Don't Put All Your Acres in One Basket:
Heterogeneous Risk Preferences in CRP Participation*

Owen Rask †

November 25, 2025

Abstract

The U.S. Conservation Reserve Program (CRP) is often framed as a conservation initiative, yet it also functions as one of the largest agricultural transfer programs, paying farmers $2 billion in aggregate annual rents to retire land from production. These payments offer income stability but prohibit production on that land for at least a decade. Despite the program's scale, little is known about how farmers weigh this tradeoff or how risk preferences shape their decisions. This paper develops a dynamic land-allocation model with a two-year CRP lock-in to study that decision. Calibrating the model to county-level Iowa corn-grain producers reveals that even risk-neutral farmers allocate a substantial share (72% of the monetary limit) to the CRP, and that risk aversion amplifies participation, though with pronounced spatial heterogeneity. Within counties, CRP allocation falls by 9 percentage points when farm size doubles. At the observed average farmer constant relative risk aversion ($\gamma = 4.2$), model enrollment exceeds the current state cap by 1.3 million acres and county-level caps by an average of 13,114 acres. The option to enroll acres in the CRP raises expected per-farm annual income by $30,000 on average across Iowa's counties. Taken together, the results suggest that while the CRP increases farmer welfare greatly, uniform acreage caps are misaligned with heterogeneous local conditions and risk preferences, limiting the program's ability to act as effective income insurance.

Keywords: Agriculture, Risk, Conservation Reserve Program
JEL Codes: Q15, D81, Q20

---

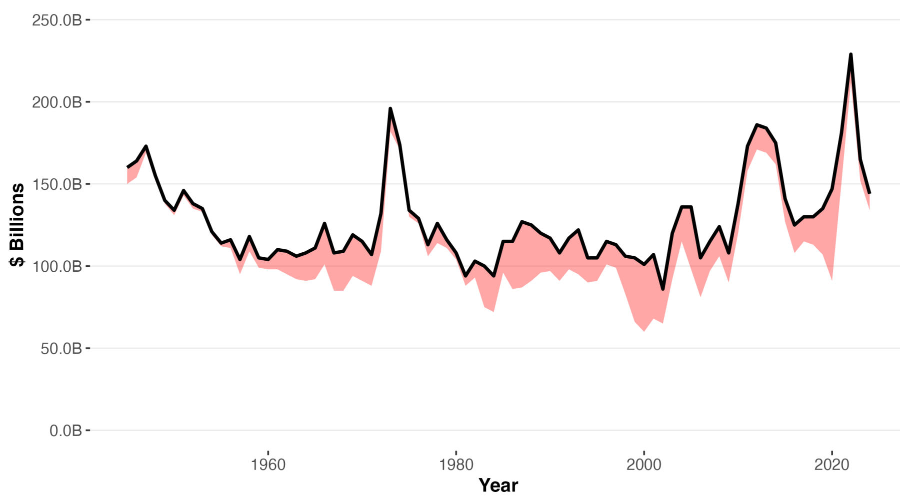
*All errors are my own.

†Rask: Yale University

1 Introduction

Farming is a risky enterprise: volatile prices, rising input costs, and unpredictable weather create persistent uncertainty. Yet, as Figure 1 shows, U.S. net cash farm income has historically remained both high and notably stable over the past century. This resilience reflects not only natural endowments and technology, but also decades of government programs that buffer farmers against risk, represented by the red highlight, which has historically kept net cash farm income above $100 billion (in 2024 dollars). One of the major federal support programs is the Conservation Reserve Program (CRP), which pays farmers fixed annual rents to retire land from production for 10–15 years[1], transferring roughly $2 billion to farmers annually.

Figure 1: U.S. Net Cash Farm Income: 1945 - 2024



Note: Figure plots U.S. agricultural sector net cash farm income from 1945 to 2024 in 2024 dollars. The black line is the total yearly net cash farm income, while the red highlight represents the portion of the total that is from direct government payments. Data comes from U.S. Department of Agriculture, Economic Research Service (2025).

Despite its scale and its role in stabilizing farm income (acting as a quasi-insurance against bad yields), little is known about how farmers decide to enroll land in the CRP. Participation is voluntary, offering guaranteed annual payments but locking land out of production for years, limiting flexibility to respond to the volatile market conditions. The program often treats farmers as homogeneous, yet they differ widely

[1] See Hellerstein (2017) for a history of the evolution of the CRP and its enrollment mechanisms.

in risk tolerance, operated acreage, and knowledge of their fields' quality, factors that greatly influence CRP involvement. Understanding this forward-looking decision process is essential for designing CRP policy that is both cost-effective and efficient.

To address this gap, this paper models how farmers allocate farmland under risk, treating the CRP as a stable income alternative to crop production. I develop a dynamic land allocation model in which a representative farmer chooses each year how much land to allocate between farming and the CRP in the next year. Land enrolled in CRP is locked for two years and yields a guaranteed payment, while farmed land generates stochastic income due to price and yield shocks. I calibrate this model using publicly available data on corn-grain farmers in Iowa.[2] The model predicts two policy-relevant objects, (i) the payment-feasible model predicted enrollment given the \$50,000 payment limit, and (ii) the risk-responsiveness of that choice to risk aversion (the change in enrollment as constant relative risk aversion increases). I then investigate what factors most influence (i) and (ii), compare model-implied enrollment to the program's current statutory acreage caps, and lastly quantify the welfare benefits of the program.

This paper has five primary results. First, on average, even risk-neutral farmers allocate 72% of their monetary limit (\$36,000) to the CRP, with participation increasing and then plateauing as risk-aversion (γ) rises. Holding risk-preferences fixed, participation remains heterogeneous across Iowa counties. This cross-county dispersion is large and is well explained by local fundamentals: higher mean yields and larger non-conservation subsidies are associated with lower limit utilization, while greater yield volatility leads to higher utilization.

Second, counties differ in risk-responsiveness, with responsiveness being amplified where mean yields and non-conservation farm subsidies are larger and dampened where CRP rental rates and policy caps are greater. Third, within counties, CRP usage declines by roughly 9 percentage points when farm size doubles, and this gradient is stable across γ. Fourth, the statewide CRP cap is sufficient only under risk neutrality ($\gamma = 0$); at the PSID estimated risk aversion ($\gamma = 4.2$) the model implies roughly 1.3 million acres above the cap, with counties, on average, 13,114 acres over their caps. Fifth, the welfare farmers gain from having the option to enroll in the CRP versus not is on average about \$30,000 annually across Iowa's counties. Taken together, these results underscore the substantial benefits farmers gain from CRP access, but also reveal a sizable spatial misalignment between uniform policy caps and heterogeneous individual and county conditions.

This study contributes to four main strands of literature. The first strand ex-

[2] I am currently working to obtain access and prepare field-level SSURGO soil, PRISM weather, and restricted USDA field-level microdata to enable more granular calibration

amines how farmers and policy instruments interact with the CRP. Studies such as Cramton et al. (2021), Miao et al. (2016), and Aspelund and Russo (2025) analyze how modifications to the program's auction design and enrollment mechanism could improve the program's cost-effectiveness and efficiency. Other studies investigate the behavioral drivers of enrollment, such as how uncertainty or the quality of information provided influences participation (Isik and Yang, 2004; Wallander et al., 2023). Lastly, studies such as Cornish et al. (2022) and Yu et al. (2022) explore the CRP's interaction with other federal programs, examining how programs such as crop insurance influence CRP participation.

The second strand of literature emphasizes the role of heterogeneous risk attitudes among individuals. Foundational contributions by Barsky et al. (1997) and Kimball et al. (2009) establish methods for inferring individual risk aversion from job-gamble questions. Guan and Wu (2017) explicitly model heterogeneity in farmer risk preferences, demonstrating decreasing absolute risk aversion and warning against assuming homogeneity across farmers. Recent works such as Finger et al. (2023) and Orduño Torres et al. (2019) elicit farmer risk preferences using survey and lottery experiments, providing direct evidence of the variability of attitudes toward risk. This research also connects to a broader literature on how risk preferences influence entrepreneurial choices, such as in Hall and Woodward (2010).

