Optimal Insurance Scope: Theory and Evidence from US Crop Insurance

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Abstract

We face many risks in our lives, but these are typically covered by distinct insurance policies. Separate policies cover income loss and medical costs from a health shock, or damage to farms, homes, cars and lives from a natural disaster. To better insure consumption, is it optimal to have a single, 'aggregate' contract that pays more when many shocks occur simultaneously, but less when positive shocks self-insure negative shocks? Not necessarily, because an aggregate policy leads to *moral hazard on diversification* - actions that make it more likely that, if one risk occurs, they all do. We study this in 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. We analyze reforms in the FCIP that changed the scope of insurance, and provide evidence for this moral hazard. After a large increase in the premium subsidy for aggregate policies, farmers moved from separate to aggregate policies, and they reduced crop diversity, reduced irrigation, farmed less land, conserved more land, and insured price risk - all reducing the diversification of risk they face. This increased the variance of farm yield by 6% to 40%, depending on the crop. We estimate that the fiscal externality from the reduction in diversification was \$3-\$4, which outweighed approximately \$1 of increased insurance value from aggregate insurance. Conversely, after corrective reforms that de-aggregated the scope of insurance, farmers increased crop diversity and increased irrigation. More generally, we discuss how scope has widespread relevance in insurance design.

Keywords: Crop insurance, contract design, optimal policy, welfare

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1 Introduction

We face a wide variety of risks in our lives: health shocks cause uncertain medical spending and income loss; natural disasters damage property, lives and businesses. Yet the insurance that we buy 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 receives a higher payout if they are also lose their job than if they are employed, since marginal utility is higher. Similarly, if there are simultaneous positive and negative shocks, the latter is 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. This suggests that ideal policy has broad 'scope': many or all risks to consumption should be insured in a single 'aggregate' policy. Is this first-best, or is there an efficiency rationale for separate contracts?

Relative to separate policies, an aggregate policy distorts the incentive to diversify risk. Diversification makes it less likely that all risks occur simultaneously, and more likely that some do and some don't. By construction, an aggregate policy pays relatively more in the former state of the world and less in the latter. As a result, incentives to diversify are weakened in an aggregate policy. Precisely because of the insurance, the insured does not bear all the costs of their (lack of) action, and diversify less than is socially optimal. This is the familiar insurance/incentive trade-off, but on the dimension of scope: once more insurance is provided in a state of the world, actions are taken to make that state more likely, without regard to the insurer's cost.

This moral hazard takes multiple forms and occurs in many settings. Diversification can be distorted ex-ante: in crop insurance, farmers can plant a diverse mixture of crops, or partially irrigate their farm, or farm more land, all to ensure that even if one risk realizes, they don't all do so. Diversification can be distorted ex-post: in health insurance with a family deductible, the cost to the first family member getting sick is increased (as the family deductible is higher than an individual deductible), but if one member uses medical care this lowers the marginal price for the other family members. In both cases, an aggregate (or family) contract incentivizes actions that make all risks realize (or not) in lock-step. These actions are chosen without regard to the impact on costs, and hence are suboptimal. These actions need not change mean risk, just make it less likely that something goes wrong, and more likely that everything or nothing does.

We begin by formalizing these insights theoretically. We set up a general model of multiple risks and arbitrary correlation between them, without any parametric assumptions, in which a planner is setting the scope of the insurance policy. We have three results. First, aggregate policies provide higher farmer income in the worst states of the world - they offer better targeted insurance. Second, if the farmer can take an action that increases the diversification amongst their fields, their incentives to do so are weaker under an aggregate policy than under a separate policy. Third, the welfare cost of the fiscal externality due the (lack of) diversification is higher in an aggregate policy than a separate policy.[1] This is distinct from classical moral hazard, in which the mean risk is affected. This model and it's implications are applicable to a wide variety of settings in which the scope of policy needs to be set by a planner or insurer.

We study the scope of insurance in the context of the Federal Crop Insurance Program (FCIP). The FCIP is a government run and financed insurance program that protects farmers against any hazard to their crops.[2] In the FCIP, farmers can enroll their fields into separate or aggregate policies.[3] The former insures each field independently, the latter insures total yield for a given crop. Different crops are never insured together.[4] The FCIP also gives farmers large subsidies toward their insurance premia, typically between 50 and 85% of the premium. The premium and subsidy percentage depend on the farmer's choice of separate or aggregate scope. The FCIP has made multiple policy changes that affect the scope of insurance.

In 2009, the subsidy for aggregate insurance increased to be 20% higher per premium dollar than separate insurance. The aim was to equate the *dollar* amount of subsidies between the two policy types, which required a higher *percetange* subsidy for aggregate policies since they have a lower premium. The subsidy is difference between the actuarially fair premium and the portion paid by the farmer. But since the premium is actuarially fair, it equals expected indemnities. Hence, equalizing the dollar amount of subsidy between the two policies is equivalent to equalizing the expected fiscal cost to the government: the difference between expected indemnities paid out and the portion the farmer pays in. This means that a farmer swapping from separate to aggregate following the 2009 reform is designed to be budget neutral to the government. This is important for the eventual welfare analysis.

We use two complementary empirical strategies to evaluate the effects of this reform. First, using farm-level data from a long-running USDA survey, we can compare the change, pre- and post-reform, within farms that swapped to aggregate insurance to farms that remained in separate. Second, using the universe of insurance information, at a county-crop level, we can compare crops treated with the policy change to crops that were not treated. Whenever possible, we implement both approaches and find economically identical results.

The 2009 subsidy increase had a large effect on the scope of insurance. We find that 25% of insured acres moved from separate to aggregate insurance. We do not find any effects on total acres insured, indicating that the effect is driven by previously insured farms swapping to aggregate, not new farms entering the program.

As the scope of insurance was broadened, farmers took fewer actions to diversify the risk on their

[1] In the main paper we analyze only the most general model, but to build intuition and link to the literature we show in appendix A.2.1 these conclusions hold in a specific parametric model that builds off the canonical Baily-Chetty framework: making a contract more aggregated better provides insurance for farmer income but at the cost of moral hazard that decreases diversification.

[2] The private market for crop insurance is essentially non-existent.

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

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

farm. The variance of total yield increased on farms that swapped to aggregate insurance. We compare the distribution of total yield on farms that swapped to aggregate insurance, pre- and post-swap, with those that did not swap. Using this difference-in-differences design, we find that the standard deviation for farms that swapped increased by 6, 20 and 40% for soy, wheat and corn respective, more than for farms that remained in separate insurance. Since more diversified farms are less likely to have extreme total yield outcomes, this shows that farms that swapped to aggregate insurance diversified less.

We analyze changes to specific farming practices that lead to the increase in variance of yield. First, as the scope of insurance was broadened, crop diversity decreased by up to 17%. Planting a mixture of crop species or sub-species diversifies the risk a farm faces, but is more profitable in a separate policy.We study diversity within wheat. There are four sub-species of wheat recognized by the FCIP: winter, spring, durum and khorasan. Winter wheat is high-yield and high-risk: it is planted in the fall and must survive the winter; spring wheat is lower yield and lower risk: it is planted in the spring and need not survive the winter; khorasan and durum are low-yield but hardier and drought resistant varieties. Following the 2009 reform, farms that moved from separate to aggregate insurance moved to a less diverse mixture of wheat, relative to those that remained in separate insurance, consistent with the theoretical predictions.

Second, as the scope of insurance was broadened, the proportion of the farm irrigated fell by 6%. Irrigation is an important but costly form of self-insurance against drought, a hazard that can affect an entire farm at once. Irrigating some or all of a farm increases the mean yield and diversifies the risk profile of the farm, as no longer will the entire farm succeed or fail with variation in rainfall. Irrigating one field and not the other is profitable in separate insurance, where the failiure of the latter need not impact the success of the former. But not in aggregate insurance. This explains why, as farmers moved to aggregate policies, they reduced the proportion of their farm that was irrigated by 6%.

Third, as the scope of insurance was broadened, 44% of acres moved from yield to revenue coverage. In addition to choosing separate or aggregate policies, farmers can choose to yield (quantity) coverage or revenue (price $\times$ quantity) coverage. Since crop price risk is perfectly correlated across fields, there is a natural complementarity between aggregate insurance and revenue coverage - including price risk makes a loss on all fields simultaneously more likely. This interaction between revenue coverage and aggregate insurance is not priced in, and so farms that swapped to revenue coverage after moving to aggregate insurance increased the fiscal cost of the program.

Fourth, as the scope of insurance was broadened, farmers who swapped to aggregate policies rented out 10-20% less land and increased their participation in conservation programs by 10%. Having a larger farm is a natural method of diversifying risk. Any particular hazard is less widespread if many other fields are farmed. Moreover, the FCIP regulations state that any acreage in a county that a farmer has a financial interest in is included in that farmer's aggregate unit. This includes fields rented out for a fixed cash payment, in which the owner will never receive any share of the output, but which will be included in their insurance indemnity payout. For both of these reasons, following the 2009 subsidy increase, farmers rented out less land and enrolled it in conservation programs, reducing diversification.

We evaluate the welfare impact of the 2009 reform. On the benefit side, we estimate that aggregate policies deliver at most \$1 per acre of extra insurance value, relative to separate policies (the average farmer paid premium is approximately \$20 per acre). We use a parsimonious model in which the high-dimensional joint distribution of farm yield is reduced to three states: all fields fail, some fields fail, no fields fail. Aggregate policies pay more in the former and latter states, separate policies more in the middle state. Using pre-reform data, we estimate the probabilities and payoffs in each of the states of the world. Using the known premium and payout differences between the policies, we compute changes in farmer wealth in the three states of the world - assuming the probabilities do not change (i.e. assuming no moral hazard). Given the changed payoffs, we compute the change in willingness-to-pay for an aggregate policy in an expected utility framework. We estimate (an upper bound of) \$1 per acre of extra insurance value.

We study the fiscal costs of moral hazard induced by farmer behavioural changes. Despite the subsidy increase designed to be budget neutral, we show, in the raw time series, that fiscal cost of aggregate policies was approximately \$8.50 per acre higher than separate policies in the post-reform period. We distinguish genuine moral hazard (causing an efficiency loss through 'burnt money') from simply mispriced premia or overly generous subsidies (which are transfers from the government to the farmer). We demonstrate that the farmer behavioural changes described above - crop diversity, irrigation, revenue coverage and land use - account for \$3-\$4.50 per acre of the increased fiscal cost. Hence, we conclude that the efficiency costs of moral hazard due to changed farmer actions are markedly higher than the estimated insurance benefits.

Recognizing the drawbacks of the initial 2009 policy change, there were subsequent reforms in 2015 and 2022 that partially 'de-aggregated' the aggregate policies. In 2015, instead of irrigated and non-irrigated acreage entering into a single unit, they were split into distinct aggregate policies. This muted the incentive to distort irrigation choices, because no longer would a successful irrigated crop detract from an insurance payout on a failed non-irrigated crop. As a result of this 'de-aggregation', the amount of irrigation increased by 1-2% - as much as it fell by in 2009. Similarly, in 2022, instead of all types of wheat being combined into one policy, each type of wheat could be insured in distinct aggregate policies. A farmer in aggregate insurance could now benefit from one type of wheat succeeding without impacting payouts on failed types. We find this almost entirely reversed the distortion in diversity choices by farmers caused by the 2009 reform: In 2022 diversity rose by 14%, relative to the 17% fall after 2009.

The design of contract scope and the implications for moral hazard on correlation are applicable beyond crop insurance. Analogous scope dimensions include: family vs individual cost-sharing in health insurance; separate vs combined cost-sharing for different categories of medical expenses (inpatient, outpatient, drugs); insuring weekly vs yearly vs lifetime income through the tax and transfer system; family vs individual means-testing for unemployment insurance; insuring job loss vs income loss. In all these cases, the risk can be defined at differing degrees of aggregation. Often, but not universally, the aggregate quantity (e.g. total medical expenditure, family income) directly enters welfare. But the moral hazard incentive to reduce diversification of risk under aggregate contracts remains, and can provide a rationale for separate contracts.

Literature Review. We contribute to multiple literatures. First, our exploration of the scope of insurance policies adds a new dimension to the study of contract design in insurance. Marone and Sabety (2022) and Ho and Lee (2020) study the 'vertical' design of health insurance contracts - choice over how much of a given risk to cover. Solomon (2022) studies firm incentives to bundle policies together and the extent to which this helps or hurts the underlying market failure due to selection, and Nguyen (2018) the welfare consequences of only allowing family enrollment in public health insurance (i.e. prohibiting selective enrollment of some family members but not others). Note those papers are about combining policies, not aggregating or separating the underlying risks. Designing various aspects of health insurance contracts, such as networks of providers (Ho and Lee (2019), Shepard (2022)) or drug formularies Lavetti and Simon (2018), so as to attract low cost consumers can be thought of as an instance of defining the scope being insured. Our contribution is to conceptualize scope formally, and offer a framework that unifies related insights from these disparate settings.

Second, there have been numerous[5] studies of the effects of changes in the FCIP on farmer behaviour. Second, 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 12. That is, to our knowledge, the only other paper to study changes in contract scope choice on the take-up of crop insurance. Relatively, our contributions are: to move beyond take-up to study distortions in farmer behaviour induced by the shift to aggregate insurance, to delineate specific production practices that farmers changed to reduce diversification, to place this in a general theoretical framework and to estimate welfare effects.

There is a related literature studying the projected changes in risk to agriculture due to climate change. Klosin and Vilgalys (2022) estimate the impact of increasing extreme heat on corn yields.

[5]Smith and Goodwin (1996) document a link between crop insurance and chemical input use, with insured farms spending about $4 less 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 soy. Huang et al. (2018) show that farmers adapt their crop choices to private information on soil health in the period prior to 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 far lower than subsidy cost. Cornaggia (2013) finds a causal link between the expansion of insurance and productivity. The papers cited typically use annual measures of crop yield published by the National Agricultural Statistics Service which are collected from a select sample of farms. They are noisy and do not cohere with the crop insurance data, the universe of which is available every year. Analyses using NASS yield data are often sensitive to choices necessary to ensure alignment with crop insurance data (e.g. whether to censor counties for which acres insured erroneously exceeds acres planted).

In addition to increasing the mean risk, climate change is also expected to increase the spatial correlation between yields through various mechanisms. Lesk et al. (2021) show that increased frequency of simultaneous adverse temperature and moisture weather events are projected to decrease yields by 7-9% over and above to when each factor is modelled independently. Cheng and Yin (2022) show that the spatial correlation of grain production increased from 1995 to 2020. Tack and Holt (2016) show that spatial correlation is higher in years with extreme weather events (e.g. the intensity of drought) and since the frequency of extreme weather events is projected to increase with climate change so too is the spatial correlation. Burke and Emerick (2016) find that existing adaptations have done very little to mitigate the expected impact of climate change. Alternatively, the degree to which irrigation might mitigate these risks is explored by, for example, Braun and Schlenker (2023) who find cooling externalities from irrigation. Kukal and Irmak (2020) demonstrates that irrigation dramatically reduces inter-annual variation in crop yields by a factor of 2, and many studies, for example, Troy et al. (2015) Sharda et al. (2019), Wang et al. (2021) and Sweeney et al. (2003), find substantial increases in yield for irrigated crops. Our contribution is to conceptualize the trade-off in the design of insurance scope as risk changes, and to demonstrate that diversification behaviours and therefore spatial correlation in yield are endogenous to insurance design.

The rest of the paper proceeds as follows. Section 2 investigates the scope of insurance broadly, and provides a general model to study optimal scope. Section 3 gives institutional background for the FCIP, describes the policy changes we study and the econometric methods we use. Section 4 demonstrates that reforms to the scope of insurance caused moral hazard that decreased diversification and increased the variance of farm yields. Section 5 conducts a welfare analysis of the main policy change. Section 6 analyzes the effect of later, corrective reforms that narrowed scope and caused farmers to re-diversify. Section 7 concludes. The appendix provides proofs, supplementary figures and robustness checks.

2 The Optimal Scope of Insurance

To understand the scope of insurance and its widespread relevance, we give some examples from social insurance.[6] This is far from exhaustive, as the question of scope applies to almost every risk and insurance contract.

Insuring individual versus family risk is a dimension of scope pertinent to many settings. In health insurance, deductibles or out-of-pocket maxima can be defined individually or shared by the family. Unemployment insurance can insure individual or family income (e.g. by reducing individual benefits based on spousal income). The tax and transfer system more broadly might implicitly insure family income through joint filing, or treat everyone individually.

The time period over which risk is insured is an instance of scope. Health insurance contracts are

[6]Scope is also relevant for many risks that are typically privately insured, such as annuities or life insurance. In those cases, one margin of scope is whether it is individual or couple mortality/longevity that is being insured. For example, most life insurance contracts pay out when the (single) holder dies - and a couple might both buy these separate contracts if they desire - but joint policies pay out when the first or last of the couple dies.

typically annual, encouraging concentration of spending within a year. Unemployment insurance might replace every day, week, or month of lost income. The tax and transfer system typically insures annual income, but for example the U.S. corporate tax code allows for losses to be deducted against taxes for 5 years, implicitly smoothing income over that period.

Most insurance settings feature multiple risks that might be insured separately or together. Health insurance usually combines inpatient and prescription drug coverage, but is often distinct from dental insurance. Crop insurance, as we study, features multiple crops and fields of each. Every field of corn and every field of soybeans can be insured separately, or all the corn together but separately from all the wheat, or the entire farm together.

We assume that the aggregate quantity (e.g. farm income, or family income) is welfare relevant. The natural question is: why should the optimal insurance contract depend on anything else?

2.1 An example

Consider a farmer who has 2 corn fields. Denote the yield in field i by X_i. The possible yield outcomes in dollars (per Table 1) are: $X_1 = X_2 = 80$, $X_1 = 140, X_2 = 60$, $X_1 = 60, X_2 = 140$, $X_1 = 120, X_2 = 120$. Assume each outcome occurs with probability 1/4. The expected yield is 100 on each field.

There are two insurance contracts available, an aggregate and a separate contract. The aggregate contract insures aggregate yield up to \$200, the expected aggregate yield. The separate contract insures each field up to its expected yield of \$ 100, regardless of the yield on the other field. Formally, the indemnities paid are:

$$\text{Indemnity}_{Agg} = \max\{0, 200 - (X_1 + X_2)\} \tag{1}$$

$$\text{Indemnity}_{Sep} = \max\{0, 100 - X_1\} + \max\{0, 100 - X_2\}. \tag{2}$$

The premia charged for each policy are actuarially fair: they equal the expected indemnity. Under the aggregate policy, the expected indemnity and hence the premium are equal to 10, compared to 30 under the separate policy.

Accounting for yield, any indemnity received, and the premium paid (p_{agg} or p_{sep} respectively), the farmer's final income under each of these policies is

$$\text{Final Farmer Income}_{Agg} = \max\{X_1 + X_2, 200\} - p_{Agg} \tag{3}$$

$$\text{Final Farmer Income}_{Sep} = \max\{X_1, 100\} + \max\{X_2, 100\} - p_{Sep}. \tag{4}$$

For each of the yield outcomes, in Table 1 we summarize the indemnity, premium and farmer income under each of the two policies.

Yield Outcome	$X_1 = X_2 = 80$	$X_1 = 140, X_2 = 60$	$X_1 = 60, X_2 = 140$	$X_1 = X_2 = 120$
Probability	1/4	1/4	1/4	1/4
	Aggregate Policy			
Indemnity	40	0	0	0
Premium (act. fair)	10			
Farmer Income	190	190	190	230
	Separate Policy			
Indemnity	40	40	40	0
Premium (act. fair)	30			
Farmer Income	170	210	210	210

Table 1: Indemnity and farmer income under different yield scenarios for aggregate versus separate contracts and yield scenarios

Aggregate policies typically provide more insurance value by generating higher farmer income in the worst state of the world ($190 vs $170). This is their primary advantage over separate policies.

Now, suppose there are two costly (hidden) actions the farmer can take. The first increases diversification, so that the probability of the four yield outcomes becomes $\{0, 1/2, 1/2, 0\}$ instead of $\{1/4, 1/4, 1/4, 1/4\}$. The second decreases diversification and changes the probabilities to $\{1/2, 0, 0, 1/2\}$. The key assumption is that the actions are hidden, and so prices do not respond to them. Table 2 shows how expected final farmer income changes due to these actions, relative to the original distribution of yields.

Type of Action	Increased Diversification	Decreased Diversification
Counterfactual Probability	$\{0, 1/2, 1/2, 0\}$	$\{1/2, 0, 0, 1/2\}$
	Aggregate Policy	
Expected Farmer Income	190	210
Change in Expected Income due to Action	-10	10
	Separate Policy	
Expected Farmer Income	210	190
Difference in Income due to Action	10	-10

Table 2: Changed farmer income under actions that increase or decrease the diversification.

Table 2 shows that the incentives to take actions to change diversification depend critically on the contract. For example, under the aggregate contract, the farmer is willing to pay $10 for the action that decreases diversification. The planner's cost, inversely, is $10 higher under that action - because they pay the farmer more. Hence, at a cost of $9, the farmer would take the diversification-increasing action, delivering a private gain of $1. They would not account for the $10 in additional fiscal cost that the planner incurs. he overall welfare loss would be $9. This logic, flipped, applies to the separate policy.

This is analogous to the standard incentive/insurance tradeoff in, for example Baily (1978) and Chetty (2006): once insurance makes a state of the world more attractive, people put in less effort to avoid that state, or more effort to seek out that state, without accounting for the public cost.[7] This prevents insurance being too generous in that state of the world, as it induces a behavioural response from the farmer.

Intuitively, the scope of the insurance contract changes who the residual claimant to a successful yield is. This creates an agency problem. When one field is doing badly, the farmer no longer cares about investing in the second field, as they are no longer stand to profit from it: a dollar of yield on the second field reduces the indemnity on the first field by a dollar. In this case, the government is the residual claimant to yield on the second field, and hence the action they find socially optimal will often not be in the farmer's interest. The same agency problem occurs, inverted, under separate insurance. The agency problem occurs in the standard setting: when insurance is offered in the bad state of the world, the claim to marginal gains in that state of the world shifts from the agent to the planner, inducing a wedge between private and socially optimal actions.

In summary, there are three implications. First, since the aggregate policy leads to more income in the worst state of the world, it will typically provide more insurance value to a risk averse farmer than a separate policy. Second, actions that increase the correlation between field yields will be more attractive to a farmer in an aggregate policy, while actions that diversify the field yields will be more attractive in a separate policy. Third, farmers' actions will diverge from the social optimum, because they do not internalize the effect on the fiscal cost of the program. This means that the insurance benefits of aggregate contracts need to be traded off against their incentive effects.

These three facts hold generally, as the formal model shows.

2.2 General Model

In this section we show that the incentive/insurance trade-off is relevant in a very general setting. Aggregate insurance: 1) provides more insurance than separate insurance, but 2) induces more diversification-decreasing and correlation-increasing moral hazard that 3) exacerbates the fiscal externality for a utilitarian planner.

For concreteness we adopt the language of farms and fields, but the following model applies to any setting in which scope is relevant, and multiple risks might be aggregated (or not) into a combined policy.

A farmer has n 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 pays an indemnity $\iota(x)$ in state of the world x, that generally depends on the outcomes on all fields. The planner charges the farmer an actuarially fair premium $p = E_X[\iota(X)] = \int_X \iota(x)\pi_x dx$,

[7]For an explicit Baily-Chetty style formula, see appendix A.2.1.

to be paid in all states of the world. The farmer's final income is $\sum_i X_i + \iota(X) - p$ and their utility function over income is U, which we assume to be twice continuously differentiable and concave.

The farmer can put *uncontractable* costly effort toward changing the diversification / correlation between their fields.[8] The farmer chooses action e at convex cost $\psi(e)$ that affects the density of the joint distribution of yield $\pi_x = \pi_x(e)$.

