Inattention, Information Frictions, and Insurance Choices: Evidence from U.S. Agriculture

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Abstract

Farmers frequently make suboptimal crop insurance choices, leading to financial inefficiencies and welfare losses. This paper develops a structural two-stage model of insurance demand that separately identifies the roles of inattention, inertia, and costly information acquisition. In the first stage, farmers decide whether to reconsider their current plan in response to farm characteristics and external shocks. In the second stage, attentive farmers evaluate available options and incur costs to acquire information about plan-specific attributes, including expected indemnities. Using detailed administrative data, we estimate substantial frictions at both margins. Counterfactual simulations show that eliminating inattention increases welfare by 9.6 percent, while removing both inattention and information frictions raises welfare by 11.1 percent, with the largest gains concentrated in high-stakes regions such as the central Corn Belt. The findings underscore the importance of modeling behavioral and informational frictions separately and offer guidance for designing targeted interventions in complex choice environments.

Keywords: behavioral biases, expected indemnity, rational inattention, inertia, welfare effects.

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1 Introduction

Why do individuals persistently remain in dominated insurance contracts, even when financial stakes are high? This paper studies how behavioral and informational frictions shape insurance choices in the U.S. crop insurance market. Despite widespread participation and high subsidies, many farmers often fail to review or optimize their coverage. This behavior mirrors patterns documented in other insurance markets and raises questions about the underlying mechanisms driving suboptimal choice.

Suboptimal insurance decisions have been documented across various markets and are typically attributed to a combination of frictions: high information costs, limited attention, and behavioral biases such as inertia. Information frictions arise when individuals face cognitive or time constraints in acquiring and processing plan-specific attributes (McCall, 1970; Stigler, 1961). These frictions reduce consumers' ability to make welfare-maximizing choices (Bhargava et al., 2017; Handel and Kolstad, 2015). For instance, Bhargava et al. (2017) show that a majority of employees in a U.S. firm selected dominated health plans due to misunderstandings of cost-sharing features, incurring sizable financial losses.

Behavioral biases such as status quo bias, heuristic decision-making, and inattention further distort plan selection (Ericson and Starc, 2012; Handel, 2013; Montanari, 2023). Even when better options exist, many individuals fail to reconsider past choices due to perceived switching costs or effort. Inattention—defined as the failure to review available alternatives—is often distinct from the cost of evaluating those alternatives once engaged. Recent evidence suggests that attention and information acquisition operate on separate margins and respond to different incentives (Boehm, 2024; Heiss et al., 2021). This distinction motivates our modeling approach, which separates these frictions and identifies them using farm-level variation.

While most of the empirical evidence comes from health and consumer insurance markets, similar patterns are observed in agriculture. Farmers make complex insurance decisions under risk and uncertainty, and behavioral frictions are similarly present. Du et al. (2017) and Du (2025) show that U.S. farmers often forgo more generous crop insurance plans and exhibit strong persistence in prior choices, even after substantial policy changes. These studies suggest meaningful switching costs but do not separately identify information frictions. Crop insurance, which covers over 400 million acres annually, provides a valuable setting to examine how

attention and information costs affect high-stakes financial decisions.

This paper develops and estimates a structural model of insurance demand with endogenous information acquisition. We model farmers' decision-making in two stages. In the first stage, they decide whether to reconsider their current plan based on farm characteristics and external shocks such as policy changes or provider exits. In the second stage, conditional on paying attention, they choose among available plans and incur costs to learn about uncertain attributes such as expected indemnities. This structure allows us to distinguish between frictions at the extensive margin (inattention) and those at the intensive margin (information acquisition).

Our model builds on the framework in Heiss et al. (2021) and incorporates a rational inattention mechanism based on entropy costs (Brown and Jeon, 2024; Gabaix, 2014; Sims, 2003). Information costs vary with plan complexity, forecast precision, and the density of insurance agents. Estimation is based on administrative data from over 10,000 farms and 40,000 insurance decisions across multiple years.

The results show that inattention is more likely among smaller farms and in years without policy changes or extreme weather. Among attentive farmers, plan choice responds more strongly to net returns once information costs are considered. Estimated switching costs under full information are approximately \$54 but fall to \$17–\$28 when information frictions are included, suggesting that much of the observed inertia reflects limited information rather than true costs of switching.

We use the estimated model to quantify welfare effects. Eliminating inattention increases welfare by 9.6 percent, while removing both inattention and information frictions raises welfare by 11.1 percent. Welfare gains are concentrated in the central Corn Belt, where production risk is higher and plan differences are more salient. These gains are not driven by preference heterogeneity but by variation in baseline frictions. The results highlight the importance of modeling attention and information acquisition as distinct processes and underscore the potential value of targeted interventions—such as increasing agent density or providing clearer plan comparisons—in improving decision quality.

The remainder of the paper is structured as follows: Section 2 reviews the institutional features of the crop insurance market. Section 3 describes the data and variable construction.

Section 4 presents descriptive and reduced-form evidence. Section 5 introduces the structural model. Section 6 presents the estimation results. Section 7 reports the welfare analysis. Section 8 concludes.

2 Background

This section provides an overview of the U.S. crop insurance market, describes the sample insurance contracts and their key features, compares major plan types, and explains the use of expected indemnity as a key input in modeling farmers' insurance choices.

Crop insurance is a vital risk management tool for U.S. farmers, offering protection against financial losses due to adverse weather, low yields, and price fluctuations. Administered through the Federal Crop Insurance Program (FCIP), it provides two main types of coverage: yield insurance, which protects against production shortfalls, and revenue insurance, which protects against yield and price risks. These policies are subsidized by the federal government to reduce farmers' costs and encourage widespread participation.

Participation in crop insurance has expanded substantially over the past few decades. In 1990, about 90 million acres were insured, less than 30% of eligible cropland. By 2020, nearly 400 million acres were covered, including over 90% of major crops such as corn, soybeans, and wheat. This growth reflects policy changes that increased premium subsidies, broadened coverage options, and made insurance mandatory for accessing certain federal farm programs.

When purchasing crop insurance, farmers face a wide range of options. The first choice is between individual and group insurance plans.[1] This study focuses on individual plans, which were the dominant option during the sample period. Within these plans, farmers select a coverage type, a coverage level (ranging from 50% to 100% in 5% increments), and a unit structure: basic unit (BU), optional unit (OU), or enterprise unit (EU).[2] Each unique combination of

[1] Individual insurance plans are based on a farm's own yield or revenue, while group plans rely on aggregated data such as county-level yields or revenue.

[2] A BU includes all acreage of a crop in which the farmer has a 100% share or leases under a cash rent agreement. BUs can be subdivided into OUs based on sections, Farm Service Agency (FSA) farm numbers, or irrigation practices. An EU combines all acres of a crop in a county, regardless of ownership or rental status, into one unit. By pooling fields with varying yields, EUs are less likely to trigger indemnities than BUs or OUs. As shown in Table A1, EUs receive higher subsidy rates across all coverage levels. To qualify for EU coverage, a farmer must combine at least two BUs or OUs of the same crop located in different sections or linked to different FSA farm numbers. A fourth option, whole farm units (WU), combines all insured acres of all crops in a county, but since WUs represent less than 1% of the data, they are excluded from the analysis.

these elements constitutes a distinct insurance contract.[3] As a result, the full choice set for farms in our sample includes 21 distinct plans, summarized in Table 1.

During the sample period, farmers had access to three individual insurance plans: Plan 90 (APH; Actual Production History), a yield insurance plan, and two revenue insurance plans, Plan 25 (RA, Revenue Assurance) and Plan 44 (CRC, Crop Revenue Coverage). Yield insurance compensates farmers when actual yields fall below a guaranteed level, calculated as the product of the coverage level and the approved historical yield (APH).[4] Indemnities under yield insurance are computed by multiplying yield losses by the projected corn price, which is based on the average February settlement prices of CME futures contracts. Farmers may insure between 55% to 100% of the projected price, with 100% being the most common.

Revenue insurance compensates farmers when actual revenue, defined as harvest prices multiplied by actual yield, falls below the revenue guarantee. The guarantee is calculated as the product of the projected price, APH yield, and coverage level. The projected price is set as the higher of two values: the base price (determined before planting) or the harvest price (determined before harvest).[5]

Plans 90, 25, and 44 all insure against yield or revenue shortfalls but differ in how indemnities are triggered and priced. Plan 90 is a yield-based contract, appealing in regions with stable prices but variable yields. Plans 25 and 44 provide revenue coverage, offering protection against both price and yield risk. The main difference lies in how they calculate revenue guarantee: Plan 25 is based on the base price, with an optional harvest price feature, while Plan 44 automatically uses the higher of the base or harvest price, making it more attractive in volatile markets. These design features influence farmer preferences based on their exposure

[3]In our analysis, we do not model farmers' unit type choice explicitly. Instead, we assume that farmers retain their existing unit choices when switching between insurance plans or coverage levels. This assumption reflects the fact that unit type decisions are primarily driven by unobserved characteristics of insured plots, such as size, spatial separation, distance, soil quality, and production conditions, which tend to be stable over time. Furthermore, differences in premiums and subsidies across unit types are already embedded in the calculated premium and subsidy values, as explained in a later section.

[4]The APH yield is the farmer's average historical yield, typically based on 4 to 10 years of production history. Farmers are required to report actual production and planted acreage annually. The APH yield is updated using a rolling average of recent yields over a fixed period (e.g., the past 10 years).

[5]Under Plan 44, the base price is the average settlement price of the CME September contract from mid-December to mid-January, and the harvest price is the average settlement price of the same contract during August. For Plan 25, the base price is the average settlement price during the first 10 trading days of February for the CME December contract, and the harvest price is the average November settlement price of that same contract. In Plan 44, the harvest price cannot exceed the base price by more than \$1.50/bushel. Plan 25 offers a fall harvest price option, allowing the revenue guarantee to be based on the higher of the harvest price or the base price. If this option is not selected, the guarantee is determined solely by the base price.

to price versus yield risk, expectations about future prices, and risk tolerance. Plan 44 offers greater upside in rising markets, whereas Plan 25 without the harvest price option is cheaper but provides less protection.

In modeling insurance choices, we characterize each plan using three key variables: premium, subsidy, and expected indemnity. The expected indemnity is the average payout a farmer can expect, given stochastic yield and price outcomes and conditional on plan and coverage level. It captures core contract elements and reflects the main financial trade-offs across plans. This approach follows a well-established literature that emphasizes actuarially fair value or expected net benefits as central to insurance demand (e.g., Just et al., 1999).

Although crop insurance contracts are complex, most farmers in our sample are experienced operators managing sizable farms. The average farm cultivates over 240 acres, and many farmers consult insurance agents or accountants. However, heterogeneity is substantial: the standard deviation in farm size is 309 acres, with some managing thousands of acres through business entities and others running smaller operations with limited administrative support. As a result, information frictions, such as misunderstanding plan features, relying heavily on agent advice, or failing to update risk beliefs, may be more binding for certain groups. These frictions likely play a key role in plan uptake and switching, particularly for more complex products. This motivates our focus on decision quality and the use of expected indemnity as a proxy for perceived value.

While agents may influence decisions by clarifying plan details or offering tailored advice, we do not explicitly model their role. Our focus is on farmer demand and how choices respond to observable financial features. Agents are generally paid through fixed commissions, and although their guidance can shape farmer behavior—especially in the presence of information frictions or trust-based relationships—this influence is reflected only indirectly in the observed contract choices. Investigating agent incentives and broader supply-side dynamics is an important direction for future research but is outside the scope of this study.

3 Data

This study uses insurance unit-level records for corn from 2001 to 2010 across major producing states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North

Dakota, Ohio, and South Dakota.[6] Each record is identified by a unique insurance policy number, which typically includes multiple units on the same farm. These units are planted with the same crop and linked to a specific insurance plan. An insurance unit represents a parcel of land for which a premium is assessed and on which claims may be filed. Thus, the policy number is both crop- and farm-specific, uniquely identifying each farm.

To construct a unique farm identifier, we combine the insurance policy number with the county's Federal Information Processing System (FIPS) code. These identifiers allow farms to be tracked over time, resulting in an unbalanced panel. The panel's unbalanced nature primarily reflects crop rotation: because the dataset includes only corn, units that switch to crops like soybeans in later years are excluded. The insurance records also provide additional information, including the farm's state and county, insurance provider, acreage, Actual Production History (APH) yields, insurance plan type, coverage level, unit type, premiums, and subsidies.

3.1 Construction of Plan Attributes

We model farmers' insurance choices based on three key contract attributes: premium, subsidy, and expected indemnity. Since only the premium and subsidy of the chosen plan are observed, we impute these values for all available plans in each farmer's choice set using USDA Risk Management Agency (RMA) pricing methods. This allows plan comparisons to reflect farm-specific conditions.

