Welfare and Risk Impacts of the One Big Beautiful Bill Act (OB3) for Illinois farmers

Henrique Monaco[*], Gary Schnitkey[†] and Nicholas Paulson[‡]

Abstract

This study compares welfare and risk changes from OB3 policy to the 2018 Farm Bill (FB2018) using a multi-year, simulation-based portfolio optimization framework for Illinois farmers. Farmers choose among crop insurance and Commodity Title I programs to maximize expected utility. OB3 increases welfare for all farms, with average certainty equivalent (CEQ) gains of $15.80/acre for soybeans and $10.47/acre for corn. Most farms experience reductions in tail-risk (CVaR), though some—especially corn farms—see increases, indicating the programs can act as income support rather than solely as risk management. Policy changes alter enrollment patterns: PLC becomes more attractive for soybeans, ARC-CO gains appeal for corn, and SCO/ECO adoption was high. Results highlight the importance of considering program interactions, crop-specific responses, and the balance between risk reduction and income support when designing farm policy.

Keywords: One Big Beautiful Bill Act (OB3), Crop insurance, Commodity Title I, Portfolio, Risk Management, Government Programs, Farm Bill.

[*]Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA. hc30@illinois.edu

[†]Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA. schnitke@illinois.edu

[‡]Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA. npaulson@illinois.edu

1 Introduction

U.S. agricultural producers face considerable financial risks due to volatile crop yields and prices. These challenges are amplified by global market shocks, geopolitical uncertainties, climate variability, and evolving policy frameworks. To mitigate these risks and provide a safety net, federally subsidized programs, including crop insurance and Commodity Title I, are widely adopted by American farmers. Typically, changes to these programs are enacted through the Farm Bill, however, they were recently revised under the One Big Beautiful Bill Act (OB3) (Rep. Arrington, 2025). While revisions point to an overall improvement from a farmers perspective, both from an increased income or/and reduction in risk, it has not yet been quantified in the literature.

This paper evaluates the impact of these changes by comparing outcomes under the 2018 Farm Bill (FB2018) with those under OB3. The analysis frames crop insurance together with Commodity Title I programs as components of a portfolio optimization problem. Assets, or programs, selection affect not only expected returns but also risk exposure and overall welfare. Based on a simulation-based optimization framework, the study examines the welfare and risk outcomes for representative Illinois farmers choosing among available program combinations under uncertainty, with a forward-looking horizon of three years.

Risk-return trade-offs in finance are often evaluated in a portfolio analysis (i.e., Sahamkhadam et al., 2018), where several different models are considered to compare portfolios and assess whether changes increases expected returns, reduce risk, or achieve both. Applications of portfolio analysis are also seen in agriculture risk management (i.e., Langemeier and Liu, 2020; Lenfestey and Langemeier, 2023). Since Commodity Title I programs and crop insurance are intended to provide a safety net while also reducing risk, understanding this trade-off helps policymakers assess the direction in which program changes are shifting these objectives. Moreover, given the extensive number of available choices—often restricted by program rules, such as choosing between ARC or PLC, or how an underlying policy interacts with a supplemental coverage—and specific parameters, a portfolio provides a useful

structure for capturing farmer decision-making in response to government incentives, as well as for analyzing program interactions and the costs they impose on policymakers.

Several studies have pointed to inefficiencies when overlapping coverage occurs—for example, when farmers enroll in both ARC programs and RP insurance—leading to higher government outlays without comparable reductions in risk (Biram et al., 2019; Luckstead and Devadoss, 2019). Further, Cooper and O'Donoghue (2011) demonstrate that overlapping programs lead to notable inefficiencies due to poor targeting and redundant coverage, exacerbating government expenditures without proportional farmer benefit. Overlap concerns and risk reduction effectiveness have been raised by other authors in similar settings (Coble and Barnett, 2013; Cooper et al., 2015; Luckstead and Devadoss, 2019; Tsay and Paulson, 2024).

More recently, Gaku and Tsiboe (2024) evaluated the effectiveness of the combination of government programs and crop insurance in increasing returns but also in decreasing risk. Findings suggest that profit enhancement not necessarily translate into lower risks, agreeing with the above-mentioned studies where decisions and optimal choices might not always be efficient.

Crop insurance differs from Title I programs in that it requires a premium payment, though a large portion is subsidized by the federal government to promote adoption. Premiums should be actuarially fair, which means indemnities should match expected premiums. Thus, the subsidized share constitutes an income transfer to farmers. Title I programs operate similarly, with payments triggered under specific conditions and functioning as transfers when activated. These features imply that any proposed change to subsidy levels or program rules has both welfare and fiscal implications that merit careful assessment.

Changes include increased subsidies and policy parameters change that will likely result in larger payments, but may also shift farmers' optimal portfolio choices (Luckstead and Devadoss, 2019). While such proposals will benefit farmers, the extent of these gains, their distribution, and the associated taxpayer costs remain unquantified. Understanding these

trade-offs—across farms, crops, programs, and risk profiles—is essential to designing effective and equitable policy.

Wang et al. (2003) highlight how generous crop insurance subsidies encourage expanded agricultural production, including on marginal or risk-prone lands, consequently impacting environmental sustainability and economic efficiency. In addition, larger-scale operations disproportionately benefit from subsidies, raising substantial equity concerns and suggesting potential improvements in policy targeting (Goodwin and Mishra, 2006). These result present a critical trade-off inherent in subsidy design: balancing farmer risk protection against unintended consequences such as market distortions and unintended industry consolidation.

This paper provides a comprehensive assessment of these policy changes. Specifically, it addresses four central questions: (i) How much better-off are farmers under OB3 when compared to the previous (2018) Farm Bill, in terms of certainty equivalent welfare? (ii) Should farmers change their enrollment decisions, switching between programs in response to new incentives? (iii) What is the cost of these changes to policymakers, and how do they compare to benefits in terms of income gains and risk reduction? (iv) Which farmers might benefit the most, and how do farm-specific factors and risk preferences affect outcomes?

The empirical application focuses on Illinois, a major agricultural state with widespread crop insurance adoption, concentrating on corn and soybeans, the two dominant crops grown in the region. The portfolio choices include Title I programs (Agriculture Risk Coverage at the county level (ARC-CO) and Price Loss Coverage (PLC)) alongside individual insurance products such as Revenue Protection (RP), RP with Harvest Price Exclusion (RP-HPE), and Yield Protection (YP), and area-based options such as Supplemental Coverage Option (SCO) and Enhanced Coverage Option (ECO). One key change from OB3, is that ARC-CO does not prevent farmers from enrolling in SCO. Building on previous studies that often analyze a narrow subset of programs, this work includes a broader and new set of policy combinations coupled with specific farm characteristics, capturing realistic and complex farmer choices.

Moreover, this paper extends the literature by offering a multi-year forward-looking simulation-based assessment of a comprehensive set of policy portfolios under the newly passed OB3 program rules, capturing both enrollment changes and distributional outcomes. Results deliver insights on the welfare, behavioral, and budgetary implications of Farm Bill reforms.

2 Background

2.1 Commodity Title I and Crop Insurance

U.S. agriculture policy offers a variety of risk management strategies through government-backed programs. These can be categorized into two broad categories: Commodity Title I and the federal crop insurance program (FCIP).

The United States Department of Agriculture (USDA) operates programs whose objective is to provide a safety net for American farmers. The Commodity Title I program includes the Agriculture Risk Coverage at the county level (ARC-CO), Agricultural Risk Coverage at the farm level (ARC-IC), and Price Loss Coverage (PLC). These programs are managed by the Farm Service Agency (FSA) and were covered under Title I of the Agricultural Improvement Act of 2018 (Public Law 115–334, 2018), known as the 2018 Farm Bill. Recently, changes to the Farm Bill was done through the OB3.

These programs, often referred as counter-cyclical programs or title I programs, are designed to offer protection to both prolonged and widespread price and/or revenue declines (Gaku and Tsiboe, 2024). Payments depend on prices and sometimes yields, creating an inter-year dynamism, even though farm election to these programs is made annually since the 2018 Farm Bill. In addition, program enrollment is an election tied to base acres, which are determined from historical acres and updated only occasionally through federal legislation. ARC-CO and PLC comprises of the vast majority of enrolled base acres. Farms must choose between the two for each crop and elections must be done by March 15^{th} of

each year[1]. They are based on FSA county-level yields and national marketing year average (MYA) cash prices, and are fully funded by the government making enrollment free of cost for farmers. Details of programs mechanics are provided in subsection Appendix A.1.

The Federal Crop Insurance Program (FCIP) operates under permanent statutory authority, with changes and updates included in the Farm Bill under Title XI (Crop Insurance Title). FCIP has been widely used in the United States. From 2000 to 2022, the average annual participation represented 81% of eligible acres, an average of 293 million acres (Economic Research Service of Agriculture, 2025). In Illinois, 95%, 94% and 94% acres of corn, wheat, and soybeans, respectively, were insured with a Revenue Protection (RP) policy in 2024 Schnitkey et al. (2024a). Unlike government support programs, insurance policies have an associated premium that farmers must pay. However, a great part of most policies are subsidized by the federal government.

Crop insurance is provided by private insurers through in a private / public partnership that is managed by the Risk Management Agency (RMA). RMA sets premiums and specific policies that can be sold by agents, sharing underwriting gains or losses with these companies/agents. Under the federal crop insurance program, farmers have farm-level (individual) coverage plans that vary from 50% to 85%. Farm-level policies include Revenue Protection (RP), Revenue Protection with the Harvest Price Exclusion (RP-HPE) and Yield Protection (YP), known as COMBO products (Coble et al., 2010). Add-on coverage is available and is based on county-level parameters. COMBO add-on policies include, among others[2], the Enhanced Coverage Option (ECO) and Supplemental Coverage Option (SCO). Details of COMBO products and COMBO add-on products are provided in subsection Appendix A.2 and subsection Appendix A.3. ECO and SCO are relatively new programs, and adoption has not gained much traction as RP. In Illinois, ECO enrollment in 2024 represented 12% and 7% of insured acres for corn and soybean, respectively. SCO enrollment was about 5% for each crop Schnitkey et al. (2024a).

[1] In 2025, the enrollment decision deadline was changed to April 15th.

[2] Area Risk Protection Insurance (ARPI) is another add-on area based policy

A key difference between crop insurance and Commodity Title I is the crop insurance intra-year focus, which means that parameters and indemnities (payments) are crop-year dependent, and do not carry dynamics over multiple years[3]. Among COMBO policies, farmers must choose one policy and associated coverage level, and any additional area-based policies by March 15th in each year. Differently than Commodity Title I programs, prices are based on futures prices. Main differences associated with Commodity Title I and FCIP are summarized in Table 1.

