Optimal Insurance Scope: Theory and Evidence from US Crop Insurance

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Abstract

Distinct risks are typically insured separately. A single 'aggregate' contract that pays more when many shocks occur simultaneously, but less when positive shocks offset negative shocks, is utility-increasing absent moral hazard. However, an aggregate contract discourages diversification, leading to a novel insurance-incentive trade-off. We study the US Federal Crop Insurance Program (FCIP), where farmers can choose the 'scope' of their policy - whether to insure each field separately, or all fields of the crop as an aggregate unit. Starting in 2009, the FCIP introduced a large subsidy increase for aggregate insurance. We show that farms that moved to aggregate insurance reduced crop diversity and irrigation, farmed less and conserved more land, and insured price risk — all reducing the diversification of their risks. This increased the variability of farm yield by 14%, raising the fiscal cost of aggregate insurance by about $1.5 billion per year. We derive and estimate a 'Baily-Chetty'-style formula for the optimal contract scope. We find that an aggregate policy is never welfare maximizing, but that the optimal policy lies partway between separate and aggregate. More generally, we discuss scope's widespread relevance in insurance design.

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1 Introduction

People face a broad variety of risks in their lives: health shocks cause uncertain medical spending and income loss; natural disasters damage property, lives, and businesses. Yet the insurance that we purchase against those risks is typically fragmented — it covers spending on health, or risks to income, but not both. A planner who wants to insure consumption would prefer that an individual who has a car accident receive a higher payout if they also lose their job than if they are employed, since their marginal utility of consumption is higher. Similarly, if there are simultaneous positive and negative shocks, the latter are implicitly 'self-insured' by the former, and the optimal policy need not pay out very much. This interaction cannot occur when risks are insured separately. For this reason, the insured individual prefers a policy with broad 'scope'; many or all risks to consumption should be insured in a single 'aggregate' contract.

However, there is a cost to aggregate contracts: they affect the incentive to diversify risk. By construction, an aggregate policy pays less than separate contracts when there is an idiosyncratic shock — some bad outcomes materialize, others do not. An aggregate policy pays more when there is a systemic shock — many bad outcomes occur simultaneously. Diversification makes systemic shocks less likely, and makes idiosyncratic shocks more likely. Therefore, an aggregate contract reduces incentives to diversify. This is the familiar insurance-incentive trade-off, but on the novel dimension of scope. When the insured has more protection against systemic losses, they reduce investments that make systemic shocks less likely, without regard to the insurer's increased cost. This trade-off provides a testable efficiency rationale for insuring separate risks in separate contracts.

The scope of an insurance contract has broad applications. Analogous scope dimensions include family versus individual unemployment insurance; separate versus combined cost-sharing for medical expenses (inpatient, outpatient, drugs) in health insurance; insuring weekly, yearly, or lifetime income in the tax and transfer system; insuring job loss or income loss. In all these cases, a contract can insure risk at different degrees of aggregation. A planner must trade off the insurance benefits of an aggregate contract against induced behavioral distortions.

We examine optimal scope both theoretically and empirically. In Section 2, we set up a general model with two risks and arbitrary correlation between them, in which a planner is setting the scope of an insurance policy.[1] Mirroring our empirical context, an insurance designer sets a personalized price for each insured agent, removing concerns about adverse selection that would arise in a competitive market. Our model augments the standard insurance-incentive trade-off in which the planner wants to offer more protection, but this impacts the agent's incentives to reduce risk. In our model, the agent chooses costly actions to prevent each risk from occurring, *and* a level of diversification that determines the extent to which risks are idiosyncratic or systemic.

[1] In Appendices A.1, A.4 and A.5, we show that the qualitative conclusions remain true in both an extended general model with more risks, weaker assumptions and in a four-state extension of the simple binary loss two-state model commonly found in the literature.

We have three main results. First, in terms of insurance value to the insured agent, an aggregate policy is preferred to a separate policy. A separate contract cannot tailor its payouts against one risk to whether or not the other risk has occurred. In contrast, an aggregate contract pays more when a systemic shock occurs and less when an idiosyncratic shock does. This moves money from lower to higher marginal utility states, increasing the agent's welfare. Second, as the contract moves from separate to aggregate, the agent diversifies less. Since diversification makes idiosyncratic shocks more likely, and systemic shocks less likely, the agent's incentives to diversify are weakened in an aggregate contract. Third, the level of diversification an agent undertakes in a separate contract is socially optimal, under an aggregate contract it is inefficiently low, and imposes a fiscal externality on the insurance program. These results illustrate a novel incentive-insurance trade-off on insurance scope. This rationalizes the potential efficiency of separate contracts, as are commonly observed.

We empirically study the effects of scope in the context of the Federal Crop Insurance Program (FCIP) (Section 3). The FCIP is a government-run and government-financed insurance program that protects farmers against any hazard to their crops. In the FCIP, farmers can enroll their fields into separate or aggregate policies.[2] The former insures each field independently; the latter insures the total yield for a given crop. In both cases, different crops are never insured together. That is, the choice is between each corn field having its own contract or all corn entering one aggregate contract, but neither of these will interact with wheat insurance.[3] The FCIP also gives farmers large subsidies toward their insurance premiums, ranging from 50% to 85% of the premium depending on the coverage level. The premium and subsidy both depend on the farmer's choice of scope.

To identify the effects of scope, we leverage a policy change that made aggregate insurance cheaper (Section 3.2). Prior to the policy change, the subsidies for aggregate and separate insurance were identical. Then, starting in 2009, the FCIP increased the subsidy for aggregate insurance, but not for separate insurance, by an average of 16%. Different crops were made eligible at different times for the cheaper aggregate insurance. The policy change led many farms to switch to aggregate insurance, allowing us to study the changes in diversification that ensued.

To evaluate the reform to scope, we use two complementary empirical strategies (Section 3.4). First, we use a 'between-crop' strategy. Using the universe of insurance data at a county-crop level, we compare insurance choices and diversifying actions among crops treated with the policy change to crops that were not (yet) treated. Second, we use a 'between-farm' comparison. We employ farm-level data from a long-running USDA survey that only covers treated crops.[4] We compare the changes in diversification actions on farms that switched to aggregate insurance to those that remained in separate insurance. Since insurance choice is endogenous, we instrument for it with pre-treatment county exposure. Whenever possible, we implement both approaches and the results

[2] In the official terminology, aggregate units are known as 'enterprise' units, and separate units are 'optional' units.

[3] Although the FCIP introduced whole-farm policies, in which all crops are insured together, there is essentially no advantage to enrolling in these compared to an aggregate policy for each crop, and take-up has been close to zero.

[4] Even though the USDA survey collects information on a wider variety of crops, some treated and some control, it only surveys farmers about insurance scope for three crops, all of which were treated in 2009.

are identical in sign and similar in magnitude.

The subsidy increase had a large effect on the scope of insurance (Section 4.1). Over 20% of insured acres moved from separate to aggregate insurance. There was no change in the total number of acres insured in treated crops. This indicates that take-up of aggregate insurance is driven by previously insured farms switching from separate policies, not by previously uninsured farms entering the program, or farms switching from control crops to treated crops.

As the scope of insurance was broadened, farmers diversified less. We demonstrate this in terms of ex-ante actions and ex-post outcomes. As our primary ex-post outcome, we show that the variability of total farm yield increased when farms moved to aggregate insurance (Section 4.2.1). Since a diversified farm is unlikely to have widespread failure, the variability of total farm yield is a good proxy for inter-field diversification. The reduction in diversification as farmers move to aggregate policies increases the coefficient of variation of farm yield by 4–19% (a 14% pooled effect), depending on the crop. Since insurance payouts are a convex function of farm yield, the increase in variability adds to the cost of providing aggregate insurance.

To understand the mechanisms that drove the decrease in diversification, we analyze three specific production choices that farmers altered as they switched to aggregate insurance.

First, as the scope of insurance was broadened, crop diversity decreased by up to 18% (Section 4.3.1). Planting a mixture of crop species or sub-species diversifies the risk a farm faces. We focus on diversity in four 'small grains' — wheat, barley, canola and oats — that each have two main varieties: winter and spring.[5] As farms moved to aggregate insurance, they planted less diverse mixtures of small grains. The average effect is equivalent to each farm moving from a 50:50 to a 68:32 mixture of winter and spring varieties. In a subsequent 2022 policy change, aggregate insurance was 'de-aggregated' by variety for wheat only. Winter wheat and spring wheat could now be insured in distinct aggregate policies, each attracting the high subsidy. This nullifies the incentives to distort wheat diversity, and we show that wheat diversity increased by almost as much as it initially fell.

Second, farms reduced irrigation by 6% as they moved to aggregate insurance (Section 4.3.2). Irrigation is an important but costly form of self-insurance against insufficient rain. Irrigating a portion of a farm increases the average yield and diversifies risk, as the whole farm is no longer susceptible to widespread drought. The diversification effect of irrigation on the farm is not included in the premium of an aggregate policy. As a result, at the margin, farms that move to aggregate insurance reduced their irrigation.

Third, farmers who switched to aggregate policies rented out 6% less land and increased their participation in conservation programs by 7% (Section 4.3.3). Having a larger farm diversifies risk because any particular hazard affects less of the farm. Moreover, the FCIP regulations state that

[5] The winter variety is high-yield and high-risk: it is planted in the fall and must survive the winter; the spring variety is lower yield and lower risk: it is planted in the spring and does not face the risks posed by winter conditions.

any acreage in a county in which a farmer has a financial interest is included in that farmer's aggregate unit. This includes fields rented out for cash payment, for which the owner will never receive any share of the output, but could still interfere with their aggregate unit payout. For both of these reasons, farmers who moved to aggregate policies reduced diversification by renting out marginal land and instead enrolling it in a conservation program.

Finally, as a purely financial choice, we show that as farmers moved to aggregate insurance, they were 44% more likely to include price risk in their policy (Section 4.3.4). In addition to choosing between separate or aggregate policies, the FCIP offers both yield (quantity) and revenue (price × quantity) insurance coverage. As price is common to all fields of a crop, revenues are mechanically more correlated than yields. Since aggregate insurance discourages diversification (i.e., encourages correlation), revenue coverage is a natural complement to aggregate insurance. This interaction between revenue coverage and aggregate insurance is not priced into the premiums farmers pay. This explains the take-up of revenue coverage and increased insurance payouts as farms switched to aggregate policies.

To evaluate the welfare impact of the subsidy, we quantify the costs and benefits of farms moving to aggregate insurance. The primary cost is the increase in insurance payouts to aggregate policy-holders due to changes in farmer production choices. The primary benefit of an aggregate policy is better income-smoothing, as more protection is offered against systemic risks but less against idiosyncratic risks. However, secondary benefits and costs may arise if diversification affects costs and expected yields. The farmer might realize additional benefits from reducing diversification if that allows for higher productivity (e.g., crop specialization) but this must be weighed against utility costs from increased variance in their income. The government may incur increased costs if the reduction in diversification also decreases the mean yield (e.g., irrigation). Our measure of cost is model-agnostic: we compare the total change in payouts due to any changes in farmer behavior. This captures actions that affect mean yield, diversification, or both. It includes the specific ex-ante production decisions we observed (e.g. crop diversity, irrigation) as well as possible unobserved farmer actions.

We estimate the impact on insurance payouts of behavioral changes as farms switch to aggregate insurance (Section 5.1). Payouts (net of premiums) for aggregate insurance increased by $10.40 per acre, which is approximately 20% of average insurance payouts under separate insurance. Scaled by 145 million acres enrolled in aggregate insurance, this translates to an increase of total program cost per year of approximately $1.5 billion, against a $10.5 billion annual FCIP program cost. The majority of the payout increase comes from the unpriced interaction between revenue coverage and aggregate insurance; changes in irrigation, wheat diversity and farm size explain a smaller portion. The remainder could be explained by various other production practices that we do not observe, such as seed choice, fertilizer use and fallow decisions, that can contribute to diversification through differences in field-by-field application.

We quantify the increased value in aggregate policies by calibrating a model for farmer utility

(Section 5.2). We specify a parsimonious model in which the high-dimensional joint distribution of farm yield is reduced to three states: a systemic risk occurs (i.e., all fields receive an insurance payout), an idiosyncratic risk occurs (i.e., some fields receive a payout, some do not), or no risk occurs. We use pre-reform, separate insurance data to estimate the probabilities and payoffs in each of these states. Using these estimates, and the administratively defined premiums and subsidies in separate and aggregate insurance, we calibrate the insurance value as if each farm swapped to an aggregate policy. Our estimates are sensitive to assumptions on risk aversion, but generally the first dollar of aggregate insurance has benefits that exceed costs.

With the farmer utility and costs in hand, we derive and estimate a Baily-Chetty (see Chetty (2006)) style formula that trades off the insurance value of scope against changes in farmer behavior. We include first-order changes to farmer utility that arise from non-marginal policy shifts. Specifically, we parameterize the space of contracts between aggregate and separate and evaluate the costs and benefits of each, assuming it is the only policy offered. The benefit of each additional dollar of 'aggregate-ness' is decreasing, since the insurance value diminishes. Inversely, the marginal costs increase as the fiscal impacts of diversification are stronger for a progressively more aggregate contract. We find that a fully aggregate contract is never optimal. The exact location depends on assumptions regarding risk aversion, but in our upper (i.e., most aggregate) estimate, it lies roughly halfway between a fully separate and a fully aggregate contract.

Literature Review. We contribute to multiple literatures. First, there is an extensive and long-standing literature studying the optimal scale of insurance as balanced against moral hazard[6] and adverse selection.[7] Relatedly, a literature, going back to Holmstrom (1982), examines optimal contract design when there are multiple tasks (or multiple team members) that require effort.[8] Most relevantly, Breuer (2005) and Lee et al. (2024) show that the optimal insurance contract with two risks or repeated losses, respectively, is generally a complicated function of the entire joint distribution of losses.[9] Our contribution is to introduce and formalize the concept of contract scope, which determines whether insurance focuses on systemic or idiosyncratic risk,[10] and to show

[6]For example, Baily (1978), Chetty (2006), and many subsequent papers.

[7]For example, Fluet and Pannequin (1997), Solomon (2024a) and Nguyen (2018) have studied how bundling multiple risks together alleviates or exacerbates the problem of adverse selection. Relatedly, various papers (e.g. Ho and Lee (2019), Shepard (2022), Lavetti and Simon (2018), Geruso et al. (2019), Starc and Town (2015), Wagner (2023)) show how bundling insurance with other contract features (e.g. prescription drug formulary design) can select for a low-cost insured pool.

[8]Additional papers studying optimal multidimensional contracts include Holmstrom and Milgrom (1987), Gibbons and Murphy (1992) and Baker (2002).

[9]In Appendix A.3 we study how the optimal contracts derived in Breuer (2005) and Lee et al. (2024) relate to our definitions of separate and aggregate contracts.

[10]There is an imperfect analogy to the banking literature in which the implicit public insurance through bailouts affects ex-ante risk-taking behavior. Specifically, when implicit social insurance is only provided for systemic shocks, not bank-specific idiosyncratic risks, banks correlate their portfolios with one another (see, e.g. Acharya et al. (2015), Farhi and Tirole (2012), Acharya and Yorulmazer (2007) and Gropp et al. (2011)). A policy to reduce systemic risk has the flavor of separate insurance: Philippon and Wang (2022) suggest a tournament structure for bailouts that encourages banks to do well when their peers do poorly, thereby dampening incentives to correlate their portfolios.

how incentives to diversify risk are directly relevant to changes in scope.[11]

Second, there have been numerous studies of the effects of changes in the FCIP on farmer risk-mitigation behaviors such as chemical and water usage, crop choice, and farm specialization.[12] The most closely related work is Bulut (2020), which analyzes the 2008 subsidy to aggregate insurance and exhibits time series evidence on the take-up of aggregate insurance. Their evidence on take-up is consistent with our causal analysis in Figure 1. Relatedly, there is a literature studying the projected changes in the spatial concentration of agricultural risk due to climate change.[13] Our contribution is to show how the nature of risk — idiosyncratic versus systemic — is endogenous to farmer decisions and the incentives provided by insurance.

2 The Optimal Scope of Insurance

In this section we formalize the idea of scope in insurance design and explain a fundamental insurance/incentive trade-off. An extended model with greater detail, N risks, welfare results, and weaker assumptions is in Appendix A. To match our empirical analysis of crop insurance, we use the terminology of farmers as agents and fields as distinct risks. However, as we discussed, our model applies to any setting in which there are multiple risks that might be aggregated (or not) into a combined policy.

A farmer has 2 fields. Their yields are $X = (X_1, X_2)$, and π_X is the density of their joint distribution function. The farmer chooses three actions: field-specific efforts e_1 and e_2 and a level of diversification d, at (separable utility) cost $\psi(e_1, e_2, d)$. Field-specific efforts $e_i, i = 1, 2$ shift[14] the marginal distribution of yield on field i, without affecting the correlation structure. These actions capture 'regular' moral hazard that affects mean output, as is considered in typical binary risk settings such as Baily (1978) and Chetty (2006). In contrast, diversification d affects the correlation structure of the joint distribution but not the marginal distribution of yield on either field.[15]

[11]The analogue in an agency theory setting with multiple projects is whether contracts depend on either total output or project-specific output, which will affect the agent's incentives to choose projects with correlated outcomes.

[12]Smith and Goodwin (1996) document a link between crop insurance and chemical input use, with insured farms spending about $4 less per acre in total on inputs than non-insured farms. Deryugina and Konar (2017) show that 1% higher crop insurance acreage increases water withdrawals for irrigation by 0.2%. Annan and Schlenker (2015) show that crop insurance reduces farmers' incentives to adapt to extreme heat, with insured corn and soybeans about 50% more sensitive to extreme heat than uninsured corn and soybeans. Huang et al. (2018) show that farmers adjust their crop choices based on private information about soil health during the period before planting and insurance choice deadlines, and exploit the exclusion of this information by the crop insurance program. Wang et al. (2021) find that crop insurance participation is generally associated with lower yield and higher variability of yield. O'Donoghue et al. (2009) find that increased crop insurance subsidies lead to more farm specialization and moderately higher efficiency, but that the gains are far lower than subsidy cost. Cornaggia (2013) find a causal link between the expansion of insurance and productivity.

[13]Klosin and Vilgalys (2022) estimate the impact of extreme heat on corn yields while Tack and Holt (2016) show that extreme weather events will increase the spatial correlation of risk, a trend that has already begun (Cheng and Yin (2022)). Various papers (e.g., Burke and Emerick (2016), Braun and Schlenker (2023), Kukal and Irmak (2020), Troy et al. (2015), Sharda et al. (2019), Wang et al. (2021) and Sweeney et al. (2003)) show how mitigation behaviors can help farms adapt to changing risk.

[14]In the sense of first-order stochastic dominance.

[15]A formal definition is given in Appendix A.1.

Intuitively, reduced diversification means systemic risk (i.e., low yield on both fields) is increased, but idiosyncratic risk (i.e., low yield on one field, high yield on the other) is decreased.

The government provides an insurance contract that pays $I(X_1, X_2)$ which depends on the yield on both fields. The farmer pays an actuarially fair premium $p = E_X [I(X_1, X_2)]$. The farmer chooses e_1, e_2 and d taking the contract and premium as fixed. The farmer solves:[16]

$$V(I,p) = \max_{e_1,e_2,d} \int_X U\left(X_1 + X_2 + I\left(X_1, X_2\right) - p\right) \pi_X(e_1, e_2, d) dx - \psi(e_1, e_2, d). \tag{1}$$

The government designs the insurance contract to maximize farmer welfare, subject to budget balance, and understanding that the contract will affect the farmer's private choice of e_1, e_2 and d. The government solves:[17]

$$W = \max_{I,p} V(I,p) \quad \text{subject to: } p = E_X [I(X_1, X_2)], \quad d = d^*(I,p),\ e_1 = e_1^*(I,p),\ e_2 = e_2^*(I,p). \tag{2}$$

The government wants to maximize farmer utility by providing insurance that smooths their income. However, this might affect the farmer's incentives to put in yield-increasing or diversification-increasing effort. Our aim is to illustrate the effects of changing the scope of insurance on income-smoothing and diversification incentives.

The government is considering two types of insurance contract at natural extremes of the scope spectrum: separate and aggregate.[18] In both cases, we assume the farmer is exposed to some risk; full insurance is not possible.[19] Our question is, in the second-best world, what effect does changing scope have on insurance and income-smoothing.

Definition 1. *If $I_S(X_1, X_2) = \phi_1(X_1) + \phi_2(X_2)$ for non-negative and weakly decreasing ϕ_1, ϕ_2, we say the policy is* ***separate****.*

[16] We assume that the farmer and government's objective functions are single-peaked in e_1, e_2, and d. In particular, the first-order condition is sufficient.

[17] Similarly, we assume that the government's (hypothetical) optimal choice, of e_1, e_2 and d, that accounts for the budgetary cost of changes in diversification, is single-peaked.

[18] In Section 5.3 we parameterize the space between these two extreme contracts and solve for the optimum. In Appendix A.1 we show that the propositions hold under more general definitions of aggregate and separate contracts.

[19] In the first-best benchmark, in which the government observes (or directly chooses) e_1, e_2 and d in addition to I and p, the farmer receives full insurance and optimal diversification effort is zero (see Proposition 3 in Appendix A.1). Since all variability in farmer income has been removed, there is no reason for any costly diversification d. However, the first-best is unattainable for multiple reasons. First, in this setting where gains and losses are both possible, full insurance requires negative insurance payouts; i.e., the farmer pays the government when yields are very high. This is essentially the farmer selling the farm to the government, which might not be desirable for other reasons. Second, as we show in Proposition 4 (in Appendix A), any amount of moral hazard on e_1 and e_2 means that full insurance is no longer optimal in the constrained second-best. Notably, the unobservability of the farmer's choice of diversification does not itself nullify the attainability of first-best full insurance. But once the farmer is exposed to some risk due to moral hazard with respect to field-specific effort, the unobservability of diversification affects the form of the second-best contract.

Definition 2. *If* $I_A(X_1, X_2) = \phi(X_1 + X_2)$ *for non-negative, weakly decreasing and convex* ϕ *we say the policy is* ***aggregate****.*

The critical difference is that the amount the aggregate contract pays for marginal loss on field one increases in the loss on field two, unlike in separate insurance. In other words, it provides more cover for systemic risks, but less for idiosyncratic risks. Mathematically, the aggregate contract is convex $\left(\text{i.e., if differentiable: } \partial^2 I_A/\partial X_1 \partial X_2 > 0 \text{ , for which a sufficient condition is that } \phi'' > 0\right)$ while the separate contract is not $\left(\text{i.e., } \partial^2 I_S/\partial X_1 \partial X_2 = 0\right)$. The strongest assumption is convexity in the aggregate contract, which we justify empirically[20] and theoretically.[21]

Convexity encodes the insurance rationale for an aggregate contract: the marginal payout for a given risk should increase in the loss from the other risks. But it also distorts diversification incentives: conditional on one field doing poorly, the farmer is more protected from losses on the other field under aggregate than under separate. This protection means they invest less in ensuring that one field does well if the other does badly; that is, they diversify less.

Actual FCIP policies are of this form. For example, if each field has an expected yield of \$100, $I_S(X_1, X_2)) = \max\{0, 100 - X_1\} + \max\{0, 100 - X_2\}$ and $I_A(X_1, X_2)) = \max\{0, 200 - X_1 - X_2\}$. The farmer bears all the risk/reward until yield drops below \$100 (\$200 in aggregate), after which they are fully insured. When there are no moral hazard concerns, an aggregate policy is preferred by the farmer.

Proposition 1. *Holding farmer behavior fixed, for every separate policy there is an aggregate policy that generates higher farmer utility.*

Because total farmer income, not field income, is welfare relevant, an aggregate policy offers better insurance. Separate policies are sub-optimal since they pay more when one field does well and one badly than when both fields do moderately well, even if total yield is the same. In the example above, field yields of \$80 and \$120 would leave the farmer with higher total insurance payout and final income than \$100 on each. A contract that pays slightly less in the former state and more in the latter would be preferred. Consequently, the farmer prefers that their contract (at least) equalizes payouts and consumption across states of the world with the same total yield; i.e., an aggregate policy.

Aggregate policies provide better insurance, but at the cost of incentives to diversify risk.[22] To

[20] All FCIP contracts are convex, and for example, all vertically differentiated contracts considered by Marone and Sabety (2022) are aggregate (in total medical spending) and satisfy these conditions. On the other hand, 'donut hole' contracts, as in Medicare Part D, do not. A convex contract requires that insured's cost-sharing decreases monotonically in the additional dollars of loss, whereas the donut hole policies have coinsurance that is high, low, high and then low again as medical spending increases.

[21] Here we assume convexity, but in Appendix A.1 we show that the optimal aggregate contract, prior to any considerations of scope, is convex under any of: administrative costs (Proposition 11), costly state verification (Proposition 12), insurer risk aversion (Proposition 13), or, under DARA utility (a) field-specific moral hazard with no restriction on the contracting space (Proposition 9), or (b) 'typical' moral hazard on the size of total loss (Proposition 10).

[22] A formal definition is given in Appendix A.1, but decreased diversification makes it more likely that field yields are all high or all low at the same time, without affecting the marginal distribution of yield on each field.

understand this, suppose the first field is hit by a shock and has very low yield. In a separate policy, the farmer receives a payout for the first field. But they stand to receive the full benefit from their second field doing well, as this will not interact with their payout from the first. The farmer values states of the world — idiosyncratic failure: one field doing well and one badly — that diversification makes more likely. On the other hand, in aggregate insurance, once one field does poorly, total income is low, and so the aggregate policy is likely 'in-the-money' (below $200 in the example). This means that some or all of the potential gains on the second field will just reduce, dollar-for-dollar, the insurance payout from the first field's low yield. Once the farmer is past the aggregate deductible, they no longer care about subsequent losses. Therefore, the farmer takes fewer diversification actions that prevent systemic failure.

The farmer does not account for the impact that their lack of diversification has on the fiscal cost of providing aggregate insurance. This creates a wedge between the planner, who internalizes this fiscal externality, and the farmer, who does not. This wedge makes the aggregate contract less attractive to the planner. There is no such wedge for separate insurance, where the cost of providing insurance depends only on each field's marginal distribution and is, therefore, independent of diversification. These facts are summarized in the following proposition.

Proposition 2. *Under the separate contract, the farmer's choice of d is equal to the planner's preferred level. Under the aggregate contract it is lower than the planner's preferred level and imposes a fiscal externality on the insurance program. When the farmer is close to risk neutral, the farmer's choice of diversification is lower under aggregate than separate.*[23]

Aggregate and separate contracts are the extremes of the scope spectrum. An aggregate policy provides better insurance, but misaligned private and social diversification incentives. The inverse is true for a separate policy. In line with the theory, Sections 3, 4 and 5 demonstrate that as farms move to aggregate insurance, they reduce their diversification which increases the cost to the government of providing insurance. However, a complete welfare analysis also must account for changes to field-specific effort e_1, e_2 and any other behavioral changes induced by the switch to aggregate insurance. We conduct that welfare analysis in Section 5.3 and then derive and solve a Baily-Chetty style formula for the contract with optimal scope.

3 Crop Insurance: Setting, Policy Changes, Data & Methods

3.1 U.S. Federal Crop Insurance

The vast majority of U.S. agriculture is insured through the Federal Crop Insurance Program (FCIP). The FCIP was established in 1938, but participation sharply increased in the 1980s and

[23] The assumption of low risk aversion for the final part of the proposition is sufficient but certainly not necessary. In Appendix A.6, we show in simulations calibrated to yield data that, at all plausible levels of risk aversion, the farmer chooses to diversify less under an aggregate contract than a separate. In Appendix A.5, we show in a two-risk four-state model, in which marginal increases in contract 'aggregate-ness' are readily defined, that this claim holds for all levels of risk aversion.

1990s when premium subsidies were introduced (FCI (1938)).[24] Currently, the FCIP insures over 85% of major crop acreage and 73% of eligible specialty crops, totaling over $150 billion in liabilities in 2021.[25] The annual cost of the FCIP, including premium subsidies, is approximately $10 billion. The FCIP is part of the broader 'farm safety net,' which also includes direct price subsidies, loans and credit access, and ad hoc disaster assistance.[26]

The FCIP insures crops against a wide variety of hazards. This includes risks from the natural environment (e.g., drought, flood, hail, insects), market risk (e.g., price decline) and operational risk (e.g., equipment failure). The typical policy insures yield or revenue according to the farm's historical average. The premium paid is determined by crop type, location, yield history, price variability, contract type, and other factors (United States Department of Agriculture, Risk Management Agency (2021)).[27] The government subsidizes the majority of the premium cost, and the farmer pays the rest.

3.2 Policy Change for Scope

In the FCIP, farmers choose between insuring each field of a crop separately or all of the fields in aggregate.[28] Both the separate and aggregate contracts are crop-specific. Crucially, the premium subsidies for separate versus aggregate contracts have varied over time. The subsidy change impacted different crops at different times. This variation allows us to identify the effects of the scope of the contract on other farmer behaviors.

In 2009, the subsidy for aggregate policies was increased for eleven eligible crops (grain sorghum, wheat, soybeans, corn, cotton, rice, barley, canola, flue-cured tobacco, pecans, sunflowers).[29] In 2015, three new crops were made eligible for aggregate insurance with its increased subsidy (dry peas, dry beans, and popcorn). All other crops have not been treated as of 2023. As shown in the first two rows of Table 1, prior to the reform, aggregate policies and separate policies received the same subsidy, which ranged from 38% to 67% depending on the coverage level.

[24] Rationales for the public provision of crop insurance include the Samaritan's dilemma (Deryugina and Kirwan (2018)), the aggregate nature of the risk (Solomon (2024b)) and private information (Huang et al. (2018)).

[25] The private crop insurance market is approximately 5% of the size of the FCIP (National Association of Insurance Commissioners (2024)), and typically only covers idiosyncratic risks such as hail.

[26] We focus solely on the FCIP, and show in Appendix B.17 that the FCIP policy changes we study did not substantively interact with other farm safety net programs.

[27] Because a farmer's premium is personalized to their farm's risk, a pecuniary externality from adverse selection such as occurs in competitive markets with a single price is less of a concern here. For a comprehensive analysis of the effects of contract bundling on selection, see Solomon (2024a).

[28] We show in Appendix B.3 that there is substantial variation in yield outcomes between adjacent fields and even within fields. This makes the choice to insure at the farm versus field level quantitatively consequential.

[29] The rationale for the policy was to incentivize take-up of aggregate policies by equalizing the *dollar* amount of subsidy received (United States Department of Agriculture (2009)). Since aggregate policies have lower premiums, this means the subsidy *per premium dollar* increased.

Table 1: Subsidies for Aggregate and Separate Policies

	Subsidy (%)							
Coverage Level	**50%**	**55%**	**60%**	**65%**	**70%**	**75%**	**80%**	**85%**
Separate Policies	67%	64%	64%	59%	59%	55%	48%	38%
Aggregate Policies (Pre-reform)	67%	64%	64%	59%	59%	55%	48%	38%
Aggregate Policies (Post-reform)	80%	80%	80%	80%	80%	77%	68%	56%

Notes: This table displays premium subsidy percentages for aggregate and separate policies before and after the reform. Subsidies are defined per dollar of premium and differ by coverage levels. The reform does not change the subsidies for separate policies, whereas the reform increased the subsidies for aggregate policies.

The reform increased the subsidy for aggregate policies by 13-22%, depending on the coverage level. The average increase, given the policies chosen, was 16%. Take-up of aggregate policies increased by over 20% as a result. We study the effect of insurance scope on farm production choices that impact diversification by comparing crops treated with the subsidy increase to those not (yet) treated, and, independently, by comparing farms that swapped to aggregate insurance to those that remained in separate.

3.3 Data

3.3.1 FCIP Summary of Business

Our first data source is the FCIP Summary of Business (United States Department of Agriculture (USDA) (2024)). The FCIP data include all annual crop insurance contracts. The data include contract type, acreage insured, premium paid, total potential liability, subsidy amount, insurance payout amount and loss ratios. The data are at the county-crop level, not the farm level.[30] We use FCIP data from 2003 to 2023.

