committed approximately 53% of conservation expenditure to working lands programs, with EQIP representing 70% of total working lands payments.²⁹ During the 2014-2022 fiscal years (FYs), the USDA Natural Resources Conservation Service (NRCS) obligated over \$9 billion to 330,242 EQIP contracts,³⁰ covering over 10 percent³¹ of U.S. farmland. Further, private conservation initiatives such as voluntary carbon markets, offsets under compliance emissions markets, and land conservancies increasingly facilitate the use of private resources to support conservation objectives on working lands. The implications of this shift for rural economies remain unclear.

We quantify the impact of conservation program payments on employment in agricultural and non-agricultural sectors. To mitigate concerns about endogeneity in program participation, we use

²⁶USDA, Economic Research Service, 2018 Farm Bill—Conservation, <https://www.ers.usda.gov/topics/farm-bill/2018-farm-bill/conservation>

²⁷EQIP and CRP enroll both pasture and cropland acres.

²⁸In this paper, we define the local level as the county-watershed. See Section 4.3.2.

²⁹NRCS RCA DATA VIEWER

³⁰USDA Farmers.gov: <https://www.farmers.gov/data/financial-assistance/download>

³¹USDA Farmers.gov, <https://www.farmers.gov/data/financial-assistance-download>

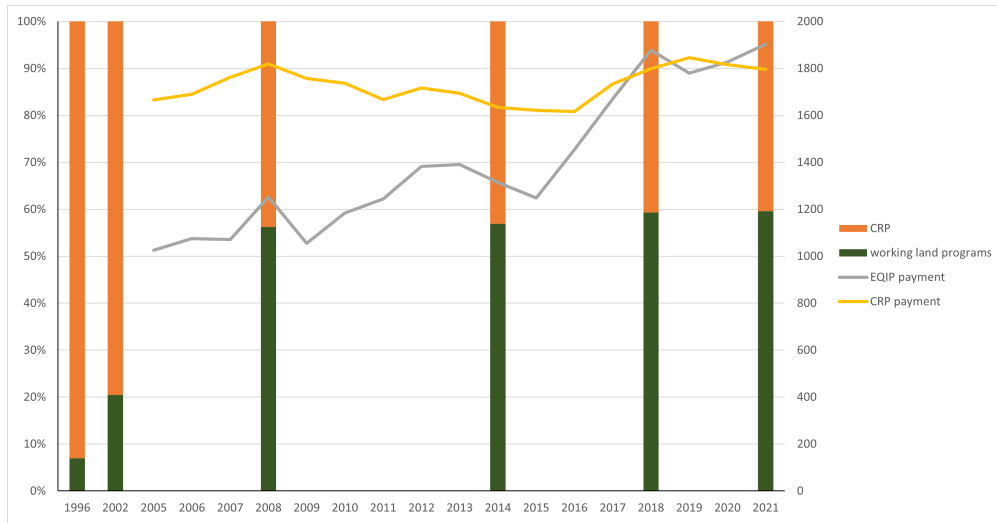


Figure 4.1: Share of conservation spending by major programs from 1996 to 2021

Note: Working lands programs include EQIP, Conservation Stewardship Program (CSP), and Conservation Technical Assistance (CTA). Working lands program data are from NRCS RCA DATA VIEWER, and CRP data are from USDA Farm Service Agency. The bars, which represent conservation spending in farm bills, correspond to the left y-axis, while the lines depicting payments for CRP and EQIP are aligned with the right y-axis.

plausibly exogenous variation in state-level funding allocations of EQIP and CRP, measured as average payments per farmland acre, which are largely shaped by federal policy priorities rather than local economic conditions. We focus on counties that border other states, enabling us to leverage cross-state variation in conservation funding while controlling for local conditions. We also control for a range of observable factors (e.g., population and weather) that may impact local labor market outcomes. Following Aglasan et al. (2024), Chen et al. (2023), and Won et al. (2024), we include fixed effects and robustness checks to address remaining endogeneity concerns. We find that both CRP and EQIP enrollment rates are associated with higher total and non-agricultural employment. However, while EQIP enrollment rates significantly increase agricultural employment, CRP enrollment rates do not significantly change agricultural employment. This is consistent with Li et al. (2023) who find that CRP does not harm total employment. Although they did not find a significant impact of CRP on non-agricultural employment overall, they observed a positive effect of CRP on recreational sector employment.

We use our econometric estimates to characterize the trade-offs between dollars in working lands programs and land retirement programs (see Figure 4.2). Our results imply that reallocating state-level conservation funding from land retirement to working lands increases total employment by 0.4%, or 22.8 jobs³² per million dollars per rural county on average. Equivalently, if the additional funding for working lands is accompanied by a reduction in land retirement funds, current rural employment levels would be maintained while saving 79 cents per dollar allocated.

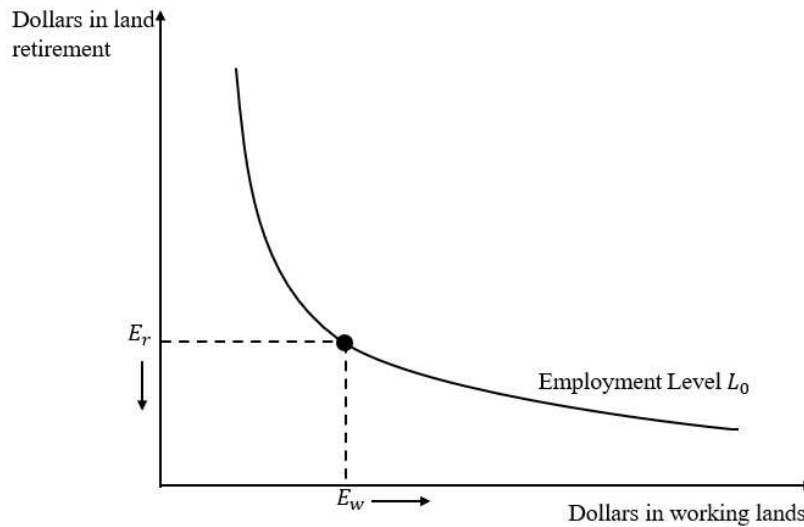


Figure 4.2: Trade-offs between dollars in working lands and land retirement

Our analysis advances three strands of literature that have investigated connections between conservation programs, the economy, and the environment. First, we contribute to the literature that has investigated the impacts of conservation programs. This literature has focused on the impacts of CRP, and results are somewhat mixed. Some studies have suggested that CRP can have negative impacts on local economic activity (Broomhall et al. 1991; Mortensen et al. 1989) while others have found that CRP’s net employment effects may be positive due to job creation in CRP-based recreation (Bangsund et al. 2004; Gascoigne et al. 2021). There is evidence that agricultural employment declines (Li et al. 2023; Sullivan et al. 2004; Leistriz et al. 2002). Siegel et al. (1991)

³²We define a job as a person working for one year.

estimated that improvements in environmental quality due to CRP can lead to an additional \$5-15 per acre of new spending on recreational activities, potentially supporting new jobs in this sector. Nonetheless, little research exists on the employment impact of conservation programs on working lands like EQIP and it remains unclear if funding working lands leads to better employment outcomes. Studies that focus on EQIP have often explored participation decisions, examining the factors that impact enrollment in conservation programs (Monger et al. 2018; Reimer et al. 2014; Nyaupane 2012; Prokopy et al. 2019; Pathak et al. 2021), decisions to exit (Wallander et al. 2019) and the additionality of conservation practices (Claassen et al. 2018; Mezzatesta et al. 2013).

Another strand of literature has explored the environmental impacts of CRP and EQIP. For example, CRP can improve water quality (Mulligan et al. 2013; Brooks et al. 2017; Yin et al. 2021), and quantity (Rao et al. 2010), build soil carbon (FAPRI-UMC 2007; Swan et al. 2018), and provide wildlife habitat (Reeves et al. 2017; Loomis et al. 2015; Riffell et al. 2006). Huang et al. (2002) found that CRP can enhance soil quality and increase resistance to water and wind erosion. Evidence for the environmental impacts of EQIP is more ambiguous. For example, Wallander et al. (2011) examined the effects of EQIP on irrigation efficiency and water conservation, but noted that EQIP payments could potentially increase overall water usage through the expansion of irrigated land. Liu et al. (2023) found that while EQIP payments have improved water quality, they have also increased soil erosion and pathogen transmission. Some EQIP-funded practices can also improve soil health and store soil carbon (Basche et al. 2020). While the environmental benefits of conservation programs are well-documented, potential economic trade-offs in rural labor markets remain understudied. Our study bridges the gap by examining the labor market impacts of these programs, contributing to a more complete understanding of the benefits and costs of agricultural conservation policies.

Finally, we build on literature that looks more generally at the impacts of environmental regulations and subsidies on labor markets. For example, environmental regulations often reduce overall employment (Greenstone 2001) and earnings (Walker 2011) with especially large impacts in energy-intensive sectors (Curtis 2018; Kahn et al. 2013). Other policies, such as carbon taxes,

can cause job losses and changing sectors of employment (Yip 2018; Azevedo et al. 2023; Carbone et al. 2020). The Endangered Species Act also impacts local employment, though some studies find a small positive effect on employment (Lewis et al. 2002; Lewis et al. 2003), while others have found a negative effect (Melstrom et al. 2018; Eichman et al. 2010; Ferris et al. 2021).

Our analysis enriches the existing literature by offering evidence of the employment impacts of alternative conservation approaches in agriculture. While numerous studies have explored the economic and environmental effects of CRP, and others have examined the environmental impacts of EQIP, our research fills a gap by studying the labor market impacts of EQIP and comparing them to the impacts of CRP. The joint analysis of the two types of conservation policy designs allows for a quantitative comparison of the labor market implications of the recent shift towards working lands conservation in both private and public conservation efforts. Our results offer policymakers and private funders of conservation a view of how shifts in conservation program funding may reshape rural labor markets. This can inform decision making and the design of payment structures that improve environmental outcomes while supporting rural livelihoods and economies.

This paper is organized as follows. The next section offers an overview of EQIP and CRP, their payment distribution across the U.S., and a conceptual model that describes the trade-offs between CRP and EQIP spending on local employment. Section 3 outlines the empirical identification strategy and econometric methods. Section 4 describes the data and presents summary statistics. Section 5 reports the main results from the regression analysis, while section 6 proposes alternative strategies to test the robustness of these findings. The final section discusses the results and concludes the paper.

4.2 EQIP, CRP, and the Economy

This section provides relevant institutional details about EQIP and CRP and describes the distribution of their payments across U.S. counties and states. We then discuss the mechanisms through which conservation payments can impact labor markets. We use a conceptual framework to discuss possible differences between working lands and land retirement programs. Finally, we discuss

how we characterize the labor market impact of reallocating conservation funds from retirement to working lands, considering both total employment levels and the composition of the jobs.

4.2.1 EQIP and CRP Background

Both EQIP and CRP are USDA programs funded by Congress (Stubbs 2023). CRP is a voluntary program established in 1985 under the Food Security Act to incentivize landowners to temporarily remove land from production, usually for a period of 10-15 years.³³ Maximum CRP payment rates are set by USDA's Farm Service Agency (FSA) based on the Soil Rental Rate (SRR).³⁴ Farmers can then bid to enroll their land in the CRP through a one-time sealed bid process, with their bids capped at the SRR. If accepted, farmers receive payments equal to their bid amount.

EQIP was established in 1996. It is the main U.S. working lands conservation program by dollars spent. EQIP provides cost-share payments to producers to undertake a wide range of conservation practices. These range from grazing to soil health to irrigation.³⁵ Therefore, land with EQIP contracts remains in production, but the nature of production can change, leading to differing demands for labor and other inputs on the land.

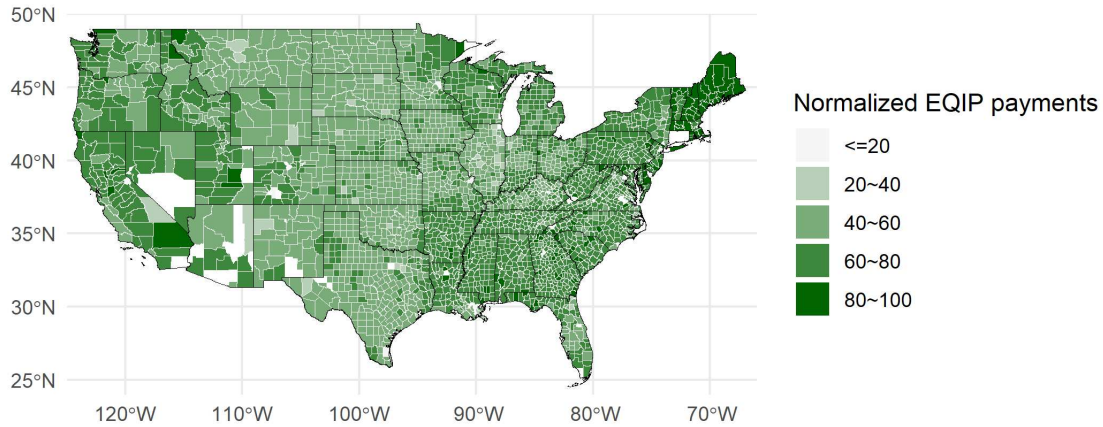
EQIP payment rates for different practices are determined at the state level by the NRCS.³⁶ Payment rates are a function of estimated practice costs, which include materials, labor, and opportunity costs such as the conversion of productive land. Each year, NRCS re-evaluates and adjusts these rates to reflect current market conditions within each state. Since payment rates vary by practice, county payments per acre depend on the mix of practices implemented. They also vary based on the cost of implementing practices, which could vary significantly across the country due to local conditions.

³³USDA Farm Service Agency webpage: Conservation Reserve Program

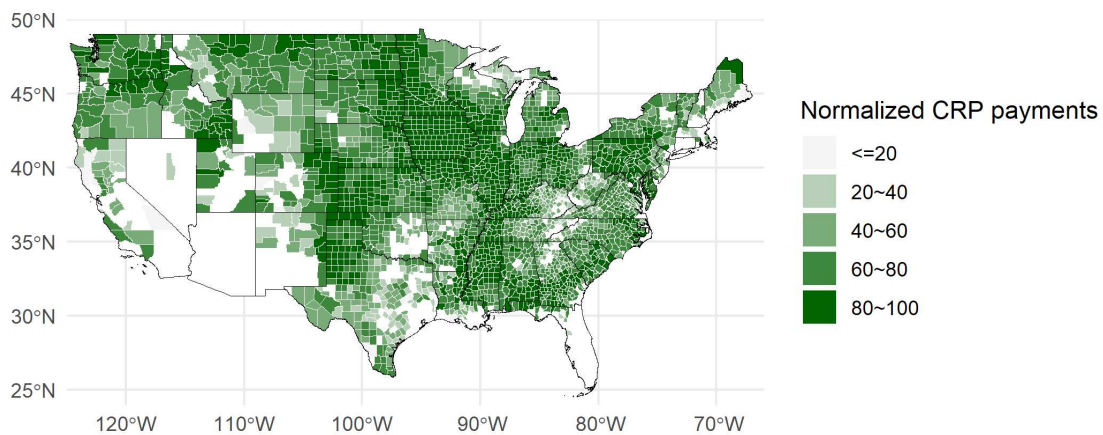
³⁴The National Office has calculated Soil Rental Rates for each county by multiplying the county average dryland rental rate (county AVGRT) by a set of soil-specific productivity factors unique to each county.

³⁵See this website summarized by Reid Hensen for a complete list of practices by type

³⁶USDA NRCS Payment Schedules webpage



(a) Normalized cumulative EQIP payments per farmland acre by county from 2009 to 2019



(b) Normalized cumulative CRP payments per farmland acre by county from 2009 to 2019

Figure 4.3: Normalized cumulative EQIP (a) and CRP (b) payments per farmland acre by county from 2009 to 2019

Note: Data are from USDA FSA. The white color (representing missing counties) indicates that no EQIP/CRP payments were reported between 2009 and 2019.

Figure 4.3a illustrates the geographical distribution of normalized³⁷ cumulative EQIP payments per farmland acre from 2009 to 2019. A darker green shade signifies larger payments per acre received by a county. For comparison, Figure 4.3b presents the distribution of the normalized cumulative CRP payments per farmland acre from 2009 to 2019. Normalizing these payments and keeping the same legend between the EQIP and CRP maps allows for a direct comparison of the relative intensity of program payments across counties. From these two figures, we observe

³⁷Normalized EQIP payment is calculated by dividing the total EQIP payments by the total farmland acres in each county. Then we scale the logged payments per acre to a 0-100 range by subtracting the minimum value and dividing by the range (max - min), transforming the data into a relative percentage.

that counties in eastern states received higher cumulative payments per farmland acre from EQIP than counties in midwestern states. Conversely, counties in midwestern states received greater cumulative payments per farmland acre from CRP compared to those in western and eastern states.

4.2.2 Impacts of EQIP and CRP on Employment

Here, we discuss the mechanisms through which agri-environmental programs can impact labor throughout the local economy. Appendix Figure AF4.1 illustrates how working lands programs (such as EQIP) and land retirement programs (such as CRP) influence both agricultural and non-agricultural factor input markets. In both cases, a payment enters the local economy in return for producers altering their use of inputs by changing practices (including land retirement in the case of CRP). The practice changes lead to different input demands, which lead to further changes in earnings throughout the economy. Changing input demands also affect agricultural production. As both farm and non-farm households experience income changes, this alters the demand for non-agricultural products and the inputs used to produce them. At the same time, environmental quality improves, potentially enhancing productivity in agricultural and non-agricultural sectors (Hornbeck et al. 2015).

With land retirement, land leaves agricultural production and demand for other inputs on the retired acres falls (though spillover effects could dampen these initial impacts (Wu 2000)). Therefore, CRP works principally through a reallocation of inputs from agriculture to non-agricultural production. With working lands conservation, land remains in production and the mix of inputs employed on the land changes. The nature of this change depends on the practices implemented. For example, retiring groundwater wells may lead to lower input demands on the land while planting cover crops may increase the demand for seeds, chemical inputs, and labor.

In both cases, farmers receive a payment. These payments should offset costs and generate minimal local surplus. In practice, producers may collect and spend surpluses (Kirwan et al. 2005; Aspelund et al. 2024) or spend them in different ways than returns from production that could complement or dampen other changes in the local economy. Therefore, the net impact of work-

ing lands payments depends on the relative sizes of these different mechanisms, and remains an empirical question.

While conservation programs may also influence wages, we focus on employment as the more policy-relevant outcome. Employment captures changes at the extensive margin, whether jobs are created or lost, whereas wages reflect adjustments at the intensive margin, which may be muted in rural areas with underemployment or limited wage flexibility. Moreover, employment effects more directly reflect shifts in labor demand from conservation practice adoption and are of greater policy relevance in regions where job creation is a key goal. For completeness, wage results are reported in Appendix 4.1.1. The total wage effects align with the employment results, likely reflecting an increase in the number of workers. However, wages per worker are not significantly affected, which is consistent with expectations in rural labor markets with limited wage responsiveness.