Table 1: Key differences between Commodity Title I programs and FCIP

Attribute	**Federal Crop Insurance Programs**	**Commodity Title I Programs**
Private/public	Both	Public
Org/agency	RMA and private insurers	FSA
Coverage	Price and Yield	Price and Yield
Prices	Futures	MYA (cash, national)
Production/yields	Farm-level (YP, RP, RP-HPE)	County-level (ARC-CO and PLC)
	County-level (SCO, ECO)	Farm-level (ARC-IC)
Acres enrolled	Insured Acres (producer's choice)	Base Acres (determined by statute)
Timing	Intra-calendar year, specific insurance period	Marketing year, with dynamics across years
Cost	Subsidized premium	No direct

When a Commodity Title I program payment is triggered, it constitutes an income transfer from the government to farmers. In the case of crop insurance, RMA aims to maintain actuarial soundness, defined as charging premiums that are sufficient to cover the present value of anticipated losses while building a reasonable reserve (Corporation, 2025). Literature often considers crop insurance premiums to be actuarially fair (Luckstead and Devadoss, 2019; Tsay and Paulson, 2024), meaning that the premium paid equals the expected value of indemnities (i.e., average payouts over time). To encourage adoption, a portion of the premiums are subsidized, and under actuarially fair pricing, the subsidized

[3]Technically, rates should readjust over time to achieve a target loss ratio, but parameters are premiums are set annually.

share constitutes a direct benefit to the producer— an income transfer representing taxpayer support for agricultural risk management. In practice, achieving truly actuarially fair pricing remains a challenge due to data limitations and the difficulty of predicting low-probability, high-impact events (Ramirez and Shonkwiler, 2017; Coble et al., 2010; Goodwin, 2015). In Illinois, for instance, the loss ratio (ratio between total insurance payments and total premiums paid) was 0.62 from 2004 to 2023 (Schnitkey et al., 2024b), meaning farmers are not recovering paid premiums.

2.2 OB3 changes to Farm Bill 2018

The One Big Beautiful Bill Act (OB3) emerged as a substitute for a traditional Farm Bill after negotiations over the latter became mired in disputes over spending priorities, payment designs, and climate-related provisions. While it allowed farm safety net enhancements to advance quickly, it also reflected a shift away from the bipartisan consensus and committee-driven process that has historically characterized Farm Bill legislation (Coppess, 2025). OB3 was signed into law (Rep. Arrington, 2025), taking effect in July 4$^{\text{th}}$ of 2025. OB3 changes in Commodity Title I and crop insurance (title XI) are summarized in Table 2. Similar changes were also done for other commodities.

Increasing statutory prices and effective reference price marketing year percent, as well as raising the ARC-CO benchmark cap and guarantee percentage, will result in higher ARC-CO and PLC payments (i.e., greater government transfers) (Monaco et al., 2025). On the other hand, increasing the loan rate for effective price decrease payments. Statutory prices will also have a 0.5% annual increase after 2031.

By increasing the coverage level of SCO coverage band from 86% to 90% down to the underlying COMBO policy, the ECO-90% would have coverage band equal zero. Hence, under OB3 ECO-90% was not included in the analysis, and ECO 95% has to have coverage band from 95% down to 90%[4].

[4]This is not explicitly stated in OB3, but we anticipated it would be implemented in this manner

Another key change is allowing farmers to chose ARC-CO and be eligible for SCO. This change creates new possible combinations to be evaluated, and can have different impacts on farmers risk management strategies. Lastly, changes were also made in base acres election and different subsidy rates for different insurance units, however, they do not directly impact this analysis.

Table 2: OB3 Changes to 2018 Farm Bill

	2018 Farm Bill	**OB3**
Commodity Title I Changes		
Corn Statutory Price ($/bu)	3.7	4.1
Corn Loan Rate for Eff. Price ($/bu)	2.2	3.3
Soybean Statutory Price ($/bu)	8.4	10.0
Soybean Loan Rate for Eff. Price ($/bu)	6.2	6.2
Eff. Ref. Price MY Avg. Percent	85%	88%
ARC-CO Benchmark Rev. Cap	10%	12%
ARC-CO Benchmark Rev. Guarantee	86%	90%
Crop Insurance Changes		
SCO Subsidy Rate	65%	80%
SCO Coverage Band	86% down	90% down
ECO Coverage Band	90%/95% down to 86%	95% down to 90%
ARC-CO + SCO	Not allowed	Allowed

3 Methods

The methodology combines a forward-looking stochastic simulation with an optimization model that selects optimal choices from a portfolio of available program and insurance options, conditional on farm and farmer characteristics. Correlated prices and yields are simulated for three crop years (2025–2027) in a path-dependent manner.

To evaluate welfare impacts from this policy change, a decision maker (farmer) who, each year, chooses which government programs to enroll and whether (and which policies and coverage levels) to purchase crop insurance. While there are no dynamic feedback effects between decisions and state variables, the state variables (prices and yields) depend

on previous realizations. Thus, the problem is formulated as a sequence of annual myopic decisions through three years. The inclusion of additional years allows for greater variation in price and yield conditions, reducing the likelihood that choices are dominated by possible clear best alternatives in the current year.

The analysis is conducted for a representative farm in each Illinois county under two policy scenarios: the 2018 Farm Bill (FB2018) and the One Big Beautiful Bill Act (OB3). The comparison focuses on quantifying welfare changes, measuring the effectiveness of OB3 in reducing risk and increasing income relative to FB2018, and identifying how heterogeneous benefits are across farms with different characteristics.

3.1 Simulating State Variables

All data is publicly available. The objective in this multi-year-ahead exercise is to use futures prices, options and historical yields to simulate monthly prices for the upcoming crop years. A total of 3,000 correlated simulated yields and monthly prices are performed. County and farm yields are simulated at harvest (assumed to be November and December for soybeans and corn, respectively).

Simulating monthly prices are critical for crop insurance, as projected and harvest prices depend on futures in different months. Likewise, marketing year averages are also based on weighted monthly values. Thus, to make sure prices are properly correlated, simulations are path dependent—meaning each of the 3,000 scenarios comprise a set of monthly prices, also correlated with yields at harvest.

Based on these simulated prices and yields, annual farm revenues, insurance premiums and payments and commodity title I payments are calculated for each scenario. Details on the simulation process and resulting simulated variables are described in subsection Appendix B.1, subsection Appendix B.2 and subsection Appendix B.3.

Representative farms are assume to have 1,000 acres and have average yield levels comparable to their counties. To better understand how farm traits relate to policy changes

benefits, different values for crop rotation are considered: 100% corn, 100% soybeans and a 50%-50% typical rotation[5]. Base acres to insured acres is assumed to be 1:1. Crop insurance is considered to be enterprise unit with associated subsidy depending on coverage level (see Table 7).

3.2 Optimization Model

The choice of the objective function is important in any optimization setting. Most studies in similar settings use either expected utility theory (Maples et al., 2022; Biram et al., 2019; Adhikari, 2015; Sherrick et al., 2004) or prospect theory (Luckstead and Devadoss, 2019; Bocquého et al., 2014). Although the latter allows losses to be penalized more than gains, experiments show that the notion that decision makers can process loss and gains differently produces relatively small changes (O'Donoghue and Sprenger, 2018). In addition, the reference point is an important choice, which has been shown to impact results (Luckstead and Devadoss, 2019) and literature lacks a clear guidance on what it should be (O'Donoghue and Sprenger, 2018). Expected utility theory does not come without assumptions and critics (Rabin, 2000; Samuelson, 1963; Allais, 1953), however, expected utility theory can capture decreasing marginal utility of income without needing to estimate complex behavioral parameters like loss aversion or reference points.

Farmers area assumed to have a constant relative risk aversion (CRRA) utility function:

$$u(w) = \begin{cases} \frac{w^{1-\varphi}-1}{1-\varphi}, & \text{if } \varphi \geq 0,\ \varphi \neq 1 \\ \ln(w), & \text{if } \varphi = 1 \end{cases} \tag{1}$$

where w is wealth (in our setting, assumed to be returns plus initial wealth), and φ is the risk preference parameter. Initial wealth is assumed to be \$3,370 per acre, the average net worth of grain farms in Illinois in 2023 (Zwilling, 2024). φ is the corresponding Arrow-Pratt

[5]for the benefits heterogeneity analysis a 75%-25% or 25%-75% corn/soybean rotation is also included

measure of relative risk aversion. As φ increases, the farmer becomes more risk averse. The optimization is ran with a range of different $\varphi \in \{0,\ 1,\ 2,\ 3,\ 4\}$ (Chiappori and Paiella, 2011; Biram et al., 2019) to represent different levels of risk aversion. Let $\mathcal{D}_t$ denote the set of annual farmer decisions in year t:

$$\mathcal{D}_t = \begin{cases} 1.\ d_t^{(1)}\text{: Enroll in either ARC-CO or PLC,} \\ 2.\ d_t^{(2)}\text{: Choose up to one COMBO policy (YP, RP-HPE, RP) with coverage level } l, \\ 3.\ d_t^{(3)}\text{: Decide to use or not use SCO, linked to } d^{(2)} \text{ and conditional on not enrolling in ARC-CO under FB2018,} \\ 4.\ d_t^{(4)}\text{: Decide to use or not use ECO, linked to } d^{(2)}\text{, with coverage level (90\% under FB2018 or 95\%).} \end{cases}$$

The optimization problem in each year can be defined as:

$$\max_{\mathcal{D}_t} \quad \mathbb{E}[u(W_t)] = \frac{1}{N}\sum_{j=1}^{N} u(W_{tj}) \tag{2}$$

where N is the total number of simulated outcomes (N=3,000). W_j represents the final wealth in each simulated outcome j in each year t, incorporating realized revenues, Commodity Title I payments and insurance indemnities net of insurance premiums from choices made. For simplicity, we assume the timing of revenue of crop insurance payments and government payments are the same.

To interpret results in monetary terms, utility is converted to certainty equivalents (CEQ), which is computed as:

$$\text{CEQ}_t = [(1-\varphi)\cdot \mathbb{E}[u(W_t)] + 1]^{\frac{1}{1-\varphi}} \tag{3}$$

The CEQ_t represents the risk-adjusted return that a farmer would accept with certainty instead of facing the uncertain distribution of outcomes associated with a given policy or strategy. This simplifies the interpretation of results, where a higher CEQ is preferred.