The third strand is the large development-economics literature on how farmers manage risk. Although in a different setting (relatively high income U.S. farmers), the CRP can be interpreted as an insurance-like instrument, providing farmers stable rental payments to smooth consumption across shocks. Classic studies by Udry (1994, 1995) in northern Nigeria show that, in the absence of complete markets, households use savings and credit-cum-insurance transactions to smooth consumption in the face of income shocks. Weather risk also distorts investment: poorer farmers shift toward safer, lower-return activities, while wealthier households undertake riskier but higher-return portfolios (Rosenzweig and Binswanger, 1993). More recent evidence sharpens this point by isolating the role of risk itself, finding that relaxing risk can spur investment more than relaxing credit (Karlan et al., 2014). The final strand of literature I contribute to is the long tradition of applying dynamic programming to model farmland decisions.[3]

The next section outlines the structure of my model while Section 3 describes the data used to calibrate it. Section 4 presents my findings and Section 5 concludes.

[3]Gallagher (2024), Yu et al. (2016), and Janssen and van Ittersum (2007) review the historical application of dynamic programming to environmental and agricultural problems. Notable recent applications include Lubowski et al. (2008) and Souza-Rodrigues (2018).

2 Methodology

2.1 Model Framework

I develop a dynamic programming framework in which a farmer chooses how to allocate a fixed amount of land, A, across two uses each period: crop production and the Conservation Reserve Program (CRP). This model is applied across counties, where each county faces unique yield processes, soil rental rates, and non-conservation government subsidies.

In each period, t, a farmer earns income from farming and from CRP-enrolled land. Income from farming is defined as:

$$\pi_t^f = A_t^f \cdot [y_c(z_{y,t}^c) \cdot p(z_{p,t}) - c + s_c] \tag{1}$$

where A_t^f is the acreage farmed in period t, $y_c(z_{y,t}^c)$ is the county-specific yield in bushels per acre conditional on the county's bad, normal, or good yield state ($z_{y,t}^c \in \{B, N, G\}$), and $p(z_{p,t})$ is the common price per bushel conditional on the market price state ($z_{p,t} \in \{B, N, G\}$).[4] Per acre input costs, c, are constant across counties while non-conservation per acre subsidies, s_c, are county specific.

Yield and price states evolve according to stochastic Markov chains with transition probabilities defined by:

$$P = \begin{bmatrix} p_{BB} & p_{BN} & p_{BG} \\ p_{NB} & p_{NN} & p_{NG} \\ p_{GB} & p_{GN} & p_{GG} \end{bmatrix} \quad \text{where } p_{ij} = \Pr(z_{t+1} = j \mid z_t = i) \tag{2}$$

with P_y^c being county specific for yield and P_p shared across counties for price transitions. CRP income in period t is given by:

$$\pi_t^{crp} = C1_t \cdot (srr_c - est) + C2_t \cdot (srr_c - 0.25 \cdot est) \tag{3}$$

where $C1_t$ and $C2_t$ are acres enrolled in the first and second year of the CRP, respectively. The government pays a county-specific soil rental rate, srr_c, and conservation practice establishment costs per acre are denoted est. I assume ongoing conservation maintenance costs in year two are 25% of initial costs.

Lastly, motivated by the fact that a substantial share of farmers' yearly income comes from off-farm sources, I include a baseline income, π_0. π_0 is fixed and serves as a consumption floor in the model, ensuring utility is well-defined in the worst states.

[4]See Section 3 for the detailed construction of the bad, normal, and good yield and price states.

I calibrate it from PSID and IPUMS CPS microdata samples, discussed in Section 3.1. Total income in a period is thus[5]:

$$\pi_{c,t} = \pi_0 + \pi_t^f + \pi_t^{crp} \tag{4}$$

Farmers maximize expected lifetime utility over an infinite horizon using the Bellman equation:

$$V(C1_t, C2_t, z_{y,t}, z_{p,t}) = \max_{C_1'} \left\{ u(\pi_{c,t}) + \beta \mathbb{E}_{z'|z} V(C1', C1_t, z_y', z_p') \right\} \tag{5}$$

where farmer utility is modeled using constant relative risk aversion (CRRA) of the form,

$$u(c) = \begin{cases} \frac{c^{1-\gamma}-1}{1-\gamma} & \text{if } \gamma \neq 1 \\ \log(c) & \text{if } \gamma = 1 \end{cases} \tag{6}$$

I assume a discount factor (β) of 0.9, and land transitions follow deterministic rules:

$$C1_{t+1} = C1' \qquad \text{(first-year CRP commitment)} \tag{7}$$

$$C2_{t+1} = C1_t \qquad \text{(second-year CRP commitment)} \tag{8}$$

Figure 2 is a diagram of the land transition process for an amount of CRP allocated land in period t. At the beginning of the year, the farmer observes the current yield and price states, as well as the CRP land already enrolled in year $t-1$ ($C1_t$) and year $t-2$ ($C2_t$). They then receive income based on these observed states: farm income depends on the realized yield and price for the current farmed acres (equal to $A - C1_t - C2_t$), while CRP income is determined by the previously enrolled land ($C1_t + C2_t$) and net rental rates. After receiving income, the farmer chooses how much of their available land to enroll in the CRP for the next period. Because $C2_t$ exits at the end of t, the land available to enroll in the next period is $A - C1_t$.[6] The acreage chosen ($C1'$) becomes $C1$ in year $t+1$, and then $C2$ in year $t+2$. After year $t+2$ it exits the program and becomes eligible for reallocation in year $t+3$.

[5] In the program, I normalize $\pi_{c,t}$ by π_0.

[6] This mirrors expiring contracts being able to be re-enrolled in the year they expire.

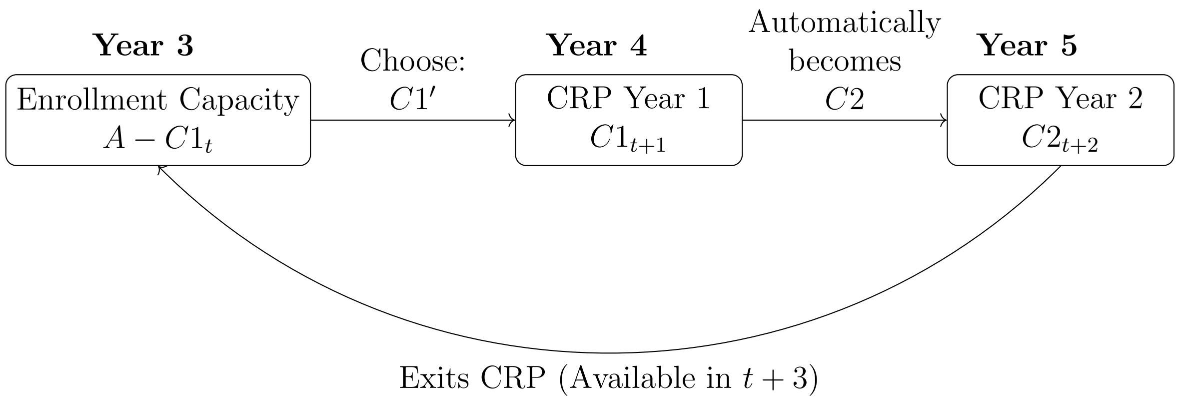


Figure 2: Movement of CRP-Enrolled Land Over Three Periods

When solving equation 5, I discretize the state space using a finite grid of land allocations. Given the CRP's $50,000 annual payment limit per person or legal entity[7], I assume farmers do not enroll more land than could qualify for rental payment. Therefore, I define the maximum land farmers can allocate to the CRP as:

$$CRP_c^{limit} = \frac{50{,}000}{srr_c} \tag{9}$$

where srr_c is the median county soil rental rate in 2024 dollars.[8] Thus, the choice of $C1'$ is restricted by

$$C1' \in \{0, \bar{C}(C1_t)\}, \quad \bar{C}(C1_t) = \min\{A - C1_t, CRP_c^{limit} - C1_t\} \tag{10}$$

For the remainder of the paper, CRP limit refers to the per-participant payment limit in equation (9), while CRP cap refers to the policy acreage ceilings (e.g., county or state policy caps currently in effect). To reduce computational burden while maintaining realistic decision granularity, I restrict enrollment choices to 2.5-acre increments. I define fixed grids over $[0, CRP_c^{limit}]$ in 2.5-acre steps for both $C1$ and $C2$, and $C_1 + C_2$ cannot exceed CRP_c^{limit} or A.[9] For each state combination, I evaluate the value function over all feasible CRP allocations using grid search and iterate until convergence.

