Comparison of Conservation Incentives

under Long-Run Yield Uncertainty and Farmer Risk Aversion

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Abstract

Consumers and policymakers are increasingly concerned with environmental sustainability in food production. Yet farm-level adoption of many conservation practices has stalled. Existing incentives for practice adoption increase farmers' expected net benefits from sustainable practices but do not help producers manage associated risks, which may be critical to risk-averse farmers. Using unique data of cover cropping (CC) in the U.S. Midwest, we show that adopting CC affects both the mean and variance of corn yield. Specifically, we identify a nonlinear effect of CC on the yield of corn: mean yields decrease and variances increase in the first few years following adoption. After this initial period, mean yields converge to those under conventional production, while the variance of yields decreases significantly. Given this relationship, we build a conceptual model to characterize CC adoption decisions of risk-averse farmers under various incentives, including price premiums, lump-sum subsidies, and green insurance. We find rich scale and compositional effects that differ across incentives. We conduct simulations to compare the cost effectiveness of the three incentives and find that offering green insurance generates the greatest incentives for adoption.

Keywords: Corn-soybean production, cover crops, risks, sustainability, vertical coordination.

JEL Codes: D81, Q18, Q56.

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1. Introduction

The desire for economic growth, coupled with the desire for limiting the resulting negative environmental impact, bring growing attention to "sustainable development" (Zilberman, 2014). As consumers and policymakers become increasingly concerned with environmental sustainability, there is pressure on firms in the agricultural supply chain to provide sustainably-produced food products that reduce soil erosion, nutrient runoff, and greenhouse gas emissions from food production (Grunert 2011; Cecchini, et al. 2019).

The primary means of attaining sustainability in food production has been through agricultural best management practice (BMP) adoption among farmers. In the U.S., federal and state-level programs promote BMP adoption by offering incentives like cost-share subsidies and, in some recent cases, reductions in crop insurance premiums to adopting farmers. Yet progress on BMP adoption has largely stalled. For example, in Indiana—a major corn- and soybean-producing Midwestern state—adoption of cover cropping (CC) has stayed roughly constant at less than 10 percent of crop acreage since 2015.

An extensive literature examines barriers to BMP adoption (see Prokopy et al. 2019 for a review). This literature focuses largely on identifying the social, behavioral, environmental, and economic factors that drive farmers' BMP adoption decisions. However, the specific form that economic incentives take is also important, but less studied. This is because adopting BMPs may have persistent and complex effects on both expected crop yield as well as higher moments of the yield distribution. For example, row crop farmers that adopt CC may experience both a reduction in mean yields and greater yield variance over an extended period of time (Gaudin et al. 2015; Plastina et al. 2018; Anderson, 2020; Thompson et al., 2020).

For risk-averse farmers, the decision of whether to adopt BMPs depends on how adoption affects the entire distribution of farm returns (e.g., Liu 2015; Oliva et al. 2020). Current incentives offered by state and federal conservation programs—like cost-shares for BMP adoption—may improve mean farm profits without influencing variance of the profit distribution, likely limiting adoption among risk-averse producers. Other features of these programs (e.g., limits on the duration of participation or the acreage the farmer is permitted to enroll) may also discourage adoption, although these barriers are not our focus here.

Our study sheds new light on the effectiveness and efficiency of various incentives in promoting BMP adoption by constructing theoretical and numerical models of farmer decisions under yield uncertainty over a relatively long period of time. Our theoretical model is dynamic and accounts for heterogeneity in farmers' risk preferences and time horizons. The latter is assumed to be correlated with land tenure status, which is thought to affect conservation adoption decisions (Bosch et al. 1995; Khanna 2001; Caswell et al. 2001; Lichtenberg 2004). Considering different decision horizons distinguishes our model from prior models of risk-averse farmers that are static (e.g., Yu et al. 2018) or assumes an infinite horizon common to all farmers (e.g., Carey and Zilberman 2002).

We use the theoretical model to compare the economic performance of three incentives for promoting BMPs: (i) price premiums paid for crop outputs produced using a BMP; (ii) cost-share subsidies; and (iii) green insurance, which compensates conservationist farmers for losses following BMP adoption that would not occur in the absence of the practice (Mitchell 1999). We focus on the example of CC, which is considered an important BMP for attaining water quality goals (e.g., ISDA 2018) and figure prominently in many recent government and private-sector agricultural sustainability initiatives. We calibrate our model using a unique dataset of experimental corn and soybean plots growing CC that spans up to 15 years and six Midwestern U.S. states.