Specifically, we assume that effort e decreases the correlation between fields, without changing the marginal distributions (in particular, expected yield). We write $\lesssim_{corr}$ for the partial order in correlation. $X \lesssim_{corr} Y$ means that X and Y have the same marginal distributions but that Y is more correlated than X, or conversely X is more diversified than Y.[9]

Assumption 1. *Effort continuously decreases the correlation between fields, $X+de$ is less correlated than X: $X(e+de) \lesssim_{corr} X(e)$ for $de > 0$.*

If the planner could directly choose e and the insurance contract ι the first-best choices would solve:

$$W = \max_{\iota,e} \int_X U\left(\sum_i x_i + \iota(x) - p(e)\right) \pi_x(e)dx - \psi(e) \tag{5}$$

$$\text{subject to:} \tag{6}$$

$$p(e) = E_X\left[\iota(X(e))\right]. \tag{7}$$

The first-order condition for first-best e is:

$$0 = \underbrace{\int_X U\left(\sum_i x_i + \iota(x) - p(e)\right) \frac{\partial}{\partial e}\pi_x(e)dx}_{\text{probability effect}} - \underbrace{\psi'(e)}_{\text{effort cost}} - \underbrace{\frac{\partial}{\partial e}E_X\left[\iota(X(e))\right] E_X\left[\frac{\partial U}{\partial p}\right]}_{\text{fiscal externality}}. \tag{8}$$

Effort effects welfare in three ways: 1) it directly changes the joint distribution of yield, 2) effort cost changes, 3) the expected indemnity changes. In the planner's first best, the effort choice by the farmer accounts for all of these impacts. However, the farmer does not internalize the fact that their effort affects the total fiscal cost of the program. The farmer instead takes ι and p as given and maximizes

$$V = \max_{e} \int_X U\left(\sum_i x_i + \iota(x) - p\right) \pi_x(e)dx - \psi(e). \tag{9}$$

$$\tag{10}$$

The inability of the government to observe e induces a wedge between social and private incentives

[8] Typically moral hazard refers to actions that affect mean risk, not the correlation between different risks. We study the case where the action affects both mean risk and correlation in appendix A.4

[9] A formal definition is in appendix A.

which we label $FE(e)$. It is the effect of effort e on the expected indemnity payment that the farmer does not account for. In particular, at the farmers optimal e^*, $FE(e^*)$ is equal to the welfare loss (in utils) from the marginal unit of effort e.[10]

$$FE(e) = \underbrace{\frac{\partial}{\partial e} E_X \left[\iota(X(e))\right] \lambda,}_{\text{fiscal externality}} \tag{11}$$

where $\lambda = E_X \left[\frac{\partial U}{\partial p}\right]$ is expected marginal utility of a dollar paid in all states of the world, i.e. the utility cost of raising an extra dollar of premium.

The fiscal externality depends on the insurance contract. Typically, at this juncture, one solves for the constrained-optimal contract ι and derives a Baily-Chetty type formula. In full generality this is harder to interpret, but we do so in appendix A.2.1. Here, we consider the two contracts that are actually offered in crop insurance: separate and aggregate, and contrast the wedge between private and socially optimal e in each case.[11] Separate insurance pays an indemnity on one field independently of the outcomes on the other fields. Aggregate insurance indemnities depend only on the sum of of the yields.

Definition 1. *If $\iota_{sep}(X) = \sum_i f_i(x_i)$ for continuous, weakly decreasing and convex f_i then we say a policy is **separate**. If $\iota_{agg}(X) = f\left(\sum_i x_i\right)$ for continuous, weakly decreasing and convex f then we say a policy is **aggregate**.*

We only assume that as yield increases, the insurance indemnity weakly decreases. Inversely, as the loss increases, the insurance indemnity weakly increases. Second, the indemnity function is convex, or, inversely, the 'cost-share' function, the amount of the loss paid by the farmer, is concave. This covers the vast majority of real insurance contracts, including all actual crop insurance contracts. [12]

For the first proposition we will assume policies feature the same shape of cost-sharing, just magnified to the scale of the field versus farm: The separate and aggregate policies are **equivalent** if $f_i(x_i) = \frac{f(x_i \cdot n)}{n}$. With these definitions we can state the central theoretical results. First, we formalize the sense in which aggregate insurance provides 'more insurance' for total yield than separate insurance,

Proposition 1. *Suppose that the separate and aggregate policies are equivalent and actuarially*

[10]This is because, at the agents optimal e^*, the first two terms of (8) sum to zero (agents FOC), and so $FE(e^*)$ is the social (benefit) of infinitesimally more (less) effort.

[11]Indeed, in many insurance settings, individual and family contracts are common and correspond to separate and aggregate contracts considered here.

[12]And for example, all the health insurance contracts considered by e.g. Chade et al. (2022). On the other hand, a contract that features a 'donut hole' such as in medicare part D, does not satisfy the assumption. Donut holes break the concavity of the cost sharing scheme, because the coinsurance rate is high (during the deductible), low (in the first coinsurance region) then high again (in the donut hole). That exception notwithstanding, the assumptions in the definition are quite weak.

fair given a distribution of yields X. Then for a range of low and high aggregate yields, $(\sum_i x_i) \in [0, \underline{c}] \cup [\bar{c}, \sum_i \overline{x}_i]$ *final farmer income is higher under the aggregate policy than the separate.*

This is the main advantage of an aggregate policy. By directly insuring the welfare relevant quantity - aggregate yield - it offers the farmer greater income in the very good and very bad states of the world. However, this extra insurance induces more moral hazard. in the form of less diversification or more correlation.

The next result implication is that farmers diversify less under an aggregate policy than a separate.

Proposition 2. *When farmer risk aversion is not too large*[13] *diversification effort is higher under the separate policy than an aggregate:* $e^*_{Sep} > e^*_{Agg}$.

This result comports with the intuition from the numerical example. Since aggregate policies leave the farmer better off when all fields do well or do badly together, their incentives to diversify are weaker than under a separate policy, which rewards some fields doing well and others doing badly. Finally, this impacts fiscal externality that the diversifying action causes on government payouts.

Proposition 3. *The fiscal externality - the cost of socially sub-optimal effort – is higher under the aggregate contract:* $FE_{Agg}(e^*_{Agg}) \geqslant FE_{Sep}(e^*_{Sep})$.

The wedge between social and private incentives arises from the farmer not accounting for the costs to the government of their correlation-changing effort. Aggregate insurance provides more insurance in the state of the world where everything goes badly at once, and farmers therefore take actions to make this state of the world more likely. This fiscal externality prevents the government from offering full insurance as in the first-best.[14]

Together these results illustrate an insurance/incentive trade-off on the scope dimension. Aggregate insurance provides more in insurance in the sense of Proposition 1, but induces more moral hazard in the sense of Proposition 3. We now move to empirical evidence for the latter fact: as farmers move aggregate insurance, they take fewer diversification-increasing and more correlation-increasing actions.

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

3.1 U.S. Agriculture and Crop Insurance

The agriculture industry accounts for 5.4% of U.S. GDP, with a fifth being farm output. Agriculture is vital, but susceptible to various risks. This include localized pest outbreaks, or idiosyncratic equipment malfunction, as well as widespread drought and adverse climactic conditions. To mitigate

[13] A sufficient condition is that the coefficient of absolute risk aversion is not too large. A necessary condition is given in the proof.

[14] For details on this distortion, see the Baily-Chetty formula in appendix A.2.1

these risks and safeguard the national food supply, the U.S. Government introduced the FCIP in the 1930s. This program saw increased participation in the 1980s and 1990s due to premium subsidies of up to 67% for farmers. Currently, the FCIP insures over 85% of major crop acreages and 73% of eligible specialty crops, totaling over $150 billion in liabilities in 2021. The FCIP is part of the broader 'farm safety net,' which also includes direct subsidies, loans and credit access, and ad-hoc disaster assistance. Our focus will be solely on the FCIP, and we give evidence in appendix B.8 that the FCIP policy changes we study did not substantively interact with other farm programs.

Why is the government involved? There are multiple reasons why crop insurance in the U.S. is essentially entirely publicly run and financed. First, as shown by Deryugina and Kirwan (2018), the Samaritan's dilemma - the fact that, should a disaster occur, the government will be politically compelled to help those in need - leads to under-investment in formal insurance. The FCIP can be thought of as encouraging farmers to pay premia in the good states of the world for the assistance in the bad states of the world that they will inevitably receive. Second, the aggregated and correlated nature of climactic risks means the private market might struggle to function (see, e.g. Cutler (1993) and Solomon (2023)). Third, private information inhibits the function of private insurance markets and often justifies public subsidy or other intervention (see, for example, Einav and Finkelstein (2011)). Huang et al. (2018) shows that farmers do hold private information generally, and we give evidence in appendix B.6 for private information about the correlation of risks a farm faces specifically.

3.2 Policy Changes

We focus primarily on a large increase to the premium subsidy in 2009. Subsequently, in section 6 we study reforms that partially rolled this back, by 'de-aggregating' aggregate insurance.

3.2.1 Primary Policy Change: 2009 Subsidy Increase

The 2008 Farm Bill, implemented in 2009, sharply increased the subsidy per dollar of premium for aggregate policies, relative to separate policies.[15][16] Figure 3 below illustrates the subsidies offered, as percentages per premium dollar. We see that the percentage subsidy increased sharply, by up to 22%, for aggregate policies, while remaining unchanged for separate policies. This reform suceeded in getting farmers to swap to aggregate insurance. We use it to estimate the insurance benefits and moral hazard costs of farmers moving to insurance with a more aggregate scope.

[15] These subsidies increased for 11 crops (grain sorghum, wheat, soybeans, corn, cotton, rice, barley, canola, flue cured tobacco, pecans, sunflowers), but not for 10 others (oats, potatoes, sweet potatoes, dry beans, sugarbeets, dry peas, pumpkins, rye, sesame, popcorn). In our between-crop analysis, these will be the treated and control crops respectively.

[16] Per United States Department of Agriculture (2008), the rationale was to try and equate the *dollar* amount of subsidy received in separate and aggregate policies. Because aggregate policies are cheaper, this requires a higher percentage subsidy. The USDA was concerned that farmers were choosing the policy with the highest dollar subsidy, regardless of whether final premium paid by the farmer was higher or lower, and this was responsible for low aggregate insurance take-up.

	Pre-2009	Post-2009
Separate	55%	55%
Aggregate	55%	77%

Table 3: Subsidies, per dollar of premium, at a 75% coverage level for separate vs aggregate insurance pre and post reform.

Crucially, this reform was designed to be **budget neutral** for any farm that swapped from separate to aggregate insurance. The reforms intention was to equate the dollar subsidy received in both policies. The subsidy is the difference between the premium and farmer-paid premium. Since the premium is set to be actuarially fair, it is equal to expected indemnity. Hence, the subsidy is the difference between expected payouts from the government, and farmer premium payments to the government. By equating these in dollar terms, a farmer who swapped from separate to aggregate should not cost the government more, if the premium and subsidy were set correctly.[17]

3.2.2 Corrective Reforms in 2015 and 2022

Until 2015, an aggregate unit included all acreage of a crop in a county, even if that acreage included different production practices (e.g. irrigated vs not) or different sub-types of the crop (e.g. spring vs winter wheat). In 2015, the definition was changed so that irrigated and non-irrigated acreage would be insured in distinct aggregate policies. In 2022, different sub-types of wheat became distinct aggregate units.

These reforms partially 'de-aggregated' the aggregate policies. We show that this removes the distortions in incentives to irrigate or plant diverse wheat types that the original aggregate policies introduced. In particular, while the 2009 reform lead to a fall in irrigation and crop diversity, the 2015 and 2022 reforms reversed these declines.

3.3 Key agricultural outcomes

The policy changes caused a change in insurance scope: either farners moved from separate to aggregate insurance, or aggregate insurance was 'de-aggregated'. We study how changes in insurance scope have downstream effects on farm production practices. The ideal data set would have field-by-field yield records for each year. This would allow for a direct analysis of the effects of farmer behavioral changes on intra-farm diversification and correlation. However, we (indeed, even the FCIP) do not observe field-by-field yield outcomes. Therefore, we take an alternate two-pronged approach: using the variance of total yield on a farm as a proxy for intra-farm diversification, and by measuring changes to specific farmer actions that affect diversification.

Our first approach studies the *variance of total yield* on a farm. Diversification actions change intra-farm correlation and consequently the variance of total yield. When fields are correlated, we expected very high or very low total yield outcomes on a farm to be more likely relative to

[17] Prior to the reform, essentially no one enrolled in separate policies, and so there are no infra-marginals.

a diversified farm. We show that the variance of total yield increased on farms that swapped to aggregate insurance after the 2009 policy change.

Our second approach studies farmer behaviours that change intra-farm diversification and correlation: *crop diversity, irrigation, farm size, and the choice of revenue versus yield insurance.* As we explain, these farming practices impact diversification and correlation ex-ante, even if data limitations do not allow us to directly compute the diversification and correlation ex-post. This ex-ante approach has a clear advantage over working with ex-post yields: we do not have to disentangle time and location specific shocks, from selection effects, from moral hazard. Instead we show that the changed scope of insurance causes farmers to change these farming practices, and argue that those practices directly affect the intra-farm correlation and diversification. We study four specific actions.

First, even though insurance policies are crop specific, many crops have multiple varieties the farmer can choose to plant. We primarily focus on wheat, which has four varieties: wheat, spring, durum and khorasan. These varieties are vulnerable to different hazards. Planting different varieties of wheat reduces the sensitivity of farm output to any one particular hazard, which therefore reduces correlation within the farm. We show that as the scope of insurance broadens farmers plant less diverse mixtures of wheat, and as the scope of insurance narrows they plant more diverse mixtures. The premium for each type of wheat receives a type-specific premium, but the diversity of wheat within an aggregate unit is not priced in.

Second, farmers choose whether or not to irrigate some or all of their crop. Irrigation allows for high yield even in dry conditions. Irrigation reduces the sensitivity of farm output to widespread shocks like drought and therefore diversifies the farms risk, reducing correlation. We show that as the scope of insurance broadens and diversification incentives weaken, farmers use less irrigation. Note, whether a particular field is irrigated or not is priced into the premium for that field. But the discount received for the aggregate unit does not account for the proportion of a farm that it is irrigated or not.

Third, land can be cropped by the owner, or rented out for cash or a share of the crop to a different operator, or enrolled in a conservation program with financial incentives. The larger a farm the less correlated yields will be, as a given shocks will affect a smaller portion of the farm. Moreover all the acreage in which a farmer has a financial interest, whether they farm it themselves or rent it out, is included in the same aggregate policy. Thus, farmers can diversify their risk by farming more land, or correlate it by farming less land (either themselves or by a tenant). We find that as the scope of policies increase, farmers rent out less land and enroll more land in conservation programs.

Fourth, farmers can choose to insure yield (quantity), or revenue (price $\times$ quantity). Since price is a risk perfectly correlated across all fields of a crop, revenue insurance makes it more likely for all fields to experience a loss or not at the same time. We find that as farms move to aggregate insurance they also move to revenue insurance, thereby increasing the correlation of the risk insured.

3.4 Data

3.4.1 USDA Agricultural Resource Management Survey (ARMS)

Our analysis of the change in production practices within-farm uses the Agricultural Resource Management Survey (ARMS). ARMS is is an annual survey conducted by the United States Department of Agriculture that collects farm level data about land use, crops planted, farm finances, chemical use, and various production practices practices. There are multiple parts to ARMS, the Phase II survey that rotates between crops and asks about production practices on a randomly selected field of that crop, and the Phase III survey, the Cost and Returns Report, which gathers detailed data about farms' finances, production practices, resource use, and costs.

We use all ARMS data from before and after the 2009 reform, combined with markers of which farms moved to aggregate insurance from the 2014 ARMS survey.[18] ARMS is randomly resampled every wave. We construct a panel by considering farms that are 1) surveyed (at least) once before and once after the 2009 policy change and 2) are surveyed in 2014 so that theire take-up of aggregate insurance is known. This allows for a within-farm difference-in-differences analysis.

3.4.2 FCIP Summary of Business

Our second main data source is the FCIP Summary of Business (of Agriculture (of Agriculture)). These data contain the universe of crop insurance purchases in the FCIP. They consist of data on the contract type, acreage insured, premium paid, total potential liability, subsidy amount, indemnity amount and loss ratios.

Unfortunately the data are not at the farm level.[19] They are available at Year, State, County, Crop, Coverage, Type, Practice, Unit (YSCCCTPU) level. Coverage refers to the level of expected yield being insured, or alternatively, the deductible a farmer pays before insurance pays an indemnity.[20] Type refers to the species of crop (e.g. winter vs spring wheat). Practice refers to cropping practices such as irrigation. Unit refers to what we have been calling the *scope* of the policy - the level of aggregation at which the risk insured is defined.[21] So a datum would record, for example, the 2023

[18]The 2014 version, known as the Tenure, Ownership, and Transition of Agricultural Land (TOTAL) survey, was more expansive than other years. It specifically collected information on acres insured under aggregate versus separate plans. This allows us to identify farms that moved to aggregate insurance.

[19]For most of our analysis, the fact that we have county level data instead of the ideal farm level data does not pose an issue. Most outcomes are 'monotonic' in the sense that an extra irrigated in a county has to mean an extra acre was irrigated on a farm. The only outcome for which this monotonicity possibly breaks 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 appendix B.15 and conclude it is not an issue.

[20]For example, if a farm has expected yield of 100 bushels and a policy with a 75% coverage level, then if actual harvest yields 75-100 bushels, no indemnity is paid, and these first 25 bushels of loss is a deductible. If yield is lower than 75 bushels, the farmer is indemnified up to 75 bushels.

[21]What we call aggregate units are officially known as *Enterprise units*, and what we call separate units are officially *Optional* units. There are two other unit types. *Whole-farm units* (in which all crops are pooled into one policy) have essentially zero take-up and so are dropped. *Basic* units are defined by ownership structure, not geography. For that reason, it is hard to order them with respect to either *Enterprise* or *Optional* units. Moreover, enrollment in basic units do not seem to respond to any of the policy changes under study.

acreage insured, premium, liability, subsidy and indemnity for all the irrigated winter wheat in Travis County, Texas that is insured by aggregate units.

Selected summary statistics are in table 4 below, split into aggregate and separate policies. The average premium is about $41 per acre for separate policies, and about $ 44 for aggregate policies. Of these premia, the separate policies receive a substantially lower subsidy than aggregate units: $22 relative to $31. The average payout for both are comparable at approximately $33. This leads to loss ratios of about 70-75% for both separate and aggregate policies.

The first three rows of the table, in red, foreshadow our results that we investigate causally in the next section: on farms in aggregate insurance, irrigation is lower, diversity is lower and revenue insurance is more prevalent.

Table 4: Policy Summary Statistics, Aggregate vs Separate

	Separate			Aggregate		
	Mean	SD	Acres x Years	Mean	SD	Acres x Years
Irrigated	0.20	0.40	0.27	0.09	0.29	0.10
Diversity (Wheat)	0.15	0.27	0.08	0.09	0.19	0.08
Revenue Insurance	0.80	0.40	1.04	0.96	0.20	1.11
Premium Per Acre ($)	40.86	45.76	1.30	44.00	23.62	1.16
Subsidy Per Acre ($)	22.44	32.75	1.30	31.23	17.27	1.16
Indemnity Per Acre ($)	32.85	71.40	1.09	33.87	70.70	0.94
Liability Per Acre ($)	357.43	274.05	1.30	472.64	239.69	1.16
Loss Ratio	0.75	1.25	1.08	0.72	1.45	0.91

Note: Acres are expressed in billions. Only crops used in the analysis are included.
Means and SD are weighted by acres insured.

The ARMS and the SOB are complementary. ARMS has farm-level data and a rich set of covariates, albeit with a smaller sample size and no control crops. The SOB has universal data and control crops, although with a smaller set of outcomes and county-crop level data.

3.5 Econometric Methods & Identification

We use two primary econometric strategies: 1) a within-farm comparison that compares farms that do and don't swap to aggregate insurance, pre and post reform; 2) a between-crop comparison that compares crops that were treated with the policy change against control crops that were not. Where possible, we run similar analyses in both and almost unversally find the same results.

DID - Within-Farm Our main analyses of changes in farm production practices due to the 2009 policy change use ARMS data. For data reasons,[22] we restrict our ARMS analsis to the three largest crops: corn, soybeans and wheat. There are no control crops present in the ARMS data,

[22] In particular, only a few crops were asked about their aggregate versus separate insurance in 2014

and so our analysis compares the change in outcomes pre and post reform on farms that, after a policy change, moved to aggregate insurance to those that did not. Since we have farm-level data, we measure outcomes and include fixed effects by farm f.

We estimate specifications of the following form (sometimes with crop fixed effects, where necessary):

$$y_{f,t} = \alpha_f + \gamma_t + \tau \mathbb{1}\left[t \geqslant \text{treatment year}\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{ft} \tag{12}$$

Outcomes of interest include irrigation, crop diversity, land use, conservation and revenue insurance enrollment. Throughout we weight, as required by ARMS, by population-representative sampling weights. We restrict our analysis to farms observed both before and after the policy changes, and for whom we can observe their choice of aggregate vs separate insurance. Here α_g denote farm fixed effects and γ_t are year fixed effects. Our single treatment effect τ is a comparison of mean changes amongst the farms that swapped to aggregate insurance relative to the to the changes in the farms that remained in separate.

TWFE - Between-Crop To analyze the 2015 and 2022 corrective policy changes, and for additional evidence on the 2009 policy change, we do a between-crop comparison using the SOB data. WWe use the fact that only certain crops were treated by each policy change. In these specifications, we measure outcomes at the county c, crop c, year t level. We include fixed effects for crops (since treatment is at the crop level) and for time. We estimate a two-way fixed effect specification of the form:

$$y_{c,c,t} = \alpha_{crop} + \gamma_t + \tau_t \mathbb{1}\left[t\right] \times \mathbb{1}\left[\text{crop} = \text{TreatedCrop}\right] + \epsilon_{c,c,t}. \tag{13}$$

Outcomes of interest include enrollment in separate insurance, crop diversity, percentage of acres irrigated and so on. Throughout we weight by acres insured.. Here α_{crop} denote crop fixed effects and γ_t are year fixed effects. The coefficients of interest are treatment effects τ_t, one for each time period.

SDID When necessary, we validate our TWFE and DID results by Synthetic Differences and Differences (SDID) (Arkhangelsky et al. (2021)). SDID generalizes synthetic control methods to the case when there are many treated units. SDID creates unit weights so that the average outcome for the treated units is approximately parallel to the weighted average for control units in the pre-period. Time weights are designed so that the average post-treatment outcome for each of the control units differs by a constant from the weighted average of the pre-treatment outcomes for the same control units. Intuitively, using only similar units and similar periods makes our estimate more robust, and the method is picking, based on the data, which control units and time periods are best for our synthetic treated group.

4 Effects of the 2009 Subsidy Increase: Scope and Moral Hazard

In this section we show that the 2009 policy changed caused many farmers to swap to aggregate insurance. Then we show that farmers that swapped to aggregate insurance changed farming practices to reduce diversification amongst their crop. We show this in two ways: first by studying changes in the distribution of aggregate yield, consistent with less diversification; second, by analyzing changes in specific measured diversification actions (irrigation, diversity, land use and revenue vs yield coverage.

4.1 Effects on Scope Choice

As a 'first-stage' we show that the 2009 aggregate insurance subsidy increase caused many farmers to swap from separate to aggregate insurance. We first show that the 2009 subsidy sharply moved treated crops from separate to aggregate[23] insurance, without any discernible change in the total acreage insured.