[7] See U.S. Department of Agriculture, Farm Service Agency (2025) for program regulations.

[8] See section 3 for more details.

[9] Each CRP_c^{limit} value is rounded down to the nearest multiple of 5 to ensure compatibility with 2.5-acre grid steps.

3 Data and Model Calibration

To calibrate the model, I choose corn-grain farmers in Iowa as the representative decision-makers. This choice is motivated by three points. First, every county in the state has land eligible for CRP enrollment, and the state receives by far the highest total CRP payments nationally (Hellerstein, 2017). Second, corn-grain is the State's dominant crop, grown ubiquitously across the state, making intercounty comparisons more realistic.[10] Third, Iowa provides exceptionally rich county-level agricultural data.

The ideal dataset for calibration would be annual USDA household- and field-level production microdata that record CRP land allocation decisions. While no public dataset meets this criterion, I am currently combining field-level soil (SSURGO) and weather (PRISM) data and applying for FSRDC access to USDA farmer household- and field-level production microdata to better approximate the ideal dataset. In the meantime, the data used to calibrate the model are taken from multiple public sources. I use PSID and IPUMS CPS microdata to estimate household-level farmer income and risk preferences. Meanwhile, all farm production and farm-related income data is sourced from the U.S. Department of Agriculture (USDA), the Farm Service Agency (FSA), and Iowa State University's Extension and Outreach program. For variables where distributions are non-normal or sample sizes are limited, I use the median as the central measure. All monetary amounts are inflated to 2024 dollars. The remainder of this section explains how I calculate the model parameters.

3.1 Farmer Household CRRA and Off-Farm Income

To calibrate π_0, I use the PSID (waves 1968-2023) and IPUMS CPS (ASEC waves 1962-2024) microdata of farmers.[11] Panel A of Table 1 provides summary statistics of the two microdata samples for all farmers and Iowa-only farmer households. Across sources, the farmer population is overwhelmingly male (PSID: 98–99%; CPS: 87–89%) and predominantly white (PSID: 94–100%; CPS: 93–100%), with average ages in the mid-40s. The primary differences arise in the PSID Iowa farmer sample,

[10] Corn-grain is predominately grown in either a corn-soybean cycle or continuously. While no official statistics are available on corn-soybean versus continuous corn production in Iowa, anecdotal evidence suggests that a two-thirds to one-third split between corn-soybean and corn continuous exists. Corn-soybean is widely used due to the soil nitrogen restoration properties of growing soybeans. I am working on updating the model to incorporate cyclical crop cycles.

[11] Farmers are directly identified in the PSID's questionnaire through occupation questions, while in the CPS they are defined as individuals who both work in the agricultural production industry and have a farm-related occupation.

who have much higher completion rates of high school (93% vs. the range of 60% in the rest of the samples), and have a \$10,000 higher average off-farm income.[12] Based on these results, in the model I set $\pi_0 = \$62{,}000$.

An advantage of using the PSID is that I am able to use their 1996 wave job-gamble questions to impute individual CRRA preferences. Following Kimball et al. (2009), I evaluate the model using all six CRRA category values,

$$\gamma \in \{0, 1.4, 2.2, 2.8, 3.5, 4.2, 6.7\}$$

After assigning risk aversion values to all 1996 PSID individuals, I subset it to farmers and compute the weighted average CRRA for that group. Those results are reported in Panel B of Table 1. The unweighted results differ minimally (4.5 and 4.1 for all and Iowa only farmers, respectively). Thus, I categorize average farmer's risk aversion as 4.2, and use that parameter when discussing the majority of my results.

Table 1: Summary statistics of PSID and CPS Farmer Samples

	PSID: All (1)	PSID: Iowa (2)	CPS: All (3)	CPS: Iowa (4)
Panel A:				
Percent Male	98%	99%	87%	89%
Percent White	94%	100%	93%	100%
Average Age	47	44	45	45
Percent with a High School Degree	61%	93%	69%	62%
HH Wghted Avg Off-Farm Income	61017	72357	62990	61432
N	2789	209	61765	2,199
Panel B:				
Weighted Average CRRA	4.3	4.1		
N	41	8		

Note: The table reports summary statistics and calculated parameter values from the PSID and IPUMS CPS microdata samples. The PSID sample includes all survey years (1968 to 2023) while the CPS sample includes the 1962 to 2024 ASEC waves. Panel A of the table reports summary statistics for the PSID and CPS samples restricted to both farmers and farmers in Iowa. Panel B reports the estimated average CRRA parameters from the PSID samples. Household weighted average off-farm income is inflated to 2024 dollars.

[12] Off-farm income in all samples is defined as all yearly income from sources besides farming assets, labor, and production.

3.2 Farmer Household Crop Production and Farm Income

Below I describe the construction and data used to calibrate the rest of the parameters in the model.

Farm Size (A): I evaluate the model using multiple different farm sizes. I primarily discuss the results using a farm size of 350 acres, which has been the stable average farm size in Iowa for the past two decades.[13] For later policy analysis, I evaluate the model using the average of each farm size bracket category from the USDA census.[14]

Corn Sell Price (p): I use monthly USDA corn price data from 1947–2024. The mean of this distribution, ($4.06 per bushel), is used as the normal state selling price farmers face.

Input Costs (c): Data from 1975–2025 on corn production costs are obtained from Iowa State University's Ag Decision Maker resource. These include costs for (1) machinery, (2) seed, fertilizer, and chemicals, (3) labor, and (4) land. I construct a distribution of total costs per acre and use the binned median, $735 per acre, as the input cost.

County Government Subsidies (s): I divide the dollars of government and federal programs (excluding conservation and wetlands subsidies) received by operation per county by the amount of corn-grain acres harvested per county for the 2002 to 2022 USDA Censuses. Each county's average of this distribution is used as the model's county estimate of per-acre subsidy.

County Yield (y): I use USDA county-level corn-grain yield data and restrict the sample to 2013–2023 to reduce bias from long-run technological change. The county-specific median yield across this period is used as the county's normal yield state.

County CRP Soil Rental Rate (srr): Soil rental rate data are collected from the FSA's CRP rental dataset from 1986–2024. The median soil rental rate by county is used.

CRP Establishment Cost (est): Detailed CRP establishment cost data is limited, so I estimate these parameters from a 2022 USDA ERS report[15] on producer conservation cover practice costs. Based on the report, I assume a $100 establishment cost

[13] In the 2022, 2017, 2012, 2007, 2002, and 1997 censuses, the average farm size in Iowa was 345, 355, 345, 331, 350, and 334 acres, respectively.

[14] This includes the farm sizes of 5, 30, 60, 80, 120, 160, 200, 240, 380, 750, 1500, and 2500 acres.

[15] See Pratt and Wallander (2022) for specifics.

per acre[16], with a 25% maintenance cost in the second period.