4.2.3 Reallocating Conservation from Land Retirement to Working Lands

We develop a model to illustrate the impact of reallocating conservation funds from retirement to working lands programs. We will use this model in our empirical analysis to quantify the net effect of reallocating funds. We define total employment in a local economy, which depends on the state level conservation expenditure on retirement (E_r) and working lands (E_w) as the sum of agricultural and non-agricultural employment:

$$L(E_r, E_w) = L_a(E_r, E_w) + L_{na}(E_r, E_w) \quad (4.1)$$

where $L_a(E_r, E_w)$ and $L_{na}(E_r, E_w)$ are agricultural and non-agricultural employment, respectively. The impact of changes in conservation expenditure can be approximated using the differential of $L(E_r, E_w)$:

$$dL = \left(\frac{\partial L_a}{\partial E_r} + \frac{\partial L_{na}}{\partial E_r} \right) dE_r + \left(\frac{\partial L_a}{\partial E_w} + \frac{\partial L_{na}}{\partial E_w} \right) dE_w \quad (4.2)$$

This differential describes the total change in employment as a function of changes in expenditure on each type of program. We use Equation 4.2 to describe the change in employment from a reallocation of S conservation dollars from retirement ($dE_r = -S$) towards working lands ($dE_w = S$). In the empirical analysis of this paper, we use econometric estimates to quantify the impact of this change on total labor:

$$\Delta \hat{L} \approx \left(\frac{\partial L_a}{\partial E_r} + \frac{\partial L_{na}}{\partial E_r} \right) \times (-S) + \left(\frac{\partial L_a}{\partial E_w} + \frac{\partial L_{na}}{\partial E_w} \right) \times S \quad (4.3)$$

The impact on agricultural labor is:

$$\Delta \hat{L}_a \approx \frac{\partial L_a}{\partial E_r} \times (-S) + \frac{\partial L_a}{\partial E_w} \times S \quad (4.4)$$

And the impact on non-agricultural labor is:

$$\Delta \hat{L}_{na} \approx \frac{\partial L_{na}}{\partial E_r} \times (-S) + \frac{\partial L_{na}}{\partial E_w} \times S \quad (4.5)$$

Where $\Delta \hat{L} = \Delta \hat{L}_a + \Delta \hat{L}_{na}$. Parameterizing this model requires estimating the impact of state-level conservation payments on local labor market outcomes.

Finally, note that we can use Equation 4.2 to solve for the slope of the iso-employment curve depicted in Figure 4.2. By taking the differential of the left-hand side of Equation 4.1 and setting dL to 0, we can solve for $(dE_r)/(dE_w)$:

$$\frac{dE_r}{dE_w} = -\frac{\frac{\partial L}{\partial E_w}}{\frac{\partial L}{\partial E_r}} \quad (4.6)$$

This slope describes the change in funds to retirement that would leave total employment constant after a small increase in funds for working lands. While this slope in isolation does not describe an optimal policy, it can highlight the potential for conservation dollars to support rural economic outcomes at a lower program cost.

4.3 Empirical Analysis

In this section, we describe our econometric model and its identification. Then, we describe how we use the model's coefficient estimates to describe the impact of reallocating conservation funds to working lands programs.

4.3.1 Econometric Model Setup

Our econometric approach follows the methods of Li et al. (2023) and Liu et al. (2023), developing a fixed effect model to describe the relationship between state-level EQIP and CRP payments per farmland acre and local economic outcomes. A reduced-form econometric model that captures the net effect of each program on labor outcomes is specified as follows:

$$\ln(y_{imst}) = \beta_{1s}\ln(EQIP_{dt}) + \beta_{2s}\ln(CRP_{dt-1}) + \gamma_{ims}X_{imt} + \alpha_{ms} + \delta_{jst} + \epsilon_{imst} \quad (4.7)$$

y_{imst} is the economic outcome under consideration in county i , watershed m , sector s , and year t . Our unit of observation is a county-watershed. A watershed is an area of land that drains rainfall and snowmelt into streams and rivers. We define a watershed here based on 4-digit hydrologic unit codes³⁸. We examine total employment, the unemployment rate, and employment in agricultural and non-agricultural sectors.

$EQIP_{dt}$ is the state-level EQIP payments per farmland acre³⁹ in state d and year t . CRP_{dt-1} is the state-level CRP payments per farmland acre in state d and year $t-1$. The fiscal year in the EQIP data is the practice-applied fiscal year, so it does not require lagging. However, the fiscal year in the CRP data is the year in which a contract is signed. Since CRP practices are typically applied one year after the contract is signed, a one-year lag is necessary (Li et al. 2023). The coefficients

³⁸More info can be found at <https://pubs.usgs.gov/wsp/wsp2294/>

³⁹Total farmland acres are fixed in 2012. Eligible land for Farm Bill programs, as defined by the NRCS, includes areas used for producing agricultural commodities, livestock, or forest-related products, such as cropland, rangeland, pastureland, and non-industrial private forestland.

β_{1s} and β_{2s} estimate the marginal effect of changes in state-level EQIP and CRP payments per farmland acres, respectively, on the labor market outcome.

X_{imt} is a vector of controls for time-varying and invariant characteristics at the observation (county-watershed) level. It also includes state-level controls relevant to county-watershed m . Observation-level controls incorporate variables such as weather controls, the distance from each county-watershed to the nearest city with over 50,000 people, local population, expected subsidy amount per acre, and the latitude and longitude of each county-watershed unit center. First, temperature and precipitation fluctuations have been shown to influence labor supply (Somanathan et al. 2021; Graff Zivin et al. 2010). Carleton et al. (2016) observed that extreme temperatures affecting crop yields tend to drive unskilled agricultural workers toward the manufacturing sector. Second, larger cities typically provide a more diverse range of employment opportunities, which can result in spillover effects in surrounding areas. In addition, they serve as substantial markets for goods and services produced in nearby rural economies (Tacoli 1998). Consequently, labor markets in rural regions can be both directly and indirectly influenced by their proximity to larger urban centers. Third, population size can directly influence the absolute number of people employed in a region. Sullivan et al. (2004), in their analysis of CRP impacts, control for population size to account for its direct influence on local employment levels when assessing program effects. In Appendix 4.1.2, we present employment per capita results as an alternative measure of employment outcomes to serve as a robustness check.

We use the expected crop insurance subsidy per acre from the previous 3 years (rolling average of the subsidy per acre from year $t-1$, $t-2$, and $t-3$) to control for other agricultural support programs from the federal government. Higher crop insurance subsidies indicate a greater degree of government assistance, which can affect farmers' income stability, risk management strategies, and production decisions (DeLay et al. 2023). This, in turn, influences labor demand and supply in the agricultural sector. Finally, we use county-watershed latitude and longitude to control for spatial trends in employment. To address concerns that soil characteristics may impact program en-

rollment and payment levels, we include county-watershed level acres in different land capability classes as a robustness check, as shown in Appendix 4.1.3.

State-level controls include weighted crop price (Li et al. 2023), corn insurance premium per farmland acre, political parties in government (2008, 2012, and 2016 election results by state), sales tax, median property tax, tax burden, and the average conservation program payment per farmland acre in neighboring states. First, crop prices play a significant role in determining agricultural revenues, personal income, and overall employment (Weber et al. 2015). Participation in conservation programs is also impacted by crop prices (Holland et al. 2020; Reimer et al. 2014; Hellerstein et al. 2011; Adjei et al. 2024). Babcock et al. (2008) predict that given constant 2008 crop prices and no change in CRP policy, two million acres of CRP land may annually revert to crop production. Secchi et al. (2007) estimate that if corn prices stabilize at \$3 (equal to \$4.2 in 2024⁴⁰) a bushel, approximately half of Iowa's two million CRP acres could be returned to crop production. Gill-Austern (2011) suggests a \$1 per bushel increase in Corn Belt corn prices could reduce CRP-enrolled acreage by over 130,000 acres. While empirical evidence is less clear for EQIP, it is plausible that crop prices also influence the opportunity costs of implementing practices encouraged by EQIP, especially if practices impact yields. Second, we use corn insurance premium per farmland acre at the state level to control for state-level insurance prices.

In addition, the political party of state governors in the U.S. influences labor market outcomes (Beland 2015). State-level tax policies indeed play a significant role in shaping the agricultural sector's development and influencing farmers' decisions regarding conservation program participation. To account for this, we include tax variables as controls in our model. Finally, we control for the average EQIP and CRP payments per farmland acre in neighboring states to account for potential spillover effects on local labor markets. As a robustness check (in Appendix 4.1.4), we also include state-level GDP per capita to control for the impacts of other state-level economic conditions that could affect both labor markets and the opportunity cost of enrolling in conservation programs.

⁴⁰Based on an estimated average annual inflation rate of 2 percent from 2007 to 2022.

We use fixed effects to control for unobservable factors that could affect both conservation program payments and labor market outcomes. α_{ms} is a watershed fixed effect, which accounts for unobserved environmental conditions across different locations. δ_{jst} denotes region-year fixed effects, controlling for unobserved, time-varying market and policy conditions that are common to all county-watersheds within a region j . In this study, we use eight Bureau of Economic Analysis (BEA) regions—New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West—each comprising states with similar economic and social conditions.⁴¹ We also explore alternative fixed effects and present evidence that watershed and region-year fixed effects are the most appropriate for this analysis, balancing the need to control for unobserved factors with the need for variation in our data (see Appendix 4.2). To enhance the interpretability of our estimates, we employ a logarithmic transformation on both the independent variables and the dependent variables. This step is crucial in the statistical analysis process as it effectively normalizes variables that are otherwise skewed or span several orders of magnitude. Logging is also advantageous because the coefficients derived from a log-log model can be directly interpreted as elasticities (Wooldridge 2012). The last term, ϵ_{imst} , represents the regression error, capturing variation from unobserved factors or omitted variables. Standard errors are clustered at the state level to account for unobserved policy variations or economic conditions that may be shared within a state.

4.3.2 Identification Strategy

The key identification assumption necessary to obtain unbiased estimates using this model is that decisions to participate in conservation programs are independent of all unobserved factors. Specifically, in this study, to obtain unbiased estimates of β_{1s} and β_{2s} , the state-level EQIP payments per farmland acre ($EQIP_{dt}$) and the state-level CRP payments per farmland acre (CRP_{dt-1}) must be independent of the regression error term, ϵ_{imst} , after conditioning on observable controls and fixed effects.

⁴¹Learn more about the process of drawing BEA regions: <https://www2.census.gov/geo/pdfs/reference/GARM/Ch6GARM.pdf>

Given the voluntary participation nature of EQIP and CRP programs, a selection bias exists. As Li et al. (2023) suggest, owners of lower-quality land might be more inclined to engage in conservation programs due to reduced opportunity costs. Research also indicates that participant farmers may be operating in more environmentally sensitive areas and hold distinct conservation priorities compared to other farmers (Nickerson et al. 2009). Second, local economic conditions could influence individual conservation enrollment decisions, and these decisions could, in turn, impact local employment conditions (Nickerson et al. 2009; Wallander et al. 2011). Finally, there may be unobserved factors that affect both farmers' program participation decisions and local employment. In summary, given the potential endogeneity issues, incorporating robust econometric techniques into the analysis is crucial. In this study, we employ a multi-faceted approach to mitigate potential endogeneity concerns and strengthen identification.

We take multiple steps to identify the impact of conservation program payments on local labor markets. First, we limit our sample to areas where the economy is primarily agriculture-dependent. Specifically, we consider only rural counties where the cropland area accounts for more than 10 percent of the total county area. Previous studies (Li et al. 2023) used all counties as samples without focusing specifically on rural areas where agriculture is a primary industry. Analyses using all counties estimate an average effect that includes counties in which agriculture represents just a small fraction of the county economy. This can underestimate effects for economies with a large agricultural presence. Li et al. (2023) introduced the variable of metropolitan trends and concluded that it can significantly impact local employment. This further supports our focus on rural areas that are highly dependent on agricultural production.

Second, we divide our county-level observations into county-watershed units to better account for the heterogeneity of environmental conditions within a county. Hamilton et al. (1998) suggest performing sub-county level analysis, especially for programs with uneven enrollment patterns. Therefore, in this study, we shift our observation unit from county to county-watershed. For county-level data, we distribute it to county-watersheds based on the percentage of the county area in each watershed. This adjustment allows us to control for unobserved environmental and

hydrological conditions by including watershed fixed effects. In Appendix 4.1.5, we show the robustness results using county-level observations.

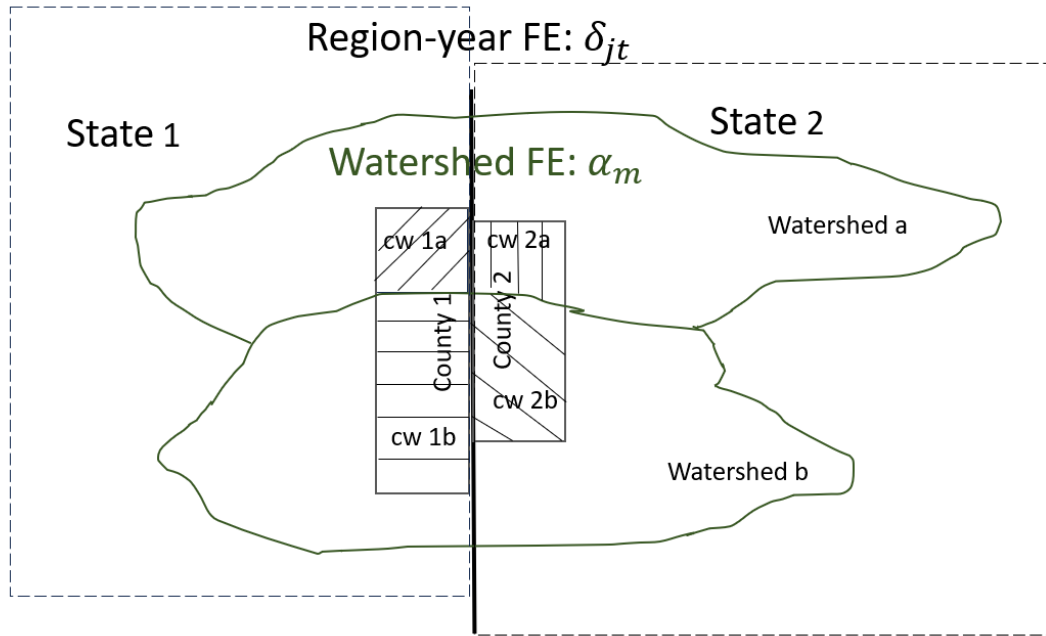


Figure 4.4: Identification across state borders

Note: In the given example, County 1 is split into two county-watershed (cw) units, cw 1a and cw 1b, each corresponding to watersheds a and b, respectively. Similarly, County 2 is divided into cw 2a and cw 2b.

Third, we limit our sample to the county-watershed observations on state boundaries, as illustrated in Figure 4.4, and follow the approach in Brown et al. (2020). This approach allows us to exploit policy discontinuities (EQIP and CRP funding allocation) at state borders while maintaining ecologically relevant units of analysis. Both programs are known to be oversubscribed: from 2010 to 2020, only about 31% of EQIP offers were accepted (Happ 2021), and CRP rejection rates ranged from 8.4% in 2010 to as high as 81.6% during the 2016 general signup (Rosenberg et al. 2024). As a result, total EQIP payments are largely driven by the availability of program funding and priorities, while CRP payments are constrained by acreage caps set through federal policy. Both factors are determined at the national level and are plausibly exogenous to short-run labor market conditions at the county-watershed level. To control for differences in the size of states and

better isolate policy-driven variation, we divide total payments by state-level farmland acreage. In Appendix 4.1.6, we present a robustness check using state-level payments per farmland acre, excluding the county of interest from the calculation of the independent variables. In Appendix 4.1.7, we further examine the robustness of our results by using total state-level EQIP and CRP payments as independent variables, without normalizing by farmland area.

Specifically, EQIP funds are allocated based primarily on environmental rather than economic considerations. NRCS national headquarters distributes funding to state offices according to environmental priorities and, in some cases, historical funding patterns (GAO 2017). Based on GAO (2017)'s study, although national guidelines recommend using current data on environmental concerns, many states rely on past treatment data or the proportion of funded applications due to limited access to updated information. Within states, allocations are further guided by statutory requirements, environmental goals, and resource availability. This emphasis on environmental over economic factors supports the assumption that state-level EQIP payments are exogenous to local labor market conditions. This approach leverages the quasi-experimental variation in conservation program incentives across state lines, enhancing our ability to identify the effects of program payments on local employment outcomes while minimizing potential endogeneity concerns.

We follow a similar strategy for CRP. Individual CRP enrollment is determined by Environmental Benefits Index (EBI) scores, which incorporate factors such as wildlife habitat, water quality, erosion control, air quality, long-term benefits, and cost. A federal-level EBI cutoff score is then applied, determined by the acreage cap, and all offers exceeding that threshold are accepted. While cost is one component of the EBI, individual bids from counties are unlikely to influence the national cutoff score, making the resulting payment levels largely policy-driven and environmentally motivated. As such, state-level average CRP payments per farmland acre also reflect federal conservation priorities rather than local labor market conditions. This approach further reduces endogeneity concerns, especially after controlling for watershed fixed effects and region-by-year fixed effects, which account for differences in labor market conditions and the opportunity cost of CRP participation.

Finally, we employ a multi-level fixed effects model: watershed fixed effects ($\alpha_{m,s}$) account for time-invariant environmental conditions (e.g., climate patterns, geologic history, hydrologic characteristics, ecosystem types, and general land cover and land use patterns) across farmlands on the same state border, while region-year fixed effects (δ_{jst}) capture all time-varying market conditions common to county-watersheds within a region. This approach assumes that all observations on the same state borders and within the same watersheds experience a set of similar shocks in each region-year (conditional on county level controls and state level tax policies and political parties), enabling us to isolate the effects of conservation programs by leveraging cross-state policy variations while controlling for local environmental and economic factors.

Given our identification strategy, variation in state-level EQIP and CRP payments per farmland acre across two counties within the same watershed but in different states and conditional on observable controls and fixed effects are plausibly exogenous to local enrollment decisions. To further assess the robustness of our estimates, we employ an alternative specification by incorporating Lewbel IV methods (Lewbel 2012). We also explore alternative ways to map county data into county-watersheds, estimate county-level models, and test the robustness of our results to the inclusion and omission of different sets of controls. These approaches and specifications serve to validate our main findings and provide additional insights into the relationship between conservation program payments and local employment outcomes.

4.3.3 Describing Employment Tradeoffs

We use the coefficient estimates from Equation 4.7 to describe the net impact of reallocating conservation funds from land retirement (CRP) to working lands (EQIP). Let the estimated coefficients in Equation 4.7 for total employment be $\hat{\beta}_1$ and $\hat{\beta}_2$ for EQIP and CRP respectively. These coefficients represent the elasticities of total employment with respect to state-level EQIP (e_w) and CRP (e_r) payments per farmland acre, respectively. To parameterize Equation 4.2, we begin with $\hat{\beta}_1$ and $\hat{\beta}_2$ as:

$$\hat{\beta}_1 = \frac{\partial \ln L}{\partial \ln e_w} = \frac{e_w}{L} \frac{\partial L}{\partial e_w} \quad (4.8)$$

$$\hat{\beta}_2 = \frac{\partial \ln L}{\partial \ln e_r} = \frac{e_r}{L} \frac{\partial L}{\partial e_r} \quad (4.9)$$

where e_w and e_r are EQIP and CRP payments per farmland acre. Then we solve for the partial derivatives:

$$\frac{\partial L}{\partial e_w} = \hat{\beta}_1 \frac{L}{e_w} \quad (4.10)$$

$$\frac{\partial L}{\partial e_r} = \hat{\beta}_2 \frac{L}{e_r} \quad (4.11)$$

We then express state level total expenditures, E_w and E_r , as a function of payments per farmland acre, and given fixed farmland acres in a state, F :

$$E_w = e_w \times F \quad (4.12)$$

$$E_r = e_r \times F \quad (4.13)$$

Thus, we can express baseline payments per farmland acre in terms of expenditures in a state:

$$e_w = \frac{E_w}{F} \quad (4.14)$$

$$e_r = \frac{E_r}{F} \quad (4.15)$$

Then, we calculate the partial derivatives of payments per farmland acres with respect to expenditures:

$$\frac{\partial e_w}{\partial E_w} = \frac{1}{F} \quad (4.16)$$

$$\frac{\partial e_r}{\partial E_r} = \frac{1}{F} \quad (4.17)$$

Combining Equations 4.12 and 4.13 with the definition of total labor, total labor can be expressed as $L(e_w(E_w), e_r(E_r))$. To obtain the impact of a change in E_w on total employment, we differentiate this expression with respect to state-level conservation expenditures and substitute in

Equations 4.10, 4.11, 4.16, and 4.17.

$$\frac{\partial L}{\partial E_w} = \frac{\partial L}{\partial e_w} \times \frac{\partial e_w}{\partial E_w} = \left(\hat{\beta}_1 \frac{L}{e_w} \right) \left(\frac{1}{F} \right) = \hat{\beta}_1 \frac{L}{e_w \times F} = \hat{\beta}_1 \frac{L}{E_w} \quad (4.18)$$

Similarly, for expenditure on land retirement programs:

$$\frac{\partial L}{\partial E_r} = \hat{\beta}_2 \frac{L}{E_r} \quad (4.19)$$

Applying Equations 4.18 and 4.19 to Equation 4.2, we have:

$$dL = \left(\hat{\beta}_1 \frac{L}{E_w} \right) dE_w + \left(\hat{\beta}_2 \frac{L}{E_r} \right) dE_r \quad (4.20)$$

This implies that an S dollar reallocation of funds from retirement to work lands programs at the state level becomes:

$$\Delta \hat{L} \approx \left(\hat{\beta}_1 \frac{L}{E_w} \right) \times S + \left(\hat{\beta}_2 \frac{L}{E_r} \right) \times (-S) \quad (4.21)$$

This demonstrates how we parameterize Equation 4.3 using estimated parameters $(\hat{\beta}_1, \hat{\beta}_2)$. Given this, the slope of the iso-employment curve for a county-watershed described in Equation 4.6 is:

$$\frac{dE_r}{dE_w} = - \frac{\hat{\beta}_1 E_r}{\hat{\beta}_2 E_w} \quad (4.22)$$

Similarly, this approach can be applied to sector-specific employment, to obtain $\Delta \hat{L}_a$ and $\Delta \hat{L}_{na}$, representing changes in agricultural and non-agricultural employment, respectively.