Within the SOB data, we compare our 3 focus treated crops (wheat, soy and corn) that were treated with 10 that were not.[24] We analyze the percentage of acres for a given crop in a county that are enrolled in separate insurance, as well as the (log of) acres enrolled in any insurance We estimate the following two specifications, at the level of county c, crop c and year t, the results are in figure 9

$$\frac{\text{Acres in Separate Insurance}_{c,c,t}}{\text{Acres in Any Insurance}_{c,c,t}} = \alpha_{crop} + \gamma_t + \tau_t \mathbb{1}[t] \times \mathbb{1}[\text{Treated} = \text{Crop}] + \epsilon_{c,c,t}. \tag{14}$$

$$\text{Acres in Any Insurance}_{c,c,t} = \alpha_{crop} + \gamma_t + \tau_t \mathbb{1}[t] \times \mathbb{1}[\text{Treated} = \text{Crop}] + \epsilon_{c,c,t}. \tag{15}$$

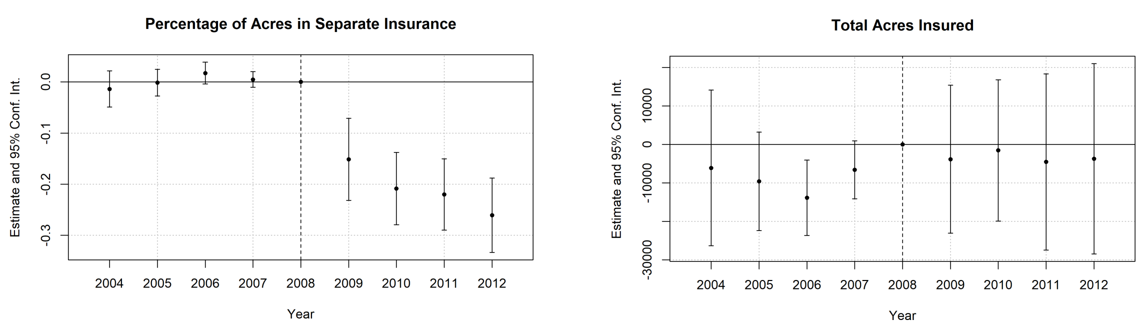

Figure 1: Treatment effect of being a crop eligible for the expanded aggregate subsidy on: panel (a) the percentage of acres enrolled in *separate* insurance; panel(b) the log of acres enrolled in *any* insurance. The estimating equations are (14) and the coefficients τ_t are graphed. Observations are weighted by acres insured.

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

[24]The control crops are: oats, potatoes, sweet potatoes, dry beans, sugarbeets, dry peas, pumpkins, rye, sesame, popcorn. To check for robustness to an improper control group and any pre-trends, we also run the synthetic DiD which gives a very similar estimate of 20% (s.e. = 1%).

We see a sharp movement away from separate insurance for the crops treated with the aggregate insurance subsidy. An increase in subsidy rates by up to 22% unsurprisingly causes farmers to swap into this type of insurance. In 2009 we see a treatment effect of 15%, which increases to 25% by 2012. We do not see any significant change in total acres insured, implying that farms previously in separate insurance, not previously uninsured farmers, who are are moving to aggregate insurance.

4.2 Moral Hazard

As farmers move to aggregate policies, the theory predicts they will take fewer diversifying actions within their farm. Ideally, we would observe yield on each field within the farm and directly check for changes in correlation. However, our data do not allow for this. Instead, we proceed in two alternate and complementary ways. First, by proxying for intra-farm correlation with the variance of total farm yield. Second, by showing that particular, ex-ante actions by the farmer that affect diversification (e.g. crop diversity, irrigation) go down.

4.2.1 Effects on the Aggregate Yield Distribution

We cannot observe field level outcomes. To study correlation between fields, we use the variance of total farm yield as a proxy. The following result simply says that the more diversified a farm is, the less likely it is to have very low or very high total yield, since fields are unlikely to all do well or all do badly at the same time.

Lemma 4.1. *Define the total farm yield as* $A(X) = \sum_i X_i$. *If* X *is more diversified than* Y, $X \precsim_{corr} Y$, *then* $Var(A(X)) \leqslant Var(A(Y))$.

Ideally, we would observe each farm's yield many times. This would enable us to study the distribution of total farm yield, within each farm. However, due to the small size of ARMS (and the fundamentally short time period of this analyses) this is not possible. The second best is to study the distribution of yield across farms that swapped to aggregate insurance, before and after they swapped, and compare this to the change in farms that did not swap.

We compare the standard deviations (S.D.) of the yield distribution in in two ways. First, define $S.D.^{c}_{Pre,Sep}$ to be the variance of yield per acre of crop $c \in \{\text{corn, wheat, soybeans}\}$ over all farms who did not swap to aggregate units over all observations from 2003-2008. Similarly we define the variance for the farms that did swap, in the pre and post period.

Second, to account for any time trends and aggregate shocks that may have occurred, , we estimate, separately for each crop, for farm f in year t: $\frac{\text{Yield}}{\text{Acre}}_{ft} = \gamma_t + \epsilon_{ft}$.

We compute the residuals from this regression, and define the variance of the residualized yield per acre as $\widetilde{S.D.}^{Corn}_{Pre,Sep}$ and so on, analogously to above.

With the standard deviations, raw or residualized, of farm yield in hand, we analyze a difference-in-differences of standard deviations (S.D):

$$\text{DiD } S.D. = S.D.^c_{Post,Agg} - S.D.^c_{Pre,Agg} - \left(S.D.^c_{Post,Sep} - S.D.^c_{Pre,Sep}\right) \tag{16}$$

$$\text{DiD } \widetilde{S.D.} = \widetilde{S.D.}^c_{Post,Agg} - \widetilde{S.D.}^c_{Pre,Agg} - \left(\widetilde{S.D.}^c_{Post,Sep} - \widetilde{S.D.}^c_{Pre,Sep}\right). \tag{17}$$

The mean difference-in-differences of standard deviations and jackknifed 95% confidence intervals are reported in table 5 below.

Outcome	Corn	Wheat	Soybeans
DiD $S.D.$	18.32***	4.84***	0.59***
95% C.I.	(17.86, 19.09)	(4.37, 5.38)	(0.41, 0.77)
DiD $\widetilde{S.D.}$	19.5***	5.05***	1.5***
95% C.I.	(18.92, 20.07)	(4.61, 5.53)	(1.35, 1.70)
Baseline S.D.	44.35	24.82	12.74
Number of Farms	1,059	499	1,004

Table 5: Estimates of the difference-in-difference of variances. The quantities estimated are defined in equation 16. 95% confidence intervals are computed by jackknife.

The table demonstrates that farms that move to aggregate insurance have a substantially change total yield variance than those that remain in separate insurance. This differs by crop: the increase for corn is 18.32, which is 41% of the baseline standard deviation, for wheat is 4.84 (20% of baseline) and for soy is 0.59 (6% of baseline). When residualizing on farm and year fixed effects, the results are similar. The change is smaller for corn and wheat, but larger for soy.

Overall, we find the variance of farm yield increases post-reform on the farms that swap to aggregate insurance. This is evidence consistent with farmers taking fewer diversifying actions. We now study particular actions in farm production that lead to the decrease in diversification and explain this increase in the variance of total yield.

4.2.2 Crop Diversity

The choice of crops or crop varieties is fundamental to a farm's risk exposure. Farmers can diversify their risk by planting crops or varieties sensitive to different hazards. This decreases the correlation within the farm. Therefore, we expect insurance scope to directly interact with crop diversity. We expact that as farmers move to aggregate insurance, they plant a less diverse mixture of crop types.

We focus on wheat. The FCIP categorizes wheat into four varieties: winter, spring, durum and khorasan. The varieties of wheat present different risk-reward trade-offs. Winter wheat is planted in the fall and harvested in the spring. Because of this long growing period, yields are typically higher.[25] However, winter wheat is vulnerable to damage or destruction should winter conditions be too harsh. This trade-off is most relevant in the colder northern mountain states such as North Dakota and Montana for which wheat diversity is an active margin of risk management. Warmer, southern states typically do not face this trade-off, as the mild winters means that winter wheat is unambiguously preferred.

Spring, durum and khorasan wheat are all planted in the spring and harvested in the late summer. The shorter growing season means lower average yield, but with lower variability due to reduced exposure to winter hazards. Moreover, durum and khorasan are more drought resistant than typical varieties of winter or spring wheat, making these a natural hedge against the risk of drier conditions (Alison Samuel and Louisa Dines (2023)). A wheat farmer in northern states can self-insure against the cold by planting a variety of winter versus spring varieties and hedge against drier conditions by including durum or khorasan against the more common hard winter or hard spring varieties U.S. Wheat Associates (2023).

We analyze the effects of moving to aggregate insurance on wheat diversity. Our measure of diversity is Shannon entropy. Specifically, if $p_{v,f,t}$ is the proportion of wheat of variety v in farm f and year t, with $\sum_v p_{v,f,t} = 1$, then the entropy is given by

$$\text{Entropy}_{f,t} = -\sum_v p_{v,f,t} \ln \left(p_{v,f,t}\right). \tag{18}$$

We estimate the following specification. We include different fixed effects in different specifications for robustness.

$$\text{Crop Diversity (Entropy)}_{f,t} = \alpha_f + \gamma_t + \mu_c + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{ft} \tag{19}$$

The coefficients of interest are τ. Estimates are in table 6.

[25] For details on harvest dates, see, for example, United States Department of Agriculture (USDA) (2023)

Outcome	**Estimate of** τ	
Crop Diversity (Entropy)	-0.057^{**} (0.029)	-0.052 (0.04)
Farm FE	✓	✓
Year FE		✓
N	XX	XX

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

Table 6: Within-farm DID estimates of the change in crop diversity (measured using Shannon entropy) outcomes before and after 2009 for farms that swap to aggregate insurance, relative to farms that remain in separate insurance. The estimating equation is (19) and the coefficients τ are presented. Observations are weighted the ARMS prescribed weights to ensure population representativeness.

In either specification we find a decline in diversity on farms that swap to aggregate of 0.05-0.06, relative to the change on separate farms. A decline in entropy of 0.06 is equivalent to, in a farm with two varieties of wheat, moving from a 50/50 mixture to 65/35. This is evidence for moral hazard on diversification consistent with the theory: as farmers move to aggregate insurance, they reduce their diversity, thereby making large correlated shocks more likely.

This policy was partially reversed in 2022, and we find that the diversity results are also reversed, as we show in section 6.1

4.2.3 Irrigation

Irrigation is a important form of self-insurance. It increases the mean yield, and reduces the variance of yield as sensitivity to drought is substantially reduced.[26] Irrigation is expensive. [27] For farms using on-farm water the average energy cost for irrigation pumps in 2018 was approximately \$48 or \$38 (from wells or surface water respectively) per acre irrigated. For the 1/3 of acres irrigated with off-farm water, the water cost is almost \$100. These flow costs exclude expensive equipment costs that needs to be amortized, and the break-even period is often 7-10 years. For reference, the average gross revenue per acre of cropland is on the order of \$800-\$1000 depending on the crop.[28]

By irrigating some of their land (which is empirically common[29]), a farmer can ensure that if a widespread drought occurs at least some of their crop can survive. The effect on mean yield is priced into the policy: premia are lower and the expected yield that is insured is higher if irrigated. However, the diversification effects of irrigating a portion of a farm, which is particularly important for aggregate policies, is not. Our theory shows that as farms move to aggregate policies, they should irrigate less of their farm. This is because if the non-irrigated fields do poorly, the farmer no

[26]See, for example, Troy et al. (2015), Sharda et al. (2019) and Sweeney et al. (2003).
[27]Source: (United States Department of Agriculture (2019).
[28]Source: Schnitkey and Sherrick (2021).
[29]Per the United States Department of Agriculture (2019), of farms that did some irrigation, 40% earned all their money from irrigated crops, and 60% earned money from a combination of irrigated and non-irrigated crops.

longer stands to gain from the irrigated fields doing well, since every dollar of gain from the latter offsets a dollar of indemnity on the former.

To study the effects suggested by the time series, we use the farm-level ARMS data to estimate the following within-farm specifications at the level of farm f, crop c (corn, soy or wheat) and year t, with and without crop fixed effects for robustness. The coefficients of interest are τ. Estimates are in table 7.

$$\text{Percentage of Farm Irrigated}_{f,t,c} = \alpha_f + \gamma_t + \mu_c + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{ft} \tag{20}$$

$$\text{Any Irrigation on Farm}_{f,t,c} = \alpha_f + \gamma_t + \mu_c \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{ft} \tag{21}$$

Outcome	**Estimate of** τ	
Percentage of Farm Irrigated	−0.06**	−0.06**
	(0.02)	(0.03)
Any Irrigation on Farm	−0.16*	−0.16
	(0.08)	(0.1)
Farm FE	✓	✓
Year FE	✓	✓
Crop FE		✓
N	723	723

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

Table 7: Wuthin-farm DID estimates of the change in irrigation outcomes before and after 2009 for farms that swap to aggregate insurance, relative to farms that remain in separate insurance. The estimating equation is (20) and the coefficients τ are presented. Observations are weighted the ARMS prescribed weights to ensure population representativeness.

We find that, within farms, 6% less of the crop is irrigated. On the extensive margin, 16% of crops stop irrigating at all. This is consistent with the theoretical predictions.

As an additional robustness check, in B.3 we use the SOB data and a between-crop strategy to confirm these effects. Corn, soy and wheat are the treated crops. As controls, we choose 7 (annual) crops[30] that were not treated with the subsidy increase. There we estimate a treatment effect on the percentage of acres that are irrigated of 1.5%. Note, this contrasts all the treated crop (including farms that did not swap to aggregate) with all the control crop. Thus, since we estimated take-up of 25% in Figure 9, this is identical to the within-farm estimates from Table 7. The raw time series

[30] Oats, Potatoes, Sweetpotatoe, Sugarbeets, Pumpkins, Rye, Sesame

in B.3 also demonstrates the irrigation does decline after 2009, by amounts consistent with the evidence above.

4.2.4 Price Risk - Revenue vs Yield Insurance

In addition to the choice of scope (aggregate vs separate) a farmer can choose between insuring *yield* (quantity) or *revenue* (price $\times$ quantity). The price insured is the expected harvest price at the time of insurance purchase, which is based on futures exchange prices. This choice of yield vs. revenue insurance is independent of the scope choice between aggregate and separate policies. A farmer can choose any combination of aggregate revenue, aggregate yield, separate revenue, or separate yield policies.[31] However, since price risk is perfectly correlated across acres, we expect a natural complementarity between revenue and aggregate insurance (this is formalized in proposition 6 in the appendix).

To analyze this, we estimate the following within-farm specification using the ARMS data, with different fixed effects to check for robustness. The outcome is measured at farm f, crop c (corn, soy or wheat) and year t.

$$\text{Enrolled in Revenue Insurance}_{f,t,c} = \alpha_f + \gamma_t + \mu_c + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{ft} \tag{22}$$

The coefficients of interest are τ. Estimates are in table 8.

Outcome	**Estimate of** τ		
Enrolled in Revenue Insurance	0.44***	0.46***	0.19
	(0.16)	(0.18)	(0.23)
Farm FE	✓	✓	✓
Year FE			✓
Crop FE		✓	
N	XX	XX	XX

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

Table 8: Within-farm DID estimates of the change in irrigation outcomes before and after 2009 for farms that swap to aggregate insurance, relative to farms that remain in separate insurance. The estimating equation is (22) and the coefficients τ are presented. Observations are weighted the ARMS prescribed weights to ensure population representativeness.

We find a strong complementarity between enrolling in aggregate insurance and choosing revenue

[31] More detail on the structure of contracts and indemnities in each of these four cases can be found in appendix B.17. Note: revenue insurance is priced differently from yield insurance, and aggregate insurance is priced differently from separate, but their interaction is not priced. This is what generates the moral hazard and fiscal externality.

coverage. The farms swapped to aggregate insurance were 19%-46% more likely to change to revenue insurance relative to the farms that remained in separate insurance. Since the interaction between revenue coverage and aggregate insurance was not priced in, this exerted a fiscal cost on the program, as we show in section 5.2. As additional evidence, in appendix B.4 we use a between-crop comparison that demonstrates that eligibility for aggregate insurance increases revenue coverage take-up by 15-20% (significant at the 1% level).

4.2.5 Land Use and Conservation

A direct determinant of diversification across fields is the size of the farm. A small farm is, all else equal, less diversified than a larger farm. On a small farm, a shock can wipe out the entire crop. A much larger farm has more geographic diversification and any given shock will affect less of the total crop. Farmers who enroll in aggregate insurance would like their entire farm to succeed or fail together, and by reducing the size of the farm this is made more likely. Thus, we expect farmers who move into aggregate insurance to, at the margin, have incentives to farm less land.

Additionally, by regulation, an aggregate unit combines all 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 does not have a claim to any of the output of the acres rented out. This means if land a farmer owns and operates does poorly, but landed rented out does well, the farmer might not receive an aggregate insurance indemnity even if they receive none of the upside from the rented acres.

These imply that after a farmer moves to aggregate insurance, they have an incentive to stop renting out land and to farm less land. Both of these reduce the size of the aggregate unit being insured, thereby decreasing diversification and increasing correlation.

We study this using within-farm evidence from ARMS. We restrict to the four crops for which we have data on aggregate unit enrollment: corn, wheat, soybeans and cotton. We use a DID design to compare farms before and after the 2009 policy change that did and didn't move to aggregate insurance. We estimate the following specification for each of the four outcomes: $\mathrm{y}_{farm,t} \in \frac{\text{Acres Rented Out}_{farm,t}}{\text{Acres Operated}_{farm,t}}, \frac{\text{Acres Rented Out}_{farm,t}}{\text{Acres Owned}_{farm,t}}, \text{Income from Rent}_{farm,t}, \text{Any Income Received from Conservation Progr}$

$$\mathrm{y}_{f,t} = \alpha_f + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{23}$$

$$\tag{24}$$

The coefficients of interest are τ. Estimates are in table 9.

Outcome	Estimate of τ
Acres Rented Out For Free/Acres Operated	-0.03***
	(0.01)
Acres Rented Out/Acres Owned	-0.06**
	(0.03)
Income from Rent	$-3,847$***
	(1279)
Any Income from Conservation Programs	0.13***
	(0.04)
Income from Conservation Programs	$2,423$
	(1643)

** p<0.05, *** $p < 0.01$

Table 9: DID estimates of the change in land-use outcomes before and after 2009 for farms that swap to aggregate insurance, relative to farms that remain in separate insurance. The estimating equation is (23) and the coefficients τ are graphed. Observations are weighted the ARMS prescribed weights to ensure population representativeness.

We find that farms that swap to aggregate insurance reduce the land that they rent out, both as a proportion of land owned (6%) and operated (22%) and receive less rental income ($ 3,847). And the acres that were previously rented out do not seem to subsequently be farmed by the owner. Instead, they are enrolled into a conservation program, as evidenced by the increase in aggregate-insured farms that are enrolled in any conservation program (13%) and in income from conservation programs ($2,423) which replaces over 60% of the lost rental income.

This is consistent with farmers that swap to an aggregate policy reducing the number of acres in the aggregate unit. This reduces the diversification across the fields, increases the correlation within the aggregate unit and makes it more likely that the acres in the aggregate unit will succeed or fail in unison.

5 Cost-benefit Analysis of the 2009 Reform

The 2009 expansion of the subsidy that moved farmers into aggregate insurance caused substantial moral hazard, but also offered greater insurance value. In this section we evaluate the net welfare impact by estimating the costs and benefits of the 2009 policy change.

5.1 Benefits: The Value of Aggregate Insurance

Aggregate insurance provides more income in the states of the world where all risks realize or all do not, whereas separate insurance provides more income in the state of the world where some risks realize and some do not. We will compute the additional insurance value of an aggregate policy over a separate policy *assuming both are actuarially fair*. Moreover, we will compute the additional insurance value assuming no moral hazard. To the extent these two assumptions are not true, they will enter into the costs we estimate in section 5.2,

Each field's yield is continuous, and some farms have many fields, making the state space very high dimensional. For tractability, we project onto a simpler set of three states. Define three

- The B(ad) state of the world: all fields on the farm receive an indemnity ($\approx 14\%$)
- The M(oderate) state of the world: some fields on the farm receive an indemnity, some do not. ($\approx 28\%$)
- The G(ood) state of the world: no fields on the farm receive an indemnity. ($\approx 58\%$)

As before, label underlying yield in state of the world θ to be X_θ. Write π_θ for the probability of each state occurring. Suppose an insurance contract costs premium p in all states of the world (of which portion s is subsidized) and pays indemnities ι_B, ι_M in the B and M states of the world. The expected utility for a farmer in this contract is

$$V(p, s, \iota_B, \iota_M) = \pi_B u(X_B + \iota_B - p(1-s)) + \pi_M u(X_M + \iota_M - p(1-s))) + \pi_G u(X_G - p(1-s))).$$

We define the WTP to be the certainty equivalent, with wealth equal to expected yield, $w = E(X)$, to the payoffs offered by that insurance contract:

$$u(w - WTP) = V(p, s, \iota_B, \iota_M).$$

We begin by estimating the WTP for a separate contract pre-reform. The ingredients of V_{sep} are computed as follows. 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 $\hat{\pi}_B, \hat{\pi}_M, \hat{\pi}_G, \hat{\iota}_B \hat{\iota}_M$.[32] Next, p and s are directly recorded in the data. Mechanically we know $X_B + \iota_B$ (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 good state of the world yield is equal to expected yield: $X_G = E(X)$, and expected yield is defined in the data. The main uncertainty lies in estimating X_M. In the data we can see the indemnities paid in the state of the world where some fields fail and some do not, but the yield on the fields that do not fail are not observed. Hence, we parametrize $X_M = \alpha X_B + (1-\alpha) X_G$ for $\alpha \in (0, 1)$ and compute the insurance value for many possible values of α.

How do these state-contingent payoffs change under an aggregate contract? The premium falls, in our data by about $\Delta p \approx 20\%$. The subsidy increases, $\Delta s \approx 18\%$. $X_B + \iota_B$ remains the same[33],

[32]We use the same model as for the computation of costs, equations (25) discussed in more detail in the next section. Details regarding estimates of $\hat{\pi}_B, \hat{\pi}_M, \hat{\pi}_G, \hat{\iota}_B, \hat{\iota}_M$ are in appendix B.2.

[33]This is important: both separate and aggregate contracts provide substnatial insurenace in the worst states of the world, with the only difference coming from changed premia. This means we do not face issues regarding the sensitivity of insurance value to far left tail outcomes, since under both policies substantial insurance is already provided in those states of the world.

since if all fields fail the farmer will be indemnified up to the coverage level in either policy. We assume no moral hazard in this section, instead accounting for that as a cost in the next section. This means that the probabilities of loss π_S and underlying yields X_θ remain the same for each state θ.

The final variable we need is ι_M, the insurance payout in the state of the world when some fields fail. We assume actuarial fairness, and so ι_M must decrease to exactly cancel out with the lower premia:.[34] $\pi_M \Delta\iota_M = \Delta p$ In summary, relative to a separate contract, an aggregate contract features a decrease in premium, an increase in subsidy and an decrease in indemnity in the middle state of the world.

This pins down WTP_{Agg} as solving

$$u(w - WTP_{Agg}) = V(p - \Delta p, s + \Delta s, \iota_B, \iota_M + \Delta\iota_M)$$

where p, s, ι_B, ι_M are the parameters for separate insurance. To reiterate, the aggregate charges a lower premium, offers a higher subsidy, but pays less in the M state of the world. On net, in an aggregate policy, the farmer is better off in the G and B states of the world, and worse off in the M state of the world.

The additional WTP for an aggregate contract, over-and-above a separate contract, is $\Delta WTP = WTP_{Agg} - WTP_{Sep}$. We compute this for each pre-reform contract we observe in the data and report the final ΔWTP on a per acre basis. Note, this WTP is computed as if every separately insured farm in the pre-reform period swaps to aggregate. We later explore the possibility of selection on WTP.

We assume that utility is of constant relative risk aversion (CRRA) form. Estimates of the coefficient of relative risk aversion γ for US farmers range from 0.4 to 0.6 (see Bar-Shira et al. (1997), Menapace et al. (2013)). We calculate additional WTP under four scenarios: $\gamma \in \{0.4, 0.6, 1, 2\}$. The final free paramter is α, which controls how high X_M is in the medium state of the world. We calculate WTP under the full range of $\alpha \in (0, 1)$. The results are in figure 2. The blue curve represents baseline estimates, the red curve adds an adjustment for take-up, which is explained below.

Since a coefficient of relative risk aversion well beyond anything estimated in the literature is needed to get the additional WTP per acre for aggregate insurance above a dollar, we take \$1 as an upper bound. For reference, the average net premium for an aggregate policy is approximately \$20, and so this additional WTP represents approximately 5% of the premium.