Our numerical results suggest conservation indemnities and cost shares induce larger scale of adoption on the landscape than price premiums. This is because indemnities and cost shares increase mean farmer returns and either decrease or leave unchanged the variance of farmer returns. In contrast, price premiums increase both mean and variance of returns, limiting adoption among risk-averse farmers. We also find that distinct compositional effects arise under different instruments; relatively more risk-averse farmers are more likely to adopt CC under indemnities, whereas less risk-averse farmers are more likely to adopt under cost-shares and premiums. This is important as risk aversion is often correlated with other farmer economic and demographic characteristics that are important to policymakers.

Our paper is organized as follows. In Sections 2 and 3, we introduce a novel and extensive dataset of experimental corn yields under different numbers of years growing CC—which we refer to as "CC years"—and estimate corn production functions with and without CC. This motivates our interest in using CC as a case study for our analysis and provides novel insight into the effect of CC adoption on yield distributions. The use of panel experimental yield data over a long span of time ensures a clear identification of treatment effects. It is also of particular descriptive value as existing work typically simulates the effects of CC adoption (e.g., Thompson et al. 2020) or estimates the effect of CC adoption using relatively short-term datasets. Inspired by the new empirical findings, we develop a two-period model in Section 4 to characterize effects on BMP adoption under different incentives. In Section 5, we calibrate the theoretical model using our empirical estimates of corn production functions with and without CC and government statistics. Simulation outcomes show substantial differences across the three incentives in the effectiveness and cost efficiency.

2. Data

We obtained a panel yield dataset as part of a meta-data set collected by a team of researchers at Purdue University. The data consists of 430 pairs of observations from 28 experiment sites located in six states across the Mississippi River Basin in the U.S. Midwest over the period 2001–2018. The six states include Illinois, Indiana, Iowa, Minnesota, Missouri, and Wisconsin. Corn is grown on all the plots.

Each pair of fields are identical in location, soil type, slope, weather conditions, and nutrient application, except that the treated field grows a cereal rye CC and the control field does not. Plots with no CC are referred to as "conventional" plots, and neighboring plots growing CC are, somewhat obviously, "CC" plots. CC plots have continuously grown CC over different numbers of years. Figure 1 shows the distribution of observations by CC years.

[Figure 1 approximately here]

The dataset records yield of each plot in a given year. Table 1 displays summary statistics of the yield. The unit of measurement is metric ton per hectare (MT/ha) and, for corn, one metric ton equals 39.37 bushels. We also collect information on factors that may affect the yield based on prior literature, including data on weather conditions and soil quality (e.g., Schlenker and Roberts 2009). Variables measuring weather conditions include total precipitation (in inches) over the period May through July of the corresponding year—which corresponds to the typical corn growing season—along with monthly average temperature over the same period (in degrees F). Variables measuring soil quality are CC biomass (in MT/ha), the amount of nitrogen applied (in kilograms/ha), and the field slope (in degrees of angle). Applied nitrogen could have been in the form of ammonium sulfate or liquid manure in addition to anhydrous ammonia. Nitrogen was added at a replacement rate to both the control and treatment plots.

[Table 1 approximately here]

3. Empirical Corn Production Functions Following Cover Crop Adoption

Heterogeneity in CC years allows us to trace the trajectory of yield distributions over time and is critical to our econometric specification and modeling. We first use an ordinary least squares (OLS) model to demonstrate basic patterns in the yield distribution over time following CC adoption. We then use maximum likelihood estimation (MLE) to simultaneously estimate CC effects on the mean and variance of yield over time.