County Yield ($z^c_{y,t}$) **and Price** ($z_{p,t}$) **States and Shocks**: To construct the yield and price state transition matrices, I discretize year-to-year variation into three states: Bad, Normal, and Good. For yield, I first remove the long-run trend of technological progress (e.g., improved seeds, fertilizer, and machinery) by estimating a linear regression of average county-level corn-grain yield on time for each Iowa county from 1930 to 2023 of the form,

$$Yield_{c,t} = \alpha_c + \beta_c \cdot Year_t + \epsilon_{c,t} \tag{11}$$

The residuals, $\epsilon_{c,t}$, capture short-run shocks unrelated to long-term trends. I classify county yield state using the distribution of these residuals: years below the 25th percentile are classified as Bad, above the 75th percentile as Good, and the remainder as Normal. I then compute a Markov transition matrix for each county by counting one-year transitions across states and normalizing rows into probabilities. This classification captures county-specific volatility rather than structural yield improvement. The same procedure is done for corn-grain prices from 1947 to 2024, using the annual USDA marketing price as the dependent variable.[17]

To construct the yield shock multipliers, I estimate county-specific scaling factors that adjust baseline yields in Bad and Good years relative to Normal years. Restricting the detrended categorized residual yield data to 2013–2023, I classify each observation by yield state and compute the average yield within each group. The Bad and Good state multipliers are then defined as the ratio of their respective mean yields to the mean yield in the Normal state:

$$\text{Bad Ratio} = \frac{\mathbb{E}[\text{Yield} \mid \text{Bad}]}{\mathbb{E}[\text{Yield} \mid \text{Normal}]}, \quad \text{Good Ratio} = \frac{\mathbb{E}[\text{Yield} \mid \text{Good}]}{\mathbb{E}[\text{Yield} \mid \text{Normal}]} \tag{12}$$

An identical process is done using the real corn sell price (not restricted in years) distribution to construct the price state multiplier.

[16]For new farms, the report shows that establishment costs for grassland range from $25 to $107 per acre, while habitat and tree practices range from $150–$200 per acre. Additionally, CRP participants are typically eligible for cost-share programs, offsetting up to 50% of installation costs. Thus, the $100 approximation is consistent with these typical practices, once cost-share assistance is considered.

[17]The USDA crop marketing price is the average price received across the state for all grades and qualities of that crop.

4 Results

To evaluate how farmers respond to different levels of risk aversion, I simulate land allocation decisions by county using policy functions from Equation 5. For each Iowa county and CRRA coefficient (γ) policy function, I simulate 10,000 farmer paths over a 70-year horizon. Farmers start in normal yield and price states with no CRP enrollment. In each period, they observe current states and CRP commitments, realize income based on observed conditions, and decide how much land to allocate for the next year. Yield and price evolve stochastically via Markov processes. From these simulations, I compute average long-run shares of land farmed, enrolled in the CRP, and chosen to enroll by county, risk preference, and farm size.

When comparing results between counties with different CRP limits, I report the average percentage of enrolled CRP land of the county's total CRP monetary limit for 350-acre farms (again, the average farm size in Iowa) of the form:

$$\text{CRP Limit Share} = \frac{\text{Percent of County CRP Acres}}{\text{CRP limit}} \cdot 350 \tag{13}$$

I refer to this measurement as the CRP limit share moving forward. I have three results sections. Section 4.1 investigates the model's land-allocation behavior across (4.1.1) and between (4.1.2) counties. Section 4.2 investigates how county-specific factors (4.2.1), heterogeneous risk-preferences (4.2.2), and farm size (4.2.3) influence CRP participation. Lastly, Section 4.3 describes the policy implications of my model, describing how the model's predicted CRP enrollment relates to current CRP acreage restrictions (4.3.1) and the welfare benefits the CRP provides (4.3.2).

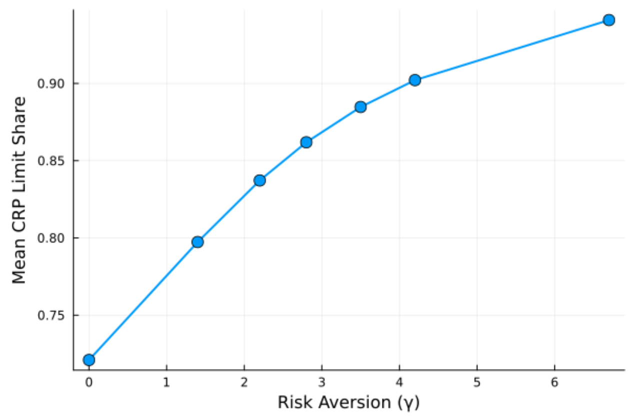
4.1 Model and Simulation Behavior

4.1.1 Aggregate CRP Participation and Risk Aversion

To examine the macro-behavior of the model, Figure 3 plots the relationship between γ and the average county CRP limit share across all of Iowa's 99 counties for 350-acre farms. As expected, more risk-averse farmers allocate a larger share of their CRP limit. Notably, even risk-neutral farmers ($\gamma = 0$) are predicted to utilize 72% of their CRP limit, reflecting how the inherent volatility of farming makes guaranteed CRP payment attractive even absent risk aversion.

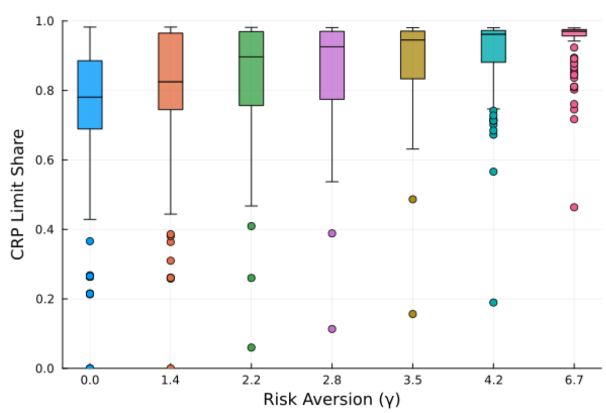
Figure 4 shows the full cross-county distribution of CRP limit share at each γ for 350-acre farms using boxplots. While the median and interquartile range shift up with γ, dispersion remains sizable at lower to moderate risk aversion and narrows as γ increases. A handful of counties remain far from the bulk, plotted as points beyond the whiskers (defined as $1.5 \cdot IQR$) and illustrate the meaningful heterogeneity in local incentives.

Figure 3: Average CRP Limit Share vs Risk Aversion Parameter: Iowa



Note: Figure plots the average CRP limit share across all Iowa counties for all risk aversion parameters, γ for 350-acre farms. CRP limit share is the average share of a county's CRP enrollment multiplied by its farm size (350), divided by its CRP limit. Average share of CRP enrollment is calculated from 10,000 simulated farmer paths for 70 years.

Figure 4: Distribution of CRP Limit Share for Risk Aversion Parameters: Iowa



Note: Figure plots boxplots that represent the distribution of Iowa's 99 county's CRP limit shares for a given γ for 350-acre farms. CRP limit share is the average share of a county's CRP enrollment multiplied by its farm size, divided by its CRP limit. Average share of CRP enrollment is calculated from 10,000 simulated farmer paths for 70 years.