4.4 Data and Summary Statistics

In this section, we describe the data used in our empirical analysis. We use 2012 cropland area data from USDA National Agricultural Statistics Service (NASS) Quick Stats and county land area statistics from the U.S. Census Bureau to calculate the percentage of cropland area within each county. For our main specification, we focus on those counties in cropland regions where cropland

area constitutes over 10 percent of the total land area, resulting in a sample of 1,928 counties (out of 3,244 total counties). We then cross-reference this dataset with Rural-Urban Continuum Codes (RUCC) from USDA to identify rural counties, yielding 1,244 rural counties with more than 10 percent of area in cropland. Further refinement is made by selecting rural counties situated on state boundaries, narrowing the sample to 437 counties. Additionally, we obtain watershed data from the Environmental Protection Agency (EPA) and define watersheds using 4-digit Hydrologic Unit Codes (HUCs), subdividing each county into county-watersheds. This results in 767 county-watershed units. Given the geographical overlap, a single county could be divided among multiple watersheds, and a watershed could include areas from several counties. Adhering to these selection criteria, and after integrating conservation payment data and eliminating null values, our final study sample includes 299 counties and 523 county-watershed units.

To allocate county-level variables to county-watershed units, we primarily use the area share of each county-watershed within the county. This spatial disaggregation allows for finer geographic analysis but carries potential limitations. Specifically, the area-based method assumes that employment and other outcomes are evenly distributed across a county, which may not hold if cropping systems or economic activity differ substantially across watersheds. For example, watersheds with less labor-intensive agriculture could be assigned an overstated share of employment. To address this concern, we conduct a robustness check using population share as an alternative allocation method, based on the assumption that employment is more concentrated in populated areas. This approach helps capture heterogeneity in land use intensity and local economic structure. Results using this alternative method are presented in Appendix 4.1.8. While each has limitations, the consistency of findings across approaches reinforces the robustness of our analysis.

4.4.1 EQIP and CRP Payments Data

We obtain county-level CRP data from the USDA FSA website⁴² and the county-level EQIP data from the USDA Forest Service Research Data Archive⁴³. From the line chart in Figure 4.1, which utilizes the second y-axis, we can see that with the heightened emphasis on working lands, payments for EQIP have shown a steady rise, even surpassing the obligations of CRP in 2018. According to the EQIP data, 3,160 counties implemented a total of 193 EQIP practices between 2009 and 2019. During this period, the total payments allocated to EQIP amounted to over 6.9 billion dollars. This compares to over 20 billion dollars allocated to CRP.

After merging the EQIP data with the lagged CRP data and allocating county data to county-watersheds, the resultant dataset spans from 2009 to 2019. We then aggregate the county-level payments to state level and calculate state-level CRP and EQIP payment per farmland acre by dividing the payments for each program by the total farmland acres in 2012 in the state, obtained from USDA NASS Quick Stats. Table 4.1 displays the summary statistics for these data within rural agricultural-dependent counties, considering rural border counties and all rural counties. Farmland acres, total EQIP and CRP payments and enrolled acres at both the county and state levels, and state-level payments per farmland acre are reported in the table. As indicated in the table, the mean state-level payments per farmland acre of rural border county-watersheds are similar to those of all rural county-watersheds. The consistency in the payment patterns between border and non-border areas enhances the generalizability of our findings to the broader rural context. We apply the method from Sloggy et al. (2025) to further assess the representativeness of border rural counties compared to all rural counties, as detailed in Appendix 4.1.9.

4.4.2 Dependent Variables

We measure private sector employment in both agricultural and non-agricultural sectors. The employment data used in this study are sourced from the Quarterly Census of Employment and

⁴²USDA FSA, Conservation Reserve Program Statistics

⁴³EQIP U.S. data at state, county and individual practice level for soil and environmental health, 2009-2018

Table 4.1: Summary statistics of EQIP and CRP data on border and all rural counties

Variable	Units	Number of Obs.		Mean		Standard Deviation		Min		Max	
		Border	All rural	Border	All rural	Border	All rural	Border	All rural	Border	All rural
CRP acres (county)	1000 acres	9923	22926	25.90	20.00	41.45	32.79	0	0	277.51	303.59
CRP county payment	\$ million	9923	22926	1.38	1.14	1.68	1.46	0	0	14.62	14.62
CRP state payments	\$ million	9923	22926	69.54	72.59	59.24	59.24	0.29	0.17	360.77	360.77
CRP payment rates (state)	\$ per farm acre	9923	22926	2.841	2.81	2.041	2.01	0.121	0.121	12.555	12.555
EQIP acres (county)	1000 acres	9923	22926	4.22	3.64	9.36	7.52	0	0	158.18	158.18
EQIP county payment	\$ million	9923	22926	0.27	0.23	0.34	0.30	0	0	5.43	8.31
EQIP state payments	\$ million	9923	22926	16.12	17.70	11.76	14.52	0.82	0.82	80.61	84.28
EQIP payment rates (state)	\$ per farm acre	9923	22926	0.936	0.948	0.908	0.974	0.033	0.033	6.61	13.535
State total farmland	million acres	9923	22926	28.77	32.23	25.17	31.05	1.60	0.68	127.25	127.25

Note: “All rural” columns summarize data for rural counties with over 10% cropland; “Border” columns focus on rural counties at state borders. This table presents summary statistics for the EQIP and CRP datasets independently, before their integration with additional variables. The number of observations exceeds those in our estimation tables due to missing employment data.

Wages⁴⁴ (QCEW). We calculate the annual average employment by averaging the monthly employment figures for each year. Subsequently, we apply the proportion of each county's area within a watershed to distribute the employment data accordingly across the county-watershed units. To identify the agricultural sector, we utilize the 2-digit North American Industry Classification System (NAICS) codes, specifically NAICS 11, which corresponds to agriculture, forestry, fishing, and hunting. All remaining private industries are categorized under the non-agricultural sector. The QCEW data contain some suppressed values to protect employer confidentiality. In our analysis, we exclude observations where employment is reported as zero or suppressed. We focus our analysis on the higher, 2-digit NAICS aggregation level because fewer observations are suppressed. We compute the values for each of these indicators using data adjusted by the proportion of the county's area that falls within each watershed. The summary statistics of the dependent variables are presented in Table 4.2.

It is worth noting that H-2A workers⁴⁵ are included in the QCEW in some states but not others, and there is no dataset indicating which states include those workers. To address this inconsistency, we conduct a robustness check by excluding the five states⁴⁶ with the highest H-2A employment as shown in Appendix 4.1.10. County-level unemployment rates are sourced from the BEA.

4.4.3 Control Variables

We control for several time-varying and -invariant factors, the summary statistics for which are presented in Table 4.2. We control for weather conditions by incorporating temperature and precipitation, along with their squared terms to account for potential non-linear influences. The weather data are sourced from the National Oceanic and Atmospheric Administration (NOAA)

⁴⁴In QCEW, the monthly employment data represents the number of workers covered by unemployment insurance who worked during, or received pay for, the pay period that included the 12th day of the month.

⁴⁵The H-2A program authorizes U.S. employers and U.S. agents who satisfy specific regulatory requirements to recruit foreign nationals into the United States for temporary agricultural positions (U.S. Department of Labor).

⁴⁶USDA ERS: H-2A Temporary Agricultural Job Certifications Continued To Soar in 2022

Table 4.2: Summary statistics of the dependent and control variables on border counties and all rural counties

Variable	Number of Obs.		Mean		Standard Deviation		Min		Max	
	Border	All rural	Border	All rural	Border	All rural	Border	All rural	Border	All rural
Total employment	4561	11591	3200.9	3682.01	4801.18	5454.77	0.06	0.06	31308.26	49382.58
Ag employment	4561	11591	108.49	104.51	270.38	226.39	0	0	3575.21	3843.42
Non-ag employment	4561	11591	3092.41	3577.51	4750.77	5393.96	0.05	0.05	31048.13	49302.33
Unemployment rate(%)	4561	11591	5.83	5.87	2.92	2.9	1.5	1.5	19.3	20.6
Distance	4561	11591	1.162	1.038	0.616	0.577	0.238	0.095	3.239	3.434
Total precipitation	4561	11591	54.556	54.706	43.27	43.909	0.003	0.003	248.213	248.213
Average temperature	4561	11591	22.138	22.233	2.913	3.232	14.003	12.29	29.274	29.638
Latitude	4561	11591	38.515	38.387	3.901	4.501	30.796	27.732	48.776	48.879
Longitude	4561	11591	-93.403	-93.152	7.514	7.888	-120.795	-122.798	-75.803	-74.425
Crop price	4561	11591	7.126	6.966	1.906	1.833	3.942	3.66	12.658	12.658
Crop insurance subsidy per acre	4561	11591	23.973	24.427	11.453	12.513	3.475	1.57	122.02	200.956
Corn premium per farmland	4561	11591	6.541	6.375	5.898	5.84	0.028	0.015	25.973	25.973
Median property tax rate	4561	11591	0.011	0.012	0.005	0.005	0.002	0.002	0.018	0.018
Tax burden rate	4561	11591	0.095	0.094	0.012	0.012	0.068	0.068	0.147	0.147
Sales tax rate	4561	11591	1.687	1.701	0.218	0.199	1.065	1.065	1.946	2.015
CRPpayrate near	4561	NA	2.832	NA	1.975	NA	0.121	NA	12.555	NA
EQUIPpayrate near	4561	NA	1.042	NA	1.043	NA	0.033	NA	6.61	NA

Note: “All rural” columns summarize data for rural counties with over 10% cropland; “Border” columns focus on those at state borders. “Total employment”, “Ag employment”, and “Non-ag employment” represent average jobs over the year. The unemployment rate is expressed as a percentage.

Monthly U.S. Climate Gridded Dataset⁴⁷. The temperature data, expressed in degrees Celsius, represent the yearly average derived from monthly averages of daily average temperatures. The precipitation data, presented in millimeters, signify the mean of the monthly totals accumulated throughout the year. From Table 4.2, throughout our study period, the average temperature was approximately 22 degrees Celsius, while the average monthly precipitation hovered around 54 millimeters. County-level population data are sourced from BEA.

Data on latitude, longitude, and population (city-level⁴⁸) are extracted from Esri⁴⁹, which is based on the 2020 U.S. Census. To account for urbanization effects, we measure the distance from each rural border county-watershed to its nearest city with a population exceeding 50,000. The dataset shows that there are 871 cities with over 50,000 residents. Distances are calculated from the geographic center of each rural county-watershed to its nearest city, with measurements presented in decimal degrees for increased accuracy. It is important to note that some border counties may actually be closer to larger cities located in adjacent states, a geographical nuance that is illustrated in Appendix Figure AF4.2. We allow for this in our calculation of the distance to the nearest city to ensure a more accurate representation of each county-watershed's true urban accessibility. Data on total crop insurance subsidy amount and reported acreage are obtained from the USDA Risk Management Agency⁵⁰ (RMA), serving as indicators of agricultural policy trends in each county. To account for farmers' expected insurance subsidy for the current year, we calculate three-year rolling averages of subsidy per acre.

Given our focus on counties situated along state borders, our study also incorporates variables that exhibit variability across these state lines. These include state averages of federal corn insurance premiums per farmland acre, sourced from the USDA RMA, used as an indicator for

⁴⁷<https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00332>

⁴⁸The city-level population data are solely used to identify cities with populations exceeding 50,000. The control variable for population in the main specification is at the county level, and the data source differs from that used for city-level data.

⁴⁹Esri is a company in geographic information system (GIS) software, location intelligence, and mapping.

⁵⁰USDA Risk Management Agency, State/County/Crop Summary of Business

state-level crop insurance trends, as corn is cultivated in every U.S. state. We calculate a weighted crop price index⁵¹ using crop price data from NASS Quick Stats, and 2009 crop acreage data from USDA FSA⁵². State level political parties in power are represented by presidential election results from 2008 (New York Times⁵³), 2012 (NBC News⁵⁴), and 2016 (USA Today⁵⁵). We also control for state-level taxes, including sales tax (Federation of Tax Administrators), median property tax (Tax Foundation), and tax burden⁵⁶ (Tax Foundation). Finally, we also control for state-level EQIP and CRP payments per farmland acre in neighboring states for our main specification.

4.5 Results

This section presents our findings in two main parts. First, we report our primary results, which demonstrate the effects of state-level EQIP and CRP payment per farmland acre on total employment, agricultural employment, non-agricultural employment, and unemployment rate. Then, we examine the net effect of reallocating funds from land retirement to working lands. We do this first for overall employment. Then, we examine impacts by sector to quantify changes in the composition of rural employment. In the following section, we explore the robustness of our results to alternative identification strategies.

4.5.1 Estimated Impacts on Employment

Table 4.3 presents the estimated effects of state-level EQIP and CRP payments per farmland on total employment and unemployment rate using a panel fixed effect model as specified in Equa-

⁵¹For a given national crop j in year t , p_{jt} represents the national price. Then the index for state q is $p_{qt} = \sum_j p_{jt} \times w_{jq}$, where w_{jq} represents the proportion of each crop j 's cropland acreage relative to the state total.

⁵²USDA FSA Crop Acreage Data. We use time invariant crop weights so the price index does not vary as a function of producer acreage choices.

⁵³Election Results 2008: <https://archive.nytimes.com/>

⁵⁴Presidential election results: <https://www.nbcnews.com/politics/2012-election/all/president/>

⁵⁵2016 Election Results: <https://www.usatoday.com/elections/results/2016-11-08/presidential/>

⁵⁶Tax burden represents the ratio of state and local tax contributions made by residents to the state's portion of the national economic output.

tion 4.7. The “Border” column displays our primary specification results, while the subsequent columns demonstrate the robustness of these findings by extending to all rural counties to explore the stability of our estimates beyond state border counties. There may be some concern about the inclusion of endogenous controls (Wooldridge 2005), while omitting these controls may introduce bias. Therefore, in Appendix 4.1.4, we present results including and excluding different sets of controls. Robustness of results to this exercise provides suggestive evidence that our results are not driven by omitted factors (Schlenker et al. 2007).

Our estimates reveal that state-level EQIP payments per farmland acre positively influences total employment and decreases the unemployment rate. These effects remain robust when the analysis is expanded to include all rural counties. Specifically, a 1 percent increase in EQIP payments per farmland acre corresponds to a 0.093 percent rise in total employment, holding all other factors constant. Given an average of 3,200 total employees on average over a year in each county-watershed and 18 million dollars allocated to EQIP per state annually, this translates to approximately 0.017 additional local jobs per \$1,000 increase in state-level EQIP spending, and a reduction in the unemployment rate by 0.00004 percentage points per year. Results for all rural counties reflect a similar pattern, albeit with slightly smaller magnitudes.

Additionally, our findings indicate that state-level CRP payments per farmland acre have a positive and significant impact on total employment but do not significantly decrease the unemployment rate, though the point estimate is negative. A 1 percent increase in state-level CRP payments increases total employment by 0.075 percentage. Similarly, given the average 67 million dollars in CRP funding per state, each additional thousand dollars spent in CRP at the state level will increase the total employment by 0.0036 jobs per year in each county watershed. Note that the coefficient for CRP in our main specification is close to that of EQIP, but the impact of an additional dollar is smaller due to the larger baseline level of CRP funding, resulting in a smaller proportional change in the payment per farmland acre from a one-dollar increase.

The lack of a significant effect on the unemployment rate may reflect differences in how employment and unemployment are measured. Total employment captures absolute job increases,

Table 4.3: The effects of conservation payments on total employment

	ln(Total employment)		ln(Unemployment rate)	
	Border	Allrural	Border	Allrural
ln(EQIPpay)	0.093** (0.033)	0.052* (0.022)	-0.129** (0.043)	-0.102** (0.036)
ln(CRPpay)	0.075* (0.035)	0.039 (0.031)	0.015 (0.027)	0.015 (0.035)
ln(EQIPpay neighbor)	0.045 (0.036)		-0.004 (0.029)	
ln(CRPpay neighbor)	0.009 (0.026)		-0.019 (0.019)	
Num.Obs.	4561	11 591	4561	11 591
R2	0.980	0.976	0.858	0.807
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
FE: factor(Watershed)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Observation-level controls include: weather controls, the distance from each county-watershed to the nearest city with over 50,000 population, the latitude and longitude of each county-watershed unit center, the county level expected crop subsidy premiums per acre, and population. State-level controls include: average EQIP and CRP payments per farmland acre in neighboring states, weighted crop price, corn premium per farmland acre, political parties, sales tax, median property tax, and tax burden. The “Border” column presents primary specification results for state border county-watersheds in rural areas with more than 10% cropland. The “All rural” column includes all county-watersheds in rural areas exceeding 10% cropland. The dependent variable and the independent variables—EQIPpay, CRPpay, total employment, and unemployment rate—are logged. Standard errors are clustered at the state level. The values in parentheses are the standard errors.

while the unemployment rate reflects only those actively seeking work within the labor force. CRP-funded activities, such as land retirement and environmental restoration, may create new job opportunities in sectors like recreation (as shown in Appendix 4.3), which can draw in individuals previously outside the labor force, such as retirees, homemakers, or discouraged workers. These new entrants raise total employment but do not affect the measured unemployment rate. In addition, many of the jobs created may be part-time, seasonal, or informal, and thus not fully captured in standard unemployment statistics. As a result, CRP appears to increase employment primarily through the extensive margin, rather than by reducing unemployment among active job seekers.