Expected indemnity reflects the anticipated payout when yields or prices fall below insured thresholds. Because it is not directly observable ex ante, farmers form expectations based on available information, subject to the information frictions central to our analysis. We simulate expected indemnities using county-specific yield distributions, county-level yield trends, and local price-yield dependence structures, allowing for geographic heterogeneity in production risk. This approach accounts for regional differences, such as a greater drought risk in some counties, which affects both yield distributions and the price-yield correlations. By grounding the simulations in each county's historical data, the constructed expected indemnities reflect localized risk exposure and variation in insurance demand. This procedure captures the core

[6] In later analyses, particularly those involving endogenous information acquisition, we exclude records from the year a farm first enters the sample. Because entry years vary across farms, this ensures that all observed insurance decisions are made with a default insurance plan in place. As a result, records from 2010 are excluded, and the effective analysis period is 2002-2010.

financial value of each plan.

This method aligns with standard economic models that emphasize actuarial value in insurance demand (e.g., Brown and Jeon, 2024; Just et al., 1999). We also compute the variance of expected indemnities across plans to proxy for uncertainty and perceived value differences, factors shown to affect both choice behavior and learning (Brown and Jeon, 2024).

Appendix B details the procedures used to reconstruct premiums, subsidies, and expected indemnities. Table 1 presents summary statistics, including means and standard deviation, for these attributes across coverage levels, averaged over all sample crop years for the three insurance plans. Premiums and subsidies generally increase with coverage. For Plan 90, premiums increase from 5.56 at 50% coverage to 28.91 at 85%, while expected indemnity increases from 0.08 to 1.41. Plan 25 has higher premiums, ranging from 14.00 to 43.86, and significantly higher expected indemnity, from 14.78 to 46.28. Plan 44 has lower premiums, increasing from 8.28 to 46.88, with more stable indemnities ranging from 5.55 to 46.16. Overall, Plan 25 provides the highest expected indemnities, while Plan 44 offers more stable indemnities at lower premiums.

3.2 Control Variable Construction

We construct a set of variables used the empirical models developed in later sections. These variables capture factors that influence farmers' attention to, and decision-making in, crop insurance choices.

To reflect both farm-level characteristics and external shocks, we include variables related to farm size, historical yields, policy changes, natural disasters, and changes in insurance providers.

Farm-level characteristics. We include total planted acreage, average yield, and yield variability across insurance units within each farm. These variables capture heterogeneity in production scale and risk, which may affect both information needs and insurance preferences.

Policy changes. We account for major changes in the crop insurance environment associated with the 2002 and 2008 U.S. Farm Bills, which were enacted in those years and took effect in 2003 and 2009, respectively. These legislative changes significantly altered subsidy structures and plan offerings, particularly by increasing subsidies for enterprise units under the 2008 bill. To capture the effects of these changes, we include year-specific dummy variables for

2003 and 2009.

Natural disasters. To identify extreme weather events that could prompt reassessment of insurance choices, we construct a binary indicator for whether a county experiences a disaster in a given year. A county is classified as affected if its loss ratio, indemnities divided by total premiums, exceeds two standard deviations above the sample mean. According to USDA Cause of Loss reports, such events are typically driven by drought or excessive moisture. Across the sample, we identify 230 disaster-year events across 219 counties.

Insurance provider changes. The crop insurance industry has experienced significant consolidation. In 2021, six major firms accounted for over 84% of the national market. Our sample includes 29 Approved Insurance Providers (AIPs), with varying durations of participation. Some exited the market permanently, others merged or temporarily suspended operations. Table A2 summarizes annual farm enrollment by AIP.

We interpret gaps in an AIP's sales records as reflecting changes in business status, such as market exit or merger. When AIPs merge or are acquired, farmers are typically notified and given the option to switch providers. If they do not switch, coverage continues under the acquiring firm. While such changes may not require action from the farmer, they may prompt reconsideration of insurance decisions, especially when accompanied by changes in insurance agents. We define a binary variable f_{it}, which equals 1 if farmer i experiences a change in both AIP and agent in year t, and 0 otherwise. This captures forced reevaluation of plan choice.

To ensure comparability over time, we retain farms observed in the data for at least three years and exclude each farm's first appearance, when no prior insurance choice is observed. Thus, the constructed variables are used to explain variation in plan retention or switching behavior from the second year onward.

In our study, we include farms that appear in the sample at least three times. For subsequent analyses, we exclude each farm's initial appearance due to the lack of prior information regarding their insurance plans. Therefore, for every sample farm, we observe the default plan in place starting from their second entry and in all subsequent observations.

Information costs. To proxy for variation in the cost of acquiring accurate information about crop insurance, we construct two county-level measures: the availability of insurance agents and the predictability of yields based on observable weather conditions.

Agent availability is measured using a county-level weighted agent density. For each Approved Insurance Provider (AIP), we compute the product of its number of agens and its market share in the county, where marke share is defined by insured acreage. This weighting accounts for the broader influence of dominant insurers. The weighted agent counts are then summed across all AIPs to obtain the county-level density. Across counties, the average weighted agent density is 11.58, with a standard deviation of 6.43.

Yield predictability is measured by estimating the extent to which corn yield can be explained by weather conditions. Specifically, we regress county-level corn yields on three variables: growing degree days (GDD), overheating degree days (ODD), and total precipitation during the growing season (April–September). GDD is defined as the cumulative daily degree-days within the temperature range of $[8°\text{C}, 32°\text{C}]$, while ODD captures heat stress as degree-days above 34°C. Precipitation refers to total rainfall during the growing season. The absolute prediction error, defined as the absolute difference between observed and predicted yields, is used to quantify yield unpredictability. The regression is estimated using data from 1910–2022, and prediction errors are merged with the analysis sample for 2001–2010. Larger prediction errors indicate greater uncertainty and are interpreted as higher information costs.

4 Preliminary Analysis

This section presents descriptive and reduced-form evidence on farmers' insurance choices to motivate the structural model. We first document limited switching behavior and then examine how plan selection responds to exogenous shocks, including policy reforms, natural disasters, and forced reevaluation of plans triggered by simultaneous changes in both insurance provider and agent. These responses provide insight into the role of inattention, information frictions, and behavioral inertia. We also define the concept of stake in insurance decisions, measured by the variance in expected indemnities across plans, and assess its importance using regression and discrete choice models. Together, these findings inform the rational inattention framework employed in the structural estimation.

4.1 Insurance Choices and the Impact of Exogenous Shocks

Consistent with the literature, farmers often remain with the insurance plan selected in the previous year rather than switch to an alternative. In a related study, Du (2025) provides an in-depth analysis of this pattern and its implications. Rather than repeat those results here, we refer readers to that paper for further details on the identification and measurement of inertia in crop insurance choices.[7] In the analysis that follows, we focus on how responses to exogenous shocks help distinguish among potential behavioral frictions, namely, inattention, inertia, and information acquisition costs, that may underlie observed persistence.

Across the full sample of 1,485,654 farm-year observations, switching occurs in only 29% of cases, while 71% of farmers retain the default plan from the prior year. While this persistence could reflect optimal behavior under high switching or information costs, it may also result from limited attention or inertia. Distinguishing among these mechanisms is a central goal of the structural model.

To better isolate the role of information frictions, we examine insurance choices in the presence of exogenous shocks that plausibly increase attention and prompt reoptimization. Specifically, we analyze behavior before and after major events: forced plan switches, unusually severe natural disasters, and policy changes introduced by the 2002 and 2008 Farm Bills. These shocks increase the salience of insurance decisions by altering plan availability, modifying program parameters, or changing perceived risk.

Similar to Handel (2013), who studies employee health plan choices under active and passive enrollment regimes, our setting features a comparable form of "active" decision-making when farmers experience simultaneous changes in both their insurance provider (AIP) and agent. These changes effectively force a reevaluation of insurance choices. We classify the same group of farmers one year prior to this forced reevaluation as the control group.

We follow Du (2025) to examine the effects of natural disasters. Specifically, we define treatment counties as those that experienced unusually large indemnity payments in prior years, counties with a loss ratio more than two standard deviations above the mean over the sample period, based on county-level annual Summary of Business data, and compare affected

[7] This study uses the same underlying sample as Du (2025). For a detailed discussion of farmers' switching behavior and inertia in insurance decisions, including descriptive patterns and empirical strategies, see that paper.

farmers to those in the same counties prior to the disaster.[8] For policy reforms, we define 2003 and 2009 as the post-reform periods corresponding to the implementation of the 2002 and 2008 Farm Bills, respectively, using 2002 and 2008 as the baseline years.

Table A5 summarizes the effects of these shocks on insurance choices. Two main patterns emerge. First, plan type adjusts in response to shocks. Following the 2002 Farm Bill, the share of farmers selecting revenue insurance rose from 66% to 71%; after the 2008 Farm Bill, it increased from 83% to 85%. In disaster-affected areas, revenue insurance use is higher (78%) and yield insurance use lower (22%) than in unaffected areas (72% and 28%, respectively), consistent with increased risk salience of learning. Similarly, forced switches slightly increase revenue insurance use (from 83% to 84%) and reduce yield insurance (from 17% to 16%).

Second, coverage levels respond more substantially. After the 2008 Farm Bill, the share selecting high coverage (at or above 75%) increased from 41% to 54%, with a corresponding decline in low coverage. Smaller shifts follow the 2002 Farm Bill, disasters, and forced reevaluations. These patterns suggest that when shocks raise the salience of insurance decisions or provide new information, farmers adjust their choices accordingly. In contrast, under stable conditions, limited attention and information frictions may contribute to the observed persistence.

4.2 Stake in Crop Insurance Choices

The rational inattention framework models decision-making under limited information by allowing individuals to allocate attention optimally based on the expected value of information. In discrete choice settings such as insurance plan selection, individuals weigh the benefits of acquiring information about difficult-to-observe product attributes against the cognitive or time costs of doing so (e.g., Brown and Jeon, 2024; Matějka and McKay, 2015). Information acquisition is therefore endogenous and depends on the stakes involved, which refer to the potential consequences of making a suboptimal choice.

Matějka and McKay (2015) formalizes this mechanism, demonstrating that individuals acquire more information as the variance of unknown attributes increases. This behavior improves choice quality but requires greater cognitive effort. Building on this insight, Brown and Jeon

[8]Loss ratio is defined as indemnity divided by total premium. See Du (2025) for a detailed description of the disaster classification and related summary statistics.

(2024) predicts a U-shaped relationship between stakes and decision quality. When stakes are low, choice quality tends to be high because the available options are similar. At intermediate levels, choice quality may deteriorate due to limited attention allocated to evaluating differences. At high stakes, individuals invest more effort in information acquisition, resulting in improved decisions. Information frictions are reflected in the relative influence of observed and unobserved attributes. In the context of crop insurance, when expected indemnities are difficult to evaluate, their effect on plan choice is diminished relative to observable features such as premium costs. As stakes increase, farmers are more likely to evaluate the unobserved component, narrowing the disparity in influence between indemnities and out-of-pocket premiums.

To test these theoretical predictions, we define and quantify the concept of stake in the context of crop insurance decisions. We examine its distribution and spatial variation, identify key empirical determinants, and estimate a discrete choice model to assess the role of information frictions. We then analyze behavioral patterns, including the persistence of default plan selections and adjustments following exogenous shocks.

As discussed earlier, indemnities are not observable at the time of plan selection. Even under rational expectations, estimating indemnity requires the information of beliefs over future yields and prices, as well as an understanding of how different plan structures convert these outcomes into payouts. Consequently, indemnity is an unobserved attribute at the time of choice. In our analysis, we define the stake as the variance in expected indemnities across the set of available plans. This variance represents the uncertainty farmers face when evaluating their options.

Using the full sample from 2002 to 2010, the mean stake is 319.56, with a standard deviation of 340.02. The third quantile is 458.19, indicating that 75% of farmers face stake values below this level. Figure A1 displays the distribution. The density is concentrated at the lower end, with a sharp peak and a long right tail. Most farmers experience relatively low variance in expected indemnities, while a smaller subset face substantially greater uncertainty.

Economically, stake reflects the riskiness of expected payouts associated with a farmer's set of insurance options and serves as a proxy for the risk-adjusted value of information. It is shaped by yield and price volatility, production characteristics, and plan structure. At the farm level, higher average yields result in larger absolute indemnity fluctuations, which increase

the stake. Greater historical yield variability also contributes to higher stakes by indicating increased future yield uncertainty. Although farm size may not directly affect per-acre stake, it can influence overall risk exposure through diversification or aggregation effects.

At the county level, flatter yield trends are associated with lower stakes. Regional exposure to weather risk, such as drought, contributes to higher yield volatility and therefore higher stakes. In revenue-based plans, counties with a negative price-yield correlation generally exhibit lower stakes. Temporal factors such as commodity price fluctuations and changes in program rules also affect stake levels by altering the structure or predictability of insurance payouts over time.