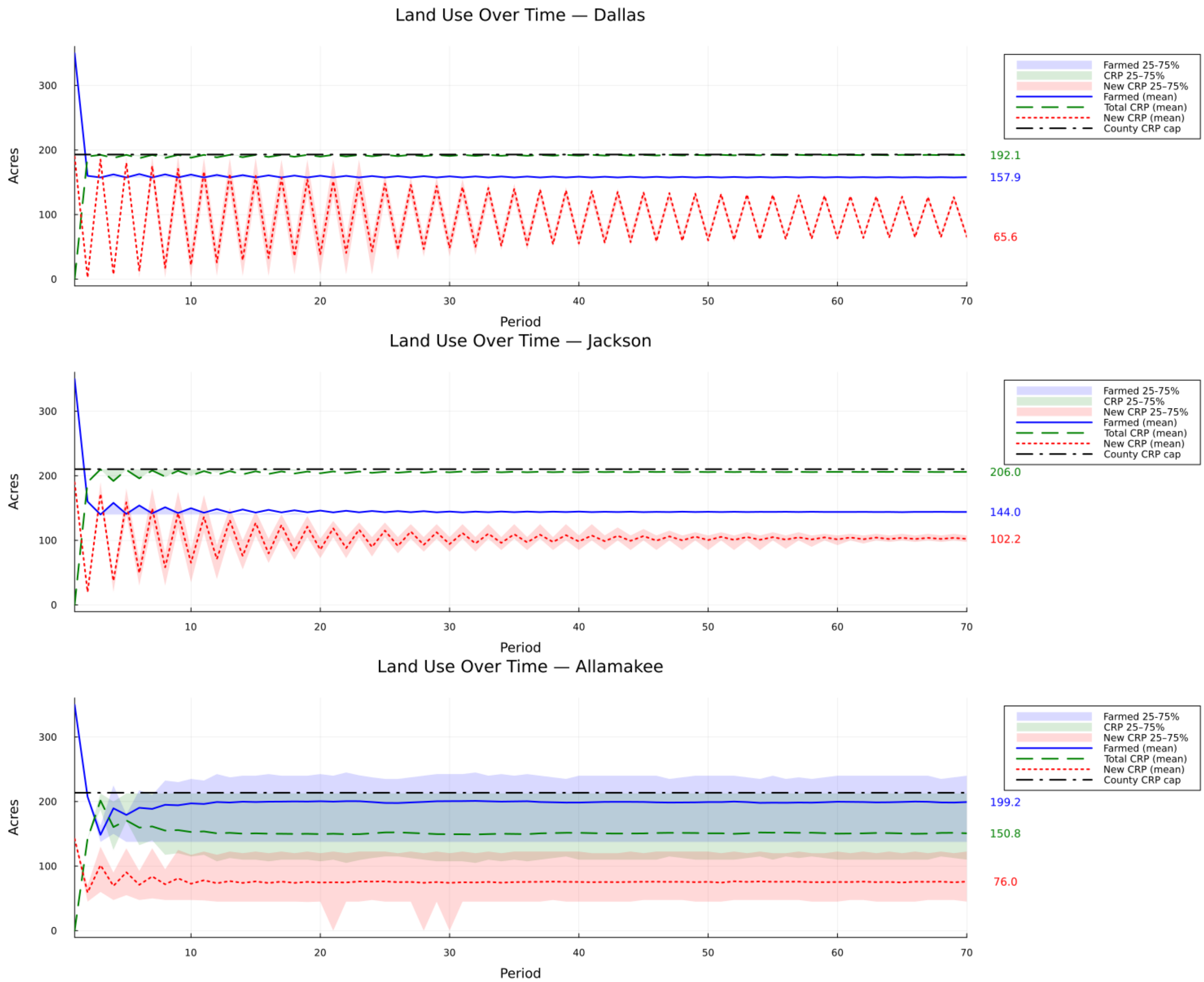
4.1.2 Model County Behavior and Simulation Paths

I next examine the county-level simulation dynamics of the model. Figure 5 presents the simulated time-series plots of the average CRP land allocation from 10,000 simulations for 70 years for three representative Iowa counties: Dallas, Jackson, and Allamakee. These counties correspond to the 95th, 50th, and 5th percentiles of CRP limit share land allocation, respectively, when $\gamma = 4.2$ and A = 350.

For each county at time t, the solid blue line shows the average total land in acres farmed, the dashed green line represents the average total land enrolled in the CRP in that period (C_1+C_2), and the red dotted line indicates the land chosen that period to be newly enrolled in CRP for the next period (C_1'). The similarly-colored shaded areas around each line depict the simulations at the 25% and 75% percentiles. The black dash-dotted line is the county's specific CRP limit.

Several patterns emerge. First, all three counties approach their steady-state allocations quickly, usually in $t < 15$. For Dallas and Jackson counties, where CRP enrollment is 98% and 96% of their CRP limit, they enroll (C_1') the majority of their CRP limit in year 1, and a much smaller amount in year 2 (red dotted line). This results in a converging oscillating choice pattern in Jackson, eventually spreading that allocation evenly across the two periods, while in Dallas they continue to enroll more in odd periods. In Allamakee, which enrolls 70% of its CRP limit, the highlights (25% to 75% of simulation runs) show that notable variation between simulation runs emerges when a county is not utilizing the majority of its CRP limit.

Figure 5: County-Level Simulation Dynamics



Note: Figure presents the simulated land trajectories over 70 periods for three Iowa counties under $\gamma = 4.2$ and A = 350. Dallas, Jackson, and Allamakee correspond to the 95%, 50%, and 5% of CRP limit share enrollment. The lines represent the average land farmed in acres (blue, solid), total CRP land enrolled in acres (green, dashed), and chosen CRP land to enroll (red, dotted), and the county's CRP limit in acres (black dot-dashed line) across 10,000 simulations each period. Shaded same-colored bands indicate the 25th and 75th percentile trajectories for the respective line. The values at the far right of each line represent the steady-state land values.

4.2 Mechanisms of CRP Take-up

4.2.1 County-Level Factors

To investigate what is driving county participation differences, I regress the county-specific parameters on the CRP limit share using OLS of the form,

$$y_{CLS,c} = \beta_0 + \beta_1 srr_c + \beta_2 sub_c + \beta_3 \mu_{y,c} + \beta_4 \sigma_{y,c} + \beta_6 CRP_{LR,c} \tag{14}$$

where srr_c, sub_c, and $CRP_{LR,c}$ are the county-specific per acre average soil rental rate, government subsidy, and CRP acre limit to farm size ratio ($\frac{CRP_c^{limit}}{A}$). $\mu_{y,c}$ and $\sigma_{y,c}$ are the stationary weighted mean and standard deviation of the county-specific baseline yield, weighted by the county-specific yield state and multiplier probabilities.[18]

Table 2 reports the OLS estimates from equation 14. The largest effects by magnitude come from the yield variables. A 10 bu/acre increase in mean yield is associated with a 7 percentage-point lower CRP limit share. I see a similar pattern with yield standard deviation. A 10 bu/acre increase in yield SD (i.e., more volatile yields) is associated with a 6 percentage-point higher limit utilization

Turning to policy and price variables, soil rental rate and the limit-to-farm-size ratio are not statistically significant ($p = 0.233$ and $p = 0.873$). The effect of a county's soil rental rate is likely diminished due to measuring the outcome as the CRP limit share. By contrast, non-conservation government subsidies per acre are negative and significant, with a $10 per acre increase in non-conservation government support associated with a 3 percentage point decrease in CRP limit share. Intuitively, higher non-CRP support (crop insurance) raises the attractiveness of farming relative to CRP. Overall, cross-county differences in expected returns (mean yield), risk (yield SD), and non-CRP subsidies explain much of the variation in how fully counties utilize their CRP limits, while limit design itself shows little residual explanatory power once outcomes are scaled by the limit.[19]

[18] See Appendix 6.1.1 for description of stationary mean and yield calculation.

[19] I also estimate specifications that include yield-state persistence terms (PR(Bad→Bad)). These covariates were statistically insignificant (e.g. $p = 0.867$), once mean yield and yield dispersion were included, likely because persistence is correlated with the stationary moments summarized by $\mu_{y,c}$ and $\sigma_{y,c}$. Their inclusion did not materially change other coefficients; results available upon request.

Table 2: County-Specific Variable Regression Results

Variable	**Coef**	**Std. Error**	**t**	**p-value**
Constant	2.000	0.593	3.371	0.001
Soil rental rate	0.001	0.001	1.201	0.233
Govt subsidy ($/acre)	-0.003	0.000	-8.036	0.000
Mean yield	-0.007	0.001	-5.996	0.000
Yield SD	0.006	0.002	3.428	0.001
Cap / Farm size	0.077	0.438	0.176	0.860

Note: The table reports the regression results from equation 14. There are 99 observations in this regression taken from the 99 counties in Iowa.

