The Effect of Actuarial Updates on Private to Public Risk Transfers in Agricultural Insurance

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Abstract

Public-Private Partnerships (PPPs) are a common approach for offering agricultural insurance, but their stability can be threatened by asymmetric information which allows private insurers to strategically transfer risk to the public sector. This study quantifies the economic value of routine premium rate updates in mitigating the ability of private insurers to extract economic rents via underwriting gains within the U.S. Federal Crop Insurance Program (FCIP). Using a counterfactual simulation on program data from 2001-2023, we model potential underwriting gains for private insurers by counterfactually simulating underwriting gains in a scenario where premium rating updates are delayed. Results indicate that forgoing a single annual rate update would allow private insurers to capture an additional $1.6 billion in underwriting gains on average, equivalent to 16% of total premiums.

Keywords: crop insurance; premium rate; subsidies; actuarial science, reinsurance; risk transfer

JEL codes: Q14, G22, G32, Q18; R52

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1. Introduction

Agricultural insurance represents an essential tool for mitigating risks inherent in agricultural production by providing farmers with protection against unpredictable weather events, price volatility, and other adverse conditions. In addition to the direct benefits to farm profitability (Gaku & Tsiboe, 2024), agricultural insurance can also help foster rural economic development (Azzam et al., 2021; Lee, 2021), and improve food security (Lusk, 2017; Savary et al., 2012). Given the complexity and high-risk nature of agricultural activities, the design and implementation of effective agricultural insurance systems are dependent upon appropriate institutional frameworks (Mahul & Stutley, 2010).

A unique challenge associated with insuring agricultural production is that risks tend to exhibit widespread geographic correlation which can make it difficult for private insurance companies to achieve actuarially sustainable risk pooling (Harwood et al., 1999). This challenge has partly motivated the use of Public-private partnerships (PPPs) which have become increasingly prominent in structuring agricultural insurance globally. Specifically, since the early 1990s, there has been a notable shift from purely public insurance systems, particularly multiple peril crop insurance (MPCI) schemes prevalent from the 1950s through the 1990s in Latin America and Asia, towards market-driven approaches involving private insurers supported by government initiatives (Mahul & Stutley, 2010).[1] These PPP arrangements, characterized by governmental support via

[1] Prominent examples of PPP agricultural insurance schemes can be observed in countries including the United States (Turner et al., 2023), China (Wang et al., 2011), Portugal (Coelho, 2024), Turkey (Bora, 2010), France (Enjolras & Sentis, 2011), Mexico (International Bank for Reconstruction and Development & The World Bank, 2013), Russia (Bobojonov et al., 2014), and Brazil (Loyola et al., 2016).

premium subsidies and reinsurance backing (Bora, 2010; Burgaz, 2010; Maria Bielza et al., 2008; Meuwissen et al., 2018; Wang et al., 2011), generally exhibit improved financial outcomes relative to solely public sector models (Mahul & Stutley, 2010).

Nevertheless, PPP models in insurance are not without challenges. Due to the fact that many PPPs are structured to allow private insurance companies to selectively offload some of the underwriting risks back to the public sector, asymmetric information is a prominent concern (Chang et al., 2024; A. Ker & Ergun, 2007; A. P. Ker & McGowan, 2000), (K. H. Coble et al., 2007a; Vedenov et al., 2004, 2006). Such informational asymmetries could potentially undermine the financial and risk management benefits intended by PPP schemes. This paper aims to assess how such disproportionate risk transfers in agricultural insurance can be mitigated through frequently updated sound actuarial practices.

As a backdrop for this study, we focus on the United States' Federal Crop Insurance Program (FCIP) which is the predominant provider of agricultural insurance for one of the world's largest agricultural markets. In 2024, the FCIP managed an insurance portfolio comprising 543 million acres with a total insured liability of $192 billion across over 140 commodities. The PPP structure within the FCIP involves private insurance companies, known as Approved Insurance Providers (AIPs), which distribute and manage federal crop insurance policies in accordance with guidelines stipulated in the Standard Reinsurance Agreement (SRA) (Risk Management Agency [RMA], 2025).[2] Since premiums under the FCIP are set by the USDA Risk Management Agency (RMA), AIPs cannot directly set premium rates but can strategically cede or retain underwriting risks to

[2] Of the 13 RMA-designated insurers in 2022, six with U.S.-domiciled parent companies accounted for 28% ($1.0 billion), and seven with foreign-domiciled parents in Australia, Bermuda, Canada, Japan, and Switzerland, accounted for 72% ($2.7 billion) of total Administrative & Operating (A&O) subsidies and underwriting gains.

the Federal Crop Insurance Corporation (FCIC) based on if the AIPs believe a given policy's premium rate is accurately reflecting the risk of the policy.

Informational asymmetries may allow AIPs to identify risks that are not adequately reflected in existing premium rates which in turn potentially allow for excess underwriting gains to be captured by the AIPs. However, frequent rate revisions by RMA can potentially mitigate this effect. This study estimates the economic value of RMA's rate revisions by assessing potential underwriting gains that could be captured by an AIP in the absence of a rate update. To achieve this, the research uses a counterfactual simulation that compares hypothetical loss outcomes under a scenario without premium updates ("no-update scenario") to the actual outcomes observed after rate revisions. A critical component of this simulation is the "roll-back" method (Tsiboe, 2025), where actuarial data for the current year are replaced with data from the preceding year, and premiums are recalculated based on actual observed losses. This approach incorporates not only the direct impacts on risk transfer between stakeholders but also the dynamic market responses, reflecting changes in crop insurance demand due to altered premium rates. The simulation was retrospectively conducted using RMA's Summary of Business and Actuarial Data Master that includes 49 commodities and seven insurance plans, covering approximately 82% of the FCIP's liability and 71% of the acreage insured from 2001-2023.

Overall, the results suggest that forgoing a routine premium rate update would, on average, lead to an additional $1.6 billion in annual underwriting gains paid to AIPs from 2002-2024 (equivalent to 16% of total FCIP premium volume). These gains are the result of strategic risk transfers that would be possible because of AIPs being able to independently evaluate premium rates using a more current information set than what was reflected in RMA set premium rates. Additional analysis that allows AIPs to combine other information sources (in addition to the typical

information set used by RMA to set premium rates) for their evaluation of premium rates suggests that some combinations of data that capture soil quality, past weather, and historical prices allow AIPs to identify policies that are more likely to lead to higher underwriting gains. However, we also find that the full set of constraints imposed by the SRA keep AIPs from being able to fully act on what the additional information would suggest maximizes underwriting gains. On net this suggests additional information sources produce changes in underwriting gains that are statistically indistinguishable from underwriting gains obtained using the same information that is currently used by RMA to set premium rates.

These results contribute to literature in several ways. First, we contribute to the literature on RMA premium rating methods and more generally on the effects that premium rating practices have on how underwriting risks are distributed in private-public insurance partnerships. Unlike extensive prior research that explored enhancing the actuarial performance of the FCIP including reform to its ratemaking methodology (Carriquiry et al., 2008; Goodwin, 1994; Goodwin & Hungerford, 2015; Park et al., 2019; Ramirez et al., 2011; Skees & Reed, 1986; Woodard et al., 2011), technology-induced yield trends (Adhikari et al., 2012; Seo et al., 2017), heteroscedastic yields (Annan et al., 2014; Harri et al., 2011), and the accommodation of extra sources of information (soil and weather) to improve rates (Liu & Ramsey, 2023a; Rejesus et al., 2015a; Tsiboe & Tack, 2022a; Woodard & Verteramo-Chiu, 2017), this analysis specifically addresses how updates impact the risk sharing integrity of the program.

Second, we provide one of the few analyses focused on the FCIP's Standard Reinsurance Agreement (SRA) and the role that it plays in the actuarial success of the FCIP. Past literature has used stylized versions of SRA to evaluate alternative premium rating methods (Liu & Ramsey, 2023a; Tsiboe & Tack, 2022a; Turner et al., 2024) via the commonly used "cede-retain"

framework (K. H. Coble et al., 2007a; Harri et al., 2011). These simplified versions of the SRA, in addition to omitting many of the constraints the SRA imposes, have exclusively focused on the proportional reinsurance component of the SRA (i.e. the part that allows AIPs to cede risk to the government). However, the actual SRA also contains a non-proportional reinsurance component that graduates retained gains and losses commensurate with the loss ratio on retained policies (i.e. as loss ratios increase, the share of the loss or gain that the AIP retains decreases). Additionally, the SRA's proportional reinsurance component is applied at the state level[3] with different reinsurance terms applied depending on which state AIP is operating in. In other words, although previous use of the SRA via the cede-retain framework is valuable from the perspective of evaluating the strength of alternative rating methods, the outcomes that follow, in many cases, would not be allowed to happen within the FCIP due to the additional constraints the SRA places on AIPs. Alternatively, our own analysis simulates a representative AIP constrained by the complete set of SRA dynamics.

2. Background on Reinsurance and Actuarial Updates in US Agricultural Insurance

2.1 FCIP reinsurance fund allocation

The SRA is a contract between the FCIC and AIPs dictating the terms of their partnership and the sharing of underwriting risks in exchange for a share of potential underwriting profits. Since premium rates are set by RMA, meaning AIPs do not have the ability to alter their underwriting portfolio through setting premium rates, the SRA allows the AIPs to retain risks, or alternatively cede (transfer) risks to the Federal Government, by designating individual crop insurance policies to reinsurance funds (Assigned Risk, Developmental, or Commercial). The AIPs must allocate

[3] i.e. an AIP operating in multiple states cannot pool polices across states. In other words, gains in one state cannot offset losses in another state

policies to reinsurance funds within thirty days following the crop insurance sales closing dates, typically just before the planting season. This timing allows companies to use available information to determine the level of risk they wish to retain or cede for each policy. Although predictions about future growing conditions are limited at this stage, insurers have access to extensive data on the insurance policy itself, including historical loss experience (K. H. Coble et al., 2007a). Different parameters of each of the funds allow AIPs to retain or cede different proportions of premiums and associated liabilities (proportional reinsurance) and to share with the FCIC different amounts of the eventual underwriting gains or losses on retained premiums and liabilities (non-proportional reinsurance). In this section we focus mainly on the parameters that set the limits on fund allocation (cessions and retention) and the percentage of interest in premium and associated ultimate net losses that AIPs must maintain in their retained share in each fund.

Table 1 summarizes the parameters of the SRA with Panel A providing the relevant parameters for the 1998-2011 reinsurance years while panel B is relevant for 2012 onward. Focusing on the current terms of the standard reinsurance (panel B), the proportional reinsurance terms stipulate limits on fund allocation and retention within each fund. With respect to fund allocation, a maximum of 75% of an AIPs book of business within each state (as measured by premiums) can be allocated to the assigned risk fund and at least 25% must be allocated to the commercial fund.[4] Once insurance contracts have been allocated to either the ARF or CF, AIPs have some discretion as to how much of their book of business they want to retain. Within the ARF, the retention share is set at 20% whereas the CF allows for retention shares between 35%-100% in 5% increments.

[4] Prior to 2012, a third fund, the development fund, was available but this fund has been discontinued since 2012.

The non-proportional reinsurance terms outlined in panel B dictate what proportion of the loss associated with retained portion of polices in each fund must be borne by the AIP and what percentage of any underwriting gain is kept. With respect to losses, for contracts designated to the assigned risk fund, AIPs bear between 0% and 7.5% of the loss on their retained interest depending on the size of the loss.[5] For interest retained in the commercial fund, the portion of the loss the AIP is responsible for ranges between 0% and either 65% (group 1 states) or 42.5% (group 2 and 3 states). [6] The share of underwriting gains AIPs keep also varies by loss ratio ranging from 3% to 22.5% in the assigned risk fund. Within the commercial funds, this share goes from 5.5%-76% in group 1 states and 5.5%-97.5% for group 2 and 3 states.[7] Overall, these parameters create differences in the total potential loss and AIP is responsible for or the gain they keep. For example, the maximum loss of underwriting on policies placed in the Assigned Risk Fund is capped at 16% of the retained premium.[8] Conversely, the potential for underwriting gains in this fund is limited, with a maximum of 11.4% of the remaining premium. In contrast, in the commercial fund, AIPs can realize gains up to 35.35% to 42.88% on the retained premium depending on the state, but they also face higher risks, with potential losses of up to 51.50% to 94% of retained premium.

Table 2 displays the national-level outcomes of FCIP reinsurance from 1998 to 2023. From 1998-2023, an average of 20.57% of gross premiums were allocated to the ARF (column 2) with the

[5] The portion of the loss AIPs bear is based on a bracketed loss ratio ranges where the portion of the loss the AIP is responsible for decreases as the loss ratio increase.

[6] There are currently three groups of states that are roughly grouped by historic loss ratios. Group 1 states have the lowest historic loss ratios and receive relatively less favorable reinsurance terms (on the basis that insuring in these states is relatively less risky) compared to Group 2 and 3 states that historically have had higher loss ratios. Current group 1 states are: Illinois, Indiana, Iowa, Minnesota, and Nebraska.

[7] Prior to the changes to the standard reinsurance agreement for the 2012 reinsurance year, the proportion of loses and gains borne by the AIP varied by policy type (catastrophic, revenue, and other) for the commercial fund (and now discontinued development fund). From 2012 onward, these proportions were fixed within each fund and do not vary by policy type.

[8] This is calculated by summing the range of each loss ratio bracket multiplied by the retained share corresponding to each bracket (i.e. (1.6-1)*.075+(2.2-1.6)*.06+(5-2.2)*.03+(5)*0 = 0.165)

remaining going to either the commercial fund or development fund (for years prior to 2011). For policies allocated to the Assigned Risk Fund, AIPs retained approximately 19% interest in the premium and associated liability (column 3), aligning closely with the stated 20% mandate[9]. In contrast, for those policies placed in the Commercial Fund, the share of AIPs' interest remained relatively stable at around 94% of the premium and associated liability (column 4). The final two columns of table 2 report the ratios ceded to retained loss ratios and indemnities which conveys the relative actuarial performance of policies ceded to the FCIC compared to policies retained by AIPs. From 1998-2023, the ceded to retained loss ratio averaged 2.4 indicating that the loss ratio associated with policies ceded to the FCIC was approximately 2.4 times higher than the loss ratio of policies retained by the AIPs. Similarly, the average ceded to retained indemnities averaged 2.8, indicating approximately 2.8 times as many indemnities were paid on ceded policies compared to retained policies. This is consistent with past literature that has shown AIP generally are effective at identifying and ceding relatively more risky policies to the FCIC (K. H. Coble et al., 2007a; A. Ker & Ergun, 2007; A. P. Ker & McGowan, 2000; Vedenov et al., 2004, 2006).