3.3 Policy change impacts

To evaluate the policy change impact on farmers, the CEQ is computed for each policy scenario and the difference ΔCEQ (CEQ under OB3 minus CEQ under 2018 FB) is calculated for each year. Values for years in the future are discounted considering a discount rate of 4%. The difference in CEQ can be interpreted easily, as a positive number means farmers are better-off under the OB3, and the magnitude can be compared across farms.

Although a positive ΔCEQ means that a farmer is better-off under OB3, the welfare gain may result from a combination of changes in expected returns and risk. It is possible for risk to increase while ΔCEQ remains positive, if higher expected returns offset the additional risk. To evaluate the effectiveness of OB3 in reducing risk and providing a safety net, differences between policies are calculated for two metrics: (i) expected returns of optimal choices, and (ii) the Conditional Value-at-Risk (CVaR) at the 20% level. The CVaR at 20% represents the mean return across the worst one-fifth of simulated outcomes and is a coherent measure of risk (Artzner et al., 1999) that provides an intuitive measure of performance in particularly poor years. Furthermore, by dividing the difference in CVaR at 20% by the difference in expected returns, a measure of tail-risk reduction by increased subsidy dollar is obtained.

Traditionally, literature focus on coefficient of variation when evaluating risk reduction (Gaku and Tsiboe, 2024; Cooper et al., 2015; Coble and Dismukes, 2008; Cooper, 2010) which closely relates to the CRRA function, however, since it includes both negative and positive deviations, we argue that a left tail-risk measure is more appropriate for settings with insurance, given its primary design to protects against poor outcomes. A 20% threshold is used because agricultural safety-net programs, such as crop insurance and Title I, are de-

signed not only to cover extreme disasters but also to stabilize income across a broader range of "bad years." In contrast, a 5% or 10% tail would target only rare catastrophic outcomes, which are more relevant to private reinsurance than to annual government programs.

Optimal decision choices and the estimation of additional subsidy amount of both scenarios are also compared, providing an idea of how much enrollment would change and how much possible benefits would cost to the government.

Finally, results will vary with farm parameters (crop rotation, yield levels and variability), county parameters (yield levels and variability and ARC/PLC yields) and decision-maker risk preference. Thus, to evaluate the heterogeneity of results given these parameters, in the spirit of Cooper et al. (2015) a simple regression analysis is provided. It is important to note that the outcomes of interest are generated from an optimization model, meaning that policy and insurance choices are endogenously determined. As such, the regression is not intended to identify causal relationships. Instead, it serves as a descriptive tool to "linearize" the complex, nonlinear decision model and to assess how changes in underlying farm characteristics are associated with variation in welfare gains (e.g., certainty equivalent differences) across scenarios.

To examine the drivers of heterogeneity in modeled welfare outcomes, the following regression is estimated:

$$\Delta Y_{it} = \mathbf{X}'_{it}\boldsymbol{\beta} + \tau_t + \varepsilon_{it} \tag{4}$$

where the dependent variable ΔY_n is the difference in CEQ, Expected Returns or CVaR at 20% for OB3 minus 2018 FB policy scenario, for under specific parameters i. τ_t represent year fixed effect and the error term ε_{it} captures idiosyncratic variation. The vector of covariates $\mathbf{X}_n$ includes farm-specific parameters that are defined at the bottom of Table 6.

4 Results

4.1 Welfare Gains

As expected, the average net benefit for all years from OB3 for Illinois farmers is positive, as shown in Figure 1. All farmers are better-off under OB3, regardless of farm parameters and risk preferences. There is also little difference in welfare among risk aversion parameters, but a bigger difference depending on crop rotation. Soybean farmers, on average, benefit more than corn farmers consistently across all risk aversion. On average certainty equivalent (CEQ) increased $15.80/acre for soybean farms and $10.47/acre for corn farms.

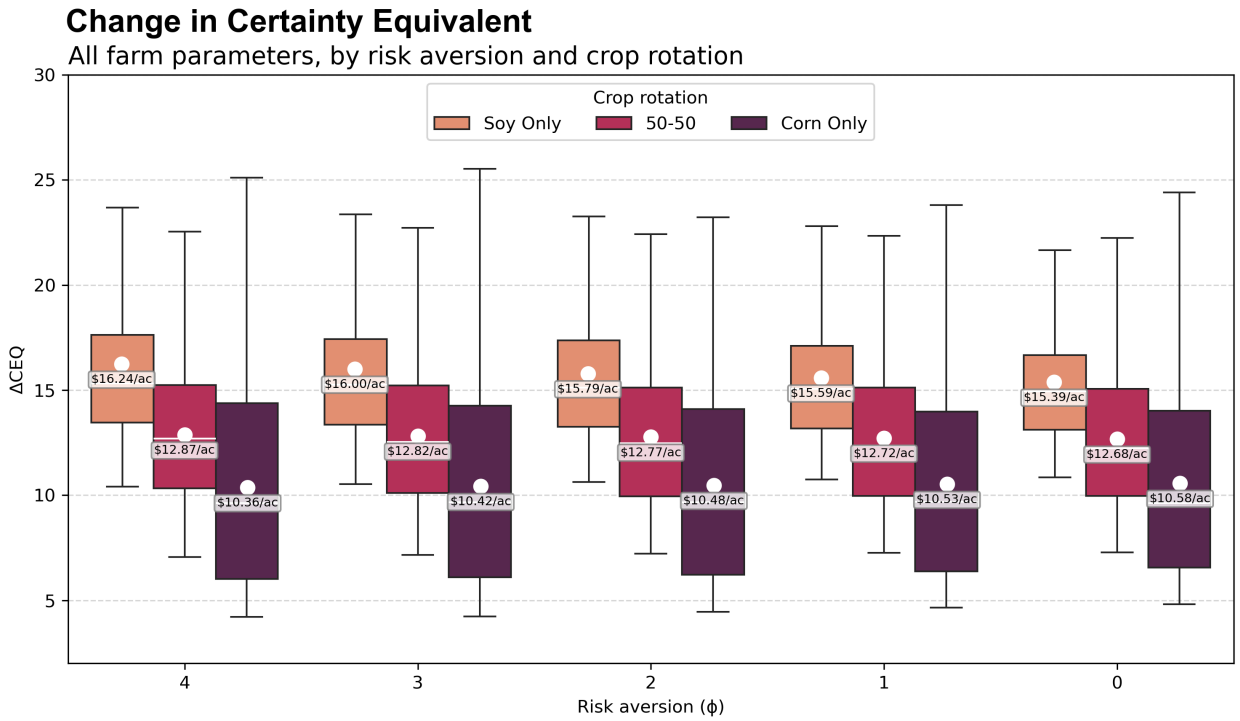


Figure 1: ΔCEQ by farm risk aversion and crop rotation.

4.2 Risk Reduction Effectiveness and Taxpayer Costs

Figure 2 shows the additional mean return (subsidy) and the CVaR at 20% changes from FB2018 to OB3 scenario. A positive change in average returns mean that farmers expected returns increased in OB3 relative to the FB2018. Likewise, a positive CVaR change represent

a reduction in tail-risk (meaning the left tail moved further to the right). The diagonal dotted line shows where the additional return equals the additional tail-risk reduction. Essentially, points on this line mean the new policy resulted in a government transfer without any impact in the relative tail-risk, shifting its entire distribution (mean and CVaR) to the right. Points to the right of the line had greater tail-risk reduction compared to expected returns increase and the opposite is true for points on the left. Each point in the chart represent one farm in one of the several parameter combinations in all years. Shapes differ in the percentage of crop considered. Big dots represent the average across a risk aversion and crop rotation.

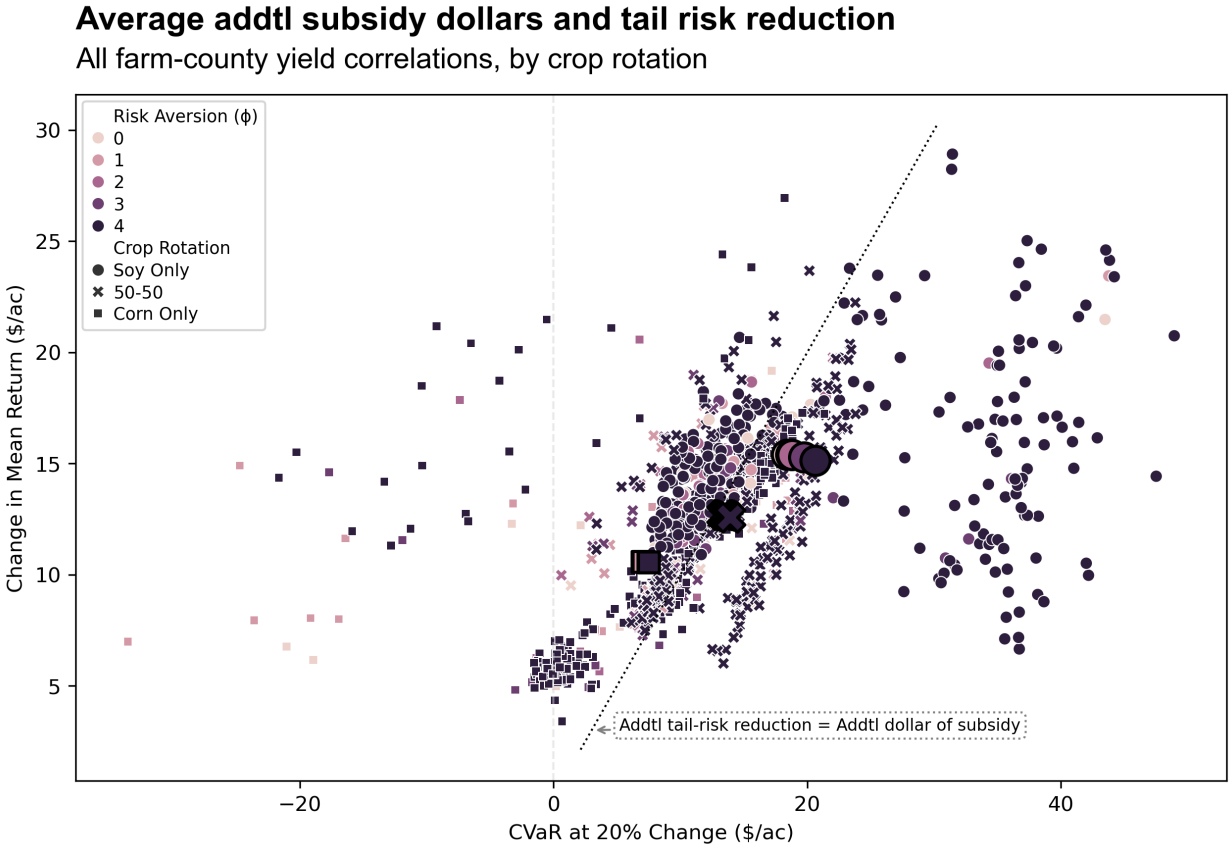


Figure 2: Expected returns and CVaR at 20% changes.