4.2.2 Risk-Preferences

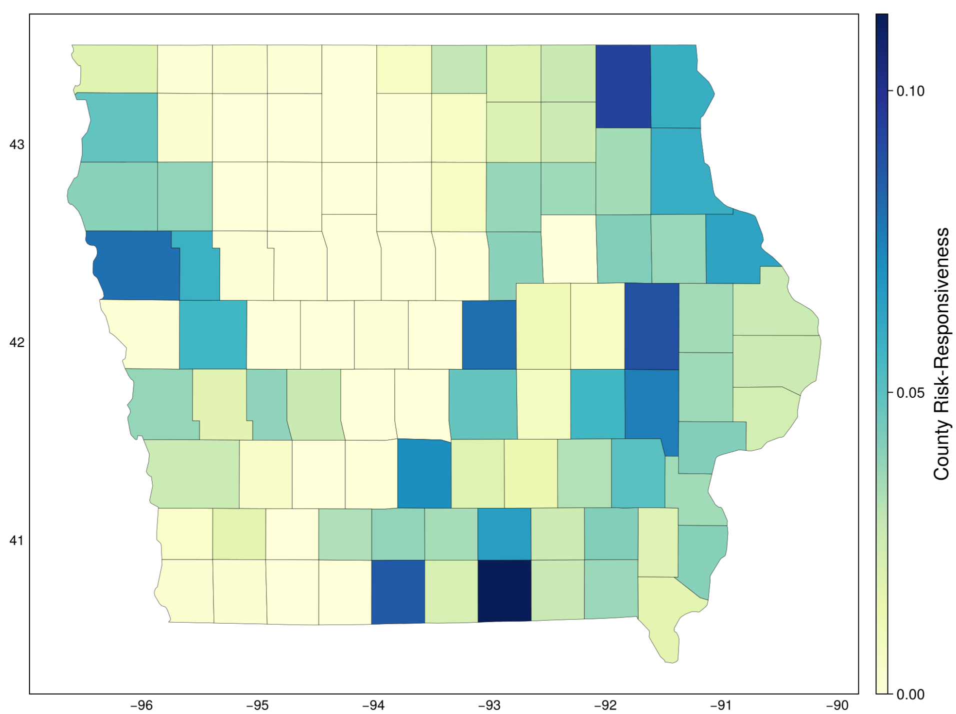
I next examine how individual counties differ in their CRP allocation to increasing risk aversion. Figure 6 presents a county-level map of Iowa showing the risk-responsiveness of each county. I define risk-responsiveness as how much a county's CRP limit share rises when the risk parameter increases for 350 acre farms: $\frac{\partial(CRPLimitShare)}{\partial\gamma}$. In Figure 6, counties with the largest risk-responsiveness are shown in navy blue, while those least responsive are white.

Most counties are light-to-mid tones, implying modest positive responsiveness (CRP limit share increases by roughly 2 to 6 percentage points for a unit increase in γ). Darker pockets indicate places where CRP uptake grows quickly with risk, on the order of 8 to 12 percentage points. The least responsive counties are located in a vertical stretch in the central west of the state, counties such as Kossuth, Webster, and Taylor. I explain this visual heterogeneity in risk-responsiveness by re-estimating equation 14 with the dependent variable replaced by each county's risk-responsiveness. Table 3 reports these results.

Three patterns stand out. First, mean yield is the most notable predictor, where a 10 bu/acre increase in mean yield is associated with about a 2 percentage point increase in CRP limit share per 1 unit increase in γ. In contrast, yield SD is not statistically significant, suggesting risk-responsiveness is not strongly related to county production volatility. Second, program incentives matter. A $10 per acre increase in soil rental rates (government subsidies) is associated with less (more) responsiveness, on the magnitude of decreasing (increasing) CRP limit utilization by 1 percentage point per 1 unit increase in γ. Finally, a larger CRP limit-to-farm ratio dampens the slope, and raising the ratio by 0.10 is related to decreasing responsiveness by 1.4 percentage points per 1 unit increase in γ.

Intuitively, counties with higher mean yields start from lower CRP use (in the level regression) but shift more aggressively toward CRP as risk aversion rises, producing a steeper slope. When soil rental rates are higher, the return to CRP is strong even at low γ, pushing counties toward high CRP use and leaving little room for further increases as risk aversion rises, thus responsiveness flattens. In contrast, higher non-conservation subsidies make farming more attractive at low γ, so as γ increases there is more headroom to reallocate acreage toward CRP, yielding a steeper response. Overall, differences in mean yield and policy instruments (soil rents, subsidies, and limit ceiling) explain most of the geographic variation in how sensitive CRP limit utilization is to risk aversion.

Figure 6: County-Level Risk Responsiveness



Note: Figure presents all 99 counties of Iowa and their respective risk-responsiveness when farm size is 350 acres. Risk-responsiveness is measured as the change in the county's CRP limit share divided by the change in the risk parameter (γ). Dark blue sections indicate counties with greatest risk-responsiveness, while white indicates the least risk-responsive.

Table 3: County Risk Responsiveness Slope Regression Results

Variable	**Coef**	**Std. Error**	**t**	**p-value**
Constant	-0.178	0.088	-2.018	0.046
Mean yield	0.002	0.000	11.300	0.000
Yield SD	-0.000	0.000	-0.885	0.378
Soil rental rate	-0.001	0.000	-4.065	0.000
Govt subsidy ($/acre)	0.001	0.000	14.759	0.000
Cap / Farm size	-0.140	0.065	-2.143	0.035

Note: The table reports the regression results from equation 14. Risk-responsiveness is measured as the change in the county's CRP limit share divided by the change in the risk parameter (γ).

4.2.3 Farm Size

To examine how CRP allocation varies with farm size, I evaluate the model at the average of the USDA's 2022 farm-size categories,

$$A \in \{5, 30, 60, 80, 120, 160, 200, 240, 380, 750, 1500, 2500\}$$

and, for each level of risk aversion γ, estimate the within–county relationship between the CRP and farm size using a fixed-effects OLS regression of the form,

$$y_{c,A} = \alpha_c + \omega ln(A) + \epsilon_{c,A} \tag{15}$$

where $y_{c,A}$ is the long-run share of the acreage enrolled in the CRP at size A. At $\gamma = 4.2$, I estimate $\widehat{\omega} = -0.13$ (s.e. 0.004), implying that, within a county, larger farms allocate a smaller share of their acreage to the CRP.

In particular, a doubling of farm size (30 to 60 or 750 to 1,500) lowers the model's predicted CRP share by 9 percentage points (roughly 5.4 and 135 acres, respectively).[20] This within-county estimate $\widehat{\omega}$ is stable and negative across risk preferences, with point estimates varying by only 0.005 across γ.[21]

[20] Because the model is linear in $\ln(A)$, the change in share moving from A_1 to A_2 is $\widehat{\omega}\ \ln(A_2/A_1)$. Doubling A would equal $\Delta y = \omega ln2 \approx -0.130 \cdot 0.6931 \approx -0.090$

[21] Specifically, the coefficients on $\omega = -0.131, -0.127, -0.128, -0.130, -0.130, -0.132$ for $\gamma = 0, 1.4, 2.2, 2.8, 3.5, 6.7$, respectively.

4.3 Model Policy Implications

4.3.1 Model CRP Allocation Against Current Policy Limits

We next benchmark the model's steady-state CRP enrollments against current policy caps. As of 2025, the CRP imposes county-level participation caps, typically restricting enrollment to roughly 25% of a county's farmland (U.S. Department of Agriculture, Farm Service Agency, 2021). Using the 2022 USDA Census of Agriculture counts of farms and farmland by county[22], I compute each county's permitted CRP acreage under this cap.

To construct the model predicted enrollment at all risk aversion levels, I (i) take the model's steady-state CRP acres for a representative farm of size A with CRRA γ in county c, (ii) multiply by the number of farms in that county–size bin, and (iii) sum across all size bins. Summing across counties is how I derive the model's state predicted CRP enrollment. I compare these state and county model-optimal totals to the policy limits in tables 4 and 5, respectively.