3.1 Ordinary-Least-Squares Yield Estimates

We first regress the yield of both conventional (indexed by c) and CC (indexed by s) plots on the weather and soil quality variables as well as CC years (where applicable) and state fixed effects. For simplicity, we assume that yields are independent across plots and time conditional on the control variables. We specify yield of plot-year i as

$$(1) \qquad y_i^j = f\left(\mathbf{X}_i^j; \boldsymbol{\beta}^j\right) + \epsilon_i^j, j \in \{c, s\}$$

where $\mathbf{X}_i^j$ is a column vector of control variables (including a constant, CC years, other year-specific controls, and state fixed effects) for plot-year i and ϵ_i is a random, homoscedastic error term. The vector $\boldsymbol{\beta}^j$ contains parameters to be estimated.

We assume $f(\cdot)$ is linear for simplicity. Table 2 summarizes our regression results. Columns (1) and (2) indicate that the soil quality variables play insignificant roles at the 95%

confidence level. High temperatures in July reduce crop yields for both conventional and CC plots. Additional precipitation reduces yields for conventional plots but not CC plots, whereas higher May temperatures increase CC yields but not conventional yields. Critically, CC years does not have any significant impact on CC yields.

Because the soil variables do not help explain yield and contain missing observations, we remove them to be able to add 10 percent more observations to the estimation. Column (3) shows the results from re-estimating CC yields. Our parameter estimates are largely robust to this change, except that the average May temperature no longer significantly affects CC yields.

Prior literature suggests that CC years may have a nonlinear effect on CC yields. We explore this by adding squared CC years to our regression model. Column (4) in Table 2 shows that tenure has a significant nonlinear impact on CC yields, suggesting that the mean yield of CC plots increases with CC years at a decreasing rate.

[Table 2 approximately here]

3.2 Maximum Likelihood Yield Estimates

The OLS results in Section 3.1 are silent on the effect of CC years on the variance of yields. We hence study the relationship between yield variance and CC years using MLE. Assume yields take the same form as in (1), but now assume the error terms ϵ_i^j are heteroskedastic. Formally, let $\epsilon_i^j \sim N(0, g_i^j)$ where $g_i^j = g(\mathbf{Z}_i^j; \boldsymbol{\alpha}^j)$, with $\mathbf{Z}_i^j$ being a vector of control variables, including a constant, that influence yield variance. The likelihood contribution from plot-year *i* is then

$$(2) \qquad L_i^j = \phi\left(\left[y_i^j - f(\mathbf{X}_i^j; \boldsymbol{\beta}^j)\right] / \sqrt{g(\mathbf{Z}_i^j; \boldsymbol{\alpha}^j)}\right),$$

where $\phi(\cdot)$ is the standard normal density.

Because most of our observations are from plots with one or two years of CC, the functional form of $f(\cdot)$ and $g(\cdot)$ need to be relatively simple to identify heterogeneity due to CC years. Inspired by the nonlinear relationship between yield and CC years revealed by the OLS estimates in Table 2, we impose a kinked functional form on $f(\cdot)$ and $g(\cdot)$. Formally, we divide the range of CC years from our dataset into three segments, $[0, \dots, \tau_1, \dots, \tau_2, \dots, \tau_3]$ where τ_3 is 15. We specify two indicator variables, $d_{iT}^{j}, = 1\left(X_i^{years,j} \in (\tau_T, \tau_3]\right), T = 1,2$, where $X_i^{years,j}$ is the CC years for plot-year *i*. Note that $X_i^{years,c} = 0\ \forall i$, and hence $d_{iT}^{c} = 0\ \forall T$. Given that every pair of plots differ only in whether CC is grown, we specify $f(\cdot)$ and $g(\cdot)$ simply as

$$(3) \qquad f\left(\mathbf{X}_i^j, \boldsymbol{\beta}^j\right) = \beta_0^j + \beta_1^j d_{i1}^j + \beta_2^j d_{i2}^j \quad \text{and} \quad g\left(\mathbf{Z}_i^j, \boldsymbol{\alpha}^j\right) = \alpha_0^j + \alpha_1^j d_{i1}^j + \alpha_2^j d_{i2}^j.$$

We searched over all possible combinations of indicators, using Akaike's and Bayesian Information Criteria to determine which indicators fit our data the best. The information criteria reach the lowest levels with $\tau_1 = 3$ and $\tau_2 = 7$, cutting the range into three segments of years 1 to 3, 4 to 7, and 8 to 15.