Even though change in expected returns is positive, some farmers (especially risk-neutral corn only) may experience a greater lower tail-risk (see negative CVaR change). Although this is more frequent in more risk-neutral farmers, the increase in tail-risk is also present on risk-averse ones. This highlights how defining risk is important: a positive change in

risk-adjusted returns does not necessarily imply that really poor outcomes (or risk) are minimized. In particular, the CRRA utility function does not solely penalize downside or tail risk—it also assigns diminishing marginal utility to high gains and penalizes deviations from certainty more broadly. In contrast, Conditional Value at Risk (CVaR) focuses exclusively on the lower tail of the distribution, capturing losses in the worst-case scenarios. As the goal of these programs is to provide a safety net and also to reduce risk, this result highlight an important distinction for policymakers that aim to make policies more focused on risk reduction or increasing income only (a direct income transfer).

Table 3 provide more details of changes in risk and returns from OB3. All risk aversion parameters are summarized together. By dividing CVaR at 20% ($) change by change in mean return ($), we obtain the risk-return trade-off. The risk-return trade-off can be seen as the tail-risk reduction per additional dollar of subsidy, a measure of effectiveness of tail-risk reduction. Soybean only farmers subsidy does reduce tail-risk (CVaR at 20%) by 1.26 on average, whereas for corn only on average only 0.60 cents is reduced. Thus, results indicate that achieving the same level of risk reduction for corn would require higher costs (subsidy) than for soybeans.A negative number would mean that the farmer received additional subsidy and increased its own risk, as discussed above.

Table 3: Summary statistics for difference between OB3 and FB2018

	Expected Return ($/ac)			Tail-Risk (CVaR20) ($/ac)			Risk-Return Trade-off		
	Soybean Only	50/50	Corn Only	Soybean Only	50/50	Corn Only	Soybean Only	50/50	Corn Only
Mean	$15.31	$12.64	$10.56	$19.27	$13.62	$7.31	1.26	1.09	0.60
Std	$3.24	$3.29	$4.24	$10.77	$4.74	$8.25	0.73	0.31	0.65
Min	$6.65	$6.01	$3.40	$7.13	$0.61	-$33.56	0.61	0.06	-4.80
Max	$28.91	$23.67	$26.95	$48.93	$23.81	$21.34	5.52	2.23	1.58

The additional expected return from Commodity Title I payments and crop insurance indemnities can also be interpreted as additional taxpayer dollars from OB3 compared to FB2018. Caution must be taken when extrapolating results, since one should consider the probabilities of each farmer being of the respective farm parameter, which is out of the scope

of the analysis. However, this gives an idea (at least some bounds) of the increased subsidy that farmers would receive. Results indicate that in the next three years government could spend a range of \$3.40/ac/year to \$28.91/ac/year in payments and insurance premiums subsidies among Illinois corn and soybeans farms.

4.3 Optimal choices

As far as enrollment, Table 4 summarizes the optimal choices and average RP coverage level depending on risk parameter φ and crop rotation. This discussion is focused on corn or soybean only. This is an independent view of choices. A similar table with all combinations of optimal choices are presented in Table 5. ECO-95 is not included in the table, but it was part of all optimal decision choices. ECO 90% (under FB 2018) YP and RP-HPE are not listed since was not a choice in any setting, highlighting their were dominated by other choices.

OB3 allowed farmers to choice SCO combined with ARC-CO. This combination was present both for corn and soybeans in many instances, suggesting that farmers were previously constrained (see Table 5). SCO was practically a unanimous choice for corn in both policy scenarios, and became unanimous in OB3 for soybean. ECO-95 was chosen in all portfolios. This suggests that the increased subsidy and coverage levels will likely increase enrollment in these products. PLC had very little enrollment under FB2018 in soybean farms, but become more apparent under OB3. For corn, the opposite was observed, were ARC-CO become more apparent under OB3 compared to a PLC domination under FB2018. That might be partially explained by the larger relative increase in statutory prices for soybeans compared to corn. Although statutory prices impact both ARC-CO and PLC, it has a larger impact on PLC. Further, corn had its marketing loan rate increased, limiting payments when prices are low.

Regarding the COMBO policy, only RP was selected as a choice. Interestingly, under OB3, both corn and soybean had their average coverage level reduced. The reduction was

slightly higher for risk neutral farms. This suggests that part of the risk mitigation by RP was substituted by Commodity Title I programs or SCO/ECO.

Table 4: Policy Choices and Average RP Coverage by Crop and Risk Aversion (φ), % of scenarios chosen or RP Average Coverage %

Policy	φ	ARC-CO		PLC		SCO		Avg. RP Coverage	
		Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean
FB2018	0	0%	100%	100%	0%	100%	0%	76.4%	84.5%
	1	0%	99%	100%	1%	100%	1%	76.2%	84.4%
	2	0%	99%	100%	1%	100%	1%	76.0%	84.2%
	3	0%	99%	100%	1%	100%	1%	75.8%	84.2%
	4	0%	99%	100%	1%	100%	1%	75.6%	84.0%
OB3	0	12%	73%	88%	27%	100%	100%	74.5%	78.7%
	1	11%	71%	89%	29%	100%	100%	74.4%	78.6%
	2	9%	70%	91%	30%	100%	100%	74.2%	78.5%
	3	9%	65%	91%	35%	100%	100%	74.0%	78.4%
	4	9%	61%	91%	39%	100%	100%	73.9%	78.2%
Δ	0	12%	-27%	-12%	27%	0%	100%	-1.9%	-5.9%
	1	11%	-28%	-11%	28%	0%	99%	-1.9%	-5.8%
	2	9%	-29%	-9%	29%	0%	99%	-1.8%	-5.7%
	3	9%	-34%	-9%	34%	0%	99%	-1.8%	-5.8%
	4	9%	-39%	-9%	39%	0%	99%	-1.8%	-5.8%

Table 5: Number of Choices and Average RP Coverage by Risk Aversion (φ), Crop, and Policy Scenario

φ	Crop	Optimal Choice	Count			Avg. RP Coverage		
			FB2018	OB3	Δ	FB2018	OB3	Δ
0	Corn	ARC + ECO95 + RP	0.1%	0.0%	-0.1%	80.0%		
		ARC + SCO + ECO95 + RP	0.0%	12.0%	12.0%		75.9%	
		PLC + SCO + ECO95 + RP	99.9%	88.0%	-11.9%	76.3%	74.3%	-2.0%
	Soybean	ARC + ECO95 + RP	99.4%	0.0%	-99.4%	84.6%		
		ARC + SCO + ECO95 + RP	0.0%	74.1%	74.1%		79.0%	
		PLC + SCO + ECO95 + RP	0.6%	25.9%	25.3%	80.0%	77.6%	-2.4%
1	Corn	ARC + SCO + ECO95 + RP	0.0%	11.5%	11.5%		75.9%	
		PLC + SCO + ECO95 + RP	100.0%	88.5%	-11.5%	76.1%	74.2%	-1.9%
	Soybean	ARC + ECO95 + RP	99.3%	0.0%	-99.3%	84.5%		
		ARC + SCO + ECO95 + RP	0.0%	71.6%	71.6%		79.0%	
		PLC + SCO + ECO95 + RP	0.7%	28.4%	27.7%	80.0%	77.7%	-2.3%
2	Corn	ARC + SCO + ECO95 + RP	0.0%	9.9%	9.9%		75.6%	
		PLC + SCO + ECO95 + RP	100%	90.1%	-9.9%	76.0%	74.1%	-1.9%
	Soybean	ARC + ECO95 + RP	99.3%	0.0%	-99.3%	84.3%		
		ARC + SCO + ECO95 + RP	0.0%	69.6%	69.6%		78.9%	
		PLC + SCO + ECO95 + RP	0.7%	30.4%	29.7%	80.0%	77.6%	-2.4%
3	Corn	ARC + SCO + ECO95 + RP	0.0%	9.6%	9.6%		75.3%	
		PLC + SCO + ECO95 + RP	100.0%	90.4%	-9.6%	75.9%	74.0%	-1.9%
	Soybean	ARC + ECO95 + RP	99.3%	0.0%	-99.3%	84.2%		
		ARC + SCO + ECO95 + RP	0.0%	66.7%	66.7%		78.8%	
		PLC + SCO + ECO95 + RP	0.7%	33.3%	32.7%	80.0%	77.7%	-2.3%
4	Corn	ARC + SCO + ECO95 + RP	0.0%	8.7%	8.7%		75.2%	
		PLC + SCO + ECO95 + RP	100.0%	91.3%	-8.7%	75.7%	73.9%	-1.8%
	Soybean	ARC + ECO95 + RP	99.0%	0.0%	-99.0%	84.1%		
		ARC + SCO + ECO95 + RP	0.0%	63.9%	63.9%		78.5%	
		PLC + SCO + ECO95 + RP	1.0%	36.1%	35.0%	80.0%	77.7%	-2.3%

4.4 Welfare Gains Heterogeneity

Finally, a regression is performed to linearize the model outcomes and assess possible drivers of welfare gains. Results are summarized in Table 6. Results are a combination of same-decisions welfare increase, but also a change in decision that resulted in greater welfare. Risk aversion was not found to significantly influence CEQ, but it does influence CVaR, where more risk averse farmers reduced tail-risk by a greater extent, which was expected. It also was associated with lower expected returns for soybeans, again due to a risk-return trade-off.

Soybean-related characteristics stand out as the strongest drivers of relative differences in gains. Higher soybean average yields were significantly associated with larger improvements in CEQ, Expected Return, and CVaR in both soybean-only and mixed systems. Greater soybean yield variability (standard deviation) also had a strong positive effect across all three outcomes, indicating that the programs and insurance products respond favorably to variability in soy yields.

For corn, the significant variables show a different pattern. Higher corn average yields were associated with smaller gains in CEQ and Expected Return, though they did improve CVaR, pointing to a stronger emphasis on downside protection rather than boosting average performance. Higher corn yield variability reduced Expected Return while improving CVaR, suggesting a trade-off where volatility shifts benefits toward tail-risk protection.

Rotation mix effects were also clear. A higher share of corn in mixed rotations was significantly associated with smaller gains in CEQ, Expected Return, and CVaR compared to more diversified or soybean-heavy rotations.