We estimate a fixed effects panel regression to examine the determinants of stake, controlling for farm and year fixed effects. The specification includes farm-level covariates such as acres planted, APH yield, and historical yield variability. Results are reported in Table A3. The coefficient on acres is negative and statistically significant, indicating that larger farms are associated with lower stakes. This finding is consistent with diversification benefits or reduced variance in aggregate outcomes due to scale. In contrast, both APH yield and yield variability have strong positive effects. Higher average yields increase the potential size of indemnities, while greater yield volatility raises uncertainty in payout distributions. Together, these factors contribute to higher economic stakes in insurance plan selection.

Figure A2 maps county-level average stake values across major agricultural states, with darker shading denoting higher levels. Counties located in the core Corn Belt, including Iowa, Illinois, Indiana, and parts of Nebraska and Missouri, exhibit higher average stakes relative to more peripheral regions such as Kansas, Michigan, and Ohio.

This spatial pattern reflects underlying agronomic and economic conditions. Corn Belt counties typically feature higher yields, which elevate the potential indemnity value and thus increase the financial consequences of insurance decisions. These regions also exhibit greater adoption of revenue-based insurance products, which are more sensitive to both yield and price fluctuations. In areas with negative price-yield correlations, such as parts of the western Corn Belt, revenue insurance amplifies payout variability.

Moreover, larger and more commercially oriented farms, common in the Corn Belt, face greater financial exposure, making insurance choice more consequential. In contrast, counties

with lower stakes often have smaller farms, more stable yields, or rely on simpler insurance products with lower payout variability. The observed spatial heterogeneity in stakes is therefore consistent with regional differences in crop risk, revenue potential, and insurance complexity.

Figure A3 presents the time series of average stake values from 2002 to 2010. The average stake increased steadily from under $100 in 2002 to nearly $500 by 2010, with a notable jump between 2007 and 2008. This increase coincides with the sharp rise in commodity prices during that period, driven by global demand growth (particularly from China), expansion of U.S. biofuel mandates, and tightening global grain supplies. Corn prices rose significantly in 2007-2008, boosting expected crop revenue.

Using USDA data on APH yields and farm-level received prices, we compute that average annual crop revenue rose from approximately $265–320 per acre in the early 2000s to over $500-800 per acre after 2007. When expressed as a share of revenue, the average stake corresponds to about 60% of expected crop revenue over the period, peaked at 126% during the 2008 commodity boom. These values underscore the economic relevance of insurance plan selection. Although the dollar magnitude of stake may appear moderate, its proportion relative to revenue highlights the potential for substantial welfare losses from suboptimal choices, particularly for risk-averse farmers.

4.3 Stakes and Evidence of Information Friction

We estimate a logit model of insurance plan choice, where the dependent variable y_{itj} indicates whether farmer i selects plan j in year t. Explanatory variables include plan-specific characteristics and farm-level controls. Table 2 reports results from three model specifications.

The first specification, the Net Return Model, assumes that farmers observe and assign equal weight to three plan attributes: the premium (p_{ijt}), the subsidy (s_{ijt}), and the expected indemnity (EI^m_{ijt}). These are aggregated into a composite net return measure: $s_{ijt} + EI^m_{ijt} - p_{ijt}$.

The second specification, the OP + EI Model, relaxes the equal-weighting assumption and allows separate coefficients on the out-of-pocket premium cost, defined as $OP_{ijt} = p_{ijt} - s_{ijt}$, and expected indemnity EI^m_{ijt}. This captures potential information frictions if farmers assign different levels of attention to each attribute. The third specification, the Interaction Model, extends the second by including interaction terms between the stake variable σ_{it} and both OP

and EI^m, allowing the marginal effects of plan attributes to vary with decision stakes.

All specifications include the variance of expected indemnity EI^V_{ijt} to account for risk aversion. Under the assumption of normally distributed outcomes and constant absolute risk aversion (CARA), expected utility depends only on the mean and variance of payouts. In this context, the coefficient on EI^V_{ijt} corresponds to $-\frac{1}{2}\gamma$, where γ is the coefficient of absolute risk aversion.

Additional covariates include farm-level controls such as acreage (proxying for scale and risk-management capacity), average yield, and yield variability. Farm fixed effects D_i absorb time-invariant unobservables such as soil quality and management differences, while year fixed effects D_t capture time-varying shocks including policy changes and commodity price movements.

The specification for the Interaction Model is given by:

$$y_{itj} = \alpha_0 + \alpha_p OP_{itj} + \alpha_m EI^m_{itj} + \alpha_V EI^V_{itj} + \alpha_{\sigma_1} OP \times \sigma_{it} + \alpha_{\sigma_2} EI^m \times \sigma_{it} + D_i + D_t + \varsigma_{itj}. \quad (1)$$

To limit the influence of outliers, we winsorize the stake variable at the 99th percentile. The resulting values, ranging from 0 to 1433, are used in estimation. The results are consistent with theoretical predictions. Higher net returns, lower out-of-pocket costs, and higher expected indemnity increase the likelihood of plan selection. The variance of expected indemnity enters negatively, consistent with risk-averse preferences. The implied estimates of absolute risk aversion, $\hat{\gamma} = -2\hat{\alpha}_V$), range from 18×10^{-5} to 24×10^{-5}, which are substantially higher than the median estimate of 3×10^{-5} reported by Cohen and Einav (2007) in the context of automobile insurance deductibles. Farm-level variables, including acreage, average yield, and yield variability, are significant and consistently negative across specifications, suggesting that observable farm characteristics are correlated with the likelihood of selecting a given plan, possibly due to unmodeled heterogeneity in preferences or constraints.

Model comparisons are conducted using likelihood ratio tests. Replacing the composite net return measure in Model 1 with its disaggregated components in Model 2 yields a significant improvement in fit (LRT = 2,883.2, $p < 0.01$). This supports the view that farmers do not treat net return as a single bundled attribute but instead respond to individual plan components. Model 3 further improves fit by allowing the effects of OP and EI^m to vary with decision stakes (LRT = 7,939.2, $p < 0.01$).

Figure 1 plots the marginal effects of OP and EI^m as a function of stake. At low stake levels, farmers place more weight on OP (marginal effect = -0.0727) than on EI^m (0.0641). As the stake increases, the marginal effect of OP becomes less negative (-0.0455), while the effect of EI^m declines (0.0412). The convergence in marginal utility suggests that farmers engage more fully with trade-offs as decisions become more consequential, consistent with predictions of rational inattention. The significant improvement in model fit under Model 3 supports the hypothesis that attention to plan attributes is endogenous and responsive to the economic stakes of the decision.

5 Empirical Model

We develop a two-stage discrete choice model of insurance plan selection that incorporates endogenous information acquisition. Farmers first decide whether to actively consider available plan options, a process influenced by farm characteristics and external shocks. Conditional on paying attention, they choose among plans based on both observed and unobserved attributes. The model separates fixed attention costs from marginal costs of acquiring information, allowing for flexible patterns of limited consideration and imperfect information. This framework builds on rational inattention theory and provides a basis for structural estimation and welfare analysis.

5.1 Model Structure

We model insurance decisions as a two-stage process. In the first stage, farmers decide whether to pay attention to the set of available plans. In the second stage, attentive farmers choose among alternatives, while inattentive farmers remain with their default plan from the prior year. This structure follows Heiss et al. (2021) and incorporates endogenous information acquisition as in Matějka and McKay (2015) and Brown and Jeon (2024).

Stage 1: Attention

Let $a_{it} \in \{0, 1\}$ denote whether farmer i in crop year t pays attention. The latent propensity to pay attention is modeled as:

$$a_{it}^* = X_{it}\alpha + \varepsilon_{it}, \tag{2}$$

where X_{it} includes farm-level characteristics (e.g., total acreage) and external attention triggers (e.g., policy changes or natural disasters). Larger farms face greater financial exposure and thus have stronger incentives to evaluate plan alternatives. We standardize acreage prior to estimation. The error term ε_{it} follows a standard logistic distribution.

The probability that farm i pays attention in year t is:

$$\Pr(a_{it} = 1 | f_{it}, X_{it}) = \begin{cases} \frac{1}{1+\exp(-X_{it}\alpha)} & \text{if } f_{it} = 0, \\ 1 & \text{if } f_{it} = 1, \end{cases} \tag{3}$$

where $f_{it} = 1$ indicates a forced reevaluation, occurring when the farmer experiences simultaneous changes in both insurer and agent.

Stage 2: Plan Choice and Information Acquisition

Farmers who do not pay attention ($a_{it} = 0$) remain with their default plan from the prior year. Attentive farmers ($a_{it} = 1$) select a plan from the available set. Plan utility depends on observed and unobserved attributes. Observable attributes include the out-of-pocket premium p_{itj}; the unobserved component is the expected indemnity v_{itj}, which requires effort to assess.

Under full information, farmers have complete knowledge of all relevant attributes of each alternative, and thus the utility from plan j is:

$$u_{itj} = \beta(-p_{itj}) + \beta v_{itj} + \gamma_i y_{it-1j} + \epsilon_{itj}, \tag{4}$$

where y_{it-1j} indicates whether plan j was chosen in the revious year, and $\gamma_i \sim \mathcal{N}(\gamma_0, \sigma_\gamma^2)$ captures individual switching costs or inertia.

However, expected indemnities are not directly observable and must be learned. Following Matějka and McKay (2015) and Brown and Jeon (2024), we model information acquisition as costly and endogenous. Farmers observe premiums, but must expend effort to evaluate indemnities. acquire information about v_{itj} only if the benefit of precision exceeds the cost. The stakes of the decision, captured by the prior variance σ_{it}^2 across expected indemnities,

influence the marginal value of information.

Utility under endogenous information acquisition is:

$$u_{itj}^{'} = a(\sigma_{it}, \tau)\beta(-p_{itj}) + b(\sigma_{it}, \tau)\beta v_{ijt} + \gamma y_{it-1j} + \epsilon_{itj}^{'}, \tag{5}$$

where $a(\cdot)$ and $b(\cdot)$ are attention-adjusted weights on the premium and indemnity, respectively, and defined as:

$$\begin{aligned}
\kappa(\sigma_{it}; \tau) &= \sqrt{\frac{6\sigma_{it}^2}{\pi^2\tau^2} + 1}, \\
a(\sigma_{it}; \tau) &= \frac{\kappa(\sigma_{it}; \tau)}{\sqrt{\kappa(\sigma_{it}; \tau)^2 + \tau^2 \left(\kappa(\sigma_{it}; \tau) - 1\right)^2}}, \\
b(\sigma_{it}; \tau) &= \frac{\kappa(\sigma_{it}; \tau) - 1}{\sqrt{\kappa(\sigma_{it}; \tau)^2 + \tau^2 \left(\kappa(\sigma_{it}; \tau) - 1\right)^2}}.
\end{aligned}$$

The intuition behind the weights is as follows. The weight on the observed attribute (premium cost), $a(\sigma_{it})$, exceeds the weight on the unobserved attribute (expected indemnity), $b(\sigma_{it})$, because the latter requires costly information acquisition. Under full information, both weights are equal. As stakes increase or information becomes less costly, the gap between $a(\cdot)$ and $b(\cdot)$ narrows, leading to more balanced weights (Brown and Jeon, 2024).

A key feature of the model is that high stakes (σ_i) encourage more intensive information acquisition. When stakes are low, the variance in outcomes is limited, and farmers rely on defaults or simple heuristics. As stakes rise, the cost of making a poor choice increases, motivating farmers to invest more in reducing uncertainty. At high levels of σ_{it}, farmers approximate fully informed decision-makers.

This framework captures two distinct frictions: a binary attention decision and a continuous information acquisition margin. The former reflects fixed or random costs of reconsideration; the latter captures the marginal cognitive cost of evaluating uncertain attributes. We treat attention as conditionally exogenous, leveraging forced reevaluation events for identification. This separation allows us to estimate information costs among attentive farmers without imposing strong assumptions about foregone utility from unconsidered alternatives.

The cost parameter τ_{it} varies across farms and over time:

$$\tau_{it} = \exp(K_{it}\phi_K + M_{ct}\phi_M), \tag{6}$$

where K_{it} includes farm-level factors such as average yield. Higher yields may signal not only greater expected revenue but also superior production practices and managerial ability, both

of which increase a farmer's capacity and incentive to process complex insurance information. The vector M_{ct} captures county-level features of the local information environment, such as the availability of insurance agents and the predictability of yields based on weather data. All variables are normalized to the $[0, 1]$ interval.

Under the assumption that both the prior distribution and idiosyncratic taste shocks follow the Cardell distribution (Brown and Jeon, 2024),[9] the conditional choice probability for an attentive farmer is:

$$P_{itj} = \frac{\exp\left[a(\sigma_{it}, \tau)\beta(-p_{itj}) + b(\sigma_{it}, \tau)\beta v_{itj} + \gamma y_{it-1j}\right]}{\sum_{k \in J} \exp\left[a(\sigma_{it}, \tau)\beta(-p_{itk}) + b(\sigma_{it}, \tau)\beta v_{itk} + \gamma y_{it-1k}\right]}. \tag{7}$$

Inattentive farmers choose the default plan by construction.