Accounting for selection into aggregate insurance. The preceding analysis computed the additional insurance value assuming all farms in the three crops swapped to aggregate insurance. However, it is likely that farms that swapped to aggregate insurance were those for whom the

[34] The policies are designed to be actuarially fair relative to the gross, pre-subsidy, premium, not the post-subsidy premium.

increased insurance value was more pronounced.

To quantify this, we compute a measure of take-up of aggregate policies after the reform. Unfortunately we cannot match farms WTP for aggregate insurance (from the pre-reform period) to their take-up (or not, from the post-reform period). Instead we compute the average take-up of aggregate insurance at the county-crop level and then reweight each farms WTP for aggregate insurance by the ex-post take-up for their crop and county. Our measure of county-crop cc take-up is the ratio of acres in that county-crop who enroll in aggregate insurance in 2012 to acres enrolled in any insurance in 2008.

$$\text{Aggregate Insurance Take-up}_{cc} = \frac{\text{Acres in Aggregate Insurance}_{cc,2012}}{\text{Acres in Any Insurance}_{cc,2008}}$$

The results are the red curves is in Figure 2. There is an statistically significant[35] but economically small relationship between additional insurance value and take-up. The additional WTP for aggregate insurance increases by approximately 5-10% at most. For our preferred estimate of $\gamma = 0.6$, or even $\gamma = 1$, the upper bound of \$1 is still valid.

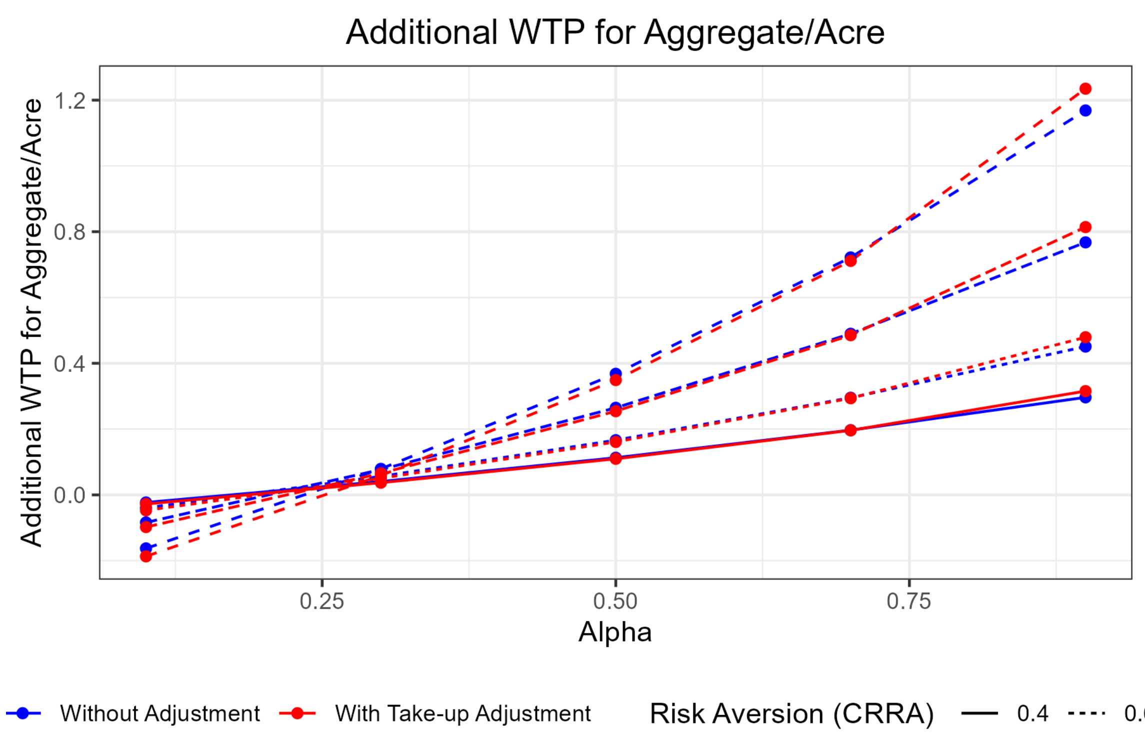

Figure 2: Additional WTP for aggregate insurance over separate insurance, with and without an adjustment for differential take-up

The computations above demonstrate that the pure insurance value of an aggregate policy is at

[35] If we regress the take-up measure on WTP the coefficient is 0.011 with a standard error of 0.003

most \$1 per acre higher than for a separate policy. This assumed both policies were actuarially fair and that there was no behavioural change in the form of changes indemnities (i.e. moral hazard) when farmers swapped to aggregate insurance. Both of these assumptions might be incorrect and would generate costs that need to be weighed against the \$1 per acre benefit.

5.2 Costs: The Fiscal Impact of Moral Hazard

In section 4 we demonstrated that the 2009 reform lead to a reduction in farmer diversification behaviour and an increase in the variance of aggregate risk. In this section, we estimate the impact on the cost of crop insurance - the fiscal externality - of the reduced diversification actions.

We begin with the raw time series of the difference in total net costs of separate versus aggregate policies. Define the net fiscal cost per acre insured as

$$NFC = \frac{\text{Indemnity - (Premium - Subsidy)}}{\text{Acres Insured.}}$$

This is simply the money paid out by the government minus premia actually paid by the farmers to the government, divided by acres insured. We compute this separately for separate and aggregate policies in figure 3.

Recall, as explained in section 3.2, the policy change in 2009 was designed to be *budget neutral*. The reform aimed to equalize dollar subsidies between aggregate and separate policies. If the premia for both separate and aggregate policies were actuarially fair and therefore equal to expected indemnities, then equalizing the subsidy amounts should equalize the dollar net fiscal cost for the government between the two policies. This is simply because if $E(\text{Indemnity}) = \text{Premium}$ then $NFC = \frac{\text{Subsidy}}{\text{Acres Insured}}$, and the subsidies were equalized post-reform.

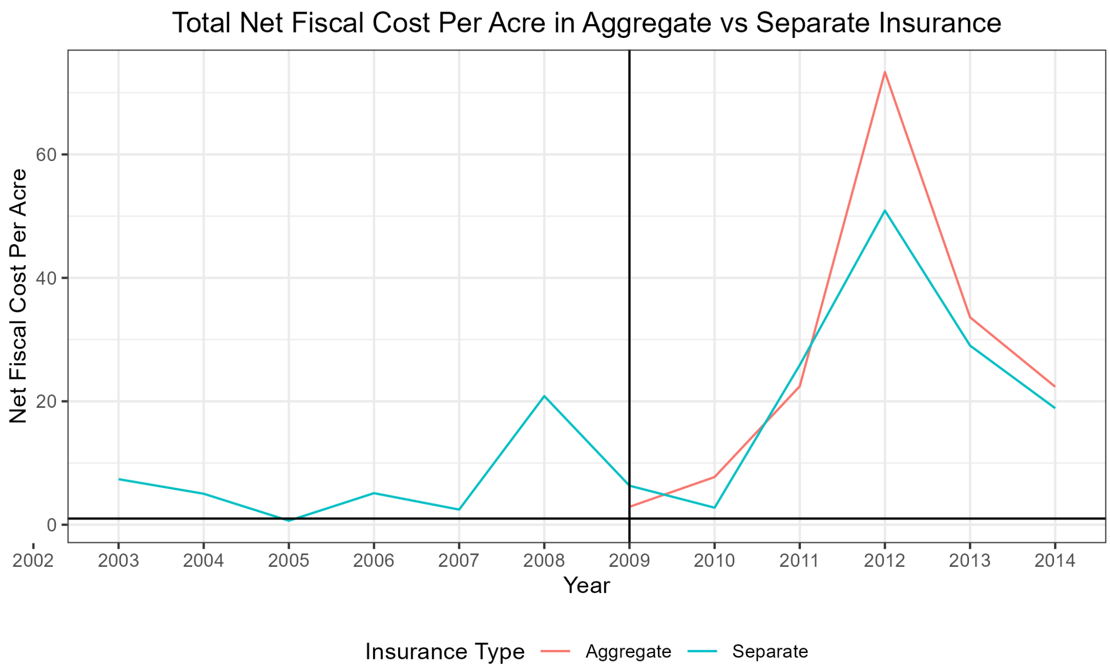

Figure 3: Realized net fiscal cost to the government (indemnities minus farmer paid premia) in separate versus aggregate policies.

Figure 3 shows that, in the post-reform period, aggregate policies are substantially more costly than separate policies. The average difference between an aggregate acre and a separate acre (weighted by the number of acres) is approximately $8.50. Of this, about $4, or half, is due to higher indemnities.

Clearly, as 3 shows, the policy change was not budget neutral. This could be caused by two factors.

1. The premia might not be actuarially fair for aggregate policies, or the subsidies set too high.
2. Farmer actions that decreased diversification might have caused increased indemnities.

These causes have am important distinction. The first is a transfer (we call this an 'implicit subsidy') from the government to the farmer, with no efficiency consequences. The second involves higher costs to the government without increased farmer benefit, and so decreases efficiency. To understand this, recall that farmers who move to aggregate insurance will adjust their diversification action. They will balance the private costs and benefits of changing their action. What the farmer doesn't internalize are changes to the yield conditional on being below expected yield, where the government has to pay more, or pay more often, but the farmer still ends up with expected yield minus premium as their final income. For example, if the farmer is to be indemnified up to $100, they do not care if yield is $90, or $50, and so will not account for the additional fiscal cost of the latter when they make their diversification choice.

To distinguish the fiscal externality due to changed diversification actions from the implicit subsidy, we directly measure how much extra indemnity is due to the unpriced farmer actions (irrigation, diversity, land use[36] and revenue coverage). Since we know how much these unpriced farmer actions changed due to the movement to aggregate insurance (from section 4), we can then counterfactually estimate: how much lower would indemnities have been should farmer actions have remained at their pre-policy change levels. We proceed as follows.

1. Estimate indemnities in aggregate policies as a function of unpriced actions $e = \{$Diversity, Irrigation %, Revenue Insurance, Acres$\}$.
2. Using the model from step (1), predict indemnities in aggregate policies at observed, *inclusive of moral hazard*, levels of e_{Agg}.
3. Impute the counterfactual 'no moral hazard' level of $e_{NoMH} = e_{Agg} - \frac{\Delta e}{\Delta \text{scope}}$ where the causal effects of scope on actions $\frac{\Delta e}{\Delta \text{scope}}$ come from section 4.
4. Using the model from step (1), predict indemnities in aggregate policies at counter-factual levels of e_{NoMH} *without moral hazard.*
5. The difference between (4) and (2) is our estimate of the additional fiscal impact of moral hazard caused by the scope change.

To implement step (1), we estimate:

$$\begin{aligned} \text{Indemnity} = \alpha + \beta_0 \text{Premium} + \beta_1 \text{Subsidy} \\ + \beta_2 \{\text{Diversity, Irrigation \%, Revenue Insurance, Acres}\} + \epsilon \end{aligned} \tag{25}$$
$$\tag{26}$$

We include premium and subsidies in the specification as we are trying to isolate the impacts of changed farmer actions from an implicit subsidy (too low a premium or too high a subsidy). We estimate the probability of an indemnity separately from the indemnity, conditional on there being one, to deal with the noise introduced by many instances of zero indemnity. We normalize indemnities, premia and subsidies to be per acre , to account for farms of different sizes. The coefficients β_2 and represent the extent to which the indemnity are affected by the unpriced actions in which we have documented behavioural distortions after farmers swapped to aggregate insurance. Estimates of β_2 for equation 25 are in the Table 4 below. The left panel is estimated on corn, wheat and soybeans, the right panel only on on wheat such that the diversity effect can be estimated.

[36] 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.

Covariate	β_2 **Estimates (all crops)**
Acres	0.006***
	(0.0006)
Within Farm Irrigation %	-9.3***
	(1.9)
Revenue Coverage	12.65***
	(1.5)
N	21,005

Covariate	β_2 **Estimates (wheat only)**
Acres	0.001
	(0.001)
Within Farm Irrigation %	-9.2***
	(1.9)
Revenue Coverage	28.2***
	(3.4)
Diversity	-26.3**
	(11.8)
N	1,432

Figure 4: Estimates of β_2 from equation 25. The left panel uses all three crops (wheat, soy, and corn) while the right panel is only estimated using wheat, so that diversity can be included. *** represents significance at the 1%, level, ** at the 5% level, * at the 10% level.

Table 4 shows that these diversification actions have a strong effect on indemnities, conditional on the premium. For example, higher 10% within-farm irrigation is leads to 93c less in expected indemnity.

Given estimates in equations (25) for indemnities as a function of actions, we first predict indemnities at observed, post-reform levels of actions for each farm in aggregate insurance in the data. These include behavioural changes, and so this is our estimate for expected indemnities at e_{agg}, as in step (2). Then, for each farm, we compute their counter-factual action choices without moral hazard using the causal effects estimated in section 4. We re-predict indemnities using these counterfactual action $e_{NoMH} = e_{Agg} - \frac{\Delta e}{\Delta \text{scope}}$, per step (4). We take the difference between (4) and (2) for each farm, divide by acres on that farm, and this is our estimate of $\frac{\text{Fiscal Externality}}{\text{Acre}}$, which can be found in table 10.

Diversification Action	Land Use (acres farmed)	Irrigation (within-farm)	Revenue Coverage	Diversity (wheat only)
Change in action	-0.06	-0.05	+0.46	-0.057
$\frac{\text{Fiscal Externality}}{\text{Acre}}$	\$-0.14	\$0.46	\$3.06	\$1.46

Table 10: Estimates of the net fiscal cost due to farmer behavioural changes. Each column represents a different diversification behaviour. The second row

The total estimated fiscal cost, when all actions are changed at once, is \$3.39 per acre for all crops, and \$3.85 per acre for wheat (including diversity effects). We estimated the insurance benefits to be at most \$1 per acre, although \$0.60 is more realistic. In either case, the estimated fiscal costs due to moral hazard substantially outweigh the benefits.

These fiscal costs were calculated only using the four diversification actions we can observe in the data. There are other diversification actions, such as the type of seed planted, fertilizer applied and so on which we cannot observe in the insurance data. This suggests that the true fiscal cost is even higher than estimated. Of the raw difference \$8 per acre in raw fiscal cost (from Figure 3), we have accounted for \$3.39 (or \$3.85 for wheat). The remaining cost is either due to unobserved moral hazard, mispriced premia, or aggregate shocks such as the 2012 drought, the spatial distribution of which might have affected aggregate policies more than separate.

Sensitivity to 2012. The drought in 2012 was an extreme event, with the highest insurance payouts in our data sample. To check that the effects we pick up are not due only that year, we rerun the fiscal cost analysis above excluding 2012. The analogous total fiscal cost due to the decreased diversification behaviours is \$1.76 per acre for all three crops, and \$4.46 for wheat. Hence, while 2012 did drive about half of the effect for corn and soy, the estimated \$1.76 is still above our realistic predictions on insurance value. On the other hand, for wheat, a more drought resistant crop, excluding 2012 heightened the estimate of total fiscal cost.

6 Corrective Reforms

We found that irrigation and crop diversity were distorted downwards by the 2009 subsidy increase. To address these concerns, the USDA made policy changes in 2015 and 2022 that 'de-aggregated' aggregate policies. In 2015, irrigated and non-irrigated crop to be in distinct aggregate contracts, and, in 2022, different varieties of wheat to be split into their own aggregate contracts.

These changes remove the incentive to distort irrigation or crop diversity due to the structure of aggregate policies. This lead to farmers partially or fully reversing the irrigation and diversity declines that we observed in 2009.

6.1 2022 Corrective Reform: Aggregate Policies Split by Wheat Type

Prior to 2022, all four varieties of wheat would be insured by the same aggregate policy. This dulled the incentive to plant a diverse mixture of wheat. From 2022 onwards, each variety could have its own aggregate unit. Owing to the lack of recent ARMS data, our analysis here uses the SOB data to do a between-crop comparison. .

Our first specification is within-crop (wheat), and compares diversity of wheat insured in aggregate policies to wheat insured in separate policies. We estimate, where $S_{c,u,t}$ is the diversity measure (entropy) for the wheat in county c insured in unit u (Separate or Aggregate) in year t:

$$S_{u,t} = \alpha_u + \gamma_t + \tau_t \mathbb{1}\left[t\right] \times \mathbb{1}\left[u = \text{ Aggregate}\right] + \epsilon_{u,t}. \tag{27}$$

The coefficient of interest is τ_{2022} the extra entropy amongst acres insured in aggregate acres in the treated year. The results are in figure 5 below. The estimated treatment effect is an increase of entropy by approximately 0.03 in 2022 and 0.04 in 2023.

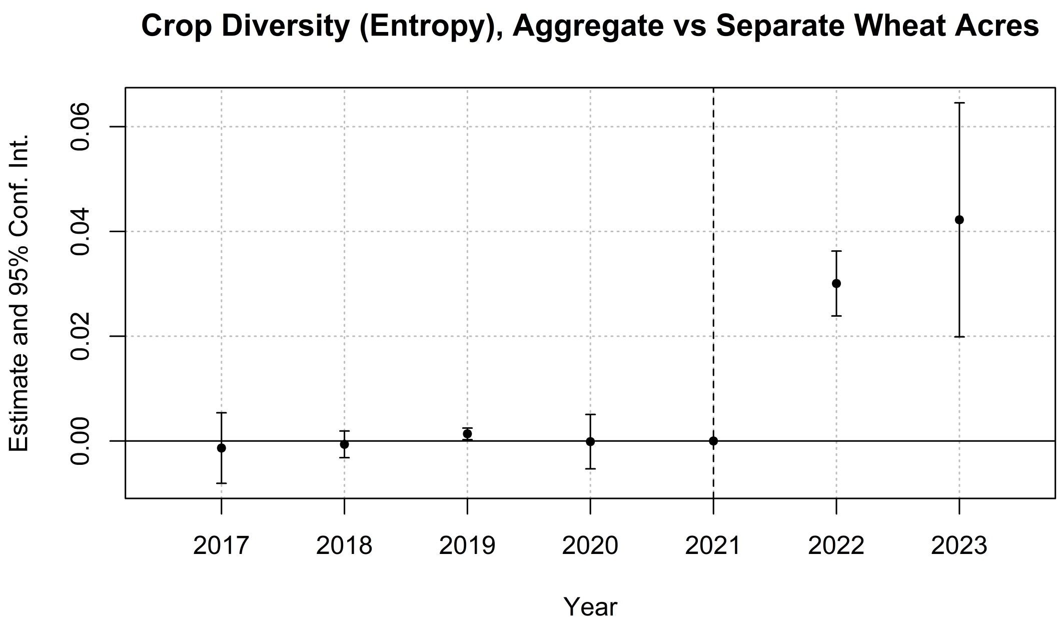

Figure 5: Treatment effect of being insured in aggregate units on crop diversity (entropy), before and after the 2022 policy change. The estimating equation is (27) and the coefficients τ_t are graphed. Observations are weighted by acres insured.

Wheat diversity increases by 0.03 in 2022 and 0.04 in 2023. An increase of diversity of 0.03 is equivalent, in a county with two varieties, to moving from a mixture of 62/38 to 50/50. An increase of 0.04 is equivalent to moving from 64/36 to 50/50. This almost entirely reverses the decrease in diversity of 0.06 from the 2009 reform.

This suggests that as aggregate policies are 'de-aggregated' and split by type of wheat, the incentives to distort diversity are substantially removed. However, this comparison of diversity in aggregate policies to diversity in separate policies might confuse treatment for selection: farms that plant a diverse mixture of crop might select into aggregate insurance after the reform, without any farmer actually changing their variety mixture. We check for this in appendix B.5, by compare wheat diversity at a county level (with no unit distinction) to appropriate control crops. Even though insurance unit is changable, county is not, and so there is no selection issue. The control crops are barley, oats and canola. These are all considered 'small grains' by the USDA. Crucially, the primary choice for all of these crops, as for wheat, is whether to crop high yield, high risk varieties adapted to fall planting, or lower risk, lower yield varieties in the spring. We find an identical effect: diversity increases by 0.03 in 2022 and 0.04 in 2023.

This confirms our finding: the de-aggregation of aggregate policies by wheat type almost completely vitiates the incentive to reduce diversity within aggregate policies.

6.2 2015 Reform: Aggregate Policies Split by Irrigation

Prior to 2015, irrigate and non-irrigated acreage of a crop would be combined into the same aggregate policy. For the reasons discussed, this reduces the incentive to irrigate for those that swap move to aggregate insurance. In 2015, a insurance policy was created - 'aggregate split by irrigation practice'. This 'de-aggregated' the aggregate policy and meant that the irrigated and non-irrigated acreage would have distinct policies and not interact in any way, while both receiving the generous premium subsidies. We study the extent to which this reversed the reduction in irrigation seen after 2009.

The take-up of this new aggregate policy split by irrigation practice was relatively limited. For the three crops we focus on (corn, wheat and soy) only 9%, 5% and 8% of acres in any aggregate insurance (which are about half of all insured acres) were in this sub-type. This means do not have the power to detect effects even as large as the 2009 effect in ARMS. Consequently, to increase power we use the SOB data, which has the universe of policies in it but data only at the country level.

We analyze whether the percentage of acres hat are irrigated in the county increases for the three treated crops, relative to 9 other annual control crops[37] that were not treated. We study irrigation at the county level, not at the county x insurance type level, to account for possible switching between insurance types. This reduces power but ensures we are actually seeing irrigation changes.

We estimate, for county-crop cc in year t, the following specification. We begin in 2012 as this is when the effects of the 2009 policy change have been realized. The coefficients of interest are τ_t the differential change in irrigation for the treated crops. They are shown in 8.

$$\left(\frac{\text{Insured acres with irrigation}}{\text{All insured acres}}\right)_{c,c,t} = \alpha_{crop} + \gamma_t + \tau_t \mathbb{1}\left[t\right] \times \mathbb{1}\left[\text{crop} = \text{Treated Crop}\right] + \epsilon_{c,c,t} \quad (28)$$

[37]Oats, potatoes, sweet potatoes, sugarbeets, pumpkins, rye, sesame. To account for a possibly imperfect control, we also run synthetic difference-in-differences to confirm our results

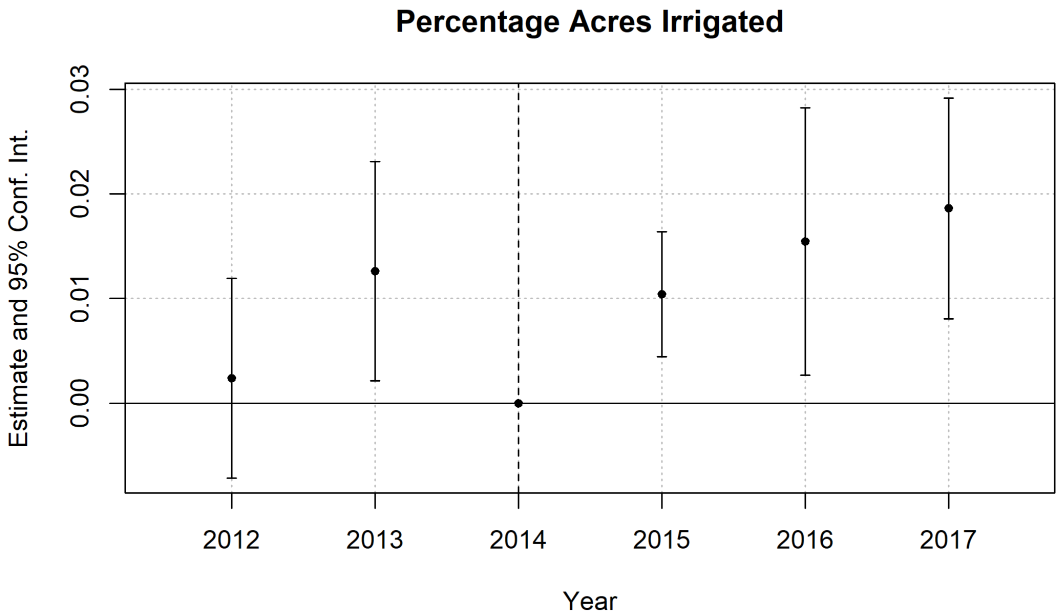

Figure 6: Treatment effect on corn, wheat and soy of the change to distinct aggregate policies by irrigation, relative to the control crops. The estimating equation is (28) and the coefficients τ_t are graphed. Observations are weighted by acres insured.