Summary Statistics. Table 2 presents summary statistics from the FCIP data, split into aggregate and separate policies. The average premium is approximately \$46 per acre for separate policies, and about \$45 for aggregate policies. These premiums insure expected yield of approximately \$440 (separate) to \$513 (aggregate) per acre. Of these premiums, the separate policies receive a substantially lower subsidy than aggregate policies: \$25 relative to \$32. The average payouts are similar: \$35 for separate versus \$32 for aggregate. This leads to loss ratios (premiums relative to payouts) of about 70% for both separate and aggregate policies.

[30] For most of our analysis, the farm-level implications of results estimated at the county-crop level are clear. Most outcomes are 'monotonic' in the sense that, e.g., an extra irrigated acre in a county has to mean an extra acre was irrigated on a farm. The only outcome for which this implication might not hold is crop diversity, where we might have crop diversity increasing at the county level while it decreases at the farm level. We give more detail and check for this in Section 4.3.1.

The bottom four rows of the table foreshadow the patterns that we investigate causally in the next section: farms in aggregate insurance irrigate less, plant a less diverse crop mixture, and choose revenue (rather than yield) insurance. This could be due to moral hazard or selection. Our empirical methods aim to remove the latter to isolate the former.

Table 2: Summary Statistics

	Separate			Aggregate		
	Mean	SD	Acres x Years	Mean	SD	Acres x Years
Premium Per Acre ($)	46.32	58.25	0.93	44.87	23.30	1.08
Subsidy Per Acre ($)	25.21	34.96	0.93	31.55	16.25	1.08
Payout Per Acre ($)	35.19	102.74	0.93	32.34	66.64	1.07
Insured Amount Per Acre ($)	439.66	501.80	0.93	513.94	258.84	1.08
Loss Ratio	0.72	1.32	0.93	0.70	1.44	1.07
Irrigated	0.21	0.41	0.93	0.08	0.27	1.08
Revenue Insurance	0.76	0.43	0.93	0.96	0.21	1.08
Yield Insurance	0.19	0.39	0.93	0.03	0.18	1.08
Diversity (Small Grains Only)	0.08	0.20	0.12	0.02	0.10	0.10

Notes: This table presents summary statistics for all insured crops, differentiated by enrollment in aggregate versus separate insurance. The data are all FCIP insured field crops from 2003 to 2023. Acres are expressed in billions. Means and standard deviations are weighted by acres insured. The diversity measure is calculated only for the 'small grains' (wheat, oats, canola and barley).

The advantage of the FCIP data is that it covers all crops, treated and not treated, and it includes the universe of crop insurance contracts. The main disadvantages are that the data are at the county, not farm level, and that only a narrow set of outcomes are measured (for example, most farm production practices, except those on which insurance is priced, are not included).

3.3.2 USDA Agricultural Resource Management Survey (ARMS)

To complement the FCIP data, we use the Agricultural Resource Management Survey (ARMS). ARMS is an annual survey conducted by the USDA that collects farm-level data about land use, crops planted, farm finances, chemical use, and various other production practices.[31] ARMS is randomly resampled every year. We construct a panel by considering farms that 1) were surveyed once before and once after the policy change and 2) were surveyed in years in which data on the scope of insurance is collected. This allows for a within-farm difference-in-differences analysis.

[31] There are multiple parts to ARMS. The Phase II survey rotates between crops and asks about production practices on a randomly selected field of that crop. The Phase III survey, the Cost and Returns Report, gathers detailed data about farms' overall finances, production expenses, resource use, and costs. The outcomes in Phase III (in particular, yield per acre) are observed each year and therefore allow us to run an event study. However, Phase II rotates between crops, hence outcomes are only observed once before and once after treatment. This is why our primary ARMS analyses are difference-in-differences.

Subject to these requirements, we use all ARMS data from 2003 to 2022.

The advantages of ARMS are the broad set of data collected about production practices and the farm-level granularity. There are two important disadvantages. First, we have scope data only on three crops, wheat, corn and soy, that were all treated in 2009. Because we cannot perform a between-crop comparison, we instead compare farms that swap to aggregate insurance to farms that do not, and instrument for the endogenous take-up choice. Second, ARMS is a far smaller dataset, leading to precision issues at times.

The FCIP and ARMS data are complementary. The drawbacks of the former are the strengths of the latter, and vice versa. Whenever possible, we perform the same analysis in both settings with similar results.

3.4 Econometric Methods & Identification

We use two primary econometric strategies: 1) a between-crop specification that compares crops that were treated with the policy change against control crops that were not; 2) a within-farm comparison that compares farms that do and don't swap to aggregate insurance, pre- and post-reform.

TWFE - Between-Crop. We use the FCIP data and a between-crop analysis that exploits the fact that different crops were treated at different times, or not at all, by the policy change. In these specifications, we measure outcomes at the county, crop, and time-to-treatment t level. We include fixed effects for county-crop $\alpha_{county,crop}$ and for calendar year γ_{year}. Observations are weighted by acres insured and standard errors are clustered at the crop level. We estimate a two-way fixed effect specification:

$$y_{county,crop,t} = \alpha_{county,crop} + \gamma_{year} + \tau_t \mathbb{1}[t] \times \mathbb{1}[\text{Crop} = \text{Treated}] + \epsilon_{county,crop,t}. \quad (3)$$

Identification relies on a parallel trends assumption: absent treatment, outcomes for the treated and control crops would have evolved in parallel. In Appendix B, we check the robustness of our results to the well-documented issues that arise in TWFE specifications with staggered treatment.

DiD - Within-Farm. We use the ARMS data to compare outcomes on farms that swapped to aggregate insurance after treatment to those that did not. We study the three crops on which we have scope data from ARMS: corn, soybeans and wheat — the three most-planted crops (by acreage) in the US.

We estimate difference-in-differences specifications. Outcomes of interest include irrigation, crop diversity, land use, conservation choices and revenue insurance enrollment. We include fixed effects for farms α_f and years γ_{year}. Standard errors are clustered at the farm level, and we weight by

ARMS prescribed weights to ensure population representativeness. We estimate:

$$y_{f,year} = \alpha_f + \gamma_{year} + \tau \mathbb{1}\left[year \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{ft}. \quad (4)$$

Instrumental Variable Correction. Our primary identification concern is that the treatment indicator is an endogenous farm choice. To overcome this, we instrument for post-treatment insurance choice with the pre-treatment county-level treatment exposure. Specifically, we compute, in each county and in the year prior to treatment, the proportion of insured acres, premium dollars, payout dollars and liability dollars that were in crops about to be treated. Instrumental relevance is essentially mechanical: a farm in a county that grows entirely treated crops is more likely to swap to aggregate insurance than a farm in a county that grows almost entirely untreated crops. We illustrate the strength of the first-stage in Appendix B.1.

The exclusion restriction is that the instrument affects the outcomes only through the decision to swap to aggregate insurance. A threat to the exclusion restriction would be if certain counties were on differential trends that were correlated with their pre-treatment crop mixture. These concerns are mitigated because our other empirical method, the between-crop comparison, accounts for type of county-level confounding by comparing treated and control crops within the same county.

We will estimate specification (4) and the IV version (4IV). The results are very similar in magnitude, although the latter are less precise. Specification (4) is a valuable complement to (3) since it is estimated on farm-level outcomes and does not rely on comparability of the treatment and control crops. The IV correction, which uses variation at the county level, functions as a robustness check to the farm-level specification.

DiD - Variability of Yield. While specification (4) is ideal when we observe data at the farm level, an important outcome - the variability in yield per acre - cannot be measured at the farm level in the same way. This is for two reasons. First, variability requires multiple observations of yield per acre to compute, and so cannot be measured at the farm-year level. Second, since ARMS is randomly resampled each year, there are essentially no farms observed multiple times both before and after the reform.

We overcome these issues by pooling farms based on year and eventual treatment status after 2009: farms that swap to aggregate versus farms that remain in separate. We label this eventual scope decision by s. We compute the variability of yield per acre in each of these pools in each year and estimate the specification:

$$y_{s,year} = \alpha_s + \gamma_{year} + \tau \mathbb{1}\left[year \geqslant 2009\right] \times \mathbb{1}\left[\text{Farms that Swap to Aggregate }\right] + \epsilon_{s,year}. \quad (5)$$

To overcome similar endogeneity concerns, we will also estimate a version of (5) that uses the same IV design, which we label (5IV). Specification (5) allows us to see if the cross-section of farms that swap to aggregate insurance becomes more variable than those that remain, controlling for any pre-reform difference in variability.

4 Results - Aggregate Insurance and Reduced Diversification

This section analyzes the impact on farmer behavior of changes in insurance scope. We show that the subsidy increase caused many farmers to switch from separate to aggregate insurance. We demonstrate that, after swapping to aggregate insurance, farmers reduced the diversification on their farms.

Ideal Data. Ideally, we could observe yield on each field and directly compute intra-farm diversification. Unfortunately, these data are not available. Instead, we take a two-pronged approach. First, we use an 'ex-post' proxies for decreased diversification: increased variability across farms in total farm yield. Second, we study changes in 'ex-ante' production practices that impact diversification: crop diversity, irrigation and farm size. Additionally, as a purely financial mechanism to affect correlation across fields, we study the inclusion of price risk in the insurance contract.

4.1 Effects on Scope Choice

The increase in subsidy to aggregate insurance caused a sharp increase in take-up.[32] Using the FCIP data, we analyze the proportion of insured acres that are in separate insurance. Figure 1 displays the estimated coefficients from the between-crop event study specification (3).

Following the subsidy increase, there is a substantial movement from separate insurance to aggregate insurance. In the first year post-treatment, 15% of acres swapped to aggregate insurance, rising to over 20% after five years. This is a sharp change to the scope of insurance. In Appendix B.14, we show that there is no change in the total acres insured. Thus, it is farms previously in separate insurance, not uninsured farmers, that are moving to aggregate insurance. Moreover, this demonstrates that farms are not swapping from control to treated crops in order to receive the aggregate insurance subsidy.[33]

4.2 Moral Hazard: Reduced Diversification

4.2.1 Effect on the Variability of Farm Yield

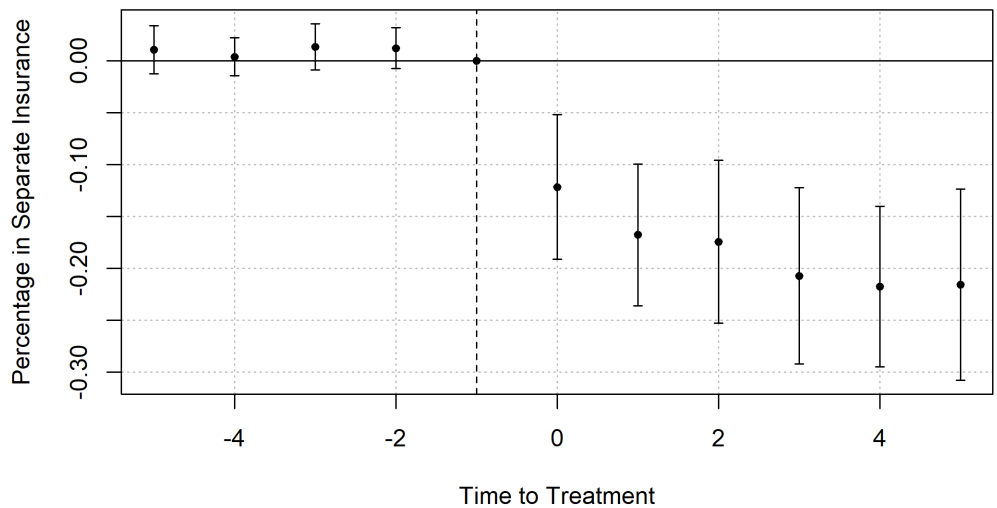
We proxy for intra-farm diversification with the variability of total farm yield. When a farm is more diversified, it is less likely that all fields do well or poorly simultaneously. Hence, increased farm-level variability is consistent with (but doesn't necessarily imply) reduced field-level diversification. This is formalized in Proposition 17 in Appendix A.7.

We estimate specification (5) where the outcome is the coefficient of variation of farm yield per

[32] These results are similar to the time-series evidence in Bulut (2020).

[33] There are large fixed costs to farming a new crop, both agricultural and financial. In particular, since the FCIP insures crops based on historical average yield, when no such history exists the crop is insured based on 65% of the county's historical average. This is a large insurance-based disincentive to farm a new crop, on top of all the agricultural and informational costs involved.

Figure 1: The Impact of Subsidy Increases on Scope Choice



Notes: This figure displays estimates of the impact of the policy change on enrollment in separate insurance. The outcome is the percentage of all insured acres that are enrolled in separate insurance. The estimating equation is (3). Standard errors are clustered at the crop level, and the coefficients τ_t are graphed with 95% confidence intervals.

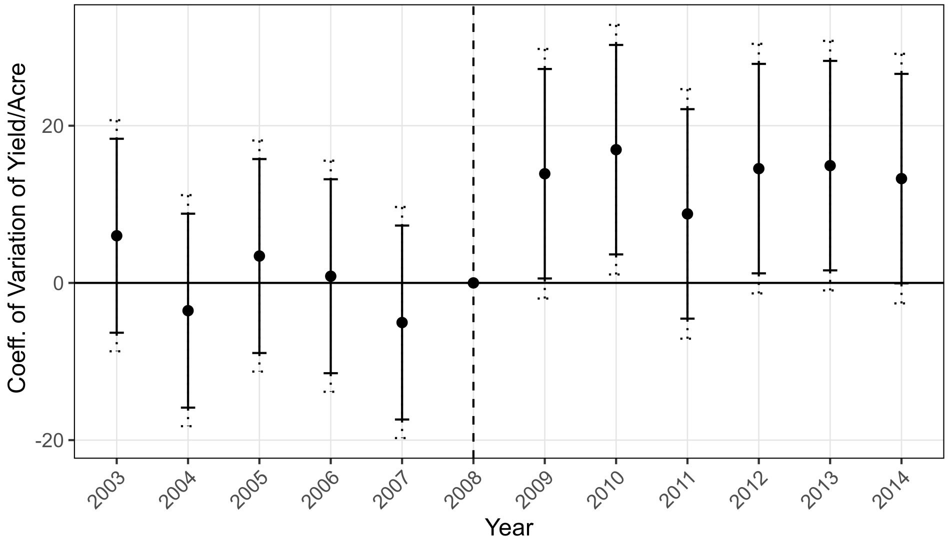
acre[34], defined at the level of pre- versus post-reform and whether a farm swapped into aggregate insurance or remained in separate.[35] The results are in Figure 2. The top panel shows the event study when the crops are pooled (and crop fixed effects are included). The bottom panel shows the crop-specific DiD estimates, with and without the IV correction.

The coefficient of variation of yield substantially increased in the cross-section of farms that moved to aggregate insurance. Pooled over all crops, the variability increased by 14% of the mean yield. This ranged from 4% (soy) to 19% (corn). This is direct evidence for an increase in systemic risk: the cross-section of farm yields have increased in variability. This is consistent with each farm becoming more variable, but could also be due to an increase in between-farm variability. To rule out the latter, in Appendix B.4, we estimate the within-farm variability changes on the small sample of farms that were surveyed at least twice before or twice after the reform. The (noisy) results there demonstrate that the effect we observe here is driven largely by within-farm increases in variability, consistent with reduced diversification at the farm level. Additionally, we show in Appendix B.20 that these results are robust to alternate measures of variability.

[34]The coefficient of variation is equal to the standard deviation divided by the mean.

[35]The FCIP data do not include data on farm yield, only insurance payouts. For that reason we cannot estimate specification (3) for this outcome.

Figure 2: The Effect of Scope Reforms on the Variability of Farm Yield



Variability of Farm Yield/Acre	DiD				DiD with IV			
	Corn	**Wheat**	**Soy**	**All Crops**	**Corn**	**Wheat**	**Soy**	**All Crops**
Coeff. of Variation	18.58*	17.63·	4.13	13.45**	37.24	5.75	4.33	15.55
	(8.39)	(8.68)	(3.73)	(4.14)	(24.17)	(23.34)	(6.83)	(10.01)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Crop FE				✓				✓
N Farms	1,059	499	1,004	2,562	1,059	499	1,004	2,562
F-statistic	-	-	-	-	277	41	80	161

Notes: This figure displays estimates of the impact of the policy change on the variability of farm yield per acre. The outcome is the coefficient of variation of farm yield per acre. In the top panel, the estimating equation is (5), time-specific treatment effects are estimated, all three crops are included as well as crop fixed effects. 95% (dotted) and 90% (solid) confidence intervals are reported. In the bottom panel, a single (DiD) treatment effect is estimated for specification (5), separately for each crop as well as for all crops combined (with crop fixed effects included). Standard errors are reported in parentheses. */**/*** denotes statistical significance at the 10%/5%/1% levels. Observations are weighted by the ARMS prescribed weights to ensure population representativeness.

4.3 Mechanisms for Decreased Diversification

To explain the increase in the variability of yield (Section 4.2.1), we study three farmer production decisions that impact the ex-ante diversification of their crop.

4.3.1 Crop Diversity

Planting multiple varieties of a crop increases farm diversification. However, this is not incorporated into the pricing of an aggregate unit.[36] As farmers move to aggregate insurance, their incentive to plant a diverse mixture of crops is weakened. We formalize this in Proposition 19 in Appendix A.7.

We focus on four 'small grains': wheat, barley, canola and oats. These four crops have similar sub-types recognized by the FCIP. Each crop has two primary varieties: spring and winter. The spring variety is planted in March or April and harvested in the late summer. The shorter growing season means lower average yield, but with no risk from winter hazards. In contrast, the winter variety, planted in November or December, must survive the winter. If it does, expected yields are higher. If a farmer chooses aggregate insurance, all varieties of the crop are included in that policy. If they choose separate insurance, each variety is insured separately.

We measure crop diversity with Shannon entropy.[37] Specifically, if $p_{w,f,t}$ ($p_{s,f,t}$) is the proportion of winter (spring) variety of the crop in unit (farm or county) i and year t, with $p_{w,f,t} + p_{s,f,t} = 1$, then the entropy is given by

$$\text{Entropy}_{f,t} = p_{s,f,t} \ln\left(p_{s,f,t}\right) + p_{w,f,t} \ln\left(p_{w,f,t}\right). \tag{6}$$

Higher entropy means more diversity, and if only one variety is planted the entropy will be zero.

In the top panel of Figure 3, we estimate the between-crop specification (3), comparing wheat, canola and barley (which were treated in 2009) against oats (which was not treated). In the bottom panel, we estimate within-farm specification (4) that compares wheat farms that swapped to aggregate to those that did not, with and without the IV correction.

After the reform, crop diversity declines by approximately 0.03 (between-crop) to 0.09 (within-farm). The difference is due to only approximately a quarter of the acres in the treated crops (top panel) actually taking up aggregate insurance, whereas all of the treated farms (bottom table) have changed scope. A reduction in entropy of 0.09 is equivalent to a farm moving from a 50:50 to a 68:32 mixture of winter:spring wheat. This is direct evidence for a reduction in diversification as farms move to aggregate insurance.

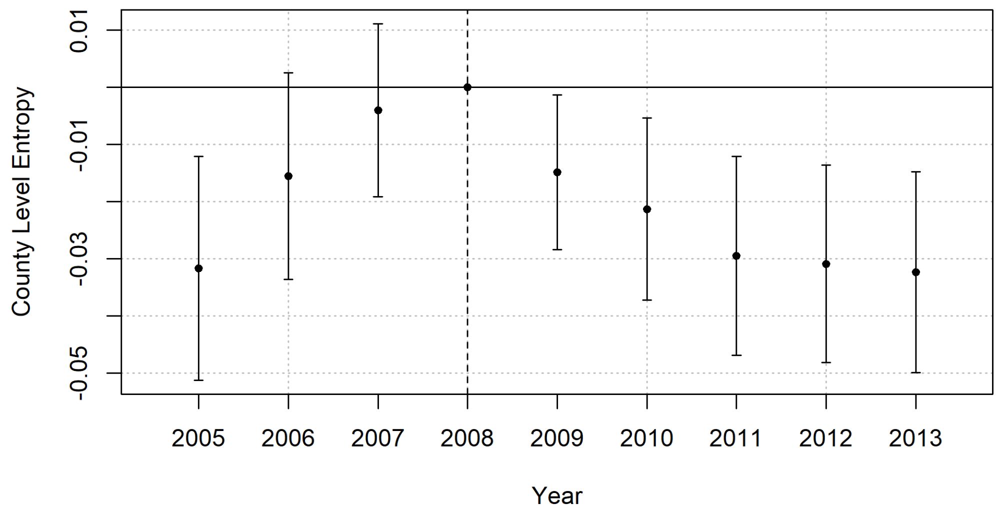
Policy Reversal in 2022 Until 2022, if a farmer chose aggregate insurance, all varieties of a crop (e.g. spring and winter wheat) were included in one policy. In 2022, the FCIP made an additional policy change that 'de-aggregated' aggregate insurance for wheat only. Specifically, a farmer who planted spring and winter wheat could now have distinct aggregate policies for each. This removes the incentive to reduce diversification introduced by the the initial 2009 policy change.

Our ARMS data ends prior to 2022, and so we use the FCIP data to conduct a within-wheat

[36] The expected yield and price insured for each field do vary with the variety of crop planted. However, the premium for an aggregate policy, relative to the field specific separate policy, does not incorporate the level of diversification.

[37] Using alternate measures of diversity such as the Inverse Simpson Index or Gini-Simpson Index yield identical results, which we report in Appendix B.13.

Figure 3: The Effect of Scope Reforms on Crop Diversity



Estimate of τ	DiD	DiD with IV
Entropy	−0.13**	−0.09*
	(0.06)	(0.05)
Farm FE	✓	✓
Year FE	✓	✓
N	363	363
F−statistic	-	11

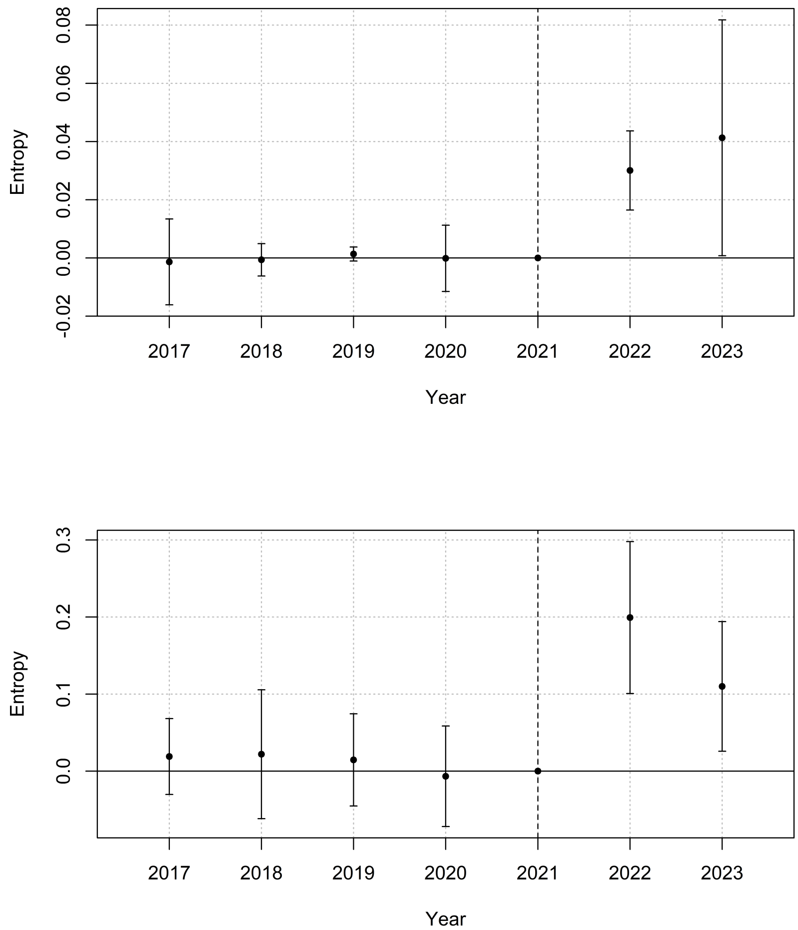
Notes: This figure displays the effect of aggregate insurance enrollment on crop diversity, before and after the 2009 policy change. The outcome is the entropy of the mixture of crops grown, defined in (32). The top panel compares three treated crops (wheat, canola and barley) to the control crop (oats). The estimating equation is (4), observations are weighted by acres insured and 95% confidence intervals are displayed. The bottom panel compares wheat farms that swapped to aggregate insurance to those that did not. The estimating equation is (3), weighted by the prescribed ARMS population weights, and */**/*** denotes statistical significance at the 10%/5%/1% levels.

comparison. The within-wheat comparison is preferred since a) one of the control crops was distinctly treated with eligibility for aggregate insurance in 2023, polluting our comparison,[38] and b) as shown in Appendix B, there is no selection bias to be concerned about. That is, no wheat acres moved from separate to aggregate after 2022; rather those already within aggregate changed their behavior. We estimate specification (5) at the county level with entropy as the outcome. The results are in the top panel of Figure 4.

Because we do not have farm-level data available for this policy change, there is a concern regarding the implications of county-level changes in diversity for farm-level diversity. In particular, suppose

[38]Nevertheless, in Appendix B.16, we use synthetic DiD to run a between-crop analysis and obtain very similar results.

Figure 4: The Effect of ‘De-aggregating’ Reforms on Crop Diversity



Notes: This figure shows the change in crop diversity before and after the 2022 policy change that ‘de-aggregated’ aggregate insurance by variety for wheat. The outcome is the entropy of the mixture of crop grown, defined in (32). The treated group are wheat acres enrolled in aggregate insurance, the control group are wheat acres enrolled in separate insurance. The estimating equation is (5) and the coefficients τ_t are graphed with 95% confidence intervals. The top panel is estimated on all counties in the dataset, the bottom panel restricts to counties with zero wheat diversity prior to the policy change (i.e., in 2017-2021). Observations are weighted by acres insured.

a county is majority winter wheat prior to the reform, but at some farms are majority spring wheat. If the only treatment effect was that those majority spring wheat farms planted more spring wheat, *county-level* diversity would increase, but *farm-level* diversity would decrease on every farm. To check for this, we also estimate specification (5) restricted to counties with zero entropy prior to the reform. For those counties, since all farms are growing the same variety of wheat prior to the reform, any increase in county-level diversity must mean farms are also becoming more diverse. This is also an additional check against selection: since all farms were growing the same single type of wheat prior to the reform, there is no selection bias based on differential pre-treatment diversity.

Those results are in the bottom panel of Figure 4.

Diversification increases sharply after the policy reversal. As aggregate policies are 'de-aggregated' by wheat type, the incentive to reduce diversification is completely removed. This is true in the entire sample of counties, and even more strongly in the sub-sample of counties that had no wheat diversity prior to the reform. This confirms that farm-level diversification, as well as county level diversification, must have increased.

4.3.2 Irrigation

Irrigation is an important farming choice. Irrigation is costly but allows for high yield even in dry conditions. Irrigating a portion of a farm reduces sensitivity to precipitation and diversifies the farm's risk.[39] Almost half of US farms irrigate a portion of their farm, rather than irrigating none or all of their farm.[40]

A farm with no irrigation can entirely fail if there is a drought, whereas if a portion is irrigated it can produce high yields even if the rest of the farm does not. There is substantial heterogeneity in the returns to irrigation. As we show in Appendix B.8, the returns to irrigation are zero or marginally positive on vast portions of US cropland. This makes irrigation an active margin of adjustment for a substantial portion of farms.

Irrigation's effects on mean yield are, to an extent, included in each *field's* insurance premium: the insured quantity is higher and the price per bushel of insured yield is decreased, owing to the lower variance. However, the impact on diversification based on what proportion of the *farm* is irrigated is not priced into aggregate policies. Hence, since partially irrigating a farm increases diversification, we expect this to occur less as farms move to aggregate policies. We formalize this in Proposition 21 in Appendix A.7.

To test this, we analyze the proportion of acres that are irrigated relative to acres in any insurance. We estimate both the between-crop specification (3) and the within-farm (4). The results are shown in Figure 5.

The percentage of acres irrigated falls sharply in both specifications after the policy change. This is consistent with the incentive for aggregate policyholders to reduce their diversification.[41]

4.3.3 Land Use and Farm Size

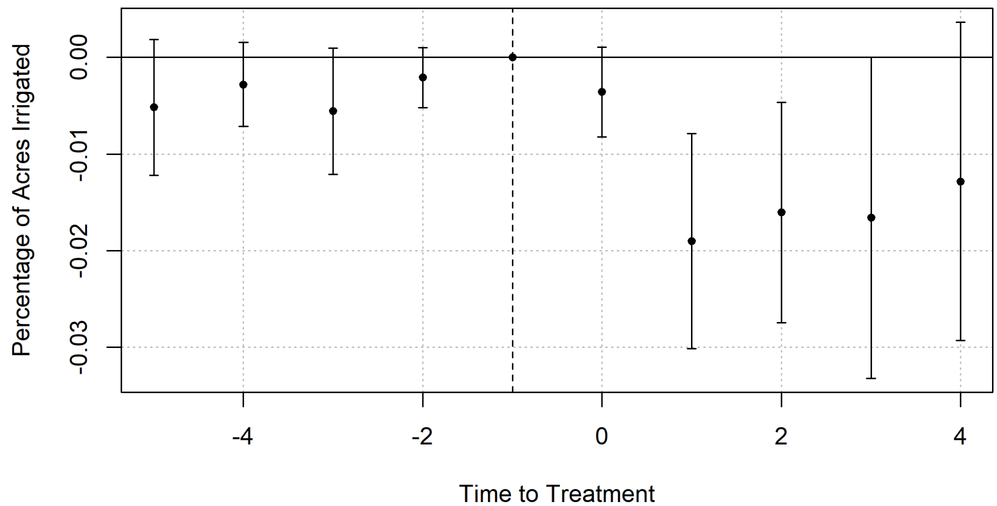
A large farm is more diversified than a small farm. On a small farm, a particular hazard can wipe out the entire crop. A much larger farm has more geographic diversification and any given shock

[39] See, for example, Troy et al. (2015), Sharda et al. (2019) and Sweeney et al. (2003).

[40] In 2018, Table 22 of United States Department of Agriculture (2019) shows that of 231,474 US farms, 26,169 irrigate none of their crop, 82,134 irrigate all of their crop, and the remainder irrigate a portion.

[41] In Appendix B.15 we perform the analysis separately for the western and eastern half of the US. The latter region has higher precipitation and relies less on irrigation. Thus, we expect irrigation to be more elastic in the East, whereas it is almost essential in the West. Consistent with this, the treatment effect is twice as large in the eastern states as in the western.

Figure 5: The Effect of Scope Reforms on Irrigation



Estimate of τ	DiD		DiD with IV	
Percentage of Farm Irrigated	−0.08 (0.05)	−0.06** (0.03)	−0.23*** (0.06)	-0.27 (0.17)
Farm FE	✓	✓	✓	✓
Crop x Year FE		✓		✓
N	735	735	733	733
F-statistic	-	-	7	3

Notes: This figure displays the effect of aggregate insurance enrollment on irrigation. The outcome is the proportion of all insured acres that are irrigated. The top panel estimates specification (3), weighted by total acres, with standard errors clustered at the crop level. 95% confidence intervals are shown. The bottom panel estimates specification (4), with various fixed effects as shown, weighted by the prescribed ARMS population weights. */**/*** denotes statistical significance at the 10%/5%/1% levels.

will affect less of the total crop. Hence, the incentives to farm marginal land should be dulled in an aggregate policy. We show this formally in Proposition 20 in Appendix A.7.

Additionally, by regulation, an aggregate unit combines all of the insurable crop in a county in which the farmer has a 'financial interest'. This includes land rented out and operated by others, even if the owner receives a fixed payment and does not have a claim to any of the output of the rented acres. This means if land a farmer owns and operates does poorly, but land rented out does well, the farmer might not receive an aggregate insurance payout even if they receive none of the upside from the rented acres. That is, rented-out land can 'pollute' the landowners' aggregate insurance policy.