The yield variability ratio is the inverse of the implied correlation between county and farm yields (see subsection Appendix B.3 for discussion). Soybean farms with lower farm–county yield correlations (implied by higher farm–county std. ratios) saw proportionally larger gains in CEQ, Expected Return, and CVaR. The opposite was observed for corn, where a high correlation with the county was associated with higher CEQ.

Table 6: Linear regressions for ΔCEQ, ΔExpected Return, and ΔCVaR

	Δ CEQ			Δ Exp. Return			Δ CVaR		
Variable	Corn	Soybean	Mixed	Corn	Soybean	Mixed	Corn	Soybean	Mixed
Intercept	17.06*	4.15*	11.89*	21.00*	8.46*	14.88*	-21.75*	-38.32*	-5.71*
RiskAversion (φ)	0.02	0.01	0.03	0.05	-0.16*	-0.04*	0.16*	0.33*	0.15*
CornAvgYield	-0.01		-0.02*	-0.02*		-0.03*	0.07*		0.00
CornCYieldStd	-0.01		-0.06*	-0.05*		-0.07*	0.36*		-0.01
CornStdRatio	-0.33*		-0.71*	-0.28		-0.74*	0.12		-0.66*
CornPLCYield	0.01		-0.01	-0.00		0.00	0.08*		-0.05*
SoyAvgYield		0.06*	0.07*		0.03*	0.07*		0.25*	0.12*
SoyCYieldStd		1.10*	0.78*		1.08*	0.82*		1.25*	0.67*
SoyStdRatio		0.98*	0.94*		0.82*	1.03*		2.48*	0.78*
SoyPLCYield		0.00	0.08*		-0.05*	0.02		0.57*	0.47*
CornPercent			-5.32*			-4.70*			-8.99*
R^2 Adj.	0.85	0.61	0.70	0.75	0.69	0.68	0.83	0.27	0.60
Obs.	1418	1162	4035	1418	1162	4035	1418	1162	4035

* $p < 0.01$. Year fixed effects included but omitted from rows. Mixed crop rotation includes Corn/Soy rotations of 25%-75%, 50%-50% and 75%-25%. CornPercent represent the share of corn in the mixed crops Outliers were trimmed out of the regression (5%). φ is the risk aversion parameter. AvgYield is the average yield (same for county and farm). CYieldStd is the standard deviation of county yields. StdRatio is the ratio between farm and county yield std. PLCYield is the yield utilized for PLC payments.

5 Conclusion and Policy Implications

This study used a multi-year, simulation-based portfolio optimization framework to evaluate Illinois crop insurance and Commodity Title I decisions among Illinois farmers. Choices, risk, welfare were compared between the new OB3 policy and the previous Farm Bill (FB2018).

Across farms, most experienced reductions in tail-risk (CVaR) under OB3, though some—particularly among corn producers—saw increases. This raises an issue for policy

makers regarding the core nature of the programs. Even though crop insurance is a risk management tool, its effects could be washed when combined with Commodity Title I programs and the overall effect result in increased tail-risk. Nevertheless, on average, each additional subsidy dollar reduced tail-risk by $1.26 for soybeans and $0.60 for corn.

Policy design changes are also expected to shift farmer choices. PLC became relatively more attractive than ARC-CO for soybeans while the opposite was observed for corn. This shift is partially caused by the fact that statutory prices increased relatively more for soybeans, and its loan rates was not raised (as was the case for corn). ARC-CO was also frequently paired with SCO- a new possibility under OB3.

SCO and ECO enrollment were both higher under both scenairos (more accentuated under OB3), suggesting there may be benefits not currently captured by farmers, given historical low adoption. RP remained the dominant COMBO policy, with lower coverage levels observed under OB3 compared to FB2018.

From the government's perspective, annual expenditures under OB3 could range from $3.40/ac to $28.91/ac in payments and premium subsidies across Illinois corn and soybean farms.

Gains in CEQ were heterogeneous across farms, with their magnitude varying with yield variability, county–farm yield correlation, and average yields— though differently for each crop.

Taken together, these results show that while OB3 delivers broad welfare gains to Illinois farmers, the balance between risk reduction and income support depends critically on program interactions and crop-specific responses. Understanding how design changes influence both risk outcomes and farmer choices will be essential for aligning future farm policy with its stated goals.

References

Adhikari, S. (2015). Optimal Coverage Level and Producer Participation in Supplemental Coverage Option in Yield and Revenue Protection Crop Insurance. San Francisco. Num Pages: 19.

Agency, F. S. (2025). Commodity Loan Rates | Farm Service Agency.

Akima, H. (1970). A New Method of Interpolation and Smooth Curve Fitting Based on Local Procedures. *J. ACM*, 17(4):589–602.

Allais, M. (1953). Le Comportement de l'Homme Rationnel devant le Risque: Critique des Postulats et Axiomes de l'Ecole Americaine. *Econometrica*, 21(4):503–546. Publisher: [Wiley, Econometric Society].

Artzner, P., Delbaen, F., Eber, J., and Heath, D. (1999). Coherent Measures of Risk. *Mathematical Finance*, 9(3):203–228.

Biram, H. D., Coble, K. H., Harri, A., and Park, E. (2019). Does Double Coverage Mean Double Trouble? A Look at the Interaction Between ARC and RP. Birmingham, Alabama. Issue: 284286.

Bocquého, G., Jacquet, F., and Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics*, 41(1):135–172.

Chiappori, P.-A. and Paiella, M. (2011). RELATIVE RISK AVERSION IS CONSTANT: EVIDENCE FROM PANEL DATA: Chiappori and Paiella Relative Risk Aversion Is Constant. *Journal of the European Economic Association*, 9(6):1021–1052.

Coble, K., Knight, T., Goodwin, B., Miller, M., and Rejesus, R. (2010). A Comprehensive Review of the RMA APH and COMBO Rating Methodology Final Report.

Coble, K. H. and Barnett, B. J. (2013). Why do we subsidize crop insurance? *American Journal of Agricultural Economics*, 95(2):498–504.

Coble, K. H. and Dismukes, R. (2008). Distributional and Risk Reduction Effects of Commodity Revenue Program Design. *Review of Agricultural Economics*, 30(3):543–553. Publisher: [Oxford University Press, Agricultural & Applied Economics Association].

Cooper, J., Hungerford, A., and O'Donoghue, E. (2015). Interactions of Shallow Loss Support and Traditional Federal Crop Insurance: Building a Framework for Assessing Commodity Support Issues for the Next Farm Act. Issue: 205310.

Cooper, J. C. (2010). Average Crop Revenue Election: A Revenue-Based Alternative to Price-Based Commodity Payment Programs. *American Journal of Agricultural Economics*, 92(4):1214–1228. Publisher: John Wiley & Sons, Ltd.

Cooper, J. C. and O'Donoghue, E. J. (2011). Identifying and Reducing Overlap in Farm Program Support. Issue: 103261.

Coppess, J. (2025). Farm Bill in Reconciliation: What the Byrd Rule Exposes but Does Not Resolve. *farmdoc daily*, 15(112).

Corporation, F. C. I. (2025). 2025 Crop Insurance Handbook.

Economic Research Service of Agriculture (2025). Crop Insurance at a Glance. Technical report.

FCIC (2009). 2009 FCIC 11010 Rate Methodology Handbook Actual Production History (APH) Summary of Changes.

Gaku, S. and Tsiboe, F. (2024). Evaluation of alternative farm safety net program combination strategies. *Agricultural Finance Review*, ahead-of-print(ahead-of-print). Publisher: Emerald Publishing Limited.

García, O. (1981). Simplified method-of-moments estimation for the Weibull distribution. *New Zealand Journal of Forestry Science*, 11:304–306.

Goodwin, B. K. (2015). Agricultural Policy Analysis: The Good, The Bad, and The Ugly. *American Journal of Agricultural Economics*, 97(2):353–373. Publisher: [Agricultural & Applied Economics Association, Oxford University Press].

Goodwin, B. K. and Mishra, A. K. (2006). Are "Decoupled" Farm Program Payments Really Decoupled? An Empirical Evaluation. *American Journal of Agricultural Economics*, 88(1):73–89. Publisher: John Wiley & Sons, Ltd.

Higham, N. J. (2002). Computing the nearest correlation matrix—a problem from finance. *IMA Journal of Numerical Analysis*, 22(3):329–343.

Iman, R. L. and Conover, W. J. (1982). A distribution-free approach to inducing rank correlation among input variables. *Communications in Statistics - Simulation and Computation*, 11(3):311–334. Publisher: Taylor & Francis.

Langemeier, M. and Liu, Y. (2020). Comparing Net Return to Land and Risk for Alternative Leasing Arrangements. *Journal of the ASFMRA*, 2020. Publisher: American Society of Farm Managers and Rural Appraisers.

Lenfestey, G. K. and Langemeier, M. (2023). A Portfolio Approach to Grain Marketing and Crop Insurance Strategies for an Indiana Case Farm. *ProQuest Dissertations and Theses*, pages 106–106. Place: United States – Indiana Publisher: Purdue University.

Luckstead, J. and Devadoss, S. (2019). Implications of Commodity Programs and Crop Insurance Policies for Wheat Producers. *Journal of Agricultural and Applied Economics*, 51(2):267–285. Publisher: Cambridge University Press.

Maples, W. E., Giri, A. K., Coble, K. H., and Subedi, D. (2022). Impact of government programs on producer demand for hedging. *Applied Economic Perspectives and Policy*, 44(3):1126–1138. Publisher: John Wiley and Sons Inc.

Miranda, M. J. (1991). Area-Yield Crop Insurance Reconsidered. *American Journal of Agricultural Economics*, 73(2):233–242. Publisher: [Agricultural & Applied Economics Association, Oxford University Press].

Monaco, H., Coppess, J., Paulson, N., and Schnitkey, a. G. (2025). Farm Bill in Reconciliation: ARC/PLC Payment Projections; Policy Design Lab Update. *farmdoc daily*, 15(122).

O'Donoghue, T. and Sprenger, C. (2018). Reference-Dependent Preferences. In Bernheim, B. D., DellaVigna, S., and Laibson, D., editors, *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 1 of *Handbook of Behavioral Economics - Foundations and Applications 1*, pages 1–77. North-Holland.

Ozaki, V. A., , Barry K., G., , and Shirota, R. (2008). Parametric and nonparametric statistical modelling of crop yield: implications for pricing crop insurance contracts. *Applied Economics*, 40(9):1151–1164. Publisher: Routledge _eprint: https://doi.org/10.1080/00036840600749680.

Rabin, M. (2000). Risk Aversion and Expected-Utility Theory: A Calibration Theorem. *Econometrica*, 68(5):1281–1292.