Likelihood Function

We estimate all parameters via maximum likelihood. Let y_{it} denote the observed plan choice for farmer i in year t. The likelihood contribution for farmer i, observed from $t = 2$ onward, is:

$$\mathcal{L}_i(\theta) = \prod_{t=2}^{T} \left[p_{it}^a P_{itj} + (1 - p_{it}^a) \cdot 1\{y_{it} = y_{it-1}\}\right], \tag{8}$$

where p_{it}^a is the probability that farmer i pays attention in year t, equal to 1 in cases of forced reevaluation.

Integrating over unobserved heterogeneity yields the full likelihood:

$$\mathcal{L} = \prod_i \iint \mathcal{L}_i(\theta)\, \phi(\gamma_i)\, d\gamma_i, \tag{9}$$

where $\phi(\cdot)$ denotes the standard normal density. We approximate the integral using Gaussian quadrature. The model captures both fixed costs of consideration and marginal costs of acquiring information, providing a tractable basis for counterfactual analysis and welfare evaluation.

5.2 Identification Strategy

The empirical model jointly estimates farmers' insurance plan choices, attention decisions, and information acquisition. Identification of key parameters, including attention, preferences

[9] This assumption imposes marginal independence and equal variances across alternatives, yielding a closed-form expression for choice probabilities under rational inattention. While restrictive, it offers substantial computational tractability and facilitates structural estimation. Brown and Jeon (2024) show through simulations that the model remains robust even when the true prior deviates from the Cardell distribution (e.g., normal priors), with negligible bias in estimated parameters. In our context, this assumption allows us to isolate the role of information frictions while preserving the key economic intuition that variance in expected indemnities governs information acquisition.

over plan attributes, information costs, and inertia, relies on multiple sources of variation. This section outlines how these components are separately identified and how the model distinguishes overlapping frictions, such as inattention and costly information acquisition.

Under full information (Equation 4), attentive farmers observe all plan attributes. Utility from plan j depends on the expected indemnity (v), out-of-pocket premium (p), and inertia related to the prior year's plan (y_{it-1j}). In this setting, v and p enter symmetrically with a common coefficient β, reflecting a shared marginal utility of income. Deviations from this symmetry in the endogenous information setting (Equation 5) capture frictions arising from uncertainty, particularly the cost of learning about indemnities.

Expected indemnities are uncertain and require cognitive effort to evaluate, while premiums and subsidies are typically known. The model captures this asymmetry through the weighting functions $a(\sigma_{it};\tau)$ and $b(\sigma_{it};\tau)$, which scale the impact of p and v in utility as a function of the prior variance σ_{it}^2 and marginal information cost τ. These functions provide key variation for identifying τ. Greater variance in expected indemnities increases the value of information, thereby raising the weight placed on v via $b(\sigma_{it};\tau)$.

Identification of τ leverages this nonlinearity, along with cross-sectional and temporal variation in indemnity dispersion. Further variation arises from heterogeneity in the cost function, modeled as a function of farm and county characteristics (K_{it}, M_{ct}) in Equation 6. For example, farms with higher yields may face distinct information costs due to differences in revenue risk, scale, and processing capacity.

Separating the extensive margin of attention from the intensive margin of information acquisition presents a central identification challenge. While both frictions are influenced by farm characteristics, the model separates them using quasi-experimental variation in forced-attention cases. Specifically, when both the farmer's insurance provider and agent change in year t, the farmer is assumed to pay attention ($a_{it} = 1$), regardless of their preferences or unobserved characteristics. These cases identify behavior under full attention. In contrast, endogenous attention decision (Equation 2) depends on observed covariates X_{it} and is modeled separately from the acquisition process.

This framework identifies both (i) the extensive margin, whether the farmer considers alternative plans, and (ii) the intensive margin, the extent of information acquired conditional

on paying attention. Although the structural model includes only the cost of information acquisition (τ) in utility, the welfare analysis presented in a later section captures the effects of both frictions. The welfare loss from limited attention is quantified by comparing outcomes under full attention and full information (the benchmark) to those under endogenous attention with full information. The additional welfare loss due to costly information acquisition is obtained by comparing the endogenous attention with full information case to the case in which both attention and information acquisition are endogenous.

Finally, identification of inertia (γ) relies on within-farm variation over time in plan utilities. Inertia reflects a tendency to remain with the previous year's plan (y_{it-1j}), conditional on its relative utility. When a farmer retains a dominated plan, the behavior is attributed to switching frictions rather than stable preferences. Rich variation in plan attributes and payouts across farms, years, and regions allows the model to distinguish inertia from true preference persistence.

6 Estimation Results

This section presents estimation results for the full-information and endogenous information acquisition models. We then quantify the marginal cost of information for all sample farms, emphasizing spatial heterogeneity across counties.

6.1 Estimation Results

Due to computational constraints, the model is estimated using a random subsample of 10,000 farms, comprising 42,222 choice situations and 886,662 alternatives (i.e., combinations of insurance plans and coverage levels). All continuous farm-level variables (e.g., total acreage, mean yield across insurance units) and county-level variables (e.g., insurance agent density and yield forecast errors) are standardized to have a mean of zero and a standard deviation of one.

Table 3 reports the parameter estimates for both the full information model and the endogenous information acquisition model. Estimates for the attention and plan choice stages in the latter are generally similar in sign and magnitude to those from the full-information model. Accounting for information costs improves precision, as reflected in smaller standard errors and higher log-likelihood values, due to the additional behavioral structure incorporated

in the extended specification.

In the attention stage, three external triggers significantly increase the probability that farmers engage in crop insurance decisions: the 2002 and 2008 Farm Bills, implemented in 2003 and 2009 (captured by D_{2003} and D_{2009}, respectively), and the occurrence of catastrophic weather events (D_{Disaster}. Among these, the 2008 Farm Bill, which substantially revised insurance subsidies, has the strongest effect. Farm characteristics also matter: larger farms are more likely to pay attention, likely due to greater financial exposure and potential losses.

In the plan choice stage, net return, defined as the negative out-of-pocket premium (i.e., subsidy minus premium, or $-OP$) plus expected indemnity, has a significant effect in the full information model, with an estimated coefficient of 0.88. Given the standard deviation of the original (unstandardized) net return variable is 16.27, this implies a marginal effect of approximately 0.05 per dollar increase in net return (0.88/16.27).

In contrast, the endogenous information acquisition model suggests that farmers are more responsive when they choose to become informed. The estimated coefficient is approximately 1.75, corresponding to a price response of 0.15 per dollar change in negative OP and 0.09 per dollar change in expected indemnity. This greater responsiveness indicates that informed farmers are better able to distinguish among insurance plans and respond more strongly to financial incentives. Unlike the full information model, which assumes complete knowledge of plan attributes, the endogenous model accounts for frictions in learning and choice, leading to higher estimated sensitivity among those who actively acquire information.

The switching cost parameter γ, modeled as normally distributed with mean γ_0 and standard deviation σ_γ, captures the cost of deviating from the default plan. The γ_0 is 2.70 in the full information and 2.56 in the extended model. Using the implied marginal utility of information from the full information model (0.05), the mean switching cost is approximately \$54 (2.70/0.05). In the extended model, the implied switching cost ranges from about \$17.1 to \$28.4 (2.56/0.15 to 2.56/0.09), depending on the assumed price coefficient. The lower estimates reflect the explicit modeling of information frictions, which separate true switching costs from behaviors driven by limited attention or costly information acquisition. In contrast, the full information model attributes all plan inertia to switching costs, likely leading to overestimation. The estimated standard deviation σ_γ ranges from 2.23 to 2.82 across the two models, indicating

considerable heterogeneity in switching costs.

We next examine the determinants of information acquisition costs. All included covariates are statistically significant and consistent with expectations. Farms with higher average yields face lower information costs, likely because they operate in more stable environments where indemnity expectations are easier to form. In contrast, farms with low yields face greater uncertainty, increasing the complexity and cost of information processing.

Insurance agent density significantly reduces information costs. Agents serve as intermediaries, providing expertise on crop insurance policies, indemnity structures, and risk management. Their presence lowers the effort required for farmers to obtain and interpret relevant information. Moreover, greater agent availability facilitates identification of competent advisors, enhances service quality through competition, and may encourage innovation in information delivery.

Finally, weather-related information is critical for forming yield and indemnity expectations. When forecast accuracy is low, reflected in higher prediction errors, farmers face greater difficulty estimating expected indemnities, increasing reliance on external data and raising the marginal cost of accurate information.

6.2 Information Cost

Using the estimated parameters and the definition of marginal information cost in Equation 6, we compute information costs for all sample farms across the study years. The mean marginal cost of information is 0.81, with a standard deviation of 0.12. The top panel of Figure 2 shows the empirical distribution. The distribution is right-skewed, with a sharp mode near 0.85, indicating that most farmers face moderate information costs. The density declines rapidly above 1.0, suggesting that high costs are rare. Few observations fall below 0.6, implying a lower bound on the effort or resources required to obtain relevant information. While concentrated in a relatively narrow range, information costs vary substantially across individuals.

The middle and bottom panels of Figure 2 display the evolution of marginal information costs and the variance of expected indemnity (stakes) over time. Information costs decline modestly, while stakes rise sharply between 2006 and 2008 before falling. These opposing trends yield a correlation of –0.54 between the two series. The pattern is consistent with the

rational inattention framework, which predicts greater information acquisition when stakes are higher (Brown and Jeon, 2024). The decline in information costs likely reflects improvement in data availability, increased familiarity with insurance products, or reductions in cognitive or logistical barriers to acquiring information.

Within-year variation in both series remains substantial, as reflected in large error bars. This indicates persistent heterogeneity in decision-making conditions across farmers and regions. Under rational inattention, decision quality depends jointly on the cost of acquiring information and the value of being informed. Lower information costs do not guarantee improved outcomes if higher stakes increase the complexity of the decision environment. These dynamics highlight the need to jointly consider both costs and stakes when assessing information frictions and their welfare implications.

Figure 3 maps the spatial distribution of information costs across counties in the U.S. Corn Belt and surrounding regions. Costs are generally lower in the central Corn Belt, particularly Iowa, northern Illinois, and parts of Indiana, where production conditions are stable, agent density is high, and information infrastructure is well developed. In contrast, higher costs are concentrated along the periphery, especially in parts of Kansas, Nebraska, and the Dakotas, where production variability is greater and access to reliable information is more limited. Elevated costs are also observed in southern Missouri and eastern Kentucky and Tennessee, reflecting weaker integration with corn agricultural networks. The map reveals pronounced spatial heterogeneity, with a clear gradient from information-rich central counties to fragmented, higher-cost regions at the margins.

To identify the drivers of information costs, we decompose their exponential components based on Equation 6. Each factor's contribution is computed as the product of its estimated coefficient and standardized value, evaluated prior to exponentiation. This approach quantifies the relative influence of each variable on overall costs.

Results indicate that forecast error (MAE) and agent density each account for approximately 36% of the total information cost, while average yield contributes the remaining 28%. These findings suggest that forecast accuracy and agent access are the primary determinants of information costs. Higher forecast error increases uncertainty about expected yields, raising the value of precise information for risk management. In contrast, greater agent density

improves access to insurance expertise and reduces the effort needed to acquire relevant information. Policies that enhance yield forecasting and expand agent networks are thus likely to be effective in reducing information frictions.

7 Counterfactual Analysis

We apply the estimated model to the full sample and conduct two counterfactual analyses to isolate the roles of inattention and information acquisition costs in farmers' crop insurance decisions. These exercises allow us to evaluate (i) the first-best outcome in which all farmers are fully informed and attentive, and (ii) the separate contributions of inattention and information frictions to welfare losses.

We begin by implementing the full estimated two-stage model, as reported in Table 3, to simulate observed behavior under endogenous attention and information acquisition. This case, referred to as the endogenous information scenario, proceeds in two steps.

Step 1: Determining attention status. For each farm, we compute the probability of paying attention using the latent attention propensity in Equation 2 and the corresponding probability function in Equation 3, based on the parameter estimates in Table 3. A farm is classified as attentive if it experiences an external trigger (e.g., a simultaneous change in AIP and agent) or if its predicted attention probability exceeds 0.5. Otherwise, it is assumed to retain the default plan or continue with the previous year's choice.

Step 2: Modeling active choices. For attentive farmers, we simulate plan choices by allowing farmers to determine how much information to acquire about expected indemnities. They weigh prior beliefs against acquisition costs and select plans based on the resulting utility values computed from Equation 5. Simulations incorporate the full set of estimated parameters, including random coefficients for switching inertia.

We then conduct two counterfactual exercises to quantify welfare gains from removing frictions:

First-best scenario (benchmark): All farmers are assumed to be fully attentive and fully informed. There are no frictions in acquiring or processing information. Farmers make optimal choices based on complete information, using the utility function in Equation 4.

Full information scenario: All farmers are required to make active choices (i.e., full attention), but information acquisition remains costly and endogenous. Plan utilities are evaluated using Equation 5, as in the endogenous model.