2.2 FCIP premium rating updates

As previously mentioned, AIPs do not have the authority to alter the premium rates for FCIP policies. These premium rates are instead set by RMA in accordance with what is referred to as loss-cost ratio rate making which is essentially designed to set the premium rate for an insured unit equal to the expected loss (K. Coble et al., 2020; K. H. Coble et al., 2010). The purpose of this section is to provide a brief overview of how premium rates are set for individual-level, on-farm

experience insurance plans which include actual production history [APH], yield protection [YP], revenue protection [RP], and RP with harvest price exclusion [RP-HPE] plans.[10]

For individual, yield-based insurance plans (YP and APH), the premium rate per dollar of liability can be written as:

$$\tau(\theta) = \frac{E[I(y)]}{\theta \ddot{y}} = \frac{1}{\theta \ddot{y}} \int_0^{\theta \ddot{y}} (\theta \ddot{y} - y) f(y) dy \quad (1)$$

where, $I(y)$ is the indemnity, which is a function of the realized yield, y[11]. The product of the coverage level, θ, and the approved yield, $\ddot{y}$[12], is equivalent to the insurance guarantee (also known as the insured liability). The probability density function of y is represented by $f(y)$. An underlying premise of FCIP crop insurance policies is that $f(y)$ is conditional on the underlying risk profile of the insured producer which is not directly observed. In other words, the expected indemnity, $E[I(y)]$, is not known and must be approximated using observable characteristics of the producer. Within the FCIP, this is done by comparing the producer's historic yield against the yields of peers under the assumption that more productive farms are less risky.[13] This process of adjusting a producer's premium rate based on their relative yield is represented in RMA's "continuous rating formula" (Milliman & Robertson, 2000; Risk Management Agency [RMA], 2000, 2009). The continuous rating formula is specified by the following equation:

$$\tau_{ijt} = \left[\alpha_{jt}\left(\bar{y}_{ijt}/\bar{y}_{ct}\right)^{\beta_{jt}} + \delta_{jt}\right] F_{ijt}^{\theta} F_{ijt}^{u} \quad (2)$$

[10] Individual-level, on-farm experience insurance plans are those that base indemnities solely on the outcomes of each individual farm, as opposed to group-level or index plans that utilize the average outcomes or a spatial index to determine indemnities.

[11] More formally, the indemnity is the maximum of zero or the difference between the insured liability and the actual realized yield, i.e. $I(y) = max[0, \theta \ddot{y} - y]$.

[12] The approved yield is a modified version of the farmers actual production history (APH) that has been adjusted upwards through various elements of the RMA's actuarial process, such as yield exclusion, yield substitution, and trend adjustments.

[13] This is assumption is based on an early body of research (Botts & Boles, 1958; Skees, 1986).

Where τ_{ijt} represents the premium per dollar of insurance liability for a producer, i , that is part of an insurance pool, j , in crop year, t. [14] The term α_{jt} represents what is called the reference rate while δ_{jt} is a catastrophic fixed loading factor, both of which are set by RMA. The producers' average yield is represented by $\bar{y}_{ijt}$ (often referred to as the rate yield) and the average yield of all producers in the county is represented by $\bar{y}_{ct}$. The term β_{jt} is referred to as the continuous rating exponent which is a negative value by design which when applied to the term $(\bar{y}_{ijt}/\bar{y}_{ct})$ effectively scales down the premium rate when a producer's yield is higher than the average county yield. Finally, F_{ijt}^{θ} represents a scaling factor that alters the final rate based on a producer's chosen coverage level. Similarly, F_{ijt}^{u} adjusts the rate based on the producer's insurance unit election (u_{ijt}) which determines if individual fields are separately insured or aggregated into a single policy.

To this point, the description of the premium rating process has focused on yield-protection policies exclusively. For individual revenue protection policies (RP and RP-HPE), an additional step is required to set a premium rate that accounts for the additional risk (i.e. price risk) associated with revenue-based contracts. This is done by simulating price and yield distributions with the assumption that the distributions are correlated and then calculating a "revenue load" by subtracting off a simulated yield-only rate from a simulated revenue rate. This revenue load is then added to the calculated rate for the yield insurance plans (YP and APH).

The total premium paid for an insurance contract can be written as $P = \tau(.)\theta\ddot{y}$, where $\tau(.)$ represents the premium paid per dollar of liability and, $\theta\ddot{y}$, captures the insured liability. Since FCIP insurance contracts are subsidized, the final cost to the producer is $P * S(\theta, u)$ where $S(\theta, u)$

[14] "Insurance pools" refer to smallest group of producers that receive the same crop insurance premium rate before any individual adjustments are made to account for the individual characteristics of the producer. Currently, RMA defines insurance pools by the combination of county, crop, crop type, and production practice.

is a nationally set subsidy rate that is dependent on the producer chosen coverage level and insurance unit structure. Although the cost a producer pays for a crop insurance contract is driven by their own characteristics (past yields) and choices (coverage level and unit structure), a large portion of the final premium rates is driven by RMA determined rating parameters (α, δ, β) which are updated periodically.[15]

3. Data and Variable Construction

Data for our analysis primary comes from RMA's Summary of Business by Type, Practice, and Unit Structure (SOBTPU) for crop years 2001-2023. Each observation in this dataset records aggregate insurance information for a group of insured producers that share similar characteristics. These groups are defined such that everyone in the group belongs to the same insurance pool (i.e. the smallest group of producers that face the same crop insurance county base rate) which is defined by the county, crop, crop type, and production practice (ex: irrigation status, organic certification). Additionally, everyone in a group also chooses the same crop insurance policy (defined by the choice of insurance plan, coverage level, and unit structure election). Specific information available in the SOBTPU includes the coverage level (θ_{ijt}), net insured acres (A_{ijt}), liability (L_{ijt}), total premium (P_{ijt}), subsidy amount (S_{ijt}), and indemnity amount (I_{ijt}). Several calculations were made to obtain additional metrics including the premium per dollar of liability (τ_{ijt}) which was calculated as the total premium divided by total liability. The subsidy per dollar of premium (s_{ijt}) calculated as the subsidy amount divided by the total premium.

Data from the summary of business was supplemented with data from RMA's Actuarial Data Master to attach relevant actuarial information (continuous rating parameters) to each observation

[15] Each county-crop pair has its own review cycle which is typically either 3 or 5 years (K. H. Coble et al., 2010).

in SOBTPU. Administrative and Operating (A&O) expense subsidy factors were obtained from RMA's Insurance Control Elements database while state-level reinsurance fund allocation ratios were obtained from annual RMA published reinsurance reports.

Actuarial information retrieved that is relevant for our study, includes the county reference rate (α_{jt}), fixed rate (δ_{jt}), rating exponent (β_{jt}), county reference yield ($\bar{y}_{cjt}$), and differential factors for coverage level (F_{ijt}^{θ}) and unit structure (F_{ijt}^{u}).[16] One actuarial value this is not explicitly available in the ADM is the, but is needed for our analysis, is the rate yield ($\bar{y}_{ijt}$). However, this can be calculated by rearranging the continuous rating formula so that the rate yield is a function of all other known values (equation 1).[17] For an in-depth discussion on the continuous rating formula and how each component in equation (1) relates to the premium rate a producer faces, see (Tsiboe & Turner, 2023).

$$\bar{y}_{ijt} = \bar{y}_{cjt}\left[\left(\frac{\tau_{ijt}}{F_{ijt}^{\theta}F_{ijt}^{u}} - \delta_{jt}\right)\frac{1}{\alpha_{jt}}\right]^{\frac{1}{\beta_{jt}}} \tag{3}$$

The data set was limited to only including insurance plans that have premium rates assigned using the continuous rating approach (i.e. the approach used for the most participated in crop insurance plans including YP, RP, and RP-HPE). Prior to 2011, different, but analogous (in terms of the type of protection offered), plans to the YP, RP, and RP-HPE plans were available. To reconcile this difference in the data over time, entries in the data previously classified as APH in both the

[16] For observations with missing coverage level differential factors, estimated values were derived by specifying a regression where the differential is modeled for each crop and crop year as a multivariate quadratic function of the coverage level and the reference rate at the 65% coverage level (K. H. Coble et al., 2010).

SOBTPU and ADM databases were recoded to YP, CRC entries were recoded to RP, and RA and IP entries were recoded to RP-HPE.

Table 3 summarizes the study sample which contains 4,019,531 SOBTPU records belonging to 680,641 insurance pools and covering 42 commodities.[18] On average, a single observation covers 1,302 acres and carries $472,000 in insured liability at a 71% coverage level. The mean premium for crop insurance coverage was $47,000, of which $29,000 (62%) was covered by premium subsidies. Total premium expressed as a percentage of total liability averaged $0.13 and the average subsidy per dollar of premium was $0.63. Table 3 also reports the same summary statistics individually for 7 major crops. Descriptive statistics for additional crops are provided in Table S1 of the online appendix.

To gauge the scope of actuarial revisions, an update rate is computed for each crop year: the share of actual insured acreage in which a given parameter differs between the incumbent and successor ADM files. Annual update rates from 2002 to 2023 (Figure 1) track the RMA's triennial review cycle: near-universal updates 2004 (96.25%), 2005 (100%), 2009 (96.06%), 2018 (97.57%), and 2021 (96.56%) are followed by mid-cycle years with far fewer changes. Parameter-specific patterns echo the aggregate series, except that the rating exponent saw almost no changes before 2012. A discontinuity in county-reference-yield updates reflects a methodological shift in 2011, when transitional yields were replaced by acre-weighted averages of producer-reported yields.

Figure 2 reveals pronounced differences in how often actuarial parameters are updated across crops and states. Field crops lead by a wide margin, with an average 77.7% of insured acreage receiving

[18] The crops included alfalfa seed, almonds, avocado, banana, barley, buckwheat, camelina, caneberries, canola, clary sage, coffee, corn, cotton, cranberries, cucumbers, dry beans, dry peas, flax, forage, grapefruit, grass seed, mandarin/tangerine, millet, mint, mustard, oats, onions, orange, papaya, peaches, peanuts, potatoes, rice, rye, safflower, sesame, sorghum, soybeans, sugar beets, sugarcane, sunflowers, sweet corn, tangelo, tangors, tobacco, tomatoes, triticale, walnuts, and wheat

an update each year. They are followed by forages (64.4%), vegetables (60.5%), nuts (57.2%), and fruits (48.0%). Among individual field crops, corn experiences the most frequent revisions—an average update rate of 86.0 percent—followed by peanuts (78.4%), sorghum (78.0 percent), cotton (75.4%), sugarcane (74.7%), barley (74.7%), rice (74.0%), wheat (73.7%), canola (71.6%), soybeans (71.6%), sunflowers (71.3%), and sugar beets (70.2%). Update intensity also varies sharply across states; fruits, nuts, and vegetables grown in regions where they command only a small share of total insured acreage tend to receive fewer revisions.

4. Simulation Design

This section outlines the counter-factual simulation used to gauge how revisions to premium-rating parameters influence public-to-private risk sharing in the FCIP. This simulation primarily takes place in two steps. First, we simulate the effect that a given revision to the premium rating parameters have on typical insurance outcomes (i.e. collected premiums, loss ratios, etc). Second, we take those outcomes and use them as inputs for simulating reinsurance outcomes while adhering to SRA policy dynamics and strategic AIP behavior.

4.1 Insurance simulation

The simulation of insurance begins by constructing two loss-experience datasets for every crop year:

- Up-to-date scenario – the actual book of business recorded in the SOBTPU, which already embeds the RMA ADM updates.
- No-update counterfactual – the identical set of policies repriced with the ADM parameters from the previous crop year.

Because the RMA omits the current year and the two preceding years of losses when computing rates, the prevailing year's contract choices form an out-of-sample test for both the incumbent and successor ADMs (Figure S1). For example, 2019 producer decisions can be evaluated under both the 2018 and 2019 ADMs—neither of which incorporated 2019 loss data when they were built.

The baseline simulation keeps producer behavior fixed across scenarios. As a robustness check, this assumption is later relaxed by estimating price elasticities and allowing crop insurance demand to alter based on updated premium rates. Treating demand as fixed isolates the mechanical impact of ADM revisions on underwriting flows while providing a transparent baseline for policy evaluation. Each SOBTPU entry's insured acres (A_{ijt}), liability (L_{ijt}), indemnity (I_{ijt}), subsidy per dollar of premium (s_{ijt}), and calibrated rate yield ($\bar{y}_{ijt}$) [Equation (1)] are fixed at their observed values for the update year. Next, two premium rates are calculated for each entry: one with updated parameters (r_{ijt}^{b}) and one without (r_{ijt}^{a}). Formally,

$$r_{ijt}^{b} = \left[\alpha_{jt}\left(\bar{y}_{ijt}/\bar{y}_{cjt}\right)^{\beta_{jt}} + \delta_{jt}\right] F_{ijt}^{\theta_t} F_{ijt}^{u_t} \tag{4}$$

$$r_{ijt}^{a} = \left[\alpha_{jt-1}\left(\bar{y}_{ijt}/\bar{y}_{cjt-1}\right)^{\beta_{jt}} + \delta_{jt-1}\right] F_{ijt-1}^{\theta_t} F_{ijt-1}^{u_t} \tag{5}$$

$$\text{s.t } r_{ijt}^{b} \times 0.8 \leq r_{ijt}^{a} \leq r_{ijt}^{b} \times 1.2 \qquad \text{and} \qquad r_{ijt}^{k} \in (0,1), \forall k = a, b$$

Parameters for the update scenario (r_{ijt}^{b}) come from the current year (t), while those for the no-update scenario (r_{ijt}^{a}) are from the previous year ($t-1$). The 20% range limit on (r_{ijt}^{a}) is based on strict RMA guidelines that limit premium rate increases to up to 20% annually along with observational data that suggests premium rate changes exceeding ±20% are uncommon in the FCIP (Tsiboe, 2025). Total premiums (P_{ijt}^{b} for updates and P_{ijt}^{a} for no-updates) are calculated by adjusting the observed SOBTPU total premium (P_{ijt}) according to the ratio r_{ijt}^{a}/r_{ijt}^{b} for the no-update case

and taken as the observed entry for the update case. Subsidy amounts under each case are then determined by $S_{ijt}^{k} = s_{ijt}P_{ijt}^{k}, \forall k = a, b.$

4.2 Reinsurance simulation

The conceptualization of the reinsurance simulation draws on the existing body of work on how AIPs make reinsurance fund allocation and retention decisions subject to the terms in the SRA (K. H. Coble et al., 2007b; DeLay & Walters, 2024; A. Ker & Ergun, 2007; A. P. Ker & McGowan, 2000; Mason et al., 2003; Miranda & Glauber, 1997; Vedenov et al., 2004, 2006). Insurance providers must assign each newly written crop-insurance policy to one of the SRA reinsurance funds within 30 days of the sales-closing date, typically before planting begins. At that point little is known about the coming season's weather, but firms possess extensive historical information on the contract itself and on the producer's prior performance. The FCIC prices every policy so that the actuarily fair total premium (producer payment plus subsidy) equals its own estimate of the expected indemnity. As shown previously, that estimate is generated by a rating system that starts with county-level loss experience for the crop and then layers on policy-specific factors such as coverage level, production-history yield, insurance plan, unit structure, and crop-type or practice.