For both of these reasons, farmers in aggregate policies are disincentivized from renting out or farm-

Figure 6: The Effect of Aggregate Insurance on Land Use

Outcome	DiD	DiD with IV
Acres rented out / Acres owned	−0.06**	-0.06
	(0.03)	(0.12)
Received any conservation income?	0.07***	0.057**
	(0.02)	(0.029)
Farm FE	✓	✓
Year FE	✓	✓
N	4,417	3,863

Notes: This figure displays the effect of aggregate insurance enrollment on land use and conservation decisions. The outcomes are the proportion of acres owned that are rented out, and whether a farm received any income from a conservation program. The specifications (4) and (4IV) are estimated, with farm and time fixed effects, weighted by the prescribed ARMS population weights. */**/*** denotes statistical significance at the 10%/5%/1% levels.

ing marginal land. To study this, we estimate the within-farm specification (4) for two outcomes: acres rented out relative to acres owned and whether any income is received from conservation programs. The results are in Table 6. These outcomes are not observed in the FCIP data and so a between-crop comparison is not possible.

We find that farms that swap to aggregate insurance reduce the land that they rent out, as a proportion of land owned, by 6%. However, the acres that were previously rented out are not subsequently farmed by the owner. Instead, they are 7% more likely to be enrolled in a conservation program. This is especially likely if the marginal acres are, geographically or in hazard exposure, detached from and therefore uncorrelated with, the bulk of the owner-operated farm.[42]

4.3.4 Price Risk

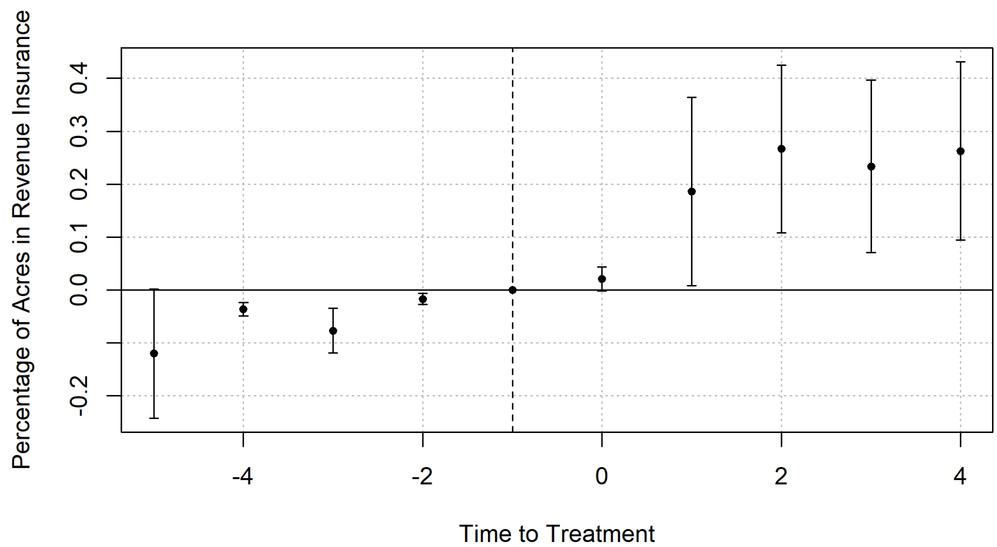
As a purely financial means by which to influence the correlation across fields, we show that farmers included price risk in their contract when they moved to aggregate insurance. In addition to the choice of scope (aggregate versus separate) a farmer can choose between insuring *yield* (quantity) or *revenue* (price × quantity).[43] Since price is perfectly correlated across acres, including price risk in the contract mechanically increases correlation in the risks being insured. We show this formally in Proposition 18 in Appendix A.7. Hence, since aggregate insurance pays more when risks are correlated, as farms move to aggregate insurance, they are incentivized to move from yield to revenue coverage.

We study the proportion of acres in revenue insurance relative to acres in any insurance. We

[42] To quote a farmer on a popular online agriculture forum: "When I was farming some riskier ground... I carried separate units... Now, I've since given up/lost the poorer ground I've went (sic) to [aggregate] units" (Community (2011)).

[43] The price being insured is the difference between harvest-time prices (typically July) and futures prices at the time of insurance choice (typically March).

Figure 7: The Effect of Scope Reforms on Revenue Insurance



Estimate of τ	DiD		DiD with IV	
Revenue Insurance Perc.	0.44*** (0.16)	0.46*** (0.18)	0.55*** (0.18)	0.61* (0.32)
Farm FE	✓	✓	✓	✓
Crop x Year FE		✓		✓
N	778	778	778	778
F-statistic	-	-	24	12

Notes: This figure displays the effect of aggregate insurance enrollment on revenue insurance (versus yield insurance) takeup. The outcome is the proportion of all insured acres that are enrolled in revenue insurance. The left panel estimates specification (3), weighted by total acres, with standard errors clustered at the crop level. 95% confidence intervals are shown. The right panel estimates specification (4), with various fixed effects as shown, weighted by the prescribed ARMS population weights. */**/*** denotes statistical significance at the 10%/5%/1% levels.

estimate the between-crop specification (3) and the within-farm (4). The results are shown in Figure 7.

We find a strong complementarity between enrolling in aggregate insurance and insuring price risk. The crops treated with the subsidy were almost 30% more likely to choose revenue insurance. Moreover, within soybeans, wheat and corn, the farms that swapped to aggregate insurance were 44-46% more likely to change to revenue insurance relative to the farms that remained in separate insurance. As farms insured price risk through the FCIP, they reduced their reliance on alternative price-hedging instruments. As we show in Appendix B.5, farms that swapped to aggregate insurance were 14% less likely to use a ‘production contract’, in which the price and quantity are contracted upon prior to harvest.

5 A Welfare Analysis of Optimal Scope

The increase in subsidy for aggregate policies enhanced insurance value for farmers but induced moral hazard on diversification that increased the cost of providing insurance. In this section, we quantify the costs and benefits of the reform and use these to estimate a Baily-Chetty style model for optimal scope. Importantly, our estimates account for *any* farmer behavioral changes as they switched to aggregate insurance, including diversification changes and field-specific effort changes. Moreover, since the reform was not marginal, we allow for first-order changes in farmer utility due to behavioral changes.

5.1 Costs: The Fiscal Impact of Moral Hazard

In this section, we estimate the effects on insurance payouts and premium subsidies of farmers swapping to aggregate insurance, reducing their diversification (i.e., d) and possibly changing their field-specific efforts (i.e., e_1, e_2). Importantly, we measure the total change in government cost, caused by either the specific actions that Section 4 documented changes to, or actions we have not directly measured but that still contribute to increased insurance payouts.

We define the Actuarial Cost Per Acre = (Payout-Premium)/Acres Insured. If the premiums were correctly set to be actuarially fair, this would be zero. This does not account for the subsidy per acre, which we analyze in Appendix B.2.[44] We estimate both between-crop and within-crop specifications to study the impact of the policy change on the actuarial cost per acre.

$$\frac{\text{Actuarial Cost}}{\text{Acre}}_{county,crop,t} = \alpha_{county,crop} + \gamma_t + \tau_1[\text{Year} \geqslant 2009]_t \times \text{Treated Crop}_{crop,t} + \epsilon \quad (7)$$

$$\frac{\text{Actuarial Cost}}{\text{Acre}}_{county,crop,t} = \alpha_{county,crop} + \gamma_t + \tau_2\text{Perc. Acres in Agg.}_{county,crop,t} + \epsilon \quad (8)$$

As before, to overcome the endogeneity of take-up of aggregate insurance in the within-crop specification (8), we instrument for the percentage of acres in aggregate insurance with the pre-reform county mixture of treated versus non-treated crops. The results are in Table 9.

Table 9 shows that reform was costly. The average acre that switched to aggregate insurance cost the government \$10.40 (\$8.59) using the between-crop (within-crop) specification. Scaled by 145 million acres that swapped to aggregate insurance by 2014, this translates to approximately \$1.5 billion per year in additional FCIP expenditure. This is almost 15% of the total annual FCIP cost. We emphasize this does not account for changes in subsidies, which add to the program cost. This is consistent with the raw summary statistics for corn, soybeans and wheat in the post-reform period (see Appendix B.9) in which the actuarial cost for aggregate units was almost \$11 higher than for separate units.

[44] The subsidy is an important fiscal component of the FCIP program, but, as a transfer from the government to the farmer, does not directly bear on the question of optimal insurance.

Table 3: The Increased Actuarial Cost of Aggregate Policies

Specification:	Between-crop (scaled)	Within-crop (IV)
Actuarial Cost/Acre	10.40***	8.59***
	(1.41)	(3.15)
FE: County x Crop	✓	✓
FE: Year	✓	✓
N	164.031	104.828

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: The effect of the enrollment in aggregate insurance on the actuarial cost (insurance payout minus premium) per acre estimated using the between-crop specification (column 1) and within-crop specification (column 2). The estimating equations are (7) and (8) respectively. The estimates in column 1 are scaled by the average take-up of 39%. In column 2, the percentage of crop x county enrolled in aggregate insurance is instrumented for with the pre-reform (2008) county percentage of crops (in acres, premium dollars, subsidy dollars and payout dollars) that were treated in 2009. Standard errors are reported in parentheses.

The markedly higher actuarial cost of aggregate policies, relative to separate policies, illustrates the fiscal cost of diversification changes. Aggregate policies were priced to be actuarially fair given historical yield and assuming there were no behavioral changes relative to separate insurance. As we have documented extensively, there were behavioral distortions. The additional $1.5 billion in actuarial cost includes all the effects of farmer behavioral changes on insurance payouts - changes in diversification, changes in average risk and so on. In Appendix B.10 we disaggregate the change in net payouts by the various diversification actions we studied earlier. We find that approximately $4.50 per acre is attributed to farmers swapping to revenue insurance, $0.50 per acre from each of diversification and irrigation reductions, and $0.05 from acreage reductions. This accounts for approximately $5.05 ($5.65 for wheat) of the $10.40 in increased payouts per acre estimated from Table 9. The remaining $5.35 ($4.85 for wheat) could be due to other changes in farmer production choices that we cannot observe (for example, the types of seed used, fertilizer application, crop rotations, and the decision to leave land fallow).

5.2 Benefits: The Value of Aggregate Insurance

We estimate the benefits to farmers of moving from separate to aggregate insurance. Aggregate insurance offers greater risk protection value to farmers, which needs to be weighed against the increased fiscal cost. Moreover, since we will consider non-marginal policy changes, first-order changes in output and costs associated with reduced diversification need to be incorporated. These include increased yield from less diversification (for wheat), lower yield but lower costs as irrigation declines, reduced rent but increased conservation income and so on. Note, while Table 4 reports dollar amounts per acre for interpretability, the utility calculation is done at the farm level.

To estimate the increase in insurance value for the farmer non-parametrically, we would need rich variation in the relative price of aggregate insurance. Since there are only two different price regimes in our data, this is not possible. Instead, we specify and calibrate a model for farmer utility. To simplify the problem, we assume there are three states of the world: the B(ad) state of the world: all fields on the farm receive a payout; the M(oderate) state of the world: some fields on the farm receive a payout, some do not; the G(ood) state of the world: no fields on the farm receive a payout.

We estimate the farmer income under separate insurance based on pre-reform FCIP data. These are reported in the left column of the top three rows of Table 4. Net of expenses (which we estimate to be 60%), each acre generates approximately \$58, \$92 or \$110, when all fields fail, some fields fail, or no fields fail respectively.[45] The details are in Appendix B.7.

When a farmer moves to aggregate insurance, their payoff in the 'some fields fail' state of the world decreases, and the 'all fields fail' state of the world increases. We compute these based on changes in FCIP payouts and subsidies, and at this step assume that the difference is actuarially fair (i.e., the changes in expected payouts from the some fields fail and all fields fail states cancel out). Any increases in payouts relative to premiums that is not actuarially fair will be captured on the government cost side. As shown in the right column of the top three rows of Table 4, the farmer is approximately \$3.50 better off (\$2.50 worse off) in aggregate insurance relative to separate insurance when all (some) fields fail.

However, as we have extensively documented, when farmers move to aggregate insurance, they change their diversification behaviors. Their changes in irrigation, crop diversity, and so on have two effects. One, the probabilities of being in each state of the world change. This is shown in the second section of Table 4. After farmers change their production practices, it is more likely all or some fields fail, and less likely that none do. Second, farmers' expected yield and costs of production change. As we discuss in the next section, for marginal policy changes, an envelope theorem would imply these cancel out, but as we consider non-marginal changes, we must account for them. These changes are reported in the third section of Table 4. For example, reduced irrigation decreases costs by approximately \$8/acre, but reduces income by \$9/acre. These are also scaled by the treatment effects estimated in Section 4, and reported in the 'Per Marginal Acre' column. For example, the change in income from wheat specialization is \$7 per changed acre, but because only 15% of acres changed with the policy (Section 4.3.1), this scales to \$1.05 per acre on the farm.

The bottom section of Table 4 combines the changes in income due to differences in contract payouts and from moral hazard. The changes in costs/income offset, but do not remove, the increased insurance value from aggregate policies. Income in the all fields fail state still rises, income in the some or no fields fail states still falls.

[45] This is consistent with United States Department of Agriculture, Economic Research Service (2023) which estimates that US net farm income per acre ranges from approximately \$50-\$150.

Table 4: Agricultural Income and Expense Analysis

Parameters	**Separate**	**Aggregate**	**Source**
Net Farmer Income Without MH = Yield + Insurance Payout - Farmer Premium - Expenses			
All Fields Fail	\$58.42	\$62.94	FCIP Data
Some Fields Fail	\$92.65	\$89.96	FCIP Data
No Fields Fail	\$110.54	\$110.54	FCIP Data
Probabilities of Each State			
All Fields Fail	0.13	0.14	FCIP Data
Some Fields Fail	0.26	0.27	FCIP Data
No Fields Fail	0.61	0.59	FCIP Data
Δ Income/Expenses Breakdown	*Per Marginal Acre*	*Per Acre on Farm*	
Irrigation:			
Water Expense	\$18.50	\$3.70	ARMS
Fuel Expense	\$23.85	\$4.77	ARMS
Irrigation Income Loss	-\$45.31	-\$9.50	See Appendix B.8
Land Use:			
Conservation Income	\$112.57	\$6.75	ARMS
Rental Income	-\$120.36	-\$7.22	ARMS
Diversification:			
(Wheat) Diversity Income Change	\$7.00	\$1.05	Swenson (2006)
Net Farmer Income With MH = Net Farmer Income Without MH + ΔIncome/Expenses			
All Fields Fail	\$58.42	\$61.44	FCIP Data
Some Fields Fail	\$92.65	\$88.73	FCIP Data
No Fields Fail	\$110.54	\$109.32	FCIP Data

Notes: This table presents key parameters for analyzing the impact of moving from separate to aggregate insurance. The top section shows net farmer income under separate versus aggregate insurance, excluding moral hazard effects. The second section displays the probabilities of each state of the world, where the changes in probabilities under aggregate insurance are due to behavioral changes (moral hazard). The third section breaks down changes in income and expenses due to various factors affected by the policy shift, including irrigation changes, land use alterations, and diversification impacts. The bottom section combines the initial income changes from the insurance shift with the moral hazard-induced changes in income and expenses, to compute the final net farmer income under both insurance regimes.

5.3 Optimal Scope

In this section we analyze the trade-off for optimal scope, and estimate it using the costs and benefits from the preceding sections. Specifically, we find the optimal *single contract*, as if it were the only insurance available. As we rely on estimates from the ARMS data, we restrict our analysis to wheat, soybeans and corn throughout.

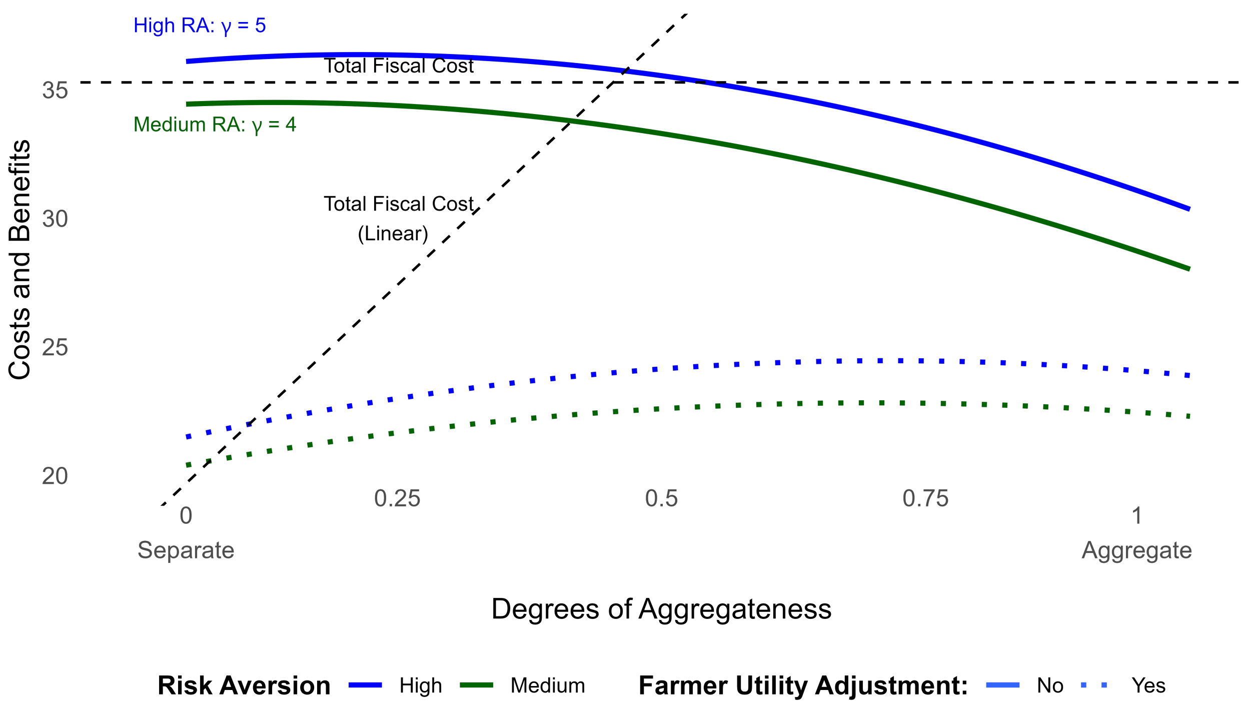
The planner chooses the 'aggregate-ness' of the contract to trade-off the costs and benefits as projected onto the three states of the world described previously. An aggregate contract pays \$1 more in the B (all fields fail) state of the world, and less in the M (some fields fail) state of the world. When the planner offers a marginally more aggregate contract, three effects occur. First, the direct insurance benefit of transferring a dollar from a low marginal utility state of the world to a high one. Second, any changes in utility and costs due to changes in farmer production decisions. If the policy change were marginal and farmers were optimizing, this would be zero. However, as we study non-marginal policy changes, this will be non-zero. Third, any changes in government payouts, net of premiums, resulting from changed farmer actions. Changes in farmer actions can also affect mean yield (e.g., irrigation), which is captured in our calculation. We do not include changes in the subsidy amount, which is a transfer from government to farmer with no direct efficiency consequences. We summarize these effects informally in (9) below.

$$\begin{aligned} \Delta\text{Welfare} &= \text{Increased Insurance Value} \\ &+ \text{Changed Farmer Utility/Costs due to Behavioral Changes} \\ &- \text{Increased Government Insurance Costs due to Behavioral Changes.} \end{aligned} \tag{9}$$

The optimal policy maximizes welfare by equating marginal benefits and costs. We derive this formally in Proposition 8 in Appendix A.1. Using the costs and benefits calculated in the preceding sections, we graphically illustrate the optimal policy. The benefits from a marginally more aggregated contract are illustrated by the colored lines in Figure 8. The solid lines include only changes in insurance value, the dashed lines include the adjustment for first-order impacts on farmer utility. The black dashed lines represent marginal government costs under two assumptions: constant marginal costs as estimated for the average county in Table 9, or linear marginal costs calibrated to match the average county's constant cost. These are, respectively, the horizontal and upward sloping black dashed lines in Figure 8. The linear estimate of marginal costs increases in the aggregateness of the contract as the costs (i.e., increased expected payouts) of reduced diversification are small when the contract is close to separate and large when the contract is close to aggregate. This is because, by definition, the payouts in a separate contract do not depend on diversification, and are only non-zero because of the mean effects of some diversification actions.

Under a high level of risk aversion (a coefficient of relative risk aversion of five), a contract marginally more aggregate than a separate contract delivers insurance benefits greater than costs. As shown by the dashed colored lines, the first-order impact of changes in farmer income and costs as the contract gets marginally more aggregate removes almost half of the insurance value. However, as the contract moves closer to aggregate, the marginal insurance value diminishes while the marginal impact of changes in farmer utility/costs becomes less negative, as the income loss/cost increase impacts the farmer when their income is higher. Under constant costs, the optimal contract is about halfway from separate to aggregate when only considering insurance value (shown by the intersection of the blue solid line and dashed horizontal black line). But the optimal contract is separate when changes to farmer utility/costs are accounted for (since the black dashed horizontal line is always above the dashed blue line). Under linear costs, the optimal contract is about halfway

Figure 8: Optimal Scope: Marginal Costs Versus Marginal Benefits



Notes: This figure illustrates the components (costs and benefits) of the Baily-Chetty formula (16) for optimal scope. The colored concave curves are the estimates of the marginal benefits of a marginally more aggregated policy at different levels of risk aversion. The solid lines include only the insurance value. The dashed lines also include changes in farmer utility from changed behaviors (i.e., these would be zero by an envelope theorem for small policy changes). The blue (green) lines use a coefficient of risk aversion of 5 (4). The horizontal line and upward sloping black lines are the marginal costs of a marginally more aggregated contract due to the fiscal externalities of changed farmer behavior. The horizontal line assumes constant marginal costs of increased aggregateness (as estimated in Table 9), the upward sloping line assumes linear marginal costs (as estimated in Table 12).

between separate and aggregate when we exclude changes to farmer utility/costs, and 10% of the way when we include them. Under lower levels of risk aversion, the insurance value of an aggregate contract is dramatically decreased, which pushes the optimal contract toward being separate.

Empirical estimates for farmer risk aversion range from 0.6 (e.g. Bar-Shira et al. (1997)) to over 4.9 (e.g. Menapace et al. (2013)). The levels of risk aversion shown in Figure 8 (coefficients of relative risk aversion of 4 and 5) are at the upper end of this range. As a result, under only the highest plausible estimates of risk aversion is the optimal contract even partially aggregate. At lower estimates of risk aversion, the optimal contract is separate.

Our method and the precise optimality condition in Proposition 8, can be applied to the wide variety of settings in which scope is relevant. The precision of these welfare calculations is naturally sensitive to the quality of the estimates of benefits and costs. In our case, the benefit side is a relatively speculative calibration, yielding quantitatively imprecise conclusions. In an ideal setting, there would be rich variation in the price of contracts of different scope, allowing for a non-parametric estimate of WTP for different levels of scope. This is a useful avenue for future work.

6 Conclusion

This paper analyzes the scope of insurance — whether multiple risks are insured in separate contracts or combined into one policy. Separate contracts provide better protection against idiosyncratic risk; aggregate contracts provide better protection against systemic risk. We show theoretically that aggregate contracts increase farmer risk protection, but that they lead the farmer to reduce their diversification, increasing systemic risk and the cost of providing insurance. In the context of the US FCIP, we demonstrate that as farmers move to aggregate insurance, they reduce various diversification behaviors (irrigation, crop diversity, and the farming and conservation of marginal acres) and they insure price risk. This leads to a marked increase in the variability of total farm yield. We derive and estimate a model of optimal insurance scope, and show that the optimal contract generally lies partway between a fully aggregate and a fully separate contract.

Our framework and model can be applied in many other settings with multiple risks that might be insured separately or together. In health insurance, different categories of care (e.g., inpatient and prescription drug coverage) could share a deductible or have their own. A family could share a deductible, or each individual could have their own. Similarly, the US tax system allows for couples to be treated as a unit, whereas unemployment insurance typically does not (i.e., spousal income does not affect the unemployment benefit someone receives). Moreover, the time period over which risk is insured is an instance of scope. Many insurance contracts are annual, encouraging concentration of losses within a year, as opposed to spreading them out over multiple years. The US corporate tax code allows for losses to be deducted against taxes for five years, implicitly insuring five years of income as the aggregate quantity. Proposals for long-term contracts to reduce reclassification risk need to account for the dynamic spending distortions that temporal aggregation would induce. Future research could apply this framework to additional risks and insurance products.

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A Theoretical Appendix

A.1 Generalized Theoretical Model

In this section we present a formal and more general model of scope for two risks. In particular, we analyze the interaction between 'regular' moral hazard that affects mean risk and moral hazard on diversification as is relevant to scope. In Appendix A.4, we extend this to N risks.

A farmer has 2 fields. The yield of field $i = 1, 2, \ldots, n$ is given by (the random variable) $X_i \in [0, \overline{x}]$. We write X for the joint distribution of yield across all fields, x for a specific realization of X, and π_x for the probability density function. The planner is utilitarian and provides an insurance contract that makes a payout $I(x)$ in state of the world x, that generally depends on the outcomes on all fields. The planner charges the farmer an actuarially fair premium $p = E_X[I(X)] = \int_X I(x)\pi_x dx$, to be paid in all states of the world.

The farmer chooses a level for three actions. Field one (two) (e_2) specific effort e_1 increases the marginal distribution of yield on that field only. Diversification effort d increases the probability that both fields have high yields or both fields have low yields simultaneously, but doesn't change the marginal distribution of yield on each field. By Sklar's theorem, we decompose the joint distribution into the product of the marginal distributions multiplied and the copula, and assume that e_1 (e_2) affects only the marginal distribution (with density $f_1(f_2)$, and CDF $F_1(F_2)$) of yield on field 1 (2) while d affects the copula (i.e., the correlation structure) but not the marginal distributions:

$$\pi_x(x_1, x_2; e_1, e_2, d) = f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d). \tag{10}$$

The cost of these actions is $\psi(e_1, e_2, d)$, which strictly increases in all arguments, is denominated in utils and paid in all states of the world. Moreover, assume the marginal cost of a small amount of effort (e_1, e_2 and d) is zero. Assume that e_i increases the marginal distribution in the sense of first-order stochastic dominance:

Definition 3. *For $i = 1, 2$, if $e_i' > e_i$ then $F_i(x_i; e_i) > F_i(x_i; e_i')$ for all x_i.*

Formally, define $\Gamma(F_1, F_2)$ to be the set of joint distribution functions with fixed marginal distributions F_1 and F_2. Following Denuit et al. (2006), we define diversification/correlation:

Definition 4. *Suppose $X, Y \in \Gamma_2$ and have CDFs F_X, F_Y respectively. We say that X is more diversified/less correlated than Y or that X precedes Y in the correlation order, written as $X \precsim Y$ when*

$$X \precsim Y \iff F_X(\boldsymbol{x}) \leqslant F_Y(\boldsymbol{x}), \quad \textit{for all } (\boldsymbol{x}).$$

The farmer's final income is $\sum_i X_i + I(X) - p$ and their utility function over income is U, which we assume to be twice continuously differentiable and concave. The farmer chooses e_1, e_2 and d to maximize their utility, taking the insurance contract I and premium p as given:

$$V(I,p) = \max_{e_1,e_2,d} \int_X U\left(\sum_i x_i + I(x) - p\right) dx - \psi(e_1,e_2,d). \quad (11)$$

The utilitarian planner's problem is to set the insurance contract I that maximizes farmer welfare, subject to farmer optimization and budget balance:

$$W = \max_{I,p} V(I,p) \quad (12)$$

$$\text{subject to: } p(e_1,e_2,d) = \alpha E_X\left[I(X(e_1,e_2,d))\right], \quad \text{(Budget Constraint)} \quad (13)$$

$$\text{subject to: } d = d^*(I,p), e_1 = e_1^*(I,p), e_2 = e_2^*(I,p). \quad \text{(Farmer Optimization)} \quad (14)$$

As in Section 2, the first-best (if the planner could directly choose e_1, e_2 and d) is full insurance.

Proposition 3. *The first-best contract is full insurance up to expected yield:* $I(X_1,X_2) = E(X_1 + X_2) - X_1 - X_2$. *First-best field-specific efforts are positive:* $e_1^* > 0, e_2^* > 0$. *First-best diversification is zero:* $d^* = 0$.

The first-best is unattainable when the farmer (not the planner) chooses e_1, e_2 and d for multiple possible reasons. First, 'full insurance' here means selling the farm to the government; the farmer is paid by the government when yields are low and pays the government when yields are high. If we require that $I(X_1,X_2) \geqslant 0$ as in a typical insurance program, this is ruled out. Second, and more substantively, when the farmer receives full insurance they have no incentive to exert any effort. This is not an issue with regards to d, since both the planner and farmer want $d^* = 0$ under full insurance. But, under full insurance the farmer has no incentive to exert any effort e_1 or e_2, whereas the planner prefers strictly positive e_1 and e_2 as they affect the cost of providing insurance. In summary, moral hazard on d alone is not sufficient to make the first-best unattainable, but moral hazard on e_1 and/or e_2 is. This is formalized in the following proposition.

Proposition 4. *If there is moral hazard only on diversification*[46]*, the first-best is attainable. If there is moral hazard on either field-specific effort,*[47] *the first-best is not attainable.*

From now on, we assume the first-best is not implementable and contrast two contracts with different scope in the second-best world: aggregate and separate.

Definition 5. *Suppose* ϕ, ϕ_s *are non-negative, continuous, weakly decreasing, and convex. If* $I_S(X) = \sum_i \phi_s(x_i)$ *then we say a policy is* ***separate****. If* $I_A(X) = \phi\left(\sum_i x_i\right)$ *then we say a policy is* ***aggregate****.*

Actual FCIP policies are of the this form. For example, if each field has an expected yield of \$100, $I_S(X) = \max\{0, 100 - X_1\} + \max\{0, 100 - X_2\}$ and $I_A(X) = \max\{0, 200 - X_1 - X_2\}$. The farmer

[46] That is, e_1 and e_2 are observable, but d is not

[47] That is, at least one of e_1 and e_2 are not observable.

bears all the risk/reward until yield drops below \$100 (\$200 in aggregate), after which they are fully insured. The strongest assumption is convexity in the aggregate contract, which we justify empirically[48] and theoretically.[49] The key characteristics of these contracts, which are sufficient as definitions,[50] are that

$$\frac{\partial^2 I_S}{\partial X_1 \partial X_2} = 0 \quad \text{and} \quad \frac{\partial^2 I_A}{\partial X_1 \partial X_2} > 0.$$

That is, under a separate contract, the payout the farmer receives from a loss on field one is independent of field two. In contrast, under an aggregate contract, a dollar of loss on field one receives a higher (marginal) payout when field two's yield is low than when it is high. For this reason, aggregate policies provide better income smoothing than separate policies. Formally:

Proposition 5. *Holding farmer behavior fixed, for every separate policy there is an aggregate policy that increases farmer utility.*

Intuitively, separate policies pay disparate amounts depending on the field-specific yields even if total yield is the same. For example, in an FCIP style policy $I_S = \max\{100 - X_1, 0\} + \max\{100 - X_2, 0\}$, the separate contract pays more when $X_1 = 120, X_2 = 80$ than when $X_1 = X_2 = 100$. A contract that smoothed income over (at least) these two states with the same total income is preferred by the farmer. This establishes that aggregate policies provide better insurance than separate. However, they distort diversification incentives. In particular, the socially optimal level of d solves

$$0 = \underbrace{\int_X U(\cdot)\frac{\partial}{\partial d}\pi_x(d)dx}_{\text{probability effect}} - \underbrace{\psi'(d)E_X\left[\frac{\partial U}{\partial p}\right]}_{\text{effort cost}} - \underbrace{\frac{\partial}{\partial d}E_X\left[I(X(d))\right]E_X\left[\frac{\partial U}{\partial p}\right]}_{\text{fiscal externality}}. \tag{15}$$

When the agent chooses their privately optimal level of d they maximize only the first two terms. They do not internalize the effect of their diversification action on the overall fiscal cost of the program. In particular, they do not account for the change in expected payout due to their diversification choice. This immediately leads to a wedge between private and socially optimal levels of d only in aggregate policies.