We find a treatment effect of 1% in 2015, rising to 2% by 2017. Because of the pre-trend we run SDID and the results are consistent. This shows that following the 'de-aggregation' of the aggregate policy in which the incentives to irrigate less were removed, irrigation increases. This is consistent with, and the converse of, the theory and the results in the evaluation of the 2009 policy change.

7 Conclusion

This paper introduced the scope of insurance - whether multiple risks are insured in separate contracts or combined into one policy. Separate contracts pay the same indemnity when one risk occurs regardless of when other risks occur. Aggregate contracts insure total income and pay more when two risks occur than the sum of payouts when each risk occurs. Aggregate contracts offer more insurance value as more is paid in the worst states of the world. But they induce a novel behavioural distortion: since aggregate contracts pay more than separate when all risks occur at once, this discourages actions that would increase diversification of risks. Due to this incentive/insurance trade-off in the variance of payouts, the optimal contract is an empirical question. We studied this tradeoff in the context of the US FCIP. We found that as farmers moved from separate to aggregate insurance, insurance value increased by approximately \$1 per acre, but the fiscal cost of behavioural distortions was over \$3 per acre, dwarfing the benefits.

Our framework and model and can be applied in many other settings. Other instances of scope include the design of individual versus family cost sharing in health insurance, the 'jointness' of the tax and transfer system, the time horizon of insurance contracts, amongst others. Studying the optimal scope in those contexts would be fruitful directions for future work.

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A Theoretical Appendix

A.1 Formal definition of increased correlation

Consider two counties X,Y that are constituted by n fields each. The yield of field i in county X is denoted x_i, and the aggregate yield in county X is given by $A(X) = \sum_i x_i$. Similarly for Y.

Define $\Gamma(F_1, F_2, \ldots, F_n)$ to be the set of joint distribution functions with marginals F_1 and F_2. Following Shaked and Shanthikumar (2007)[38] and Denuit et al. (2006), the correlation order that will be of primary interest is defined

Definition 2. *Suppose $X, Y \in \Gamma(F_1, F_2)$ and have CDFs F_X, F_Y respectively. We say that X is be less correlated than Y or that X precedes Y in the correlation order, written as $X \precsim Y$ when*

$$X \precsim Y \iff F_X(w_1, w_2) \leqslant F_Y(w_1, w_2), \quad \textit{for all } (w_1, w_2) \in \mathcal{W}.$$

Intuitively, this says that w_1, w_2 are more likely to both be small under the more correlated Y than under X. This notion of ordering of correlation is often called 'Positive Quadrant Dependance (PQD)' in the literature.[39]. This is equivalent to writing

$$X \precsim Y \iff (1 - F_X(w_1, w_2)) \leqslant (1 - F_Y(w_1, w_2)), \quad \text{for all } (w_1, w_2) \in \mathcal{W}.$$

This says that w_1, w_2 are also more likely to both be large under Y than X. This comports with the usual intuitive notion of correlation: knowing w_1 is small/large means w_2 is more likely small/large the higher the correlation is, and conversely for negative correlation it becomes more likely that when w_1 is large w_2 is small and vice versa.

A.2 Extending the general model

goes here. Assume finite states of the world The contract is defined by the set of ι_x for each x. Write out constrained second-best, (follow Amy slides), get somethign about increased insurance value (maybe FOCs can be put together to get something about covariance of x with marginal U' (they are 1-1 so this needs to be thought through)) vs fiscal cost from MH.

The planner's constrained second-best problem is

$$W = \max_{\iota,} \int_X U\left(\sum_i x_i + \iota(x) - p(e), e\right) \pi_x(e) dx \tag{29}$$

$$\text{subject to:} \tag{30}$$

$$p(e) = E_X\left[\iota(X(e))\right] \tag{31}$$

$$e = e^*(\iota). \tag{32}$$

A.2.1 A general Baily-Chetty formula for scope

Introduction, define finite number of states, define elasticities...

We examine the optimal level of indemnity in generic state of the world s. In state s, yield on field $i = 1, \ldots, F$ is written x_i^s and the vector of field yields $X^s = (x_1^s \ldots x_F^s)$. As shorthand, we write

[38] Here this ordering is called Positive Quadrant Dependence (PQD)

[39] See for example, Shaked and Shanthikumar (2007) and Denuit et al. (2006)

expected utility in state s as

$$u'(X^s) = u'\left(\sum_i x_i^s + \iota(X^s) - p, \psi\right).$$

We write the probability of this state of the world occurring as $\pi^s = Prob(X = S^s)$. For a generic state of the world, we write $u'(X)$ and π^X

Proposition 4. *The optimal indemnity, $\iota(X^s)$ in state X^s satisfies:*

$$\frac{u'(X^s) - E_X\left[u'(X)\right]}{E_X\left[u'(X)\right]} = \frac{E_X\left[\frac{\iota^X}{\iota^S}\epsilon_{\pi^X,\iota^S}\right]}{\pi_s}. \tag{33}$$

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 right hand side shows the fiscal externality due to farmer behavioural changes. When insurance increases, the farmer changes their effort level, changing the probabilities of each state realizing and hence of each indemnity being paid out. Since the farmer does not internalize the aggregate fiscal impact of these behavioural changes, it causes a fiscal externality.

To get a more intuitive sense of how what this BC formula means, we study a two-risk case.

A.3 A two-risk special case

To motivate the government's optimal insurance design problem we generalize the Baily-Chetty (Baily (1978), Chetty (2006)) formula for the optimal level of social insurance.

A farmer with wealth w farms two fields, and faces a risk in each. With probability p, a field will fail and cause a loss l. Assume this is the same for both fields, although this isn't a binding assumption. The risks may be correlated, and the probability of zero one or two losses are given by

$$P(\text{two losses}) = (1-p)^2 + \kappa, \quad P(\text{one loss}) = 2(p(1-p) - \kappa), \quad P(\text{zero losses}) = p^2 + \kappa.$$

The parameter κ indexes the degree of correlation between the two losses, where $\kappa = 0$ represents independence, $\kappa > 0$ positive correlation and $\kappa < 0$ negative correlation.

As in standard Baily-Chetty, farmer effort e can influence the mean probability of loss $p = p(e)$ with $p'(e) > 0$ and $p''(e) < 0$. But effort has another effect: Here it also reduces the correlation between the risks without affecting the mean risk: $\kappa = \kappa(e)$. Effort incurs some (separable and convex) cost ψ.

The government implements an insurance program indexed by two numbers ι_1 and ι_B, the indemnities paid out if one field fails or if both fields fail. We assume the indemnities are less than the losses, $\iota_1 \leqslant l$, $\iota_B \leqslant 2l$ (i.e. there is no over-insurance). The price of insurance is τ, paid in all states of the world, and we impose budget balance; $\tau = \left((1-p)^2 - \kappa\right)\iota_B + (2p(1-p) + \kappa)\,\iota_1$. For brevity we suppress the dependence of κ and p on e , but this is crucial. Moreover, when the planner set's ι_1 and ι_B they recognize that this affects e which affects κ and p but we suppress this too for clarity.

Given the insurance program, the farmer chooses e to maximize:

$$V = \left((1-p)^2 - \kappa\right) u(w - 2l + \iota_B - \tau) + (2p(1-p) + \kappa)\, u(w - l + \iota_1 - \tau) + \left(p^2 - \kappa\right) u(w - \tau) - \psi(e).$$

The planner, understanding the farmer's maximization, then sets indemnities in the outer problem to maximize farmer welfare while accounting for the fiscal cost:

$$\begin{aligned} &\max_{\tau,\iota_1,\iota_B} V \\ &\text{subject to:} \quad \tau = \left((1-p)^2 - \kappa\right) \iota_B + (2p(1-p) + \kappa)\, \iota_1. \end{aligned}$$

We will focus on the planner's optimal choice of ι_B relative to ι_1. Proposition 5 is a Baily-Chetty type expression in which increasing ι_B adds insurance value but at the cost of increased moral hazard. We define the terminology used in that expression.

First, we label the expectation of marginal utility as

$$\mathbb{E}[u'] = \left((1-p)^2 - \kappa\right) u'(w - 2l + \iota_B - \tau) + (2p(1-p) + \kappa)\, u'(w - l + \iota_1 - \tau) + \left(p^2 - \kappa\right) u'(w - \tau).$$

Elasticities are defined by:

$$\epsilon_{p,\iota_B} = -\frac{\partial p}{\partial e}\frac{\partial e}{\partial \iota_B}\frac{\iota_B}{p}, \qquad \epsilon_{\kappa,\iota_B} = -\frac{\partial \kappa}{\partial e}\frac{\partial e}{\partial \iota_B}\frac{\iota_B}{\kappa}.$$

The Baily-Chetty type formula then takes the form.

Proposition 5. *The optimal ι_B satisfies:*

$$\frac{u'(c_2) - \mathbb{E}[u']}{\mathbb{E}[u']} = \underbrace{\frac{1}{(1-p)^2 - \kappa}\frac{p}{\iota_B}\epsilon_{p,\iota_B}\left(2\iota_B(1-p) - 2\iota_1(1-2p)\right)}_{\textit{moral hazard on mean}} \tag{34}$$

$$+ \underbrace{\frac{1}{(1-p)^2 - \kappa}\frac{\kappa}{\iota_B}\epsilon_{\kappa,\iota_B}\left(\iota_B - 2\iota_1\right)}_{\textit{moral hazard on correlation}}. \tag{35}$$

The classical Baily-Chetty setup features one risk (e.g. unemployment risk in the overview article Schmieder and von Wachter (2016)). In that setting, the probability of remaining in the bad state of the world depends on the farmer's search effort. More generous insurance in the bad state induces less search effort - i.e. moral hazard.

In this setting with two risks, the farmer's action effects the probability distribution over states of the world in two ways. It changes the probability of either of the two risks being realized - i.e. mean risk, and it changes the probability that both risks are realized simultaneously - correlation risk.

The first line of the expression in proposition 5 relates the generosity of insurance to the moral hazard of *something* going wrong:ϵ_{p,ι_B} The second line relates the generosity of insurance to the moral hazard effect of *everything* going wrong: $\epsilon_{\kappa,\iota_B}$.

This second effect is novel. Over and above the incentives to increase decrease p when insurance is more generous, the structure of the insurance contract may induce a preference for zero or two risks being realized relative to just one. The following definition clarifies this.

Definition 3. *An insurance scheme is "separate " if $\iota_B = 2\iota_1$. A non-separate scheme has $\iota_B > 2\iota_1$. Therefore, we call an increase in ι_B, for fixed ι_1, a "more aggregate" policy.*

Intuitively, when an insurance contract treats each risk separately, the payout if one risk realizes does not depend on whether the other risk realizes. That is, the indemnity payout for both risks occurring is double the indemnity if one risk occurs.

When an insurance contract moves toward caring about aggregate risk, it treats two losses as more than twice as bad as one loss. When exactly one risk occurs, the individual loss is mitigated by the other loss not occurring. The planner might then not need to set a high indemnity in that state of the world. On the other hand, when both risks occur, the farmers aggregate loss puts them in a high marginal utility state of the world. The planner wishes to treat this second loss much more seriously than the first, since there is no cross-subsidization between the risk that occurs and the risk that doesn't.

This comports with the actual structure of aggregate vs separate contracts, explored in section 2.2. A separate crop insurance contract treats each risk individually. An aggregate crop insurance contract pays out little or nothing for an isolated crop failiure since aggregate losses are low. But when there are many simultaneous crop failures, payouts increase substantially.

The following lemma formalizes the interaction between contract structure and moral hazard that induces correlation.

Corollary 1. *For fixed elasticity $\epsilon_{\kappa,\iota_B}$, the welfare cost from moral hazard on correlation is greater for a more aggregate policy.*

Moral hazard on correlation is a bigger problem for more aggregate policies. In particular, for separate policies, it has no effect. This is the core reason why a more aggregate insurance policy need not be optimal, even if aggregate farmer loss is the welfare-relevant quantity. Aggregate insurance - that pays out more if two risks occur than double if one risk occurs - encourages farmers to make more likely the state of the world in which both risks realize, by increasing correlation through decreased effort.

A.3.1 An extended definition for aggregate policies

The aggregate contract considered in section 2.2 above is of a particular form mimics the actual FCIP aggregate contract. However, one can imagine contracts that feature 'partial-aggregateness' in that the indemnity received by one field decreases in the yields of other fields, but without aggregate yield as a sufficient statistic.

Definition 4. *If $\iota_{PAgg}(X)$ is decreasing and convex in X we say the policy is **partially-aggregate.***

Definition 4 captures the intuitive notion that the indemnity I receive for the marginal dollar of loss on field 1 should increase in the losses experienced on other fields. This targets indemnities to states of the world where aggregate yield is low, without the specific functional form of definition 1. The following lemma is analogous to proposition 3. It implies that the incentive to increase correlation in a partially-aggregate contract relative to a separate contract is present in the same way as in an aggregate contract.

Lemma A.1. *Suppose $X, X' \in \Gamma(F_1, F_2, \ldots, F_n)$ and assumption **??** holds. If $X(e) \precsim X(e + de)$ for small $de > 0$ then*

$$\Delta_{PAgg}(X) \geqslant \Delta_{Sep}(X).$$

A.4 Moral hazard on mean risk vs on correlation

In prior work, moral hazard has meant a change in the mean risk of a loss occurring due to a distortion in the behaviour of the insured. Since the insurance contract pays more money in the bad state of the world than the good, any action to make the former more likely causes a fiscal externality.

This has been studied in the context of crop insurance, as we detail in the literature review. This means that going from no insurance to any insurance introduces moral hazard that increases mean risk. Hence, we can understand the basic structure crop insurance contracts, in particular their convexity, as designed to align farmer and planner incentives and limit moral hazard.

We are not studying the movement from no insurance to any insurance that may change mean risk. We are studying the movement between separate and aggregate insurance that may change correlation between field risks. In our model, we need not assume that farmer actions that change correlation have any impact on mean risk at all. This makes it more likely for all fields to fail or all fields to succeed together, while the unconditional rate of failure or success is held constant.

This also causes a fiscal externality in aggregate policies. Aggregate policies pay relatively more when all fields fail than if just a few fields fail and most succeed. In other words, they make the really bad state - when everything fails - less bad for the farmer. As farmers are now protected against that state of the world, they take actions - reduced diversity or increased correlation - to make it more likely. This means the aggregate policies end up paying out more due to those behavioural distortions, a fiscal externality.

Actions that change correlation due to a movement from separate to aggregate insurance might have a secondary knock-on effect on mean risk. This might accentuate or mitigating the moral hazard from the initial movement from no insurance to any insurance. The particular farmer actions that change correlation that we study - most specifically irrigation - likely do have knock on effects on yield. For example, irrigation decreases mean risk and decreases correlation. Our results show that aggregate policies induce less irrigation. This suggests that the moral hazard on means, although not our primary focus, is made worse by these primarily correlation altering actions.

B Empirical Appendix

B.1 Additional Data Sets used in the Appendix

B.1.1 USDA SOB Cause of Loss

In section **??** we correlate take-up of aggregate insurance with the type of losses a county and crop have historically been affected by. This uses the Cause of Loss (COL) data published by the USDA.[40] The COL data are at the level of a year, state, county, crop (YSCC). For each YSCC combination, the month of loss, production stage of loss and cause of loss are recorded. These include, for example, drought, hail and flood.

B.1.2 Agricultural Census

The Agricultural Census is a comprehensive survey conducted by the USDA every five years, aimed at providing a complete picture of the country's agriculture sector. The survey collects data on various aspects of the agricultural sector, such as the number and size of farms, land

[40]Source: https://www.rma.usda.gov/SummaryOfBusiness/CauseOfLoss

use, crop production, fertilizer use, irrigation use, as well as information on the demographics and characteristics of farmers. The most recent Agricultural Census was conducted in 2017, and the next one is scheduled to take place in 2022.

The public data are available at the county, and for some data the county, crop level. In section **??** we will correlate aggregate insurance take-up with various measures of average farm size from the Census.

B.1.3 Climate Data

We find evidence that farmers have private information used in their insurance choices, specifically the choice of scope between aggregate and separate policies. One form this private information takes is that farmer's insurance decisions respond to pre-growing season temperatures and precipitation. These impact soil health and therefore expected crop yield, but are not priced into insurance. The data on pre-growing season precipitation and temperatures are from Schlenker and Roberts (2009)[41]. The raw data come from many weather stations in each county. We average over each county weighting by agricultural acres nearby to the weather station. This results in, for each county, the average minimum and maximum temperature for each day, and the average precipitation on each day. Precipitation is summed over and temperatures are averaged over the pre-growing season (November 1 - March 15). These form our main measures of pre-growing season private information.

B.2 Estimation Results Underlying Welfare Calculations

B.3 Between-crop 2009 Irrigation Results

We begin with the raw time series for the three focus crops. Using the universal SOB data, Figure 7 shows a moderate decline from trend in the proportion of acres irrigated (nationally) after the 2009 policy change. This is more pronounced for wheat and corn than soybeans. Moreover, the general year-to-year variation illustrates that irrigation is not a once-off decision, but is an active margin that farmers adjust, as water prices and availability change.

[41]See: http://www.columbia.edu/ ws2162/links.html

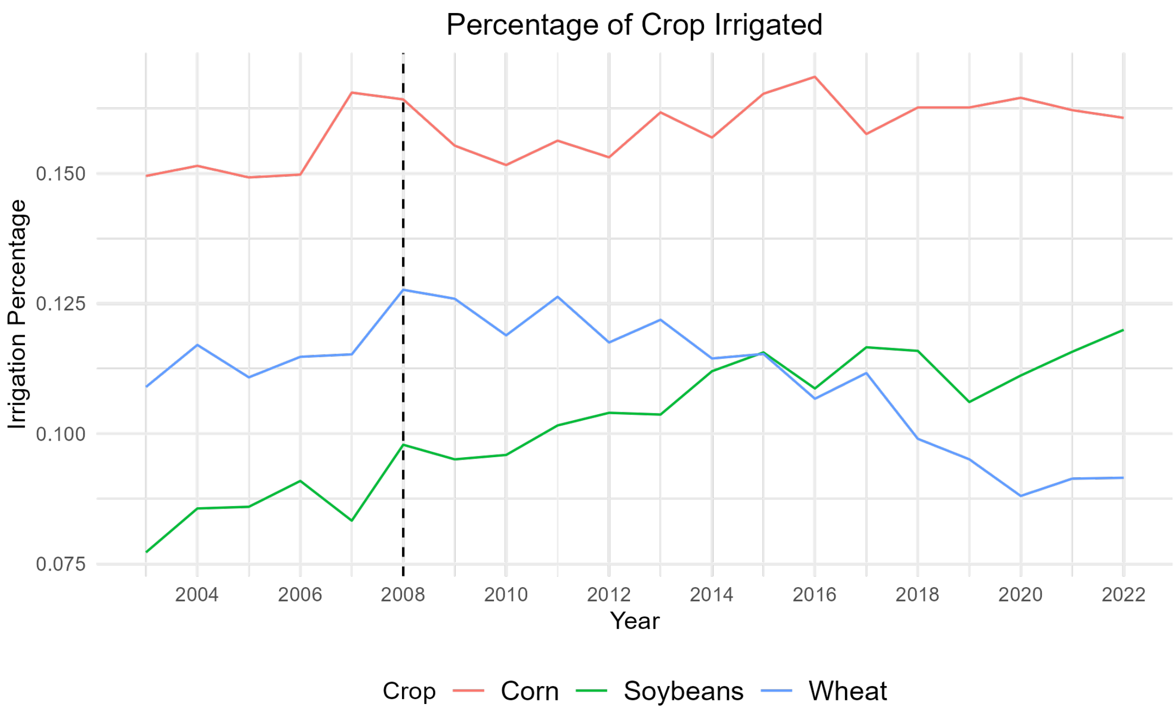


Figure 7: National Percentage of (Insured) Acres Irrigated for Corn, Wheat and Soybeans

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 dependant on irrigation. We therefore estimate the following equation separately for the east and the west. The coefficients of interest are τ_t, which are platted in figure 8.

$$\left(\frac{\text{Insured acres with irrigation}}{\text{All insured acres}}\right)_{county,crop,t} = \alpha_{county,crop}+\gamma_t+\tau_t\mathbb{1}\left[t\right]\times\mathbb{1}\left[\text{crop} = \text{Treated Crop}\right]+\epsilon_{county,crop,t} \tag{36}$$

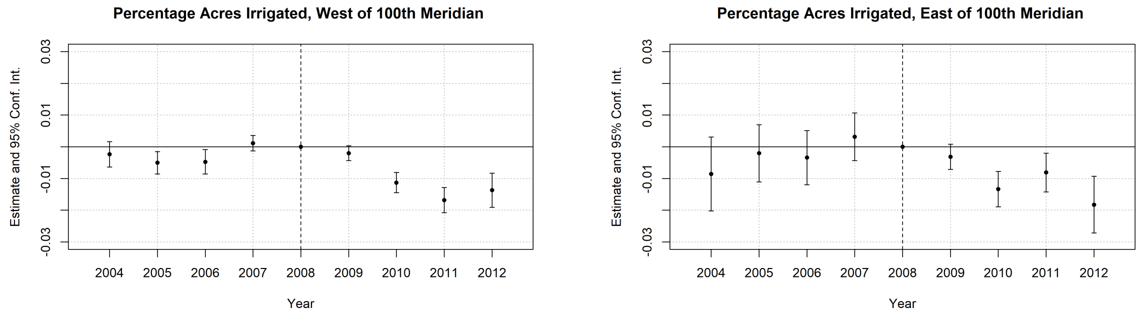


Figure 8: Treatment effect of being a crop eligible for the expanded aggregate subsidy on the percentage of insured acres that are irrigated. The left panel is for states to the west of the 100th meridian, the right panel to east. The estimating equations are (**??**) and the coefficients τ_t are graphed. Observations are weighted by acres insured.

We see, after an adjustment period, a 2% 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.

To quantify the impact of lower irrigation on yield, we use experimental estimates of the effect of irrigation on cotton, soybeans and wheat. Various extension officers and agricultural universities conduct 'variety trials', in which different varieties of crops are grown on on adjacent land. Often a variety of crop will be tested in the same location with and without irrigation. We use the differences in mean yield from those trials as our best estimate of the crop-specific treatment effect of irrigation. Details are in appendix B.14.

From these variety trials, we estimate that irrigation increases the yield per acre of cotton by 264.2%, soybeans by 17.7%, wheat by 139.2% and corn by 68.1%. Weighting by the proportion of irrigated acres by crop in 2008, we find an implied reduction in national yield of 3.5% for cotton, 0.5% for soybeans, 3.5% for wheat and 1.8% for corn, at a 3% irrigation reduction. We stress that these are national yield reduction estimates implied by our irrigation results, not directly estimated.

The decrease in irrigation is consistent with moral hazard as farmers move to aggregate insurance. This is also confirmed by within-farm estimates from ARMS in the main paper.

However, as we discuss in appendix B.9, there was also an increase in coverage levels following the 2009 reform. Hence, some part of the decline in irrigation might be due to increased insurance due to higher coverage levels, reducing the need for self-insurance such as irrigation. We investigate this in appendix B.9.2 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 reassures 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 total yield.

B.4 2015 Evidence for Complementarity of Revenue and Aggregate Insurance

The 2015 policy change, that expanded eligibility for aggregate insurance to three new crops, caused many farmers to swap to aggregate insurance, thereby broadening the scope of their policy. It also caused an increase in the take-up of revenue (rather than yield) insurance, implying a complementarity between aggregate and revenue insurance.

Movement to aggregate insurance. We first show that the 2015 eligibility expansion subsidy sharply moved treated crops from separate to aggregate insurance, without any discernible change in the total acreage insured.