The insurance provider's perspective differs. Its expected net return on a policy (equal to the premium minus expected indemnity) reflects not only the FCIC rate but any private analysis conducted by the insurance provider. Formally, the firm's expectation is a function of the FCIC rating inputs plus the firm's information set (which may or may not differ from the information used to set the FCIC rate). The allocation rule then chooses the fund designation rate that

maximizes the firm's expected return, recognizing that each fund carries different retention proportions.

Portfolio considerations further shape this decision. A firm's effective premium rate measures the inherent riskiness of its book; its geographic concentration captures diversification across states; and the number of policies written in a state proxies for the effort it can devote to selective cessions. State-specific caps on the share of premium that may be ceded under the SRA impose an additional constraint. Taken together, these policy-level and firm-level factors determine whether a given contract is retained in the Commercial Fund or shifted into the Assigned Risk Fund.

Treating each SOBTPU entry in the simulation as a crop-insurance contract, the second phase of the simulation mimics the risk sharing actions of a representative AIP constrained by the complete set of SRA dynamics (See Table 1). To replicate the precise risk-sharing sequence imposed by the SRA, every crop-insurance contract (k) issued by the representative AIP is processed separately by each state to mimic the full SRA's reinsurance dynamics summarized on Table 1. The idea here is to produce a simulated version of key reinsurance outcomes shown on Table 2

Update scenario – proportional reinsurance.

First, contracts are ranked by their expected underwriting margin ($\Delta P_{ks} = \mathrm{P}_{ks}^{\mathrm{a}} - \mathrm{P}_{ks}^{\mathrm{b}}$), defined as the difference between the premium under the incumbent ADM ($\mathrm{P}_{ks}^{\mathrm{a}}$) and the premium under the successor ADM ($\mathrm{P}_{ks}^{\mathrm{b}}$). A cumulative share of written premium is then calculated. The first 25% premium is automatically assigned to the CF to satisfy the SRA's minimum-volume requirement. Beyond that cut-off, fund assignment becomes profit-sensitive: contracts with a positive expected margin ($\Delta P_{ks} > 0$) remain in the CF, while loss-expecting or break-even contracts ($\Delta P_{ks} \leq 0$) are allocated to the ARF. The second pass applies to the SRA's retention floors within each fund. The

AIP must retain at least 20% of ARF premium and at least 35% of CF premium. Above those thresholds, retention is again profit-contingent: profitable contracts are kept; unprofitable ones are ceded to the FCIC. Each contract therefore carries two labels: its fund designation (CF or ARF) and its retention status (retained or ceded).

No-update scenario – modified proportional reinsurance.

When no rate update occurs, the underwriting margin cannot be computed because both the AIP and FCIC use the premium rate under the incumbent ADM (r^{a}_{ks}). Two adjustments are introduced. First, contracts are ordered by inverse premium rate size ($1/r^{a}_{ks}$), which place high-premium business in the ARF and low-premium business in the CF. Second, all thresholds (minimum CF volume, ARF retention floor, and CF retention band) are set to their observed state by crop year historical averages (approximately 18.8%, 18.7%, and 93.3%, respectively, across all states from 2011-2023) so that the routine mirrors actual market behavior while remaining fully tunable. All profit screens are removed meaning allocation and retention depend only on cumulative premium volume. The logic of this decision rule is that without any additional information provided with a rate update, the AIP's only signal for choosing to cede or retain a policy is the premium rate. If contracts with lower premium rates reflect less risk, then an AIP selecting lower premium rate contracts will, on average, walk away with an underwriting portfolio that has a lower variance of expected net returns. In other words, without any additional information to inform the first moment of their expected returns distribution, we assume AIPs use the remaining available information to select on the second moment and minimize variance.

Non-proportional reinsurance.

After fund designation and retention decisions are complete, acres, liabilities, premiums, and indemnities are aggregated by state, fund, and retention status. Retained premiums and indemnities flow through the SRA's stop-loss schedule, which graduates the share of gains or losses borne by the AIP as the retained loss ratio rises (see Section 2.1 and Table 1). Ceded business is transferred wholesale to the FCIC.

4.3 Aggregation and performance metrics

The simulation produces (i) retention percentages— i.e. the shares of area, liability, premium, and indemnity the AIP keeps; (ii) loss ratios for retained and ceded pools; and (iii) net underwriting results for three sub-books: the AIP's retained business (private), the FCIC's share of that retained business (public-retained), and the FCIC's ceded business (public-ceded). FCIC's total net underwriting equals the sum of its retained and ceded pools, and each agent's rate of return is expressed as net underwriting over their respective premium exposure.

Metrics are computed separately for the update and no-update scenarios, and their differences quantify the economic impact of rate revisions. In particular, "savings" are defined as the reduction in FCIC net underwriting that is not offset by a corresponding reduction in AIP net underwriting; positive savings therefore measure the economic rents removed by the update, reported both in dollars and as a share of gross premium.

4.4 Scenarios

Primary scenarios design relying on only loss experience information

The analysis begins with a baseline scenario that mirrors the RMA's current practice. Under this scenario, all four rating parameters (α, δ, β, and $\bar{y}_c$) are updated in tandem (whether on a common

or staggered calendar). Because the observed SOBTPU already reflects those updates, only the no-update counterfactual is simulated (i.e. the up-to-date state is already observed).

Subsequent targeted-update scenarios isolate the contribution of each parameter. In turn, α, δ, β, and $\bar{y}_c$ are allowed to roll forward while the remaining parameters are frozen at their previous-year values. By contrasting these targeted experiments with the baseline, the study identifies which component of the rating formula drives the largest changes in public and private net underwriting.

All scenarios compare update versus no-update outcomes only for county-crop programs that exist in both the incumbent and successor ADM files. County-crop combinations that appear for the first time, or disappear, are omitted. Although this restriction excludes areas with very recent expansions or contractions, the retained set still represents more than 80 percent of the insured volume over 2001-2023. Each impact measure is reported as the simple average of annual effects across that 23-year window.

4.5 Additional information scenarios

Our primary scenarios assume that AIPs utilize the same information sources as RMA to determine which reinsurance fund to allocate crop insurance contracts to. However, AIPs are incentivized to seek out any additional information advantage, meaning their own evaluation of premium rates may incorporate additional data sources that aren't currently used by RMA to set premium rates. In this sense, our primary scenarios represent something akin to a best-case scenario in which information sets are the same across all market participants. In these supplementary scenarios, we approach the problem from the opposite end of the spectrum and assume AIPs incorporate additional information sources to help determine how to allocate and retain contracts across reinsurance funds.

In addition to incorporating the existing information that factors into RMA set premium rates, which we refer to as the "base" information set. We also consider other information sources that an AIP might reasonably be expected to use when independently evaluating RMA set premium rates. The additional information used includes county level soil data, historical weather data, and historical price information covering projected and harvested commodity prices.

Incorporating these additional sources of information into predictions about actuarially fair premium rates is not entirely straightforward in the sense that there are not existing, vetted, parametric representations of premium rates as a function of all the potential sources of information we consider. Further, it is unlikely that every piece of information we consider is valuable in terms of improving premium rate accuracy. Consequently, a method is needed that can 1) use all available information to predict loss cost ratios (the basis for actuarially fair rates in the FCIP) without an explicit functional representation and 2) have built in regularization routines that can automatically exclude or down-weight information sources that are not deemed to be valuable in predicting loss cost ratios.

Machine learning approaches are well suited for these constraints as they are inherently non-parametric and specifically optimized for prediction tasks with robust regularization routines. Although there are many available machine learning algorithms to choose from, we use the LightGBM algorithm which is a machine learning approach based on gradient-boosted decision trees that can be used for either classification or regression tasks on tabular data (Ke et al., 2017a).

The choice of LightGBM is motivated by two observations from literature. The first being that for structured data, algorithms based on gradient-boosted decision trees tend to offer slightly better predictive accuracy over algorithms based on neural networks, especially when the dataset is large and has features that have imbalanced classes or skewed distributions(Grinsztajn et al., 2022;

McElfresh et al., 2023; Shmuel et al., 2024). The second is that LightGBM is substantially less costly (in terms of total computing time and memory overhead) to implement compared to similar performing algorithms (Ke et al., 2017b; McElfresh et al., 2023). This is an important consideration as it allows us to compute bootstrapped standard errors on the predictions.[19] Training and implementation of the machine learning algorithm was done using standard techniques. Details on the training process as well as detailed descriptions of the additional data sources are provided in the appendix (note S1).

4.5 Standard-error estimation

Inference relies on a stratified bootstrap with 100 replications. In each draw, the unit of resampling is an insurance pool—a unique combination of county, crop, crop type, and production practice. From the universe of 665 482 pools, a new sample of equal size is selected with replacement; whenever a pool is chosen, every observation for all its crop years enters the resampled dataset. The full simulation (rate update, insurance outcomes, fund allocation, retention, and stop-loss calculations) is then rerun on that bootstrap sample. The resulting distribution of 100-point estimates provides empirical standard errors for all reported impact metrics.

5. Results and Discussions

This section summarizes the simulation's key findings. First, we establish a baseline assuming no rating updates from 2002–2023, capturing actuarial outcomes and private-to-public risk transfer. We then gauge the aggregate impact of periodic rating revisions against this baseline, contrasting targeted versus comprehensive updates to reveal their relative effectiveness. Next, temporal and

[19] Typically, machine learning models return a point estimate with no measure of uncertainty. To obtain an indication of statistical significance, numerical methods (like bootstrapping) are used to obtain a measure of uncertainty on the point estimate.

spatial heterogeneity is explored, pinpointing crop years and regions where updates most curtail the industry's capacity to shift risk onto taxpayers. Finally, machine-learning results show how incorporating non-FCIP experience data can further influence risk transfers.

5.1 Establishing the baseline ("no update") scenario

Table 4 presents the primary findings from the analysis across the full sample. Under the baseline scenario (i.e. no premium rating updates occur), sixteen percent of premiums flowed into the Assigned Risk Fund (versus 20% observed historically), while within-fund retentions matched the current observed values at 18% for the Assigned Risk Fund and 93% for the Commercial Fund. Aggregating both funds, the private sector retained policies that accounted for 87% of insured acreage, 91% of liabilities, 81% of premiums, and 76% of indemnities.

The loss ratio on retained business was 0.776 compared with 0.985 on ceded business, yielding a ceded-to-retained ratio of 1.32. These figures show that the representative private sector agent in our simulation retains lower-risk policies and passes higher-risk ones to the public sector. For the public sector, the baseline simulation produces a $318 million underwriting gain or 3.15% of its $10 billion premium exposure. Private companies record $1.35 billion in underwriting gains, a 16.3% return on their $8.3 billion premium exposure.

5.2 Effect of updates

The second column in table 4 shows the change that is induced by that status quo premium rating update schedule relative to the baseline scenario established in the first column. The results show that the updating pattern imposed by RMA results in markedly different behavior among the representative AIP. The share of premiums allocated to the assigned risk funds rises by 42 percentage points relative to the no-update case indicating a much higher share of policies are seen

as undesirable to underwrite from the AIP's perspective. Concurrently, the results point to the private sector keeping a slightly larger portion of the premium they place in the Assigned Risk Fund (8.67 percentage point increase) while also trimming what they retain in the Commercial Fund (-7.20 percentage points). Across the entire portfolio, private retention falls sharply with AIPs keeping far less acreage, liabilities, premiums, and indemnities.

Loss-experience metrics point to the updated rate leading to a narrowing of the profitability gap between what the private sector keeps and what they cede. The loss ratio on retained business increases (0.08), while the loss ratio on ceded business moves downward (-0.18), reducing the ceded-to-retained ratio from roughly 1.3 to just under 1.0. In other words, the actuarial performance of the ceded and retained policies are almost identical once regular premium rating updates are imposed indicating risk is being approximately evenly distributed among the private and public sector.

Private underwriting gains on retained business drop by approximately $815 million, while public underwriting gains rise by similar amount ($791 million). As a result, annual rates of return converge: the private return on premium falls from approximately 16% to just over 10% while the public return rises to a similar level from an original value of about 3%. Overall, this leads to an estimated annual savings that occur due to regular actuarial revisions of about $1.6 billion per year or about 16% of gross premium.

5.3 Targeted vs comprehensive updates

Figure 3 highlights the heterogeneity in the main result the actual rating parameter being updated. The "Any update" panel of figure 3 represents the main effect of $1.6 billion per year in savings that occurs as a result of updating any parameter. In other words, this is the effect of the parameter

updates that were observed over this time period which for any given update included a minimum of one parameter and at most all of them. The remaining panels in figure 3 are the results of artificially restricting any observed parameter updates to only apply to a single parameter. For example the "Only reference rate updated" means that the simulation was redone allowing only the reference rate to be updated. Doing this for each parameter individually, decomposes the main effect into its constituent parts and highlight the relative value of each parameter being kept up to date. The calculated savings from keeping the reference rate, fixed rate, and rating exponent current range from 14.5% - 17.1% of the gross premium which is comparable to the main effect of 16%. Alternatively, the average savings that are estimated from keeping the reference yield up to date is 25.8% of the gross premium. This suggests that the reference yield being outdated provides AIPs with the largest information advantage (relative to all other rating parameters).