The welfare loss of limited attention is identified by comparing the full information scenario to the first-best benchmark. The additional welfare loss due to information acquisition costs is measured by comparing the full information scenario to the endogenous information case, where both inattention and information frictions are present.

Table 4 reports welfare outcomes across the three scenarios. Welfare is expressed in U.S. dollars by dividing utility-based measures by the marginal utility of income, represented by the price coefficient of 0.15 discussed earlier.

Under the first-best scenario, in which all farmers are attentive and face no cost of acquiring information, total welfare reaches $32.35 million. This value represents the upper bound of achievable welfare within the model.

In the full information scenario, farmers endogenously choose whether to pay attention but face no costs or constraints in accessing information. Total welfare in this case is $29.25 million, implying a loss of $3.10 million, or 9.57%, relative to the first-best. This difference isolates the welfare cost of inattention.

The endogenous information scenario reflects the estimated two-stage model, in which both attention and information acquisition are endogenously determined and costly. Total welfare falls to $28.75 million, corresponding to a welfare loss of $3.60 million, or 11.11 percent, relative to the first-best. Compared to the full information scenario, this represents an additional loss of $500,000 attributable to information acquisition costs.

These results indicate that inattention accounts for the larger share of welfare loss, though information frictions also impose a nontrivial cost. Reducing either constraints, through behavioral interventions that enhance attention or policies that lower information cost, could substantially improve decision-making and welfare.

Beyond aggregate effects, we examine the spatial distribution of welfare gains. County-level changes are computed by aggregating individual-level welfare changes within each county. Figure 4 presents gains from jointly eliminating inattention and information frictions. The largest gains are concentrated in the central Corn Belt, particularly eastern Iowa, northern

and central Illinois, and western Indiana, while more modest gains appear in peripheral regions such as South Dakota, Kansas, Michigan, and parts of Ohio. These patterns reflect both higher stakes and greater baseline distortions in the Corn Belt, where farms typically manage higher-revenue operations and face greater variance in expected indemnities. The compounding effect of both frictions results in larger welfare losses in these regions.

Figure A4 isolates the welfare impact of eliminating inattention. The spatial pattern closely mirrors the total gains, confirming that inattention is the primary source of welfare losses. This suggests that many farmers fail to reevaluate their insurance plans, even when superior alternatives are available, especially in high-stakes areas where suboptimal choices have larger financial consequences.

Figure A5 shows welfare gains from removing information frictions while holding attention fixed. Although the magnitude of gains is smaller, regional heterogeneity remains substantial. Counties in the Central Corn Belt exhibit the largest improvements, consistent with higher stakes and more binding information constraints. Under rational inattention, greater variance in expected indemnities raises the value of information, making farmers in these regions more responsive to such frictions.

To support this interpretation, we re-estimate the model from Column II of Table 2, adding interactions between expected indemnity and state indicators for Illinois, Iowa, and Indiana. The interaction coefficients are positive and statistically significant,[10] implying that farmers in these states placed greater weight on indemnity expectations when information was available. This suggests that information frictions were more binding in the Central Corn Belt, consistent with the larger welfare gains observed under full information. Importantly, these behavioral differences arise only under limited information; under full information, all farmers respond optimally to plan attributes. Thus, regional differences in welfare gains reflect variation in stakes and baseline constraints, rather than structural differences in preferences or responsiveness.

As described in the Data section, expected indemnities for all available plans can be computed using standard procedures. Making this information accessible at the time of plan selection may reduce frictions and improve decision quality. The distribution of welfare gains

[10]Estimation results available upon request.

under full information underscores the importance of targeting interventions where frictions are most binding. Counties with higher stakes and greater baseline distortions should be prioritized for policies such as: (i) expanding access to qualified insurance agents, (ii) improving predictive tools for yield and indemnity forecasts, and (iii) enhancing data infrastructure to reduce uncertainty and facilitate better choices.

8 Conclusion

This paper examines how behavioral and informational frictions affect farmers' crop insurance decisions. We develop a structural model that distinguishes between inattention at the extensive margin and costly information acquisition at the intensive margin, allowing for separate identification of inertia, limited attention, and information costs. This framework provides a more detailed view of suboptimal insurance choices by capturing the sequential nature of plan review and evaluation.

Counterfactual simulations quantify the welfare implications of each friction. Holding attention fixed, removing information frictions increases welfare by $3.10 million, or 9.6 percent relative to the baseline. Eliminating both inattention and information frictions raises welfare by $3.60 million, or 11.1 percent, with the majority of the gain attributable to improved attention. These results suggest that both frictions limit the efficiency of insurance choices, with inattention posing the greater constraint.

Welfare gains are concentrated in the central Corn Belt, where production risks are more salient and information frictions more binding. These findings point to the potential for targeted interventions, such as expanding access to insurance agents, improving forecast tools, or streamlining plan information, to improve decision-making in high-stakes regions. More broadly, the results highlight the importance of modeling attention and information acquisition as distinct processes when analyzing behavior in complex choice environments.

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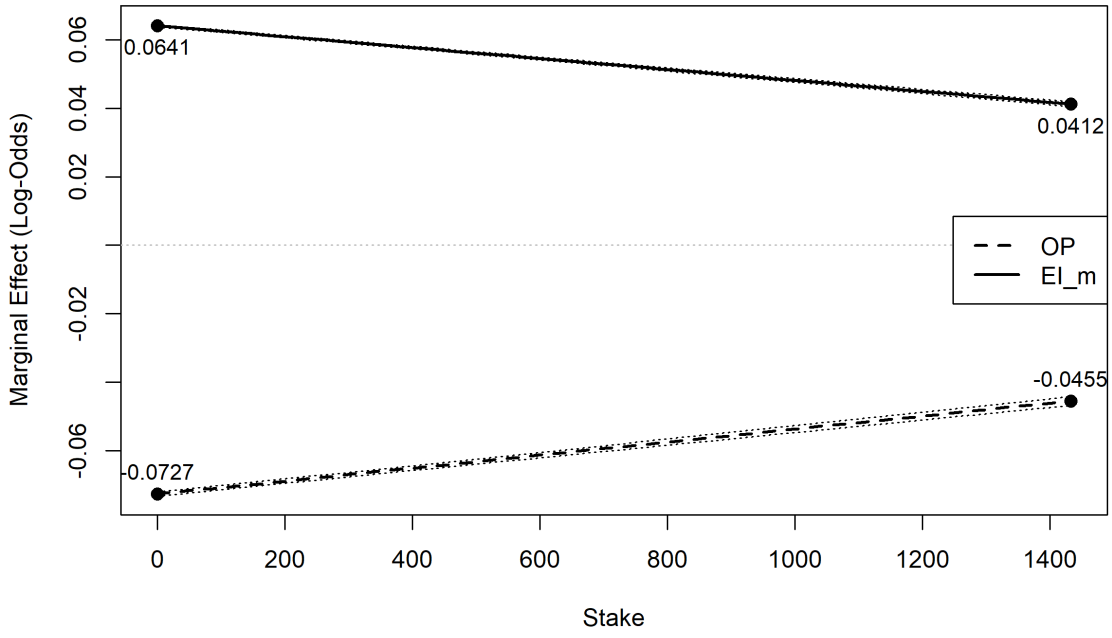


Figure 1: Marginal Effects of Out-of-Pocket Premium and Expected Indemnity.

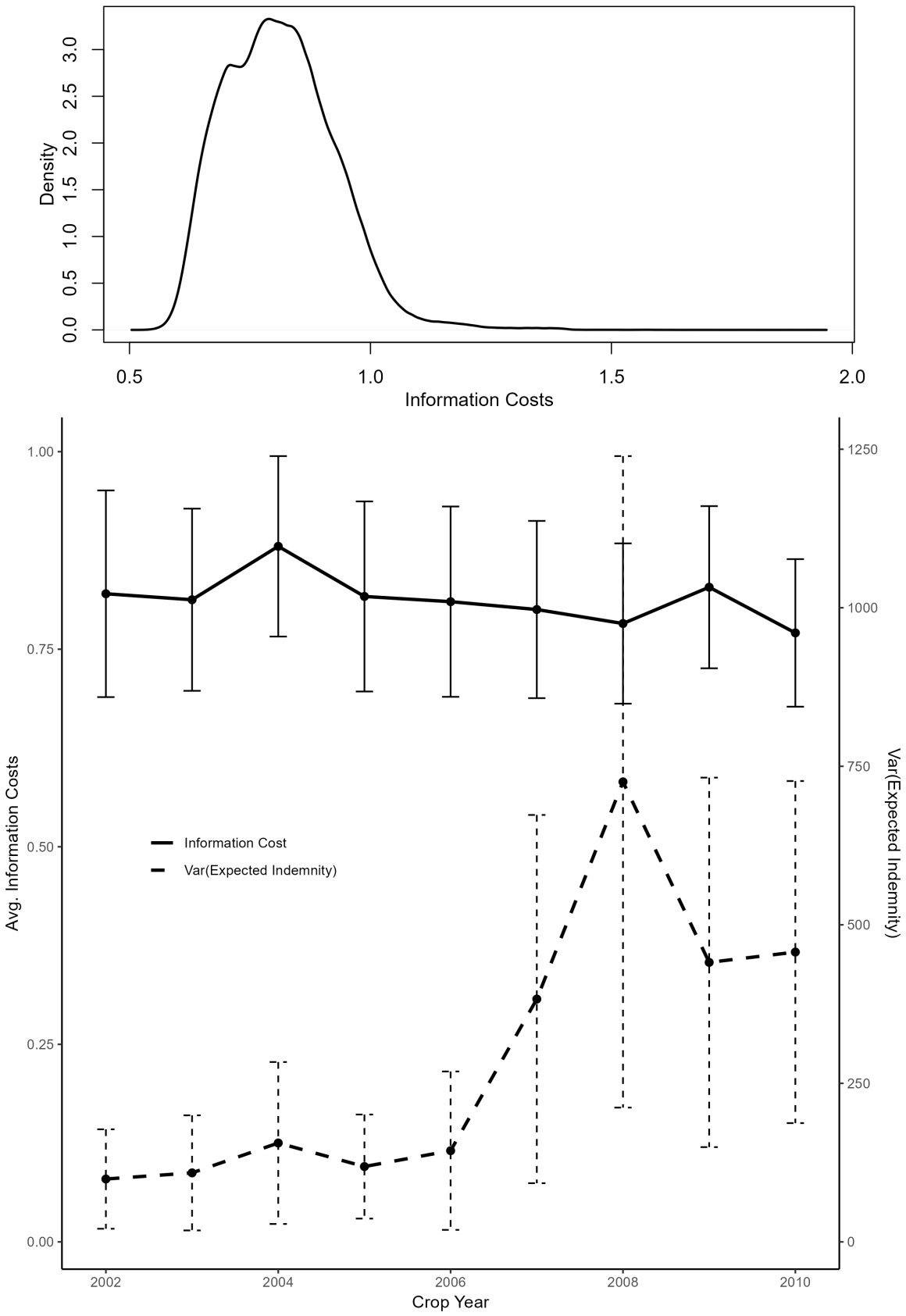


Figure 2: Marginal Cost of Information: Empirical Density (Top), Annual Averages (Middle), and Variance of Expected Indemnity (Bottom)

Note: The bottom panel shows the variance of expected indemnity (stakes) by year. Given its different magnitude, it is plotted using the secondary (right-side) axis.