We re-estimate equations 14, except now treatment occurs in 2015, the treated crops are popcorn, dry beans and dry peas, and the control crops are the 11 crops that were treated in 2009 with the subsidy expansion, and hence throughout this period were always eligible for aggregate and revenue insurance.

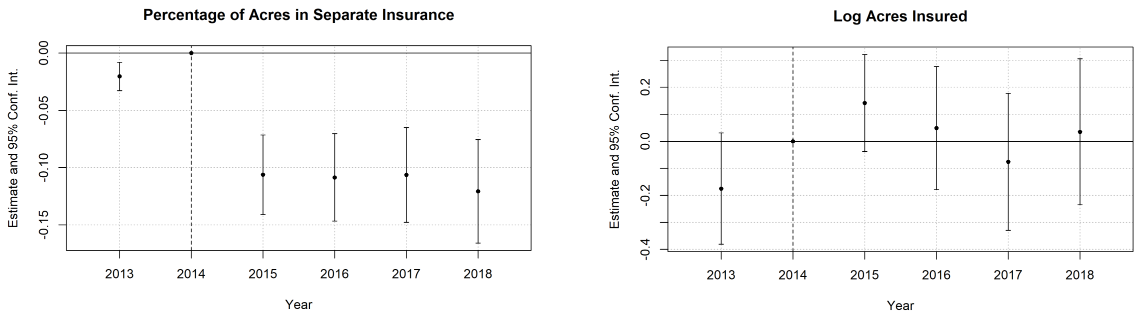


Figure 9: Treatment effect of new eligibility for aggregate insurance on: panel (a) the percentage of acres enrolled in *separate* insurance; panel(b) the log of acres enrolled in *any* insurance. The estimating equations are (14) and the coefficients τ_t are graphed. Observations are weighted by acres insured.

We see a large movement - of about 15% - away from separate insurance for the crops treated with the aggregate insurance eligibility. We do not see any increase in total acres insured. Having established the effect of the 2015 policy change on aggregate insurance take-up, we study the knock-on effect on revenue versus yield insurance.

Increase in revenue insurance. Independently of the choice of scope, a farmer can choose to insure yield (q) or revenue ($p \times q$). In both cases the quantity insured is based on a historical average of the farm's yield. The price insured is calculated at the time of insurance purchases (typically March) and is based on the expected harvest price of the commodity, from a futures exchange.[42]

How do incentives to change the scope of the policy - from separate to aggregate - affect incentives to choose yield versus revenue insurance? Intuitively, we expect aggregated insurance to be complementary to revenue insurance. If the yield on field 1 is Y_1 and on field 2 is Y_2, and revenue $R_1 = P \cdot Y_1, R_2 = P \cdot Y_2$ respectively then approximately speaking we expect $Corr(R_1, R_2) > Corr(Y_1, Y_2)$. That is, revenue is more correlated than yield, because revenue has the additional factor P in it, which is perfectly correlated across fields. The result below formalizes this.

Proposition 6. *Suppose that $P \perp Y_1$, $P \perp Y_2$ and that Y_1 and Y_2 have the same (marginal) distributions. Then we have*

$$Corr(R_1, R_2) > Corr(Y_1, Y_2).$$

This shows that adding price to the insurance contract increases correlations of outcome across fields. In combination with Proposition 3 this suggests that revenue insurance and aggregate insurance are complementary. Aggregate insurance is more attractive for more correlated field level risks, and including price in the contract increases correlation.

[42]Details of which exact contracts we classify as revenue or yield insurance are in appendix B.16.

To verify this empirically, we estimate the specification:

$$\left(\frac{\text{Acres in Revenue Insurance}}{\text{Acres in Any Insurance}}\right)_{county,crop,t} = \alpha_{crop} + \gamma_t + \tau_t \mathbb{1}\left[t\right] \times \mathbb{1}\left[\text{crop} = \text{Treated Crop}\right] + \epsilon_{county,crop,t} \tag{37}$$

The coefficients τ_t are in figure 10 below.

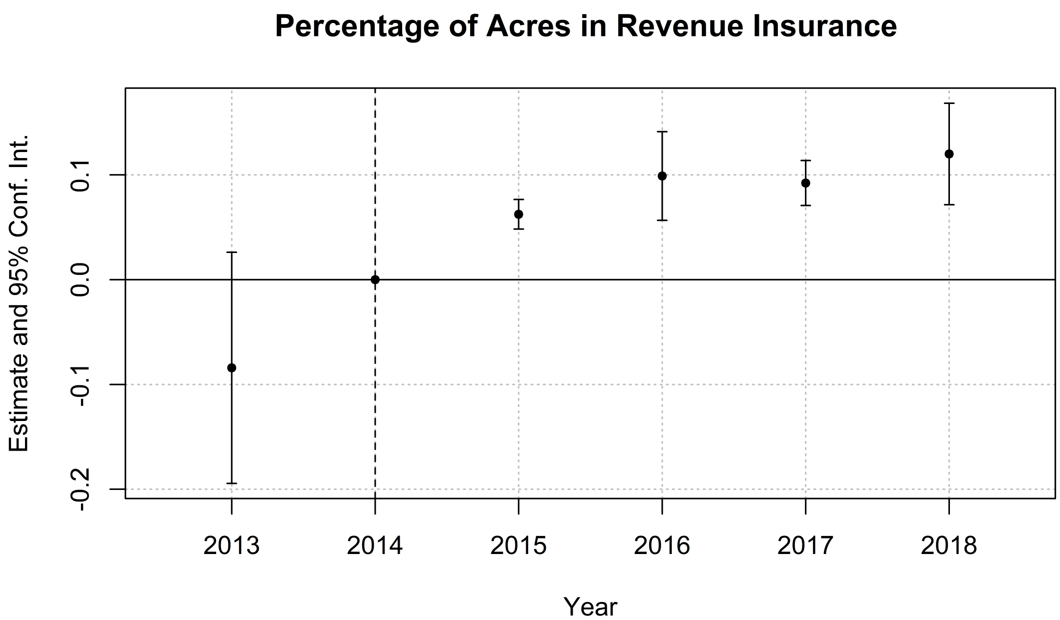


Figure 10: Treatment effect of eligibility for aggregate insurance on the percentage of crops enrolled in revenue insurance, before and after the 2015 policy change. The estimating equation is (37) and the coefficients τ_t are graphed. Observations are weighted by acres insured.

We see an 10-15% increase in revenue insurance take-up once a crop is also made eligible for aggregate insurance. This confirms the strong complementarities between revenue and aggregate insurance suggested by the theory.

Figure 10 exhibits non-parallel pre-trends. As a robustness check we implement a synthetic DiD estimator so that the control group is empirically estimated using the data instead of chosen by the researcher. We find a similarly sized effect of 10.1% (with a standard error of 2.2 %). An illustrative figure is in the appendix section B.16. Additionally, the within-farm specificaiton using ARMS data exhibits an even larger effect: 35% more of the farms that swap to aggregate insurance take up revenue insurance relative to the farms that remain in separate insurance. These confirm the event study evidence.

B.5 Between-crop Effects of the 2022 Diversity Corrective Reform

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 11 below.

$$S_{county,crop,t} = \alpha_{county,crop} + \gamma_t + \tau_t \mathbb{1}[t] \times \mathbb{1}[\text{crop} = \text{wheat}] + \epsilon_{it} \tag{38}$$

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

*** $p < 0.01$

Table 11: SDID estimates for the change in entropy following the policy change in 2022 that allowed aggregate units differentiated by type for wheat. Wheat is the treated crop, barley, canola and oats are the control crop.

The results from the between-crop SDID analysis confirm the within-wheat analysis in Figure 5. The treatment effect in 2022 is 0.03, and increased in 2023 to 0.04.

B.6 Evidence of Private Information - Correlates of Take-up

In section 3.1 we explored three different rationale for government involvement in the crop insurance market: aggregate risk, the Samiritan's dilemma and private information. These offer explanations for the FCIP broadly.

More specifically, in this section we give evidence that the scope of insurance is also a margin along which that farmers have and exploit private information. We analyze the correlates of aggregate insurance take-up following the 2009 reform. We are particularly interested in whether farms that face particular hazards, big farms vs small farms or farms with lots of spatial correlation in their acres lost were more or less likely to take up aggregate insurance. Our measure of take-up is the number of acres enrolled in aggregate insurance in 2012 divided by the number of acres enrolled in any insurance in 2008. Consistent with figure 9, the full effect of the policy change took multiple years. For this reason we use 2012 as the point of measurement for enrollment in aggregate insurance.

We regress this measure of take-up against: 1) the proportion of acres in a county on 'small' farms (less than 50 acres), the proportion on 'large' farms (greater than 2000 acres); 2) the proportion of acres lost in 2008 that were due to hazards such as drought, flood, disease and so on; 3) variance of the proportion of acres lost from 2001 to 2008 as a proxy for overall spatial correlation.

To understand the last covariate - the over-time variance as a proxy for spatial correlation - notice that two farms, both with every acre having a mean risk of failure of 50%, might have very different time series due to different correlation patterns. Suppose the first farm has no spatial correlation, so that each acre fails independently of the other. With many acres, a law of large numbers intuition suggests that the total proportion of failed acres should be close to 50% every year. On the other hand, if the second farm has perfect correlation between acres, then half the years will have failure rates of 0%, the other half with have 100% failure. Hence, fixing the mean risk, we can detect spatial correlation by looking at the variance over time. This follows from lemma 4.1.

The lemma says that, all else equal, more correlated farms should have higher variance in acres lost (also in proportion of acres lost) than less correlated farms. Finally, we also include the average proportion of acres lost from 2001 to 2008, and the square of this term. If we think of each field as a Bernoulli trial, and therefore the aggregate yield on a farm as having a binomial distribution, the variance when i.i.d. is given by $p(1-p)n$ where p is the mean failure rate and there are n fields. We want to control for this mechanical contribution of p and p^2 to variance. Instead we want to isolate the part due to differences in spatial correlation that lead to differences in aggregate yield, holding fixed p and $1-p$.

Putting this together, we estimate, for county i and crop c:

$$\begin{aligned}\frac{\text{Acres Insured in Aggregate}_{county,crop,2012}}{\text{Acres Insured }_{county,crop,2008}} = {} & \alpha_{county,crop} + \delta_c + \gamma_t + \beta_1 \text{Mean Acres Lost 2001-08}_{county,crop} \\ & + \beta_2 \text{Mean Acres Lost 2001-08}^2_{county,crop} \\ & + \beta_3 \text{Variance Acres Lost 2001-08}_{county,crop} \\ & + \beta_4 \text{Proportion lost in 2008 to hazard}_{county,crop} \\ & + \beta_5 \text{Acres on small farms}_{county,crop} \\ & + \beta_6 \text{Acres on big farms}_{county,crop} + \epsilon_{ict}\end{aligned}$$

Estimates of all the β coefficients are in figure 11.

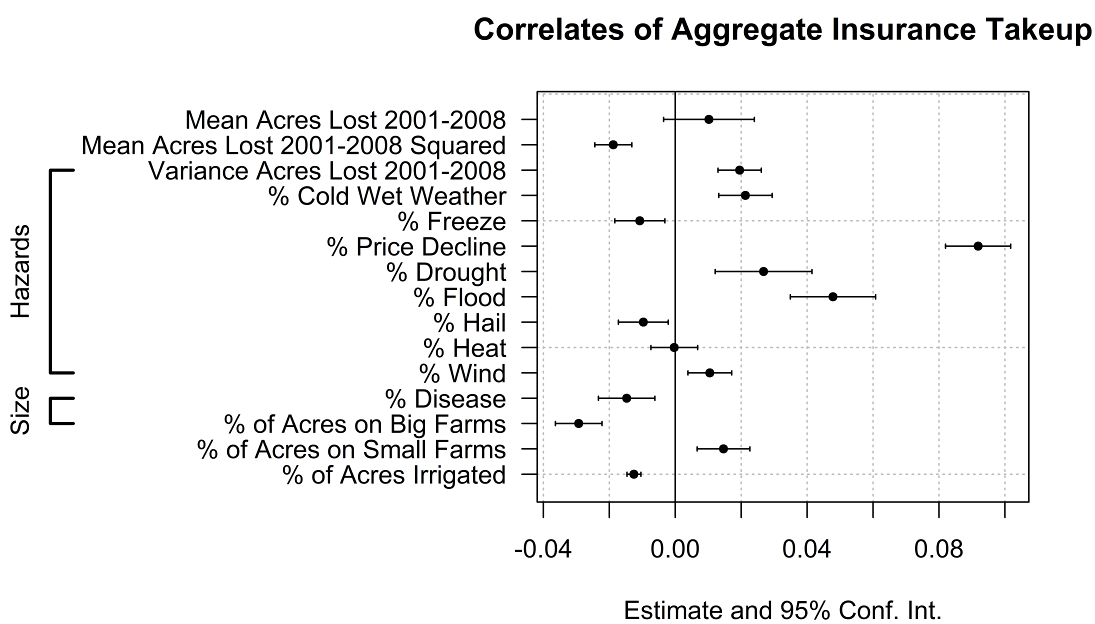


Figure 11: Correlates of aggregate insurance take-up following the 2009 policy change. The estimating equation is (**??**).

The estimates are consistent with farms who face more correlated risk being more likely to select into aggregate insurance. Small farms have less spatial diversification than large farms, explaining why counties with small farms are more likely to take-up aggregate insurance. Farms facing more widespread hazards such as price decline or drought are more likely to take-up than those facing disease or hail. And, as a summary statistic, counties with high variance of lost acres over time, a proxy for high spatial correlation of risk, are more likely to swap to aggregate insurance.

Since none of these factors is directly priced into the relative prices of aggregate vs separate policies, this demonstrates that farmers have private information about their correlation and select the scope of their policy accordingly. The infeasibility of pricing on all these pieces of private information, and the market failures that canonically ensue given private information in an insurance market, provide a rationale for government intervention and subsidy in crop insurance.

B.7 Pre-season precipitation and temperature

Most insurance choices need to be made by March 15. Planting occurs in April or May, with harvest in the late summer. Huang et al. (2018) show that climactic conditions from October until March, before the insurance election deadline, have significant effects on soil health and expected yield. These pre-growing season temperature and precipitation are not priced into the menu of crop insurance choices. As such, farmers can buy more or less insurance in a given year anticipating accounting for the soil condition.

In this section we extend the analysis of Huang et al. (2018) to show that the scope of insurance is another important margin along which farmers exploit this unpriced information about pre-growing season soil quality.

We also utilize the (updated to 2020) climactic data from Schlenker and Roberts (2009). These data consist of daily minimum and maximum temperatures, and total precipitation, for a 4x4 km grid that covers the entire contiguous US. We average the minimum and maximum temperatures, and sum the precipitation totals, over the pre-growing season period of October 1 to March 15. Since our analysis is at the county level, we take an average of these quantities for all cells in a county, weighted by the portion of the grid that is used for agriculture.

These form our three covariates of interest: pre-growing season (PGS) total precipitation, total precipitation squared, and average minimum daily temperature. The use of a quadratic specification for precipitation (e.g. see Schlenker and Roberts (2009)) is a standard way to incorporate the non-monotonicity of crop yields' responses to rain: too little or too much are both dangerous.

For each county and crop in year t we then estimate the following specification. The results are in table 12. We estimate this separately by policy regime (2009-14, 2015-19) and separately for all crops, corn only, or soy only.

$$\begin{aligned}\text{Proportion Insured in Separate}_{county,crop,t} = \alpha_{county,crop} + \delta_c + \gamma_t + \beta_1 \text{PGS Rain}_{county,crop,t} && (39)\\ + \beta_2 \text{PGS Rain}^2_{county,crop,t} && (40)\\ + \beta_3 \text{PGS Min Daily Temp}_{county,crop,t} && (41)\\ + \epsilon_{county,crop,t}. && (42)\end{aligned}$$

Table 12 shows that as pre-growing season rainfall and temperature increase (both of which are initially favourable for expected yield) there is a movement away from separate insurance and into aggregate insurance. Separate insurance gives higher indemnities in expectation but is more expensive. The non-monotonicity is as expected: for sufficiently high rainfall the direction switches

	All 09-14	All 15-19	Corn 09-14	Corn 15-19	Soy 09-14	Soy 15-19
PGS Rain	−0.003	−0.007*	−0.027***	−0.011***	0.006	−0.009***
	(0.008)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)
PGS Rain Squared	0.0004	0.0009	0.004***	0.0008*	−0.001+	0.0007*
	(0.001)	(0.0006)	(0.0007)	(0.0004)	(0.0006)	(0.0003)
PGS Min DT	−0.002	0.003*	−0.005***	−0.0007	0.002+	0.001*
	(0.003)	(0.001)	(0.0008)	(0.0006)	(0.001)	(0.0006)
Num.Obs.	49 701	40 471	12 644	10 190	10 713	9010
RMSE	0.21	0.19	0.11	0.08	0.11	0.10
Std.Errors	by: Crop	by: Crop	IID	IID	IID	IID
FE: Crop	X	X	X	X	X	X
FE: Year	X	X	X	X	X	X
FE: County	X	X	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Share of acres per county covered by separate policies, as a function of pre-growing season rainfall and temperature. The estimating equation is (39).

and farmers move back into separate insurance. The results are consistent with farmers being willing to forego the costly separate insurance exactly when conditions are good.

This is evidence consistent with farmers using scope strategically. When they receive positive private information that makes the probability of a loss lower, they move to lower coverage, lower payoff separate insurance.

B.8 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 assistance[43], and some programs not relevant to the crops we study, such as payments to dairy producers and 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 the maximum of a statutory price from the most recent farm bill, or the Olympic average of the last five years fo 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 againt 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 pay out most of the indemnity, with ARC covering some of the FCIP deductible. It is conceptually comparable to Medicare Supplement Insurance (Medigap).

[43] see the discussion in section 3.1

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 analysis of the fiscal impacts of the 2009 change in section **??** would be problematic if the same farm bill that lead to a massive expansion of the enterprise subsidy also lead 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 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:

$$\text{Income from DP}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{43}$$

$$\text{Income from CCP}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{44}$$

$$\text{Disaster Assistance Income}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it} \tag{45}$$

$$\text{Total (Non-Insurance) Gov Inc}_{farm,t} = \alpha_{farm} + \gamma_t + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{it}. \tag{46}$$

$$\tag{47}$$

The results are in table 13 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.

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)

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

Table 13: DID estimates of the change in income from other government support programsbefore and after 2009 for farms that swap to aggregate insurance, relative to farms that remain in separate insurance. The estimating equation is (43) and the coefficients τ are graphed. Observations are weighted the ARMS prescribed weights to ensure population representativeness.

Second, we study the universe of payments made by all US Government farm support programs at the county level. We use data from the Environmental Working Group (EWG)[44] that records payments made by crop and county in all of the safety net programs. The crops for which specific data is collected are: cotton, grain sorghum, corn, peanuts, soybeans wheat, rice, barley, canola, oats, dry peas, potatoes.

We compare data on county farm safety net payments to data on county insurance premia, claims and subsidies from our main data set. We restrict our main data set to be only the 11 crops above. We define the following summary measures of payments per insured acre made to farmers via the crop insurance subsidy, for county c in year y:

$$\begin{aligned}
\text{Safety Net PA}_{cy} &= \frac{\text{Total Non-Insurance Farm Payments}_{cy}}{\text{Insured Acres}_{cy}} \\
\text{Insurance Subsidies PA}_{cy} &= \frac{\text{Insurance Subsidies}_{cy}}{\text{Insured Acres}_{cy}} \\
\text{Insurance Net Payments PA}_{cy} &= \frac{\text{Indemnities + Subsidies - Farmer Premia}_{cy}}{\text{Insured Acres}_{cy}}.
\end{aligned}$$

The measure of total farm payments excluding insurance, 'Safety Net PA', captures the rest of the farm safety net. We use two measures of payments made by the government via the crop insurance program. First, we use the total subsidies paid. Second, we account for the fact that, due to the subsidies, the farmers are receiving better than actuarailly fair insurance. Hence we measure the explicit subsidy, plus the implicit subsidy given by the difference between indemnities and actual farmer paid premia.

We compute correlations at the year county level between these. The results are in table 14.

	Year Range		
Correlation	2003-2008	2009-2014	2015-2018
Safety Net PA, Insurance Net Payments PA	-0.003	-0.001	0.019
CI (95%)	(-0.020, 0.013)	(-0.017, 0.016)	(-0.001, 0.040)
Safety Net PA, Insurance Subsidies PA	-0.002	-0.009	0.051
CI (95%)	(-0.019, 0.014)	(-0.026, 0.007)	(0.031, 0.072)

Table 14: Crop Insurance vs Other Farm Support Program Payments

Table 14 shows that there is no correlation between farm insurance payments, by either measurement, and payments from the other safety net programs. This is consistent with the bulk of the safety net programs being direct subsidies, which are insensitive to farm outcomes. Moreover, there is no statistical difference between these correlations before and after the policy change under study. This confirms the within-farm ARMS evidence and further justifies our treatment of crop insurance in isolation within the main paper.

[44]Source: Environmental Working Group (2023).

B.9 Effects on Coverage Level

B.9.1 2009 Policy Change

The subsidy to aggregate insurance in 2008 meant that the farmers who moved to aggregate insurance spent substantially less on their premia. This is because, holding subsidies fixed, aggregate insurance is cheaper than separate insurance and the subsidy was much higher. In this section we demonstrate that farmers in aggregate insurance who were now less protected against certain hazards, and who had more money to spend, increased their coverage level.

Although coverage can be chosen at any 5% level from 50-85%, for ease we define "high" coverage as anything 75% or higher. We estimate the following equation:

$$\left(\frac{\text{Acres with} \geqslant 75\% \text{ coverage}}{\text{Acres with any coverage}}\right)_{county,crop,t} = \alpha_{county,crop,} + \gamma_t + \tau_t 1\left[t\right] \times 1\left[\text{crop} = \text{Treated Crop}\right] + \epsilon_{county,crop,t} \tag{48}$$

The coefficients of interest are τ_t, which are platted in figure 12. We see, after an adjustment period, a 2% decline in both parts of the country.

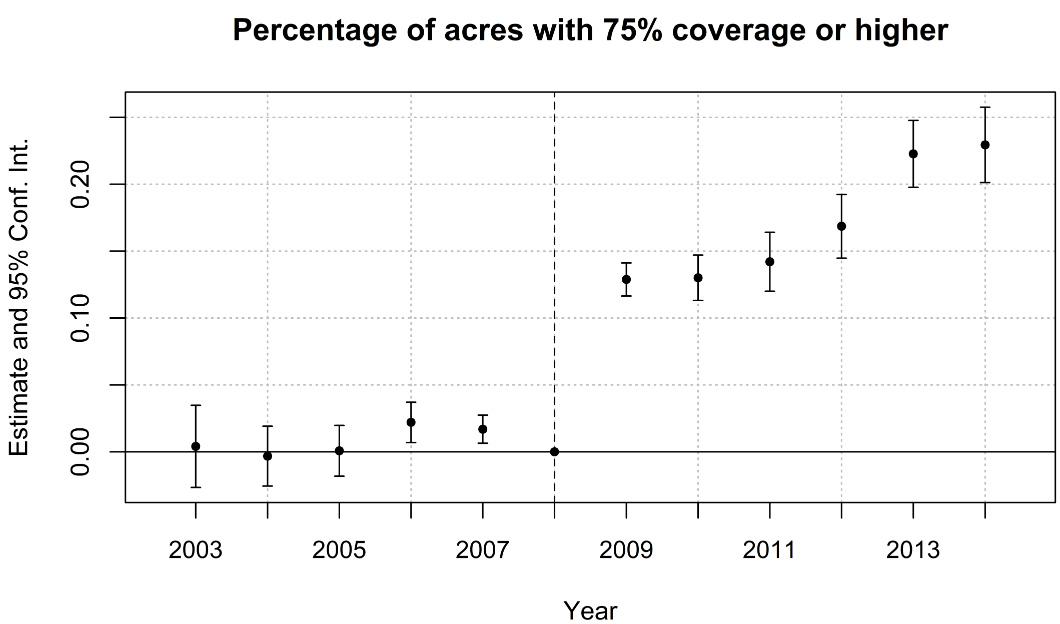


Figure 12: Change in the percentage of acres enrolled in high ($\geqslant$ 75%) coverage after the 2009 policy change.