[48] All FCIP contracts are convex, and for example, all vertically differentiated contracts considered by Marone and Sabety (2022) are aggregate (in total medical spending) and satisfy these conditions. On the other hand, 'donut hole' contracts, as in Medicare Part D, do not. A convex contract requires that insured's cost-sharing decreases monotonically in the additional dollars of loss, whereas the donut hole policies have coinsurance that is high, low, high and then low again as medical spending increases.

[49] Here we assume convexity, but in Appendix A.1 we show that the optimal aggregate contract, prior to any considerations of scope, is convex under any of: administrative costs (Proposition 11), costly state verification (Proposition 12), insurer risk aversion (Proposition 13), or, under DARA utility (a) 'typical' moral hazard on the size of total loss (Proposition 10), or (b) field-specific moral hazard with no restriction on the contracting space (Proposition 9).

[50] Supermodularity or affinity (both super and submodular) are the equivalents when the contracts are not twice continuously differentiable.

Proposition 6. *Under a separate policy, the farmer chooses the socially optimal level of d. Under an aggregate policy, the private choice of d is lower than the social optimum.*

The expected payouts in a separate policy depend only on the marginal distribution of each field's yield. When diversification changes, only the copula in the joint distribution changes, not the marginal distribution. Hence, diversification doesn't change expected payouts, and so there is no fiscal externality wedge between the privately and socially optimal level of d. Diversification still does impact expected utility under a separate policy, but the farmer internalizes this.

On the other hand, under an aggregate policy, a change in diversification increases expected payouts. This is because aggregate policy payouts are convex in total (across-field) yield, (in particular, recall that $\partial^2 I_A/\partial X_1 \partial X_2 > 0$) and diversification makes it more likely that fields do well or do badly simultaneously.

While Proposition 6 signs the wedges between social and privately optimal choices of d within aggregate insurance, or within separate insurance, it takes a further assumption to order the private choices in each contract.

Proposition 7. *For a farmer who is sufficiently close to risk neutral, their privately optimal choice of diversification is higher under the separate policy than under the aggregate.*

Less diversification effort increases expected payout and thus, farmer income, under an aggregate payout. However, it also increases the variance of farmer income. For this reason, while a risk-neutral farmer will certainly decrease their diversification in an aggregate contract, we cannot guarantee every risk averse farmer will. In Appendix A.6 we calibrate numerical simulations to estimates for production functions from the literature, and find that under any reasonable parameter values, diversification effort does indeed decrease under aggregate policies.

Optimal Contract. We now derive a Baily-Chetty style formula that optimally trades off the costs and benefits of contract scope. For analytical convenience, and eventual estimation as in Section 5, we restrict the number of states of the world to be finite.

As shorthand, we write expected utility in generic state s as

$$U'(X^s) = U'\left(\sum_i x_i^s + I(X^s) - p\right) - \psi(e_1, e_2, d).$$

We write the probability of this state of the world occurring as $\pi^s = Prob(X = S^s)$. An insurance contract is then just a vector of payouts in each state of the world.

Proposition 8. *The optimal payout, $I(X^s)$ in state X^s satisfies:*

$$\underbrace{\pi_s \times \frac{u'(X^s) - E_X\left[u'(X)\right]}{E_X\left[u'(X)\right]}}_{\textit{Insurance Benefits}} + \underbrace{\frac{\frac{\partial d}{\partial I^s}\frac{\partial}{\partial d}E_X\left[u(X)\right]}{E_X\left[u'(X)\right]}}_{\textit{first-order U impact}} = \underbrace{\frac{\partial d}{\partial I^s}\frac{\partial}{\partial d}E_X(I(X))}_{\textit{F.E. from } d} + \underbrace{\frac{\partial e_1}{\partial I^s}\frac{\partial}{\partial e_1}E_X(I(X))}_{\textit{F.E. from } e_1} + \underbrace{\frac{\partial e_2}{\partial I^s}\frac{\partial}{\partial e_2}E_X(I(X))}_{\textit{F.E. from } e_2} \tag{16}$$

This formula generalizes the standard BC formula. It demonstrates that an expansion of insurance must balance gains from consumption smoothing against moral hazard that causes a fiscal externality. The left hand side shows the utility gain from reallocating money to alow-consumption high-utility state of the world by increasing the premium (hence the money comes from the 'average' state of the world). The second term, the first-order change in utility for the farmer when they alter their level of diversification d, is zero by an envelope theorem for small changes in d. In the empirical section, since we consider non-marginal policy changes, this term will not be zero. The right hand side shows the fiscal externality due to farmer behavioral changes. When insurance increases, the farmer changes their effort level, changing the probabilities of each state realizing and hence of each payout occurring. Since the farmer does not internalize the aggregate fiscal impact of these behavioral changes, it causes a fiscal externality.

We estimate a simplified version of this equation in Section 5.

A.2 The Optimal Aggregate Contract with Only Field-Specific Moral Hazard

The analysis in Section 2 and Appendix A.1 assumes the aggregate contract is convex. That convexity generates the fiscal externality of the farmer's diversification action. In this section, we show why 'regular' moral hazard that shifts the field-specific yield distributions, prior to considerations of scope, is convex. Additionally, in Appendix A.3 we show that the optimal contract is convex under a variety of different microfoundations found in the literature.

Prior to considering their diversification effort d, assume the farmer can choose field-specific efforts e_1 and e_2. As above, assume that effort e_i affects only the marginal distribution on field i and that diversification (which here we do not allow to change) affects the correlation structure through the copula:

$$\pi(x_1, x_2) = f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d).$$

Field-specific and diversification efforts incur a cost $\psi(e_1, e_2, d)$. To ensure monotonicity of the payout in loss, we assume that field-specific effort affects the marginal distribution of yield on that field in the sense of the monotone likelihood ratio property:

Definition 6. *Field-specific effort $e_i, i = 1, 2$ satisfies $\frac{\partial}{\partial x_i}\frac{\partial f(x_i;e_i)/\partial e_i}{f(x_i;e_i)} \leqslant 0$.*

Per Lee et al. (2022) and Milgrom (1981), this ensures that high losses on a specific field allow one to infer low effort.

In this section we study the optimal general contract, prior to considerations of scope and correlation, with unrestricted field-specific moral hazard. In particular, we show that a planner who is only considering e_1 and e_2 will, under natural conditions, choose a convex contract. This justifies the assumption we start with in Section 2 and Appendix A.1 in which we show that scope operates exactly on the convexity of contract versus diversification distortion margin.

The planner offers an insurance contract $I(x_1, x_2)$, that we assume to be continuously differentiable. They charge an actuarially fair premium

$$p = \int I(x_1, x_2) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2.$$

Writing $u(x_1, x_2) = u\left(x_1 - x_2 - p + I(x_1, x_2)\right)$, the planner's problem, when optimizing only for e_1 and e_2 (i.e., prior to considerations of scope) is:

$$\max_{I(x_1,x_2),e_1,e_2} \int u(x_1, x_2) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 - \psi(e_1, e_2, d)$$

such that:

$$(e_1, e_2) = \arg\max_{a_1,a_2} \int u(x_1, x_2) f_1(x_1; a_1) f_2(x_2; a_2) c(x_1, x_2; d) dx_1 dx_2 - \psi(a_1, a_2, d)$$

$$p = \int I(x_1, x_2) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2.$$

The first constraint ensures incentive comparability, the second budget balance. We assume the first-order approach holds, so that the IC constraint is replaced by the agent's first-order conditions for a_1 and a_2.

This allows us to state our main result, in terms of the coefficient of absolute risk aversion $ARA(x) = \frac{-u''(x)}{u'(x)}$ and the coefficient of absolute prudence $AP(x) = \frac{-u'''(x)}{u''(x)}$.

Proposition 9. *The optimal contract, assuming d is fixed, is convex iff $2ARA(x) < AP(x)$.*

This is very similar to the requirement that the coefficient of absolute risk aversion decreases in income (DARA). In particular, DARA requires that $ARA(x_1, x_2) < AP(x_1, x_2)$, and so the condition in Proposition 9 requires that absolute risk aversion decreases sufficiently fast. Empirically, DARA is the overwhelmingly common finding.[51]

We now show that, under in a variety of other models from the literature, the optimal contract prior to consideration of scope remains convex.

[51] Classical studies supporting DARA include Binswanger (1980) on Indian farmers and Antle (1987) on U.S. farmers. More recent evidence from American farmers is provided by Wang et al. (2020) for Midwest corn farmers, Belasco et al. (2020) for a comprehensive study of U.S. farmers' risk preferences, and Yu and Sumner (2021) for California almond growers.

A.3 Alternate Microfoundations for Convex Optimal Aggregate Contracts

In the theoretical model in the main paper, we assumed that insurance contracts had to be non-decreasing and convex. In this section we provide additional conditions under which, before considering scope, optimal contracts will be of this form. This, in addition to the empirical prevalence of convex contracts, justifies our assumptions in Definitions 1 and 2.

A.3.1 Moral Hazard on the Total Loss

The following is adapted closely from Lee et al. (2022). The farmer begins with (maximum possible) wealth W and faces risky losses X_1 and X_2 on each of his fields. The probability of any loss occurring is p. The farmer can put in costly effort e to improve his yield. The total loss is $X = X_1 + X_2$ and we assume, in the sense of Holmström (1979)'s informativeness principle, that X is a sufficient statistic for e. As such, we restrict our search for the optimal contract to functions of the total loss. Given effort e, the cumulative distribution of the total loss is $F(x;e)$ with density $f(x;e)$ Increased effort reduces the loss in the sense of first-order stochastic dominance: $\partial F(x;e)/\partial e < 0$. Further, we assume that effort satisfies the monotone likelihood ratio property (MLRP):

$$\frac{\partial}{\partial x}\frac{\partial f(x;e)/\partial e}{f(x;e)} \leqslant 0.$$

Proceed as in Lee et al. (2022), we state their main result:

Proposition 10. *(Lee et al. (2022)) Suppose* $u'''(x) > 0$ *and* $\frac{\partial^2}{\partial x^2}\frac{\partial f(x;e)/\partial e}{f(x;e)} > 0$. *The optimal contract is convex if* $2ARA(x) < AP(x) \quad$ *for all* x.

Similarly to Proposition 9, the optimal contract, prior to considerations of scope, is convex when the coefficient of absolute risk aversion decreases fast enough.

A.3.2 Loading Costs

Arrow (1963) assumes that payouts are non-negative and that the premium incorporates a loading over and above the expected payout. The optimal contract is then characterized by:

Proposition 11. *(Arrow (1963)): When insurance entails a fixed administrative cost, the optimal contract is convex. In particular, it is full insurance below a deductible.*

Conditional on the expected payout (i.e., conditional on some amount of the premium going toward the loading) income should be equalized across states in which a payout is made. This is why full insurance is offered beyond some level of loss. However, when there is a non-zero loading, the first dollar of insurance delivers a second-order gain to the insured but a first-order (loading) cost. For this reason, small losses are not insured and the insured bears these through the deductible.

A.3.3 Costly State Verification

In contrast to the assumption of an insurance loading, Townsend (1979) assumes that, a cost must be paid to verify the state of the world. He studies the game-theoretic equilibrium between the insurer and insured when verification is a strategic choice. He derives:

Proposition 12. *(Townsend (1979)): When there is a fixed cost of state verification, the optimal contract is full insurance below a deductible.*

A.3.4 Risk Averse Insurer

We (and the two papers above) have assumed that the insured is risk averse but the insurer risk neutral. There are plausible situations in which this is not true.

Raviv (1979) studies a model in which the insurer can be risk neutral or risk averse, and the costs of providing insurance are a general function of the payout (to mimic costs of state verification). Two of his leading results are stated below.

Proposition 13. *(Raviv (1979)): When the insurer is risk averse, or the costs of verification are convex in the loss, the optimal contract is convex. In particular, it features coinsurance above a deductible.*

By either justification, either risk or cost sharing, the insured should bear some or all of the first few dollars of loss, after which they should be substantially or fully insured.

A.4 Extending the Model to N Risks

In this section we extend the analysis of the prior section to a setting with N risks. The logic and intuition are similar, however stronger definitions of correlation are required.

The first main result, Proposition 5 holds true without any additional assumptions.

However, Proposition 7 requires additional assumptions. We present two alternate sets of assumptions that are sufficient. First, a natural, but stronger generalization of Definition 4. Second, a weaker generalization of Definition 4, but a stronger definition of convexity than in Definition 2.

First, the natural generalization of the correlation order to more than two dimensions is known as the 'super-modular' order, per Denuit et al. (2006) and Shaked and Shanthikumar (2007).

Definition 7. *Consider two joint distributions $X = (X_1, \ldots, X_n)$ and $Y = (Y_1, \ldots, Y_n)$ with the same marginal distributions. We say that $X \precsim_{SM} Y$ when $E(I(X)) \leqslant E(I(Y))$ for all supermodular functions I.*

Alternately, we can define a weaker generalization of the correlation order, which we call the 'strong correlation order' (hence, $\precsim_{SC}$).

Definition 8. *Consider two joint distributions $X = (X_1, \ldots, X_n)$ and $Y = (Y_1, \ldots, Y_n)$ with the same marginal distributions. We say that $X \precsim_{SC} Y$ when*

$$P(X_i > t_i, X_j > t_j) \leqslant P(Y_i > t_i, Y_j > t_j) \text{ for all distinct } i, j \in \{1, \ldots, n\}; \text{ and}$$

$$P(X_i > t_i, X_j > t_j, X_k > t_k) \leqslant P(Y_i > t_i, Y_j > t_j, Y_k > t_k) \text{ for all distinct } i, j, k \in \{1, \ldots, n\};$$

and so on for any combination of $4, 5, \ldots n$, risks.

Clearly, when $n = 2$ this reduces to Definition 4. When $n > 2$ the additional requirements are that the probability of any $i \in \{3, 4, \ldots, n\}$ realizing as large at once is higher under the more correlated Y than under X. Definition 7 nests Definition 8 since , for example, $P(X_i > t_i, X_j > t_j)$ is the expectation of the supermodular function $1(X_i > t_i, X_j > t_j)$ and so on. However, the weaker Definition 8 needs to be paired with an assumption on the higher order derivatives of the aggregate contract:

Definition 9. *We say that an aggregate contract $I_A(X)$ is strongly-convex when all ith order cross-partial derivates are weakly positive, for $i = 2, \ldots n$.*

A sufficient condition for this is that $I_A(X) = \phi\left(\sum_i X_i\right)$ with $f''(x) > 0$ and $f^{(i)}(x) \geqslant 0$ for $i = 3, \ldots, n$. Many or all of these higher order derivatives might be zero.

With these definitions we can state the analogue of Proposition 5 for n risks:

Proposition 14. *Suppose $X, Y \in \Gamma_n$. Under a separate policy, the farmer chooses the socially optimal amount of diversification d. If either ($X \precsim_{SM} Y$ and the aggregate contract is convex (as in Definition 2) or ($X \precsim_{SC} Y$ and the aggregate contract is strongly-convex) then the farmer's choice of d under the aggregate contract is socially suboptimal.*

A.5 A Stylized Binary Loss Example

In this section we formalize the idea of scope in insurance design and explain the novel insurance/incentive trade-off that scope generates. To build intuition, here we study a simple two-risk binary loss model. An extended model with continuous loss, N risks, additional results and weaker assumptions is in Appendix A.1. All the qualitative conclusions from this simpler model carry through to the more general setting. To match our empirical analysis of crop insurance, we use the terminology of farmers as agents and fields as distinct risks. However, as we discussed, our model applies to any setting in which there are multiple risks that might be aggregated (or not) into a combined policy.

A risk-averse farmer with a concave utility function $u(\cdot)$ begins with wealth w. They have two fields that face the possibility of (binary) losses L_1 on field one and L_2 on field two. The probability that neither loss occurs is π_0, the probability that only the loss on field one (two) occurs is $\pi_1(\pi_2)$ and the probability that both do is π_B. The farmer chooses three actions: field-specific efforts e_1 and e_2, and a diversification effort d at (monetary) cost $\psi(e_1, e_2, d)$. Field-specific efforts $e_i, i = 1, 2$ shift the marginal distribution of yield on field i, without affecting the correlation structure. These actions capture 'regular' moral hazard typical to binary risk settings such as Baily (1978) and Chetty (2006). In contrast, diversification d affects the correlation structure of the joint distribution but not the marginal distribution of yield on any single field.[52] Intuitively, reduced diversification means that the fields are more likely to both have low yield, or both have high yield, at the same time.

The government provides an insurance contract $I = (I_1, I_2, I_B)$ that consists of a payout if loss one occurs, if loss two occurs, and if both losses occur. The farmer pays an actuarially fair premium: $p = \sum_{s=1,2,B} \pi_s I_s$. In sum, consumption for the farmer when there is no loss is $c_0 = w - p$, when only loss one occurs $c_1 = w - p - L_1 + I_1$, and similarly for loss two or both losses: $c_2 = w - p - L_2 + I_2$ and $c_B = w - p - L_1 - L_2 + I_B$. The farmer makes their choice e_1, e_2 and d taking the contract and premium as fixed, and solves:[53]

$$V(I, p) = \max_{e_1, e_2, d} \sum_{s=1,2,B} u(c_s - \psi(e_1, e_2, d))\pi_s(e_1, e_2, d). \tag{17}$$

As shorthand, write $u_0 = u(c_0 - \psi(e_1, e_2, d)), u'_0 = u'(c_0 - \psi(e_1, e_2, d))$ and similarly for $u_1, u'_1, u_2, u'_2, u_B$ and u'_B. Finally, write $E(u') = \sum_{s=1,2,B} \pi_s u'_s$ for the average marginal utility.

The government designs the insurance contract to maximize farmer welfare, subject to budget balance and understanding that the contract will affect the farmer's private choice of e_1, e_2 and d. The government solves:[54]

$$W = \max_{I,p} V(I, p) \quad \text{subject to: } p = \sum_{s=1,2,B} \pi_s I_s, \quad d = d^*(I, p), e_1 = e_1^*(I, p), e_2 = e_2^*(I, p). \tag{18}$$

The government wants to maximize farmer utility by providing insurance that smooths their income. However, this might affect the farmer's incentives to put in yield-increasing or diversification-increasing effort. Consider the first-best benchmark, in which the government directly chooses e_1, e_2 and d in addition to I and p.

Proposition 15. *The first-best features full insurance $I_1 = L_1, I_2 = L_2, I_B = L_1 + L_2$, no diversification effort $d^* = 0$ and positive field-specific effort $e_1^*, e_2^* > 0$.*

In the first-best the planner provides perfect income smoothing to the farmer. Since all variability in farmer income has been removed, there is no reason for any costly diversification d. The planner

[52] A formal definition is given in Appendix A.1.

[53] We assume that the farmer and government's objective functions are single-peaked in e_1, e_2 and d. In particular, the first-order condition is sufficient.

[54] Similarly, we assume that the government's optimal choice of $e_1, e_2 d$, that accounts for the budgetary cost of changes in diversification, is single-peaked.

chooses e_1 and e_2 to equalize the cost of effort with the effect that increased effort has on the budget.

When the farmer, not the planner, chooses e_1 and e_2, the first-best is not attainable. Under full insurance, the farmer has no incentive to put in any field-specific effort. The planner prefers to expose the farmer to a small amount of risk, inducing positive field-specific effort. This has a first-order impact on the budget, but no first-order impact on farmer utility, since at full insurance the farmer's marginal utility is equalized across states. On the other hand, the farmer's control over d is not, itself, sufficient to make the first-best unattainable. The planner's and farmer's preferences over diversification are aligned under full insurance: both prefer $d^* = 0$. However, as we now study, in the constrained second-best, the farmer's choice of d can impose a fiscal externality on the cost of insurance that depends on the scope of insurance.

Proposition 16. *In the constrained second-best (18), the optimal contract* (I_1, I_2, I_B) *satisfies:*

$$(I_1): \quad \frac{u_1' - E(u')}{E(u')}\pi_1 = \frac{\partial E_s[I_s]}{\partial e_1}\frac{\partial e_1}{\partial I_1} + \frac{\partial E_s[I_s]}{\partial e_2}\frac{\partial e_2}{\partial I_1} - \frac{\partial \pi_1}{\partial d}\frac{\partial d}{\partial I_1}(I_B - I_1 - I_2) \quad (19)$$

$$(I_2): \quad \frac{u_2' - E(u')}{E(u')}\pi_2 = \frac{\partial E_s[I_s]}{\partial e_1}\frac{\partial e_1}{\partial I_2} + \frac{\partial E_s[I_s]}{\partial e_2}\frac{\partial e_2}{\partial I_2} - \frac{\partial \pi_2}{\partial d}\frac{\partial d}{\partial I_2}(I_B - I_1 - I_2) \quad (20)$$

$$(I_B): \quad \underbrace{\frac{u_B' - E(u')}{E(u')}\pi_B}_{\textit{Insurance benefits}} = \underbrace{\frac{\partial E_s[I_s]}{\partial e_1}\frac{\partial e_1}{\partial I_B} + \frac{\partial E_s[I_s]}{\partial e_2}\frac{\partial e_2}{\partial I_B}}_{\textit{Fiscal externality though } e_1 \textit{ and } e_2} + \underbrace{\frac{\partial \pi_B}{\partial d}\frac{\partial d}{\partial I_B}(I_B - I_1 - I_2)}_{\textit{Fiscal externality through } d}. \quad (21)$$

This is a generalization of two-state Baily-Chetty formula the two-risk four-outcome case. It illustrates the government's trade-off between insurance value and the fiscal externality from effort (e_1 and e_2) reductions.[55] Here, there is an additional term: a fiscal externality from changes in d induced by the insurance contract.

To understand the trade-off, consider the planner's optimal level of I_B. Per (21), raising I_B increases farmer utility, since it transfers a dollar from the average state (through an increased premium) to the lowest income/highest marginal utility state. However, because the farmer has more protection when both losses occur, they reduce their field specific efforts e_1, e_2 and their diversification d. This impacts the expected cost of providing insurance, an effect which the farmer doesn't internalize. The planner trades off the increase in insurance value against the fiscal externality from changed farmer behavior.

The farmer's choice of diversification and consequent budgetary impact depend on the scope of insurance. To analyze this, we define:

Definition 10. *A contract is* ***separate*** *when* $I_B = I_1 + I_2$*, a contract is* ***aggregate*** *when* $I_B > I_1 + I_2$.

[55] The (non-mechanical, i.e., operating through changed effort) impact of changing the payout in state s on the expected total payout is $\frac{\partial E_s[I_s]}{\partial e_1}\frac{\partial e_1}{\partial I_1} + \frac{\partial E_s[I_s]}{\partial e_2}\frac{\partial e_2}{\partial I_1} = \sum_{s=1,2,B}\left[I_s\left(\frac{\partial e_1}{\partial I_2}\frac{\partial \pi_s}{\partial e_1} + \frac{\partial e_2}{\partial I_2}\frac{\partial \pi_s}{\partial e_2}\right)\right]$ and similarly for the impact of changing I_2 and I_B.

The separate contract pays the same against loss one (I_1) regardless of whether loss two occurs or not. In contrast, an aggregate contract pays more when a loss occurs if the other loss has occurred than if it hasn't. This has three important implications.

Scope Implication 1. An aggregate contract offers better insurance to the farmer than a separate contract (with the same expected payout). Since full insurance is not optimal in the second best, farmer income under separate insurance is strictly lower when both risks occur than when only one does. The separate contract could be improved upon by paying a dollar more in the former state and a dollar less in the latter; i.e., by becoming more aggregate.

Scope Implication 2. An aggregate contract reduces farmer incentives to diversify. By definition, diversification makes it more likely that one loss occurs and the other doesn't and less likely that both do. Since an aggregate contract pays less in the former and/or more in the latter, the farmer has less to gain from diversification. Formally, since diversification decreases π_B and increases π_1 and π_2, any increase in I_B or decrease in I_1 or I_2 leads the farmer to diversify less.

Scope Implication 3. In an aggregate contract, the farmer's choice of diversification is lower than the planner's preferred level, and imposes a fiscal externality on the budget. In contrast, in a separate contract, the level of diversification the farmer chooses is the same as the planner's preferred level. This is because, by definition, whether both losses occur together or in isolation does not affect payouts against each loss. Formally, in a separate contract, the expected payout depends only on the unconditional probabilities of losses one and two occurring, which we assume diversification doesn't change. Since $I_B = I_1 + I_2$ in a separate contract, the final term of equations (19)-(21) is zero. In an aggregate contract, even if the unconditional probabilities do not change, the fact that risks are more likely to occur together, when payouts are relatively higher, means that diversification impacts the expected insurance payout. That is, when $I_B > I + 1 + I_2$, changes to diversification directly impact the cost of providing insurance.

As we show in Appendix A, these implications of contract scope remain true in a much more general setting: aggregate contracts provide better insurance value than separate, reduce incentives to diversify risk, and increase the government's cost of providing insurance. The remainder of this paper demonstrates the effects of contract scope on diversification choices in crop insurance. This culminates in Section 5.3, where we empirically estimate (a version of) (19)-(21) to find the contract with optimal scope.

A.6 Numerical Simulations of Diversification Changes

An unfortunate drawback of the final part of Proposition 2 is that it doesn't necessarily apply to all levels of risk aversion. We perform numerical simulations to demonstrate and help understand the qualitative conclusion of Proposition 2: more diversification is optimal under separate insurance.

This section describes a numerical exercise to analyze the impact of diversification on expected utility under separate and aggregate insurance contracts. The exercise uses data from the FCIP dataset from 2003 to 2008 for farms with exactly two fields. The analysis is performed for various commodities and coverage levels, yielding consistent conclusions. The specific example presented here focuses on soy.

Estimating Yield on Each Field. The first step in the analysis is to fit a distribution to the yield data for each commodity. Following Sherrick et al. (2004), we fit a beta distribution for field yield. The parameters of the beta distribution (α and β) are estimated by maximizing the log-likelihood of observed probabilities of yield falling below each coverage level threshold (0.5, 0.55, ..., 0.85 of expected yield). The observed probabilities are calculated from the actual FCIP data from 2003-2008. Figure 9 shows the estimated beta distribution for soybean yields.

Fitting the Joint Distribution Next, a Gaussian copula is used to model the dependence between yields on two fields. The correlation parameter (ρ) of the Gaussian copula is estimated by maximizing the log-likelihood of observed joint probabilities of yield outcomes (both below, one above one below, neither below) at each coverage level threshold (0.5, 0.55, ..., 0.85), using data on two-field farms from the FCIP dataset. The estimated correlation parameter for soybeans is $\rho = 0.68$.

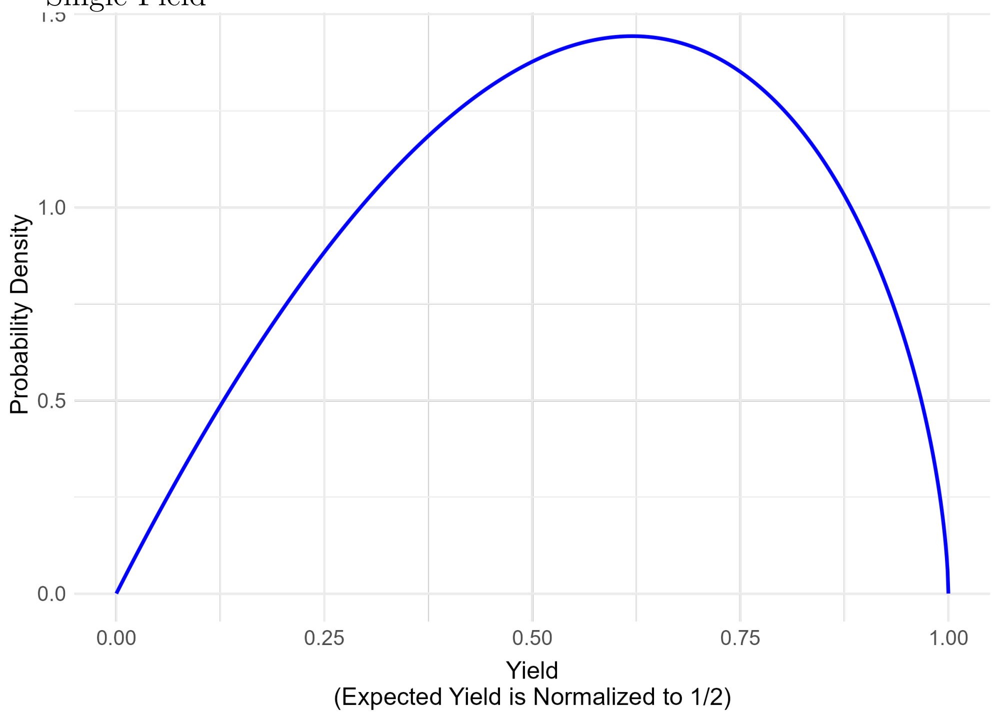
Simulating Yield Outcomes With the estimated parameters of the beta distribution and Gaussian copula, the next step is to simulate yield outcomes for two fields. First, 100,000 yield outcomes are sampled from the joint distribution using the estimated correlation parameter ($\rho = 0.68$). Then, another set of 100,000 yield outcomes is sampled from the joint distribution with a lower correlation parameter $\rho = 0.68 - 0.1$, representing a more diversified scenario. The premium for the insurance contracts is determined by the expected value of payouts under the original correlation parameter and remains fixed for the diversified scenario. This setup captures the moral hazard problem, where the farmer can change their diversification level after the premium is set. For each simulated yield outcome, the farmer's income and expected utility are computed under separate and aggregate insurance contracts, for different values of the coefficient of relative risk aversion (CRRA).

Results. The change in expected utility from increased diversification is calculated for both separate and aggregate insurance contracts, and plotted against the coefficient of relative risk aversion. Figure 10 shows this relationship for soybeans with a coverage level of 75%. The results are robust to other commodities and coverage levels.

Figure 10 demonstrates that the returns to diversification are uniformly higher under separate insurance contracts compared to aggregate insurance contracts for all coefficients of relative risk aversion (CRRA) up to 15.

This is clear evidence, which is robust to alternate specifications, that the effect on expected payout dominates the variance effect and makes diversification under aggregate contracts always less attractive than under separate.

Figure 9: Estimated Beta Distribution for Soybeans Yields on a Single Field



Notes: This figure illustrates the estimated beta distribution for soybean yields on a single field. Expected yield is normalized to be 1/2.

A.7 Relating Price Risk, Farm Size, Crop Diversity and Irrigation to Diversification

We have claimed that the ex-ante farmer behaviors studied in section 4 affect diversification. Moreover, that ex-post outcomes such as the variance of total farm yield are accurate proxies for changes in diversification. We formalize these claims below.

The Variance of Total Farm Yield as a Proxy for Diversification

Proposition 17. *As diversification decreases, the variance of total farm yield increases.*

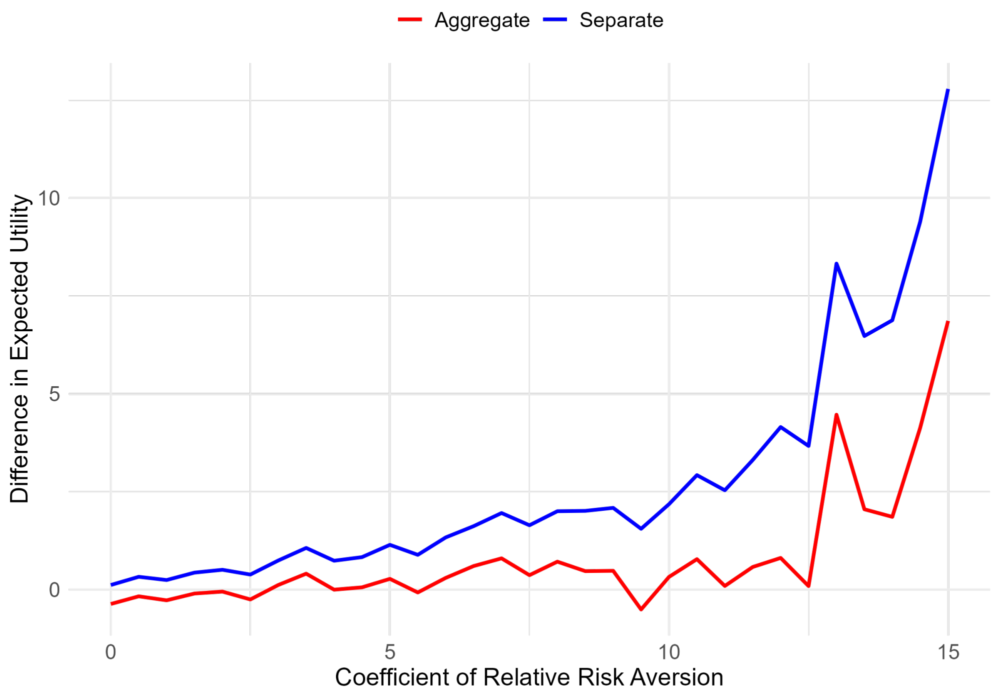
As noted in the main text, this is intuitive. A diversified farm is unlikely to have all fields do very well or very badly at the same time. As a result, it is unlikely that the total farm yield is very high or very low. In particular, the variance of total farm yield is lower when diversification is higher.