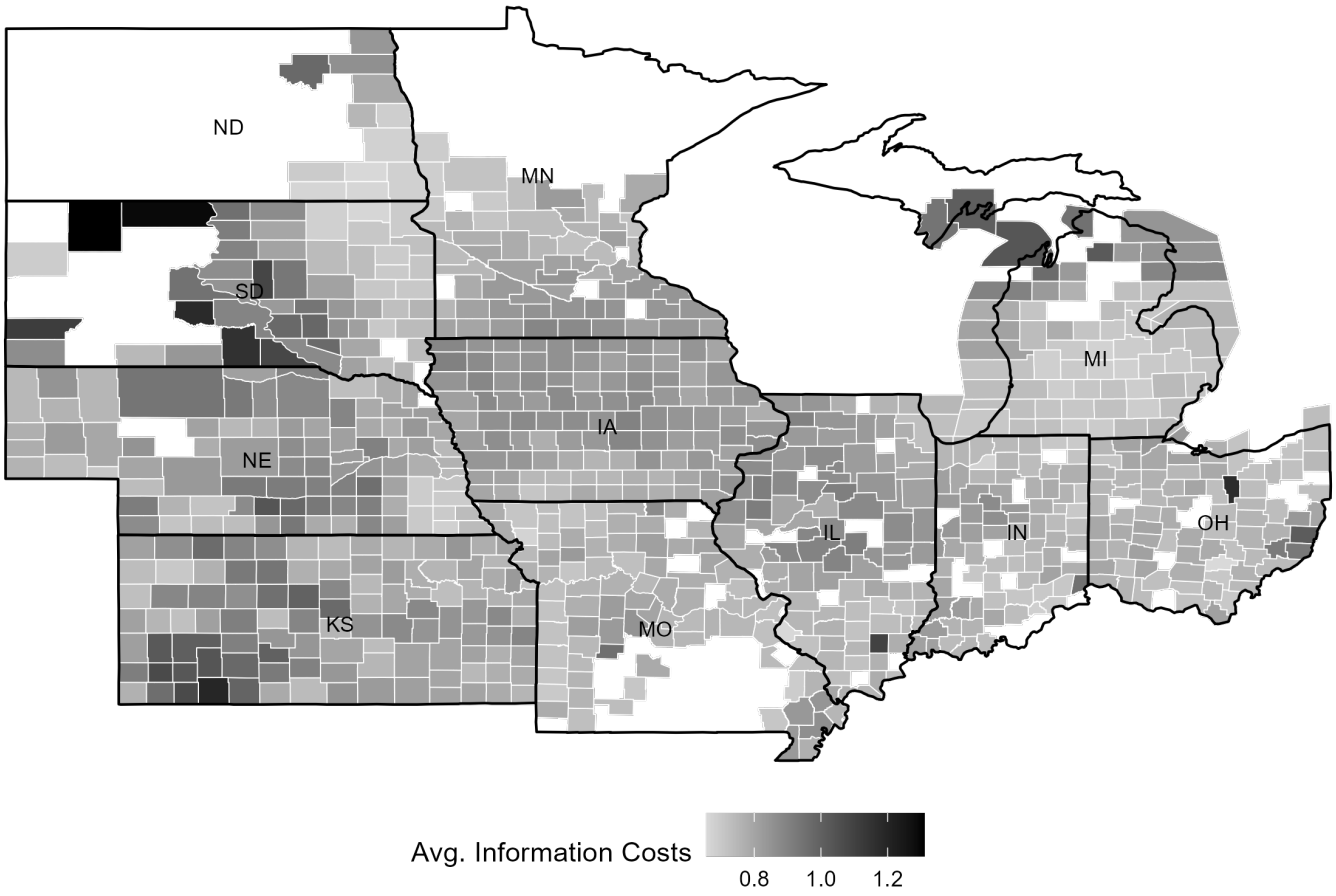


Figure 3: County-Level Marginal Cost of Information.

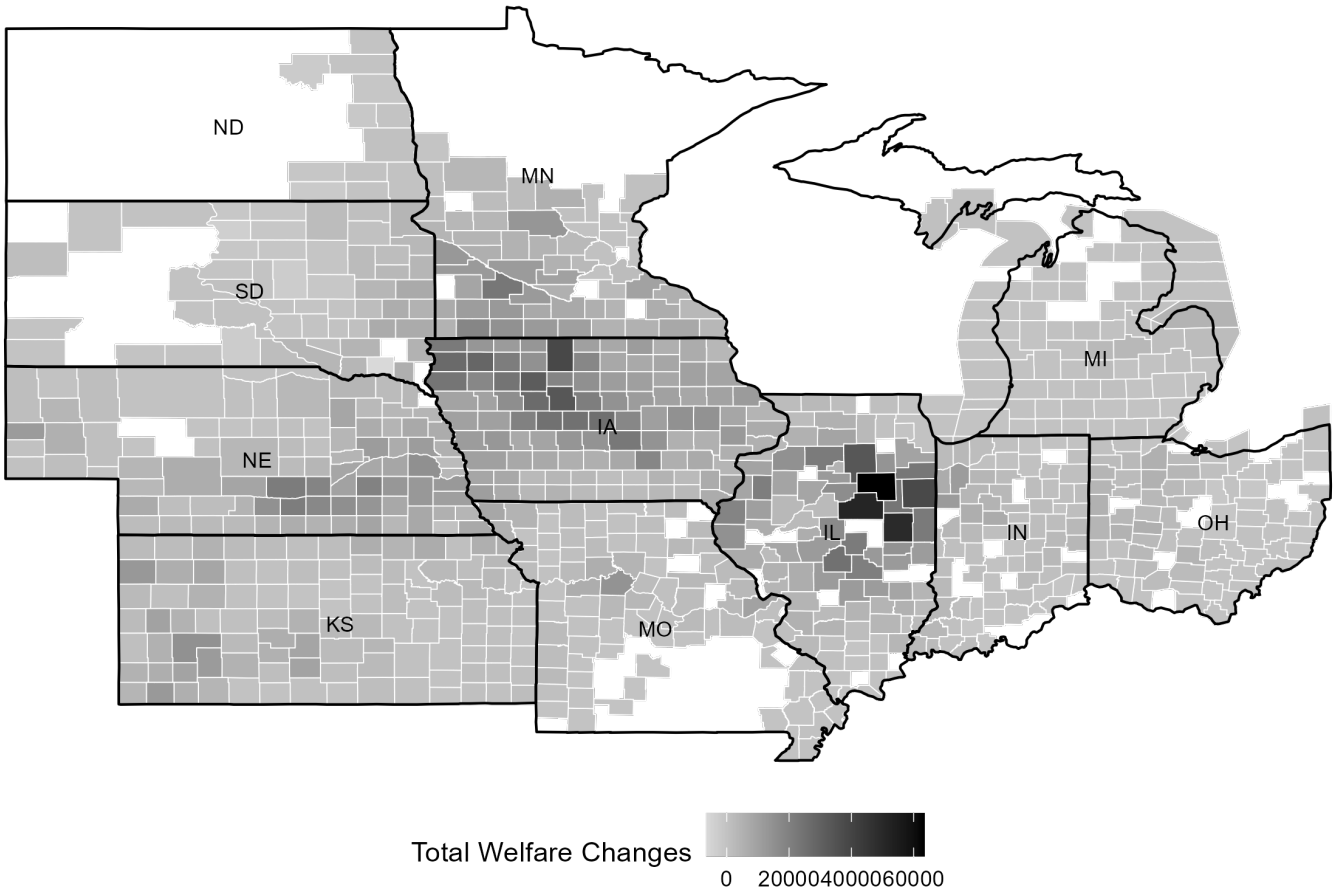


Figure 4: County-Level Total Welfare Changes.

Table 1: Summary Statistics of Premium, Subsidy, and Average Expected Indemnity.

ID	Plan	Coverage	Premium		Subsidy		Expected Indemnity	
		Level	Mean	SD	Mean	SD	Mean	SD
1	90	50	5.56	5.31	3.77	3.61	0.08	1.50
2	90	55	6.88	6.27	4.47	4.10	0.13	2.05
3	90	60	8.55	7.41	5.55	4.84	0.20	2.70
4	90	65	10.58	8.73	6.38	5.31	0.29	3.46
5	90	70	13.70	10.83	8.26	6.57	0.42	4.34
6	90	75	17.72	13.35	9.98	7.58	0.60	5.35
7	90	80	22.75	16.40	11.19	8.13	0.88	6.52
8	90	85	28.91	20.11	11.25	7.86	1.41	7.98
9	25	65	14.00	12.16	8.48	7.46	14.78	8.72
10	25	70	19.29	15.30	11.68	9.37	20.32	11.61
11	25	75	25.92	19.31	14.67	11.06	27.51	15.21
12	25	80	34.04	24.34	16.83	12.17	36.10	19.39
13	25	85	43.86	30.54	17.14	12.03	46.28	24.28
14	44	50	8.28	6.98	5.62	4.75	5.55	3.38
15	44	55	10.44	8.43	6.79	5.52	7.60	4.59
16	44	60	13.17	10.18	8.57	6.66	10.54	6.24
17	44	65	16.53	12.26	9.99	7.49	14.75	8.48
18	44	70	21.64	15.50	13.07	9.44	20.28	11.31
19	44	75	28.22	19.48	15.92	11.09	27.46	14.86
20	44	80	36.53	24.36	18.00	12.09	36.03	18.96
21	44	85	46.88	30.35	18.25	11.87	46.16	23.71

Table 2: Logit Model Regression Results with Fixed Effects

	(1) Net Return Model	(2) OP + EI Model	(3) Interaction Model
Net Return	0.056^{***}		
	(0.0001)		
OP		-0.063^{***}	-0.073^{***}
		(0.0002)	(0.0003)
EI^m		0.056^{***}	0.064^{***}
		(0.0001)	(0.0002)
EI^V	-0.00012^{***}	-0.00011^{***}	-0.00009^{***}
	(0.0000007)	(0.0000008)	(0.0000008)
OP $\times$ stake			0.000019^{***}
			(0.0000004)
$EI^m\times$ stake			-0.000016^{***}
			(0.0000002)
Acres	-0.00022^{***}	-0.00020^{***}	-0.00016^{***}
	(0.000006)	(0.000006)	(0.000005)
Yield Mean	-0.00916^{***}	-0.00954^{***}	-0.00908^{***}
	(0.00007)	(0.00007)	(0.00007)
Yield Variance	-0.00251^{***}	-0.00230^{***}	-0.00217^{***}
	(0.00005)	(0.00005)	(0.00004)
Farm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	28,563,927	28,563,927	28,563,927
Log-Likelihood	$-5{,}264{,}227$	$-5{,}262{,}786$	$-5{,}258{,}816$

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: MLE Estimates of the Two-Stage Models

	Full Information	Endogenous Information
Stage I: Attention		
Acres	0.63***	0.32***
	(0.05)	(0.004)
D_{2003}	0.21***	0.44***
	(0.06)	(0.006)
D_{2009}	2.65***	2.39***
	(0.17)	(0.02)
D_{Disaster}	0.59***	0.33***
	(0.14)	(0.006)
Stage II: Plan Choice		
Net Return	0.88***	
	(0.01)	
β		1.75***
		(0.01)
γ_0	2.70***	2.56***
	(0.03)	(0.03)
σ_γ	2.20***	2.82***
	(0.12)	(0.01)
Stage II: Marginal Cost of Information		
Mean Yield		-0.51***
		(0.004)
Agent Density		-0.03***
		(0.0003)
Prediction Error		0.96***
		(0.01)
Log-Likelihood	-56643.90	-55935.83

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Counterfactual Welfare Outcomes

Scenario	Total Welfare ($)	Loss vs. First-Best ($)	% Loss vs. First-Best
(I) First-Best	32,350,367.98	–	–
(II) Full Information	29,253,044.49	3,097,323.482	9.57%
(III) Endogenous Information	28,753,848.95	3,596,519.028	11.11%

Notes: The table reports welfare outcomes under three scenarios. (1) First-Best assumes all farmers are fully attentive and face no information acquisition costs. (2) Full Information allows endogenous attention but assumes farmers have free and perfect information. (3) Endogenous Information reflects the estimated two-stage model, in which both attention and information acquisition are endogenous and costly. Welfare losses are calculated relative to the First-Best benchmark.

Appendix

A Figures and Tables

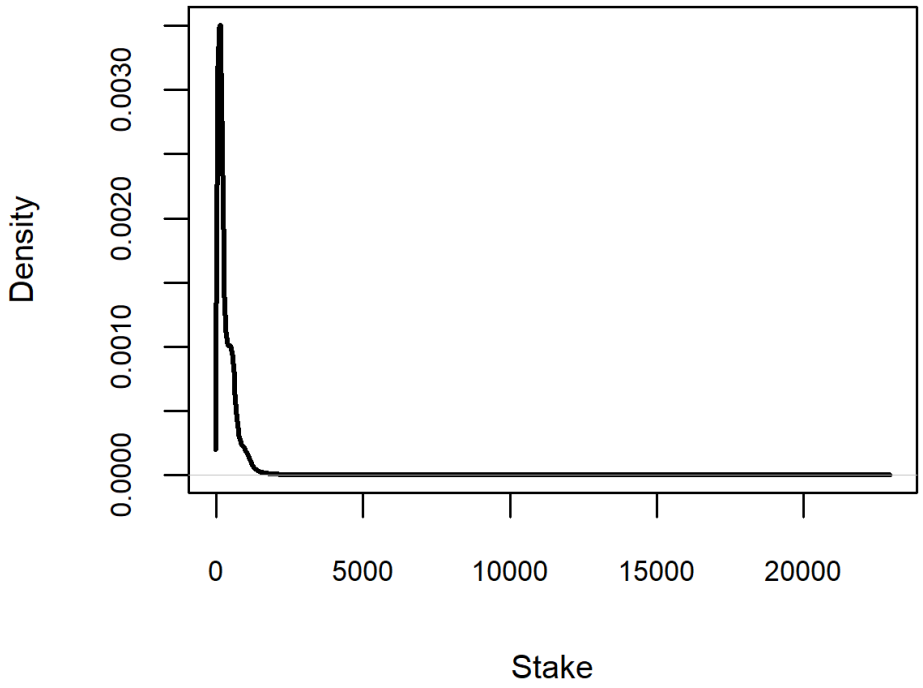


Figure A1: Density of Stakes (Variance of Expected Indemnity Across Plans in Farmers' Choice Set).