Ramirez, O. A. and Shonkwiler, J. S. (2017). A Probabilistic Model of the Crop Insurance Purchase Decision. *Journal of Agricultural and Resource Economics*, 42(1):10–26. Publisher: Western Agricultural Economics Association.

Rep. Arrington, J. C. R.-T.-. (2025). Text - H.R.1 - 119th Congress (2025-2026): One Big Beautiful Bill Act. Archive Location: 2025-05-20.

Robertson, M. . (2000). Actuarial Documentation of Multiple Peril Crop Insurance Ratemaking Procedures.

Sahamkhadam, M., Stephan, A., and Östermark, R. (2018). Portfolio optimization based on GARCH-EVT-Copula forecasting models. *International Journal of Forecasting*, 34(3):497–506. Publisher: Elsevier B.V.

Samuelson, P. (1963). Risk and Uncertainty: A Fallacy of Large Numbers. *Scientia*, 57(98):108. Publisher: Engelmann.

Schnitkey, G., Paulson, N., and Zulauf, C. (2024a). Update on Historic Use of Crop Insurance Products in Illinois. *farmdoc daily*, 14(228).

Schnitkey, G., Sherrick, B., Zulauf, C., Coppess, J., and Paulson, a. N. (2024b). Crop Insurance Loss Performance in Illinois and the Midwest. *farmdoc daily*, 14(131).

Sherrick, B. J., Barry, P. J., Ellinger, P. N., and Schnitkey, G. D. (2004). Factors Influencing Farmers' Crop Insurance Decisions. *American Journal of Agricultural Economics*, 86(1):103–114. Publisher: [Agricultural & Applied Economics Association, Oxford University Press].

Sherrick, B. J., Lanoue, C. A., Woodard, J., Schnitkey, G. D., and Paulson, N. D. (2014). Crop yield distributions: fit, efficiency, and performance. *Agricultural Finance Review*, 74(3):348–363. Publisher: Emerald Group Publishing Limited.

Tsay, J. H. and Paulson, N. D. (2024). Quantifying basis risk associated with supplemental area-based crop insurance. *Agricultural Finance Review*. Publisher: Emerald Publishing.

Wang, H. H., Hanson, S. D., and Black, J. R. (2003). Efficiency Costs of Subsidy Rules for Crop Insurance. *Journal of Agricultural and Resource Economics*, 28(1):116–137. Publisher: Western Agricultural Economics Association.

Woodard, J. D., Paulson, N. D., Vedenov, D., and Power, G. J. (2011). Impact of copula choice on the modeling of crop yield basis risk. *Agricultural Economics*, 42(s1):101–112.

Zwilling, B. (2024). Financial Summary of Illinois Farms for 2023. *farmdoc daily*, 14(190).

Appendix A Title I and Crop Insurance Mechanics

Appendix A.1 Commodity Title I Programs : ARC-CO and PLC

Mechanics of ARC-IC was omitted from this analysis because historical participation in Illinois has near zero (Agency, 2025). The Price Loss Coverage (PLC) program addresses price risk by offering protection against revenue shortfalls caused by prolonged declines in market prices. PLC payment per enrolled base acre is given by:

$$\text{PLC Payment}\,(\$/\text{base acre}) = \text{PLC Yield} \cdot 0.85 \cdot \max\left(P_{\text{Eff. Reference}} - P_{\text{Eff. Price}},\ 0\right) \tag{5}$$

$P_{\text{Eff. Reference}}$ is the effective reference price. The effective reference price is the greater of the crop statutory reference price or 88% (starting with OB3, it was 85% under FB2018) of the Olympic average MYA price, capped at 115% of the statutory reference. $P_{\text{Eff. Price}}$ is the effective price, which is the maximum of P_{loan}, the national average loan rate and P_{MYA}, the national average market price received by producers during the 12-month marketing year for the covered commodity. P_{loan} is the commodity loan rate, which acts as a price floor established under the USDA's marketing assistance loan program (Agency, 2025). PLC Yields are specific by county and administered by FSA.

Alternatively, the ARC-CO program offers revenue protection when actual county revenue falls below 90% (86% under FB2018) of a benchmark revenue. Payments are currently capped at 12%(10% under FB2018) of the benchmark revenue and payment is made in 85% of the enrolled base acres. Payments per base acre are given by:

$$\text{ARC-CO Payment}\,(\$/\text{base acre}) = 0.85 \cdot \max\left(\min\left(0.90 \cdot R_{\text{bench}} - R_{\text{actual}},\ 0.12 \cdot R_{\text{bench}}\right),\ 0\right) \tag{6}$$

Where the benchmark and actual revenues are given by yields ($Y_{\text{benchmark}}$ or Y_{actual}) multiplied by prices ($P_{\text{benchmark}}$ or P_{MYA}). The benchmark is based on a five-year from the immediate precedent year Olympic average (average excluding maximum and minimum

values) of county yields and prices, where the price is the higher of the effective reference price or the national marketing year average price (P_{MYA}). Importantly, Y_{actual} represent actual county yields. Thus, a farm's ability to accurately mitigate their losses depends on how correlated to county yields its yield is.

Under Title I programs, producers must choose between protection against price shortfalls (PLC) or protection against revenue shortfalls (ARC-CO). Even in PLC, however, payment calculations incorporate county yields, meaning that county-level yield variation remains relevant for risk exposure.

Appendix A.2 Crop Insurance: COMBO policies

In addition to Title I programs, farmers can purchase crop insurance policies known collectively as COMBO policies, which include Yield Protection (YP), Revenue Protection (RP), and Revenue Protection with Harvest Price Exclusion (RP-HPE). These insurance products allow coverage levels from 50% to 85% in 5% increments, with producers electing one policy per crop per year. Premiums are set annually by RMA based on a continuous rating formula that reflects the producer's Actual Production History (APH), the type of insurance unit selected, and various crop-specific and area-specific risk factors (FCIC, 2009; Robertson, 2000). Although premiums are designed to be actuarially fair, producers only pay a portion of them, with the remainder subsidized by the federal government. Subsidy rates depend on the insurance unit type; for example, enterprise units—which aggregate all acreage of a crop within a county—receive higher subsidies. Subsidy levels for enterprise units are summarized in Table 7.

Table 7: Federal insurance subsidies by coverage level, enterprise unit (2024)

Coverage level (Combo policies)	50%	55%	60%	65%	70%	75%	80%	85%
Subsidy (% of premium)	80%	80%	80%	80%	80%	77%	68%	53%

A typical insurance timeline in Illinois involves policy elections by March 15th, premium

billing in October, and indemnity payments, if triggered, between October and December.

Regardless of the premium amount, an indemnity is triggered when farm outcomes fall below the guaranteed level. This guarantee depends on the farm's APH, the coverage level (γ), and market prices observed through futures contracts. Projected prices for corn and soybeans are calculated using the February average of the December and November futures contracts, respectively, while harvest prices are based on October averages.

The three COMBO policies differ mainly in how they treat price changes:

- **Yield Protection (YP)**: Insures yield losses only. Guarantees are based on the APH yield and the projected price:

$$\text{YP}_{\text{payment}} = \max\left(0,\ \left(Y_{\text{APH}} \times \gamma - Y_{\text{Actual}}\right) \times P_{\text{projected}}\right) \tag{7}$$

- **Revenue Protection (RP)**: Covers both yield and price losses, guaranteeing revenue based on the higher of the projected or harvest price:

$$\text{RP}_{\text{payment}} = \max\left(0,\ \left(Y_{\text{APH}} \times \gamma \times \max\left(P_{\text{projected}},\ P_{\text{harvest}}\right) - Y_{\text{Actual}} \times P_{\text{harvest}}\right)\right) \tag{8}$$

- **Revenue Protection with Harvest Price Exclusion (RP-HPE)**: Functions similarly to RP but without upward adjustment when the harvest price exceeds the projected price:

$$\text{RP-HPE}_{\text{payment}} = \max\left(0,\ \left(Y_{\text{APH}} \times \gamma \times P_{\text{projected}} - Y_{\text{Actual}} \times P_{\text{harvest}}\right)\right) \tag{9}$$

YP is particularly beneficial for farmers whose primary concern is production risk rather than price volatility or may want to couple it with other price risk management strategy. Because RP-HPE foregoes the harvest price adjustment, it typically carries a lower premium compared to standard RP, making it an alternative for farmers who want revenue protection

but are willing to give up potential upside adjustments.

Appendix A.3 Crop Insurance: COMBO add-on policies

Beyond individual policies, farmers also have the option to purchase add-on area-based policies, such as the Supplemental Coverage Option (SCO) and Enhanced Coverage Option (ECO), which provide additional protection based on county-level outcomes. Subsidy rates for SCO and ECO are 80% and 65%. Other area-based are not discussed given low adoption. SCO offers protection from 90% (86% under FB2018) coverage down to the producer's underlying COMBO coverage level (γ). ECO extends protection from 95% (under FB2018, ECO was also available covering 90% down to 86%) down to 90%[4]. Both policies require an underlying individual insurance plan. The indemnity for each policy is calculated as follows:

$$\text{SCO}_{\text{payment}} = \max\left(0,\ \frac{s - R_{\text{actual,county}}}{s - \gamma}\right) \cdot (s - \gamma) \cdot Y_{\text{APH}} \cdot P_{\text{base}}) \tag{10}$$

$$\text{ECO}_{\text{payment}} = \max\left(0,\ \frac{s - R_{\text{actual,county}}}{p - s}\right) \cdot (p - s) \cdot Y_{\text{APH}} \cdot P_{\text{base}}) \tag{11}$$

Where:

- P_{base} is the price used to determine the SCO/ECO protection amount. It depends on the underlying COMBO policy:

$$P_{\text{base}} = \begin{cases} P_{\text{projected}} & \text{if underlying policy is YP or RP-HPE} \\ \max\left(P_{\text{projected}},\ P_{\text{harvest}}\right) & \text{if underlying policy is RP} \end{cases} \tag{12}$$

- $R_{\text{actual,county}}$ is the actual-to-expected county revenue ratio, defined as:

$$R_{\text{actual,county}} = \begin{cases} \dfrac{Y_{\text{county,actual}}}{Y_{\text{county,expected}}} & \text{for YP} \\ \dfrac{Y_{\text{county,actual}} \cdot P_{\text{harvest}}}{Y_{\text{county,expected}} \cdot \max(P_{\text{projected}}, P_{\text{harvest}})} & \text{for RP} \\ \dfrac{Y_{\text{county,actual}} \cdot P_{\text{harvest}}}{Y_{\text{county,expected}} \cdot P_{\text{projected}}} & \text{for RP-HPE} \end{cases} \tag{13}$$