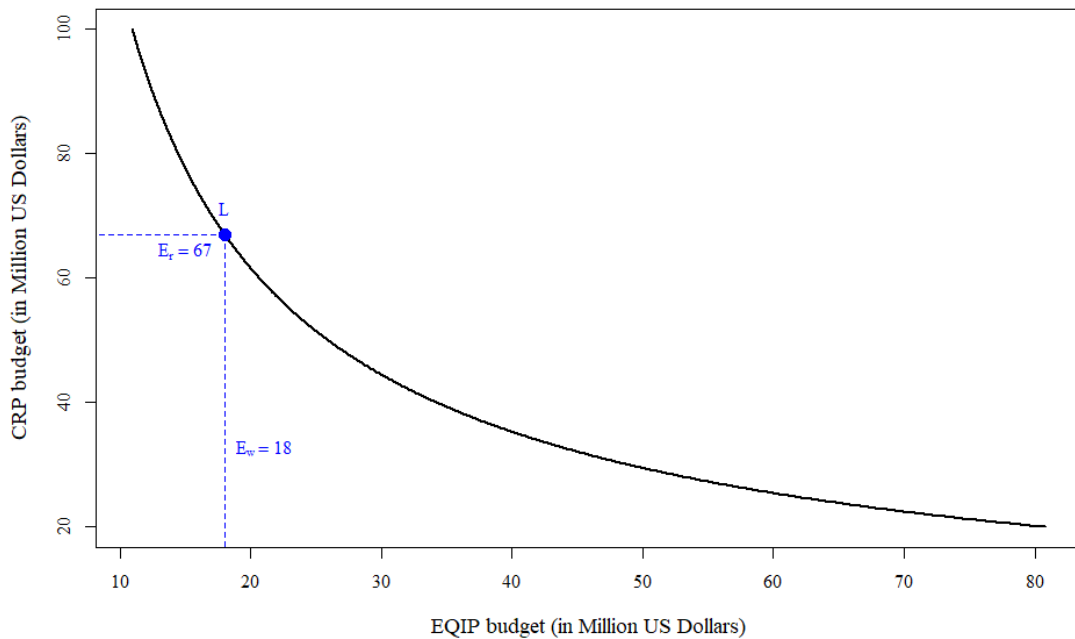


Figure 4.5: Isoquant curve for current total employment in the average county watershed.

We use our results to estimate the net impact of reallocating dollars from retirement to working lands as described in Section 4.3.3. From the results in Table 4.3, the values of $\hat{\beta}_1$ and $\hat{\beta}_2$ are 0.093 and 0.075, respectively. Using these coefficients, along with the average state-level EQIP and CRP payments and assuming a fixed amount of farmland acres at the average level, we predict that reallocating state funds from CRP to EQIP would increase employment by approximately

22.8 jobs per million dollars per year in each county.⁵⁷ The 95% confidence interval (CI) for this estimate ranges from 21.7 to 24.2, indicating that the reallocation would lead to higher overall employment levels. Figure 4.5 presents the parameterized iso-employment curve demonstrating the labor trade-off between allocating conservation funds to land retirement versus working lands at state level. We estimate an iso-employment slope at current budget allocations of -4.82 (with 95% CI: -7.9 to -2.6). This implies that to maintain the same level of employment, a \$1 million reduction in CRP would require only approximately \$207,423 in additional EQIP spending. This suggests that governments or private conservation funders interested in supporting employment in rural areas could achieve similar total employment levels at lower cost by reallocating dollars to working lands conservation and reducing retirement funds, leading to a savings of 79 cents per dollar reallocated.

4.5.2 Employment Impacts by Sector

Table A4.1 presents the estimated impact of EQIP and CRP on agricultural and non-agricultural employment. The results reveal that EQIP has a significant positive impact on both agricultural and non-agricultural employment, while CRP only shows a significant positive impact on non-agricultural employment. The positive impact of EQIP on non-agricultural employment remains but is underestimated when the sample is expanded to all rural counties. Specifically, under the main specification, a 1 percent increase in state-level EQIP payments per farmland acre is associated with a 0.366 percent increase in agricultural employment and a 0.082 percent increase in non-agricultural employment. Quantitatively, given an average of 108 agricultural jobs, 3,092 non-agricultural jobs, our findings suggest that one additional thousand dollars spent in EQIP at the state level leads to 0.0022 additional agricultural jobs and 0.014 additional non-agricultural jobs. We note the similarity between the sum of these impacts by sector and the estimated impact on total employment (0.0162 vs. 0.0166 additional jobs). These findings highlight the broad economic

⁵⁷We use the average share of each county-watershed relative to its county to convert county-watershed-level jobs to county-level jobs. Thus, an increase of 13 jobs per county-watershed corresponds to about $22.8 \times 0.57 \approx 13$ jobs at the county level.

impact of working lands programs, demonstrating their potential to increase employment across multiple sectors in rural, agriculture-dependent areas. We also explore the impacts of different types of EQIP practices (Appendix 4.4).

Table 4.4: The effects of conservation payments on agricultural and non-agricultural employment

	ln(Ag employment)		ln(Non-ag employment)	
	Border	Allrural	Border	Allrural
ln(EQIPpay)	0.366** (0.106)	0.354** (0.103)	0.082* (0.033)	0.043* (0.020)
ln(CRPPay)	-0.076 (0.175)	-0.227+ (0.120)	0.074* (0.035)	0.029 (0.028)
ln(EQIPpay neighbor)	0.139 (0.085)		0.042 (0.038)	
ln(CRPPay neighbor)	0.028 (0.062)		0.011 (0.032)	
Num.Obs.	4561	11 591	4561	11 591
R2	0.821	0.773	0.978	0.973
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
FE: factor(Watershed)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The interpretation of column names, lagged variables, standard errors, fixed effects, and control variables in this table aligns with those detailed in Table 4.3. The values in parentheses are the standard errors.

Regarding CRP, our findings indicate a negative but statistically insignificant impact on the agricultural sector. This ambiguity might be attributed to our use of the 2-digit NAICS code for agriculture, which encompasses fishing, hunting, and agricultural services. While CRP incentivizes farmers to remove land from agricultural production, they may transition to related activities within this broad category, such as fishing and hunting (Bangsund et al. 2004). This transition could potentially obscure the program's direct effect on agricultural employment. We also examine the heterogeneous impacts of EQIP and CRP on specific agricultural and non-agricultural sectors,

including a more detailed sector-specific analysis of the agricultural production sector, which encompasses NAICS 111 (crop production) and NAICS 112 (animal production and aquaculture). The results are presented in Appendix 4.3. We also want to focus more narrowly on the impact of EQIP and CRP on farm labor contractors, classified as NAICS 115115. However, the data limitations prevent us from doing so, particularly when we restrict the analysis to border rural counties, leaving us with only 68 observations.

Our findings on non-agricultural employment differ from those of Li et al. (2023), who find a positive but insignificant impact of CRP on non-agricultural employment. However, when including all rural counties, our results align with theirs. In contrast, by focusing solely on rural border counties and accounting for endogeneity through different specifications, we find that state-level CRP payments per farmland acre has a significantly positive impact on non-agricultural employment. Specifically, a 1 percent increase in state-level CRP spending corresponds to a 0.074 percent increase in non-agricultural employment. These contrasting results may be attributed to several methodological differences. First, our focus on rural and agriculture-dependent counties may capture areas where CRP has a stronger impact on local economies. Next, our treatment of endogeneity differs from Li et al. (2023)'s use of panel data fixed effects and changes in CRP enrollment stock as an explanatory variable. We also simultaneously consider the impacts of CRP and EQIP.

Here, we examine the sector-specific trade-off from reallocating conservation dollars from retirement to working lands. Using our coefficient estimates, we find that reallocating funds to working lands increases employment in the agricultural sector by 2.33 jobs per million dollars (95% CI: 1.57 to 2.96) and in non-agricultural sectors by 10.8 jobs per million dollars (95% CI: 5.8 to 16.7). Although both effects are statistically significant, the estimate for non-agricultural employment is notably less precise, as evidenced by its wider confidence interval. Appendix 4.3 discusses specific sectoral impacts in non-agricultural sectors. The greater variability in the non-agricultural estimate may also explain why the point estimate for the total employment increase is larger but similarly noisier. This underscores the complex nature of economic linkages between agricultural conservation payments and other rural sectors. While the direct impact on agricultural employment is clear,

the indirect effects on non-agricultural sectors are noisier and require further investigation to fully understand the broader economic implications of conservation payment reallocation.

4.6 Robustness Checks: Alternative Specifications

4.6.1 Lewbel IV Method

We apply the Lewbel IV method (Lewbel 2012) as an alternative estimation technique to examine the impacts of EQIP and CRP payments on local employment. Lewbel instruments are derived from the residuals of a regression of the endogenous variables on exogenous variables and rely on heteroskedasticity to construct an instrument from the residuals (Won et al. 2024; Chen et al. 2023). We first estimate the impact of the observable covariates X_{imt} on state-level EQIP and CRP payments per farmland acre, as shown in Equation 4.23 where C_{imt} is either EQIP or CRP payments per farmland acre. Then the instruments are constructed using a set of the demeaned exogenous covariates, each multiplied by the residuals derived from the first-stage equation, $(X_{imt} - \bar{X}) \widehat{\theta}_{imt}$. Two assumptions must be satisfied: heteroscedasticity in Equation 4.23 and X_{imt} is not correlated with the covariance between the first-stage error term and the error term in the main second-stage equation.

$$C_{imt} = \gamma_{ims} X_{imt} + \theta_{imt} \quad (4.23)$$

We employ the Breusch-Pagan (BP) test (Breusch et al. 1979) to examine heteroscedasticity. The BP test statistics for EQIP yield a value of 2086 and for CRP it is 2095, both accompanied by a p-value of less than 0.001. These outcomes substantiate the existence of heteroscedasticity in the first stage of the analysis. In order to evaluate the validity of the constructed instrumental variables, we apply the Hansen J test, an overidentification test, as recommended in Baum et al. (2019).

Table 4.5 presents the findings of our analysis investigating the economic impact of the CRP and EQIP. A notable challenge encountered during our analysis is the violation of the Hansen J test

Table 4.5: The effects of conservation enrollment using Lewbel IV method

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay)	0.092+ (0.053)	0.328** (0.109)	0.082 (0.055)	-0.119*** (0.033)
ln(CRPpay)	0.090** (0.033)	-0.056 (0.130)	0.085* (0.033)	-0.019 (0.024)
ln(EQIPpay neighbor)	0.046 (0.028)	0.150+ (0.084)	0.043 (0.030)	-0.006 (0.023)
ln(CRPpay neighbor)	0.009 (0.026)	0.032 (0.062)	0.012 (0.030)	-0.020 (0.017)
Num.Obs.	4561	4561	4561	4561
R2	0.980	0.820	0.978	0.855
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
IVs:	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes
Hansen J statistic	270.6	340.8	224.4	380.1
Hansen J [P value]	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: The interpretation of standard errors, fixed effects, and control variables in this table aligns with those detailed in Table 4.3. The values in parentheses are the standard errors.

in all of the regressions. The Hansen J test's null hypothesis is that the instruments are exogenous—that is, they are uncorrelated with the error term. Rejecting this null hypothesis suggests that the instruments may be endogenous, which raises concerns about their validity. Therefore, the results from the Lewbel model should be treated with caution (Chen et al. 2023). The intuition is changing the dependent variable changes the structure of the error term, which can change the correlation between the error term and the instruments, which in turn affects the Hansen J test statistic and its p-value. Given this circumstance, it may be inferred that the Lewbel IV estimation technique might not be ideally suited for our current regression framework. Additionally, the Wu-Hausman tests across all models fail to reject the null hypothesis, suggesting that state-level EQIP and CRP payments per farmland acre are exogenous to local labor market outcomes. Despite the methodological caveats, these analyses provide useful information that supports our main results. Specifically, they reinforce the statistically significant positive impact of EQIP on total employment and agricultural employment, as well as its effect in reducing the unemployment rate. Similarly, CRP payments per farmland acre show statistically significant positive effects on total and non-agricultural employment. This consistency supports the robustness of our estimations.

4.7 Discussion and Conclusion

This research provides the first empirical evidence of the impact of a working lands program on local labor markets. It allows us to describe the trade-offs of reallocating funds from land retirement to working lands programs, considering both overall employment levels and the composition of employment. An inherent challenge in evaluating such voluntary programs is the endogeneity of conservation program enrollment. This arises due to unobservable factors that simultaneously affect program participation and the outcomes of interest. To address this issue, we adopt three approaches. First, we narrow the study scope to rural counties located along state borders to control for local unobserved conditions. Then, we use state-level payments per farmland acre as independent variables. By doing so, we seek to extract the exogenous variation in state-level program payments induced by differences in state-level environmental priorities, administrative rules, and funding allocations, rather than local economic conditions. Finally, we exploit the panel nature of our data and apply watershed and region-year fixed effects. This strategy allows us to eliminate the influence of time-invariant factors at the watershed level, such as geographic or climatic characteristics and year-specific shocks shared by counties in the same region. The results reveal that both working lands and land retirement programs can support local employment, though their effects differ across economic sectors. These findings can inform policy discussions where labor market implications are crucial in shaping agricultural and environmental strategies.

In contrast to existing literature, which often suggests negative employment impacts of environmental regulations on industry (Walker 2011), our findings provide evidence that subsidies for conservation on working lands, as represented by EQIP, positively impact rural employment across multiple sectors. CRP also has a positive impact on total rural employment. These results related to the local economic impacts of conservation subsidies can inform the design and anticipated impacts of subsidies for conservation. Recent federal legislation (the Inflation Reduction Act (IRA)) relies heavily on subsidies for the adoption of green technologies such as green energy generation and electric vehicles. While quantitative results are unlikely to transfer directly to regions using

IRA subsidies, the methods and mechanisms explored here can inform future research on the local economic impacts of green subsidies.

A statistically significant association is estimated between EQIP payments and both agricultural and non-agricultural employment, demonstrating the multi-sectoral effects of this program. Non-positive impacts of CRP on agricultural employment are intuitive and suggest that removing land from agriculture may be accompanied by shifts in labor among different agricultural activities or from agriculture to other sectors such as hunting, forestry, and fishing. The positive impact of EQIP on agricultural employment could come from a few mechanisms. First, conservation practices may be more labor intense, requiring more labor per acre of production. It is also possible that subsidies for production increase production along the extensive margin, requiring more labor to accompany additional acres in production. Finally, additional income for farmers may generate more demand for local goods and services.

While both programs have positive impacts on non-agricultural employment, their mechanisms likely differ. For CRP, a reduction in agricultural acres may lead to a reduced demand for agricultural labor. Some of this labor then seeks employment in non-agricultural work, including hunting, fishing, and forestry. For EQIP and CRP, there may be an induced effect if farm households have higher incomes as a result of the payments to farmers through the program. Land enrolled in EQIP often involves the adoption of conservation practices that can generate additional job opportunities in non-agricultural sectors, such as the production and installation of conservation equipment and materials. Additionally, our results depend on the mix of conservation programs implemented. Since the practices likely have different labor demands, our findings may not generalize to every working lands program. Therefore, future work should seek to disentangle the labor market effects of specific conservation practices.

The analysis of the effect of reallocating funds from CRP to EQIP suggests that it is possible to achieve similar total employment outcomes with fewer dollars by strategically shifting funds between these types of policies. This finding implies that, given the same funding amount, shifting resources to working lands programs like EQIP would result in additional rural jobs. In our dataset,

average EQIP payments per state increased by \$6,927,402 from 2009 to 2019. If all of these funds were reallocated from CRP payments, total employment would increase by 156 jobs per county⁵⁸. However, economic efficiency requires consideration of more than just job creation; the environmental benefits of land retirement programs, such as improvements in local environmental quality, must also be considered. These potentially long-term benefits highlight that the net benefit of such programs should not be assessed solely on immediate employment impacts but should also consider their contributions to environmental sustainability and economic resilience. Future research should therefore explore the broader economic and environmental impacts of both land retirement and working lands programs to fully understand their implications.

While increasing agricultural or rural jobs might support local economies, it does not necessarily equate to enhanced growth over time (Foster et al. 2004). The relationship between agricultural productivity, commercialization, and overall economic development remains complex, as increased agricultural productivity does not always translate into proportional income gains for rural populations. In some cases, shifting labor from agriculture to non-agricultural sectors could lead to faster increases in incomes over time (Lewis 1954). Additionally, the ongoing debate regarding the relative benefits of place-based versus employee-based policies suggests that policymakers need to carefully consider whether to focus on supporting rural economies as a whole or targeting assistance directly to rural residents (Freedman 2015).

We acknowledge that in the absence of experimental variation in conservation program enrollment, we cannot rule out all sources of endogeneity. Like the challenges others in the literature have faced when examining the impacts of practice adoption on farmland values (Chen et al. 2023) and the use of crop insurance (Aglasan et al. 2024; Won et al. 2024), we employ a range of controls, identification strategies, and robustness checks to test if omitted variables drive our results. Robustness to the inclusion and exclusion of county and state level controls builds confidence in

⁵⁸We increase EQIP payments and decrease CRP payments by \$6,927,402 per state and estimate a resulting increase of 89 total jobs at the county-watershed level. To translate this into county-level effects, we use the average share of each county-watershed within its county, which is 0.569. This corresponds to an estimated increase of approximately 156 jobs per county.

our results. Schlenker et al. (2007) note that robustness to the choice of controls means that remaining confounders would have to be correlated with our target right-hand side variable (conservation enrollment rates) but not correlated with any of our included controls (weather, state tax policy, soil quality, etc.). A further limitation is that, because we use state-level conservation payments, we cannot fully rule out labor market spillovers within states. While we control for neighboring states' conservation payments to account for cross-state spillovers, within-state spillover effects remain a potential concern. Despite this, future work leveraging quasi-experimental variation in conservation practice adoption would build confidence in the relationships estimated here. Finally, we allocate county-level variables to county-watershed units based on each watershed's share of county area. While we use population shares as a robustness check, this approach may distort results if cropping systems differ across watersheds. As ongoing work, we are exploring allocation by cropland area share to better capture agricultural variation.

An important caveat to our work is that we only observe employment in the QCEW data that is reported by employers (including farms) for Unemployment Insurance. This may under-report agricultural workers, though unauthorized workers often pay into employment programs through the use of borrowed Social Security numbers (Roberts 2019). A more significant concern related to the mechanism driving our results is that farms below a certain size are not required to report employment.⁵⁹ If conservation payments increase economies of scale in production, our results could be driven by an increase in reported agricultural employment rather than an actual increase in employment. Future work connecting conservation payments to farm size can reveal if this mechanism plays an important role in increasing reported agricultural employment. An additional consideration is the inconsistent inclusion of H-2A workers in the QCEW employment data across states, without a clear dataset indicating which states include them. While this variability could potentially introduce bias—especially if H-2A employment trends differ between bordering states or correlate with changes in CRP and EQIP payments—we find this scenario unlikely given our anal-

⁵⁹Under the 1976 amendments to the Federal Unemployment Insurance Tax Act, agricultural labor is reported from farms that pay at least \$20,000 per year to employees.

ysis's scope and geographical distribution. Our robustness check, which excludes states with high H-2A employment, shows consistent results, suggesting that these discrepancies do not materially affect our conclusions.

In conclusion, the analysis of the impacts of a working lands program and land retirement on rural economies reveals the trade-offs and benefits associated with each approach from a regional economic perspective. While we cannot fully assess the cost-effectiveness of these programs without factoring in their environmental benefits, our findings provide valuable insights into how these programs contribute to rural employment. Policymakers could consider these insights when designing future strategies to support rural employment and improve local environmental outcomes. Further research is essential to refine our understanding of the combined economic and environmental impacts of conservation initiatives. By continuing to explore the intricate relationships between conservation efforts, rural employment, and environmental benefits, we can help shape policies that create sustainable, resilient rural economies while preserving our natural resources for future generations.

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APPENDICES

Appendix: Chapter 2

Table A2.1: Coefficient estimates from the discrete choice model

	Logged response		Level of the variable	
	Pre-2015	Post-2015 incl.	Pre-2015	Post-2015 incl.
Net revenue (mean)	-7.780*** (0.098)	-7.577*** (0.076)	0.00167***	0.00194***
Net revenue (SD)	1.665*** (0.052)	1.631*** (0.042)	0.00647***	0.0071***
ASC	X	X	-	-
State FE	X	X	-	-
Year trend	Annual	Annual	-	-
Lag crop	X	X	-	-
Lag tillage	X	X	-	-
Lag cover crop	X	X	-	-
First year	1995	1995	-	-
Observations	252,034	306,272	-	-
R ²	0.559	0.557	-	-
Log Likelihood	-204,713.400	-255,100.200	-	-
LR Test	519,478.000*** (df = 189)	642,244.200*** (df = 189)	-	-

*p<0.1; **p<0.05; ***p<0.01

Note: “ASC” refers to alternative-specific constants for the set of crop practice alternatives. All models control for state fixed effects, an annual trend, and lagged crop, tillage, and cover crop practices. Level estimates represent the implied means and standard deviations of the original (unlogged) response, derived from log-transformed values.