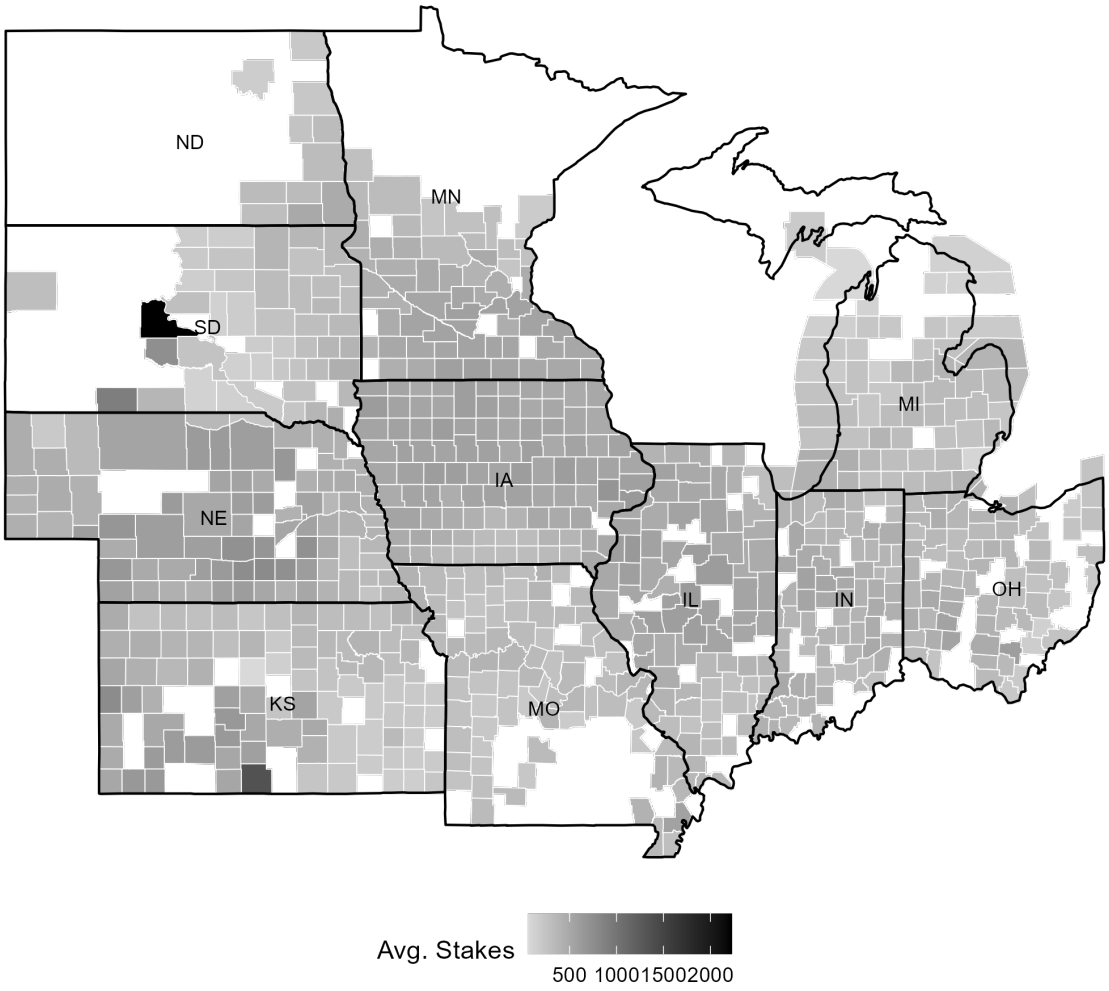


Figure A2: Average County-Level Stakes Across Sample States.

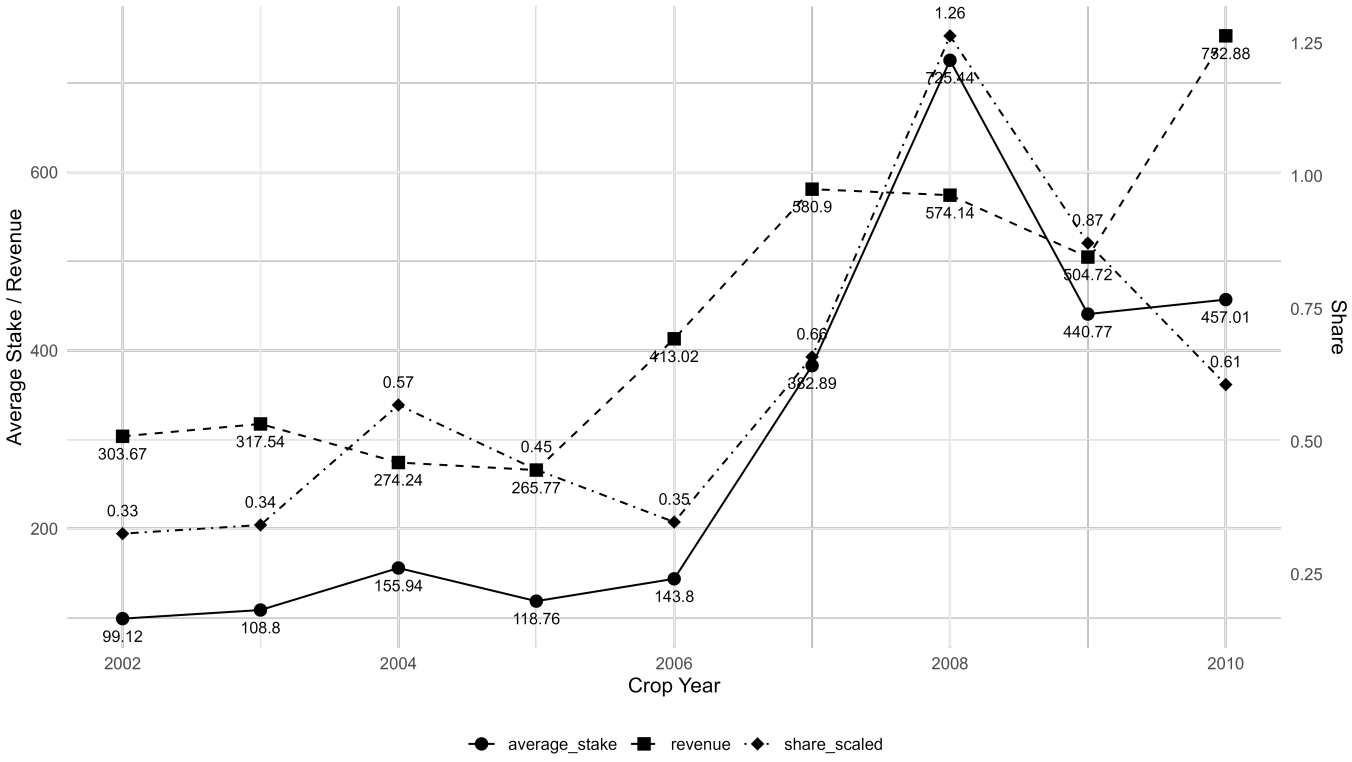


Figure A3: Average Per Acre Stake, Revenue, and Share Over Sample Period, 2002-2010.

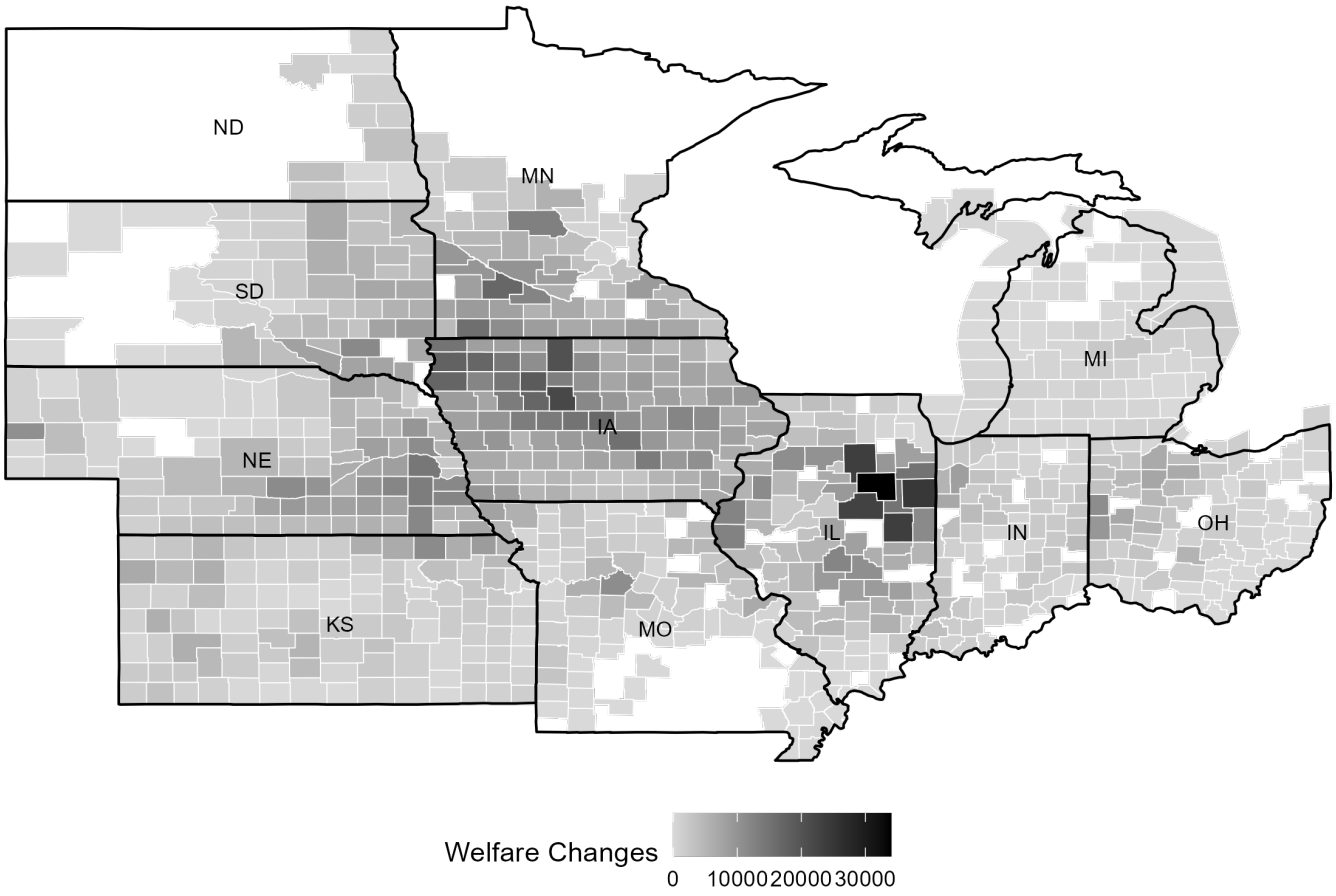


Figure A4: County-Level Welfare Changes from Removing Inattention.

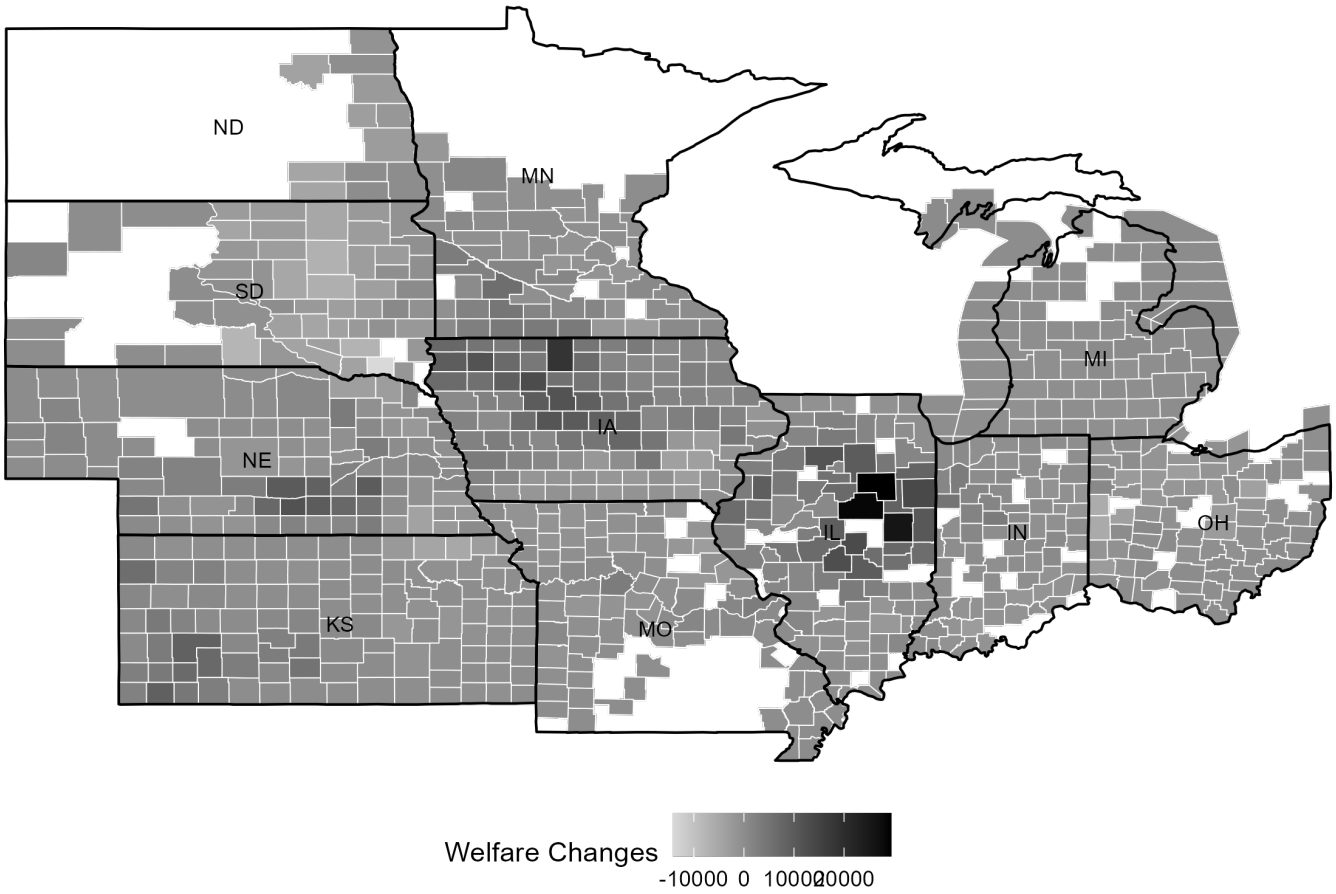


Figure A5: County-Level Welfare Changes for Removing Information Friction.