Columns (1) and (2) in Table 3 report the MLE parameters for the conventional plots, while columns (3) and (4) report MLE parameters for CC plots. Comparing columns (1) and (3), we see that CC reduces mean corn yields relative to conventional production in the first three years. From CC year 4 to 7, however, CC yields increase to ~116 percent of conventional yields. CC Yields further increase after year 7, though the increment is small. Recall also that there are very few observations after CC year 7, and hence this result should be viewed with caution. Comparing columns (2) and (4), we see that the yield variance follows the opposite trajectory over time. Indeed, variance is the same for both crops over the first three years following CC adoption. From CC year 4 to 7, the variance CC yields is about 17% smaller than that for conventional yields. From CC year 8 to 15, the variance of CC yields continues to decrease and becomes 43% smaller than the variance of conventional yields. These findings are robust to alternative specifications of the model (see Appendix 2).

As a robustness check, and to account for possible within-year correlations between conventional and CC yields, we also estimate a model in which we replace y_i^j in equation (2) with $\Delta y_i = y_i^c - y_i^s$, i.e., we estimate the mean and variance of the *difference* in paired conventional and CC plots. Our model estimates align with those reported in columns (1)–(4). In column (5) of Table 3, the positive and significant constant term suggests that the yield of CC plots is significantly lower than the yield of conventional plots in the first three years. The coefficient estimated for d_{i1}^c is positive and significantly larger than the constant, meaning that the yield of CC plots becomes significantly higher than the yield of conventional plots after growing CC for more than three years. After the seventh year of CC, though, the increase in the mean yield becomes insignificant. Again, changes in CC years 8 to 15 need to be interpreted with caution due to a relatively small number of observations. After CC year 3, the variance of the difference in yield also decreases significantly compared with the level in the first three years.

Put together, cover cropping generates yield losses on average, along with no reduction in variance over the first three years of growing CC. In the medium term, there is a small yield gain on average and a small reduction in yield volatility. In the longer term, the mean yield gain may be insignificant, but the reduction in yield volatility is significant and large. Cover cropping improves the yield distribution of farmers only after a few years, reflecting the fact that considerable time is need to restore organic matter and enhance soil quality.

[Table 3 approximately here]

4. A Theoretical Model of BMP Adoption

Our econometric results suggest that adopting CC will change the mean and variance of farmer net returns over time. Effective incentives for adoption must account for these changes. We now explore the relative performance of different incentives on the scale and composition of CC adoption using theoretical and numerical models informed by the relationships uncovered in Section 3.

We consider a two-period model. A population of risk-averse farmers grow crop outputs, which are sold to downstream retailers/processors (RP). There are two types of farmer that are distinguished by their land tenure status. A proportion ρ are "renter" farmer, indexed by superscript *r*, and face a positive probability of their lease not being renewed at the end of period 1. In general, this probability may depend on farm profit or other factors. If the lease is not renewed, we assume for simplicity that the farmer costlessly transitions to another lease. In contrast, a share $(1-\rho)$ are "owner-operator" farmers, indexed by superscript *o*, and have secure land tenure. We assume farmers of each type are homogeneous except for their risk preferences, as described later. Each type of farmer independently maximizes the present value of their utility by choosing whether to produce "conventionally" or to produce "sustainably" by adopting CC. We assume sustainable production has a higher marginal cost than conventional production, but sustainable farmers do not have to invest in any supporting asset (e.g., new farm machinery).

It is common knowledge that gains from CC come mainly from soil enhancement, but these gains arise only over time following the relationships uncovered in Section 3. Specifically, we assume that the mean yield from sustainable production is lower than the mean yield under conventional production in the first period after adoption, and the variance of yield is weakly greater. In the second period of CC, the mean yield increases and the variance of yield falls relative to conventional production.

Let the subscript $t \in \{1,2\}$ indicate the period and the superscripts s and c refer to sustainable and conventional farming, respectively. We express the mean conventional yield in any period as $\mu^c = \int_{\underline{y}^c}^{\bar{y}^c} y h^c(y) dy$, where $h^c(y)$ is the density of conventional yields with support $\left[\underline{y}^c, \bar{y}^c\right]$. The mean sustainable yield in period t is $\mu_t^s = \int_{\underline{y}_t^s}^{\bar{y}_t^s} y h_t^s(y) dy$, defined similarly. We assume $\mu_2^s \geq \mu^c > \mu_1^s$. Likewise, the variance of conventional yield is $\sigma^c = \int_{\underline{y}^c}^{\bar{y}^c} (y - \mu^c)^2 h^c(y) dy$ and the variance of sustainable yield in period t is $\sigma_t^s = \int_{\underline{y}_t^s}^{\bar{y}_t^s} (y - \mu_t^s)^2 h_t^s(y) dy$, with $\sigma_1^s \geq \sigma^c > \sigma_2^s$.