5.4 Temporal and spatial heterogeneity

Figure 3 also highlights the temporal variation that naturally occurs due to the random nature of crop insurance indemnities. Although updating rating parameters is estimated to have an average effect that results in savings for the public sector, this is not universally true every year. As is reflected in table 4, RMA performing a rating update results in AIPs ceding more liability back to the public sector. This means that if an update occurs for a year with exceptional losses, the update may result in more underwriting losses being absorbed by the public sector simply by virtue of the FCIC having more exposure to the exceptional event. This effect is most obvious for 2012 (an extreme drought year). For most of the parameters depicted in figure 3 (and especially for the reference yield and rating exponent) updates occurring in 2012 were estimated to have negative savings compared to the case of no updating.

A similar effect can be observed spatially as well. Figure 4 reports the same metrics as in figure 3, but decomposed by state. Notably, only a handful of states (OR, NV, NM, TX, OK, FL, NC, VT, MA, CT) see negative savings to the government when the rating parameters are updated. Without exception, all of these states have average annual loss ratios and cumulative loss ratios[20] that are above one for the time period our sample covers (2001-2023). These states are also typically characterized by one or more years with exception losses[21], which as described above, can lead to negative savings if rating parameter updates cause more liability to be ceded back to the government.

5.4 Value of additional information

Figure 5 reports the results of the machine learning analysis described in section 4.5. It is worth reiterating that the purpose of this section is isolate the potential value of various information sources, rather than a comparison of various premium rating methodologies meaning the analysis is done under the assumption that both RMA and AIPs are applying machine learning approaches to set and evaluate premium rates. Under the "FCIP history only" information set (i.e. all of the information that is currently used by RMA to set premium rates), the average annual underwriting gains that an AIP could extract if the event of RMA forgoing a regular premium rating update is approximately 7% of total premium volume. Interestingly, this is approximately half the effect size (16%, table 4) compared to when both RMA and an AIP are assumed to use the current RMA premium rating framework on the same information set. This suggests that the machine learning

[20] Average annual loss ratio is the simple average of each year's loss ratio while the cumulative loss ratio is calculated by summing all indemnities over the time period and dividing by the sum of all premium over the time period. In effect the average annual loss ratio applies equal weighting each year whereas the cumulative loss ratio is effectively weighted by liability (i.e. years with higher participation influence the average more).

[21] Among the states listed above, all but New Mexico have had at least one year where loss ratios exceeded 2 and 5 states had at least one year where loss ratios exceeded 3 (CT, HI, NV, OR, VT).

approach is making use of the available information to set premium rates in a way that mitigates the consequences of less frequent updates. The remaining estimates in figure 5 correspond to scenarios where AIPs are assumed to be using additional information sources beyond what is directly incorporated into the RMA premium rating framework. In every case, alternative information sets do not produce an information advantage that results in a statistically significant difference in underwriting gains suggesting that there is limited value for AIPs when using alternative information sources.

At first glance, this finding appears to contradict previous literature. For example, past studies have shown that historical weather data leads to better predictions of crop insurance losses which theoretically would allow a private insurer to extract higher underwriting gains through strategic cessation and retention of crop insurance policies (Liu & Ramsey, 2023b; Rejesus et al., 2015b; Yi et al., 2020). Similar results have been found in the case of incorporating soil information (Tsiboe & Tack, 2022a). As was mentioned in the introduction, studies of this type typically use a highly stylized version of the standard reinsurance agreement to conduct a simulation where private insurers are able to fully cede or retain policies without any limits or restrictions. This approach however ignores the fund allocation limits, retention limits within each fund, and the graduated loses and gains on the retained interest that are described in table 1. The typical metric used in these types of studies is to look at the ceded-to-retained loss ratio. When this ratio is above 1, the liability retained by the private insurer is performing better actuarially than the liability ceded back to the government. Within this framework, if introducing new information into the evaluation leads to higher ceded-to-retained loss ratios, then that is evidence that the new information would allow a private insurer to advantageously select against the government more successfully than without the added information. To create an apt comparison with previous

literature, we construct ceded-to-retained loss ratios for the scenarios represented in figure 5. Additionally, we create two iterations of this ratio for each scenario: one using the stylized version of the cede-to-retain game (as it is typically implemented) and one that uses the full dynamics of the Standard Reinsurance Agreement (as is used in this study). These ratios are reported in figure 6.

Notably, the ceded-to-retained loss ratios obtained under the Full SRA are all smaller (closer to one) compared to the same ratios obtained under the stylized SRA, representing the effects that the additional constraints of the SRA. In other words, the ceded and retained portfolios are more similar (in terms of actuarial performance) under the full SRA. The ceded-to-retained loss ratios obtained under the stylized version of the SRA indicate that "FCIP history + county weather + price", "FCIP history + county weather + county soil", "FCIP history + county weather", and "FCIP history + county soil + price" all produce ceded-to-retained loss ratios that are statistically higher than when the information set consists of "FCIP history only". This indicates that these information sets allow a private insurer to construct an underwriting portfolio that is better performing actuarily when additional information is added and the full constraints of the SRA are relaxed. Looking at the results produced under the full SRA dynamics suggests only "FCIP history + county weather + county soil" produces a ceded-to-retained loss ratio that is statistically different than the same ratio obtained using "FCIP history only". Overall, these results suggest that additional information can allow a private insurer to identify policies that are likely to be underpriced, but the full constrains of the SRA limit the ultimate underwriting gains that accrue.[22]

[22] There may also be cases where a private insurer is forced to cede or retain a policy, despite knowing that it is likely to reduce their total underwriting gains. For example, if the insurer has already hit their maximum 75% allocation to the assigned risk fund (table 1) within a state, they will be forced allocate the rest of portfolio in that state to the commercial fund.

6. Conclusion

In the global landscape of agricultural insurance, Public-Private Partnerships (PPP) that distribute the underwriting and administrative responsibilities between the public and private sector have become commonplace – particularly in large, developed countries. Although PPPs are an effective way to overcome the underwriting challenges that may prevent agricultural insurance from being solely provided by private insurers, information asymmetries remain a perpetual challenge, particularly when the PPP is set up to allow the private sector to selectively offload certain risks to the public sector. Focusing on the U.S. Federal Crop Insurance Program, this paper explores the role that timing of actuarial updates has on the economic rents that can be extracted by private insurers. By counterfactually simulating foregone actuarial updates to FCIP premium rates, our analysis simulates the effect of private market participants having a more current information set than what is reflected in premium rates. We find that this information is worth to approximately 16% of the total premium volume annually (or about $1.6 billion). In other words, our results suggest that the routine actuarial updates provided by the USDA Risk Management Agency save taxpayers approximately $1.6 billion per year compared to a scenario in which update cycles are increased by an additional year.

Our results also highlight the role that the FCIP's standard reinsurance agreement play in mitigating the effect of information asymmetries. Consistent with previous literature, we find that incorporating additional information sources including data on historical weather, prices, and soil quality hypothetically allows a private insurer to construct an actuarial superior

underwriting portfolio (i.e. one that produces higher underwriting profits). However, we also find that the constraints imposed by the Standard Reinsurance Agreement ultimately limit the extent to which a private insurer can act on the information advantage and in effect do not allow the hypothetically superior underwriting portfolio to materialize.

From a policy perspective, our results suggest that it may be possible to achieve greater government cost savings by increasing the frequency of routine premium rate updates. Current practice by RMA is to conduct actuarial updates on a 3 or 5 year cycle (depending on crop and county) meaning it is possible to apply updates at a much higher frequency. However, more research is needed to understand the optimal frequency to conduct actuarial updates and if there is declining marginal value with more frequent updates.

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Tables and Figures

Table 1: Shares of Underwriting Gains and Losses to Insurance Companies under the Standard Reinsurance Agreement 1998-2025

	Assigned Risk Fund (ARF)	Developmental Fund (DF)			Commercial Fund (CF)		
		CAT	REV	OTHER	CAT	REV	OTHER
Panel A 1998-2011 reinsurance years							
Proportional reinsurance [a]							
Fund allocation	State max of 10-75%	All non- ARF designations			All non- ARF or -DF designations		
Retention within fund	20%	35-100% in 5% increment			50%-100% in 5% increment		
Non-proportional reinsurance [b]							
Percentage of loss on retained interest by loss ratio							
1.0–1.6	5.0	25.0	30.0	25.0	50.0	57.0	50.0
1.6–2.2	4.0	20.0	22.5	20.0	40.0	43.0	40.0
2.2–5.0	2.0	11.0	11.0	11.0	17.0	17.0	17.0
>5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Percentage of gain on retained interest by Loss ratio							
0.65–1.0	15.0	45.0	60.0	60.0	75.0	94.0	94.0
0.5–0.65	9.0	30.0	50.0	50.0	50.0	70.0	70.0
<0.5	2.0	4.0	6.0	6.0	8.0	11.0	11.0
Panel B: 2012-2025 reinsurance years							
Proportional reinsurance							
Fund allocation	State max of 75%				At least 25%		
Retention within fund	20%				35%-100% in 5% increment		
Non-proportional reinsurance [b, c]							
Percentage of loss on retained interest by loss ratio							
1.0–1.6	7.5	-	-	-	65.0 [42.5]	65.0 [42.5]	65.0 [42.5]
1.6–2.2	6.0	-	-	-	45.0 [20.0]	45.0 [20.0]	45.0 [20.0]
2.2–5.0	3.0	-	-	-	10.0 [5.0]	10.0 [5.0]	10.0 [5.0]
>5.0	0.0	-	-	-	0.0 [0.0]	0.0 [0.0]	0.0 [0.0]
Percentage of gain on retained interest by Loss ratio							
0.65–1.0	22.5	-	-	-	76.0 [97.5]	76.0 [97.5]	76.0 [97.5]
0.5–0.65	13.5	-	-	-	40.0 [40.0]	40.0 [40.0]	40.0 [40.0]
<0.5	3.0	-	-	-	5.5 [5.5]	5.5 [5.5]	5.5 [5.5]

CAT = Catastrophic insurance; REV=Revenue insurance plans; OTHER = All other crop insurance plans.

[a] After all reinsurance cessions, the AIP's must retain a percentage of net book premium and associated liability that equals or exceeds 35% of its book of business. If not, the AIP's retention of net book premium and associated liability for ultimate net losses for all contracts designated in the Assigned Risk Fund in all States will be increased on a pro rata basis to make the API's retention meet the minimum retention requirement.

[b] Share of loss or gain is determined incrementally by the realized loss ratio for a company's business in each state and fund

[c] The Percentage of loss/gain on retained interest by loss ratio for the Commercial Fund varied by three state grouping where the values in the bracket are for groups 2 and 3. "State Group 1" means Illinois, Indiana, Iowa, Minnesota, and Nebraska. "State Group 2" means Alabama, Arizona, Arkansas, California, Colorado, Florida, Georgia, Idaho, Kansas, Kentucky, Louisiana, Michigan, Missouri, Mississippi, Montana, North Carolina, North Dakota, New Mexico, Ohio, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Virginia, Washington, and Wisconsin. "State Group 3" means Alaska, Connecticut, Delaware, Hawaii, Maine, Massachusetts, Maryland, Nevada, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Utah, Vermont, West Virginia, and Wyoming.

Table 2: United States Federal Crop Insurance Program Reinsurance Outcomes

Reinsurance year	Gross Liability (billion $)	Percentage of gross premium allocated to Assigned risk fund	Approved insurance provider (AIP) interest in retained liability as percentage		Ceded business by AIP to Federal Crop Insurance Corporation (FCIC)			Retained interest by AIP [a]				
			Assigned risk fund	Commercial or Developmental funds	Premium (billion $)	Indemnity (billion $)	Loss ratio	Premium (billion $)	Indemnity (billion $)	Net Gain/Loss (billion $)	Loss ratio	Rate of return on retained premiums (%)
1998	56.58	16.71	18.66	98.13	0.58	1.34	2.33	3.23	2.16	0.57	0.67	17.54
1999	67.98	23.85	20.00	98.06	1.04	2.41	2.31	4.03	2.83	0.60	0.70	14.79
2000	74.69	28.40	20.00	96.36	1.39	2.72	1.95	4.11	2.89	0.61	0.70	14.88
2001	74.94	23.75	18.33	98.80	1.23	2.50	2.04	4.82	3.52	0.70	0.73	14.58
2002	79.66	24.99	18.41	99.00	1.32	4.22	3.20	4.92	4.48	-0.10	0.91	-2.07
2003	79.48	24.92	20.00	94.44	1.62	2.47	1.53	5.10	3.91	0.74	0.77	14.48
2004	80.70	22.65	20.00	91.14	1.81	2.31	1.28	5.44	3.39	1.20	0.62	21.99
2005	78.78	23.26	17.31	90.25	1.88	1.68	0.90	5.15	2.49	1.63	0.48	31.64
2006	98.07	22.89	17.27	91.24	2.15	2.93	1.36	6.22	3.38	1.46	0.54	23.49
2007	100.18	22.23	17.39	91.22	2.45	1.93	0.79	7.29	3.22	2.34	0.44	32.09
2008	116.64	18.91	17.27	92.49	2.79	3.37	1.21	10.05	8.02	1.43	0.80	14.22
2009	119.22	22.27	17.10	93.29	3.20	3.41	1.07	10.30	4.45	3.46	0.43	33.64
2010	108.39	17.46	16.62	93.20	2.14	1.77	0.83	8.47	4.18	2.67	0.49	31.57
2011	134.14	18.25	18.70	93.31	2.86	5.23	1.83	11.22	7.53	1.95	0.67	17.42
2012	130.89	20.95	18.70	93.34	2.77	9.41	3.40	9.65	10.05	-1.47	1.04	-15.26
2013	135.31	20.13	18.70	93.19	2.82	4.67	1.66	10.11	8.62	0.69	0.85	6.82
2014	117.98	19.84	18.70	93.12	2.34	3.42	1.46	8.48	6.34	1.09	0.75	12.87
2015	118.72	20.30	18.70	93.13	2.42	2.46	1.01	8.61	4.80	2.08	0.56	24.12
2016	132.75	16.48	18.70	93.14	2.36	1.78	0.75	9.97	3.40	3.40	0.34	34.07
2017	137.53	14.61	18.70	93.41	2.28	2.24	0.98	10.76	5.09	3.32	0.47	30.89
2018	146.27	17.50	18.70	93.28	2.59	3.43	1.32	10.52	5.98	2.76	0.57	26.25
2019	149.69	13.88	18.70	93.35	2.32	4.27	1.84	11.33	9.96	0.66	0.88	5.82
2020	158.21	16.59	18.70	93.36	2.66	4.35	1.64	11.31	7.73	1.96	0.68	17.37
2021	157.43	18.76	18.70	93.43	3.26	4.51	1.38	12.58	6.76	2.81	0.54	22.37
2022	158.16	19.30	18.70	93.44	3.52	8.08	2.29	13.26	9.88	1.19	0.75	8.99
2023	176.62	24.62	18.70	93.41	4.42	6.80	1.54	13.26	10.11	1.92	0.76	14.48
2024	158.70	21.86	18.70	93.04	3.69	4.38	1.19	12.21	8.38	2.44	0.69	19.99
Averages												
1998-2010	87.33	22.49	18.34	94.43	1.82	2.54	1.60	6.09	3.76	1.33	0.64	20.22
2011-2023	143.74	18.79	18.70	93.28	2.88	4.64	1.59	10.95	7.47	1.77	0.68	16.16
2001-2023	122.85	20.27	18.40	93.38	2.54	3.82	1.52	9.21	6.07	1.68	0.66	18.41
1998-2023	116.58	20.57	18.52	93.84	2.37	3.63	1.60	8.61	5.69	1.56	0.66	18.11

[a] Includes 6.5% Net Book Quota Share.