Revenue Insurance versus Yield Insurance

Write the yield on field 1 as X_1 and on field 2 is X_2, and revenue $R_1 = P \cdot X_1, R_2 = P \cdot X_2$. Since price is perfectly correlated across fields, we have:

Proposition 18. *Suppose that $P \perp X_1$, $P \perp X_2$ and that X_1 and X_2 have the same (marginal)*

Figure 10: Impact of Risk Aversion on Expected Utility from Crop Diversification Under Different Insurance Contracts



Notes: This figure illustrates the change in expected utility resulting from increased crop diversification under separate and aggregate insurance contracts. The x-axis represents the coefficient of relative risk aversion, while the y-axis shows the change in expected utility. The analysis is based on soybeans crops with a 75% coverage level, but the results are consistent across other commodities and coverage levels. This comparison helps to understand how different insurance structures interact with farmer risk preferences to affect the benefits of diversification.

distributions. Then we have

$$Corr(R_1, R_2) > Corr(X_1, X_2).$$

Crop Diversity Suppose a farmer is allocating their n fields among T types (for example, winter, spring, durum and khorasan wheat). Denote their portfolio by the vector of (integer number of) fields of each type: $(x_1, \ldots, x_T)$ with $\sum_{i=1}^{T} x_i = n$. Assume that all the fields of type $t \in T$ are i.i.d. (i.e., all winter wheat fields have the same distribution). Define the following types of portfolio. A **single-type portfolio** has $x_{t'} = n$ for some t' and $x_t = 0$ for all other t. A **mixed portfolio** has $x_{t'}, x_t > 0$ for at least two distinct types t, t'.

Then we have the following:

Proposition 19. *Any single-type portfolio is less diversified than a mixed portfolio. Evenly mixing over t' types is more diversified than evenly mixing over $t < t'$ types.*

Farm Size Suppose a farmer has N fields. They can choose to crop or conserve them. Assume only that the returns to a conserved field are i.i.d.. The yields on the cropped fields can have any dependence pattern. We then have:

Proposition 20. *The diversification of the per-field-portfolio increases in the number of fields farmed.*

Irrigation Irrigating some fields increases diversification in two senses. First, irrigated fields are a different 'asset' to non-irrigated fields, and to the extent they are less than perfectly correlated, adding some irrigated fields will diversify the risk in the non-irrigated fields. To see this, suppose a farmer has two fields. If they do not irrigate either, yield will be (the r.v.) X_N on each, whereas if they irrigate one the yield will be X_I. Trivially, the latter portfolio is more diversified than the former:$(X_N, X_I) \precsim (X_N, X_N)$.

In particular, the variance of the yield-per-field and of the total yield are lower. Moreover, the variances will decrease as the irrigated and non-irrigated field get less correlated.

A more general statement of this follows. Suppose a farmer has N fields. They can choose to irrigate them or not. Assume that irrigated fields are i.i.d. from some distribution, and non-irrigated fields are i.i.d. from another distribution. Then we have:

Proposition 21. *Going from no irrigation to some irrigation increases diversification. Maximal diversification occurs when half the fields are irrigated and half are not.*

A.8 Diversification and the three-state model

In the text we use the fact that diversification decreases the likelihood of the 'all fields fail' or 'no fields fail' states of the world, and increases the likelihood of the 'some fields fail' states of the world. We formalize that claim here.

Lemma A.1. *If X is more diversified than Y, $X \succsim Y$, then for any c, $P\left[\wedge_i X_i > c\right] \leqslant P\left[\wedge_i Y_i > c\right]$, $P\left[\wedge_i X_i < c\right] \leqslant P\left[\wedge_i Y_i < c\right]$ and for some disjoint and subsets of fields I, I' with $I \cap I' =$ and $I \cup I' = \{1, 2, \ldots, n\}$, we have $P\left[(\wedge_{i\in I} X_i > c) \wedge (\wedge_{i\in I'} X_i < c)\right] \geqslant P\left[(\wedge_{i\in I} Y_i > c) \wedge (\wedge_{i\in I'} Y_i < c)\right]$.*

This comports with the intuitive notion of 'more correlated'/'diversified'. A more correlated set of fields, with fixed marginal distributions, are more likely to all do well or do badly together, while it is less likely that some do well while others do poorly.

B Empirical Appendix

B.1 The First Stage of the Exposure IV

To illustrate the power of our instrument in predicting take-up of aggregate insurance after the 2009 policy change, we run the following event study.

$$\text{Perc. in Separate Insurance}_{county,crop,t} = \alpha_{county,crop} + \gamma_t \tag{22}$$
$$+ \beta_1 \text{ Perc. of 2008 Insured Acres Exposed to Treatment} \tag{23}$$
$$+ \beta_2 \text{ Perc. of 2008 Premium Dollars Exposed to Treatment} \tag{24}$$
$$+ \beta_3 \text{ Perc. of 2008 Subsidy Dollars Exposed to Treatment} \tag{25}$$
$$+ \beta_4 \text{ Perc. of 2008 Insured Crop Exposed to Treatment} + \epsilon \tag{26}$$

After estimating the event study, we predict the outcome (i.e., take-up of separate insurance) for each observation and then average these predictions in each year, weighted by acres insured. The resulting year-specific predictions of take-up are plotted below. We present versions with and without county-crop fixed effects. In the version with county-crop fixed effects, we estimate using a random sample of 25% of the county-crops for computational tractability.

Both panels of Figure 11 show that the exposure IV has strong predictive power for the take-up of aggregate insurance. By 2014, the IV predicts an almost 15% drop in the percentage of acres in separate insurance, which is approximately 3/4 of the effect size seen in the between-crop comparison (Figure 1). This demonstrates the relevance of the IV.

B.2 The Effects of the 2009 Reform on Subsidies

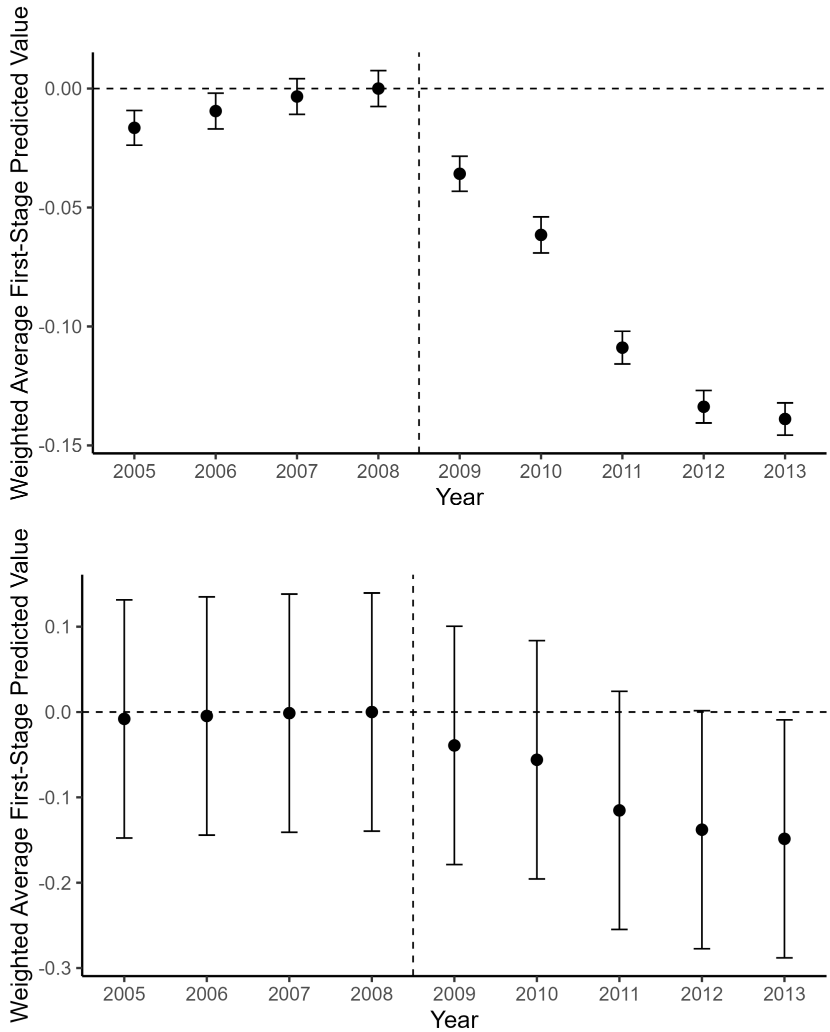
In Section 5.1, we showed that the actuarial cost (payouts minus total premiums) was higher when farms moved to aggregate insurance and changed their behavior. That analysis ignored the fact that the farmer only pays a portion of the premium, the rest is subsidized by the FCIP. In this section we study whether those that moved to aggregate policies received higher subsidies than those who remained. The intention of the FCIP was to equalize subsidies across separate and aggregate policies.

$$\frac{\text{Subsidy}}{\text{Acre}}_{county,crop,t} = \alpha_{county,crop} + \gamma_t + \tau_1[\text{Year} \geqslant 2009]_t \times \text{Treated Crop}_{crop,t} + \epsilon \tag{27}$$
$$\frac{\text{Subsidy}}{\text{Acre}}_{county,crop,t} = \alpha_{county,crop} + \gamma_t + \tau_2 \text{Perc. Acres in Agg.}_{county,crop,t} + \epsilon \tag{28}$$

As before, to overcome the endogeneity of take-up of aggregate insurance in the within-crop specification (28), we instrument for the percentage of acres in aggregate insurance with the pre-reform[56]

[56]Since wheat, soybeans and corn were all treated in 2009, the pre-reform year is 2008.

Figure 11: First-stage Predicted Values from the Exposure IV



Notes: This figure displays predicted first-stage take-up of aggregate insurance using the IV for the 2009 policy change. The top panel excludes county-crop fixed effects. The bottom panel includes them, but is estimated on a random sample of 25% of county-crops for computational tractability. Equation (22) is estimated, the predicted values are computed, and then a weighted (by acres insured) average for each year is displayed with 95% confidence intervals. We normalize the 2008 coefficient to zero.

proportion of acres, premium, subsidy and payout dollars that were in crops treated in 2009. This removes any selection effect. The results are in Table 5.

Table 5: The Subsidy Cost of Aggregate Policies

Specification:	Between-crop (scaled)	Within-crop (IV)
Actuarial Cost/Acre	−0.30	5.59***
	(0.65)	(1.46)
FE: County, Crop	✓	✓
FE: Year	✓	✓
N	164 031	104 828

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: The effect of the enrollment in aggregate insurance on the subsidy per acre estimated using the between-crop specification (column 1) and within-crop specification (column 2). The estimating equations are (27) and (28) respectively. The estimates in column 1 are scaled by the average take-up of 39%. In column 2, the percentage of crop x county enrolled in aggregate insurance is instrumented for with the pre-reform (2008) county percentage of crops (in acres, premium dollars, subsidy dollars and payout dollars) that were treated in 2009. Standard errors are reported in parentheses.

B.3 Inter-Field and Intra-Field Yield Variability

When yields across fields are perfectly correlated, there is no difference between a separate and an aggregate contract. We reproduce (part of) the results from Lobell et al. (2015), who develop a satellite-imagery based algorithm to map corn yields.

Figure 12 shows twelve different corn fields in Poweshiek County, Iowa. Each field is one mile by one mile, as marked by the black square outlines. Each of these square miles are the fields that define a separate versus aggregate contract. On average, each farm operates land in approximately 3 fields.

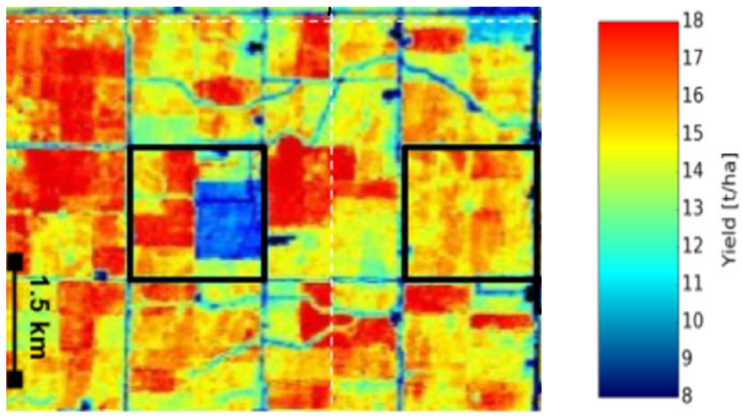
As shown in Figure 12, there is substantial variation in corn yield (measured in tonnes per hectare) within and between fields. Within the marked field on the left, yields vary from 8 to 18 tonnes per hectare. Thus, farmers can have sharply disparate outcomes on different fields on which they operate. A separate policy that pays out on a poorly performing field can differ markedly from an aggregate policy that pools high-yield with low-yield fields.

B.4 Within-Farm Variability Increases

In Section 4.2.1 we showed that the cross-sectional variability of farms increased after the reform on the farms that swapped to aggregate insurance. While this is consistent with the within-farm variance increasing due to diversification decreases, it is also possibly caused by an increase in the between-farm variance. In this section we estimate the within-farm variability changes on the much smaller sample of farms that were surveyed twice before or twice after the reform.

To isolate the within-farm component, we compute farm-level variability in the pre-2009 and post-2009 period (where these time periods are labeled p). Because there are essentially no farms for

Figure 12: Corn yields in Poweshiek County, Iowa (Lobell et al. (2015))



which we can compute this both pre- and post-reform, we include county instead of farm fixed effects. Thus, we estimate, at the farm f, pre/post-reform period p level (as well as with the same IV correction (29IV)):

$$y_{f,p} = \alpha_{county} + \gamma_p + \tau \mathbb{1}\left[t \geqslant \text{treatment year}\right] \times \mathbb{1}\left[\text{Farms that Swap to Aggregate }\right] + \epsilon_{f,p}. \quad (29)$$

The results are in Table 13 and are (noisy) evidence that, when pooling the crops, the variability increases observed in section 4.2.1 are indeed driven by within-farm variability increases, not across-farm, consistent with decreased diversification on each farm.

B.5 Revenue Insurance Crowded Out Private Price Hedging

As we showed in Section 4.3.4, as farms moved to aggregate insurance they also moved from yield to revenue insurance, thereby bringing price risk into their FCIP contract. In this section, we show that this crowded out alternative price-hedging instruments.

We focus on 'production contracts', in which the farmer contracts with a buyer of their crop prior to the harvest. This contract specifies the price and quantity of sale, and sometimes also the specific production techniques to be used. To study the effect of farms entering aggregate insurance on the use of production contracts, we estimate specification 4, where the outcome is a binary variable for whether the farm used any production contracts in that year. The results are in Table 14.

Figure 13: Within-Farm Variability Changes Post-Reform

Variability of Farm Yield/Acre	DiD				DiD with IV			
	Corn	**Wheat**	**Soy**	**All Crops**	**Corn**	**Wheat**	**Soy**	**All Crops**
C.O.V.	1.60	0.04·	10.91**	6.58	−4.4	-14.8	47.33*	60.29***
(Within-farm)	(10.6)	(9.7)	(4.8)	(4.1)	(44.9)	(9.5)	(26.7)	(22.0)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Crop FE				✓				✓
N Farms	103	52	91	246	103	52	91	246
F-statistic	-	-	-	-	4.5	11.2	2.83	5.49

Notes: This figure displays the effect of aggregate insurance on the effect of within-farm yield variability, before and after the 2009 policy change. The outcome is the coefficient of variation of yield per acre. The estimating equation is (4), observations are weighted by the prescribed ARMS population weights, and */**/*** denotes statistical significance at the 10%/5%/1% levels.

Figure 14: The Effect of Scope Reforms on Production Contracts

Estimate of τ	DiD
Entropy	−0.13**
	(0.04)
Farm FE	✓
Year FE	✓
N	3260

Notes: This figure displays the effect of aggregate insurance enrollment on the use of production contracts, before and after the 2009 policy change. The outcome is a binary indicator for the use of any production contracts on the farm. The estimating equation is (4), observations are weighted by the prescribed ARMS population weights, and */**/*** denotes statistical significance at the 10%/5%/1% levels.

Table 14 shows that as farms move to aggregate insurance they reduce their use of production contracts by 13%. As price risk is increasingly insured through the FCIP, it crowds out private market alternatives.

B.6 The Diversification Effects of Irrigation, Crop Diversity, Revenue Insurance and Acreage

We show that irrigation, revenue insurance, crop diversity and acres farmed impact diversification as stated in the paper. Specifically, we stated that more irrigation, crop diversity and acres farmed lead to more diversification in risk, whereas moving to revenue insurance decreases diversification.

To demonstrate that these farming practices impact diversification as stated, we estimate the following linear probability models for the outcomes: no fields fail, some fields fail, all fields fail. Per Lemma A.1, we expect that as diversification increases the middle state will occur more frequently, and the first and last less so.

$$\text{Probability All/Some/No Fields Fail} = \alpha + \beta_0\text{Premium} + \beta_1\text{Subsidy} + \beta_2\{\text{Diversity, Irrigation \%, Revenue Insurance, Acres}\} + \epsilon \quad (30)$$

We estimate this on wheat only (for which crop diversity is defined and estimable) and all three crops (in which case we cannot estimate a coefficient on crop diveristy). The results are in Tables 6 and 7 below.

As predicted by the theory, as the percentage of the farm that is irrigated increases, as acreage increases, or as crop diversity increases, the probability of some fields failing increases and the probability of all or no fields failing decreases. This demonstrates that diversification has decreased, since a more diversified farm has less chance of all fields doing well or doing badly at the same time. Similarly, being enrolled in revenue insurance has the opposite effect, showing that including price risk correlates (or de-diversifes) the risk.

We use these models to generate implied marginal effects for the change in actions on the probability of each state of the world. Given previously estimated indemnities in each state of the world, we can compute the implied change expected indemnities in each state given the change in probabilities. We average across states, and these form the estimates of the fiscal cost of distorted diversification actions in Table 9.

B.7 Calibration Details for Farmer WTP for Separate/Aggregate/Partially Aggregate Insurance

In this section we describe calibration of farmer utility that is used to quantify the utility gains from insurance with different degrees of scope.

We reduce the state-space to: B = all fields receive an insurance payout, M = some fields do and some do not, G = no fields receive a payout. Farmer utility, projected onto the three states of the world defined above, is given by:

$$U(p, s, I_B, I_M) = \pi_B u(X_B + I_B - p(1-s) + \pi_M u(X_M + I_M - p(1-s))) + \pi_G u(X_G - p(1-s)),$$

We assume CRRA utility: $u(x) = x^{1-\gamma}/(1-\gamma)$ for the coefficient of relative risk aversion γ. When $\gamma = 1$ this reduces to $u(x) = \log(x)$.

Using all the data for pre-reform (2003-2008) separate contracts for which we can distinguish the three states of the world defined above, we estimate $\hat{\pi}_B, \hat{\pi}_M, \hat{\pi}_G, \hat{I}_B \hat{I}_M$. Next, p and s are directly recorded in the data - we know, for each contract, what the premiums were under separate, and the relative difference in price for an aggregate policy. Similarly, we know the subsidy levels for both.

Table 6: Factors Influencing Field Failure Probabilities Across All Crops

	No Fields Fail	Some Fields Fail	All Fields Fail
Acres	-0.000009***	0.00001***	-0.0000009***
	(0.0000002)	(0.0000002)	(6e-08)
Percent Irrigated	-0.033**	0.036**	-0.003
	(0.011)	(0.011)	(0.004)
Revenue Insurance	0.015	-0.020	0.005
	(0.023)	(0.023)	(0.008)
N	68,368	68,368	68,368
R^2	0.059	0.080	0.030

Notes: This table presents regression results examining the factors influencing field failure probabilities across all three crops studied. The dependent variables are the probabilities of no fields failing, some fields failing, or all fields failing. Independent variables include farm size (Acres), irrigation status (Percent Irrigated), and insurance type (Revenue Insurance). Standard errors are in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The results suggest that larger farms and higher irrigation percentages are associated with a higher probability of some fields failing, while the effect of revenue insurance is not statistically significant. The model explains between 3

Table 7: Factors Influencing Field Failure Probabilities for Wheat Crops

	No Fields Fail	Some Fields Fail	All Fields Fail
Acres	-0.000006***	0.000006***	-0.0000001
	(0.0000009)	(0.0000009)	(0.0000002)
Percent Irrigated	-0.014	0.019	-0.005
	(0.133)	(0.133)	(0.030)
Revenue Insurance	0.182*	-0.190*	0.007
	(0.084)	(0.084)	(0.019)
Crop Diversity	-0.273*	0.288*	-0.015
	(0.158)	(0.159)	(0.036)
N	785	785	785
R^2	0.094	0.108	0.027

Notes: This table presents regression results examining the factors influencing field failure probabilities for wheat crops only. The dependent variables are the probabilities of no fields failing, some fields failing, or all fields failing. Independent variables include farm size (acres above pricing cutoffs), irrigation status (Percent Irrigated), insurance type (Revenue Insurance), and Crop Diversity. Standard errors are in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. For wheat, farm size has a highly significant but small effect on failure probabilities. Revenue Insurance and Crop Diversity show marginally significant effects, with increased diversity being associated with a higher probability of some fields failing. The model explains between 2.7

Mechanically we know $X_B + I_B$ (for example, if expected yield is \$100 on each field, and the coverage level is 80%, then in the B state of the world, each field will be indemnified up to \$80.) We assume that in the M state of the world yield is equal to expected yield: $X_M = E(X)$, and expected yield is defined in the data. Finally, we set payoffs in the G state of the world such that the contract is actuarially fair, given estimated probabilities of being in each of the three states, known premia and payoffs in the other two states of the world.

How do these state-contingent payoffs change under an aggregate contract? Payoffs in the worst state of the world, B, increase. Payoffs in the M state of the world decrease. We observe in the FCIP the difference in insurance cost, and hence in final farmer income, that would obtain under an aggregate contract. We assume a partially aggregate just scales this change in income linearly. For example, if an aggregate contract gives \$4 more per acre in income in the B state, a contract that is halfway between separate and aggregate gives \$2 more. The change in income in the M state of world is set to be actuarially fair, *assuming no behavioral change* (i.e., using the pre-reform estimated probabilities). This is consistent with the assumptions made by the FCIP when setting prices and payoffs.

B.8 The Costs and Benefits of Irrigation

We summarize the key findings from Partridge et al. (2023) that we use as inputs in our welfare model in 5.3.

Partridge et al. (2023) shows that the economic returns to irrigation vary widely across the US. We reproduce their illustration of the benefit to cost ratio in Figure 15 below.

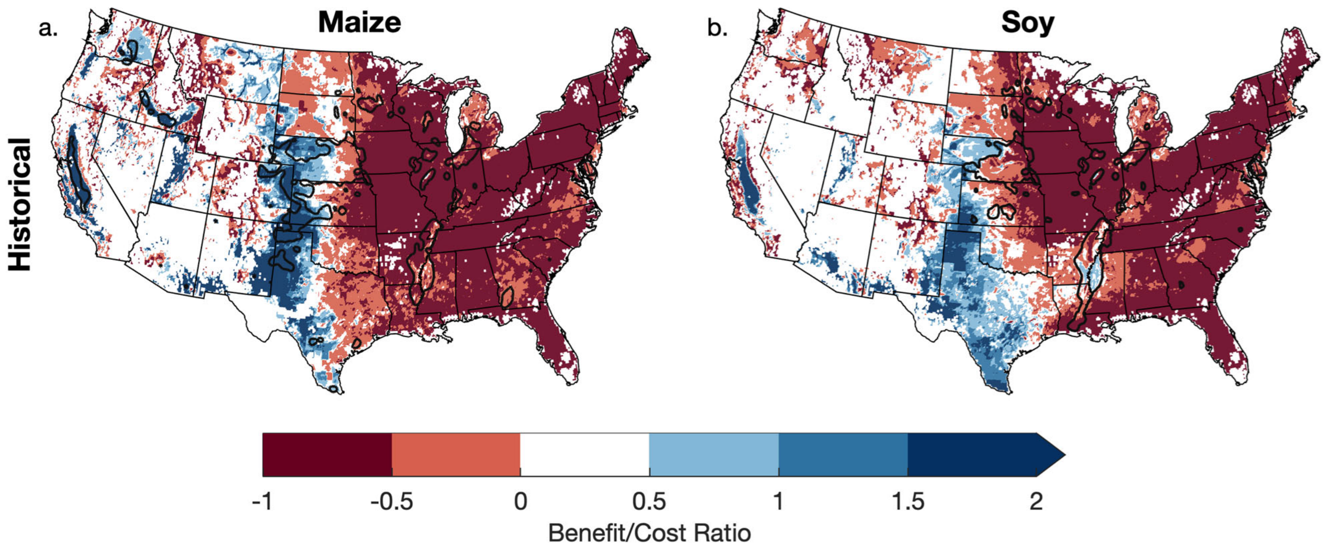
Figure 15 shows that irrigation is typically not profitable in the eastern half of the US, and with considerably more heterogeneity in the western half. In particular, substantial farmland is marginal to irrigation, such that changes in the benefits or costs, such as from crop insurance, can be dispositive.

Yield Benefits of Irrigation. We calibrate the yield benefits of irrigation using data from variety trials. Variety trials are field experiments conducted to evaluate the performance of different crop varieties under specific growing conditions. These trials typically involve planting multiple varieties of a crop in replicated plots, both under irrigated and rainfed (non-irrigated) conditions.

For wheat, we reference the Perkins County Rainfed 2023 Wheat Variety Trial Easterly and Creech (2023). For corn, we use data from the Clay County Rainfed 2021 Corn Hybrid Trial Easterly and Creech (2021). For soybeans, we draw upon the Dixon County Roundup Ready Late Maturing Soybean Variety Test from 2016 Easterly and Creech (2016).

By analyzing the yield differences between irrigated and rainfed plots across these trials, we estimate the yield benefits of irrigation. Specifically, we find that irrigation increases corn yields by approximately 14%, wheat yields by 12%, and soybean yields by 13%. ated plots, both under irrigated and rainfed (non-irrigated) conditions.

Figure 15: The Returns to Irrigation, from Partridge et al. (2023)



Notes: This figure, reproduced from Partridge et al. (2023), shows the estimated economic returns to irrigation for maize (corn) and soybeans across the US.

For wheat, we use the Perkins County Rainfed 2023 Wheat Variety Trial Easterly and Creech (2023). For corn, we use data from the Clay County Rainfed 2021 Corn Hybrid Trial Easterly and Creech (2021). For soybeans, we use the Dixon County Roundup Ready Late Maturing Soybean Variety Test from 2016 Easterly and Creech (2016).

By analyzing the yield differences between irrigated and rainfed plots across these trials, we estimate the yield benefits of irrigation. Specifically, we find that irrigation increases corn yield by approximately 14%, wheat yield by 12%, and soybean yield by 13%.

B.9 Summary Statistics Post-Reform, Restricted to Corn, Soybeans and Wheat

To cohere and compare with the results in Section 5.1, we present summary statistics for the three crops analyzed, corn, soybeans and wheat, restricted to the post-treatment period.

Table 8: Summary Statistics.

	Separate			Aggregate		
	Mean	SD	Acres x Years	Mean	SD	Acres x Years
Premium Per Acre ($)	52.07	23.52	0.22	45.95	19.08	0.29
Subsidy Per Acre ($)	27.85	12.00	0.22	31.91	13.85	0.29
Indemnity Per Acre ($)	48.03	82.24	0.22	52.79	94.07	0.29
Insured Amount Per Acre ($)	489.74	206.43	0.22	557.92	192.74	0.29
Loss Ratio	0.89	1.47	0.22	1.14	2.09	0.29
Irrigated	0.18	0.39	0.22	0.06	0.24	0.29
Revenue Insurance	0.82	0.38	0.22	0.96	0.19	0.29
Yield Insurance	0.11	0.32	0.22	0.02	0.13	0.29
Diversity (Wheat)	0.15	0.26	0.02	0.05	0.16	0.01

Notes: This table presents summary statistics for corn, soybeans and wheat in the post-treatment period (2009-2014), differentiated by aggregate versus separate. Acres are expressed in billions. Means and standard deviations are weighted by acres insured. The diversity measure is calculated only for wheat.

Table 8 shows that the actuarial cost of providing insurance - the premium minus the indemnity - was substantially higher in aggregate policies. In aggregate policies, indemnities were almost $7 higher than premiums. In separate policies, premiums were $4 higher than indemnities. In other words, due to some combination of selection and moral hazard, the actuarial cost was $11 higher in aggregate policies than separate.

B.10 Disaggregating the Increased Payouts by Diversification Actions

We quantify the impact of the change in diversification actions (irrigation, diversity, land use[57] and revenue coverage) that we studied in Section 4 on insurance payouts.

We decompose the impact of scope of the payouts per acre using $\frac{\partial \text{Payout/Acre}}{\partial Scope} = \frac{\partial \text{Payout/Acre}}{\partial a} \frac{\partial a}{\partial Scope}$, where a is a particular diversification action. We have causal estimates of the latter term from Section 4. To quantify the former, we estimate a model for the effect on expected payouts of the four diversification actions, controlling for the premium as well as crop and year fixed effects. A full description of the method and results is in Appendix B.6. From this we estimate marginal effects of changing each diversification on the expected payout, i.e., $\frac{\partial \text{Payout/Acre}}{\partial a}$ for each a. The results are in Table 9.

[57] Farm size is very coarsely included in the premium. For example, all farms with between, 200 and 399, 400 and 799 etc acres are priced identically (United States Department of Agriculture (2023)). Our measure of farm size is more precisely the acreage in excess of the lower cutoff for the category the farm falls into. This isolates the *unpriced* impact of acreage changes.

Table 9: The Fiscal Effects of Changes to Particular Farmer Diversification Actions

Farmer Action	Acreage	Irrigation	Revenue Insurance	Diversity (Wheat)
$\frac{\partial a}{\partial Scope}$	-0.06	-0.045	+0.25	-0.057
$\frac{\partial \text{Payout/Acre}}{\partial a}$	-0.0001	-11.77	18.43	-8.44
$\frac{\partial \text{Payout/Acre}}{\partial Scope}$	\$0.06	\$0.53	\$4.60	\$ 0.48

Notes: This table presents a breakdown of increases in fiscal cost when farms move to aggregate insurance by different diversification actions. The first row - the impact that the change in scope had on the diversification action - comes from the causal estimates in Section 4. The second row - the impacts of changes in diversification actions on aggregate insurance payouts, are estimated in Appendix B.6. The third row is the product of the first and second rows.

Overall, the specific farmer actions we have documented distortions in account for approximately \$5.20 (\$5.68 for wheat) of the \$6.88 in increased payouts per acre estimated from Table 9. The remaining \$1.68 (\$1.20 for wheat) could be due to other changes in farmer production choices that we cannot observe (for example, the types of seed used, fertilizer application, crop rotations, the decision to leave land fallow and so on).