We see an almost 40% rise in high coverage amongst the crops treated with the aggregate insurance subsidy relative to the control group.

This increase in coverage level in the prior section B.9.1 indicates that the farmers are facing less risk, in a sense, than before the subsidy. Even if this comes at a fiscal cost, there is social value in this risk protection. However, the higher coverage level is in the context of an aggregate policy. Farmers are gaining risk protection in the form of coverage, and losing potential indemnities by moving away from separate policies. Whether the net effect of this is smoother farmer final income (yield plus insurance claims) we turn to now.

B.9.2 2009 Irrigation Interaction with Coverage Changes

The irrigation effect presented in the main paper section 4.2.3 is possibly confounded by the coverage change shown in figure 12. The movement from separate to aggregate insurance incentives lower correlation between acres and hence less irrigation. But an increase in coverage level - an increase in formal insurance - would make the returns to self-insurance through irrigation lower. The 2009 change caused a movement into aggregate and into a higher coverage level, confounding a pure scope effect. In this section we speak to this confounding.

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 irrigaation 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 (36) as in section 4.2.3 broken down by county crops who had below or above median levels of high coverage ($\geqslant 75\%$) prior to the 2009 reform. As usual, also break down by counties to the east and west of the 100th meridian, leading to four different samples.

The results are in figure 17.

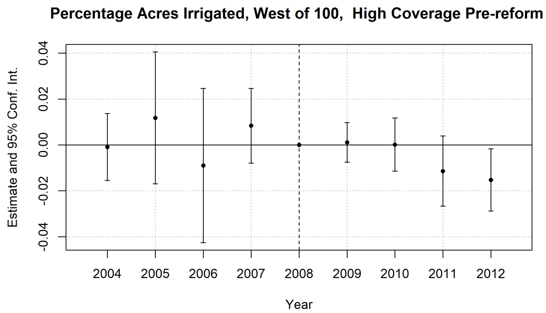


Figure 13: Caption for first subfigure.

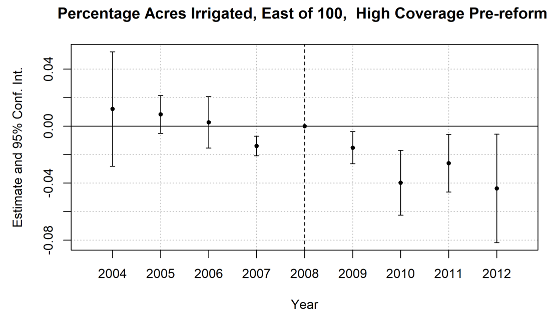


Figure 14: Caption for second subfigure.

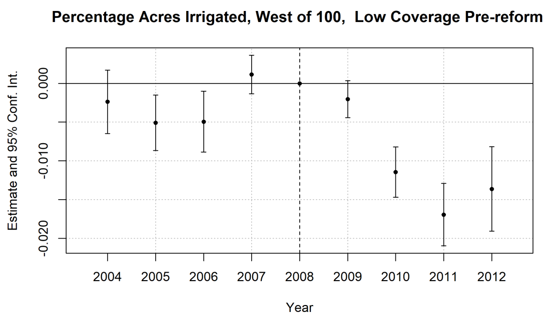


Figure 15: Caption for third subfigure.

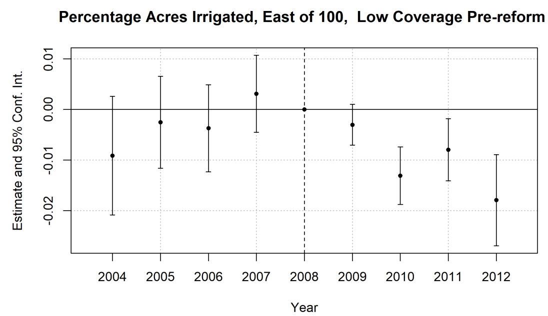


Figure 16: Caption for fourth subfigure.

Figure 17: Main caption for the figure.

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 nor economically as large as the high coverage groups.

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 about the 2009 irrigation effects being confounded by coverage changes.

B.10 Overall Effects of the 2015 and 2022 Policy Changes - Take-up of Aggregate Insurance

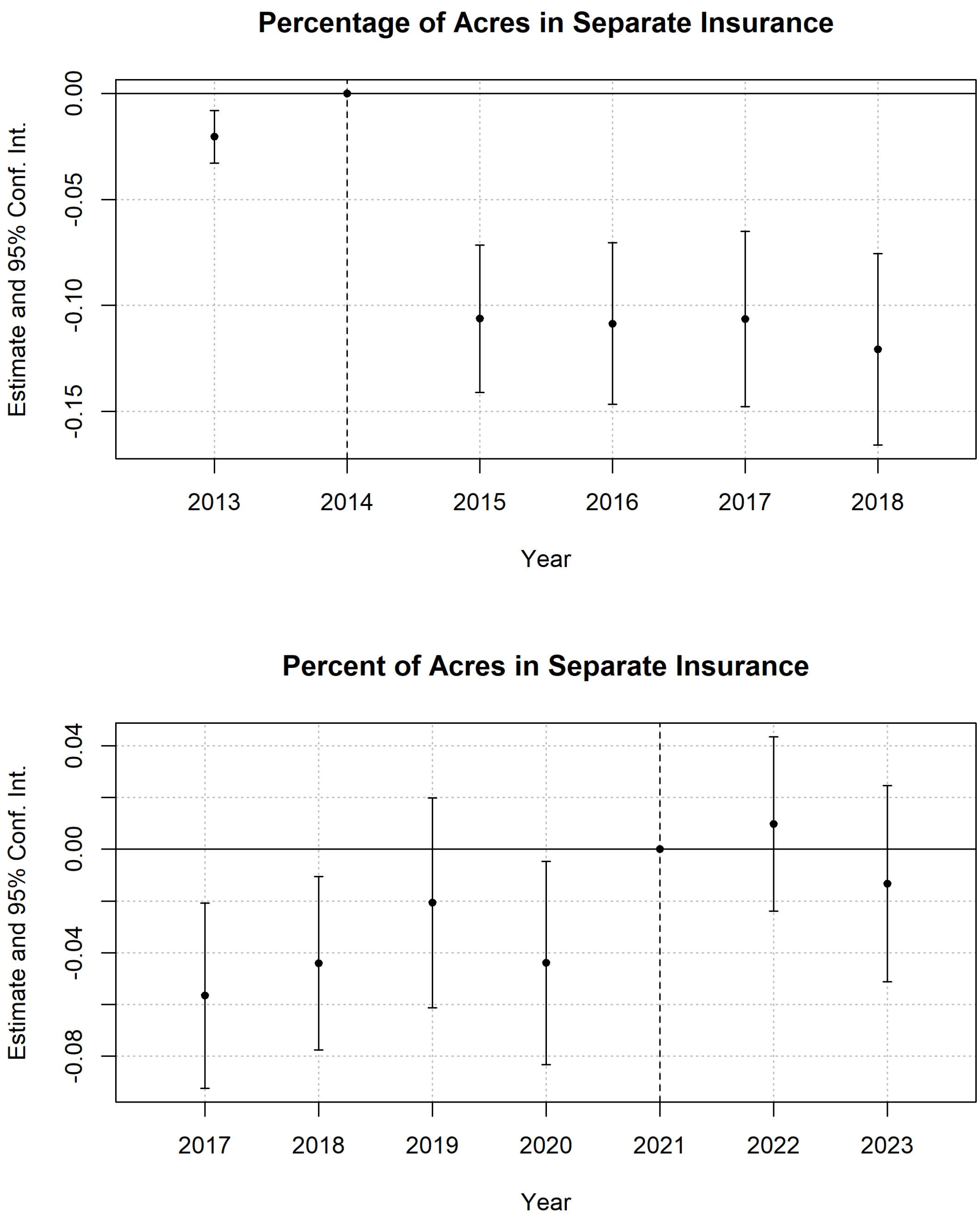


Figure 18: Event study of effect of the 2015 policy changes on the percentage of acres enrolled in high coverage . The panels split the analysis into counties to the west and east respectively of the 100th meridian.

B.11 Overall Effects of the 2015 and 2022 Policy Changes - Total Acres Insured

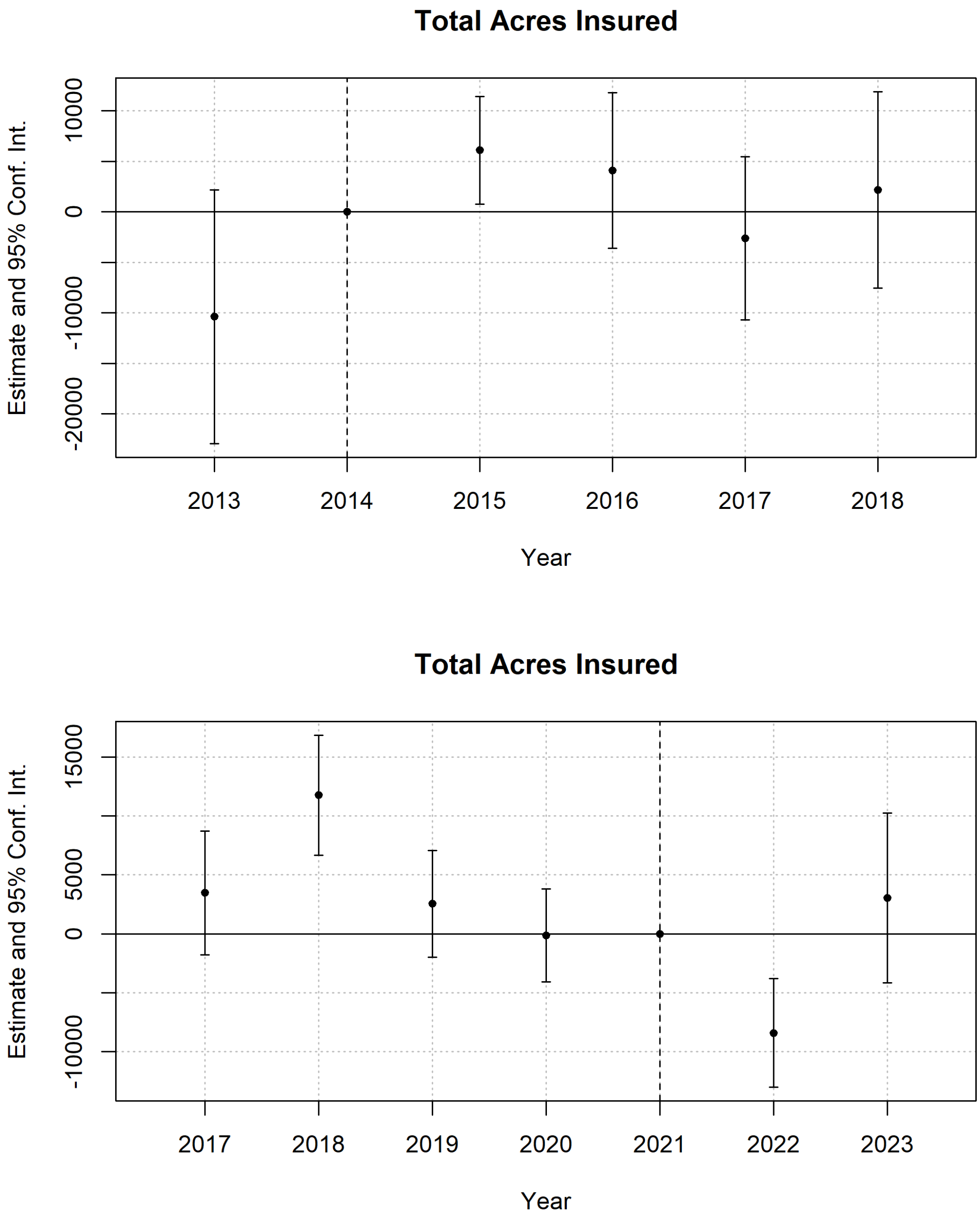
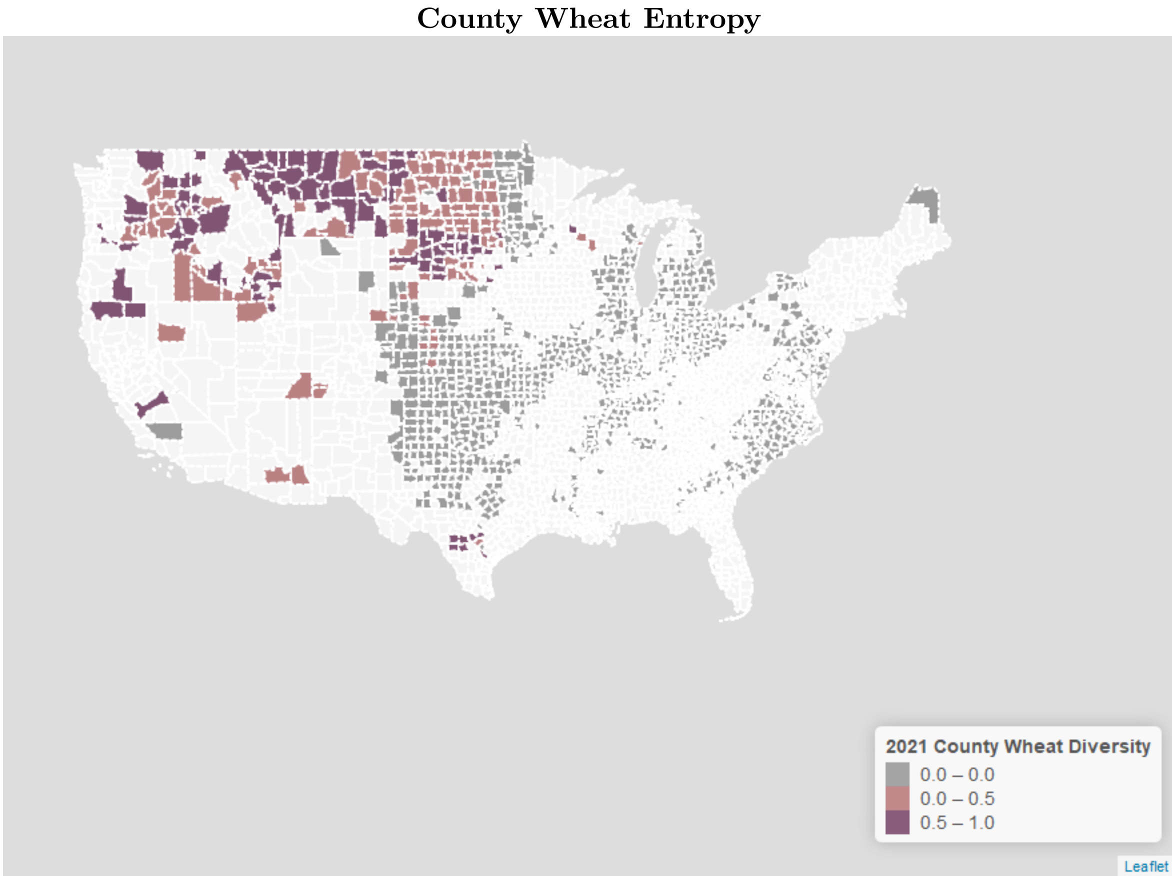


Figure 19: Event study of effect of the 2015 policy changes on the percentage of acres enrolled in high coverage . The panels split the analysis into counties to the west and east respectively of the 100th meridian.

B.12 Wheat and Barley Changes in Entropy from 2021-2022



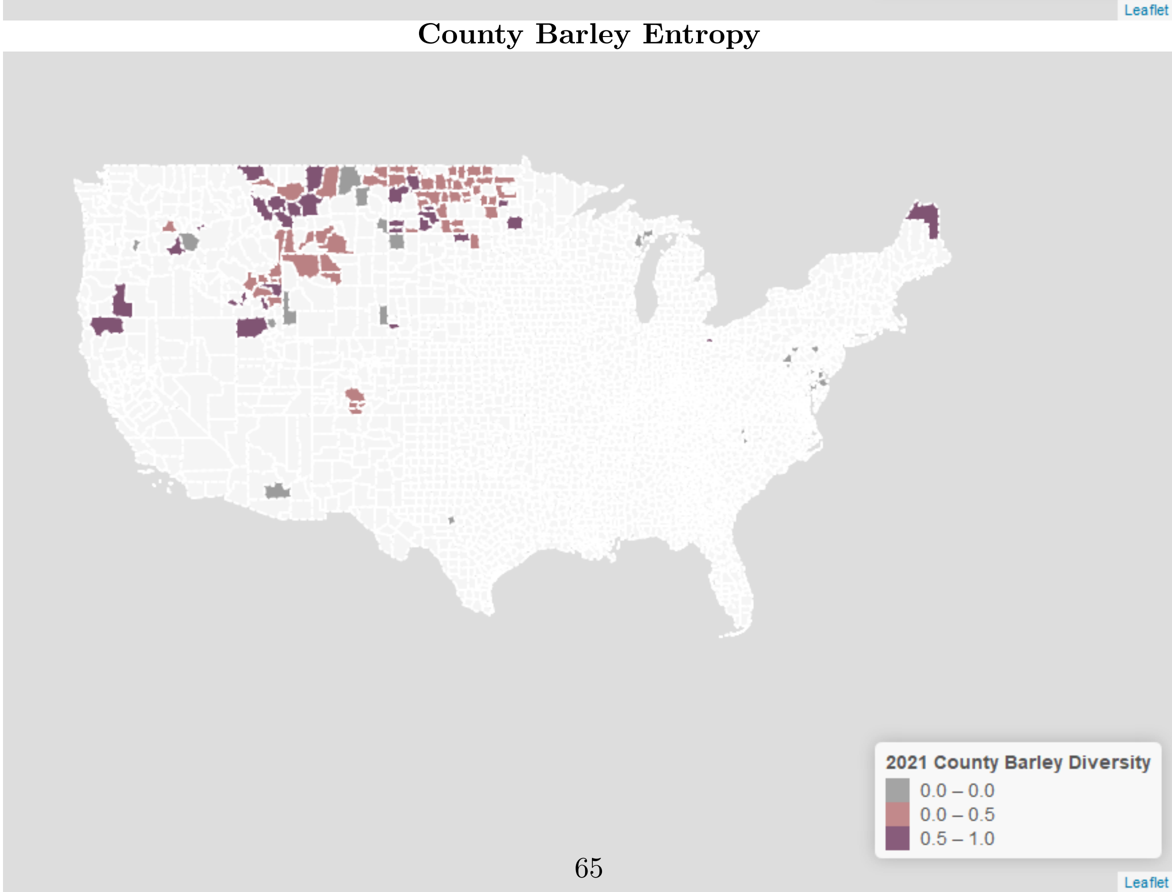


Figure 20: Geographical distribution of county diversity of wheat and barley.

This justifies the use of other small-grains as controls for wheat. Unlike wheat, oats, barley and canola were not treated with the 2022 change to definition of an aggregate unit. We therefore estimate the following specification, for county crop combination i and year t:

B.13 Analysis of Wheat Type Change in 2022

In this section we shed light on which species of wheat were introduced or removed from farms following the 2022 policy change discussed in section 4.

There are four species of wheat in the FCIC: winter, spring, durum and khorasan. Many of the counties in relatively southerly states only grow winter wheat. In the top panel of figure 20 we see many counties have no di versity at all in their wheat mix. Essentially of these grow only winter wheat. Winter wheat, if it survives the winter, often has the highest yield.

But in northerly latitudes growing winter wheat is riskier as the winters are harsher. That is why most of the northern counties grow some mixture of wheat types, per figure 20. These are the counties that are responsive to the 2022 change. In figure 21 we plot the change in entropy from 2021 to 2022 against the change in the proportion of winter wheat. Broadly there is a negative relationship: the counties with increases in entropy had decreases in winter wheat planted. But the scatter plot colours each dot according to the proportion of winter wheat in the county in 2021, before the change.

We see that the predominant group are indeed counties that were majority winter in 2021 who move to plant non-winter types in 2022. But there is also a substantial group of counties (blue and purple) in figure 21 that were minority winter in 2021 and increased their proportion of winter in 2022. These are both consistent with the story we have described. Aggregate insurance incentivizes correlation between crops and so farmers take an all-or-nothing bet, so to speak, on a type of wheat. The policy change encourages diversity by making the farmer the residual claimant to any offsetting self-insurance from planting multiple species. Hence counties that began as majority winter move to other types, and those that were minority winter move toward it.

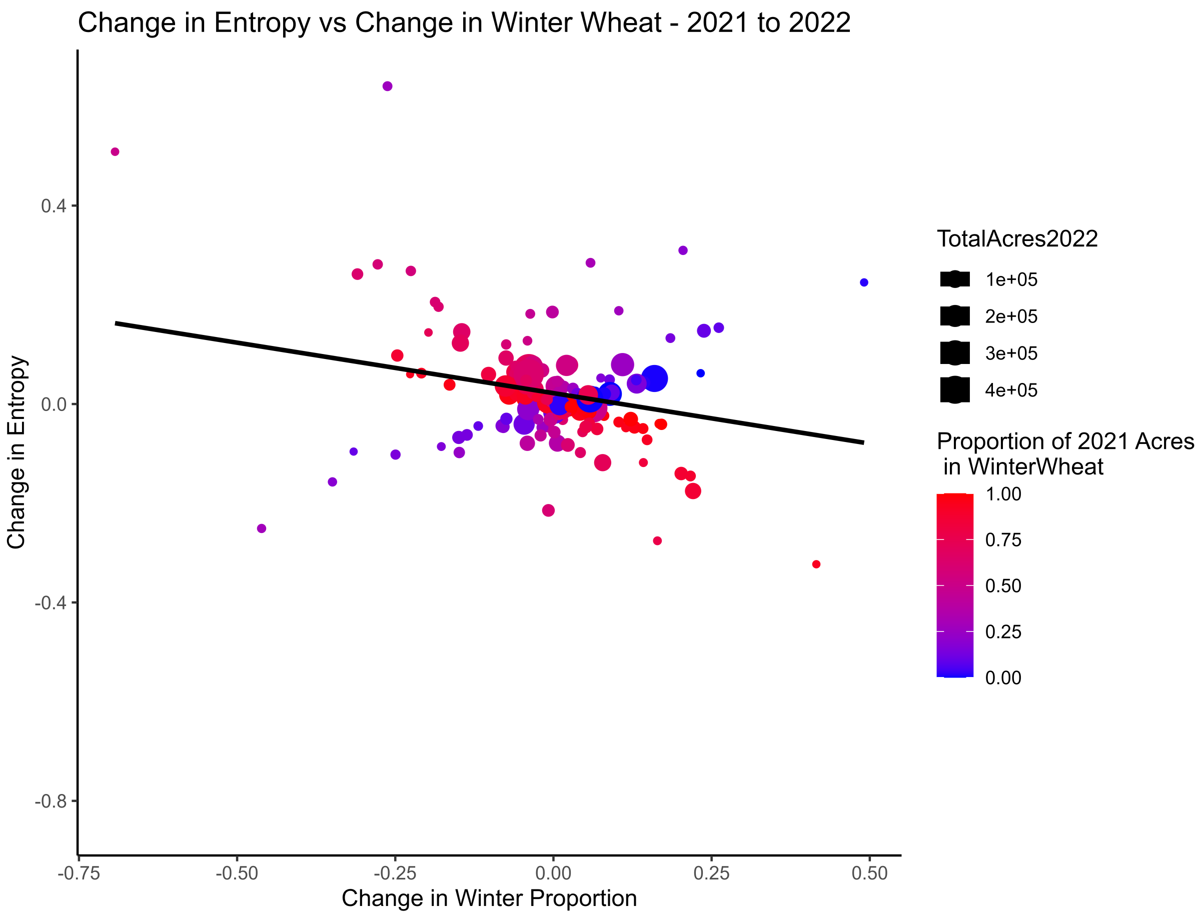


Figure 21: Scatter plot of the change in entropy against the change in proportion of winter wheat planted, from 2021 to 2022. The colour of the dots represents the proportion of winter wheat in 2021 (before the change). The size of the dots represent the number of acres of wheat in the county.