Assume that the utility function of a farm depends on the mean and variance of farmer profits, $\pi^m, m = \{r, o\}$, following Meyer (1987). Risk aversion is reflected by the disutility due to increasing variance of profits. We will define this utility function formally for each case below. The level of the farmer's risk aversion is captured by a random parameter, $\kappa \geq 0$, with a larger κ implying greater risk aversion. The risk parameter is different among farmers and follows distribution $G(\kappa)$.

4.1 Adoption without Incentives

Assume that the marginal cost of conventional production, w^c, is constant. In the absence of any incentive for adopting CC, both conventional and sustainable crops receive the competitive price, p. Profits for conventional production depend fully on the revenue received, because the costs are fixed at w^c with the land size normalized to 1 for each farmer.

We simplify matters by assuming the probability the renter farmer's lease is not renewed is equal to unity such that the farmer is effectively myopic and hence maximizes the flow utility earned each period. Utility earned by a renter farm that does not adopt CC is $u^{c,r,*} = p\mu^c - w^c - \kappa p^2 \sigma^c$. For a renter farm to continue farming, $u^{c,r,*} \geq \bar{u}$, where $\bar{u}$ is the farmer's reservation utility level.

An increment in the marginal costs of farming, w^s, occurs when growing CC. Given this extra cost and our assumptions about the distribution of yields under CC and the renter's land tenure status, no renter farmer will adopt CC because of a fall in mean yields and an increase in yield variance in period 1.

For an owner farm, the present value of utility without CC is $u^{c,o,*} = \sum_{t=1}^{2} \delta^{t-1} u^{c,r,*}$. If adopting CC, the present value of utility becomes:

(8) $$u^{s,o,*} = \sum_{t=1}^{2} \delta^{t-1} [p\mu_t^s - (w^c + w^s) - \kappa p^2 \sigma_t^s].$$

where $\delta \in (0,1)$ is the time discount factor. The owner farm adopts CC if $u^{s,o,*} \geq u^{c,o,*}$. We refer to the "critical value" of κ as the value that makes the farmer indifferent between adopting CC or not. The critical value of κ for owners is

(9) $$\hat{\kappa}^{o,*} = \frac{\sum_t \delta^{t-1} [p_t(\mu_t^s - \mu^c) - w^s]}{\sum_t \delta^{t-1} p^2 (\sigma_t^s - \sigma^c)} = \frac{\Delta E(\pi^{o,*})}{\Delta V(\pi^{o,*})},$$

where $\Delta E(\pi^{o,*})$ and $\Delta V(\pi^{o,*})$ are the change in the mean and variance of the present value of profits, respectively, following adoption. The share of owners that adopt is $\Omega^{o,*}$, equal to

$$\begin{cases} 1 & \text{if } \Delta E(\pi^{o,*}) \geq 0,\ \Delta V(\pi^{o,*}) \leq 0 \\ G(\hat{\kappa}^{o,*}) & \text{if } \Delta E(\pi^{o,*}) > 0,\ \Delta V(\pi^{o,*}) > 0 \\ [1 - G(\hat{\kappa}^{o,*})] & \text{if } \Delta E(\pi^{o,*}) < 0,\ \Delta V(\pi^{o,*}) < 0 \\ 0 & \text{otherwise.} \end{cases}$$

Intuitively, if adopting increases the present value of mean profits and decreases the present value of variance (the first condition above), then all owners will adopt. If adopting increases the present value of the mean *and* variance of profits (the second condition above), then only those farmers with sufficiently low risk aversion (i.e., where $\kappa < \hat{\kappa}^{o,*}$) will adopt, even without extra incentives offered by the downstream RP. If adopting *decreases* both the present value of the mean and variance of profits (the third condition), then only farmers with sufficiently high risk aversion will adopt; the gain in utility from reduced variance will outweigh the losses in utility from lower mean returns. Finally, if the present value of mean profits decrease and the present value of profit variance increases, then no owners will adopt.