As for the total actuarial cost in Table 9, these action-specific estimates combine the effect on government cost of changes in the mean and variance of yield. Reduced crop diversity costs the government money by increasing the variance, but could save money by reducing the probability of a claim.

B.11 Checking for Sensitivity to Violations of Parallel Trends

In this appendix, we use the honestDID package from Rambachan and Roth (2023) to check the sensitivity of our main results to violations of the parallel trends assumption. The honestDID package provides a method for estimating the robustness of difference-in-differences estimates to violations of the parallel trends assumption by considering a range of possible violations and reporting the range of estimates that would be obtained under these violations. This allows us to assess the sensitivity of our results to potential violations of the key identifying assumption.

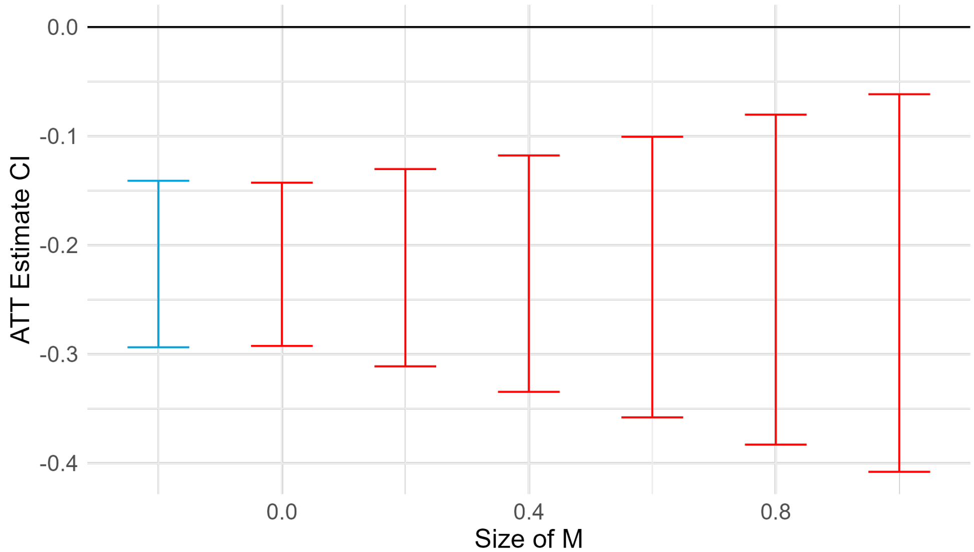
First, we consider the effect on acres in separate insurance, which is analogous to the results presented in Figure 1.

Next, the analogue of Figure 27, the total acres in insurance relative to the pre-treatment period.

Next, we consider the effect on revenue insurance, which is analogous to the results presented in Figure 7.

If we restrict the sign of the pre-trend to be positive:

Figure 16: Sensitivity Analysis of Difference-in-Differences Estimates for Acres in Separate Insurance



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for acres enrolled in separate insurance. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates widens, reflecting increased uncertainty about the parallel trends assumption.

Next, we consider the effect on crop diversity, which is analogous to the results presented in Figure 3.

If we are willing to assume that the pre-trend is positive, then the result clearly becomes much more robust.

Finally, we consider the effect on irrigation, which is analogous to the results presented in Figure 5.

B.12 Sun and Abraham (2021) Checks For Staggered Adoption

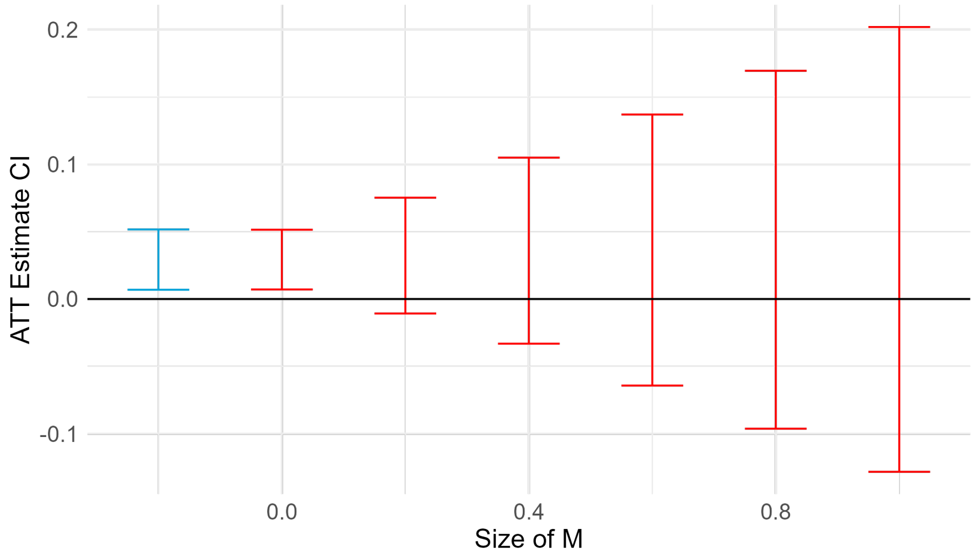
Since we exploit the staggered adoption of a policy change in a two-way-fixed-effects specification, we check that the estimates are robust to the now well-documented issues that can arise. We use the Sun and Abraham (2021) correction.

First, in Figure 23, we consider the robustness of the effect of the policy change on the proportion of acres in separate insurance as was presented in Figure 1.

Next, in Figure 24, we consider the robustness of the results on revenue insurance take-up from Figure 7.

In our analysis of crop diversity, all treated crops were treated simultaneously. As such, there is no

Figure 17: Sensitivity Analysis of Difference-in-Differences Estimates for Total Acres in Any Insurance



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for total acres enrolled in any type of insurance, relative to the year before treatment. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates.

need for a correction since there is no staggered adoption.

Finally, for the effects on irrigation, we run the analysis using only the first policy change in Appendix B.15.

B.13 Alternate Measures of Diversity

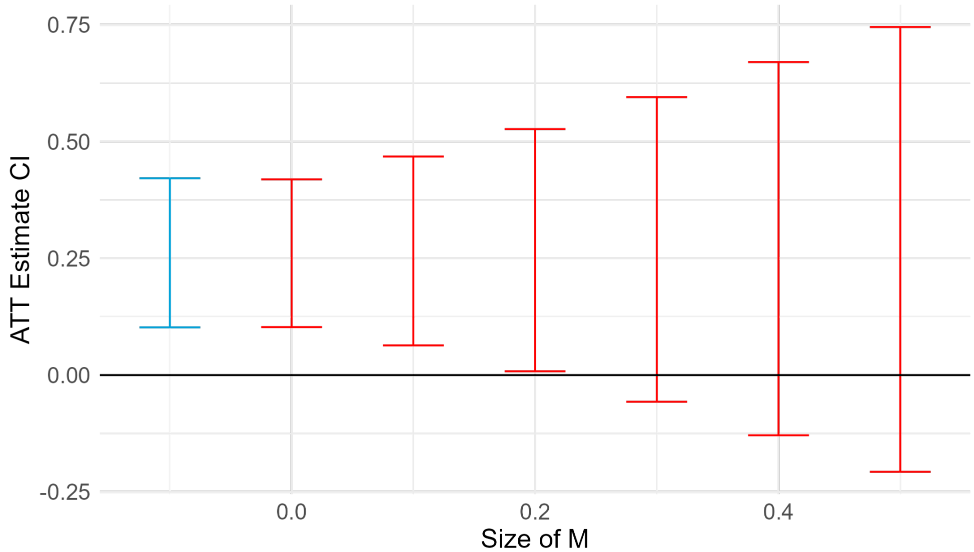
We re-run the analysis of Section 4.3.1 with alternate measures of crop diversity. The two alternate measures we use are the Inverse Simpson Index and the Gini Diversity Index. Respectively, they are defined by

$$\text{Inverse Simpson Index}_{f,t} = \frac{1}{p^2_{Spring,f,t} + p^2_{Winter,f,t}}, \tag{31}$$

$$\text{Gini Diversity Index}_{f,t} = 1 - \left(p^2_{Spring,f,t} + p^2_{Winter,f,t}\right). \tag{32}$$

When there is no diversity, and one of the p's is equal to 1, both indices are minimized. The Inverse Simpson takes the value of 1, and the Gini Diversity Index takes the value of 0. Maximal diversity is achieved at $p_{Spring} = p_{Winter} = 1/2$. In that case the Inverse Simpson Index takes the value 2,

Figure 18: Sensitivity Analysis of Difference-in-Differences Estimates for Revenue Insurance Adoption



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for the proportion of insured acres that are enrolled in revenue insurance. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates widens, reflecting increased uncertainty about the parallel trends assumption.

and the Gini Diversity Index takes the value 1/2. We re-run the analyses as in Section 4.3.1, simply with these different measures of diversity as alternate outcomes. The results are shown in Figures 25 and 26.

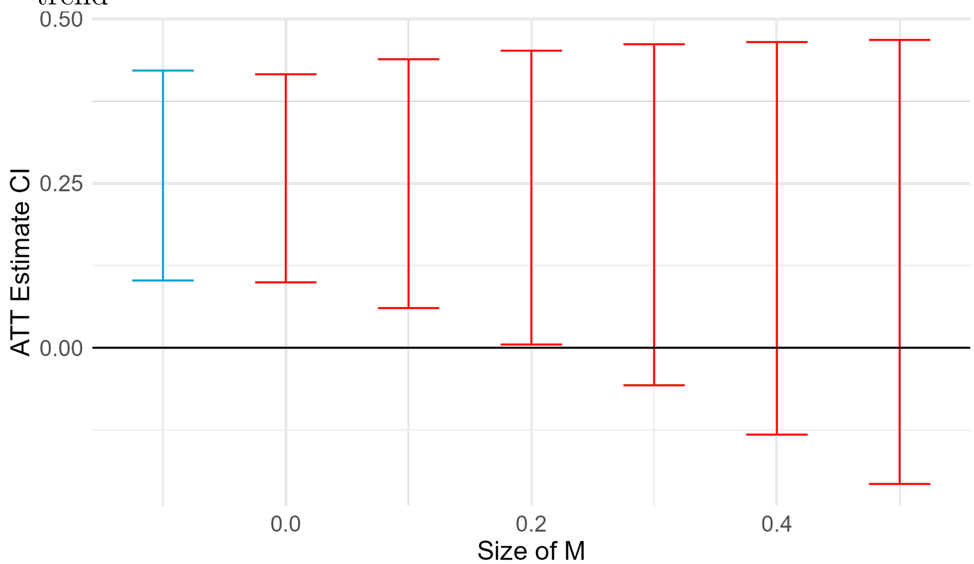
In both cases, the qualitative patterns are identical to the main specification with entropy as the outcome. We conclude that our analyses of crop diversity are not sensitive to the measure of diversity used.

B.14 Extensive Margin of Insurance Enrollment

As discussed in the main paper, we do not find any effects on the extensive margin on enrollment in any insurance. To show this, we estimate specification (3) on the 2009 treated crops, where the dependent variable is the numbers of acres, for a county and crop, enrolled in any type of insurance, divided by the acres insured in any insurance in 2008. The results are shown in Figure 27.

We see that there is no significant change in the total acres in any insurance. This indicates that the movement to aggregate insurance is from farms previously in separate insurance, not from farms previously without insurance. Moreover, this indicates that there is no movement from non-treated crops to treated crops after the policy change.

Figure 19: Sensitivity Analysis of Difference-in-Differences Estimates for Revenue Insurance Adoption, Assuming Positive Pre-trend



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for revenue insurance adoption, assuming a positive pre-trend. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates widens, reflecting increased uncertainty about the parallel trends assumption.

B.15 Between-crop 2009 Irrigation Results

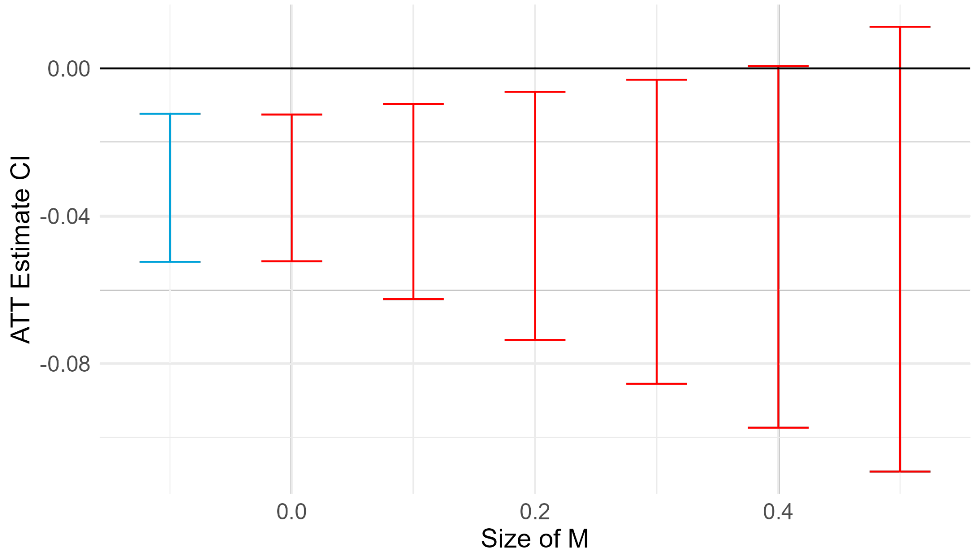
As in the literature (e.g. Annan and Schlenker (2015)) we split up our analysis into counties to the east and to the west of the 100th meridian of longitude. To the east of the 100th meridian rainfall is high and irrigation less common. Whereas in the west conditions are naturally dry and substantially more agriculture is dependent on irrigation. We therefore estimate equation (3) with outcome variable the percentage of all insured acres that are irrigated, separately for the east and the west. The coefficients of interest are τ_t, which are plotted in Figure 28.

As a robustness check, we also aggregate the data to the crop x year level and estimate an analogous specification. These results are in Figure 29.

$$\left(\frac{\text{Insured acres with irrigation}}{\text{All insured acres}}\right)_{crop,t} = \alpha_{crop} + \gamma_t + \tau_t \mathbb{1}\left[t\right] \times \mathbb{1}\left[\text{crop} = \text{Treated Crop}\right] + \epsilon_{crop,t}. \quad (33)$$

We see, in both sets of specifications and after an adjustment period, an approximately 1.5-3% decline in both the western and eastern regions The pre-2009 base rates of irrigation are approximately 29% in the west and 10% in the east.

Figure 20: Sensitivity Analysis of Difference-in-Differences Estimates for Crop Diversity



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for crop diversity. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates widens, reflecting increased uncertainty about the parallel trends assumption.

However, as we discuss in appendix B.19, there was also an increase in coverage levels following the 2009 reform. Hence, part of the decline in irrigation might be attributable to increased insurance from higher coverage levels, reducing the need for self-insurance such as irrigation. We investigate this in Appendix B.19.3 and find evidence inconsistent with this hypothesis. We find that counties with high coverage pre-reform were those with the greatest declines in irrigation. This confirms that the change in irrigation is due to changes in scope, not coverage levels.

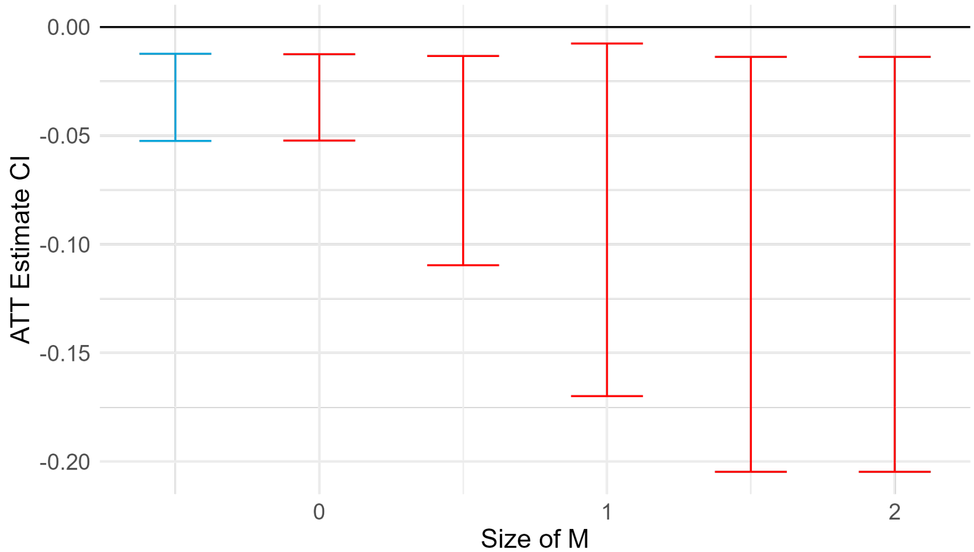
Overall, these analyses show that as farmers move to aggregate insurance, they irrigate less. This confirms our theoretical prediction: as the scope of insurance broadens the incentive to increase diversification between crop by irrigating is reduced. This has a knock-on effect on the total yield, which we explore below.

B.16 Between-crop Effects of the 2022 Reform

This section studies the take-up of separate insurance following the policy changes in 2022 that are used in the supplementary analysis in section 4.3.1. In both cases equation (3) is estimated. As in section 4.3.1, the treated crop is wheat, and the control crops are barley, oats and canola.

We begin by analyzing whether the reforms caused any shift in acres from separate to aggregate insurance. We estimate equation (3) where the outcome is the proportion of all insured acres that

Figure 21: Sensitivity Analysis of Difference-in-Differences Estimates for Crop Diversity, Assuming Positive Pre-trend



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for crop diversity, assuming a positive pre-trend. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates widens, reflecting increased uncertainty about the parallel trends assumption. The assumption of a positive pre-trend potentially biases the estimates upward, providing a conservative upper bound on the treatment effect.

are enrolled in separate insurance.

Overall, we see no effect on the proportion of acres enrolled in separate insurance. This shows that any effects of the 2022 policy change we now study are due to different decisions by farms who are already enrolled in aggregate insurance. We now study the change in diversification following the 2022 corrective reform. Details of the reform are in section 4.3.1.

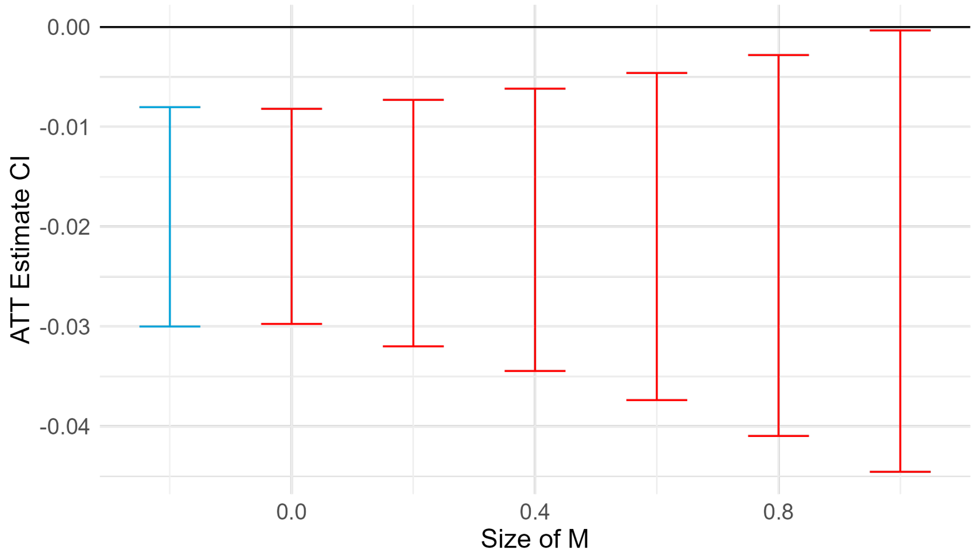
We estimate the change in entropy at a county level. To ensure robustness to pre-trends and our choice of controls, we estimate this between-crop effect using synthetic difference-in-differences. In SDID, the control unit is chosen to match on the latent structure. We estimate the 2022 and 2023 effects separately. The results are in table 10 below.

The results from the between-crop SDID analysis confirm the within-wheat analysis in Figure 4. The treatment effect in 2022 is 0.03, and increased in 2023 to 0.037.

B.17 Interactions with Other Farm Support Programs

In addition to crop insurance, the FCIP administers other programs that financially support and subsidize farmers. These are often referred to as constituting the farm safety net. These programs include direct subsidies, payments to compensate for national crop price drops, some ad hoc disaster

Figure 22: Sensitivity Analysis of Difference-in-Differences Estimates for Percentage of Irrigated Land



Notes: This figure presents results from an Honest Difference-in-Differences (DiD) analysis for the percentage of irrigated land. The analysis uses the largest effect, which occurs two periods after treatment. The x-axis represents different values of M, which quantifies the maximum allowed violation of parallel trends in any period, expressed in terms of the standard deviation of the outcome. The y-axis shows the range of DiD estimates obtained for each M value. The vertical dashed line indicates the point estimate under the assumption of perfect parallel trends ($M = 0$). As M increases, the range of plausible estimates widens, reflecting increased uncertainty about the parallel trends assumption.

Table 10: SDID Estimates for Change in Entropy Following 2022 Policy Change in Wheat Aggregate Insurance

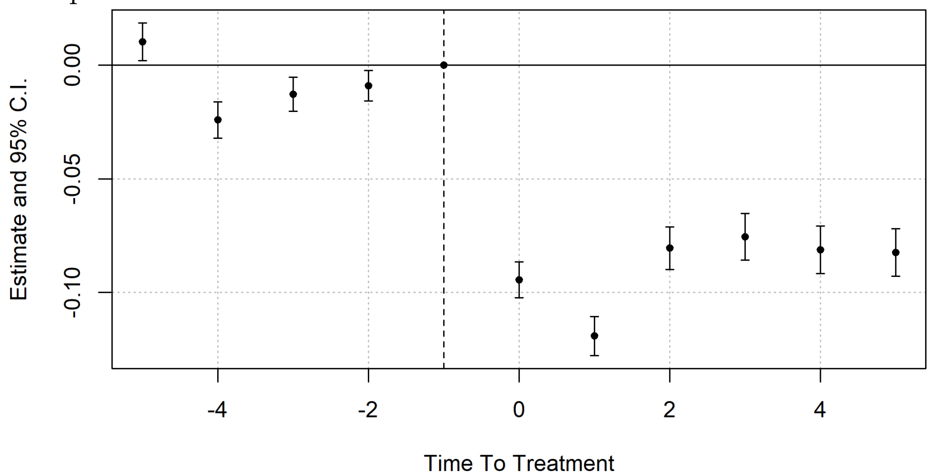
Year	SDID τ Estimate
2022	0.032***
	(0.004)
2023	0.04***
	(0.005)

Notes: This table presents Synthetic Difference-in-Differences (SDID) estimates for the change in entropy following the 2022 policy change that allowed aggregate units differentiated by type for wheat. Wheat is the treated crop, while barley, canola, and oats serve as control crops. Standard errors are in parentheses. Significance levels: *** p < 0.01.

assistance, and some programs not relevant to the crops we study, such as payments to dairy producers and payments for crops not included in the formal FCIP (Shields et al. (2010)).

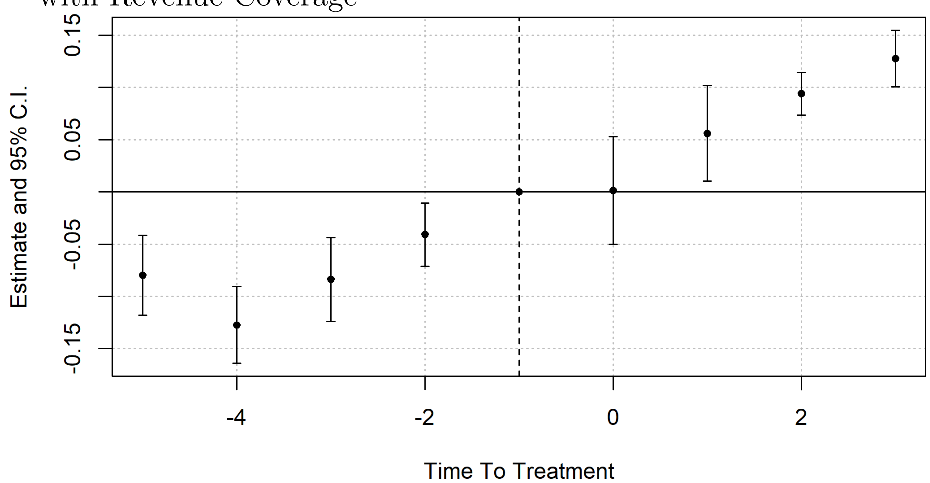
Since 2014, the safety net was streamlined to primarily consist of two programs: Price Loss Coverage (PLC) and Agricultural Risk Coverage (ARC) (Plastina (2015)). PLC provides price insurance if the average national price for a cropping year falls below a reference price. The reference price is

Figure 23: Sun and Abraham Correction for Percentage of Acres in Separate Insurance



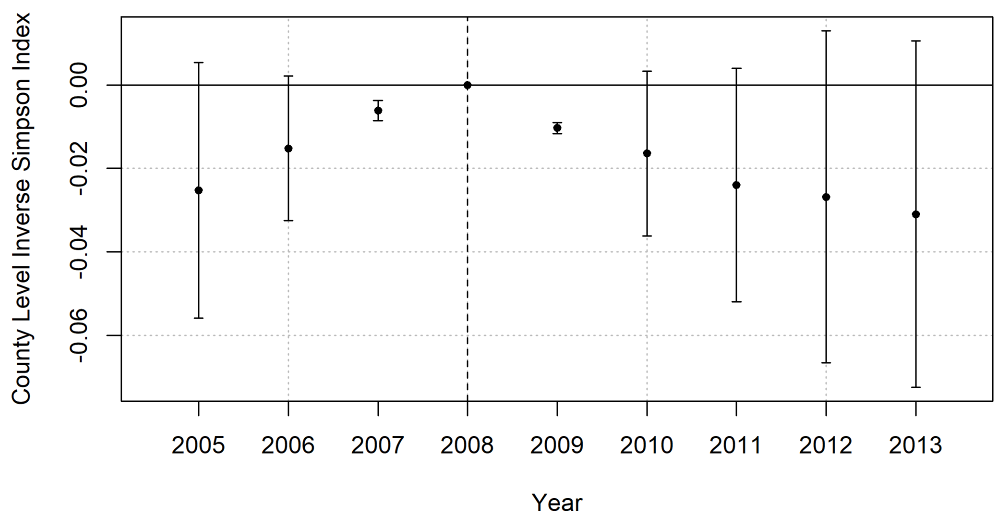
Notes: This figure presents the results of applying the Sun and Abraham correction method to estimate the effect on the percentage of acres enrolled in separate insurance. The method is designed to address potential biases in difference-in-differences estimates when treatment effects vary over time and across groups. See Sun and Abraham (2021) for more details on the methodology.

Figure 24: Sun and Abraham Correction for Percentage of Acres with Revenue Coverage



Notes: This figure presents the results of applying the Sun and Abraham correction method to estimate the effect on the percentage of acres with revenue coverage. The method is designed to address potential biases in difference-in-differences estimates when treatment effects vary over time and across groups. See Sun and Abraham (2021) for more details on the methodology.

Figure 25: Effect of Aggregate Insurance Enrollment on Crop Diversity (Inverse Simpson Index)



Notes: This figure displays the effect of aggregate insurance enrollment on crop diversity as measured by the Inverse Simpson Index, before and after the 2009 policy change. It compares three treated crops (wheat, canola, and barley) to the control crop (oats). The estimating equation is (4). Observations are weighted by acres insured and 95% confidence intervals are displayed.

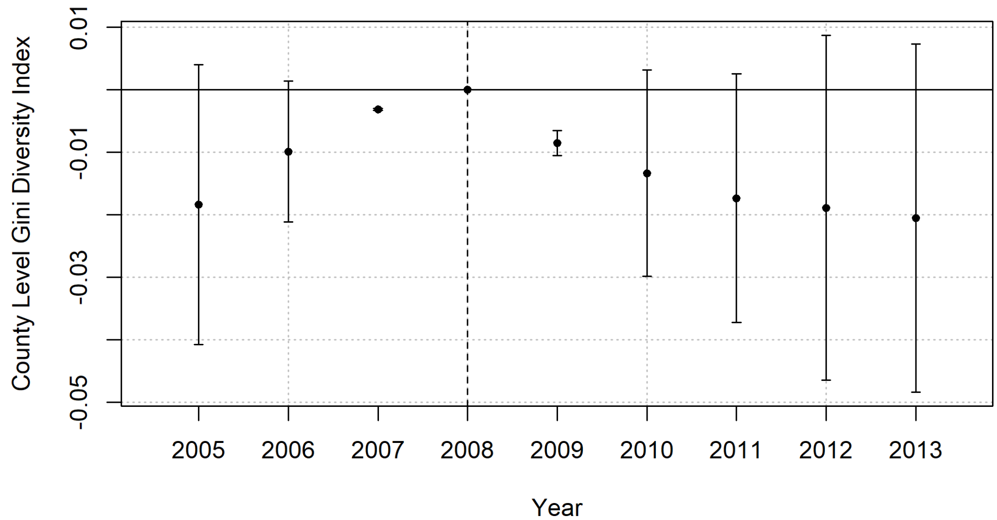
the maximum of a statutory price from the most recent farm bill, or the Olympic average of the last five years of market prices, capped at 115% of the statutory price. For major field crops, the market price is rarely below the reference price, and hence this policy is unlikely to be triggered (see Schnitkey (2022)).

ARC provides shallow revenue insurance against county revenue. If revenue for a crop in a given county falls below 86% of the expected county revenue, farmers can be indemnified up to 10% of county revenue, prorated to their acres. That only 10% of expected revenue can be indemnified is why the program is shallow. In a particularly bad year, the FCIP will be responsible for most of the insurance payout, with ARC covering some of the FCIP deductible. It is conceptually comparable to Medicare Supplement Insurance (Medigap).

A concern is that the changes to crop insurance that we study are just redirecting money to or from the other safety net programs. In particular, our welfare analysis would be problematic if the same farm bill that led to a massive expansion of the aggregate subsidy also led to reduced expenditures in other safety net programs.

We study this in two ways. First, we use the ARMS data to compare receipts from other government programs of farms that swapped to aggregate insurance to farms that remained in separate

Figure 26: Effect of Aggregate Insurance Enrollment on Crop Diversity (Gini Diversity Index)



Notes: This figure displays the effect of aggregate insurance enrollment on crop diversity as measured by the Gini Diversity Index, before and after the 2009 policy change. It compares three treated crops (wheat, canola, and barley) to the control crop (oats). The estimating equation is (4). Observations are weighted by acres insured and 95% confidence intervals are displayed.

insurance. Second, we use the data on the universe of payments made at the county level and analyze the correlation between receipts of insurance payments and/or subsidies, and all non-insurance farm payments from other government programs.