The data was constructed by the authors using primary data from Risk Management Agency Reinsurance Data (National Totals by Fund) as of 01/2025

Table 3: Means and Standard Deviations of US Federal Crop Insurance Outcomes (2001-24).

Variables	Full sample	Corn	Soybeans	Wheat	Cotton	Sorghum	Barley	Rice
Summary of business outcomes								
Coverage level (%)	70.88 (9.62)	73.33 (9.08)	72.59 (9.50)	69.10 (8.13)	64.15 (9.38)	66.87 (7.82)	69.07 (8.91)	62.20 (12.37)
Net insured area (acres)	1302 (4357)	1540 (4833)	1487 (4631)	1408 (4886)	1240 (3843)	710 (1918)	686 (1776)	1305 (3667)
Total insured liability ($ 1,000)	472 (2128)	759 (3080)	484 (1800)	234 (1028)	425 (1434)	115 (373)	101 (294)	686 (1969)
Total premium ($ 1,000)	47.06 (206.16)	67.28 (275.28)	42.42 (161.45)	37.67 (169.10)	74.22 (330.86)	23.51 (79.74)	12.88 (39.05)	40.56 (114.11)
Total subsidy ($ 1,000)	29.36 (139.07)	41.47 (186.35)	26.34 (107.75)	23.38 (107.75)	49.59 (238.51)	14.98 (53.74)	7.93 (25.77)	25.99 (71.59)
Total indemnity ($ 1,000)	39.20 (300.61)	52.68 (387.46)	26.03 (147.99)	33.90 (222.44)	92.97 (642.21)	22.75 (131.09)	11.01 (51.12)	70.67 (566.81)
Premium per dollar of liability	0.13 (0.11)	0.11 (0.09)	0.11 (0.09)	0.16 (0.11)	0.18 (0.14)	0.22 (0.15)	0.15 (0.10)	0.07 (0.06)
Subsidy per dollar of premium	0.63 (0.13)	0.63 (0.13)	0.62 (0.13)	0.63 (0.12)	0.66 (0.12)	0.65 (0.12)	0.63 (0.14)	0.62 (0.16)
Producer paid premium rate	0.05 (0.05)	0.04 (0.04)	0.04 (0.04)	0.06 (0.05)	0.07 (0.06)	0.08 (0.07)	0.06 (0.05)	0.03 (0.03)
Actuarial data master outcomes								
Reference rate	0.11 (0.09)	0.08 (0.07)	0.09 (0.08)	0.11 (0.08)	0.16 (0.12)	0.17 (0.12)	0.12 (0.08)	0.03 (0.02)
Fixed rate	0.03 (0.02)	0.03 (0.02)	0.02 (0.01)	0.03 (0.02)	0.03 (0.01)	0.04 (0.02)	0.03 (0.02)	0.02 (0.01)
Rating exponent	-1.38 (0.58)	-1.41 (0.57)	-1.58 (0.44)	-1.50 (0.49)	-1.04 (0.36)	-1.40 (0.58)	-1.40 (0.50)	-1.25 (0.63)
Coverage level differential factor @ 50%	0.66 (0.12)	0.66 (0.11)	0.62 (0.11)	0.67 (0.11)	0.70 (0.12)	0.68 (0.12)	0.70 (0.11)	0.73 (0.09)
Coverage level differential factor @ 55%	0.76 (0.12)	0.76 (0.11)	0.72 (0.11)	0.77 (0.11)	0.79 (0.13)	0.77 (0.13)	0.79 (0.11)	0.81 (0.09)
Coverage level differential factor @ 60%	0.85 (0.11)	0.85 (0.11)	0.83 (0.10)	0.85 (0.12)	0.87 (0.12)	0.85 (0.13)	0.87 (0.11)	0.89 (0.08)
Coverage level differential factor @ 65%	0.95 (0.11)	0.95 (0.11)	0.96 (0.11)	0.95 (0.12)	0.95 (0.12)	0.94 (0.14)	0.96 (0.11)	0.97 (0.08)
Coverage level differential factor @ 70%	1.08 (0.12)	1.08 (0.12)	1.12 (0.14)	1.06 (0.11)	1.05 (0.11)	1.04 (0.13)	1.06 (0.11)	1.08 (0.09)
Coverage level differential factor @ 75%	1.23 (0.15)	1.22 (0.13)	1.32 (0.18)	1.19 (0.12)	1.17 (0.10)	1.18 (0.11)	1.18 (0.09)	1.21 (0.12)
Coverage level differential factor @ 80%	1.39 (0.21)	1.39 (0.17)	1.55 (0.24)	1.32 (0.14)	1.30 (0.12)	1.33 (0.12)	1.32 (0.10)	1.37 (0.15)
Coverage level differential factor @ 85%	1.58 (0.30)	1.57 (0.23)	1.81 (0.33)	1.47 (0.20)	1.45 (0.18)	1.51 (0.18)	1.47 (0.14)	1.55 (0.22)
Basic unit differential factor	1.03 (0.03)	1.03 (0.03)	1.03 (0.03)	1.04 (0.02)	1.05 (0.02)	1.03 (0.02)	1.05 (0.03)	1.04 (0.02)
Enterprise unit differential factor	1.01 (0.03)	1.00 (0.04)	0.99 (0.04)	1.02 (0.01)	1.03 (0.01)	1.01 (0.01)	1.03 (0.01)	1.02 (0.01)
Number of insurance pools	680641	138353	186469	130565	32596	34129	24472	9815
Number of observations	4019531	1129229	1060425	739659	224859	178647	93294	45842

The data was constructed by the authors using primary data from (1) Risk Management Agency's summary of business and actuarial data master files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit.

Table 4: Impacts of actuarial updates on private to public risk transfer incentives in the United States Federal Crop Insurance Program (2002-24)

	Scenarios	
	Baseline of no updates	Current RMA update pattern expressed as level changes over no update case
Assigned risk fund allocation (%)	15.665 (0.232)	42.206*** (0.386)
Fund premium retention percentages		
Assigned risk	17.949 (0.071)	8.674*** (0.581)
Commercial	93.000 (0.040)	-7.195*** (0.439)
Annual retention percentages		
Insured area	87.319 (0.153)	-32.776*** (0.252)
Liability	91.904 (0.110)	-35.992*** (0.226)
Premium	81.247 (0.205)	-29.318*** (0.263)
Indemnity	76.812 (0.256)	-23.557*** (0.450)
Annual loss ratio [LR]		
Retained pool	0.776 (0.007)	0.082*** (0.005)
Ceded pool	0.985 (0.009)	-0.181*** (0.010)
Ceded to retained LR ratio	1.324 (0.014)	-0.324*** (0.021)
Annual net underwritings (million $)		
Retained pool – private	1346.119 (39.670)	-815.672*** (28.569)
Retained pool – public	281.893 (37.416)	-207.643*** (21.672)
Ceded pool – public	35.778 (19.236)	999.375*** (43.283)
Public (Retained + Ceded)	317.670 (50.553)	791.732*** (27.550)
Annual rate of return [net underwritings as a percentage of premium exposure]		
Private	16.247 (0.302)	-5.817*** (0.241)
Public	3.148 (0.452)	7.494*** (0.196)
Annual savings from update		
Value (million $)	-	1607.404*** (55.886)
Share of gross premium (%)	-	16.016*** (0.412)

Simulation: Actuarial Data Master [ADM] (successor) for the release year (e.g., 2023) was replaced with the ADM for the previous year (incumbent) (e.g., 2022) and the premiums were recalculated for the actual loss experience outcomes associated with the successor in the release year. Cumulative evaluation is based on loss ratio calculated over the period 1997 to the release year. Adjusted demand allows insured acres to shift based on their responsiveness to paid premium rates.

Significance levels - *p<0.1 ** p<0.05, ***p<0.01. Standard errors in parentheses are estimated by resampling insurance pools 100 times.

Figure 1: Annual variation in actuarial updates in the United States Federal Crop Insurance Program (2002-24)

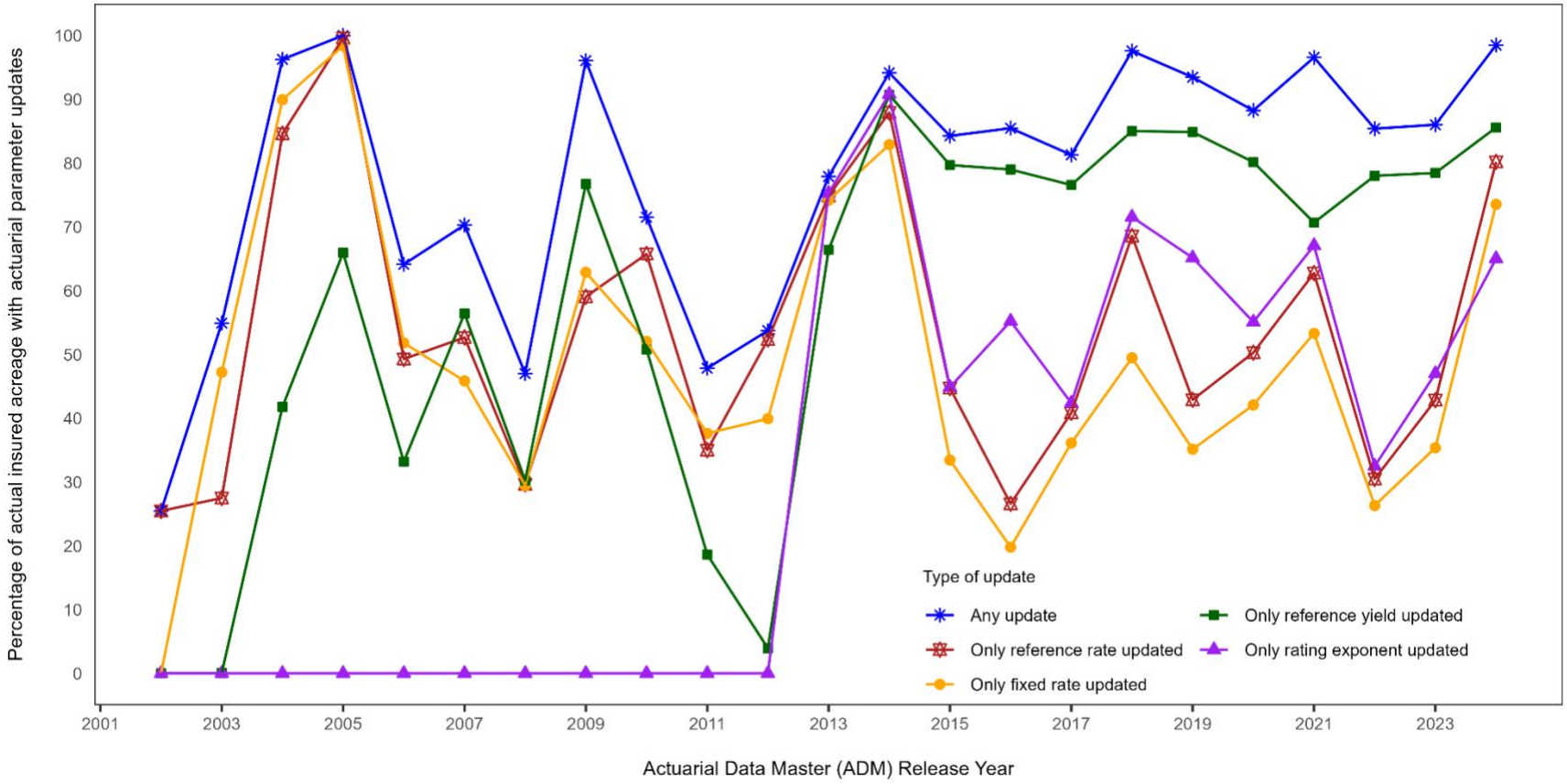


Figure 2: Variation in annual actuarial updates in the United States Federal Crop Insurance Program by state and commodity grouping (2002-24).