Appendix B State Variables

Appendix B.1 Yields

There are two sets of yields for each county: county-level and farm-level yields. County-level yield distributions are generated based on historical yield data from RMA since 1991. To construct a yield distribution for a county, historical yields must first be detrended to account for technological advancements over time (Ozaki et al., 2008). This ensures that yield variability are expressed in terms of the target year t. De-trending is performed separately for each county c using a standard linear time-trend model (Cooper, 2010):

$$\hat{y_{ct}} = \beta_{0c} + \beta_{1c}t + \varepsilon_{ct} \tag{14}$$

where $\hat{y_{ct}}$ represents the observed county c yield for t=1991...2024, β_{0c} is the intercept, β_{1c} captures the yield-trend over time, and ε is the residual term. Using the estimated trend β_{1c}, historical yields are expressed in levels in terms of a target year $\in$ {2025, 2026, 2027} (detrended yields) for each county c, expressed as:

$$y_c^{TargetYear} = \hat{y_{ct}} + \max\left(0, \beta_{1c}(TargetYear - t)\right) + \varepsilon_{ct} \tag{15}$$

Setting zero as floor for a trend adjustment ensures that adjustments are non-negative, preventing unrealistic extrapolations. Detrended yields are fitted to a Weibull distribution (Sherrick et al., 2014), where the expected yield (mean in each simulated year) and the detrended standard deviation are used to shape the two parameters of the distribution based on the method of moments (García, 1981). Farm-level yields are assumed to have the same mean as the county yield. This assumes that county yields are the average of all farmers in the county, thus, the average farmer would have the same expected yields as its county (Miranda, 1991). The variance of the farm-level yield distribution, however, should be higher than its county yields (unless all farms yields are perfectly correlated). To determine farm yields

variability RMA historical insurance premiums is used, which are rated based on farm-level data. Specifically, a farm-level Weibull distribution is calibrated with the 2024 county-level yield mean solving for its standard deviation (García, 1981) such that the calculated YP 85% premium matches the 2024 rate (Coble and Dismukes, 2008; Tsay and Paulson, 2024) considering a 1,000 acre enterprise unit rate. The procedure implicitly assumes that rates are actuarially fair.

Expected county-yields for 2025 and their coefficient of variation are shown in Figure 3 and Figure 4. As illustrated, there are regional differences within Illinois, with three distinct (Southern, Central and Northern) patterns. Southern Illinois is marked by lower yields and a higher variability. Central and Northern have higher yields and similar CV.

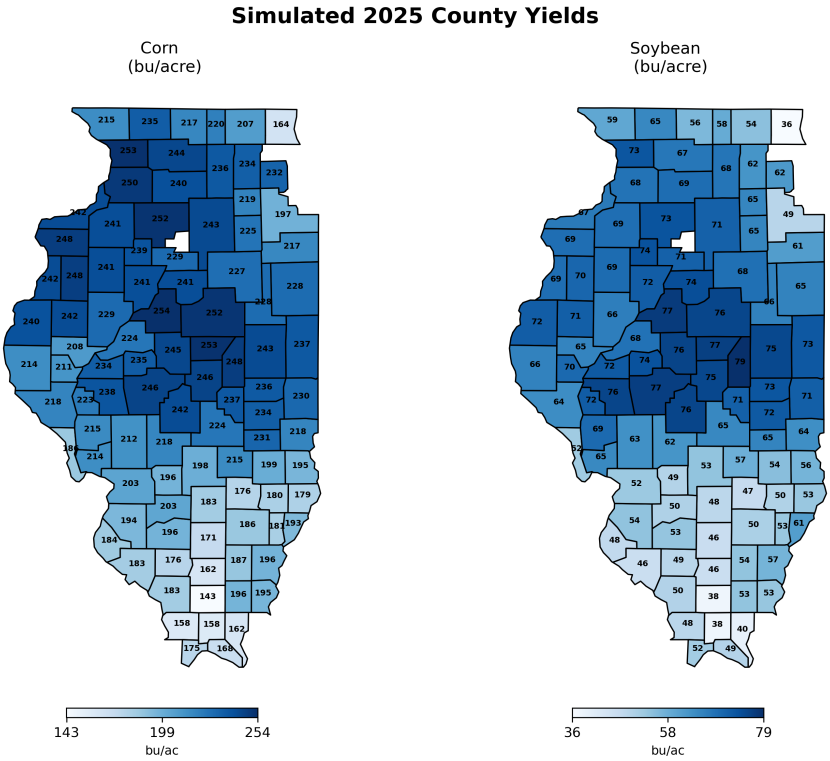


Figure 3: Simulated 2025 county expected yields.

Calculated farm-county yield standard deviation ratios are shown in Figure 5. As illustrated by lower ratios, Central Illinois farms are more homogeneous in comparison with Southern and Northern regions. Higher ratios imply greater variability among farms.

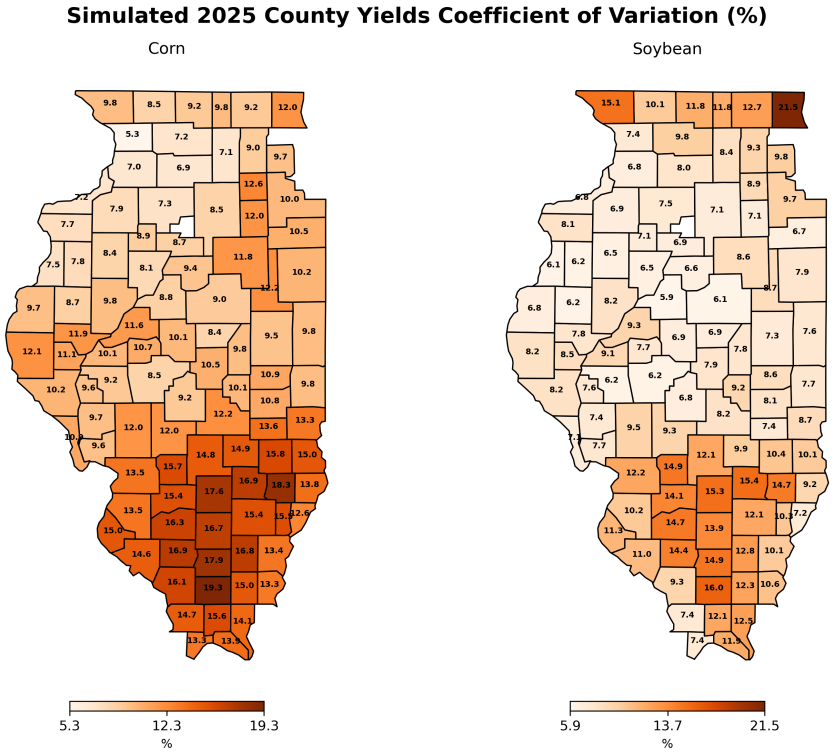


Figure 4: Simulated 2025 County yields Coefficient of Variation (%).

Appendix B.2 Prices

Based on values from March 14th, futures prices for upcoming contracts are used as average cash prices. In essence, expected cash prices, without basis, will match these futures prices at their expiration dates. From options with multiple expiration, implied volatility is derived for each month and commodity, and a lognormal distribution is fit, so a target sigma is derived for each contract expiration. For missing months, prices and volatilities are interpolated with a quadratic expression (Akima, 1970). For contracts in the future without options volume the last available implied volatility is used. Prices for each crop are assumed to follow a Geometric Brownian Motion (GBM), which can be discretized and defined as:

$$S_{t+\Delta t} = S_t \cdot \exp\left(\left(\mu - \frac{1}{2}\sigma^2\right)\Delta t + \sigma\sqrt{\Delta t} \cdot Z_t\right) \tag{16}$$

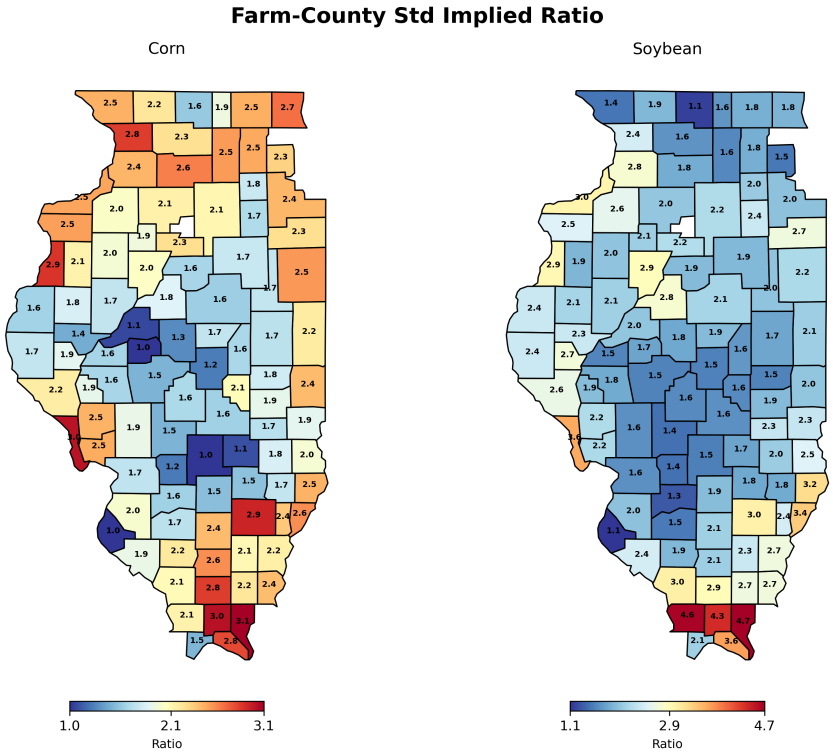


Figure 5: Farm-County Yield Variability Ratio.

where: S_t is the price at time t, μ is the drift (mean return), σ is the volatility, Δt is the time increment (1/12 (monthly time steps)) and $Z_t \sim \mathcal{N}(0, 1)$.

In each time step t the GBM process is a lognormal distribution. Using each month futures price and implied volatility, in a piecewise manner, the drift and volatility terms are calibrated so that in each maturity date the price distribution (lognormal distribution) matches these parameters (Table 8). S_0 is set to 4.57 and 10.30 dollars per bushel for corn and soybeans, respectively.