First, we run DID analyses using the ARMS data identically to the other within-farm analyses, just with different outcomes. Specifically, we run:

$$\text{Income from DP}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{34}$$

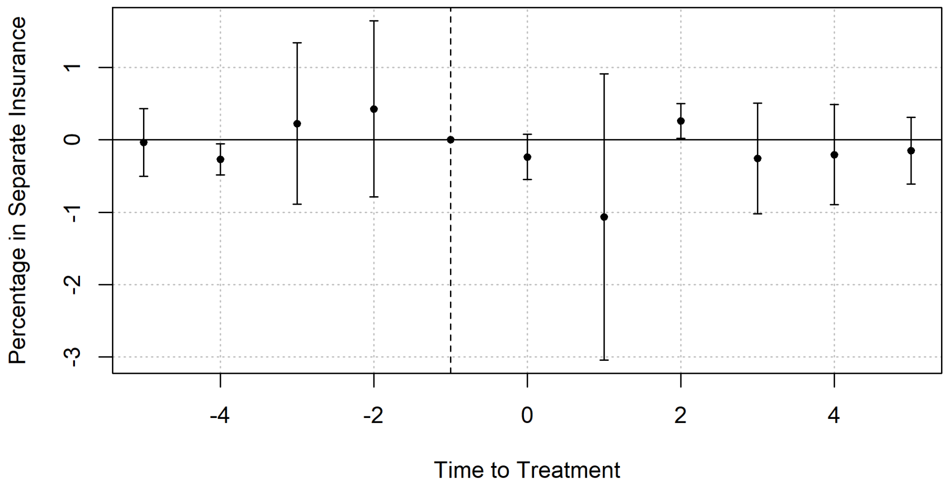
$$\text{Income from CCP}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{35}$$

$$\text{Disaster Assistance Income}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{36}$$

$$\text{Total (Non-Insurance) Gov Inc}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it}. \tag{37}$$

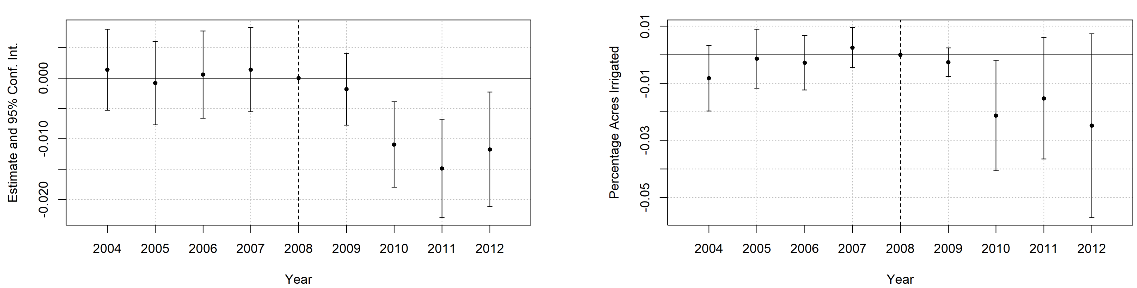
$$\tag{38}$$

Figure 27: Effect of 2009 Policy Change on Total Insured Acres Relative to 2008 Baseline



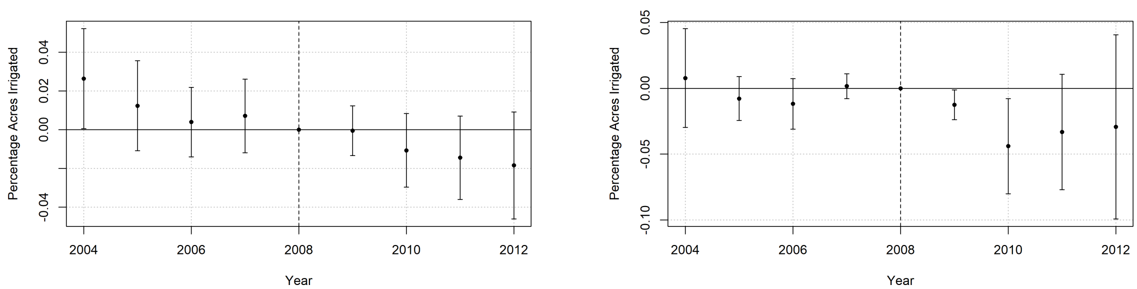
Notes: This figure shows the effect of the 2009 policy change on the total number of acres enrolled in any type of insurance for the treated crops. The dependent variable is the number of acres, for a county and crop, enrolled in any type of insurance, divided by the acres insured in any insurance in 2008. The estimating equation is (3).

Figure 28: Regional Differences in Treatment Effect of Expanded Aggregate Subsidy on Irrigated Acreage



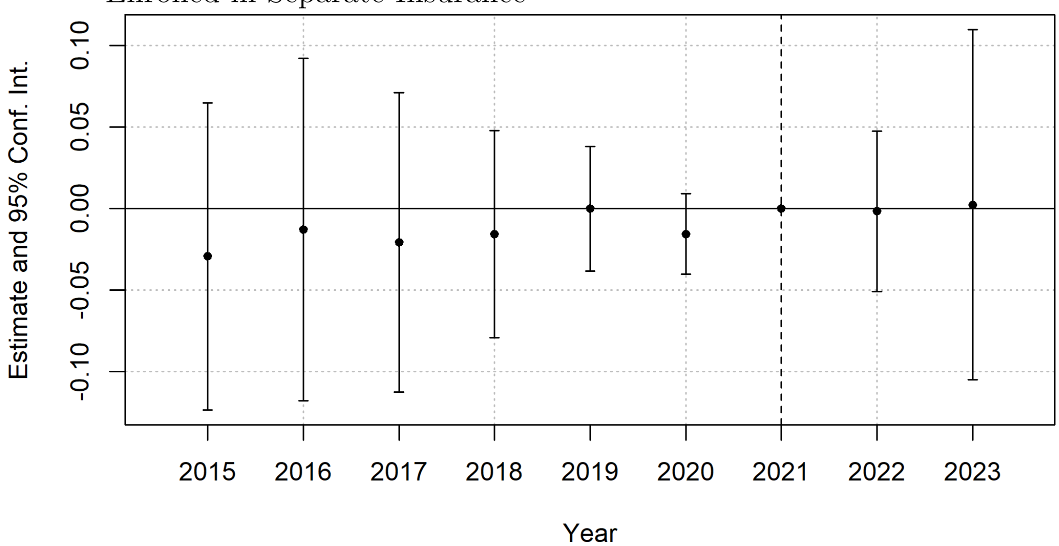
Notes: This figure illustrates the treatment effect of crop eligibility for the expanded aggregate subsidy on the percentage of insured acres that are irrigated. The left panel shows results for states west of the 100th meridian, while the right panel shows results for states east of it. The treatment effect is estimated using equation (3). The x-axis likely represents time relative to the policy change, and the y-axis shows the estimated treatment effect. Coefficients τ_t are plotted with 95% confidence intervals. Standard errors are clustered at the crop level, and observations are weighted by insured acreage.

Figure 29: Impact of Scope Reforms on Irrigation, at the Crop Level



Notes: This figure illustrates the treatment effect of crop eligibility for the expanded aggregate subsidy on the percentage of insured acres that are irrigated, analyzed at the crop level. The left panel shows results for states west of the 100th meridian, while the right panel shows results for states east of it. The treatment effect is estimated using equation (3), with the specification at the crop x year level. The x-axis likely represents time relative to the policy change, and the y-axis shows the estimated treatment effect. Coefficients τ_t are plotted with 95% confidence intervals. Observations are weighted by insured acreage.

Figure 30: Effect of 2022 Policy Changes on Percentage of Acres Enrolled in Separate Insurance



Notes: This figure presents an event study of the effect of the 2022 policy changes on the percentage of acres enrolled in separate insurance. The estimating equation is (3). Standard errors are clustered by crop, and the coefficients τ_t are plotted with 95% confidence intervals. Observations are weighted by acres insured. The x-axis represents time relative to the policy change, while the y-axis shows the estimated effect on separate insurance enrollment.

The results are in table 11 below. As seen, there is no statistically significant difference in income received from any non-insurance government programs on farms that swapped to aggregate policies relative to those that didn't. This explains our study of the crop insurance program in isolation.

B.18 Details on the Non-Constant Marginal Costs Estimates

We estimate a quadratic analogue of equation (8). Specifically, we estimate

$$\text{Actuarial Cost Per Acre}_{county,crop,t} = \alpha_{state,crop} + \gamma_t + \tau \text{Perc Acres in Agg.}_{county,crop,t} \tag{39}$$

$$+ \tau_2 \text{Perc Acres in Agg.}^2_{county,crop,t} + \epsilon \tag{40}$$

This allows for differential costs for those the county-crops that heavily select into partially aggregate insurance.

	(1)	(2)
Outcome:	Gross Fiscal Cost	
Percentage in Aggregate Ins.	−15.409***	8.701***
	(0.790)	(2.759)
Percentage in Aggregate Ins. Squared		−25.796***
		(2.829)
FE: Crop	✓	✓
FE: Time	✓	✓
N	103 660	103 660

Table 12: The effect of the enrollment in aggregate insurance on the actuarial cost per acre under linear (column 1) and quadratic (column 2) specifications. There is no IV adjustment, as we specifically want to include the endogenous take-up decision. Standard errors are reported in parentheses.

This shows that the costs of decreased diversification are concave in the take-up of aggregate insurance. Those that initially take up cost the government $8.701 per acre. By the time we are near the average takeup, 0.5, the cost is only $8.701 - 1/4 *$25.80 = $2.25 per acre.

B.19 Effects on Coverage Level

B.19.1 2009 Policy Change

The subsidy to aggregate insurance in 2008 meant that the farmers who moved to aggregate insurance spent substantially less on their premiums. This is because, holding subsidies fixed, aggregate insurance is cheaper than separate insurance and the subsidy was much higher. In this section we study how coverage changed after the 2009 reform. We find some evidence that coverage of 75%

Table 11: DID Estimates of Changes in Income from Government Support Programs (2009 Policy Change)

Outcome	Estimate of τ
Income from DP	-449
	(1506)
Income from CCP	$-1,092$
	(884)
Disaster Assistance Income	345
	(2579)
Total (Non-Insurance) Government Income	-742
	(3933)

Notes: This table presents Difference-in-Differences (DID) estimates of the change in income from various government support programs before and after 2009 for farms that switch to aggregate insurance, relative to farms that remain in separate insurance. The estimating equation is (4) and the coefficients τ are shown. Standard errors are in parentheses. DP: Direct Payments; CCP: Counter-Cyclical Payments. Observations are weighted by the ARMS prescribed weights to ensure population representativeness. None of the estimates show statistical significance at the 10%, 5%, or 1% levels.

or higher was more likely after the reform, but no evidence that coverage of 65% or higher, or 85% or higher, was more likely. We study the interaction of diversification actions with coverage above 75% and find that the changes in diversification actions are concentrated in those who remained in low coverage after the reform. In other words, increasing coverage or reducing diversification were substitutes.

The outcome of interest is the proportion of all insured acres that have coverage of 65% or more, or 75% or more, or 85% or more. We estimate equation 3 with these dependent variable. The coefficients of interest are τ_t, which are plotted in Figure 31.

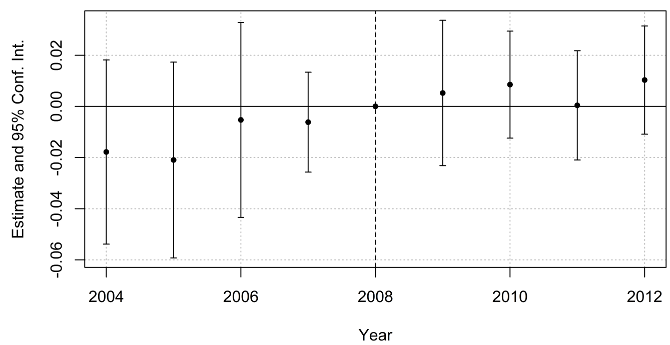
Figure 31 shows that while there is some evidence of coverage increasing at the 75% threshold, there is no such evidence at the 65% or 85% threshold. Nevertheless, we analyze whether the changes around 75% are in addition to, or instead of, the diversification reductions in the main paper.

Specifically, of our outcomes, most do not affect mean risk: revenue insurance is priced to be the same expected loss ratio as yield insurance, any extra land farmed is priced on its own yield history and crop diversity is a diversification decision. Irrigation has a large effect on mean yield as well as diversification. Our concern is that irrigation changes we studied in Section 4.3.2 are partially due to the increased coverage, not solely the shift from separate to aggregate insurance as we have been supposing. We analyze this now.

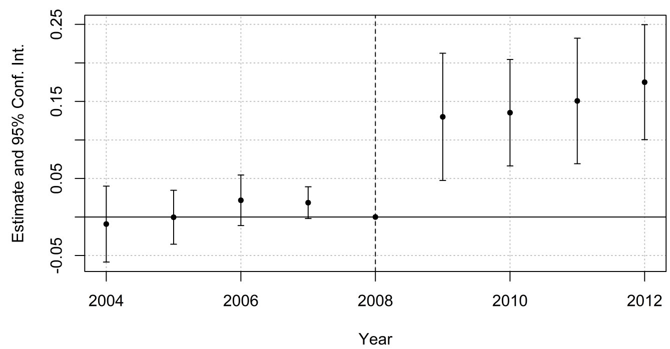
B.19.2 ARMS Treatment Effects Interaction With Coverage

To check whether the farm-level ARMS effects on irrigation, diversity etc., are polluted by coverage changes, we estimate an extension of specification (4). The concern is that it is the increased

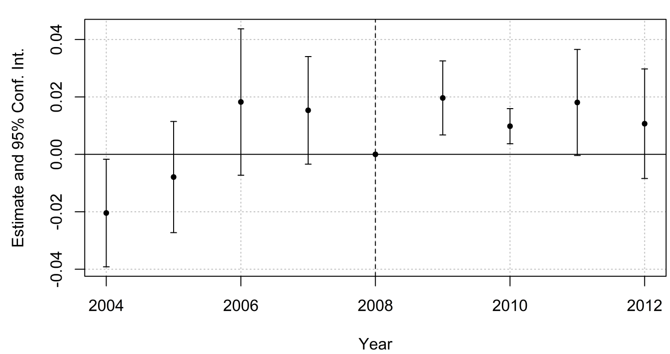
Figure 31: Changes in Enrollment for Different Coverage Levels After the 2009 Policy Change



(a) Change in the percentage of acres enrolled in 65% or greater coverage



(b) Change in the percentage of acres enrolled in 75% or greater coverage



(c) Change in the percentage of acres enrolled in 85% or greater coverage

Notes: This figure shows the changes in enrollment percentages for different coverage levels after the 2009 policy change. Panel (a) shows changes for 65% or greater coverage, panel (b) for 75% or greater coverage, and panel (c) for 85% or greater coverage. The x-axis likely represents time relative to the policy change, while the y-axis shows the percentage change in enrollment. These graphs allow for a comparison of how the policy change affected enrollment at different levels of coverage.

coverage that is leading to farmer's reducing their diversification actions. This is more plausible for irrigation, as it has a strong effect on mean yield as well as diversification. It is less plausible for crop diversity, farm size (in which not farming the marginal acres should be, for mean yield reasons, more likely to happen under higher coverage) or revenue insurance. Still, we check them all with the following specification:

$$y_{f,year} = \alpha_f + \gamma_{year} + \tau \mathbb{1}\left[t \geqslant \text{Treatment Year}\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] \tag{41}$$

$$+ \beta \mathbb{1}\left[\text{High Coverage Policy}\right] \tag{42}$$

$$+ \tau_{HC} \mathbb{1}\left[t \geqslant \text{Treatment Year}\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy}\right] \times \mathbb{1}\left[\text{High Coverage Policy}\right] + \epsilon_{ft}. \tag{43}$$

We run this for all the outcomes in Section 4. High coverage is an indicator for the farm having insurance with coverage greater than or equal to 75%. The results are in Table 13 below.

In all cases, the treatment effects are concentrated in the farms that remain in low coverage after the reform. This assuages concerns that the change in coverage level induced by the reform, not simply the scope, is driving these treatment effects.

B.19.3 2009 Irrigation Interaction with Coverage Changes

The irrigation effect presented in the main paper section 4.3.2 is possibly confounded by the coverage change shown in Figure 31.

To disentangle the coverage from the scope effect on irrigation, we break down the 2009 treated county crops into those that had, before the policy change, above versus below median levels of 'high' coverage. That is, we see if the irrigation effects we observed are due to county crops that, before the reform, already had high coverage, and for whom the confounding is weaker, rather than their complement for whom the confounding is stronger.

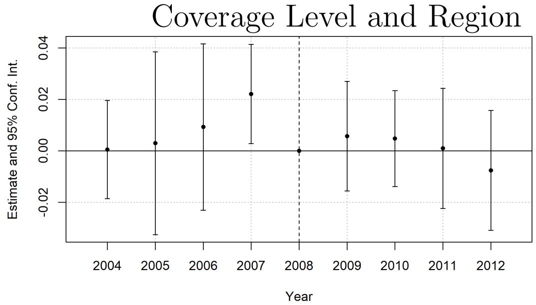
Specifically, we estimate the same specification (3) as in section 4.3.2 broken down by county-crops that had below or above median levels of high coverage ($\geqslant$ 75%) prior to the 2009 reform. As before, we also break down by counties to the east and west of the 100th meridian, leading to four different samples. The results are shown in Figure 32.

Table 13: Interaction Effects of High Coverage (>75%) on Treatment Outcomes

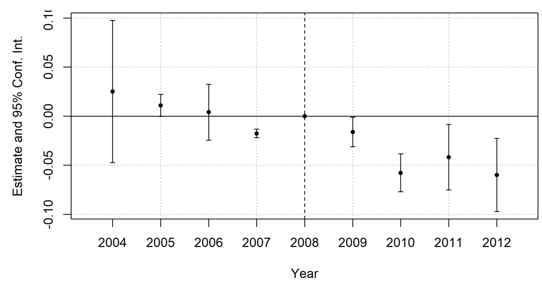
Outcome:	Revenue Coverage %	Irrigated %	Diversity	Rented Out %	Conservation %
Estimate of τ	0.67**	−0.15**	−0.06	−0.07***	0.11*
	(0.35)	(0.07)	(0.05)	(0.03)	(0.06)
Estimate of τ_{HC}	−0.62**	0.14	−0.02	−0.004	−0.05
	(0.32)	(0.09)	(0.05)	(0.02)	(0.06)
Farm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	672	735	575	3,321	3,321

Notes: This table presents estimates of the interaction between treatment effects from Section 4 and an indicator for high coverage (greater than 75%). The estimating equation is (41). τ represents the main treatment effect, while τ_{HC} represents the interaction effect with high coverage. Standard errors, clustered at the farm level, are in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. All regressions include farm and year fixed effects. Observations are weighted by the ARMS prescribed weights to ensure population representativeness.

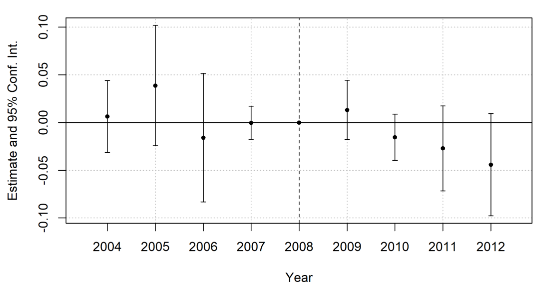
Figure 32: Irrigation Effects of 2009 Policy Change by Pre-reform Coverage Level and Region



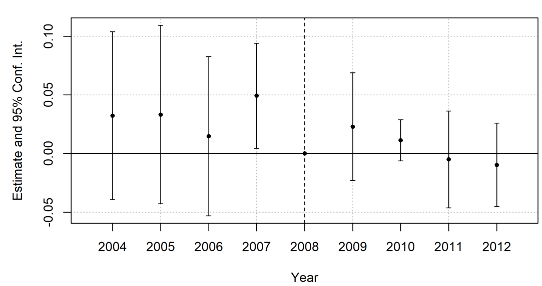
(a) West of 100th meridian, high pre-reform coverage



(b) East of 100th meridian, high pre-reform coverage



(c) West of 100th meridian, low pre-reform coverage



(d) East of 100th meridian, low pre-reform coverage

Notes: This figure shows the effects of the 2009 policy change on irrigation, broken down by pre-reform coverage levels and geographic location. The analysis uses specification (3), comparing county crops with above and below median levels of high coverage (⩾ 75%) prior to the 2009 reform. The 100th meridian divides the eastern and western regions. The x-axis likely represents time relative to the policy change, while the y-axis shows the effect on irrigation. Results indicate that the fall in irrigation after the 2009 policy reform was primarily driven by county crops that already had above median levels of high coverage, both east and west of the 100th meridian.

We see, both east and west of the 100th meridian, that the fall in irrigation after the 2009 policy reform was driven by the county crops that already had above median levels of high coverage. Those that had low levels of high coverage pre-reform never display drops in irrigation that are statistically significant from zero.

This is inconsistent with the story in which it is the post-2009 coverage increase, rather than the take-up of aggregate insurance, that drives the drop in irrigation. That story would mean that those counties that began with lower coverage, and hence had more room to increase coverage after 2009, are where the falls in irrigation are found. We observe the opposite, indicating that the drop in irrigation is strongest where the coverage effect was weakest. This mollifies our concern regarding the 2009 irrigation effects being confounded by coverage changes.

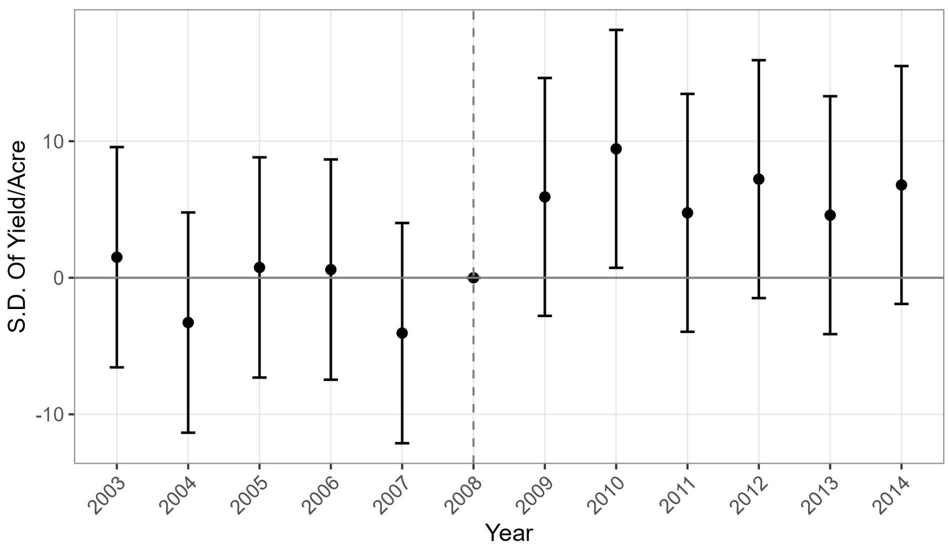
B.20 Alternate Measures of Farm Variability

In the main paper we measured between-farm variability with the coefficient of variation. This allows for a cross-crop comparison since it standardizes the variability in terms of the mean. In this section, we check robustness of these results to alternate measures of variability.

We re-estimate specification (5) where the outcome is either the standard deviation of yield per acre or the interdecile range (the difference between the 90th and 10th percentiles). The results are in Tables 33 and 34.

In both alternate measures of variability, the same pattern obtains. The farms that swap to aggregate insurance look similar prior to the reform to those that do not, but after the reform their yield variability sharply increases.

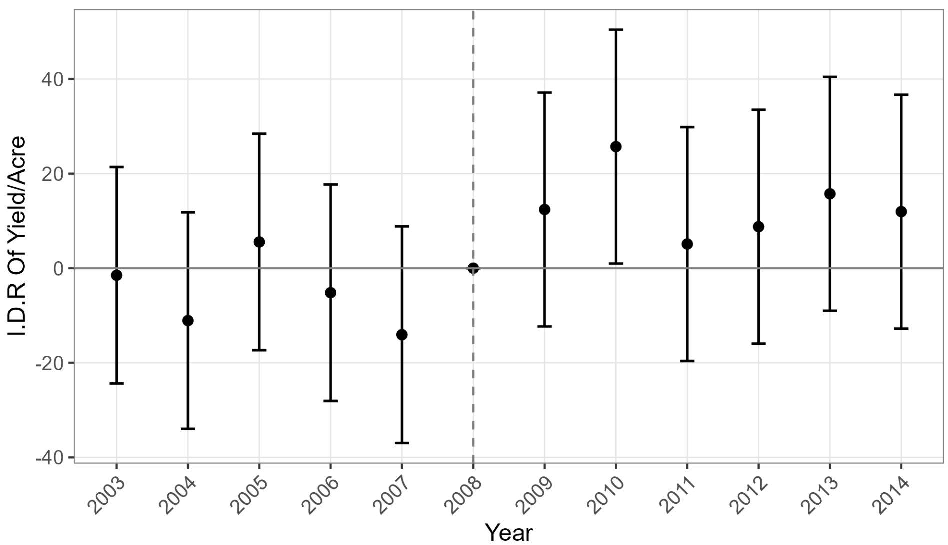
Figure 33: The Effect of Scope Reforms on the Variability of Farm Yield - Standard Deviation



	DiD				DiD with IV			
	Corn	**Wheat**	**Soy**	**All Crops**	**Corn**	**Wheat**	**Soy**	**All Crops**
S.D. of Farm	12.08***	8.27**	1.24	7.20***	21.82***	15.76	3.41	20.69***
Yield/Acre	(4.70)	(4.74)	(1.24)	(2.29)	(7.45)	(10.80)	(2.89)	(2.16)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Crop FE				✓				✓
N Farms	1,059	499	1,004	2,562	1,059	499	1,004	2,562
F-statistic	-	-	-	-	277	41	80	161

Notes: This figure displays estimates of the impact of the policy change on the variability of farm yield per acre. The outcome is the standard deviation of farm yield per acre. In the top panel, the estimating equation is (5), time-specific treatment effects are estimated, all three crops are included as well as crop fixed effects. 95% (dotted) and 90% (solid) confidence intervals are reported. In the bottom panel, a single (DiD) treatment effect is estimated for specification (5), separately for each crop as well as for all crops combined (with crop fixed effects included). Standard errors are reported in parentheses. */**/*** denotes statistical significance at the 10%/5%/1% levels. Observations are weighted by the ARMS prescribed weights to ensure population representativeness.

Figure 34: The Effect of Scope Reforms on the Variability of Farm Yield - Interdecile Range



	DiD				DiD with IV			
	Corn	**Wheat**	**Soy**	**All Crops**	**Corn**	**Wheat**	**Soy**	**All Crops**
IDR of Farm	36.11**	12.14	4.73	17.66**	87.21	−8.97	2.32	24.30
Yield/Acre	(15.39)	(11.74)	(3.65)	(6.62)	(59.42)	(33.58)	(6.93)	(17.02)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Crop FE				✓				✓
N Farms	1,059	499	1,004	2,562	1,059	499	1,004	2,562
F-statistic	-	-	-	-	3.14	1.19	0.81	3.14

Notes: This figure displays estimates of the impact of the policy change on the variability of farm yield per acre. The outcome is the interdecile range of farm yield per acre. In the top panel, the estimating equation is (5), time-specific treatment effects are estimated, all three crops are included as well as crop fixed effects. 95% (dotted) and 90% (solid) confidence intervals are reported. In the bottom panel, a single (DiD) treatment effect is estimated for specification (5), separately for each crop as well as for all crops combined (with crop fixed effects included). Standard errors are reported in parentheses. */**/*** denotes statistical significance at the 10%/5%/1% levels. Observations are weighted by the ARMS prescribed weights to ensure population representativeness.

C Proofs

C.1 Proof of Proposition 3

Proof. The planner's problem in the first-best is:

$$W = \max_{I,p,e_1,e_2,d} V(I,p,e_1,e_2,d) \tag{44}$$

$$\text{subject to: } p(e_1,e_2,d) = \alpha E_X\left[I(X(e_1,e_2,d))\right], \qquad \text{(Budget Constraint)} \tag{45}$$

The Lagrangian for the planner's problem is then, with multiplier λ on the budget constraint:

$$\begin{aligned}\mathcal{L} &= \int U(x_1 - x_2 - p + I(x_1,x_2)) f_1(x_1;e_1) f_2(x_2;e_2) c(x_1,x_2;d) dx_1 dx_2 - \psi(e_1,e_2,d) \\ &+ \lambda\left(p - \int I(x_1,x_2) f_1(x_1;e_1) f_2(x_2;e_2) c(x_1,x_2;d) dx_1 dx_2\right).\end{aligned}$$

The first-order conditions are, with the shorthand $U(x) = U(w - p - x_1 - x_2 + I(x_1,x_2))$:

$$\begin{aligned}\mathcal{L}_p &= \lambda - \int U'(x) f_1(x_1;e_1) f_2(x_2;e_2) c(x_1,x_2;d) dx_1 dx_2 \\ \mathcal{L}_{I(x)} &= U'(x) f_1(x_1;e_1) f_2(x_2;e_2) c(x_1,x_2;d) - \lambda f_1(x_1;e_1) f_2(x_2;e_2) c(x_1,x_2;d).\end{aligned}$$

From the first, we find that

$$\lambda^* = E_X[U'(x)],$$

the average marginal utility of consumption. Substituting this into $\mathcal{L}_{I(x)} = 0$ yields:

$$U'(x) = E_X[U'(x)] \quad \text{for all } x.$$

That is, the first-best is full insurance in which marginal utility (and hence income, since utility is not state dependent) is equalized across all states of the world, to, say $\overline{X}$..

The planner's first-order condition with respect to d, evaluated at full insurance, with $\lambda^* = E_X\left[U\left(\overline{X}\right)\right] U\left(\overline{X}\right)$

$$\tag{46}$$

$$0 = \int U\left(\overline{X}\right) f_1(x_1;e_1) f_2(x_2;e_2) \frac{\partial c(x_1,x_2;d)}{\partial d} dx_1 dx_2 - \frac{\partial \psi(e_1,e_2,d)}{\partial d} \tag{47}$$

$$+ U\left(\overline{X}\right) \frac{\partial E_I(x_1,x_2)}{\partial d} \tag{48}$$

Since income is constant across states, changes to d do not impact farmer utility. Moreover, since at full insurance, the insurance payout is affine in X_1 and X_2: $I(X_1,X_2) = \overline{X} - X_1 - X_2$. It immediately follows by Denuit et al. (2006) that diversification does change the expected payout. Therefore, the first-order condition becomes

$$0 = -\frac{\partial \psi(e_1, e_2, d)}{\partial d}$$

which, by assumption, is satisfied at $d = 0$ only. We conclude that $d^* = 0$ is optimal.

Now, consider field-specific effort e_1. At full insurance, there is no impact on farmer income from changes in e_1. The planner sets e_1 to trade-off the effort cost against the budgetary impact. Consider the budgetary impact of an increase in e_1 to e_1'. By assumption, this increases the marginal distribution on field one in the FOSD sense, but does not change the marginal distribution on field two or the correlation structure (i.e., the copula) :$F_1(x_1; e_1') \succ_{FOSD} F_1(x_1; e_1)$. By Theorem 1 in Scarsini (1988), this implies that the expected value with respect to any increasing function is higher under (e_1', e_2, d) than (e_1, e_2, d). In particular, for the insurance payout:

$$E_{e_1', e_2, d}[I(X_1, X_2)] < E_{e_1, e_2, d}[I(X_1, X_2)].$$

If $e_1 = 0$, this shows that increasing effort by a marginal $e_1' > 0$ has a first-order impact on the budget, but no first-order cost impact (since we assumed that $\frac{\partial(\psi(e_1, e_2, d))}{\partial e_1} |_{e_1=0}= 0$). Hence, $e_1^* > 0$ is optimal. A similar argument applies to e_2^*. This concludes the proof.

□

C.2 Proof of Proposition 4

Proof. First, suppose that the planner gives the farmer full insurance, with e_1 and e_2 observable but d not. As in the proof of Proposition 3, there is no benefit to any diversification as the farmer's income is equalized in all states of the world. Thus, the farmer chooses $d^* = 0$, which is the planner's optimum given the first-best full insurance contract.

Second, suppose that the planner gives the farmer full insurance but e_1 and e_2 are not observable. As in the proof of Proposition 3, since the farmer's income is equalized in all states, there is no return to any field-specific effort. So the farmer chooses $e_1^* = e_2^* = 0$. Per Proposition 3, this is not first-best.

□

C.3 Proof of Proposition 5

Proof. Suppose not. Label the supposedly optimal contract by $I(\cdot)$. Then for some total yield $Y = \sum_i X_i$ there is a non-degenerate distribution of payouts $I_Y(X)$ out depending on the field-by-field yields X. Consider instead the contract $\hat{I}(X) = \hat{I}(Y) = E_{X:\sum X=Y}[I(X)]$ that pays, at each total yield Y, the expectation of payouts from I, averaged over all field-by-field yields X that sum to the same total yield $Y = \sum X$. This generates the same expected payout, because it pays the same in expectation at each total yield Y. In other words, the budget constraint continues to be valid. The new contract is preferred since:

$$
\begin{aligned}
E\left[U(I(X))\right] &= \int_X \pi_x U\left(\sum x_i + I(x) - p\right) dx \\
&= \int_Y \int_{X:\sum X_i = Y} \pi_x U\left(\sum x_i + I(x) - p\right) dx dy \\
&< \int_Y U\left(\int_{X:\sum X_i = Y} \pi_x \left(\sum x_i + I(x) - p\right) dx\right) dy \\
&= \int_Y U\left(E_{X:\sum X_i = Y}\left[Y + I_Y(x) - p\right]\right) dy \\
&= E\left[U(\hat{I}(X))\right],
\end{aligned}
$$

where the inequality follows from the risk aversion of the farmer. This new contract delivers strictly higher utility.