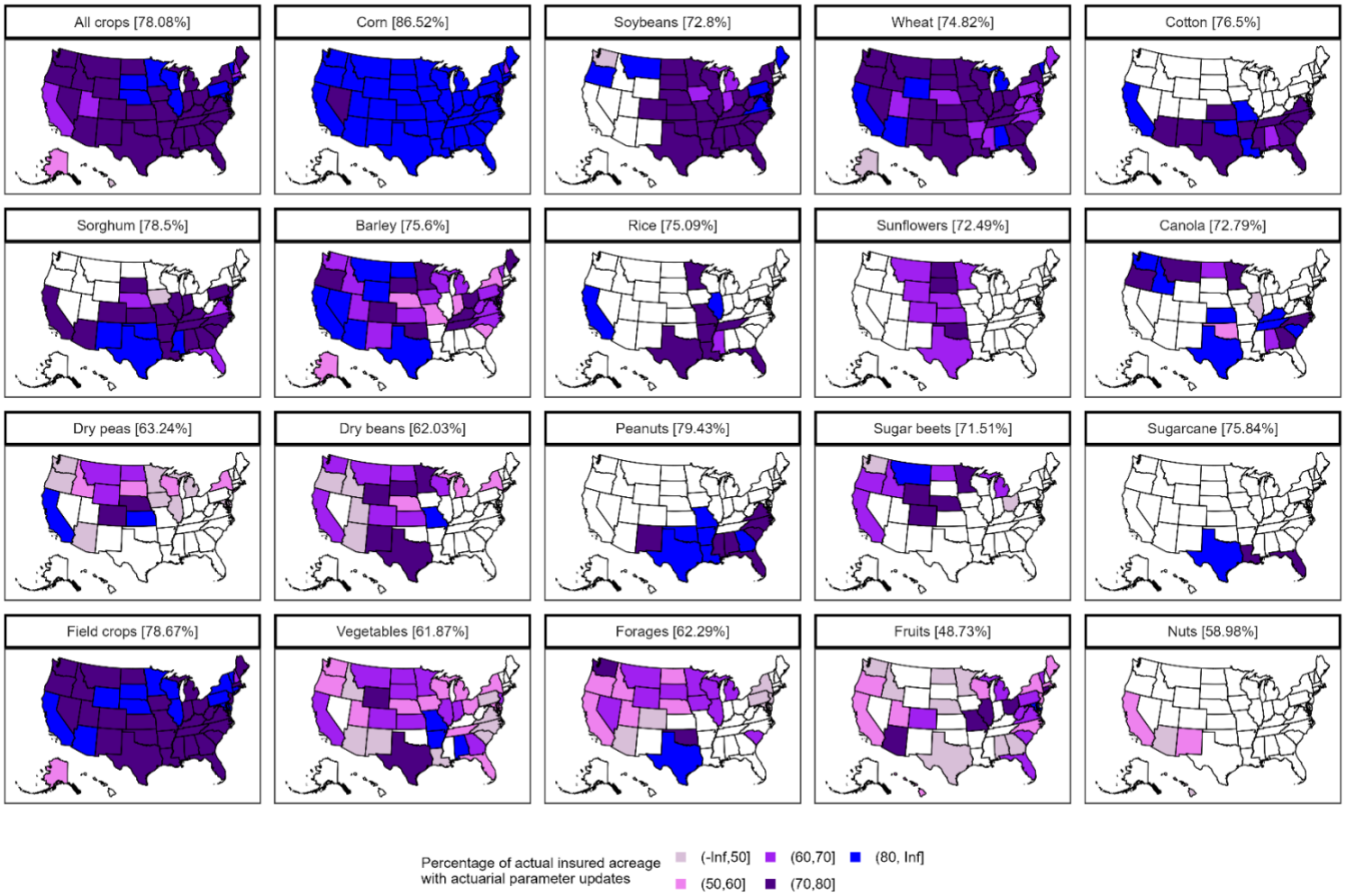


Figure 3: Temporal variation in the impacts of actuarial updates on net underwriting savings in the United States Federal Crop Insurance Program (2002-24)

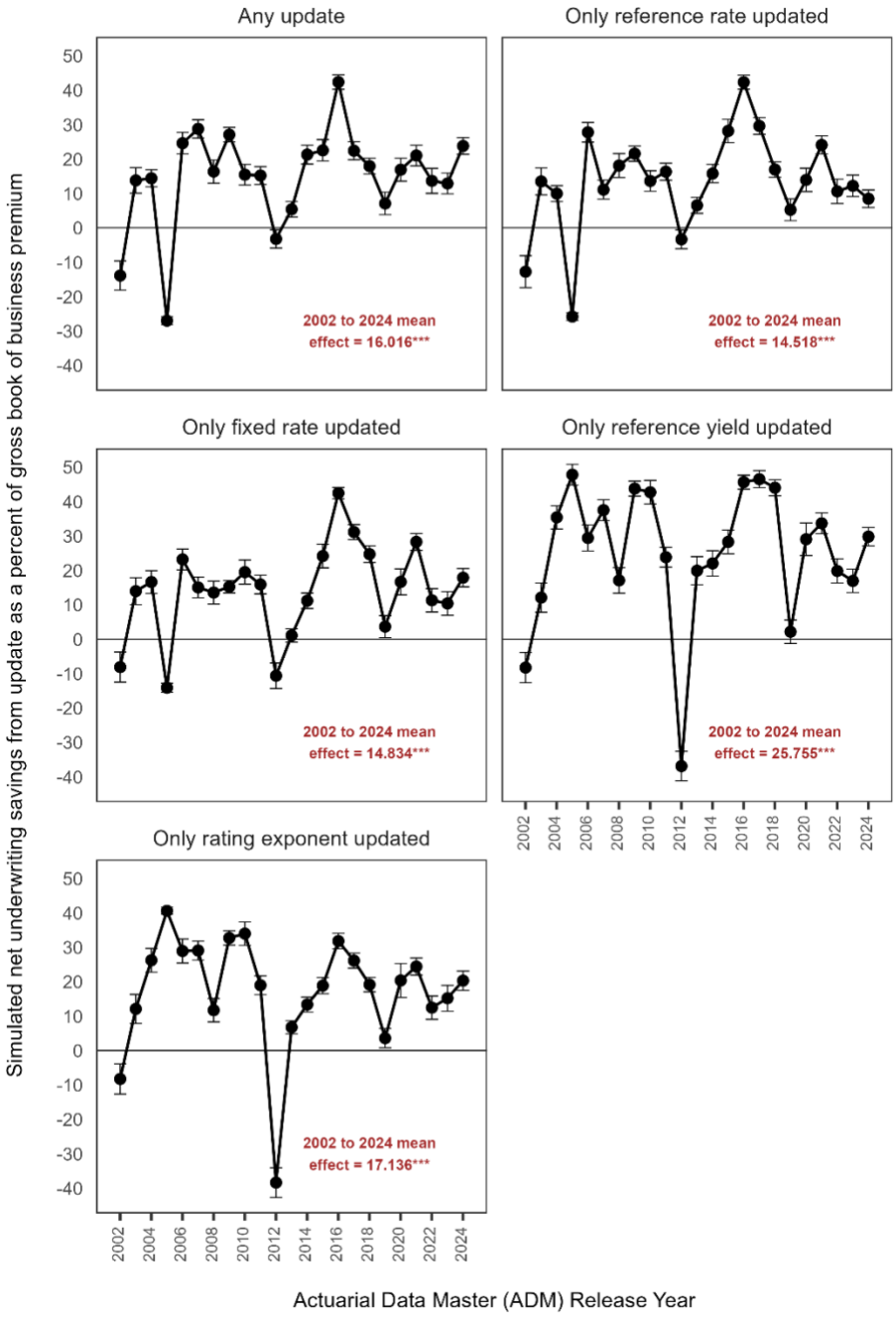


Figure 4: Net underwriting savings from actuarial updates in the United States Federal Crop Insurance Program by state (2002-24).

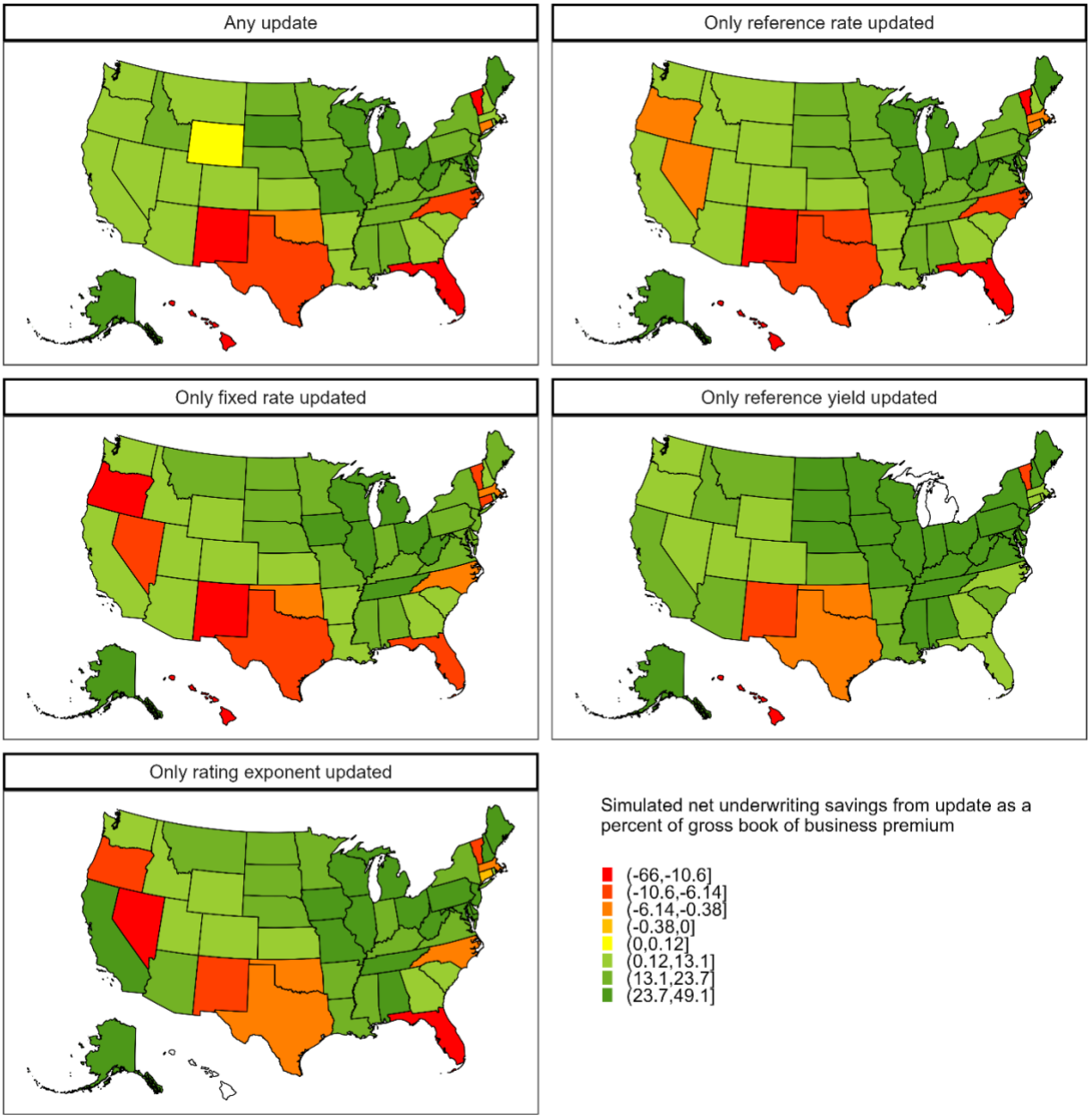
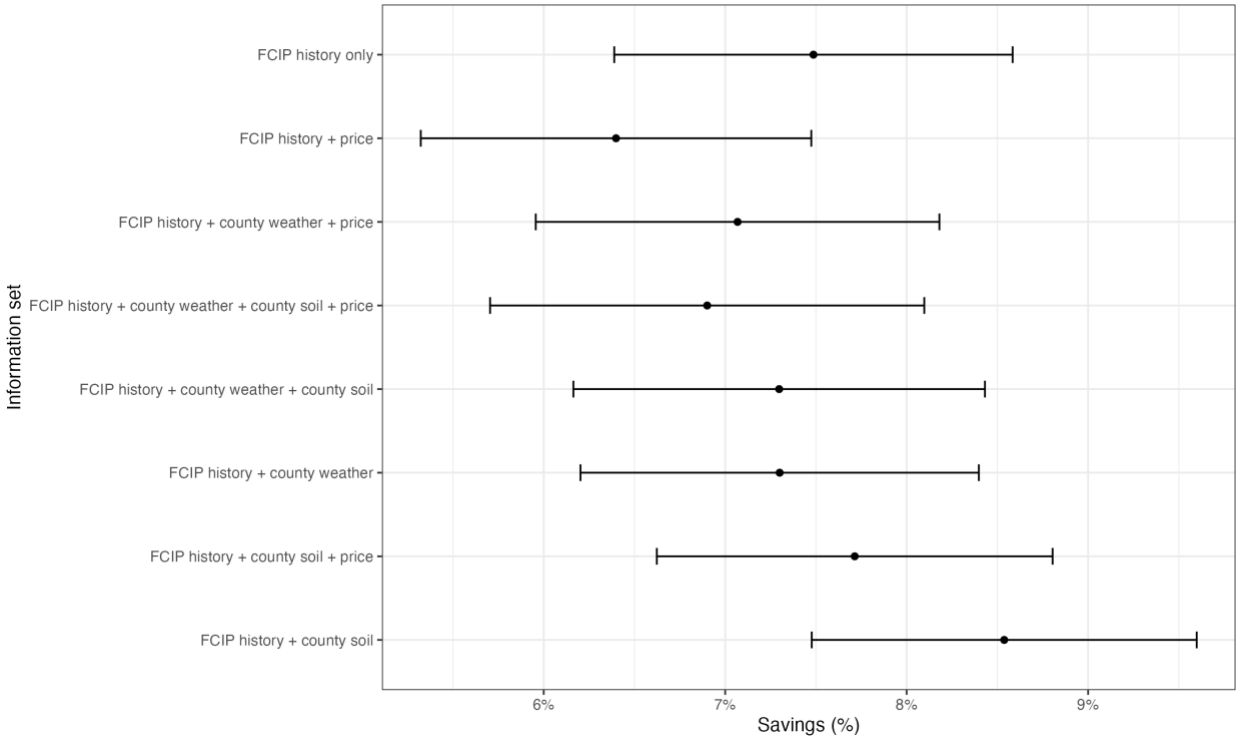
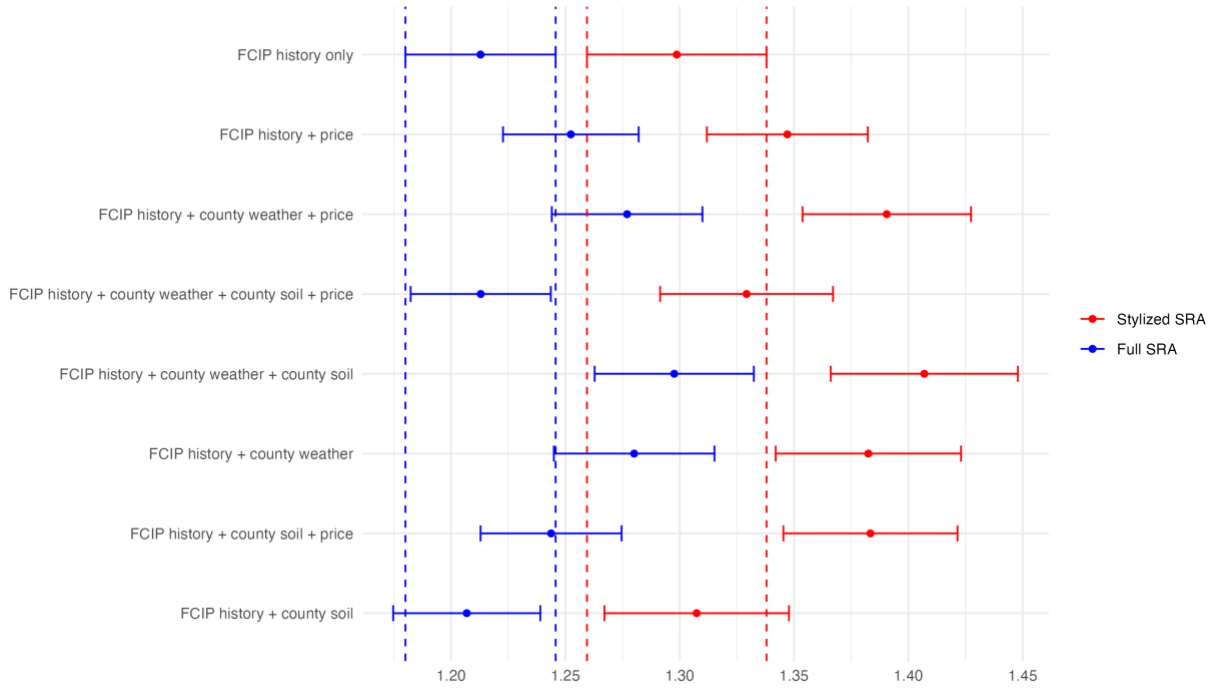