Table A2.2: Yield penalty by crop, payment Level, and management practice (t/ha) under SSP3.70 climate change scenario

Crop	Payment (\$ per tCO ₂ e)	Exogenous Price			Endogenous Price		
		NT	Cover crop	Reduced N	NT	Cover crop	Reduced N
Corn	0	0.8855	0.1755	0.2584	0.8738	0.1796	0.2610
Corn	190	0.8928	0.1776	0.2623	0.8824	0.1821	0.2657
Soybeans	0	0.1619	0.0425	0.0250	0.1628	0.0434	0.0254
Soybeans	190	0.1637	0.0430	0.0253	0.1647	0.0440	0.0258

Source: Author's statistics from simulation results.

Note: These are average yield differences based on producer choices. The "NT" columns report the yield penalty from switching from full tillage to no-till. The "Cover crop" columns represent the average yield penalty from adopting cover crops (i.e., from no cover crop to cover crop). The "Reduced N" columns show the yield penalty from reducing fertilizer application, specifically, from full fertilization to 90% of baseline nitrogen for corn, and from full to zero fertilizer application for soybeans.

Table A2.3: Coefficient estimates for discrete choice model (including all variables)

Variable	Estimate	Std. Error	z-value	Pr(> z)
(Intercept):Corn_FT_1	-315.850844	29.332697	-10.767876	0.000e+00 ***
(Intercept):Corn_NT_0	138.892508	4.630582	29.994609	0.000e+00 ***
(Intercept):Corn_NT_1	-8.541921	32.842274	-0.260089	7.948e-01
(Intercept):Corn_RT_0	90.117868	3.832100	23.516575	0.000e+00 ***
(Intercept):Corn_RT_1	-115.743700	32.680593	-3.541665	3.976e-04 ***
(Intercept):Soybeans_FT_0	9.218950	2.300959	4.006568	6.161e-05 ***
(Intercept):Soybeans_FT_1	-339.871409	26.721780	-12.718891	0.000e+00 ***
(Intercept):Soybeans_NT_0	147.838731	4.783553	30.905634	0.000e+00 ***
(Intercept):Soybeans_NT_1	-132.869776	32.752983	-4.056723	4.977e-05 ***
(Intercept):Soybeans_RT_0	107.341816	4.036161	26.595031	0.000e+00 ***
(Intercept):Soybeans_RT_1	-169.271621	32.659446	-5.182930	2.184e-07 ***
profit	-7.780291	0.098389	-79.076837	0.000e+00 ***
state_abbrIL:Corn_FT_1	-0.082841	0.178046	-0.465278	6.417e-01
state_abbrIL:Corn_NT_0	0.162215	0.034595	4.688995	2.746e-06 ***
state_abbrIL:Corn_NT_1	-0.140717	0.190890	-0.737164	4.610e-01
state_abbrIL:Corn_RT_0	-0.195943	0.031612	-6.198440	5.703e-10 ***
state_abbrIL:Corn_RT_1	-0.539397	0.187885	-2.870896	4.093e-03 **
state_abbrIL:Soybeans_FT_0	0.060262	0.024087	2.501808	1.236e-02 *
state_abbrIL:Soybeans_FT_1	0.416077	0.184573	2.254266	2.418e-02 *
state_abbrIL:Soybeans_NT_0	0.253853	0.037386	6.789979	1.122e-11 ***
state_abbrIL:Soybeans_NT_1	0.262752	0.190724	1.377655	1.683e-01
state_abbrIL:Soybeans_RT_0	-0.204950	0.034005	-6.027089	1.669e-09 ***

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Variable	Estimate	Std. Error	z-value	Pr(> z)
state_abbrIL:Soybeans_RT_1	-0.037429	0.202854	-0.184512	8.536e-01
state_abbrIN:Corn_FT_1	0.155545	0.181139	0.858704	3.905e-01
state_abbrIN:Corn_NT_0	0.223979	0.040138	5.580183	2.403e-08 ***
state_abbrIN:Corn_NT_1	0.348024	0.200118	1.739096	8.202e-02 ..
state_abbrIN:Corn_RT_0	-0.453175	0.041493	-10.921727	0.000e+00 ***
state_abbrIN:Corn_RT_1	0.095928	0.188940	0.507718	6.117e-01
state_abbrIN:Soybeans_FT_0	0.445658	0.028731	15.511483	0.000e+00 ***
state_abbrIN:Soybeans_FT_1	0.776412	0.190706	4.071258	4.676e-05 ***
state_abbrIN:Soybeans_NT_0	0.857084	0.042897	19.979897	0.000e+00 ***
state_abbrIN:Soybeans_NT_1	1.104757	0.200466	5.510944	3.569e-08 ***
state_abbrIN:Soybeans_RT_0	0.123557	0.043580	2.835146	4.580e-03 **
state_abbrIN:Soybeans_RT_1	0.892726	0.202703	4.404111	1.062e-05 ***
state_abbrKS:Corn_FT_1	0.861297	0.243102	3.542943	3.957e-04 ***
state_abbrKS:Corn_NT_0	0.347855	0.089414	3.890389	1.001e-04 ***
state_abbrKS:Corn_NT_1	0.785304	0.292496	2.684840	7.256e-03 **
state_abbrKS:Corn_RT_0	0.254296	0.081784	3.109344	1.875e-03 **
state_abbrKS:Corn_RT_1	0.557511	0.262332	2.125209	3.357e-02 *
state_abbrKS:Soybeans_FT_0	1.656255	0.054075	30.629120	0.000e+00 ***
state_abbrKS:Soybeans_FT_1	2.452421	0.220247	11.134853	0.000e+00 ***
state_abbrKS:Soybeans_NT_0	1.888300	0.086713	21.776489	0.000e+00 ***
state_abbrKS:Soybeans_NT_1	2.280350	0.260310	8.760124	0.000e+00 ***
state_abbrKS:Soybeans_RT_0	1.505875	0.082615	18.227632	0.000e+00 ***
state_abbrKS:Soybeans_RT_1	2.207182	0.253229	8.716147	0.000e+00 ***
state_abbrKY:Corn_FT_1	1.806450	0.531454	3.399068	6.762e-04 ***

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Variable	Estimate	Std. Error	z-value	Pr(> z)
state_abbrKY:Corn_NT_0	1.067707	0.252066	4.235815	2.277e-05 ***
state_abbrKY:Corn_NT_1	3.221821	0.402411	8.006301	1.110e-15 ***
state_abbrKY:Corn_RT_0	-1.152955	0.448280	-2.571953	1.011e-02 *
state_abbrKY:Corn_RT_1	1.882112	0.694294	2.710830	6.711e-03 **
state_abbrKY:Soybeans_FT_0	0.231768	0.219632	1.055258	2.913e-01
state_abbrKY:Soybeans_FT_1	1.073571	0.751297	1.428958	1.530e-01
state_abbrKY:Soybeans_NT_0	1.164337	0.266247	4.373144	1.225e-05 ***
state_abbrKY:Soybeans_NT_1	3.221476	0.427492	7.535767	4.863e-14 ***
state_abbrKY:Soybeans_RT_0	-1.059602	0.426926	-2.481933	1.307e-02 *
state_abbrKY:Soybeans_RT_1	2.894535	0.680254	4.255081	2.090e-05 ***
state_abbrMI:Corn_FT_1	0.983744	0.207677	4.736896	2.170e-06 ***
state_abbrMI:Corn_NT_0	-0.215540	0.059160	-3.643355	2.691e-04 ***
state_abbrMI:Corn_NT_1	0.263816	0.281810	0.936148	3.492e-01
state_abbrMI:Corn_RT_0	-0.015478	0.051654	-0.299647	7.644e-01
state_abbrMI:Corn_RT_1	0.982890	0.201523	4.877316	1.075e-06 ***
state_abbrMI:Soybeans_FT_0	0.153641	0.036043	4.262736	2.019e-05 ***
state_abbrMI:Soybeans_FT_1	1.316173	0.216039	6.092289	1.113e-09 ***
state_abbrMI:Soybeans_NT_0	0.346132	0.061093	5.665697	1.464e-08 ***
state_abbrMI:Soybeans_NT_1	0.543181	0.284599	1.908585	5.632e-02 ..
state_abbrMI:Soybeans_RT_0	0.261658	0.052889	4.947328	7.524e-07 ***
state_abbrMI:Soybeans_RT_1	1.274798	0.229860	5.545977	2.923e-08 ***
state_abbrMN:Corn_FT_1	-0.527020	0.241027	-2.186560	2.877e-02 *
state_abbrMN:Corn_NT_0	-1.166513	0.060213	-19.373046	0.000e+00 ***
state_abbrMN:Corn_NT_1	-1.936278	0.495059	-3.911203	9.184e-05 ***

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Variable	Estimate	Std. Error	z-value	Pr(> z)
state_abbrMN:Corn_RT_0	-0.097219	0.033975	-2.861470	4.217e-03 **
state_abbrMN:Corn_RT_1	-0.678333	0.263969	-2.569748	1.018e-02 *
state_abbrMN:Soybeans_FT_0	0.319754	0.027071	11.811788	0.000e+00 ***
state_abbrMN:Soybeans_FT_1	-0.007144	0.240364	-0.029721	9.763e-01
state_abbrMN:Soybeans_NT_0	-0.922742	0.064170	-14.379699	0.000e+00 ***
state_abbrMN:Soybeans_NT_1	-1.099134	0.372285	-2.952401	3.153e-03 **
state_abbrMN:Soybeans_RT_0	0.210359	0.036661	5.737956	9.583e-09 ***
state_abbrMN:Soybeans_RT_1	-0.374766	0.286975	-1.305920	1.916e-01
state_abbrMO:Corn_FT_1	1.570301	0.185667	8.457616	0.000e+00 ***
state_abbrMO:Corn_NT_0	0.122891	0.058711	2.093172	3.633e-02 *
state_abbrMO:Corn_NT_1	0.948174	0.204002	4.647864	3.354e-06 ***
state_abbrMO:Corn_RT_0	-0.005231	0.053083	-0.098552	9.215e-01
state_abbrMO:Corn_RT_1	1.428024	0.179569	7.952532	1.776e-15 ***
state_abbrMO:Soybeans_FT_0	1.831758	0.036616	50.026822	0.000e+00 ***
state_abbrMO:Soybeans_FT_1	2.898453	0.192399	15.064790	0.000e+00 ***
state_abbrMO:Soybeans_NT_0	1.844756	0.058514	31.526610	0.000e+00 ***
state_abbrMO:Soybeans_NT_1	2.683591	0.206682	12.984159	0.000e+00 ***
state_abbrMO:Soybeans_RT_0	1.769770	0.052874	33.471337	0.000e+00 ***
state_abbrMO:Soybeans_RT_1	3.295331	0.189940	17.349326	0.000e+00 ***
state_abbrNE:Corn_FT_1	0.508267	0.291157	1.745683	8.087e-02 ..
state_abbrNE:Corn_NT_0	0.413945	0.053948	7.673063	1.688e-14 ***
state_abbrNE:Corn_NT_1	0.497726	0.279171	1.782872	7.461e-02 ..
state_abbrNE:Corn_RT_0	-0.019687	0.053335	-0.369125	7.120e-01
state_abbrNE:Corn_RT_1	0.457979	0.277769	1.648779	9.919e-02 ..

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Variable	Estimate	Std. Error	z-value	Pr(> z)
state_abbrNE:Soybeans_FT_0	0.065372	0.042588	1.534989	1.248e-01
state_abbrNE:Soybeans_FT_1	0.485041	0.323927	1.497376	1.343e-01
state_abbrNE:Soybeans_NT_0	0.696943	0.058153	11.984638	0.000e+00 ***
state_abbrNE:Soybeans_NT_1	0.770350	0.292532	2.633386	8.454e-03 **
state_abbrNE:Soybeans_RT_0	0.259906	0.056707	4.583290	4.577e-06 ***
state_abbrNE:Soybeans_RT_1	0.885843	0.275388	3.216713	1.297e-03 **
state_abbrOH:Corn_FT_1	0.108010	0.219327	0.492462	6.224e-01
state_abbrOH:Corn_NT_0	0.491760	0.045929	10.706930	0.000e+00 ***
state_abbrOH:Corn_NT_1	0.453622	0.211111	2.148737	3.166e-02 *
state_abbrOH:Corn_RT_0	-0.576314	0.052599	-10.956741	0.000e+00 ***
state_abbrOH:Corn_RT_1	-0.399281	0.232477	-1.717507	8.589e-02 ..
state_abbrOH:Soybeans_FT_0	1.370450	0.033784	40.564477	0.000e+00 ***
state_abbrOH:Soybeans_FT_1	1.754171	0.203588	8.616282	0.000e+00 ***
state_abbrOH:Soybeans_NT_0	1.937137	0.047903	40.438860	0.000e+00 ***
state_abbrOH:Soybeans_NT_1	2.148400	0.203217	10.571958	0.000e+00 ***
state_abbrOH:Soybeans_RT_0	0.965094	0.053391	18.076123	0.000e+00 ***
state_abbrOH:Soybeans_RT_1	1.895532	0.223132	8.495127	0.000e+00 ***
state_abbrSD:Corn_FT_1	0.580764	0.288528	2.012849	4.413e-02 *
state_abbrSD:Corn_NT_0	-0.486927	0.088839	-5.481009	4.229e-08 ***
state_abbrSD:Corn_NT_1	-0.547441	0.552395	-0.991033	3.217e-01
state_abbrSD:Corn_RT_0	0.123743	0.057470	2.153191	3.130e-02 *
state_abbrSD:Corn_RT_1	0.677364	0.294238	2.302093	2.133e-02 *
state_abbrSD:Soybeans_FT_0	0.628580	0.045556	13.798012	0.000e+00 ***
state_abbrSD:Soybeans_FT_1	1.400818	0.270177	5.184816	2.162e-07 ***

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Variable	Estimate	Std. Error	z-value	Pr(> z)
state_abbrSD:Soybeans_NT_0	-0.029817	0.093153	-0.320084	7.489e-01
state_abbrSD:Soybeans_NT_1	0.517481	0.437125	1.183827	2.365e-01
state_abbrSD:Soybeans_RT_0	0.751831	0.059487	12.638674	0.000e+00 ***
state_abbrSD:Soybeans_RT_1	1.525338	0.291011	5.241520	1.593e-07 ***
state_abbrWI:Corn_FT_1	0.131637	0.287197	0.458353	6.467e-01
state_abbrWI:Corn_NT_0	-0.195878	0.082635	-2.370389	1.777e-02 *
state_abbrWI:Corn_NT_1	-0.219173	0.499472	-0.438808	6.608e-01
state_abbrWI:Corn_RT_0	0.077396	0.063836	1.212424	2.254e-01
state_abbrWI:Corn_RT_1	-0.077114	0.346459	-0.222578	8.239e-01
state_abbrWI:Soybeans_FT_0	-0.962599	0.050122	-19.205046	0.000e+00 ***
state_abbrWI:Soybeans_FT_1	0.016334	0.337043	0.048463	9.613e-01
state_abbrWI:Soybeans_NT_0	-0.648613	0.088023	-7.368696	1.723e-13 ***
state_abbrWI:Soybeans_NT_1	-1.228800	0.508190	-2.417991	1.561e-02 *
state_abbrWI:Soybeans_RT_0	-0.623519	0.070479	-8.846924	0.000e+00 ***
state_abbrWI:Soybeans_RT_1	-0.127911	0.381950	-0.334890	7.377e-01
year:Corn_FT_1	0.154593	0.014583	10.600942	0.000e+00 ***
year:Corn_NT_0	-0.070592	0.002314	-30.507634	0.000e+00 ***
year:Corn_NT_1	0.000179	0.016364	0.010942	9.913e-01
year:Corn_RT_0	-0.046055	0.001914	-24.061767	0.000e+00 ***
year:Corn_RT_1	0.053811	0.016280	3.305250	9.489e-04 ***
year:Soybeans_FT_0	-0.004057	0.001149	-3.531135	4.138e-04 ***
year:Soybeans_FT_1	0.166931	0.013296	12.555273	0.000e+00 ***
year:Soybeans_NT_0	-0.074512	0.002391	-31.168869	0.000e+00 ***
year:Soybeans_NT_1	0.062617	0.016326	3.835422	1.253e-04 ***

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Variable	Estimate	Std. Error	z-value	Pr(> z)
year:Soybeans_RT_0	-0.054053	0.002017	-26.801719	0.000e+00 ***
year:Soybeans_RT_1	0.080707	0.016265	4.961842	6.983e-07 ***
lag_cropSoybeans:Corn_FT_1	-0.504857	0.104173	-4.846322	1.258e-06 ***
lag_cropSoybeans:Corn_NT_0	0.123740	0.028997	4.267371	1.978e-05 ***
lag_cropSoybeans:Corn_NT_1	0.031855	0.129055	0.246832	8.050e-01
lag_cropSoybeans:Corn_RT_0	0.127701	0.026319	4.852103	1.222e-06 ***
lag_cropSoybeans:Corn_RT_1	-0.114710	0.117809	-0.973689	3.302e-01
lag_cropSoybeans:Soybeans_FT_0	-3.442324	0.018140	-189.759389	0.000e+00 ***
lag_cropSoybeans:Soybeans_FT_1	-2.859981	0.107640	-26.569843	0.000e+00 ***
lag_cropSoybeans:Soybeans_NT_0	-3.288268	0.031520	-104.321721	0.000e+00 ***
lag_cropSoybeans:Soybeans_NT_1	-2.868753	0.116476	-24.629647	0.000e+00 ***
lag_cropSoybeans:Soybeans_RT_0	-3.612843	0.029777	-121.331148	0.000e+00 ***
lag_cropSoybeans:Soybeans_RT_1	-3.539796	0.122719	-28.844623	0.000e+00 ***
lag_tillageNT:Corn_FT_1	0.215826	0.435010	0.496140	6.198e-01
lag_tillageNT:Corn_NT_0	8.390557	0.102010	82.252433	0.000e+00 ***
lag_tillageNT:Corn_NT_1	8.760686	0.255909	34.233596	0.000e+00 ***
lag_tillageNT:Corn_RT_0	3.667208	0.117759	31.141740	0.000e+00 ***
lag_tillageNT:Corn_RT_1	4.169881	0.357310	11.670211	0.000e+00 ***
lag_tillageNT:Soybeans_FT_0	-0.077594	0.150716	-0.514835	6.067e-01
lag_tillageNT:Soybeans_FT_1	0.387199	0.411499	0.940947	3.467e-01
lag_tillageNT:Soybeans_NT_0	8.364650	0.102767	81.394600	0.000e+00 ***
lag_tillageNT:Soybeans_NT_1	8.632415	0.249854	34.549836	0.000e+00 ***
lag_tillageNT:Soybeans_RT_0	3.641420	0.121587	29.949151	0.000e+00 ***
lag_tillageNT:Soybeans_RT_1	4.947356	0.324253	15.257685	0.000e+00 ***