It remains to prove that the new contract is convex (in total yield). To that end, consider two possible aggregate yields Y_1 and Y_2 and label $Y_\alpha = \alpha(Y_1) + (1-\alpha)Y_2$ for $\alpha \in [0,1]$.

We have:

$$
\begin{aligned}
\hat{I}\left(\alpha Y_1 + (1-\alpha)Y_2\right) &= \frac{1}{Prob(Y = Y_\alpha)} \int_0^{Y_\alpha} \left(I(x) + I(Y_\alpha - x)\right) \pi(x, Y_\alpha - x)\, dx \\
&\leqslant \frac{1}{Prob(Y = Y_\alpha)} \int_0^{Y_\alpha} \left(I(x) + \alpha I(Y_1) + (1-\alpha)I(Y_2) - I(x)\right) \pi(x, Y_\alpha - x)\, dx \\
&= \frac{1}{Prob(Y = Y_\alpha)} \int_0^{Y_\alpha} \left(\alpha I(Y_1) + (1-\alpha)I(Y_2)\right) \pi(x, Y_\alpha - x)\, dx \\
&= \alpha I(Y_1) + (1-\alpha)I(Y_2) \\
&= \frac{1}{Prob(Y = Y_1)} \alpha \int_0^{Y_1} I(x + Y_1 - x)\pi(x, Y_1 - x)\, dx \\
&+ \frac{1}{Prob(Y = Y_2)} (1-\alpha) \int_0^{Y_2} I(x + Y_2 - x)\pi(x, Y_2 - x)\, dx \\
&\leqslant \frac{1}{Prob(Y = Y_1)} \alpha \int_0^{Y_1} \left(I(x) + I(Y_1 - x)\right) \pi(x, Y_1 - x)\, dx \\
&+ \frac{1}{Prob(Y = Y_2)} (1-\alpha) \int_0^{Y_2} \left(I(x) + I(Y_2 - x)\right) \pi(x, Y_2 - x)\, dx \\
&= \alpha \hat{I}(Y_1) + (1-\alpha)\hat{I}(Y_2),
\end{aligned}
$$

where the inequalities follow from the convexity of $I(\cdot)$. □

C.4 Proof of Proposition 6

Proof. We first prove that $I_S(X)$ is super- and sub-modular (i.e., affine). This is intuitively clear but formally, first, note that

$$\sum_i \phi_i(x_i \wedge y_i) + \sum_i \phi_i(x_i \vee y_i) - \sum_i \phi_i(x_i) - \sum_i \phi_i(y_i) = 0 \tag{49}$$

since for every i we have

$$\phi_i(x_i \wedge y_i) + \phi_i(x_i \vee y_i) = \phi_i(x_i) + \phi_i(y_i). \tag{50}$$

This implies, from Denuit et al. (2006),that $E(I_S(X))$ does not change with diversification d.

Now, we show that $I_A = f\left(\sum_i x_i\right)$ is supermodular. By the definition of meet and join, we have that

$$\sum_i x_i \wedge y_i \leqslant \sum_i x_i, \sum_i y_i \leqslant \sum_i x_i \vee y_i. \tag{51}$$

Hence there exist λ_x, λ_y such that

$$\sum_i x_i = \lambda_x \left(\sum_i x_i \vee y_i\right) + (1-\lambda_x)\left(\sum_i x_i \wedge y_i\right) \tag{52}$$

$$\sum_i y_i = \lambda_y \left(\sum_i x_i \vee y_i\right) + (1-\lambda_y)\left(\sum_i x_i \wedge y_i\right). \tag{53}$$

Moreover, by (50) we have that $\lambda_x + \lambda_y = 1$. Hence we have,

$$\phi\left(\sum_i x_i\right) + \phi\left(\sum_i y_i\right) = \phi\left(\lambda_x \left(\sum_i x_i \vee y_i\right) + (1-\lambda_x)\left(\sum_i x_i \wedge y_i\right)\right) \tag{54}$$

$$+ \phi\left(\lambda_y \left(\sum_i x_i \vee y_i\right) + (1-\lambda_y)\left(\sum_i x_i \wedge y_i\right)\right) \tag{55}$$

$$\leqslant \lambda_x \phi\left(\sum_i x_i \vee y_i\right) + (1-\lambda_x)\phi\left(\sum_i x_i \wedge y_i\right) \tag{56}$$

$$+ \lambda_y \phi\left(\sum_i x_i \vee y_i\right) + (1-\lambda_y)\phi\left(\sum_i x_i \wedge y_i\right) \tag{57}$$

$$= \phi\left(\sum_i x_i \vee y_i\right) + \phi\left(\sum_i x_i \wedge y_i\right) \tag{58}$$

where the inequality follows from the convexity of ϕ. Hence I_A is supermodular. This implies, from Denuit et al. (2006), that $E(I_A(X))$ decreases with diversification d.

Now, consider the planner's first-order condition.

$$0 = \underbrace{\int_X U(\cdot)\frac{\partial}{\partial d}\pi_x(d)dx}_{\text{probability effect}} - \underbrace{\psi'(d)E_X\left[\frac{\partial U}{\partial p}\right]}_{\text{effort cost}} - \underbrace{\frac{\partial}{\partial d}E_X\left[I(X(d))\right]E_X\left[\frac{\partial U}{\partial p}\right]}_{\text{fiscal externality}}. \tag{59}$$

In contrast, the farmer's first-order condition is simply the first two terms. They do not account for the third term; they do not internalize the fiscal externality of their choice of d.

However, we showed above that for the separate contract, $E\left[I_S\right]$ does not change with d. Hence, the third term is zero and the farmer optimal choice of d is identical to the planner's.

On the other hand, under the aggregate contract, the third term is positive since diversification decreases the expected cost of insurance.

This implies that at the privately optimal choice of d, the slope of the planner's FOC is positive. By the assumption of single-peakedness, it follows that the socially optimal choice of diversification is higher than the farmer's private choice. This completes the proof.

□

C.5 Proof of Proposition 7

Proof. The farmer's choice of d under the insurance contract $I(X_1, X_2)$

$$\max_d \int_X U(x_1 - x_2 - p + I(x_1, x_2))\pi_x(e_1, e_2, d)dx_1dx_2 - \psi(e_1, e_2, d).$$

Denoting $Y = x_1 - x_2 - p + I(x_1, x_2)$ and decomposing U around the expected payout $E_d(Y)$ with a second-order Taylor expansion we have:

$$\max_d \left\{U\left(E_d[Y]\right) + \frac{1}{2}U''\left(E_d[Y]\right)\text{Var}_d(Y) - \psi(e_1, e_2, d)\right\},$$

where the expectations (and higher moments) depend on the choice of d.

Hence, the first-order condition for d trades off the variance reducing effects of d with any increases/decreases in expected income $E_d[Y]$ and changes in the cost of effort $\psi(e_1, e_2, d)$:

$$U'\left(E_d[Y]\right)\frac{\partial E_d[Y]}{\partial d} + \frac{1}{2}U''\left(E_d[Y]\right)\frac{\partial \text{Var}_d(Y)}{\partial d} + \frac{1}{2}U'''\left(E_d[Y]\right)\text{Var}_d(Y)\frac{\partial E_d[Y]}{\partial d} - \frac{\partial \psi(e_1, e_2, d)}{\partial d} = 0.$$

When the contract is aggregate, as shown in the proof of Proposition 6, $E_d\left[I_A\right]$ decreases in d. In contrast, when the contract is separate $E_d\left[I_S\right]$ does not change with d. Hence, when the farmer is close to risk-neutral (U'' and higher derivatives ≈ 0), the returns to reducing d, at any level of

d, are strictly higher under an aggregate contract than a separate. It follows that the farmer will choose a lower level of d^* under an aggregate contract than a separate when they are sufficiently close to risk neutral.

□

C.6 Proof of Proposition 8

Proof. The planner sets payouts in each state of the world $(I_1, \ldots, I_S)$ to maximize

$$\max_{(I_1,\ldots,I_S)} E_X \left[u \left(\sum_i x_i + I(X) - p \right) \right] - \psi(e_1, e_2, d) \tag{60}$$

noting that $\pi^X = \pi^X(e_1, e_2, d)$ and that e_1, e_2 and d are chosen by the farmer who optimizes given $(I_1, \ldots, I_S)$.

The first-order condition with respect to the payout in a particular state s, I^s, is given by

$$\pi^s u'(X^s) - \frac{\partial p}{\partial I^s} E_X \left[u'(X) \right] + \underbrace{\frac{\partial d}{\partial I^s} \frac{\partial}{\partial d} E_X \left[u(X) \right]}_{\text{envelope thm term}}. \tag{61}$$

The final term, if the farmer were optimizing, would be zero by an envelope theorem. Because we will take this to data, we do make this assumption.

But $\frac{\partial p}{\partial I^s}$ has direct and behavioral components. Specifically we have:

$$\frac{\partial p}{\partial I^s} = \frac{\partial}{\partial I^s} \sum_{x=1,\ldots,s,\ldots,S} I^x \pi^x(e_1, e_2, d) \tag{62}$$

$$= \pi^s + \frac{\partial d}{\partial I^s} \sum_{x=1,\ldots,s,\ldots,S} I^x \frac{\partial}{\partial d} \pi^x(e_1, e_2, d) \tag{63}$$

$$+ \frac{\partial e_1}{\partial I^s} \sum_{x=1,\ldots,s,\ldots,S} I^x \frac{\partial}{\partial e_1} \pi^x(e_1, e_2, d) + \frac{\partial e_2}{\partial I^s} \sum_{x=1,\ldots,s,\ldots,S} I^x \frac{\partial}{\partial e_2} \pi^x(e_1, e_2, d) \tag{64}$$

$$= \pi^s + \frac{\partial d}{\partial I^s} \frac{\partial}{\partial d} E_X(I(X)) + \frac{\partial e_1}{\partial I^s} \frac{\partial}{\partial e_1} E_X(I(X)) + \frac{\partial e_2}{\partial I^s} \frac{\partial}{\partial e_2} E_X(I(X)). \tag{65}$$

$$\tag{66}$$

Rearranging yields

$$\frac{u'(X^s) - E_X \left[u'(X) \right]}{E_X \left[u'(X) \right]} + \frac{\frac{\partial d}{\partial I^s} \frac{\partial}{\partial d} E_X \left[u(X) \right]}{\pi_s E_X \left[u'(X) \right]} = \frac{\frac{\partial d}{\partial I^s} \frac{\partial}{\partial d} E_X(I(X))}{\pi_s} + \frac{\frac{\partial e_1}{\partial I^s} \frac{\partial}{\partial e_1} E_X(I(X))}{\pi_s} + \frac{\frac{\partial e_2}{\partial I^s} \frac{\partial}{\partial e_2} E_X(I(X))}{\pi_s} \tag{67}$$

as required.

□

C.7 Proof of Proposition 9

Proof. The first-order approach allows us to replace the incentive compatibility constraint with the first-order conditions:

$$0 = \int u(x_1 - x_2 - p + I(x_1, x_2)) \frac{\partial f_1(x_1; e_1)}{\partial e_1} f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 - \frac{\partial \psi(e_1, e_2, d)}{\partial e_1}, \tag{68}$$

$$0 = \int u(x_1 - x_2 - p + I(x_1, x_2)) f_1(x_1; e_1) \frac{\partial f_2(x_2; e_2)}{\partial e_2} c(x_1, x_2; d) dx_1 dx_2 - \frac{\partial \psi(e_1, e_2, d)}{\partial e_2}. \tag{69}$$

The Lagrangian for the planner's problem is then, with multipliers λ on the budget constraint and μ_1, μ_2 on the first-order conditions for e_1 and e_2:

$$\begin{aligned}
\mathcal{L} = & \int u(x_1 - x_2 - p + I(x_1, x_2)) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 - \psi(e_1, e_2, d) \\
& + \lambda \left(p - \int I(x_1, x_2) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 \right) \\
& + \mu_1 \left(\int u(x_1 - x_2 - p + I(x_1, x_2)) \frac{\partial f_1(x_1; e_1)}{\partial e_1} f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 - \frac{\partial \psi(e_1, e_2, d)}{\partial e_1} \right) \\
& + \mu_2 \left(\int u(x_1 - x_2 - p + I(x_1, x_2)) f_1(x_1; e_1) \frac{\partial f_2(x_2; e_2)}{\partial e_2} c(x_1, x_2; d) dx_1 dx_2 - \frac{\partial \psi(e_1, e_2, d)}{\partial e_2} \right).
\end{aligned}$$

The first-order conditions are, with the shorthand $u(x) = u(x_1 - x_2 + I(x_1, x_2) - p)$:

$$\begin{aligned}
\mathcal{L}_p = & \lambda - \int u'(x) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 \\
& - \mu_1 \left(\int u'(x) \frac{\partial f_1(x_1; e_1)}{\partial e_1} f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2 \right) \\
& - \mu_2 \left(\int u'(x) f_1(x_1; e_1) \frac{\partial f_2(x_2; e_2)}{\partial e_2} c(x_1, x_2; d) dx_1 dx_2 \right) \\
\mathcal{L}_{I(x)} = & u'(x) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) - \lambda f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) \\
& + \mu_1 u'(x) \frac{\partial f_1(x_1; e_1)}{\partial e_1} f_2(x_2; e_2) c(x_1, x_2; d) + \mu_2 u'(x) f_1(x_1; e_1) \frac{\partial f_2(x_2; e_2)}{\partial e_2} c(x_1, x_2; d).
\end{aligned}$$

Now, take the farmer's FOC with respect to e_1 and e_2, (68) and (69), and differentiate with respect to p:

$$0 = \int u'(x) \frac{\partial f_1(x_1; e_1)}{\partial e_1} f_2(x_2; e_2) c(x_1, x_2; d) dx_1 dx_2, \tag{70}$$

$$0 = \int u'(x) f_1(x_1; e_1) \frac{\partial f_2(x_2; e_2)}{\partial e_2} c(x_1, x_2; d) dx_1 dx_2. \tag{71}$$

Substituting (70) and (71) into $\mathcal{L}_p$ yields $\lambda = E\left[u'(x)\right]$. Substituting this value for λ into $\mathcal{L}_{I(x)}$ yields

$$\mathcal{L}_{I(x)} = u'(x) f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d) - E\left[u'(x)\right] f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d)$$
$$+ \mu_1 u'(x) \frac{\partial f_1(x_1; e_1)}{\partial e_1} f_2(x_2; e_2) c(x_1, x_2; d) + u'(x) f_1(x_1; e_1) \frac{\partial f_2(x_2; e_2)}{\partial e_2} c(x_1, x_2; d).$$

Dividing by $f_1(x_1; e_1) f_2(x_2; e_2) c(x_1, x_2; d)$, and rearranging, yields the pointwise optimization condition:

$$\frac{1}{u'(x)} = \frac{1}{E\left[u'(x)\right]} \left[1 + \mu_1 \frac{\partial f_1(x_1; e_1)}{\partial e_1} \Big/ f_1(x_1; e_1) + \mu_2 \frac{\partial f_2(x_2; e_2)}{\partial e_2} \Big/ f_2(x_2; e_2)\right]. \tag{72}$$

This is a generalization of the optimality condition in Holmström (1979) and Lee et al. (2022), who argue that $\mu_1, \mu_2 > 0$. In other words, the incentive constraints bind.

To study the shape of the optimal contract, we differentiate (72):

$$\frac{\partial I(x_1, x_2)}{\partial x_1} = 1 - \frac{\mu_1 \frac{\partial}{\partial x_1} \frac{\partial f_1(x_1; e_1)/\partial e_1}{f_1(x_1; e_1)} u'(x)^2}{E\left[u'(x)\right] u''(x)} \tag{73}$$

$$\frac{\partial I(x_1, x_2)}{\partial x_2} = 1 - \frac{\mu_2 \frac{\partial}{\partial x_2} \frac{\partial f_2(x_2; e_2)/\partial e_2}{f_2(x_2; e_2)} u'(x)^2}{E\left[u'(x)\right] u''(x)} \tag{74}$$

Differentiating again, and substituting the first derivatives, we arrive at

$$\frac{\partial^2 I(x_1, x_2)}{\partial x_1 \partial x_2} = \frac{\mu_1 \mu_2 \frac{\partial}{\partial x_1} \frac{\partial f_1(x_1; e_1)/\partial e_1}{f_1(x_1; e_1)} \frac{\partial}{\partial x_2} \frac{\partial f_2(x_2; e_2)/\partial e_2}{f_2(x_2; e_2)} u'(x)^3 \left(2u''(x)^2 - u'''(x) u'(x)\right)}{u''(x)^3 \left(E\left[u'(x)\right]\right)^2}. \tag{75}$$

Since $\mu_1, \mu_2 > 0$, $\frac{\partial}{\partial x_1} \frac{\partial f_1(x_1; e_1)/\partial e_1}{f_1(x_1; e_1)}, \frac{\partial}{\partial x_2} \frac{\partial f_2(x_2; e_2)/\partial e_2}{f_2(x_2; e_2)} < 0, u'(x) > 0, u''(x) < 0$, we have that

$$\frac{\partial^2 I(x_1, x_2)}{\partial x_1 \partial x_2} > 0 \iff u'(x) u'''(x) - 2(u''(x))^2 > 0$$

from which the condition follows.

□

C.8 Proof of Proposition 14

First, some preliminary notation. To establish Proposition 14, the key step is to show that $E_X\left[I_A(X)\right]$ is higher for 'more correlated' distributions.

The critical decomposition that allows this is a generalization of Lemma 1.6.12 in Denuit et al. (2006). As notation, we write $\mathcal{I}_k \in \{1, 2, \ldots, n\}^k$ to denote the set of unique combinations of k

indices drawn *without replacement* from $\{1, 2, \ldots, n\}$. In other words,

$$\mathcal{I}_1 = \{\{1\}, \{2\}, \ldots, \{\{n\}\},$$

$$\mathcal{I}_2 = \{\{1,2\}, \{1,3\}, \ldots, \{1,n\}, \ldots \{n-1, n\}\}$$

and so on. For an element $I_k = \{i_1, i_2 \ldots i_k\} \in \mathcal{I}_k$, we denote the kth order partial derivative of a function g with respect to the indices in i_k by:

$$d^{I_k} g = \frac{\partial^k g(X)}{\partial x_{i_1} \ldots \partial x_{i_k}}.$$

For example, if $I_3 = \{1, 2, 4\}$ then

$$d^{I_k} g = \frac{\partial^3 g(X)}{\partial x_1 \partial x_2 \partial x_4}.$$

Similarly, for an index set of size k, we define the probability that the corresponding dimensions of X are big as:

$$P^{I_k}(t_{I_k}) = P(X_{i_1} > t_{i_1}, \ldots, X_{i_k} > t_{i_k}).$$

Again, or example, if $i_3 = \{1, 2, 4\}$ then

$$P^{I_3}(t_1, t_2, t_4) = P(X_1 > t_1, X_2 > t_2, X_4 > t_4).$$

Finally, denote a vector of length n with entries t_i for all $i \in I_k$ and zeroes elsewhere as 0_{I_k}. For example, if $I_2 = \{1, 3\}$ then $0_{I_k} = (t_1, 0, t_3, 0, \ldots, 0)$.

With these abbreviations, the crucial lemma is:

Lemma C.1. *For any function g satisfying the conditions in Massey and Whitt (1993),*

$$E\left[g\left(X_1, \ldots, X_n\right)\right] = g(0, \ldots, 0) + \sum_{k=1}^{n} \left(\sum_{I_k \in \mathcal{I}_k} \int_{t_{i_1}} \cdots \int_{t_{i_k}} P^{I_k}(t_{I_k}) d^{I_k} g(0_{I_k}) dt_{i_1} \ldots dt_{i_k} \right).$$

This is proved by repeated application of Lemma 1.6.12 in Denuit et al. (2006). With this in hand, we can prove the main proposition.

Proof. For an aggregate contract $I_A(X)$, by Lemma C.1 we have that

$$E_X\left[I_A(X)\right] = I_A(0, \ldots, 0) + \sum_{k=1}^{n} \left(\sum_{I_k \in \mathcal{I}_k} \int_{t_{i_1}} \cdots \int_{t_{i_k}} P_X^{I_k}(t_{I_k}) d^{I_k} I_A(0_{I_k}) dt_{i_1} \ldots dt_{i_k} \right).$$

If $X \precsim_{SC} Y$ then $P^{I_k}(t_{I_k})$ as defined above is always smaller under X than Y:

$$P_X^{I_k}(t_{I_k}) < P_Y^{I_k}(t_{I_k}).$$

If the aggregate contract is strongly convex, then $d^{I_K}(0_{I_k}) \geqslant 0$ for all I_k. It follows that

$$E_X\left[I_A(X)\right] < E_Y\left[I_A(Y)\right].$$

That is, the expected payout increases for more correlated distributions in the sense of $\precsim_{SC}$.

Alternately, if $X \precsim_{SM} Y$ then immediately, since convexity implies supermodularity, we have that the expected payout increases for the more correlated distribution in the sense of $\precsim_{SM}$. In either of these situations, the fiscal externality term in the planner's first-order condition 59 increases is positive. By the assumption of single-peakedness, this shows that socially optimal diversification is higher than the farmer's privately optimal diversification, as required.

Finally, for separate contracts, all cross-derivatives of order two or higher are negative. As such, the expression from Lemma C.1 reduces to the first-order terms, such that for $X \precsim Y$:

$$\begin{aligned} E_X\left[I_S(X)\right] &= I_S(0,\ldots,0) + \sum_{k=1}^{n} \int_{t_k} P_X(x_k > t_k) \frac{\partial I_X\left(0,\ldots,0,\overbrace{t_k}^{k\text{th term}},0\ldots,0\right)}{\partial x_k} dt_k \\ &= I_S(0,\ldots,0) + \sum_{k=1}^{n} \int_{t_k} P_Y(x_k > t_k) \frac{\partial I_S\left(0,\ldots,0,\overbrace{t_k}^{k\text{th term}},0\ldots,0\right)}{\partial x_k} dt_k \\ &= E_Y\left[I_S(Y)\right], \end{aligned}$$

since, by assumption, X and Y have the same marginal distributions. In other words, the expected insurance payout does not change with diversification in a separate contract. It follows that there is no fiscal externality to diversification under a separate contract and so the farmer's privately optimal choice of d coincides with the social optimum. This concludes the proof.

□

C.9 Proof of Proposition 15

Proof. Welfare after substituting in the budget constraint is given by, where we suppress the dependence of the probabilities on effort for ease of exposition.

$$
\begin{aligned}
W = & -\psi(e_1, e_2, d) + \pi_B u(-I_1\pi_1 - I_2\pi_2 + I_B(-\pi_B) + I_B - l_1 - l_2 + w) \\
& + \pi_1 u(I_1(-\pi_1) + I_1 - I_2\pi_2 - I_B\pi_B - l_1 + w) \\
& + \pi_2 u(-I_1\pi_1 + I_2(-\pi_2) + I_2 - I_B\pi_B - l_2 + w) + \pi_0 u(-I_1\pi_1 - I_2\pi_2 - I_B\pi_B + w)
\end{aligned}
$$

The first-order conditions with respect to I_1, I_2 and I_B are respectively, where we write $-I_1\pi_1 - I_2\pi_2 - I_B\pi_B + w = c_0, c_0 + I_1 - l_1 = c_1, c_0 + I_2 - l_2 = c_2, c_0 + I_B - l_1 - l_2 = c_B$

$$0 = \pi_0 u'(c_0) + (\pi_1 - 1)u'(c_1) + \pi_2 u'(c_2) + \pi_B u'(c_B), \tag{76}$$

$$0 = \pi_0 u'(c_0) + \pi_1 u'(c_1) + (\pi_2 - 1)u'(c_2) + \pi_B u'(c_B), \tag{77}$$

$$0 = \pi_0 u'(c_0) + \pi_1 u'(c_1) + \pi_2 u'(c_2) + (\pi_B - 1)u'(c_B). \tag{78}$$

Subtracting the second equation from the first, and the third from the second yields:

$$u'(c_1) = u'(c_2) \tag{79}$$

$$u'(c_1) = u'(c_B) \tag{80}$$

after which adding the first two equations yields

$$u'(c_1) = u'(c_0). \tag{81}$$

$$\tag{82}$$

Hence, full insurance is first-best. This means that $l_1 = I_1, l_2 = I_2, l_1 + l_2 = I_B$. As such, write $u(c_0) = u(c_1) = u(c_2) = u(c_B) = u$. At this first best, changes in diversification do not affect farmer utility, nor do they impact the budget, so they only impose a cost. As such, socially optimal $d^* = 0$. Finally, socially optimal e_1^* and e_2^* equalize the budgetary saving from increased effort with the cost of effort $\psi(e_1, e_2, d)$.

□

C.10 Proof of Proposition 16

Proof. This closely follows the proof of Proposition 8. The difference is the specific form that the fiscal externality from diversification takes.

By the definition of diversification, the marginal distribution does not change. In particular, the unconditional probability of field one experiencing a loss is $p_1 + p_B$. For this to remain constant with diversification changes we have that $\frac{\partial p_1}{\partial d} = -\frac{\partial p_B}{\partial d}$. Similarly, for the entire marginal distributions to remain constant we have that

$$\frac{\partial p_B}{\partial d} = \frac{\partial p_0}{\partial d} = -\frac{\partial p_1}{\partial d} = \frac{\partial p_2}{\partial d}.$$

Therefore,

$$\frac{\partial}{\partial I_B} E_X(I(X)) = \frac{\partial d}{\partial I_B} \sum_{s=1,2,B} \frac{\partial p_s}{\partial d} I_s = \frac{\partial d}{\partial I_B} \frac{\partial p_B}{\partial d}(I_B - I_1 - I_2).$$

This is the first-order condition for I_B. The conditions for I_1 and I_2 are derived similarly.

□

C.11 Proof of Lemma 17

Proof. Recalling that $A(X) = \sum_i X_i$, clearly $(A(X) - E(A(X)))^2$ is a convex function of X. It follows that $Var(A(X)) = (A(X) - E(A(X)))^2 \leqslant (A(Y) - E(A(Y)))^2 = Var(A(Y))$ when $X \precsim Y$ by Denuit et al. (2006). □

C.12 Proof of Proposition 18

Proof. Write $E(Y_1) = E(Y_2) = \bar{Y}$. We use the identities:

$$Var(XY) = Var(X)Var(Y) + Var(X)\bar{Y}^2 + Var(Y)\bar{X}^2 \tag{83}$$

and when $Cov(X, Y_1) = Cov(X, Y_2) = 0$ then

$$Cov(XY_1, XY_2) = Var(X)\bar{Y}^2 + Cov(Y_1, Y_2)\bar{X}^2 + Cov(Y_1, Y_2)Var(X). \tag{84}$$

Computing we have that

$$Corr(R_1, R_2) = \frac{\bar{Y}^2 Var(P) + \bar{P}^2 Cov(Y_1, Y_2) + Var(P)Cov(Y_1, Y_2)}{\bar{Y}^2 Var(P) + Var(P)Var(Y) + Var(Y)\bar{P}^2}.$$

Hence, if $Cov(Y_1, Y_2) \geqslant 0$ we have that

$$\begin{aligned}
Corr(R_1, R_2) \geqslant Corr(Y_1, Y_2) &\iff \frac{\bar{Y}^2 Var(P) + \bar{P}^2 Cov(Y_1, Y_2) + Var(P)Cov(Y_1, Y_2)}{\bar{Y}^2 Var(P) + Var(P)Var(Y) + Var(Y)\bar{P}^2} \geqslant \frac{Cov(Y_1, Y_2)}{Var(Y)} \\
&\iff \frac{\bar{Y}^2 Var(P)\frac{1}{Cov(Y_1, Y_2)} + \bar{P}^2 + Var(P)}{\bar{Y}^2 Var(P)\frac{1}{Var(Y)} + Var(P) + \bar{P}^2} \geqslant 1 \\
&\iff \bar{Y}^2 Var(P)\frac{1}{Cov(Y_1, Y_2)} \geqslant \bar{Y}^2 Var(P)\frac{1}{Var(Y)} \\
&\iff Var(Y) \geqslant Cov(Y_1, Y_2)
\end{aligned}$$

which always holds (this just says, rearranged, that the correlation coefficient is less than 1). If $Cov(Y_1, Y_2) \leqslant 0$ then we would reverse the inequality twice going from the first to second and third to fourth lines, arriving at the same expression.

□

C.13 Proof of Proposition 19

Proof. First, we introduce some new notation. Consider two vectors of length T whose elements have an equal sum: $(x_1, \ldots, x_T), (y_1, \ldots, y_T)$, $\sum_{i=1}^T x_i = \sum_{i=1}^T y_i = n$. Write $x_{(i)}$ for the ith lowest element of x $\left(\text{i.e., } x_{(1)} \leqslant x_{(2)} \leqslant \cdots \leqslant x_{(T)}\right)$.

Following Denuit et al. (2006), we define:

Definition 11. *Vector y majorizes x when*

$$\sum_{i=k}^{T} x_{(i)} \leqslant \sum_{i=k}^{T} y_{(i)} \textit{ for all } k = 1, 2 \ldots, T.$$

Proposition 6 from Denuit et al. (2006) shows that when the share-vector of a portfolio majorizes the share-vector of another, the former portfolio is more correlated/less diversified than the latter in the supermodular sense which (as we show below) implies the standard correlation order in Definition 4.

Then, to the proposition: a single-crop portfolio has share vector $x = (n, 0, \ldots, 0)$ clearly majorizes the share vector of any single-type portfolio. Then, from Denuit et al. (2006) Proposition 6.3.13, it follows that the single-type portfolio is higher than any mixed portfolio in the supermodular order. Then, since the indicator functions for a vector being elementwise greater or smaller than a fixed vector are supermodular, it follows that the single-type portfolio is more correlated/less diversified than a mixed type portfolio in the sense of definition 4. Similarly, since $(\frac{1}{2}, \frac{1}{2}, 0, \ldots, 0)$ majorizes $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}, 0, \ldots, 0) \ldots$ majorizes $(\frac{1}{n-1}, \ldots, \frac{1}{n-1}, 0)$ majorizes $(\frac{1}{n}, \ldots, \frac{1}{n}, \frac{1}{n})$, the second half of the statement holds as well. This completes the proof.

□

C.14 Proof of Proposition 20

Proof. If they crop k of their N fields, their per-field-portfolio can be represented by the $N + 1$ share-vector

$$P_n = \left(\underbrace{1, 1, \ldots, 1}_{k \text{ times}}, \underbrace{0, \ldots, 0}_{n-k \text{ times}}, \underbrace{n-k}_{\text{number of conserved fields}} \right)$$

. By the definition of majorization in the proof of Proposition 19, we have that P_n majorizes $P_{n'}$ for any $n < n'$. Following that proof, we see that the portfolio with n' fields cropped is more diversified than the portfolio with n fields cropped, as required.

□

C.15 Proof of Proposition 21

Proof. If the farmer irrigated k of their N fields, and doesn't irrigate the rest, write the share vector as $(k, N-k)$. Since $(0, N)$ majorizes $(1, N-1)$ majorizes $\dots$ majorizes $(N/2, N/2)$ the result follows in the same way as in the proof of Proposition 19.

□

C.16 Proof of Lemma A.1

Proof. Note that the indicator functions for $1\left[\wedge_i (X_i > c)\right]$ and $1\left[\wedge_i (X_i < c)\right]$ are supermodular, whereas $1\left[(\wedge_{i \in I}(X_i > c)) \wedge (\wedge_{i \in I'}(X_i < c))\right]$ is submodular. Since the probability is the expectation of the indicator function, the result follows by the definition of the correlation/supermodular ordering.

□

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