Figure 5: Impacts of actuarial updates on private to public risk transfer incentives in the United States Federal Crop Insurance Program (2011-24)



Note: Figure 5 reports the estimated savings (as a percentage of total premiums) to the government from performing a routine premium rating updates (compared to delaying the update by a year) under the assumption that 1) RMA and AIPs set and evaluate rates using machine learning methods and 2) AIPs incorporate additional information beyond the "FCIP history only", as defined on the x-axis.

Figure 6: Ratio of ceded to retained loss ratios, Stylized vs Full Standard Reinsurance Agreement.



Note: "Stylized SRA" represents a hypothetical version of the SRA that allows full ceding and retaining of polices with any constraints. The "Full SRA" represents ceded and retained loss ratios when the full dynamics of the SRA are incorporated (as summarized in table 1).

Appendix

Table S1: Means and Standard Deviations of US Federal Crop Insurance Outcomes by Commodity (2001-24).

Variables	DRY BEANS	SUNFLOWERS	PEANUTS	DRY PEAS	CANOLA	Field crops	Vegetables	Forages	Fruits	Nuts
Summary of business outcomes										
Coverage level (%)	68.60 (7.46)	68.35 (6.62)	66.23 (9.17)	68.69 (7.66)	71.17 (5.59)	71.09 (9.52)	67.82 (8.32)	55.58 (8.15)	58.21 (8.91)	60.35 (10.41)
Net insured area (acres)	500 (1324)	713 (1672)	427 (802)	818 (1908)	1646 (5697)	1346 (4460)	611 (1581)	520 (1951)	208 (665)	2256 (5969)
Total insured liability ($ 1,000)	177 (470)	133 (422)	220 (448)	158 (399)	354 (1563)	475 (2082)	272 (1350)	84 (379)	672 (2110)	5213 (12401)
Total premium ($ 1,000)	25.50 (81.58)	24.46 (73.43)	20.46 (55.37)	25.70 (73.62)	61.82 (291.73)	48.05 (209.96)	28.23 (90.46)	10.12 (37.61)	50.67 (170.34)	185.83 (460.87)
Total subsidy ($ 1,000)	15.62 (51.74)	16.05 (51.88)	12.31 (32.13)	15.83 (48.03)	40.09 (195.61)	29.96 (141.81)	17.37 (56.90)	7.01 (27.33)	32.87 (111.61)	115.02 (293.39)
Total indemnity ($ 1,000)	20.55 (93.46)	23.06 (99.53)	23.16 (146.07)	28.40 (113.36)	49.10 (246.11)	39.89 (305.60)	25.82 (117.85)	8.02 (61.77)	47.71 (227.85)	163.69 (864.21)
Premium per dollar of liability	0.15 (0.09)	0.20 (0.11)	0.09 (0.07)	0.16 (0.09)	0.17 (0.08)	0.13 (0.11)	0.14 (0.10)	0.14 (0.10)	0.10 (0.11)	0.04 (0.03)
Subsidy per dollar of premium	0.63 (0.12)	0.63 (0.10)	0.65 (0.13)	0.62 (0.12)	0.62 (0.12)	0.63 (0.13)	0.63 (0.13)	0.69 (0.15)	0.66 (0.14)	0.64 (0.14)
Producer paid premium rate	0.06 (0.04)	0.08 (0.05)	0.04 (0.03)	0.06 (0.04)	0.07 (0.04)	0.05 (0.05)	0.06 (0.04)	0.05 (0.04)	0.04 (0.04)	0.02 (0.01)
Actuarial data master outcomes										
Reference rate	0.13 (0.07)	0.15 (0.08)	0.07 (0.06)	0.13 (0.07)	0.12 (0.06)	0.11 (0.09)	0.12 (0.08)	0.13 (0.08)	0.10 (0.10)	0.03 (0.02)
Fixed rate	0.04 (0.01)	0.04 (0.01)	0.03 (0.01)	0.03 (0.01)	0.04 (0.02)	0.03 (0.02)	0.03 (0.02)	0.02 (0.01)	0.02 (0.01)	0.01 (0.01)
Rating exponent	-1.33 (0.67)	-1.54 (0.57)	-1.00 (0.28)	-0.66 (0.64)	-1.39 (0.61)	-1.43 (0.53)	-1.09 (0.71)	-0.77 (0.83)	-0.20 (0.47)	-1.02 (0.64)
Coverage level differential factor @ 50%	0.69 (0.12)	0.70 (0.11)	0.64 (0.09)	0.70 (0.11)	0.71 (0.10)	0.66 (0.11)	0.68 (0.12)	0.64 (0.13)	0.60 (0.16)	0.49 (0.11)
Coverage level differential factor @ 55%	0.79 (0.12)	0.78 (0.13)	0.76 (0.10)	0.84 (0.07)	0.80 (0.11)	0.76 (0.12)	0.81 (0.11)	0.80 (0.10)	0.78 (0.12)	0.68 (0.07)
Coverage level differential factor @ 60%	0.87 (0.12)	0.86 (0.14)	0.86 (0.10)	0.91 (0.05)	0.88 (0.11)	0.85 (0.11)	0.88 (0.11)	0.89 (0.09)	0.88 (0.07)	0.81 (0.07)
Coverage level differential factor @ 65%	0.95 (0.12)	0.94 (0.13)	0.97 (0.10)	0.99 (0.04)	0.96 (0.11)	0.95 (0.12)	0.97 (0.10)	0.97 (0.09)	1.00 (0.04)	0.98 (0.08)
Coverage level differential factor @ 70%	1.06 (0.12)	1.03 (0.12)	1.12 (0.11)	1.08 (0.05)	1.06 (0.10)	1.08 (0.12)	1.07 (0.11)	1.08 (0.09)	1.13 (0.08)	1.19 (0.10)
Coverage level differential factor @ 75%	1.20 (0.16)	1.14 (0.08)	1.30 (0.16)	1.18 (0.07)	1.17 (0.08)	1.23 (0.15)	1.20 (0.14)	1.21 (0.13)	1.29 (0.17)	1.45 (0.13)
Coverage level differential factor @ 80%	1.35 (0.22)	1.26 (0.07)	1.50 (0.27)	1.28 (0.11)	1.29 (0.09)	1.40 (0.21)	1.33 (0.21)	1.30 (0.16)	1.43 (0.27)	1.71 (0.16)
Coverage level differential factor @ 85%	1.52 (0.32)	1.39 (0.10)	1.74 (0.40)	1.39 (0.15)	1.41 (0.12)	1.58 (0.29)	1.49 (0.31)	1.41 (0.24)	1.59 (0.39)	2.00 (0.22)
Basic unit differential factor	1.04 (0.03)	1.03 (0.02)	1.06 (0.03)	1.05 (0.02)	1.06 (0.03)	1.03 (0.03)	1.04 (0.03)	1.03 (0.03)	1.04 (0.03)	1.04 (0.02)
Enterprise unit differential factor	1.02 (0.01)	1.02 (0.01)	1.03 (0.02)	1.03 (0.01)	1.03 (0.01)	1.01 (0.04)	1.02 (0.01)	1.01 (0.01)	1.02 (0.02)	1.00 (0.01)
Number of insurance pools	17139	16383	12920	11077	6902	624196	33489	16564	5498	894
Number of observations	60888	57563	67781	41016	23420	3783943	129045	68893	29594	8056

The data was constructed by the authors using primary data from (1) Risk Management Agency's summary of business and actuarial data master files that contain insurance metrics aggregated by county, crop, crop type, production practice, insurance plan, coverage level, and insurance unit.

Table S3: Robustness checks on the impacts of actuarial updates on private to public risk transfer incentives in the United States Federal Crop Insurance Program (2002-24) - Adjusted demand

	No update	Type of actuarial data master parameter update				
		Current RMA update pattern	Only reference rate updated	Only fixed rate updated	Only rating exponent updated	Only reference yield updated
Annual gross book of business						
Area insured (million acres)	207.659 (3.897)	210.619 (3.955)	211.678 (3.950)	209.105 (3.924)	208.216 (3.914)	204.700 (3.867)
Liability (billion $)	97.111 (2.286)	98.857 (2.341)	98.919 (2.336)	98.000 (2.307)	97.575 (2.300)	95.802 (2.266)
Premium (billion $)	9.903 (0.202)	9.957 (0.202)	9.895 (0.201)	9.910 (0.202)	9.909 (0.202)	9.943 (0.204)
Subsidy (billion $)	6.162 (0.125)	6.192 (0.126)	6.151 (0.125)	6.166 (0.125)	6.167 (0.125)	6.190 (0.127)
Indemnity (billion $)	8.021 (0.175)	8.237 (0.181)	8.216 (0.181)	8.074 (0.176)	8.080 (0.177)	7.943 (0.173)
Annual retention percentages		Expressed level changes over no update case				
Insured area	87.253 (0.159)	-40.989*** (0.517)	-55.448*** (0.428)	-59.280*** (0.464)	-66.622*** (0.239)	-59.040*** (0.361)
Liability	91.866 (0.113)	-47.414*** (0.379)	-60.001*** (0.386)	-63.715*** (0.399)	-70.645*** (0.272)	-64.958*** (0.285)
Premium	81.235 (0.212)	-37.768*** (0.456)	-50.653*** (0.406)	-52.824*** (0.448)	-61.155*** (0.229)	-53.750*** (0.405)
Indemnity	76.597 (0.279)	-31.365*** (0.557)	-45.478*** (0.471)	-47.398*** (0.443)	-57.204*** (0.308)	-46.775*** (0.569)
Annual loss ratio [LR]						
Retained pool	0.773 (0.007)	0.092*** (0.010)	0.113*** (0.013)	0.059*** (0.010)	-0.017 (0.025)	-0.004 (0.019)
Ceded pool	1.000 (0.010)	-0.202*** (0.009)	-0.177*** (0.008)	-0.190*** (0.008)	-0.180*** (0.008)	-0.212*** (0.008)
Ceded to retained LR ratio	1.339 (0.015)	-0.402*** (0.021)	-0.361*** (0.022)	-0.330*** (0.022)	-0.149 (0.773)	-
Annual net underwritings (million $)						
Retained pool – private	1349.651 (41.168)	-747.805*** (29.841)	-891.550*** (31.694)	-922.874*** (31.657)	-1029.13*** (33.069)	-1056.65*** (34.365)
Retained pool – public	311.123 (38.169)	-149.471*** (24.633)	-246.971*** (27.483)	-237.055*** (30.443)	-174.181*** (30.048)	-113.573*** (26.429)
Ceded pool – public	4.818 (20.129)	864.308*** (47.222)	1082.07*** (53.511)	1270.32*** (60.962)	1314.10*** (60.046)	1466.00*** (60.353)
Public (Retained + Ceded)	315.941 (51.816)	714.837*** (28.664)	835.101*** (30.206)	1033.27*** (34.304)	1139.92*** (35.480)	1352.42*** (42.016)
Annual rate of return [net underwritings as a percentage of premium exposure]						
Private	16.465 (0.307)	-4.912*** (0.508)	-4.369*** (0.676)	-1.737*** (0.497)	-0.958 (1.041)	-4.537*** (0.817)
Public	2.969 (0.466)	7.096*** (0.279)	8.054*** (0.281)	9.810*** (0.292)	11.738*** (0.257)	13.245*** (0.267)
		Annual savings from update				
Value (million $)	-	1462.64*** (57.158)	1726.65*** (61.006)	1956.14*** (65.793)	2169.06*** (68.429)	2409.08*** (76.169)
Share of gross premium (%)	-	14.690*** (0.507)	17.450*** (0.527)	19.738*** (0.545)	21.890*** (0.511)	24.228*** (0.529)

Simulation: Actuarial Data Master [ADM] (successor) for the release year (e.g., 2023) was replaced with the ADM for the previous year (incumbent) (e.g., 2022) and the premiums were recalculated for the actual loss experience outcomes associated with the successor in the release year. Cumulative evaluation is based on loss ratio calculated over the period 1997 to the release year. Adjusted demand allows insured acres to shift based on their responsiveness to paid premium rates. Significance levels - *p<0.1 ** p<0.05, ***p<0.01. Standard errors in parentheses are estimated by resampling insurance pools 100 times.