Continued on next page

Variable	Estimate	Std. Error	z-value	Pr(> z)
lag_tillageRT:Corn_FT_1	-0.246697	0.459903	-0.536410	5.917e-01
lag_tillageRT:Corn_NT_0	1.489093	0.165049	9.022144	0.000e+00 ***
lag_tillageRT:Corn_NT_1	1.881798	1.052291	1.788287	7.373e-02 ..
lag_tillageRT:Corn_RT_0	7.729947	0.076641	100.858636	0.000e+00 ***
lag_tillageRT:Corn_RT_1	7.703502	0.214830	35.858622	0.000e+00 ***
lag_tillageRT:Soybeans_FT_0	0.026485	0.110350	0.240006	8.103e-01
lag_tillageRT:Soybeans_FT_1	0.353963	0.380992	0.929056	3.529e-01
lag_tillageRT:Soybeans_NT_0	1.335457	0.184365	7.243562	4.370e-13 ***
lag_tillageRT:Soybeans_NT_1	1.693533	1.064597	1.590774	1.117e-01
lag_tillageRT:Soybeans_RT_0	7.743920	0.077724	99.633243	0.000e+00 ***
lag_tillageRT:Soybeans_RT_1	8.116522	0.232550	34.902233	0.000e+00 ***
lag_CoverCrop1:Corn_FT_1	6.575921	0.128171	51.305718	0.000e+00 ***
lag_CoverCrop1:Corn_NT_0	-0.159073	0.238556	-0.666816	5.049e-01
lag_CoverCrop1:Corn_NT_1	5.935431	0.228892	25.931195	0.000e+00 ***
lag_CoverCrop1:Corn_RT_0	-0.230435	0.219124	-1.051618	2.930e-01
lag_CoverCrop1:Corn_RT_1	6.056144	0.214983	28.170403	0.000e+00 ***
lag_CoverCrop1:Soybeans_FT_0	0.405393	0.139007	2.916355	3.541e-03 **
lag_CoverCrop1:Soybeans_FT_1	6.030086	0.132937	45.360552	0.000e+00 ***
lag_CoverCrop1:Soybeans_NT_0	0.107539	0.227880	0.471912	6.370e-01
lag_CoverCrop1:Soybeans_NT_1	5.488086	0.220362	24.904853	0.000e+00 ***
lag_CoverCrop1:Soybeans_RT_0	0.074143	0.224222	0.330670	7.409e-01
lag_CoverCrop1:Soybeans_RT_1	5.734536	0.215149	26.653829	0.000e+00 ***
sd.profit	1.665427	0.051862	32.112581	0.000e+00 ***

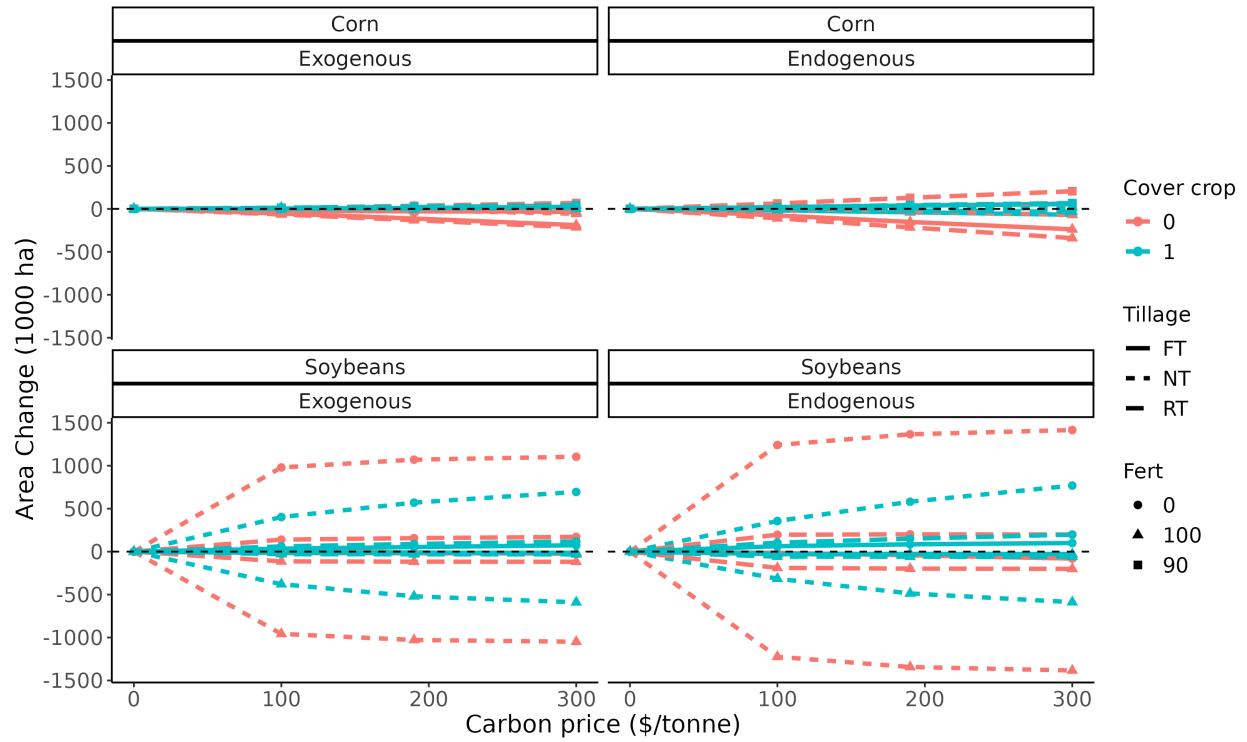


Figure A2.1: Disaggregated area changes by crop, cover cropping, tillage, and fertilizer across carbon price scenarios under SSP3.70 climate scenario

Appendix: Chapter 3

Table A3.1: Sensitivity analysis: elasticity of transformation effects on land use change and emissions

Category	Type	Elasticity Range	Model Result	Lower Bound	Upper Bound
Land Use Change	Forest	{-0.75, -0.25}	-236.33	-314.59	-162.91
	Unmanaged	{-0.75, -0.25}	-140.66	-185.46	-93.99
	Cropland	{-0.75, -0.25}	-421.10	-443.78	-400.34
	Pasture	{-0.75, -0.25}	-823.51	-865.27	-777.19
Emissions	Crop to CRP	{-0.75, -0.25}	-1,926.22	-2,039.33	-1,824.98
	Total in U.S.	{-0.75, -0.25}	1,143.29	52.48	2,283.98
	Total Worldwide	{-0.75, -0.25}	2,029.67	1,070.10	3,030.80

Note: Land use changes measured in thousands of hectares. Emissions measured in thousands of tonnes CO₂ per year. Results show 95% confidence intervals from sensitivity analysis varying elasticity of transformation parameters.

Source: Authors' simulation results.

Table A3.2: Correspondence of sectors in GTAP-CRP and GTAP 11

Sector in GTAP-CRP	Description	Sectors in GTAP 11
pdr	rice: seed, paddy (not husked)	pdr
wht	wheat: seed, other	wht
gro	other Grains: maize (corn), sorghum, barley, rye, oats, millets, other cereals	gro
v_f	veg and fruit: vegetables, fruit and nuts, edible roots and tubers, pulses	v_f
osd	oil Seeds: oil seeds and oleaginous fruit	osd
c_b	cane and Beet: sugar crops	c_b
pfb	fibres crops	pfb
ocr	other Crops	ocr
Lstk CRP	livestock row milk wool CRP	ctl, oap, rmk, wol
frs	forest	frs
ProcFood	processed Food	cmt, omt, vol, mil, pcr, sgr, ofd, b_t
Mnfc	Manufacturing	fsh, coa, oil, gas, oxt, tex, wap, lea, lum, ppp, p_c, chm, bph, rpp, nmm, i_s, nfm, fmp, ele, eeq, ome, mwh, otn, omf
Services	other services	elv, gdt, wtr, cns, trd, afs, otp, wtp, atp, whs, cmn, ofi, ins, rsa, obs, ros, osg, edu, hht, dwe

Table A3.3: Correspondence of regions in GTAP-CRP and GTAP 11

Region in GTAP-CRP	Description	Regions in GTAP 11
US	United States	usa
RNAmerica	Rest of North America	can, mex, xna
Chk	China and Hong Kong	chn, hkg
Eur	Europe	aut, bel, bgr, hrv, cyp, cze, dnk, est, fin, fra, deu, grc, hun, irl, ita, lva, ltu, lux, mlt, nld, pol, prt, rou, svk, svn, esp, swe, gbr, che, nor, xef, alb, srb, blr, rus, ukr, xee, xer, kaz, kgz, tjk, uzb, xsu, arm, aze, geo
CSAfri	Central and Southern Africa	ben, bfa, cmr, civ, gha, gin, mli, ner, nga, sen, tgo, xwf, caf, tcd, cog, cod, gnq, gab, xac, com, eth, ken, mdg, mwi, mus, moz, rwa, sdn, tza, uga, zmb, zwe, xec, bwa, swz, nam, zaf, xsc, xtw
SEAisa	Southeast Asia	khm, idn, lao, mys, phl, sgp, tha, vnm, xse
RAsiaO	Rest of Asia and Oceania	aus, nzl, xoc, jpn, kor, mng, twn, xea, brn, bgd, ind, npl, pak, lka, xsa, afg
MENA	Middle East and North Africa	bhr, irn, irq, isr, jor, kwt, lbn, omn, pse, qat, sau, syr, tur, are, xws, dza, egy, mar, tun, xnf
CSAmer	Central and South America	arg, bol, bra, chl, col, ecu, pry, per, ury, ven, xsm, cri, gtm, hnd, nic, pan, slv, xca, dom, hti, jam, pri, tto, xcb

Table A3.4: Emission factors associated with land cover transitions across AEZs in the U.S. (in Mg CO₂e per hectare)

AEZ	CROP2FOR	CROP2PAST	FOR2CROP	FOR2PAST	PAST2CROP	PAST2FOR	CROP2CRP	PAST2CRP	UMAN2CROP	UMAN2PAST	Total
AEZ1	0	0	0	0	0	0	0	0	0	0	0
AEZ2	0	0	0	0	0	0	0	0	0	0	0
AEZ3	0	0	0	0	0	0	0	0	0	0	0
AEZ4	0	0	0	0	0	0	0	0	0	0	0
AEZ5	0	0	0	0	0	0	0	0	0	0	0
AEZ6	0	0	0	0	0	0	0	0	0	0	0
AEZ7	-376	-54	376	331	91	-279.212	-54	0	91	0	125.788
AEZ8	-411	-63	411	393	99	-294.132	-63	0	99	0	170.868
AEZ9	-439	-71	439	490	113	-313.395	-71	0	113	0	260.605
AEZ10	-441	-127	441	368	123	-279.480	-127	0	123	0	80.520
AEZ11	-419	-111	419	355	111	-276.329	-111	0	111	0	78.671
AEZ12	-398	-93	398	309	103	-269.906	-93	0	103	0	59.094
AEZ13	-243	-62	243	395	53	-139.652	-62	0	53	0	237.348
AEZ14	-255	-62	255	429	65	-147.755	-62	0	65	0	287.245
AEZ15	-291	-70	291	534	106	-173.050	-70	0	106	0	432.950
AEZ16	-395	-119	395	713	204	-215.933	-119	0	204	0	667.067
AEZ17	0	0	0	0	0	0	0	0	0	0	0
AEZ18	0	0	0	0	0	0	0	0	0	0	0
Total	-3668	-832	3668	4317	1068	-2388.844	-832	0	1068	0	2400.156

Source: Plevin et al. (2014).

Table A3.5: The land cover changes in U.S. in 1000 hectares

AEZ	Forest	Unmanaged	Cropland	Pastureland	CRP
AEZ 1	0	0	0	0	0
AEZ 2	0	0	0	0	0
AEZ 3	0	0	0	0	0
AEZ 4	0	0	0	0	0
AEZ 5	0	0	0	0	0
AEZ 6	0	0	0.01	-0.01	0
AEZ 7	2.37	0	-14.01	-206.02	217.67
AEZ 8	-25.72	-123.56	-103.33	-516.33	768.94
AEZ 9	-10.01	-8.71	-33.93	-42.24	94.89
AEZ 10	-81.82	0	-198.61	-52.59	333.02
AEZ 11	-52.98	0	-35.98	-9.78	98.73
AEZ 12	-84.94	0	-0.91	-16.05	101.9
AEZ 13	-0.11	0	0	0.08	0.02
AEZ 14	-0.95	0	0.01	0	0.94
AEZ 15	-0.16	0	-0.01	-0.02	0.2
AEZ 16	0	0	0	0	0
AEZ 17	0	0	0	0	0
AEZ 18	0	0	0	0	0
Total	-254.32	-132.27	-386.76	-842.96	1616.31

Source: Authors' simulation.

Table A3.6: Emissions from land cover changes across all AEZs in the U.S. (1,000 tCO₂e per year; full version of Table 3.4)

AEZ	Crop-Forest	Crop-Pasture	Forest-Crop	Forest-Pasture	Pasture-Crop	Pasture-Forest	Crop-CRP	Pasture-CRP	Unmanaged-Crop	Total
AEZ 1	0	0	0	0	0	0	0	0	0	0
AEZ 2	0	0	0	0	0	0	0	0	0	0
AEZ 3	0	0	0	0	0	0	0	0	0	0
AEZ 4	0	0	0	0	0	0	0	0	0	0
AEZ 5	0	0	0	0	0	0	0	0	0	0
AEZ 6	0	0	0	0	0	0	0	0	0	0
AEZ 7	-2.31	0	0	0	0	-30.63	-27.16	0	0	-60.10
AEZ 8	0	0	46.12	169.68	0	0	-298.04	0	89.43	7.19
AEZ 9	0	0	58.86	81.46	0	0	-102.22	0	15.63	53.73
AEZ 10	0	0	712.36	220.05	0	0	-1081.08	0	0	-148.67
AEZ 11	0	0	526.66	163.75	0	0	-272.98	0	0	417.43
AEZ 12	0	0	614.07	387.25	0	0	-144.39	0	0	856.93
AEZ 13	0	0	0.04	1.42	0	0	-0.01	0	0	1.45
AEZ 14	0	0	0.73	12.61	0	0	-0.16	0	0	13.18
AEZ 15	0	0	0.59	1.72	0	0	-0.17	0	0	2.14
AEZ 16	0	0	0	0	0	0	0	0	0	0
AEZ 17	0	0	0	0	0	0	0	0	0	0
AEZ 18	0	0	0	0	0	0	0	0	0	0
Total	-2.31	0	1959.43	1037.95	0	-30.63	-1926.22	0	105.07	1143.29

Source: Authors' simulation.

Table A3.7: The impact of CRP on land prices for different land covers in U.S. (full version of Table 3.7)

AEZs	U.S. total	Forestland	Agricultural	Cropland	Pastureland	CRPland
AEZ 1	0	0	0	0	0	0
AEZ 2	0	0	0	0	0	0
AEZ 3	0	0	0	0	0	0
AEZ 4	0	0	0	0	0	0
AEZ 5	1.79	1.79	1.79	1.80	1.56	1.79
AEZ 6	1.85	1.85	1.85	1.86	1.57	1.85
AEZ 7	3.63	0.68	3.87	1.80	1.61	20.30
AEZ 8	3.34	0.68	3.50	1.76	1.60	20.28
AEZ 9	2.22	0.66	2.31	1.76	1.58	20.21
AEZ 10	2.23	0.66	2.77	1.75	1.58	20.23
AEZ 11	1.62	0.66	1.91	1.65	1.56	20.19
AEZ 12	1.17	0.65	1.95	1.63	1.56	20.18
AEZ 13	0.67	0.65	1.74	1.72	1.55	20.16
AEZ 14	0.83	0.65	2.13	1.72	1.56	20.18
AEZ 15	1.51	0.66	2.59	1.71	1.57	20.21
AEZ 16	0.65	0.65	1.55	1.19	1.55	1.19
AEZ 17	0	0	0	0	0	0
AEZ 18	0	0	0	0	0	0

Note: All values are expressed in percent changes.

Source: Authors' simulation.

Appendix: Chapter 4

Appendix 4.1 Additional Robustness Checks

In this section, we present several additional robustness checks, including different distribution methods for creating county-watershed observations from county-level data, and the addition or removal of controls. We also examine the resulting effects on employment per population.

Appendix 4.1.1 Results on Wages and Wages Per Employment

This section presents a robustness check using total wages and wages per employment as alternative outcomes to our main employment measures. Table A4.1 reports the detailed results. We find that conservation payments significantly increase total wages, but have no significant effect on wages per worker in either sector. The alignment between total wage effects and employment results suggests that conservation programs increase labor demand primarily at the extensive margin, further supporting the robustness of our main findings.

Table A4.1: The effects of conservation payments on agricultural and non-agricultural wages

	ln(Ag wages)		ln(Non-ag wages)	
	Total	Per employment	Total	Per employment
ln(EQIPpay)	0.349** (0.111)	-0.017 (0.014)	0.090+ (0.047)	0.008 (0.020)
ln(CRPPay)	-0.041 (0.192)	0.035 (0.021)	0.109* (0.050)	0.035+ (0.018)
ln(EQIPpay neighbor)	0.141 (0.088)	0.002 (0.012)	0.047 (0.050)	0.005 (0.020)
ln(CRPPay neighbor)	0.024 (0.062)	-0.004 (0.012)	0.033 (0.045)	0.022 (0.018)
Num.Obs.	4561	4561	4561	4561
R2	0.813	0.494	0.965	0.488
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
FE: factor(Watershed)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The interpretation of column names, lagged variables, standard errors, fixed effects, and control variables in this table aligns with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.2 Results on Employment Per Population

This section presents the results of our robustness check using employment per population as an alternative measure to our main employment outcomes. Table A4.2 presents the detailed results of this analysis. Our findings indicate significant positive effects of conservation payments on employment per population across various sectors. Importantly, these results are consistent with our main findings, reinforcing the robustness of our primary conclusions.

Table A4.2: The effects of conservation payments on employment per population

	ln(Total employment/Pop)	ln(Ag employment/Pop)	ln(Non-ag employment/Pop)	ln(Unemployment rate)
ln(EQIPpay)	0.085* (0.036)	0.374** (0.106)	0.073+ (0.037)	-0.130** (0.043)
ln(CRPPay)	0.084+ (0.042)	-0.085 (0.175)	0.083+ (0.043)	0.015 (0.027)
Num.Obs.	4561	4561	4561	4561
R2	0.330	0.577	0.328	0.858
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.3 Robustness Check with Land Capability Controls

This section presents the results of our robustness check, which involves adding additional observation-level controls—specifically, land capability classes—to address concerns that soil quality may impact conservation program enrollment, especially for the CRP.

We obtained the Soil Capability for Agriculture data from Esri’s Living Atlas of the World⁶⁰. This dataset includes eight classes for the Nonirrigated Capability Class, as detailed in the USA SSURGO data⁶¹. For simplicity, we aggregated the eight soil capability classes into three categories. Classes I–IV are suitable for mechanized crop production, albeit with increasing limitations from Class I to Class IV. Classes V–VII are unsuitable for regular cultivation and are better suited for permanent cover such as grasses or trees. Class VIII has severe limitations, making it suitable only for recreation or wildlife purposes. This aggregation clarifies land use capabilities and simplifies the analysis. We then calculated the acreage that falls into each class within each county watershed unit. The regression results, presented in Table A4.3, show that incorporating soil capability controls does not affect the estimated impacts of state-level EQIP and CRP payments per farmland acre on local employment, although land capability itself may also be significant.

⁶⁰Analyzing Soil Capability for Agriculture in the Living Atlas of the World

⁶¹USA SSURGO—Nonirrigated Capability Class

Table A4.3: The effects of conservation payments on the labor market with land capability controls

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay)	0.095** (0.035)	0.407*** (0.110)	0.085* (0.035)	-0.117* (0.044)
ln(CRPPay)	0.072* (0.035)	-0.067 (0.173)	0.070+ (0.035)	0.019 (0.025)
Class1	0.364 (0.355)	3.345* (1.412)	0.188 (0.326)	-0.041 (0.180)
Class2	-0.667+ (0.382)	-2.999 (2.707)	-0.803* (0.392)	-0.276 (0.259)
Class3	-0.484 (3.708)	13.513 (10.542)	0.385 (3.976)	6.668*** (1.806)
Num.Obs.	4561	4561	4561	4561
R2	0.980	0.826	0.978	0.859
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.4 Adding and Removing State Level Controls

In this section, we examine the robustness of our findings by modifying state-level controls in the model. Specifically, we test the impact of adding state-level GDP data from the BEA and state-level population data from the U.S. Census Bureau for 2009-2019. Additionally, we explore the effects of removing certain state-level controls, such as EQIP and CRP payments per farmland acre in neighboring states, state-level crop prices, state-level tax variables, and political party variables, sequentially. By doing so, we aim to isolate the influence of the state level shock on employment outcomes.