At the state level, Table 4 shows that the current state aggregate CRP cap (just under 7.5 million acres) can accommodate the model's predicted CRP enrollment if all farmers are risk-neutral (when $\gamma = 0$). However, at the PSID estimated average farmer risk aversion ($\gamma = 4.2$), the model implies almost 8.8 million acres, roughly 1.3 million acres above the cap. In fact, current state policy limits are insufficient for any γ category above 0.

At the county-level, there is significant heterogeneity in how current policy limits accommodate the model's predictions. Assuming $\gamma = 4.2$, Table 5 displays the model predicted CRP enrollment and CRP cap for 10 counties spanning the deciles of predicted CRP allocation, from the 0th percentile (Decatur) to the 100th percentile (Kossuth). A few counties, like Decatur, lie comfortably below their caps (23,000 acres), while more, like Delaware and Floyd, exceed their cap by notable margins (34,000 and 29,000, respectively). Only a handful of counties (including Humboldt and Cass) have predicted amounts that lie essentially at or close enough to their caps. However, on average across the 99 counties, aggregate county model predicted acreage exceeds current policy caps by 13,114 acres.

Taken together, these patterns suggest the uniform, static acreage caps are poorly aligned with the spatial variation in expected farm returns, risk, and CRP value. Many counties have excess demand for CRP acreage, while others have slack. These results suggest the implementation of more flexible or data-driven caps that scale with county fundamentals.

[22] I include all three USDA operator categories: owners, part-owners, and tenants.

Table 4: Model State CRP Enrollment Against Cap

Gamma	Model CRP Acres	CRP Cap
0.0	7,326,186	7,494,541
1.4	8,237,100	7,494,541
2.2	8,406,842	7,494,541
2.8	8,444,731	7,494,541
3.5	8,639,201	7,494,541
4.2	8,792,870	7,494,541
6.7	9,138,840	7,494,541

Note: The table reports the aggregated total model predicted acres farmer's enroll in the CRP alongside the state CRP acre cap for Iowa. Model CRP Acres is calculated by summing across the multiplied county simulated steady-state CRP share for each farm size (A) by the total number of those categorical sized farms for that county. CRP Cap is defined as 25% of the total county farmland acres aggregated across counties. County data is sourced from the 2022 census of agriculture.

Table 5: Model CRP Enrollment by County ($\gamma = 4.2$)

County	Model CRP Acres	CRP Cap
Decatur	34,531	57,895
Humboldt	56,877	55,821
Wapello	67,380	48,898
Cass	73,682	75,130
Allamakee	83,910	76,113
Page	87,440	72,991
Keokuk	92,999	69,370
Harrison	98,271	93,596
Floyd	104,721	75,449
Delaware	120,526	86,464
Kossuth	163,747	146,136

Note: The table reports the total model predicted acres farmer's enroll in the CRP when $\gamma = 4.2$ alongside the county CRP acre cap for a selection of Iowa counties. Model CRP Acres is calculated by multiplying the county simulated steady-state CRP share for each farm size (A) by the total number of those categorical sized farms for that county. CRP Cap is defined as 25% of the total county farmland acres. County data is sourced from the 2022 census of agriculture.

4.3.2 CRP Welfare Analysis

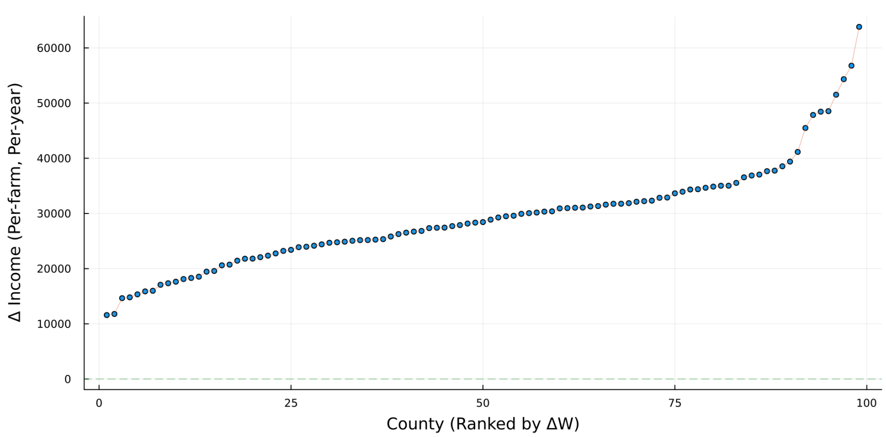
My final set of results conducts a welfare analysis of the CRP. I quantify welfare by comparing the model predicted farmer income with versus without access to the CRP. For each county, I re-solve and simulate the model at the empirically estimated averages for farm size and risk aversion ($A = 350, \gamma = 4.2$) where CRP enrollment is disabled through restricting $C_1' = 0$, so that $C_1 = C_2 = 0$ for all t. Let $\pi_{n,t}^{with}$ and $\pi_{n,t}^{wo}$ denote per period farm income in simulation n and year t under the baseline (CRP allowed) and counterfactual (farm-only), respectively. I define county-level welfare as the Monte Carlo average income difference

$$\Delta W = \frac{1}{NT} \sum_{n=1}^{N} \sum_{t=1}^{T} (\pi_{n,t}^{with} - \pi_{n,t}^{wo}), \tag{16}$$

where N is the number of simulated farms $(10,000)$ and T is the horizon (70 years). ΔW measures the expected per-farm, per-year income gain from having the option to participate in the CRP.

Across Iowa's 99 counties, access to the CRP increases expected per-farm annual income by $29,245. Figure 7 ranks counties by their welfare gains. While a handful of counties exhibit gains above $40,000, most cluster between $20,000 and $30,000, indicating sizable but heterogeneous benefits from CRP access.

Figure 7: CRP Welfare Gain Across Counties



Note: Figure presents the ranked welfare gain for Iowa's 99 counties when risk-aversion $(\gamma) = 4.2$ and farm size is 350 acres. Welfare is defined as the expected per-farm, per-year income difference between the baseline (CRP access) and a farm-only counterfactual in which CRP enrollment is disabled. Units are in 2024 dollars.

5 Conclusion

This paper builds and calibrates a land-allocation model with a two-year CRP lock-in to study how risk preferences, local agronomic conditions, and farm size shape farmers' participation in the Conservation Reserve Program. Calibrated to county-level data for Iowa corn-grain producers, the model produces two central objects: a county's (i) steady-state CRP enrollment and (ii) risk-responsiveness, how that enrollment changes as risk aversion (γ) rises. At the aggregate level, steady-state enrollment increases with γ and notably, even risk-neutral farmers ($\gamma = 0$) allocate 72% of their monetary limit on average.

At the county-level, I find significant heterogeneity both in levels (limit utilization) and slopes (risk-responsiveness). County differences in limit-utilization follow from varied mean yields and volatility, and non-conservation subsidies. Risk-responsiveness is largely influenced by mean yields, non-conservation subsidies, CRP soil rental rates, and limit-to-farm-size ratios. Together, these results say that where baseline farming returns are strong or subsidized, the marginal effect of risk preferences on CRP uptake is larger, while where CRP is already very attractive (high SRR or tight cap relative to A), risk preferences matter less at the margin.

Within counties, CRP allocation falls with farm size, implying that doubling farm size lowers CRP limit share by 9 to 10 percentage points. Benchmarking the model to policy caps shows meaningful gaps. Statewide, the current CRP aggregate cap could accommodate model-implied enrollment only for risk-neutral preferences, while at $\gamma = 4.2$ (PSID-estimated), the model predicts about 1.3 million more acres than today's cap allows. At the county level, while there is substantial heterogeneity, on average counties exceed their caps by 13,114 acres. Lastly, the CRP delivers substantial but heterogeneous welfare gains: access to CRP raises county expected per-farm annual income anywhere from \$10,000 to just over \$60,000.