Table A1: Crop Insurance Premium Subsidies

Coverage Level (%)	50	55	60	65	70	75	80	85
BU/OU	67	64	64	59	59	55	48	38
EU	80	80	80	80	80	77	68	53

Note: Adopted from Shields (2015), Table 1. BU, OU, and EU refer to business, optional, and enterprise units, respectively.

Table A2: Number of Farms Purchased from Individual AIPs

ID	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
1	56,722	51,866	49,870	56,729	58,536	60,527	57,381	58,677	57,318	57,809	67,539
2	42,759	41,629	41,379	46,982	56,128	59,176	57,473	59,897	59,036	59,497	56,822
3	20,824	21,152	22,943	33,960	35,795	33,219	42,645	38,540	38,143	38,869	38,860
4	13,080	11,471	10,610	10,277	9,731	9,535	8,123	8,387	8,668	8,774	8,836
5	7,369	7,328	6,564	3,820	3,689	3,490	3,129	3,267	3,104	3,024	2,898
6	6,425	8,619	9,188	12,410	13,918	13,508	29,367	30,144	30,053	32,328	33,036
7	3,691	4,747	7,365	14,227	15,468	17,547	17,768	22,018	21,793	21,872	24,581
8	22,850	22,956	25,081	27,380	39,544	38,969	0	0	0	0	0
9	12,887	12,346	11,183	15,562	16,907	0	0	0	0	0	0
10	48,030	46,439	56,595	0	0	0	0	0	0	0	0
11	22,046	21,732	0	0	0	0	0	0	0	0	0
12	15,901	16,864	16,727	18,201	0	0	0	0	0	0	0
13	13,713	13,479	14,302	15,380	0	0	0	0	0	0	0
14	8,362	7,802	7,566	10,186	9,706	9,682	0	12,060	0	0	0
15	2,038	2,018	0	0	0	0	0	0	0	0	0
16	859	869	854	0	0	0	0	0	0	0	0
17	0	421	3,724	10,144	12,559	10,177	7,792	7,652	7,757	7,604	7,187
18	0	20	1,104	2,987	3,509	4,427	4,687	5,605	5,863	6,522	6,960
19	0	0	0	1,579	0	0	0	0	0	0	0
20	0	0	738	663	4,463	6,357	5,910	9,838	10,268	9,087	9,724
21	0	0	0	0	1912	2,691	12,389	0	0	0	112
22	0	0	0	0	0	4,811	5,725	6,079	6,316	9,520	11,930
23	0	0	0	0	0	3,188	4,871	6,267	7,017	0	0
24	0	0	0	0	0	94	203	1,407	1,799	2,378	4,430
25	0	0	0	0	0	0	1,769	2,075	2,251	2,427	3,941
26	0	0	0	0	0	0	0	397	526	0	0
27	0	0	0	0	0	0	0	0	11,845	11,919	0
28	0	0	0	0	0	0	0	0	0	8,694	7,999
29	0	0	0	0	0	0	0	0	0	524	607

Note: The numbers in the table represent the number of farms represented by unique policy numbers purchased the products from individual insurance providers or AIPs. The names of the AIPs are covered in the data by RMA.

Table A3: Regression Results of Stake

Variable	Estimate
Acres	-0.009^{***}
	(0.002)
Yield Mean	7.40^{***}
	(0.06)
Yield Variance	0.88^{***}
	(0.04)
Farm Fixed Effect	Yes
Year Fixed Effect	Yes
Adj. R^2	0.74

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Distribution of Farms by Number of Years and Number of Optimal Plan Changes

Years in Sample			Number of Optimal Plan Changes		
Years	# of Farms	Share	# of Changes	# of Farms	Share
2	85,945	0.25	0	103,908	0.30
3	72,993	0.21	1	107,222	0.31
4	54,844	0.16	2	61,767	0.18
5	31,986	0.09	3	31,752	0.09
6	29,950	0.09	4	18,067	0.05
7	21,919	0.06	5	10,725	0.03
8	12,844	0.04	6	5,569	0.02
9	31,065	0.09	>7	2,536	0.01
Total	341,546	1.00		341,546	1.00

Note: The left panel shows the distribution of farms by the number of years they are observed in the sample. The right panel shows the distribution of farms by the number of insurance plan changes made during the sample period.

Table A5: Impact of Exogenous Shocks

	Forced Switch (t)		Disaster		FB 2002		FB 2008	
	$t-1$	t	Control	Treatment	Before	After	Before	After
Yield Insurance	0.17	0.16	0.28	0.22	0.34	0.29	0.17	0.15
Revenue Insurance	0.83	0.84	0.72	0.78	0.66	0.71	0.83	0.85
Low Coverage	0.63	0.59	0.62	0.55	0.59	0.55	0.59	0.46
High Coverage	0.37	0.41	0.38	0.45	0.41	0.45	0.41	0.54

Note: Low coverage refers to coverage levels below 75%, and high coverage refers to levels greater than or equal to 75% (i.e., 75%, 80%, or 85%).

B Construction of Premiums, Subsidies, and Expected Indemnities

B.1 Premium and Subsidy Reconstruction

Farmers only reveal premiums and subsidies for the plan they selected. To compare across alternatives, we reconstruct these variables for all available plans in each farmer's choice set.

Step 1: We begin by reconstructing premiums for all coverage levels of the chosen insurance plan for each individual insurance unit, using RMA-published actuarial documents and parameters. This includes state- and county-level rate information, reference yields, rate differentials, discounts for unit types and other coverage options.

We validate this reconstruction by comparing the estimated premium for the selected plan to the observed value.

Step 2: Using the validated methodology, we reconstruct premiums for all coverage levels of unchosen plans. This ensures each farmer faces a consistent set of imputed plan options.

Subsidies are computed as plan- and unit-specific proportions of the total premium using USDA's subsidy rate tables (Table A1).

B.2 Expected Indemnity Calculation

The expected indemnity represents the average payout a farmer anticipates from an insurance contract. Because this is not observed ex-ante, we simulate it based on historical yield and price distributions, assuming rational expectations.

The estimation process follows four main steps:

Step (i): Joint Simulation of Yields and Prices

We estimate a Gaussian copula for each county using: detrended county-level corn yields (1960-2021, from NASS),[11] and monthly changes in December futures prices from February to December (from CME).

We use the LOWESS (Locally Weighted Scatterplot Smoothing) procedure, which fits local regression to different segments of the data, generating a smooth curve that captures the trend without assuming a specific parametric model. By subtracting this estimated trend, we obtain

[11] The data is available at https://quickstats.nass.usda.gov/.

the detrended yields for copula estimation. The second input for the copula model is the price difference between February (projected harvest price or base price) and December (harvest price) for the December futures contract.

We apply kernel density estimation to the detrended yields and price changes to transform them into uniform marginals on the $[0, 1]$ scale, as required for copula modeling. The fitted Gaussian copula is specified as follows:

$$C_\rho(U_Y, U_P) = \Phi_\rho\left(\Phi^{-1}(U_Y), \Phi^{-1}(U_P)\right),$$

where $U_Y = F_Y(Z_Y)$ and $U_P = F_P(Z_P)$ represent the uniform marginals of the detrended yields (Z_Y) and price changes (Z_P), respectively. Φ^{-1} is the inverse CDF of the standard normal distribution and Φ_ρ is the joint CDF of the bivariate normal distribution with correlation coefficient ρ, which captures the linear dependence between the two variables. Maximum likelihood estimation is used to estimate ρ. With the estimated $\hat{\rho}$, specific to each sample county, we simulate 5,000 pairs of random values, u_Y and u_P, from the copula. These values are uniformly distributed between 0 and 1 and can be interpreted as quantiles of the marginal distributions. To obtain random values from specific marginal distributions, we use the inverse CDF of the marginals to transform u_Y and u_P, i.e., $z_Y = F_Y^{-1}(u_Y)$ and $z_P = F_P^{-1}(u_P)$.

Step (ii): Yield Simulation

In this step, z_Y is drawn based on individual units in the insurance data sample. For each unit, we first determine its quantile location within four quantiles, defined by the 25th, 50th, and 75th percentiles of yields from all units within the same county and crop year.[12] To draw yield residuals from F_Y for each unit, we assume that the detrended yields of other units within the same quantile across the sample period follow the same distribution F_Y. Using the u_Y values generated in Step (i), we then draw 5,000 samples of yield residuals from F_Y corresponding to each quantile. The final part in Step (ii) involves reintroducing the county-level trend that was removed during the detrending process. This trend, previously estimated using the LOWESS procedure, is added back to the sampled residuals. This trend adjustment is based on the APH yields of all units within the same county over time.

Step (iii): Price Simulation

We use the price changes from Step (i) to generate 5,000 simulated price change based on

[12]The unit yields are APH yields, not actual annual yields, and represent average yield performance under normal production conditions.

the u_P values obtained earlier. These simulated price changes are then converted into harvest prices by adding the February futures price of the corresponding year for each simulated unit.

Step (iv): Computing Expected Indemnities

We simulate the expected indemnities for all coverage levels under each insurance plan in the choice set. For Plan 90, the expected indemnity for unit i at a given coverage level $\phi \in [50\%, ..., 85\%]$ is defined as:

$$EI_i^{90} = \frac{1}{N}\sum_{n=1}^{N} P_t^{Feb} \max(\phi \bar{Y}_i - z_Y^n, 0),$$

where $N = 5,000$, P_t^{Feb} is the base price (February futures price), $\bar{Y}_i$ is the APH yield for unit i in year t, and z_Y represents the simulated yields for unit i in year t.

For Plan 25, at each coverage level $\phi \in [65\%, ..., 85\%]$, the expected indemnity for unit i is defined as follows:[13]

$$EI_i^{25} = \frac{1}{N}\sum_{n=1}^{N} \max\left(\phi \max(P_t^{Feb}, z_P^n)\bar{Y}_i - z_Y^n z_P^n, 0\right), \quad \text{if harvest price option is chosen;}$$

$$EI_i^{25} = \frac{1}{N}\sum_{n=1}^{N} \max\left(\phi P_t^{Feb} \bar{Y}_i - z_Y^n z_P^n, 0\right), \quad \text{otherwise.}$$

For Plan 44, at each coverage level, $\phi \in [50\%, ..., 85\%]$, the expected indemnity for unit i is defined as:

$$EI_i^{44} = \frac{1}{N}\sum_{n=1}^{N} \max(\phi \max(P_t^{Feb}, z_P^{44,n})\bar{Y}_i - z_Y^n z_P^{44,n}, 0)$$

where $z_P^{44,n} = z_P^n$ if $z_P^n - P_t^{Feb} < 1.5$ and $z_P^n - P_t^{Feb} > -1.5$, accounting for the price variation limits under Plan 44.

We also compute the variances of the expected indemnities for individual plans for farm i. For example, the variance for Plan 90 is defined as follows:

$$Var_i^{90} = \frac{1}{N}\sum_{n=1}^{N} \left[P_t^{Feb} \max(\phi \bar{Y}_i - z_Y^n, 0) - EI_i^{90}\right]^2,$$

where EI_i^{90} denotes the average expected indemnity calculated above. The variances for other plans are defined similarly. This represents the within-plan variation in expected indemnity, which measures the uncertainty of expected indemnity for each available plan.

[13]The choice of the harvest price option is taken directly from the data without explicit modeling.