In addition to simulating 'cash prices', projected prices and harvest prices are simulated. Projected prices are the February average and the harvest prices are the October average of the December and November futures contracts for corn and soybeans, respectively. Projected prices for 2025 are known ($4.70 for corn and $10.54 for soybeans). Another GBM process is used so at maturity the lognormal distribution matches their mean prices and sigma. In essence, it represents a GBM with zero drift and calibrated to match implied volatility at

Table 8: Futures Contract Prices (in log) and Volatility for Corn and Soybeans (January and August contracts for soybean are omitted)

Corn					**Soybean**				
Date	Code	Price	μ	σ	Date	Code	Price	μ	σ
5/15/2025	ZCK25	4.59	1.520	0.081	5/15/2025	ZSK25	10.16	2.317	0.055
7/15/2025	ZCN25	4.68	1.533	0.127	7/15/2025	ZSN25	10.30	2.328	0.091
9/15/2025	ZCU25	4.45	1.474	0.178	9/15/2025	ZSU25	10.13	2.307	0.126
12/15/2025	ZCZ25	4.51	1.484	0.200	11/15/2025	ZSX25	10.18	2.309	0.145
3/15/2026	ZCH26	4.64	1.510	0.209	3/15/2026	ZSH26	10.35	2.323	0.160
5/15/2026	ZCK26	4.71	1.525	0.214	5/15/2026	ZSK26	10.41	2.329	0.164
7/15/2026	ZCN26	4.75	1.529	0.230	7/15/2026	ZSN26	10.49	2.333	0.184
9/15/2026	ZCU26	4.57	1.520	0.230	9/15/2026	ZSU26	10.26	2.328	0.184
12/15/2026	ZCZ26	4.55	1.515	0.230	11/15/2026	ZSX26	10.24	2.326	0.184
3/15/2027	ZCH27	4.66	1.539	0.230	3/15/2027	ZSH27	10.35	2.337	0.184
5/15/2027	ZCK27	4.72	1.552	0.230	5/15/2027	ZSK27	10.41	2.343	0.184
7/15/2027	ZCN27	4.74	1.556	0.230	7/15/2027	ZSN27	10.47	2.349	0.184
9/15/2027	ZCU27	4.55	1.515	0.230	9/15/2027	ZSU27	10.33	2.335	0.184
12/15/2027	ZCZ27	4.54	1.513	0.230	11/15/2027	ZSX27	10.36	2.338	0.184

expiration. These contracts are assumed to move with the 'cash prices', so Z_t is the same as in $S_{t+\Delta t}$.

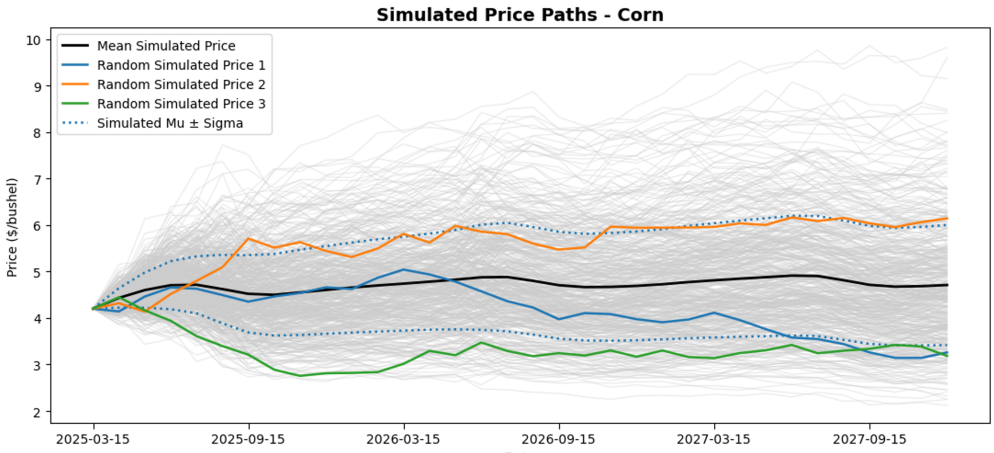
Finally, national marketing year average (MYA) prices are key parameters in Commodity Title I programs. To simulate them, a weighted least squares (WLS) regression is performed regressing observed national cash prices on nearby futures prices, controlling for monthly seasonality. Cash prices are obtained from NASS. Specifically, the model is estimated separately for corn and soybeans using the following specification:

$$\text{NationalCashPrice}_t = \alpha + \beta \cdot \text{FuturesPrice}_t + \sum_{m=2}^{12} \gamma_m D_{m,t} + \varepsilon_t \tag{17}$$

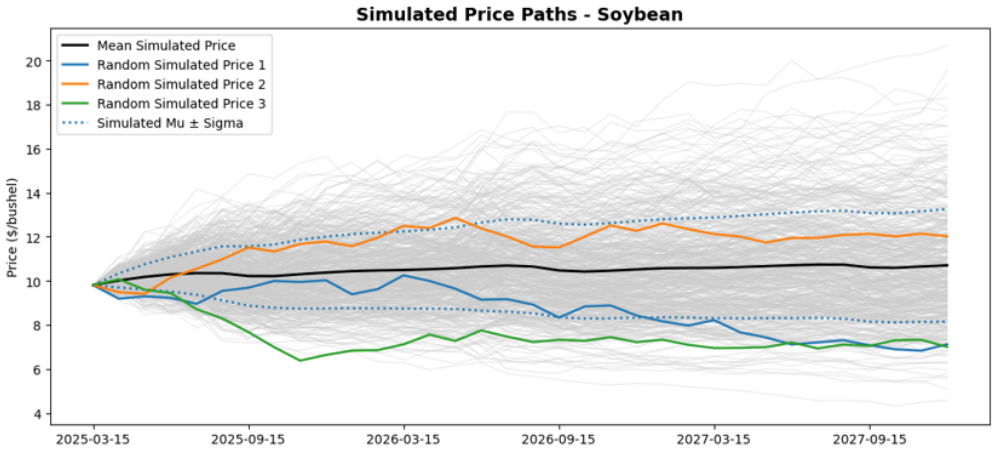
where FuturesPrice_t is the nearby futures contract price, $D_{m,t}$ are month dummies (with January omitted), and ε_t is the error term. To account for the fact that more recent observations may be more predictive of current relationships, the regression applies exponentially increasing weights over time $w_t = \exp(\lambda \cdot t)$ where t indexes observations in chronological order and λ is scaled so that it increases linearly from 0 for the oldest observation to 1 for the most recent one. This approach captures evolving market relationships while preserving seasonality and trend effects in the futures-to-cash price linkage. After simulating cash

prices, simulated national cash prices are obtained from Equation 17 and the MYA for each commodity is calculated as the average from September to August, using historical seasonal weights for each month.

Prices paths were simulated based on futures prices and implied volatility, and are shown in Figure 6. Differences to target futures prices and sigmas are minimum (less than 0.01), meaning in each time t, the lognormal distribution matches the desired distribution, preserving the path-dependent characteristic. To illustrate that, three random paths are shown in orange, green and blue. Note that these are correlated with each other.



(a) Corn Simulated Prices



(b) Soybean Simulated Prices

Figure 6: Simulated commodity monthly prices.

Appendix B.3 Correlation

After simulating yields and prices, it is crucial to impose a proper correlation between them. The correlation between county-yields, farm-yields and prices is imposed in a temporal but also spatial level. Several methods exist to model and establish dependency structures between variables. Woodard et al. (2011) underscore that accurately modeling county-to-farm yield distributions is highly sensitive to the dependence structure used, which significantly influences policy outcomes. Such modeling precision is crucial because incorrect assumptions can either exaggerate or underestimate the risk protection provided by insurance programs. Among these, the Iman and Conover (IC) procedure (Iman and Conover, 1982) is widely used in actuarial science and similar settings (Tsay and Paulson, 2024; Coble et al., 2010), offering a straightforward approach to generating correlated random uniform variables.

The IC procedure is a robust method to simulate N correlated random uniform variates for m variables with a specified rank correlation matrix $\rho_{m\times m}$. The process begins by generating a matrix $\widetilde{Z}_{N\times m}$ of uncorrelated standard normal variates. Using the Cholesky decomposition of ρ, denoted as $\varsigma(\rho_{m\times m}) = C_{m\times m}$ such that $C^\top C = \rho$, the IC procedure transforms these variates into correlated uniform random variates through the expression:

$$\widetilde{U}_{N\times m} = \Phi\left(\left(\varsigma(\rho)\,\widetilde{Z}^\top\right)^\top\right), \tag{18}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function applied element-by-element. The matrix $\rho_{m\times m}$ must be positive definite (PD), or can be forced to be PD by reconstructing it and using the spectral decomposition procedure proposed by Higham (2002). The resulting correlated uniforms can then be used to simulate random variables from the desired marginal distributions while preserving the specified dependency structure (in essence, a normal copula) via the inverse distribution method. For prices, these correlated uniforms are transformed into $W_t \sim \mathcal{N}(0,1)$, by resampling these at each t, making sure the same sample is used at harvest for the Weibulls distribution. By doing so, we ensure that

corn and soybean prices processes are correlated overtime, and at harvest month both are correlated with yields.

The correlation structure used is based on the historical rank correlation matrix, which is a robust measure of correlation. It ensures all county/commodity combinations are cross-sectionally correlated, regardless of their respective marginal distributions.

Lastly, non-observed farm-county yields correlation must be estimated. Following the definition proposed by Miranda (1991), and assuming farm average yields are the same as county average yields, farm yields can be decomposed into a coefficient (call β) that represents the sensitivity to systematic factors affecting yields in that area (or county) and a orthogonal non-systemic component (ϵ):

$$Y_{f,i} = \beta_i Y_c + \varepsilon_i \tag{19}$$

Thus, from the definition of β_i in the linear projection of $Y_{f,i}$ on Y_c:

$$\beta_i = \frac{\text{Cov}(Y_{f,i}, Y_c)}{\text{Var}(Y_c)} = \frac{\rho_i \, \sigma_{Y_{f,i}} \, \sigma_{Y_c}}{\sigma^2_{Y_c}} = \rho_i \cdot \frac{\sigma_{Y_{f,i}}}{\sigma_{Y_c}} \tag{20}$$

where $\sigma_{Y_{f,i}}$ is the farm-yield standard deviation and σ_{Y_c} the county-yield standard deviation. Given that by definition the weighted sum of farm yields is the county yield, the weighted sum of β_i must equal to one. Thus, an average farm can be thought as having a β_i equals to one and we can express ρ_i as:

$$\rho_i = \frac{\sigma_{Y_{f,c}}}{\sigma_{Y_f,i}} \tag{21}$$

The county-farm correlation is implicitly derived from $\sigma_{Y_{f,c}}$, which is estimated empirically from detrended yields, and $\sigma_{Y_f,i}$ was implied by crop insurance premiums. Farm yields and prices correlation are assumed to be the same as the county yields and prices.