B.14 Details on Variety Trials for Estimates of Irrigation on Yield

The trials used to compute the treatment effects were as exhaustive as possible. Our criteria were that the same variety had to be trialled, in the same location and year, under irrigated and dryland conditions.

For corn, we use variety trials conducted at Springfield and Milan, Tennessee by Sykes et al. (2019) in 2019. Over 30 varieties were tests under dryland and irrigated conditions at these locations, with details in Sykes et al. (2019). We take the average yield at each location, for each of early, medium and full season yields. We take the ratio of the average yield for irrigated to dryland. We take a simple average of this ratio of over the 3 seasons $\times$ 2 locations which leads to our estimate of 68% higher irrigated yield than dryland. We use the proportion of acres irrigated for corn in 2008, which is 16.4%, in combination with a treatment effect of 3% on acres irrigated, to compute an implied 1.8% change in national corn yield.

For wheat, we use 2021 variety trials in Box Butte County, Nebraska conducted by The University of Nebraska (2023). They estimate an irrigated wheat yield of 135.9, a dryland yield of 56.8. Hence we take 139% as the causal difference in yield due to irrigation. We use the proportion of acres irrigated for wheat in 2008, which is 12.7%, in combination with this treatment effect of 3%, to compute an implied 3.5% change in national cotton yield.

For soy, we use variety trials at Springfield and Milan, Tennessee by Sykes et al. (2022). We average over the four maturity groups, with all varieties used. From this estimate a 17% higher irrigated yield than dryland. We use the proportion of acres irrigated for soy in 2008, which is 11.7%, in combination with this treatment effect of 3%, to compute an implied 0.5% change in national soy yield.

For cotton, we use variety trials conducted by Texas A&M Agrilife Research and Extension Centre (2023) at Halfway, Lubbock and Lamesa in 2000. The varieties tests under irrigated and dryland conditions were All-Tex Excess and Tamcot Sphinx (Halfway), All-Tex Atlas, All-Tex Excess, Deltapin,e 2156 Seedco, 9023 Tamcot Sphinx (Lubbock), All-Tex Atlas, Paymaster Tejas, Tamcot Sphinx, Paymaster 2326 BG/RR, Paymaster 2326 RR (Lamesa). We take the ratio of irrigated to dryland yield for all these varieties, and average the ratio across varieties and location to get that irrigation causes yield to be 264% higher than dryland. We use the proportion of acres irrigated for cotton in 2008, which is 46.9%, in combination with this treatment effect of 3%, to compute an implied 3.5% change in national cotton yield.

B.15 Robustness of Wheat Diversity Results to Aggregation Issues

It is possible for the level of aggregation of our data to cause issues with our crop diversity analysis. It is possible that county level diversity increases while farm level diversity decreases, or vice versa. To understand this, suppose there is a county with two farms on it. The first farm has 60 acres of winter wheat. The second farm as 20 acres of winter wheat and 20 acres of spring wheat. Overall the county has 80 acres of winter and 20 acres of spring wheat.

Suppose after the policy reform the farm with 60 acres of winter wheat is unchanged, whereas the farm that was half/half now becomes fully spring wheat. Notice that that farm has become less diverse: it went from being half/half spring and winter to fully spring. But the county has gone from 80/20 to 60/40, and so diversity has increased. The reason for this non-monotonicity is that the majority type at the county level need not be the majority type at the farm level. A farm can move toward the majority type (decreasing diversity) while the county gets more diverse, if that farm majority type is the county minority type.

To check our results are robust to this issue, we re-run the analysis from section 4.2.2 restricting to counties that had zero entropy (so no diversity - they all grew one type of wheat) before the reform, but were in the northern states of Nebraska, South Dakota, North Dakota, Montana in which moving between types of wheat is plausible.[45] By looking at counties with no diversity - that all grew the same type of wheat - we can be sure that if the county becomes more diverse so too do the farms. This is because if the farms and county all start at zero acres of, say, winter wheat, we recover monotonicity since the crop that is majority (in fact, entirety) of the counties is also the entirety of the farms.

We reproduce figure 5 restricted to this subset of counties. The result is in figure 22 below.

[45] If we include all counties with zero entropy, the overwhelming majority are southern states that only grow winter wheat before and after the reform. These overwhelm the states in which changes take place.

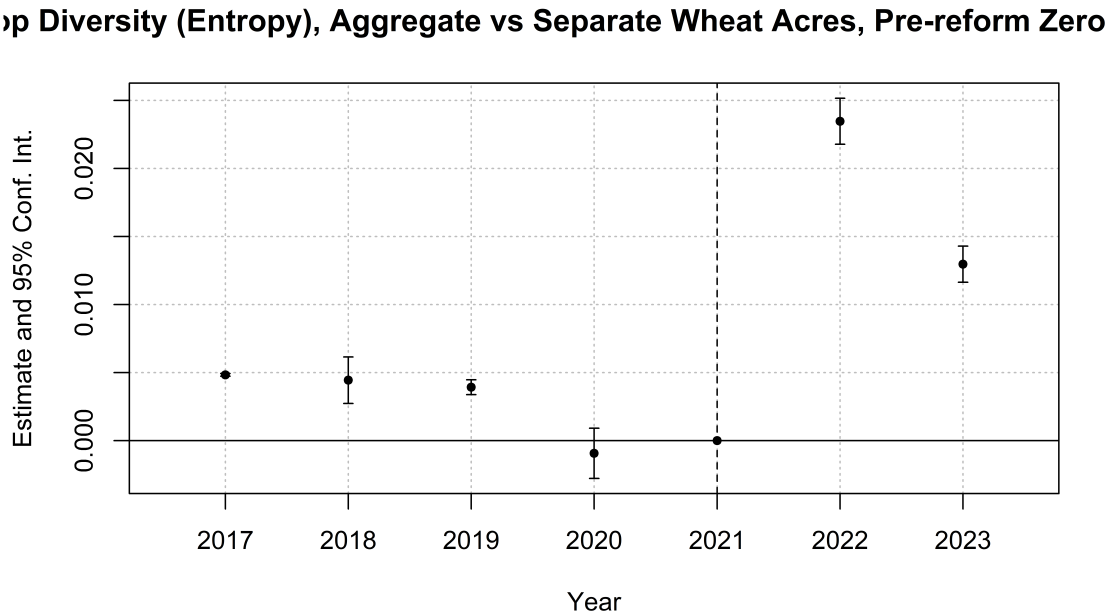


Figure 22: Entropy in wheat aggregate units versus separate units, restricted to counties Nebraska, South Dakota, North Dakota, Montana with no pre-reform diversity.

Just as in the main paper, diversity increases by approximately 2.5% in these counties. As discussed above, due to this sample restriction, this must mean diversity at a farm level increased as well.

B.16 Further Analysis for Revenue Insurance

In this section, detail is provided on which contracts are classified as revenue protection contracts and which as yield protection. We also present robustness checks using the within-farm ARMS data, as well as a between-crop SDID figure referenced in the main text as a robustness checks.

Many different contracts are offered by the FCIP. The following were classified as yield protection, revenue protection, or neither.

- Yield insurance contracts: Actual Production History (APH), Yield Protection (YP)
- Revenue insurance contracts: Revenue Protection (RP), Crop Revenue Coverage (CRC), Revenue Assurance (RA)

All remaining contracts were excluded from the yield vs revenue analysis section. These include: contracts that insure areas larger than a farm (e.g. county-based insurance), wind index products, and a hybrid product called Revenue Protection with Harvest Price Exclusion (RPHPE). RPHPE sits somewhere between YP and RP products. Under an RPHPE contract, the guaranteed revenue for the farmer is defined as expected yield times pre-harvest price, whereas the indemnity is calculated based on the difference between guaranteed revenue and actual revenue (using the harvest price). Hence, partial price insurance is offered, since if the harvest price is very low, an indemnity can still be paid out, but the level the farmer is indemnified up to depends only on the pre-harvest price. This product is not very popular, and to avoid uncertainty about how to classify it we drop it from our analysis.

Next, as a first robustness check, we run the following within-farm specification using ARMS data.

$$\text{Enrolled in Revenue Insurance?}_{f,crop} = \alpha_f + \gamma_{crop} + \tau \mathbb{1}\left[t \geqslant 2009\right] \times \mathbb{1}\left[\text{Farm in Aggregate Policy }\right] + \epsilon_{f,crop} \tag{49}$$

The estimate of the treatment effect τ of interest is:

	Within-Farm ARMS
Treatment Effect	33.0%*
	(14.0%)
N	911

Figure 23: Treatment effect of eligibility for aggregate insurance on the percentage of separate and aggregate insured crops enrolled in revenue insurance, before and after the 2015 policy change. Estimated by Synthetic Differences in Differences

	Synthetic DiD
Treatment Effect	10.1%***
	(2.2%)

B.17 Contract Details: Revenue / Yield Insurance $\times$ Aggregate/Separate

To understand the precise structure of the insurance contracts, and how they interact with the choice of scope and of revenue vs yield insurance we write X_i for the realized yield on field i, $E(X_i)$ for the expected yield, p for the realized price, $\bar{p}$ for the expected price (at the time of insurance purchase), and c for the coverage level (the proportion of expected yield or expected revenue that is covered). The insurance payouts from the four types of contracts are:

$$\iota_{Sep}^{Yield} = \bar{p} \times \sum_i \max\{cE(X_i) - X_i, 0\} \tag{50}$$

$$\iota_{Sep}^{Revenue} = \sum_i \max\{c\bar{p}E(X_i) - pX_i, 0\} \tag{51}$$

$$\iota_{Agg}^{Yield} = \bar{p} \times \max\left\{\sum_i cE(X_i) - \sum_i X_i, 0\right\} \tag{52}$$

$$\iota_{Agg}^{Revenue} = \sum_i \max\left\{\sum_i c\bar{p}E(X_i) - \sum_i pX_i, 0\right\}. \tag{53}$$

C Proofs

C.1 Proof of Proposition 1

Proof. First, we show that the indemnity received is higher under separate insurance than aggregate. We have that:

$$\begin{aligned}\iota_{agg} &= f\left(\sum_i x_i\right) = f\left(\sum_i x_i \frac{n}{n}\right) \leqslant \sum_i \frac{f\left(x_i \cdot n\right)}{n} \\ &= \iota_{sep}\end{aligned}$$

where the inequality follows from the convexity of f. For any policy that pays an indemnity, the inequality is strict somewhere. It follows that the premia for the aggregate contract is lower:

$$p_{agg} = E_X\left[\iota_{agg}\right] < E_X\left[\iota_{sep}\right] = p_{sep}.$$

But then note at the highest or lowest yield $X = 0$ or $X = \overline{X}$, we have $\iota_{agg} = \iota_{sep}$. Hence, at the extreme points, the farmers income is higher under aggregate, since indemnities are equal but the premium is lower. It follows by continuity that final farmer income under aggregate policies is higher for intervals at the bottom and top of the aggregate yield distribution.

□

C.2 Proof of Proposition 2

Proof. The assumption we require on the level of risk aversion is precisely that that $\Delta U = U\left(\sum x_i + \iota_{sep}(X) - p\right) - U\left(\sum x_i + \iota_{agg}(X) - p\right)$ is submodular.

We relate this to risk aversion in two ways. First, suppose that $\iota_{sep}(X) = \sum_i f_i(x_i)$ and $\iota_{agg}(X) = f\left(\sum_i x_i\right)$ are differentiable. Then submodularity requires that $\frac{\partial^2}{\partial x_i \partial x_j}\Delta U < 0$ for any $i \neq j$. This reduces to, where $U'' - Sep = U''\left(\sum x_i + \iota_{sep}(X) - p, e\right)$ and similarly for U'_{Sep}, U''_{Agg} and U'_{Agg}:

$$\underbrace{\frac{f''(\sum x_i)}{(1+f'(\sum x_i))^2}}_{(1)} > \underbrace{\frac{U''_{Sep}(1+f'_i(x_i))(1+f'_j(x_j))}{U'_{Agg}}}_{(2)} - \underbrace{\frac{U''_{Agg}}{U'_{Agg}}}_{(3)} . \tag{54}$$

By the convexity of f and concavity of u, (1) is positive, (2) is negative and (3) is positive (including the minus). Hence, when the coefficient of absolute risk aversion $-U''/U'$ is zero or sufficiently small, this gurantees that the inequality holds. Hence small risk aversion is a sufficient condition.

If f and f_i are not differentiable, then the claim still follows by noting that for risk-neutral $U = id$, the proof goes through identically to proposition 3. Hence, by continuity, it also holds nearby.

In any case, we assume the submodularity above. It follows by Denuit et al. (2006) that, for diversification effort levels $e' < e$ ΔU is higher at e' than e. In other words: the returns to diversification are higher under a separate policy than an aggregate. Since the cost functions are the same, it follows that the optimal amount of diversifying effort is higher under a separate policy than an aggregate, as required.

If $\iota_{sep}(X) = \sum_i f_i(x_i)$ for continuous, weakly decreasing and convex f_i then we say a policy is **separate**. If $\iota_{agg}(X) = f\left(\sum_i x_i\right)$ for continuous, weakly decreasing and convex f then we say a policy is **aggregate**. $\square$

C.3 Proof of Proposition 3

Proof. We first prove that $g(X) = \iota_{Agg}(X) - \iota_{Sep}(X)$ is supermodular. First, note that

$$g(X \wedge Y) + g(X \vee Y) - g(X) - g(Y) = \sum_i f_i(x_i \wedge y_i) + \sum_i f_i(x_i \vee y_i) - \sum_i f_i(x_i) - \sum_i f_i(y_i) \tag{55}$$

$$+ f\left(\sum_i x_i \wedge y_i\right) + f\left(\sum_i x_i \vee y_i\right) - f\left(\sum_i x_i\right) - f\left(\sum_i y_i\right) \tag{56}$$

$$= f\left(\sum_i x_i \wedge y_i\right) + f\left(\sum_i x_i \vee y_i\right) - f\left(\sum_i x_i\right) - f\left(\sum_i y_i\right) \tag{57}$$

since for every i we have

$$f_i(x_i \wedge y_i) + f_i(x_i \vee y_i) = f_i(x_i) + f_i(y_i). \tag{58}$$

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

$$\sum_i x_i \wedge y_i \leqslant \sum_i x_i, \sum_i y_i \leqslant \sum_i x_i \vee y_i. \tag{59}$$

Hence there exist λ_x, λ_y such that

$$\sum_i x_i = \lambda_x \left(\sum_i x_i \vee y_i\right) + (1-\lambda_x)\left(\sum_i x_i \wedge y_i\right) \tag{60}$$

$$\sum_i y_i = \lambda_y \left(\sum_i x_i \vee y_i\right) + (1-\lambda_y)\left(\sum_i x_i \wedge y_i\right). \tag{61}$$

Moreover by (58) we have that $\lambda_x + \lambda_y = 1$. Hence we have,

$$f\left(\sum_i x_i\right) + f\left(\sum_i y_i\right) = f\left(\lambda_x \left(\sum_i x_i \vee y_i\right) + (1-\lambda_x)\left(\sum_i x_i \wedge y_i\right)\right) \tag{62}$$

$$+ f\left(\lambda_y \left(\sum_i x_i \vee y_i\right) + (1-\lambda_y)\left(\sum_i x_i \wedge y_i\right)\right) \tag{63}$$

$$\leqslant \lambda_x f\left(\sum_i x_i \vee y_i\right) + (1-\lambda_x) f\left(\sum_i x_i \wedge y_i\right) \tag{64}$$

$$+ \lambda_y f\left(\sum_i x_i \vee y_i\right) + (1-\lambda_y) f\left(\sum_i x_i \wedge y_i\right) \tag{65}$$

$$= f\left(\sum_i x_i \vee y_i\right) + f\left(\sum_i x_i \wedge y_i\right) \tag{66}$$

where the inequality follows from the convexity of f. Hence $g(X \wedge Y) + g(X \vee Y) - g(X) - g(Y) \geqslant 0$ and so g is supermodular. In particular, $\iota_{Sep}(X)$ is both super and submodular, and hence does not change with e, whereas $\iota_{Agg}(X)$ is supermodular.

Then from Denuit et al. (2006), we have that $E(\iota_{Agg}(X))$ decreases with (diversification increasing effort) e. Hence the fiscal externality is positive under the aggregate policy at any effort level, in particular the optimum. On the other hand, as noted, there is no fiscal externality under the separate policy, as changing correlation does not affect payouts. This completes the proof.

□

C.4 Proof of Proposition 4

Proof. The planner sets indemnities in each state of the world $(\iota_1, \ldots, \iota_S)$ to maximize

$$\max_{(\iota_1,\ldots,\iota_S)} E_X\left[u\left(\sum_i x_i + \iota(X) - p, \psi\right)\right] \tag{67}$$

noting that $\pi^X = \pi^X(e)$ and that e is chosen by the farmer who optimizes given $(\iota_1, \ldots, \iota_S)$.

The first order condition with respect to the indemnity in a particular state s, ι^s, is given by

$$\pi^s u'(X^s) - \frac{\partial p}{\partial \iota^s} E_X\left[u'(X)\right] + \underbrace{\frac{de}{d\iota^s}\frac{d}{de} E_X\left[u(X)\right]}_{=0 \text{ by envelope thm}}. \tag{68}$$

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

$$\frac{dp}{d\iota^s} = \frac{d}{d\iota^s} \sum_{x=1,\ldots,s,\ldots,S} \iota^x \pi^x(e) \tag{69}$$

$$= \pi^s + \frac{de}{d\iota^s} \sum_{x=1,\ldots,s,\ldots,S} \iota^x \frac{d}{de}\pi^x(e) \tag{70}$$

$$= \pi^s + \frac{de}{d\iota^s} E_x\left[\frac{\iota^x}{\pi^x}\frac{d}{de}\pi^x(e)\right] \tag{71}$$

$$= \pi^s + E_x\left[\frac{\iota^x}{\iota^s}\epsilon_{\pi^X,\iota^s}\right] \tag{72}$$

recalling that $\epsilon_{\pi^X,\iota^S} = \frac{d\pi^x(e)}{d\iota^s}\frac{\iota^s}{\pi^x}$ is the elasticity of the probability of being in (generic) state x with respect to the indemnity in (specific) state ι^s.

Rearranging yields

$$\frac{u'(X^s) - E_X\left[u'(X)\right]}{E_X\left[u'(X)\right]} = \frac{E_X\left[\frac{\iota^X}{\iota^S}\epsilon_{\pi^x,\iota^s}\right]}{\pi_s} \tag{73}$$

as required.

□

C.5 Proof of Proposition 5

Proof. The individual chooses e to satisfy the first order condition:

$$2\left(\kappa'(e) + (1-2p(e))p'(e)\right)u(\iota_1 - l - \tau + w) + \left(2(p(e)-1)p'(e) - \kappa'(e)\right)u(\iota_B - 2l - \tau + w) + u(w-\tau)\left(2p(e)p'(e) - \kappa'(e)\right) - \psi'(e) = 0.$$

The budget constraint is $\tau \to 2\iota_1(\kappa(e) + (1-p(e))p(e)) + \iota_B\left((1-p(e))^2 - \kappa(e)\right)$. The planner's problem, after substituting this in, is given by, again where we suppress the dependence of e and on ι_1, ι_B:

$$\max_{\iota_1,\iota_B} -\psi(e) + \left((p(e)-1)^2 - \kappa(e)\right)u((\iota_B - 2\iota_1)\kappa(e) + p(e)((2\iota_1 - \iota_B)p(e) - 2\iota_1 + 2\iota_B) - 2l + w)$$
$$+ 2\left(\kappa(e) - p(e)^2 + p(e)\right)u\left(\iota_B\left(\kappa(e) - (p(e)-1)^2\right) - 2\iota_1\left(\kappa(e) - p(e)^2 + p(e)\right) + \iota_1 - l + w\right)$$
$$+ \left(p(e)^2 - \kappa(e)\right)u\left(\iota_B\left(\kappa(e) - (p(e)-1)^2\right) - 2\iota_1\left(\kappa(e) - p(e)^2 + p(e)\right) + w\right)$$

For ease of exposition, define consumption if two, one or zero losses occur respectively as:

$$c_2 = (\iota_B - 2\iota_1)\kappa(e) + p(e)((2\iota_1 - \iota_B)p(e) - 2\iota_1 + 2\iota_B) - 2l + w$$
$$c_1 = \iota_B\left(\kappa(e) - (p(e)-1)^2\right) - 2\iota_1\left(\kappa(e) - p(e)^2 + p(e)\right) + \iota_1 - l + w$$
$$c_0 = \iota_B\left(\kappa(e) - (p(e)-1)^2\right) - 2\iota_1\left(\kappa(e) - p(e)^2 + p(e)\right) + w.$$

Moreover, define

$$\chi = (2\iota_1 - \iota_B)\frac{\partial e}{\partial \iota_B}\left(2p(e)p'(e) - \kappa'(e)\right) + 2(\iota_B - \iota_1)\frac{\partial e}{\partial \iota_B}p'(e) + \kappa(e) - ((p(e)-2)p(e)) - 1.$$

The planner's FOC with respect to ι_B can then be written:

$$\begin{aligned}
0 =& u(c_0)\frac{\partial e}{\partial \iota_B}\left(2p(e)p'(e) - \kappa'(e)\right) + \chi u'(c_0)\left(p(e)^2 - \kappa(e)\right) \\
&+ 2u(c_1)\frac{\partial e}{\partial \iota_B}\left(\kappa'(e) + (1-2p(e))p'(e)\right) + 2\chi u'(c_1)\left(\kappa(e) - p(e)^2 + p(e)\right) \\
&+ u(c_2)\frac{\partial e}{\partial \iota_B}\left(2(p(e)-1)p'(e) - \kappa'(e)\right) + (\chi+1)u'(c_2)\left((p(e)-1)^2 - \kappa(e)\right) - \frac{\partial e}{\partial \iota_B}\psi'(e).
\end{aligned}$$

After applying the envelope theorem from the farmer's FOC the planner's FOC becomes:

$$\begin{aligned}
0 =& \chi p(e)^2 u'(c_0) - \chi\kappa(e)u'(c_0) - 2\chi p(e)^2 u'(c_1) + 2\chi p(e)u'(c_1) + 2\chi\kappa(e)u'(c_1) \\
&+ \chi p(e)^2 u'(c_2) - 2\chi p(e)u'(c_2) + p(e)^2 u'(c_2) - 2p(e)u'(c_2) - \chi\kappa(e)u'(c_2) \\
&- \kappa(e)u'(c_2) + \chi u'(c_2) + u'(c_2).
\end{aligned}$$

Substituting

$\mathbb{E}[u'] = \left((1-p)^2 - \kappa\right)u'(w - 2l + \iota_B - \tau) + \left(2p(1-p) + \kappa\right)u'(w - l + \iota_1 - \tau) + \left(p^2 - \kappa\right)u'(w - \tau)$

and expanding χ yields

$$\begin{aligned}
0 =& \mathbb{E}[u']\left((2\iota_1 - \iota_B)\frac{\partial e}{\partial \iota_B}\left(2p(e)p'(e) - \kappa'(e)\right) + 2(\iota_B - \iota_1)p'(e)\frac{\partial e}{\partial \iota_B} + \kappa(e) - ((p(e)-2)p(e)) - 1\right) \\
&+ u'(c_2)\left((p(e)-1)^2 - \kappa(e)\right).
\end{aligned}$$

Rearranging this yields the desired expression.

□

C.6 Proof of Proposition 6

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

$$Var(XY) = Var(X)Var(Y) + Var(X)\bar{Y}^2 + Var(Y)\bar(X)^2 \tag{74}$$

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

$$Cov(XY_1, XY_2) = Var(X)\bar{Y}^2 + Cov(Y_1, Y_2)\bar{X}^2 + Cov(Y_1, Y_2)Var(X). \tag{75}$$

Computing we have that

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

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

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

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.7 Proof of Lemma 4.1

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). □