These results carry clear implications for agricultural policy. National uniform acreage caps are poor at fitting to the highly heterogeneous local land qualities and farmer preferences. If policymakers aim to expand conservation land while efficiently supporting farmer welfare, the results suggest that tailoring program rules to local conditions could drastically improve alignment between policy objectives and farmer behavior.

I plan to extend this work in many ways. First, the model abstracts from certain CRP program features, such as long (10–15 year) contract horizons, competitive enrollment, and environmental scoring. Implementing these mechanisms would provide both more realistic model behavior and policy suggestions. Second, the model is calibrated at the county-level due to data limitations, which masks within-county and within-farm land heterogeneity. I am working on combining field-level soil (SSURGO) and weather (PRISM) data to merge with restricted USDA farmer household- and field-level production microdata to calibrate the model at the field level. This degree of granularity would better align model predictions with observed farmer behavior and permit environmental welfare-based targeting, allowing the model to quantify where each additional CRP enrolled acre buys the largest environmental return per dollar.

References

Aspelund, Karl M. and Anna Russo (2025) "Additionality and Asymmetric Information in Environmental Markets: Evidence from Conservation Auctions," working paper.

Barsky, Robert B., F. Thomas Juster, Miles S. Kimball, and Matthew D. Shapiro (1997) "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study*," *The Quarterly Journal of Economics*, 112 (2), 537–579.

Cornish, Brian, Ruiqing Miao, and Madhu Khanna (2022) "Impact of changes in Title II of the 2018 Farm Bill on the acreage and environmental benefits of Conservation Reserve Program," *Applied Economic Perspectives and Policy*, 44 (2), 1100–1122.

Cramton, Peter, Daniel Hellerstein, Nathaniel Higgins, Richard Iovanna, Kristian López-Vargas, and Steven Wallander (2021) "Improving the cost-effectiveness of the Conservation Reserve Program: A laboratory study," *Journal of Environmental Economics and Management*, 108, 102439.

Finger, Robert, David Wüpper, and Chloe McCallum (2023) "The (in)stability of farmer risk preferences," *Journal of Agricultural Economics*, 74 (1), 155–167.

Gallagher, Nicholas James (2024) "Dynamic Programming Methods for Characterizing In-Season Farm Management Decisions," Dissertations and Theses 344827, Ekiti State University, Ado-Ekiti, Department of Agricultural Economics and Extension Services.

Guan, Zhengfei and Feng Wu (2017) "Modeling heterogeneous risk preferences," *Agricultural Finance Review*, 77 (2), 324–336.

Hall, Robert E. and Susan E. Woodward (2010) "The Burden of the Nondiversifiable Risk of Entrepreneurship," *American Economic Review*, 100 (3), 1163–94.

Hellerstein, Daniel M. (2017) "The US Conservation Reserve Program: The evolution of an enrollment mechanism," *Land Use Policy*, 63, 601–610.

Isik, Murat and Wanhong Yang (2004) "An Analysis of the Effects of Uncertainty and Irreversibility on Farmer Participation in the Conservation Reserve Program," *Journal of Agricultural and Resource Economics*, 29 (2), 1–18.

Janssen, Sander and Martin K. van Ittersum (2007) "Assessing farm innovations and responses to policies: A review of bio-economic farm models," *Agricultural Systems*, 94 (3), 622–636, Special Section: sustainable resource management and policy options for rice ecosystems.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry (2014) "Agricultural Decisions after Relaxing Credit and Risk Constraints," *The Quarterly Journal of Economics*, 129 (2), 597–652.

Kimball, Miles S., Claudia R. Sahm, and Matthew D. Shapiro (2009) "Risk Preferences in the PSID: Individual Imputations and Family Covariation," *American Economic Review*, 99 (2), 363–68.

Lubowski, Ruben N., Andrew J. Plantinga, and Robert N. Stavins (2008) "What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions," *Land Economics*, 84 (4), 529–550.

Miao, Ruiqing, Hongli Feng, David A. Hennessy, and Xiaodong Du (2016) "Assessing Cost-effectiveness of the Conservation Reserve Program (CRP) and Interactions between the CRP and Crop Insurance," *Land Economics*, 92 (4), 593–617.

Orduño Torres, Miguel Angel, Zein Kallas, and Selene Ivette Ornelas Herrera (2019) "Analysis of Farmers' Stated Risk Using Lotteries and Their Perceptions of Climate Change in the Northwest of Mexico," *Agronomy*, 9 (1).

Pratt, Bryan and Steven Wallander (2022) "Producers' Net Costs Influence Offers to USDA's Conservation Reserve Program," *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America*, Accessed via USDA ERS website, April 4, 2022.

Rosenzweig, Mark R. and Hans P. Binswanger (1993) "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments," *The Economic Journal*, 103 (416), 56–78.

Souza-Rodrigues, Eduardo (2018) "Deforestation in the Amazon: A Unified Framework for Estimation and Policy Analysis," *The Review of Economic Studies*, 86 (6), 2713–2744.

Udry, Christopher (1994) "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria," *The Review of Economic Studies*, 61 (3), 495–526.

——— (1995) "Risk and Saving in Northern Nigeria," *American Economic Review*, 85 (5), 1287–1300.

U.S. Department of Agriculture, Economic Research Service (2025) "Farm Income and Wealth Statistics — Net cash income," September, Updated September 3, 2025.

U.S. Department of Agriculture, Farm Service Agency (2021) "Notice CRP-939: Monitoring CRP 25 Percent County Cropland Limitation," notice, U.S. Department of Agriculture, Farm Service Agency, PDF, disposal date October 1, 2021; available from USDA FSA website.

——— (2025) "6-PL (Payment Limitation Handbook), Amendment 7,"Technical report, U.S. Department of Agriculture, Farm Service Agency, PDF, available from U.S. Department of Agriculture Farm Service Agency website.

Wallander, Steven, Laura A. Paul, Paul J. Ferraro, Kent D. Messer, and Richard Iovanna (2023) "Informational nudges in conservation auctions: A field experiment with U.S. farmers," *Food Policy*, 120 (C), None.

Yu, Jisang, Brittney Goodrich, and Atticus Graven (2016) "Processes of adaptation in farm decision-making models. A review," *Agronomy for Sustainable Development*, 36 (4), 64.

——— (2022) "Competing farm programs: Does the introduction of a risk management program reduce the enrollment in the Conservation Reserve Program?" *Journal of the Agricultural and Applied Economics Association*, 1 (3), 320–333.

6 Appendix

6.1 Technical Appendix

6.1.1 County Yield Weighted Stationary Mean and Standard Deviation

In section 4.1.2, I calculate and use the stationary weighted mean and standard deviation of the baseline average county yield in a regression to investigate what is driving the county differences in CRP allocation. Here I describe how I calculated those values for each county. The three-state yield process $Z_t \in \{B, N, G\}$ follows a first-order Markov chain with transition matrix $P \in \mathbb{R}^{3\times 3}$. The stationary (long-run) distribution $\pi = (\pi_B, \pi_N, \pi_G)$ satisfies the left-eigenvector condition $\pi' = \pi' P$ and $\sum_s \pi_s = 1$ (I assume the chain is ergodic so π is unique). Given a county's baseline yield $\bar{y}$ and state multipliers $(m_B, 1, m_G)$, define the state means $y = (y_B, y_N, y_G) = (\bar{y} m_B, \bar{y}, \bar{y} m_G)$. I summarize each county's yield process by the stationary-weighted mean and standard deviation,

$$\mu_y = \sum_{s \in \{B,N,G\}} \pi_s \, y_s \qquad \text{and} \qquad \sigma_y = \sqrt{\sum_{s \in \{B,N,G\}} \pi_s \, (y_s - \mu_y)^2}.$$

If within-state variance $v_s = \mathrm{Var}(Y \mid Z = s)$ is nonzero, the law of total variance gives $\sigma_y^2 = \sum_s \pi_s [v_s + (y_s - \mu_y)^2]$. When the long-run state probabilities are equal ($\pi_s = 1/3$), $\mu_y = \bar{y}\,(m_B + 1 + m_G)/3$.