Figure S1: Graphical Representation of the Premium Rating Parameter Updating Sequence in the United States Federal Crop Insurance Program

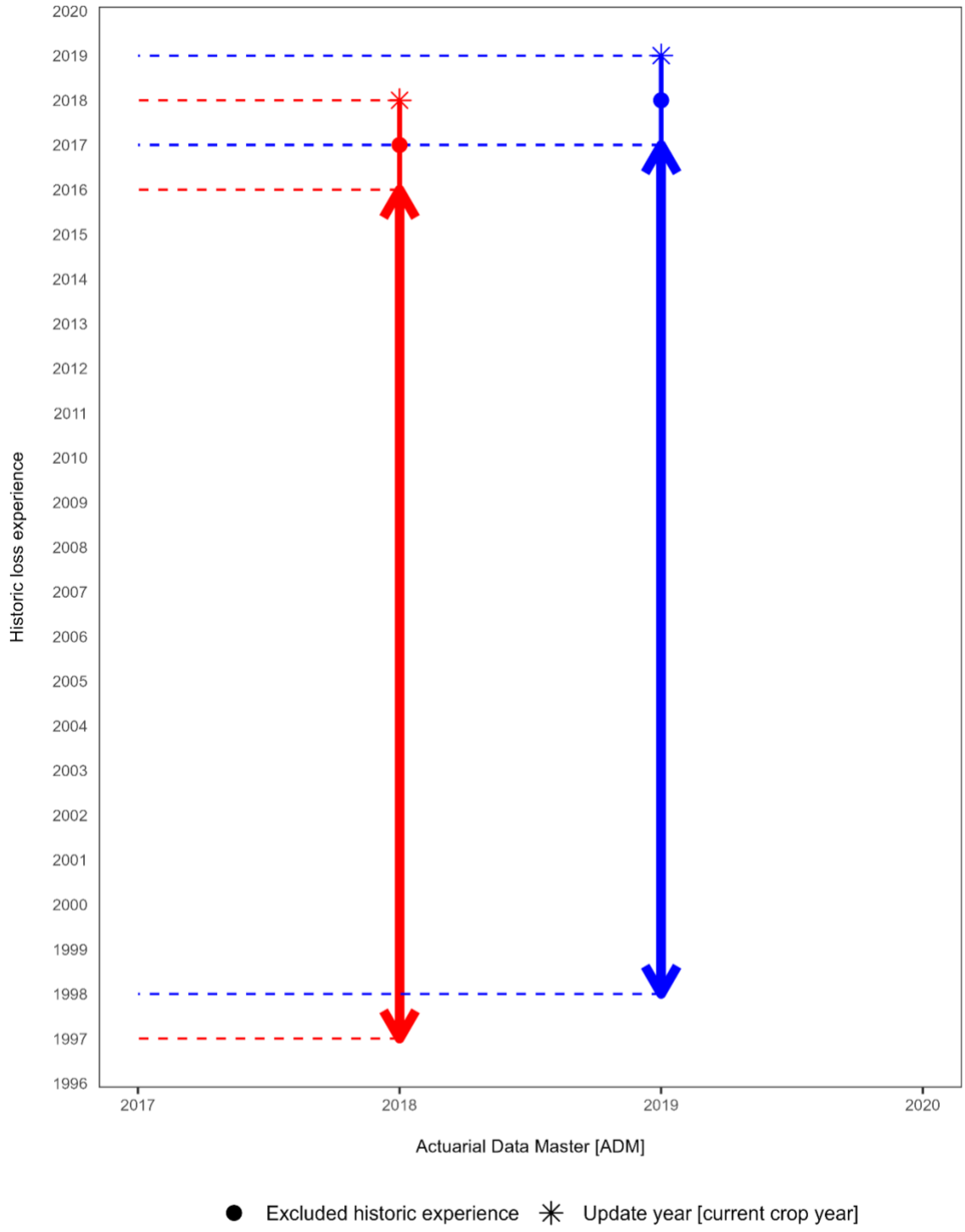
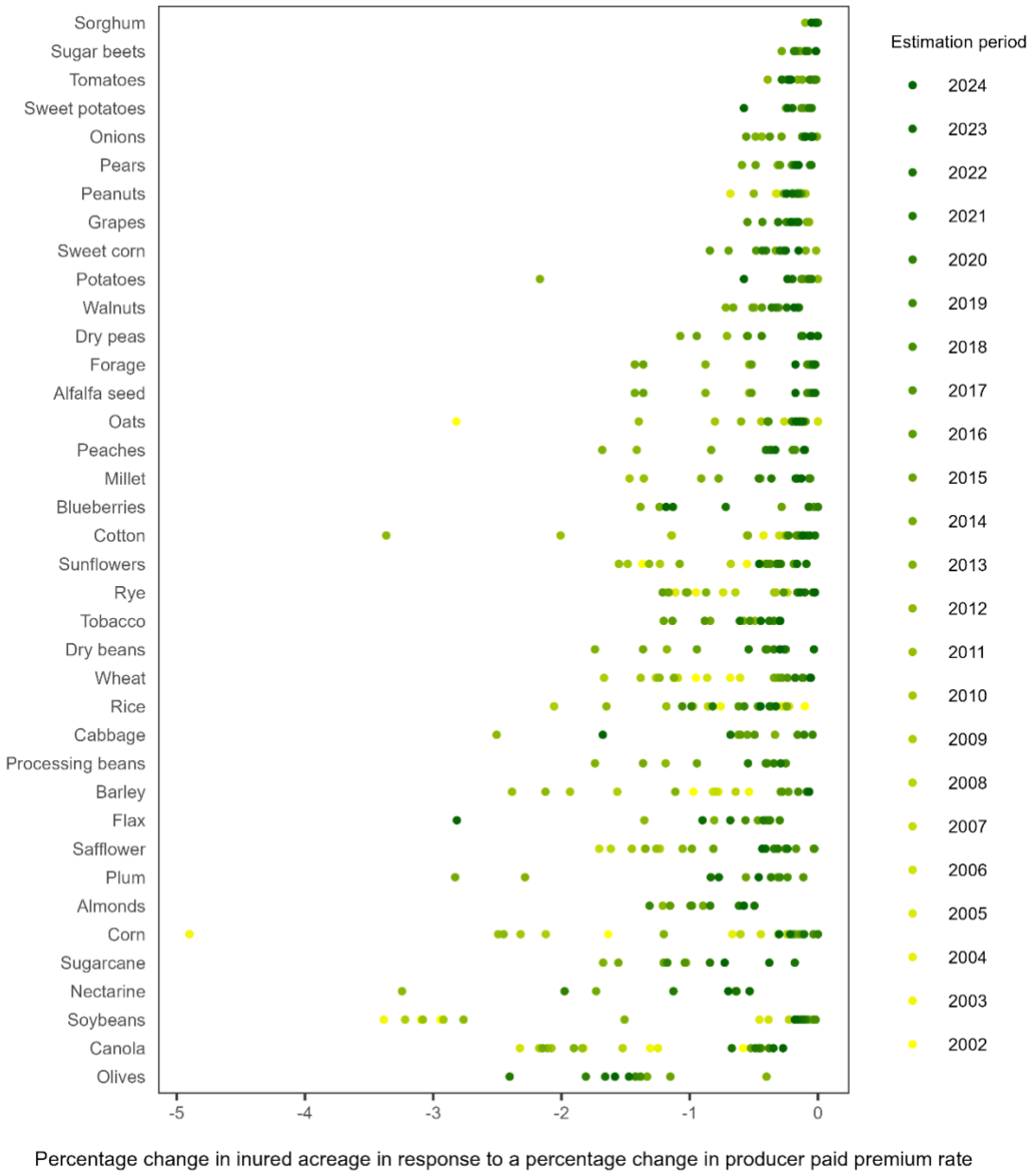


Figure S2: Estimated elasticities



Note S1 Machine learning analysis

Weather data is obtained from PRISM from 1951-2023. To construct county level data to match the spatial scope of observations in RMA's summary of business, we take raster files from prism and overlay them on the USDA cropland data layer to isolate the portions of each prism raster that cover crop land. Next we limit the temporal scope of the weather data (for variables that are averaged over time) to only include values that fall within a specific crops growing season[23]. We then average data points over the resulting subset of the prism raster to get representative temperature data for each crop and county. Overall, 22 weather variables were constructed for each county and crop which include total season precipitation, min and max recorded temperatures, average daily temperature, as well as growing degree days at a number of temperature thresholds. Annual observations from 1951-2000 were averaged to construct a set of weather normal for each county and crop, while data from 2000-2024 was used included yearly.

Soil data was obtained from the USDA's gridded soil survey geographic database. The soil properties included in our estimations are those that have previously been shown to have the potential to improve the accuracy of crop insurance premium rates (Tsiboe & Tack, 2022b). These include variables capturing soil texture (i.e. soil particle size), root zone depth, available water storage, slope, exchangeable cations, soil organic carbon, and national commodity crop productivity index. For each variable, the raster data was converted to county level weighted averages using the same spatial aggregation as for the weather data.

[23] For example, "tmin" captures minimum temperature recorded for the growing season. For corn, December weather does not factor into this metric since corn is not planted or growing in December. However, for winter wheat, December temperature would factor into the "tmin" measure.

Projected commodity prices, harvest prices, were obtained from RMA. Projected prices are reported prior to the season start and are used to setting guarantees for revenue protection insurance plans while harvest prices are reported at season end and are used for determining indemnities on revenue protection plans.

For data that is changing yearly (i.e. weather and price) 10 years of lags were computed and merged with the summary of business such that each cross-sectional observation has a 10-year weather and price history attached to it (in the same way that the base information set used by RMA contains 10-year yield histories). In most cases, the contemporaneous values of a variable are not attached to a cross-sectional observation since they would not be known to an AIP when evaluation of premium rates for the year was taking place. One exception to this is the projected price, which would be known prior to reinsurance allocations being made. Finally, indicator variables for individual counties are included in each estimation to capture unobserved differences across counties.

Training of the model was generally done in adherence to standard machine learning practices. Training was done on each crop individually, mimicking how RMA performs actuarial rate reviews (i.e. each crop individually). Because our data set follows a panel structure (i.e. we observed multiple insurance pools, at multiple points in time) cross validation was done using the panel split python package which respects the panel structure when constructing train and test splits of the data.[24] Figure ML1 displays the cross validation structure with the first split training on data from 2000-2009 and testing on 2010 while the final split trains on 2000-2023 and tests on

[24] Ignoring the panel structure could easily create a data leak between train and test splits. For example, randomly splitting without considering the time component might mean future data (which would not be known yet in reality) is being used to train on past outcomes. This temporal relationship needs to be maintained for every entity (insurance pools in our case) which the panel split package handles automatically.

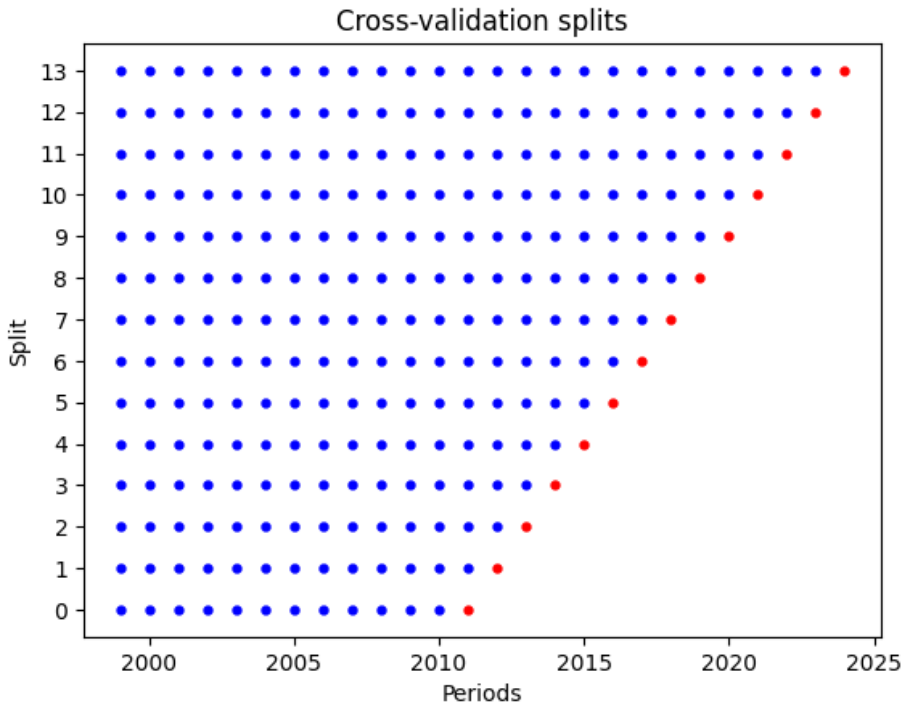
2024. Light hyperparameter tuning was performed on data from 2000-2009[25] via a random search using 10 iterations on 5 cross validation folds created using the panel split package. using data from 2000-2009 across a hyperparameter grid[26].

One special consideration is that because our outcome of interest is a loss cost ratio (indemnities divided by collected premiums) it tends to be zero-inflated given that insurance indemnities are part of the outcome (i.e. the most common outcome is that no loss occurs and thus zero indemnities are paid). To explicitly model this feature of the data, we define our model such that the target is Tweedie distributed as is common for insurance claims analysis. For each crop, we estimate an optimal power-variance parameter (which controls the shape of the target distribution) using the methodology described by (Dunn & Smyth, 2005, 2008)[27]. In practice, the estimated power variance parameters were all relatively close to one another ranging from a minimum of 1.557 to a maximum of 1.741. After initial training of the ML models was performed, a cursory check for overfitting (i.e. much better performance on training data compared to testing data) was performed via visual inspection of the root mean squared error on both training and testing splits (figure ML4). Overall, overfitting was not deemed a concern. The ratio of RMSEs for testing and training data were notably high for almonds and sugarcane, however, the base error rate for these crops was notably smaller than other commodities (i.e. even the overfitted test data has better accuracy than most other crops). Rice also exhibited slightly higher RMSEs in test data, however, this is not

[25] I.e. data that is never included in a test set of any cv fold in our primary training.
[26] The hyperparameter grid was defined by the following hyperparameters and ranges: num_leaves = [10,100], learning_rate = [0.01,0.3], n_estimators = [50,100], max_depth = [3,15], min_child_samples = [5,50], subsample = [0.5,1.0], colsample_bytree = [0.5, 1.0].
[27] This approach tends to be computationally intensive. To make it tractable, for any crop with more than 10,000 observations, we randomly sample 10,000 observations to be used in estimating the power variance parameter.

surprising as there are known actuarial issues associated with high prevented planting utilization for rice (Turner et al., 2025)

Figure ML1: cross validation splits



Notes: For each split, blue dots represent training data while red dots represent test data.