Tables A4.4 and A4.5 present the results of these robustness checks. The impact of EQIP on all total employment, unemployment rate, agricultural and non-agricultural employment remains robust across different model specifications. Similarly, the effects of CRP on total employment and non-agricultural employment are consistent with the main results, suggesting that our findings are not significantly influenced by the inclusion or exclusion of these state-level controls.

Table A4.4: The effects of adding or removing state level controls

	ln(Total employment)						ln(Unemployment rate)					
	Main	No Neighbor	No Politics	No Price	No Tax	Add GDP	Main	No Neighbor	No Politics	No Price	No Tax	Add GDP
ln(EQIPpay)	0.093** (0.033)	0.085* (0.033)	0.088* (0.037)	0.071* (0.034)	0.131** (0.043)	0.092** (0.033)	-0.129** (0.043)	-0.127** (0.044)	-0.119* (0.052)	-0.119** (0.039)	-0.124** (0.044)	-0.128** (0.044)
ln(CRPpay)	0.075* (0.035)	0.069* (0.030)	0.083* (0.035)	0.077* (0.034)	0.070+ (0.039)	0.086* (0.038)	0.015 (0.027)	0.021 (0.027)	0.000 (0.040)	0.014 (0.027)	0.009 (0.031)	0.003 (0.029)
ln(EQIPpay neighbor)	0.045 (0.036)	0.038 (0.037)	0.041 (0.036)	0.033 (0.033)	0.045 (0.036)	0.045 (0.036)	-0.004 (0.029)	0.008 (0.029)	-0.002 (0.029)	-0.001 (0.028)	-0.001 (0.028)	-0.004 (0.028)
ln(CRPpay neighbor)	0.009 (0.026)	0.010 (0.026)	0.008 (0.026)	-0.005 (0.027)	0.008 (0.030)	0.008 (0.026)	-0.019 (0.019)	-0.022 (0.019)	-0.019 (0.019)	-0.019 (0.019)	-0.019 (0.019)	-0.019 (0.019)
Politics	0.122* (0.048)	0.116* (0.048)		0.112* (0.049)	0.123** (0.044)	0.132* (0.053)	-0.231*** (0.052)	-0.231*** (0.052)		-0.226*** (0.053)	-0.192** (0.054)	-0.242*** (0.049)
Crop prices	-0.450* (0.209)	-0.422+ (0.217)	-0.394+ (0.217)		-0.572 (0.428)	-0.231 (0.242)	0.213 (0.184)	0.206 (0.189)	0.107 (0.238)		0.221 (0.221)	-0.018 (0.229)
Sales tax	0.453*** (0.077)	0.442*** (0.078)	0.448*** (0.086)	0.437*** (0.089)		0.470*** (0.079)	0.032 (0.080)	0.034 (0.080)	0.042 (0.094)	0.040 (0.080)		0.014 (0.074)
Tax burden	0.010 (0.153)	-0.005 (0.152)	-0.156 (0.169)	-0.021 (0.153)		0.013 (0.176)	-0.303* (0.120)	-0.307* (0.115)	0.011 (0.150)	-0.289* (0.127)		-0.307* (0.121)
Property tax	0.057 (0.055)	0.056 (0.055)	0.069 (0.061)	0.085 (0.062)		0.039 (0.065)	-0.039 (0.057)	-0.033 (0.056)	-0.061 (0.085)	-0.052 (0.054)		-0.020 (0.059)
State GDP per capita						0.301+ (0.174)						-0.318+ (0.164)
Num.Obs.	4561	4561	4561	4561	4561	4561	4561	4561	4561	4561	4561	4561
R2	0.980	0.980	0.980	0.980	0.979	0.980	0.858	0.857	0.849	0.857	0.856	0.860
Std.Errors	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state
FE: factor(RegionYear)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: factor(watershed)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Observation level controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The "Main" column presents the primary specification results. The "No Neighbor", "No Politics", "No Price", and "No Tax" columns indicate the removal of EQIP and CRP payments per farmland acre in the neighboring state, state-level political party variables, state-level crop prices, and state-level tax variables, respectively. "Add GDP" column represents the addition of state-level GDP per capita, excluding the county itself. The values in parentheses are the standard errors.

Table A4.5: The effects of adding or removing state level controls

	ln(Ag employment)						ln(Non-ag employment)					
	Main	No Neighbor	No Politics	No Price	No Tax	Add GDP	Main	No Neighbor	No Politics	No Price	No Tax	Add GDP
ln(EQIPpayment)	0.366** (0.106)	0.340** (0.109)	0.352** (0.108)	0.511** (0.148)	0.272+ (0.135)	0.359** (0.113)	0.082* (0.033)	0.074* (0.033)	0.078* (0.036)	0.048 (0.035)	0.127** (0.045)	0.081* (0.033)
ln(CRPPayment)	-0.076 (0.175)	-0.096 (0.169)	-0.057 (0.180)	-0.090 (0.190)	-0.042 (0.193)	-0.010 (0.130)	0.074* (0.035)	0.067* (0.029)	0.080* (0.035)	0.077* (0.034)	0.067 (0.041)	0.084* (0.038)
ln(EQIPpay neighbor)	0.139 (0.085)		0.122 (0.085)	0.166+ (0.086)	0.131+ (0.070)	0.137 (0.085)	0.042 (0.038)		0.037 (0.039)	0.036 (0.037)	0.031 (0.036)	0.042 (0.038)
ln(CRPPay neighbor)	0.028 (0.062)		0.032 (0.061)	0.033 (0.062)	-0.009 (0.059)	0.025 (0.063)	0.011 (0.032)		0.012 (0.032)	0.010 (0.033)	0.000 (0.035)	0.011 (0.032)
Politics	0.317+ (0.165)	0.298+ (0.160)		0.378+ (0.194)	0.184 (0.229)	0.378* (0.158)	0.088+ (0.049)	0.082 (0.049)		0.074 (0.052)	0.100* (0.044)	0.096+ (0.055)
Crop prices	2.877* (1.226)	2.964* (1.218)	3.023* (1.244)		2.158 (1.331)	4.168*** (1.059)	-0.669** (0.218)	-0.642** (0.222)	-0.629** (0.221)		-0.757+ (0.427)	-0.487+ (0.250)
Sales tax	-0.621 (0.376)	-0.657+ (0.370)	-0.634 (0.380)	-0.513 (0.403)		-0.522 (0.318)	0.513*** (0.076)	0.502*** (0.078)	0.509*** (0.082)	0.488*** (0.094)		0.527*** (0.078)
Tax burden	1.302* (0.486)	1.258* (0.471)	0.871+ (0.486)	1.497** (0.499)		1.323* (0.556)	-0.089 (0.161)	-0.102 (0.160)	-0.208 (0.168)	-0.135 (0.161)		-0.086 (0.180)
Property tax	0.755* (0.359)	0.752* (0.354)	0.785* (0.372)	0.577+ (0.297)		0.649* (0.289)	0.015 (0.057)	0.013 (0.057)	0.023 (0.058)	0.056 (0.065)		0.000 (0.069)
State GDP per capita						1.775* (0.822)						0.251 (0.206)
Num.Obs.	4561	4561	4561	4561	4561	4561	4561	4561	4561	4561	4561	4561
R2	0.821	0.820	0.820	0.817	0.814	0.824	0.978	0.977	0.977	0.977	0.977	0.978
Std.Errors	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state
FE: factor(Region Year)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: factor(watershed)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: The interpretation of column names, lagged variables, standard errors, fixed effects, and control variables in this table aligns with those detailed in Table A4.4. The values in parentheses are the standard errors.

Appendix 4.1.5 Results Using County Level Observations

We further assess the robustness of our findings by using county-level observations directly, rather than dividing them into county watershed units. In this analysis, we use state pair FE instead of watershed FE. All other FE and controls remain the same as in the main specification. This approach allows us to examine whether our results hold when the analysis is not influenced by the aggregation into watershed units. As shown in Table A4.6, the results remain consistent with our main findings. The positive impact of EQIP on employment remains evident, while the effect of CRP becomes insignificant; however, the sign remains consistent with our main results, reinforcing the robustness of our analysis.

Table A4.6: The effects of conservation enrollment using county level data

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay)	0.100** (0.030)	0.217** (0.073)	0.086** (0.030)	-0.111* (0.044)
ln(CRPpay)	0.022 (0.041)	-0.125 (0.113)	0.018 (0.038)	0.029 (0.078)
Num.Obs.	2574	2574	2574	2574
R2	0.955	0.469	0.953	0.855
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(State Pair)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.6 Results Using State Level Payments in the Rest of the State

As a robustness check, we re-estimate our main specifications using total state-level payments per farmland acre in the rest of the state (exclude the county of interest), rather than the total state-level payments per farmland acre and independent variables. Table A4.7 reports the results. The estimated effects remain qualitatively similar to those in the main analysis: EQIP payments are positively associated with total employment, agricultural employment, and non-agricultural employment, and are associated with a reduction in the unemployment rate. CRP payments are positively associated with both total and non-agricultural employment. These results provide additional support for the robustness of our identification strategy and the conclusion that conservation program enrollment contributes to improved rural labor market outcomes.

Table A4.7: Effects of conservation program payments in the rest of the state

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay)	0.091* (0.033)	0.370** (0.104)	0.079* (0.034)	-0.128** (0.044)
ln(CRPpay)	0.076* (0.034)	-0.088 (0.169)	0.077* (0.034)	0.015 (0.027)
Num.Obs.	4561	4561	4561	4561
R2	0.980	0.821	0.978	0.858
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.7 Results Using State Level Total Payments

Our main specification uses state-level EQIP and CRP payments normalized by farmland area to capture the intensity of conservation funding. This approach allows for meaningful comparisons across states by accounting for differences in land base. For instance, a given dollar of EQIP funding would be spread much more thinly across a large agricultural state like California than in a smaller one like South Carolina. By using payments per farmland acre, we obtain a more interpretable measure of program intensity and its marginal effect on employment.

As a robustness check, we re-estimate the model using total state-level EQIP and CRP payments as the independent variables, and include farmland area as a control. This specification allows us to test whether the results are sensitive to the way we scale conservation payments, while still accounting for differences in land endowment across states. Table A4.8 reports the results. The estimated effects remain qualitatively consistent with our main findings: EQIP payments are positively associated with total, agricultural, and non-agricultural employment, and are associated with a reduction in the unemployment rate. CRP payments continue to show positive associations with both total and non-agricultural employment. As expected, using total payments (rather than per-acre measures) leads to larger coefficient estimates, which may reflect the influence of overall program scale rather than per-unit funding intensity.

Despite this, the per-acre specification remains the preferred model, as it better reflects the distribution of conservation funding relative to land use and avoids potential endogeneity concerns. The per-acre specification provides a more conservative and interpretable estimate of program intensity across regions.

Table A4.8: The effects of conservation payments on the labor market

	ln(Total employment)		ln(Ag employment)		ln(Non-ag employment)		ln(Unemployment rate)	
	With Farm	No Farm	With Farm	No Farm	With Farm	No Farm	With Farm	No Farm
ln(EQIPpay)	0.115*** (0.031)	0.109** (0.035)	0.481*** (0.109)	0.581*** (0.143)	0.100** (0.033)	0.092* (0.038)	-0.120* (0.044)	-0.084+ (0.045)
ln(CRPPay)	0.087* (0.033)	0.085* (0.032)	-0.011 (0.132)	0.028 (0.127)	0.084* (0.034)	0.081* (0.032)	0.020 (0.028)	0.034 (0.028)
farmland	-0.025 (0.060)		0.481 (0.393)		-0.036 (0.074)		0.175* (0.068)	
Num.Obs.	4561	4561	4561	4561	4561	4561	4561	4561
R2	0.981	0.981	0.825	0.824	0.978	0.978	0.858	0.856
Std.Errors	by: state	by: state	by: state	by: state	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.8 Alternative Distribution Method to County Watershed

In the main body of our research paper, we divided the variables from county level to county watershed units by the area share. In this section, we show the robustness check by distributing the variables from county to county watershed by population share. We use the grid population data from the National Aeronautics and Space Administration (NASA) Socioeconomic Data and Applications Center (SEDAC) and aggregate it to the county and county watershed levels, then calculate the shares. As shown in Table A4.9, the positive impact of EQIP on employment remains robust even when we change the distribution method to population share. Additionally, the positive impacts of CRP on total employment and non-agricultural employment are consistent with our main findings.

Table A4.9: The effects of conservation enrollment using population share to divide the county to county-watershed

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay)	0.089* (0.034)	0.366** (0.107)	0.077* (0.035)	-0.129** (0.043)
ln(CRPpay)	0.080* (0.039)	-0.076 (0.176)	0.079+ (0.040)	0.015 (0.027)
Num.Obs.	4561	4561	4561	4561
R2	0.989	0.902	0.987	0.858
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.1.9 Subsample Representativeness

This section examines whether rural counties along state borders are representative of all rural counties in our sample. To assess this, we construct a binary indicator variable that equals one for county-watersheds located on state borders and zero otherwise. We then analyze whether this border location indicator is statistically significant in regression models examining total employment, agricultural employment, non-agricultural employment, and unemployment rates across all rural counties in our sample. If the border indicator coefficient is statistically significant, it would suggest statistically significant differences between border and non-border rural counties, potentially raising concerns about the representativeness of our identification strategy. Conversely, a statistically insignificant coefficient would indicate that rural counties along state borders are broadly similar to other rural counties in terms of our key outcome variables.

Table A4.10: Testing the representativeness of the border rural counties

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
on state borders	-0.019 (0.027)	0.115 (0.111)	-0.025 (0.028)	-0.003 (0.021)
Num.Obs.	12 320	12 320	12 320	12 320
R2	0.976	0.778	0.974	0.813
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(fips)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, and standard errors in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Table A4.10 presents the regression results. The border indicator coefficient is statistically insignificant across all specifications. These results suggest that rural counties along state borders do not statistically differ from other rural counties in terms of employment patterns and labor market outcomes. We cannot reject the null hypothesis that the border indicator coefficient equals zero. This evidence supports the representativeness of our border county subsample and strengthens the validity of our identification strategy that relies on cross-border variation.

Appendix 4.1.10 Results Excluding H-2A Concentrated States

The inclusion of H-2A workers in employment data varies significantly across states, leading to potential discrepancies in our analysis. H-2A employment is highly concentrated in states with large and labor-intensive agricultural sectors. In 2022, the top five states—Florida (14% of total H-2A jobs certified), California (12%), Georgia (9%), Washington (9%), and North Carolina (7%)—accounted for approximately 51% of all H-2A certifications. Given the potential for H-2A employment concentrations to skew our findings, we perform a robustness check by excluding states with high H-2A employment from our analysis.

Table A4.11 below presents the effects of conservation enrollment on employment after excluding states with high H-2A employment. The robustness check confirms that our initial results remain consistent even after excluding states with high H-2A employment. This consistency reinforces the validity of our findings and suggests that the observed effects are not driven by anomalies in the data from these specific states. Consequently, we can confidently assert that conservation programs have a significant impact on employment across states, regardless of the variability in H-2A worker inclusion.

Table A4.11: Effects of conservation program enrollment, excluding states with high H-2A employment

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay)	0.077* (0.031)	0.376** (0.112)	0.065* (0.031)	-0.137** (0.043)
ln(CRPPay)	0.060+ (0.035)	-0.082 (0.173)	0.059 (0.035)	0.006 (0.028)
Num.Obs.	4393	4393	4393	4393
R2	0.980	0.822	0.977	0.856
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

Appendix 4.2 Alternative Fixed Effects Analysis

In the main body of our research paper, we adopt the use of Watershed Fixed Effects (Watershed FE) and Region-Year Fixed Effects (Region-Year FE) as our primary specification. This decision is made based on an intensive comparative study that included County Fixed Effects (County FE) and State-Year Fixed Effects (State-Year FE). If we use County FE, the model controls for all time-invariant unobserved characteristics at the county level. This includes not only environmental features but also social, economic, and political aspects that could influence the dependent variable. However, there may be a risk of eliminating meaningful cross-county variation from the analysis. This appendix aims to detail the justification behind our choice and provide evidence that Watershed FE and Region Year FE balance the need to control for unobserved factors that introduce endogeneity while leaving sufficient variation to estimate impacts.

Our study focuses on conservation program payments per farmland acre, making it critical that the selected region presents substantial variations in conservation program payments and economic indicators. Accordingly, we employ equations A4.1 and A4.2 for our variation analyses.

$$Y_{ijt} = \text{Control}_{ijt} + FE + \mu_{ijt} \quad (\text{A4.1})$$

Equation A4.1 regresses all the control variables against the dependent variables, incorporating alternative fixed effects. By excluding the EQIP and CRP payments, the model focuses on other elements contributing to the variation of the dependent variable. If after this exclusion, the use of County FE does not leave enough variation on the dependent variable, the model may lack the statistical power to identify the impact of conservation program payments.

Equation A4.2 regresses all the control variables on the values of the conservation program payments per farmland acre.

$$C_{ijt}^p = \text{Control}_{ijt} + FE + \eta_{ijt} \quad (\text{A4.2})$$

The residuals provide insight into the variation in the RHS variable used to identify impacts. Consequently, we examine the standard deviation of residuals from regressions on different fixed effect levels (G-FEED 2012). This analysis helps assess the remaining variation in both the dependent variables and conservation program payments. The results are shown in Table A4.12, with agricultural employment as the dependent variable.

The column $sd(Y)$ depicts the standard deviation of residuals in the dependent variable (log of agricultural employment), when excluding enrollment rates under various fixed effect scenarios. A significant decrease is observed in the standard deviation when county fixed effects (County Year FE and County RegionYear FE) are introduced, indicating that County FE absorb significant variation in the dependent variable. We avoid StateYear fixed effects since our independent variables—EQIP and CRP payments per farmland acre—vary only at the state-year level. Including such fixed effects would absorb all identifying variation in our variables, creating perfect multicollinearity. Finally, the Watershed and RegionYear FE specification provides a better balance, retaining substantial variation in both the dependent variable and independent variable while controlling for local time-invariant factors and year-specific shocks.

Table A4.12: Residual variation under alternative fixed effects

	sd(Y)	sd(EQIP)	sd(CRP)
No FE	1.09	0.46	0.53
Region FE	1.08	0.44	0.47
State FE	0.95	0.32	0.17
Year FE	1.08	0.37	0.51
RegionYear FE	1.05	0.32	0.45
StateYear FE	0.90	0.01	0.02
Watershed FE	0.89	0.41	0.39
County FE	0.34	0.24	0.34
County Year FE	0.34	0.18	0.09
County RegionYear FE	0.33	0.15	0.08
Watershed RegionYear FE	0.87	0.24	0.35

Note: This table reports the standard deviations of residuals for three variables: the dependent variable (log of agricultural employment), state-level EQIP payments per farmland acre (logged), and CRP payments per farmland acre (logged), across different fixed effects specifications.

Appendix 4.3 Impact on Specific Ag and Non-ag Sectors

We disaggregate employment within the agricultural sector using 3-digit NAICS codes. Our analysis investigates how a percentage change in EQIP and CRP enrollment rates influences the number of jobs in agricultural production sector. We also isolate entertainment-related industries from the non-agricultural sector for a focused study, although we continue to use the 2-digit NAICS codes. The findings are presented in Table A4.13. The agricultural production sector encompasses NAICS 111 (crop production) and NAICS 112 (animal production and aquaculture). The non-agricultural sectors comprise NAICS 53 (real estate rental and leasing), NAICS 71 (arts, entertainment, and recreation), and NAICS 72 (accommodation and food services).

Table A4.13: Impacts on the employment of agricultural production and agricultural-related activities

	Agricultural production	RealEstate	Recreation	Accommodation
ln(EQIPpay)	0.323** (0.103)	-0.051 (0.066)	-0.055 (0.148)	0.037 (0.058)
ln(CRPpay)	-0.230 (0.182)	-0.027 (0.073)	0.308+ (0.172)	0.167 (0.117)
Num.Obs.	3531	3251	2793	2867
R2	0.819	0.905	0.893	0.922
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

The results demonstrate that EQIP can significantly increase the number of jobs in agricultural production. In contrast, while CRP has a negative impact on the agricultural sector, this effect is statistically insignificant. However, CRP positively and significantly impacts employment in entertainment-related industries. Specifically, a 1 percent increase in state-level EQIP payments per farmland acre leads to a 0.32 percent rise in on-farm jobs. Similarly, a 1 percent increase in CRP enrollment results in a 0.308 percent increase in recreational activities. With an average

of 1,101 people employed in the agricultural production sector, spending an additional thousand dollars in EQIP at the state level will increase on-farm jobs by 0.019 per year on average.

The results are in line with our initial hypotheses. First, the working lands program offers financial and technical support to farmers, requiring them to implement conservation practices on actively productive land. Consequently, if farmers employ labor-intensive conservation practices, it will lead to more job opportunities in crop production. On the other hand, CRP, as a land retirement program, pays farmers to remove cropland from production, which could reduce jobs in the crop production sector. However, since CRP often enrolls marginal land, the payments might allow farmers to invest more in high-quality farmland (Wu 2000), offsetting some of the potential job losses. Thus, the impact of CRP on the agricultural production sector may vary. Despite this, we hypothesize that land retirement can more efficiently improve environmental conditions in the short term, so the impact of CRP is greater than that of EQIP on entertainment sectors.

Appendix 4.4 Estimated Impacts by EQIP Practices

During our study period, there are 193 EQIP practices included in the dataset. To better account for the heterogeneous impacts of various conservation targets, we analyze the effects based on practice types. Building on the practice categorization proposed by Hensen (2021) and the definitions in the NRCS Conservation Practice Standards Information⁶², we classify these practices into four main groups. These include soil-related practices beneficial for soil health, reducing emissions, and enhancing soil carbon sequestration; water-related practices beneficial for surface water, wetlands, drainage, and water management that reduce net greenhouse gas emissions; grazing and wildlife-related practices that benefit grazing systems and enhance wildlife habitats; and other practices. Table A4.15 provides detailed information on the specific categories of these practices.

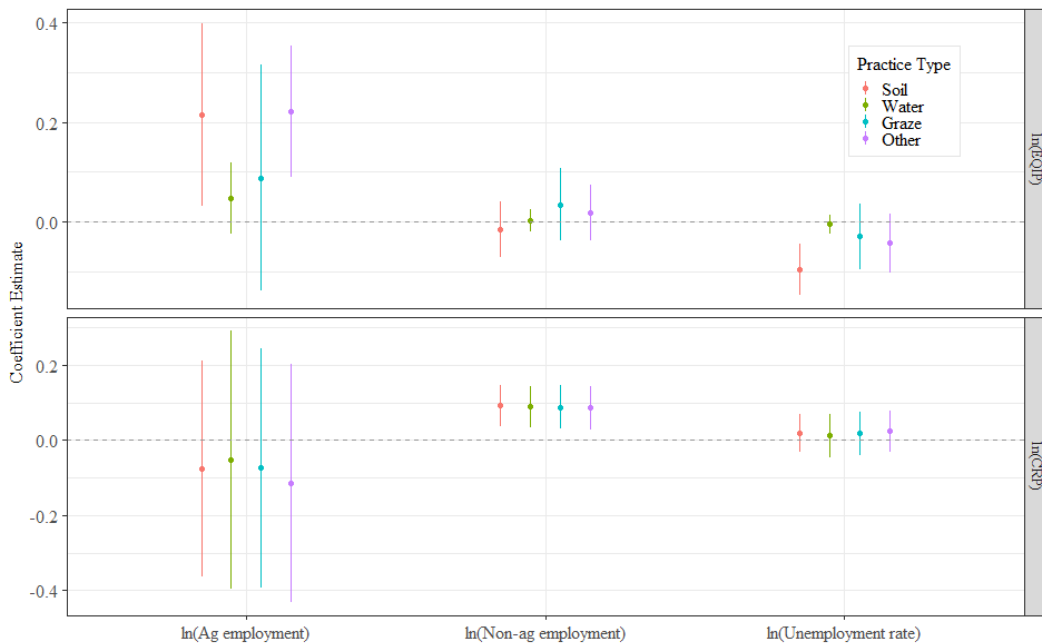


Figure A4.1: The effects of conservation payments by EQIP practices

⁶²<https://www.nrcs.usda.gov/getting-assistance/conservation-practices>

Table A4.14: Estimated impacts by EQIP practices

	ln(Total employment)	ln(Ag employment)	ln(Non-ag employment)	ln(Unemployment rate)
ln(EQIPpay soil)	-0.029 (0.062)	0.196+ (0.109)	-0.023 (0.031)	-0.094** (0.027)
ln(EQIPpay water)	-0.017 (0.024)	0.025 (0.036)	-0.004 (0.011)	0.001 (0.010)
ln(EQIPpay graze)	0.004 (0.071)	-0.057 (0.108)	0.035 (0.040)	-0.009 (0.032)
ln(EQIPpay other)	0.044 (0.062)	0.205** (0.074)	0.018 (0.036)	-0.027 (0.031)
ln(CRPPay)	0.090 (0.083)	-0.118 (0.144)	0.080* (0.032)	0.025 (0.028)
Num.Obs.	4793	4793	4793	4793
R2	0.710	0.833	0.980	0.858
Std.Errors	by: state	by: state	by: state	by: state
FE: factor(Watershed)	Yes	Yes	Yes	Yes
FE: factor(RegionYear)	Yes	Yes	Yes	Yes
Observation level controls	Yes	Yes	Yes	Yes
State level controls	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Controls, lagged variables, standard errors, and fixed effects in this table are consistent with those detailed in Table 4.3. The values in parentheses are the standard errors.

We apply our main specification to all rural county watersheds to maintain a sufficient number of observations for estimating four separate practice models. Figure A4.1 shows the effects of state level EQIP and CRP payments per farmland acre on agricultural and non-agricultural employment, as well as unemployment rate, categorized by practice types. The dot whisker plot displays 95 percent confidence intervals. The results indicate that soil EQIP practices have the potential to positively impact agricultural employment and decrease unemployment rate. Additionally, CRP consistently demonstrates a significant positive effect on non-agricultural employment across all four models. This finding underscores the robust impact of CRP on non-farm job creation, regardless of the specific EQIP practices considered in the model.

However, concerns arise regarding potential correlations between payments or practices across different categories. To address this, we included all practice types in a single model. The results, presented in Table A4.15, show similar patterns of statistical significance as in the previous analysis. Soil-related payments have a significant positive impact on agricultural employment and are associated with a reduction in the unemployment rate. The significant positive effects of CRP payments on non-agricultural employment also persist.

Table A4.15: EQIP practice codes and categories

Code	Practice Name	Soil	Graze	Water	Other
100	Comprehensive Nutrient Management Plan				1
102	Comprehensive Nutrient Management Plan - Written				1
104	Nutrient Management Plan - Written				1
106	Forest Management Plan - Written				1
110	Grazing Management Plan - Written				1
112	Prescribed Burning Plan - Written				1
114	Integrated Pest Management Plan - Written				1
118	Irrigation Water Management Plan - Written				1
122	Agricultural Energy Management Plan, Headquarters - Written				1
124	Agricultural Energy Management Plan, Landscape - Written				1
128	Agricultural Energy Management Plan - Written				1
130	Drainage Water Management Plan - Written				1
134	Conservation Plan Supporting Transition from Irrigation to Dry-land Plan - Written				1
138	Conservation Plan Supporting Organic Transition - Written				1
142	Fish and Wildlife Habitat Plan - Written				1
146	Pollinator Habitat Plan - Written				1
150	Spill Prevention, Control and Countermeasure (SPCC) Plan - Written				1
154	IPM Herbicide Resistance Weed Conservation Plan - Written				1
202	Edge-of-Field Water Quality Monitoring-System Installation				1
297	Feral Swine Management Conservation Activity - Interim				1

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
309	Agrichemical Handling Facility				1
310	Bedding				1
310	Edge-of-Field Water Quality Monitoring-Data Collection and Evaluation				1
311	Alley Cropping	1			
313	Waste Storage Facility				1
314	Brush Management		1		
315	Herbaceous Weed Control		1		
316	Animal Mortality Facility				1
317	Composting Facility				1
319	On-Farm Secondary Containment Facility				1
320	Irrigation Canal or Lateral			1	
322	Channel Bank Vegetation		1		
324	Deep Tillage	1			
325	High Tunnel System				1
326	Clearing and Snagging				1
327	Conservation Cover	1			
328	Conservation Crop Rotation	1			
329	Residue and Tillage Management, No-Till	1			
330	Contour Farming	1			
331	Contour Orchard and Other Perennial Crops	1			
332	Contour Buffer Strips	1			
333	Amending Soil Properties with Gypsum Products				
338	Prescribed Burning		1		
340	Cover Crop	1			
342	Critical Area Planting	1			
344	Residue Management, Seasonal	1			
345	Residue and Tillage Management, Reduced Till	1			
346	Residue and Tillage Management, Ridge Till	1			

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
348	Dam, Diversion				1
350	Sediment Basin				1
351	Well Decommissioning				1
353	Monitoring Well				1
355	Groundwater Testing				1
356	Dike				1
359	Waste Treatment Lagoon				1
360	Waste Facility Closure				1
362	Diversion	1			
365	Anaerobic Digester, Ambient Temperature				1
366	Anaerobic Digester				1
367	Roofs and Covers				1
368	Emergency Animal Mortality Management				1
370	Atmospheric Resource Quality Management				1
372	Combustion System Improvement				1
373	Dust Control on Unpaved Roads and Surfaces				1
374	FARMSTEAD ENERGY IMPROVEMENT				1
376	Field Operations Emissions Reduction				1
378	Pond		1		
379	Multi-Story Cropping				1
380	Windbreak/Shelterbelt Establishment	1			
381	Silvopasture Establishment	1			
382	Fence		1		
383	Fuel Break				1
384	Woody Residue Treatment				1
386	Field Border	1			
388	Irrigation Field Ditch			1	
390	Riparian Herbaceous Cover				1
391	Riparian Forest Buffer	1			

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
393	Filter Strip				1
394	Firebreak				1
395	Stream Habitat Improvement and Management				1
396	Aquatic Organism Passage				1
397	Aquaculture Ponds				1
398	Fish Raceway or Tank				1
400	Bivalve Aquaculture Gear and Biofouling Control				1
402	Dam				1
409	Prescribed Forestry				1
412	Grassed Waterway	1			
422	Hedgerow Planting				1
423	Hillside Ditch				1
428	Irrigation Ditch Lining			1	
428	Irrigation Water Conveyance, Ditch and Canal Lining, Flexible Membrane			1	
428	Irrigation Water Conveyance, Ditch and Canal Lining, Plain Concrete				1
430	Irrigation Pipeline			1	
430	Irrigation Water Conveyance, Pipeline, High-Pressure, Underground, Plastic			1	
430	Irrigation Water Conveyance, Pipeline, Low-Pressure, Underground, Plastic			1	
430	Irrigation Water Conveyance, Pipeline, Nonreinforced Concrete			1	
430	Irrigation Water Conveyance, Pipeline, Steel			1	
431	Above Ground, Multi-Outlet Pipeline				1
432	Dry Hydrant				1
436	Irrigation Reservoir			1	
441	Irrigation System, Microirrigation			1	

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
442	Sprinkler System			1	
443	Irrigation System, Surface and Subsurface			1	
447	Irrigation System, Tailwater Recovery			1	
449	Irrigation Water Management	1			
450	Anionic Polyacrylamide (PAM) Application				1
457	Mine Shaft and Adit Closing				1
460	Land Clearing				1
462	Precision Land Forming				1
464	Irrigation Land Leveling	1			
466	Land Smoothing	1			
468	Lined Waterway or Outlet	1			
472	Access Control				1
484	Mulching	1			
490	Tree/Shrub Site Preparation				1
500	Obstruction Removal				1
511	Forage Harvest Management		1		
512	Forage and Biomass Planting	1			
516	Livestock Pipeline		1		
520	Pond Sealing or Lining, Compacted Soil Treatment				1
521	Pond Sealing or Lining, Bentonite Sealant				1
521	Pond Sealing or Lining, Compacted Clay Treatment				1
521	Pond Sealing or Lining, Flexible Membrane				1
521	Pond Sealing or Lining, Soil Dispersant				1
522	Pond Sealing or Lining, Concrete				1
527	Karst Sinkhole Treatment				1
528	Prescribed Grazing		1		
533	Pumping Plant			1	
548	Grazing Land Mechanical Treatment		1		
550	Range Planting		1		

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
552	Irrigation Regulating Reservoir				1
554	Drainage Water Management				1
557	Row Arrangement	1			
558	Roof Runoff Structure				1
560	Access Road		1		
561	Heavy Use Area Protection		1		
568	Trails and Walkways				1
570	Stormwater Runoff Control				1
572	Spoil Spreading				1
574	Spring Development		1		
575	Trails and Walkways				1
576	Livestock Shelter Structure		1		
578	Stream Crossing		1		
580	Streambank and Shoreline Protection		1		
582	Open Channel				1
584	Channel Bed Stabilization	1			
585	Stripcropping	1			
587	Structure for Water Control			1	
588	Cross Wind Ridges	1			
590	Nutrient Management	1			
591	Amendments for the Treatment of Agricultural Waste				1
592	Feed Management				1
595	Integrated Pest Management (IPM)				1
600	Terrace	1			
601	Vegetative Barrier				1
603	Herbaceous Wind Barriers	1			
604	Saturated Buffer				1
605	Denitrifying Bioreactor				1
606	Subsurface Drain	1			

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
607	Surface Drain, Field Ditch				1
608	Surface Drain, Main or Lateral				1
609	Surface Roughening				1
610	Salinity and Sodic Soil Management			1	
610	Toxic Salt Reduction			1	
612	Tree/Shrub Establishment				1
614	Watering Facility		1		
620	Underground Outlet	1			
629	Waste Treatment				1
630	Vertical Drain				1
632	Waste Separation Facility				1
633	Waste Recycling		1		
634	Waste Transfer				1
635	Vegetated Treatment Area				1
636	Water Harvesting Catchment				1
638	Water and Sediment Control Basin	1			
640	Waterspreading				1
642	Water Well		1		
643	Restoration and Management of Rare and Declining Habitats				1
644	Wetland Wildlife Habitat Management				1
645	Upland Wildlife Habitat Management				1
646	Shallow Water Development and Management				1
647	Early Successional Habitat Development/Management				1
649	Structures for Wildlife				1
650	Windbreak/Shelterbelt Renovation	1			
654	Road/Trail/Landing Closure and Treatment				1
655	Forest Trails and Landings				1
656	Constructed Wetland				1

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Table A4.15 – continued from previous page

Practice Code	Practice Name	Soil	Graze	Water	Other
657	Wetland Restoration				1
658	Wetland Creation				1
659	Wetland Enhancement				1
660	Tree/Shrub Pruning				1
666	Forest Stand Improvement				1
670	Lighting System Improvement				1
672	Building Envelope Improvement				1
Total		32	21	17	123

Additional Appendix Figures

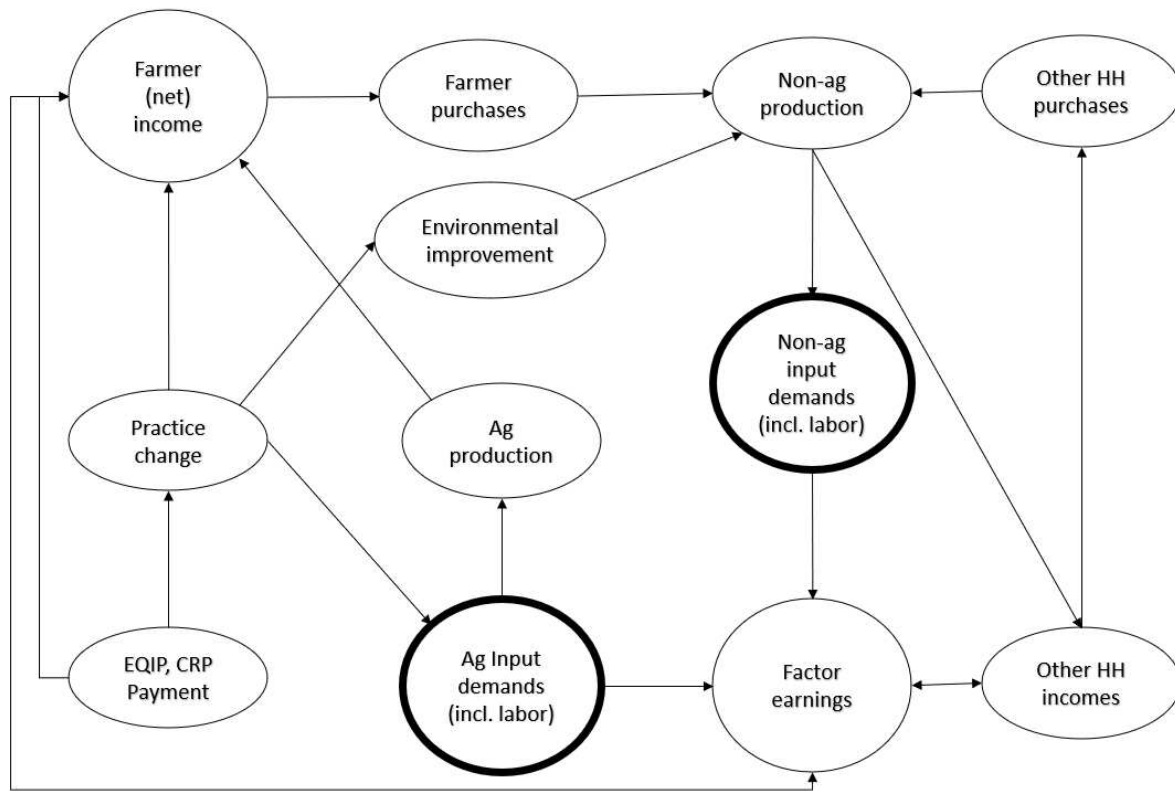


Figure AF4.1: The impact of agri-environmental program payments on local labor market and economy.

Note: The bold circles represent the dependent variables of interest in this study.

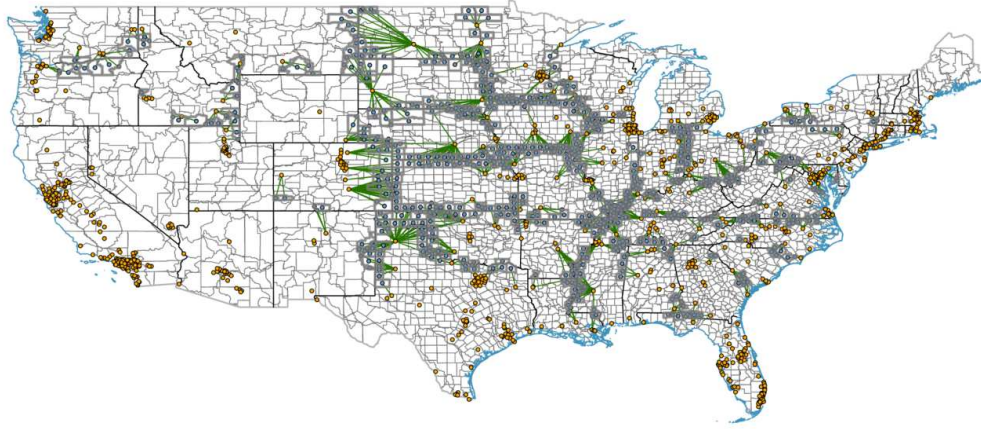


Figure AF4.2: Distance of each rural border county-watershed to the nearest city with 50,000 population

Note: The gray areas indicate the county-watersheds included in our study. Orange points represent the city with 50,000 population, and the green lines connect each county-watershed to the nearest city.