With a total of n farms in the sector, the total area of CC adopted in each period is

(10) $$a^* = (1 - \rho)\Omega^{o,*}n,$$

which is constant across periods because (i) none of those who choose conventional production in period 1 will have incentives to switch to sustainable production in period 2 (since the expected utility from doing so is initially less than that for conventional production) and (ii) none of those who chose sustainable production in period 1 will switch back to conventional production in period 2 (since the mean of yields is greater under continued sustainable production, and the variance is less).

4.2 Price Premium

Next, consider the farmers' decisions in the presence of a price premium, ν, paid to sustainable farmers. We assume this premium is the same for renters and owners, although our insights would not change qualitatively if this were not the case. Given the effect of CC on famers' profit distributions, a premium would only be needed during the first period after adoption. This premium increases the effective price of sustainable output to $p + \nu$.

Our assumptions about land tenure mean that the renter will continue to act myopically (and will do so for the rest of the scenarios we consider below). However, there may be renter farmers who adopt sustainable production given the higher effective price. The utility for a renter farm who adopts CC under the price premium in any period is

$$u^{s,r,prem} = (p + \nu)\mu_1^s - w^c - w^s - \kappa(p + \nu)^2\sigma_1^s.$$

The premium increases the mean yield, while also increasing its variance. Utility for a renter farmer who does not adopt is $u^{c,r,*}$ from above. The farm adopts CC if $u^{s,r,prem} \geq u^{c,r,*}$. The critical value of κ for renters is

$$\hat{\kappa}^{r,prem} = \frac{(p+\nu)\mu_1^s - p\mu^c - w^s}{(p+\nu)^2\sigma_1^s - p^2\sigma^c} = \frac{\Delta E(\pi^{r,prem})}{\Delta V(\pi^{r,prem})}, \qquad (11)$$

where $\Delta E(\cdot)$ and $\Delta V(\cdot)$ are defined similarly as before and the share of renters that adopt is $\Omega^{r,prem} = G(\hat{\kappa}^{r,prem})$. Increasing ν has an ambiguous effect on $\Omega^{r,prem}$. For small values of ν, the share of renters who adopt sustainable practices will likely increase. However, for large values of the premium, the share of renters who adopt sustainable practices may actually decline as the utility loss from increased variance of profits swamps the utility gain from increased mean profits. If the numerator is negative, no renter farm adopts CC regardless of ν. In other words, the price premium is effective for renter farms only if the revenue gains from the price premium outweigh the opportunity costs from foregone yields plus the increment to production costs.

For an owner farmer, the present value of expected utility from adopting CC given the price premium is

$$u^{s,o,prem} = (p+v)\mu_1^s - (w^c + w^s) - \kappa(p+v)^2\sigma_1^s + \delta[p\mu_2^s - (w^c + w^s) - \kappa p^2\sigma_2^s].$$

The farm adopts CC if $u^{s,o,prem} \geq u^{c,o,*}$. The critical value of κ is

(12) $$\hat{\kappa}^{o,prem} = \frac{(p+v)\mu_1^s - p\mu^c - w^s + \delta[p(\mu_2^s - \mu^c) - w^s]}{(p+v)^2\sigma_1^s - p^2\sigma^c + \delta p^2(\sigma_1^s - \sigma^c)} = \frac{\Delta E(\pi^{o,prem})}{\Delta V(\pi^{o,prem})},$$

and the share of owners that adopt is $\Omega^{o,prem}$, equal to

(13) $$\begin{cases} 1 & \text{if } \Delta E(\pi^{o,prem}) \geq 0,\ \Delta V(\pi^{o,prem}) \leq 0 \\ G(\hat{\kappa}^{o,prem}) & \text{if } \Delta E(\pi^{o,prem}) > 0,\ \Delta V(\pi^{o,prem}) > 0 \\ [1 - G(\hat{\kappa}^{o,prem})] & \text{if } \Delta E(\pi^{o,prem}) < 0,\ \Delta V(\pi^{o,prem}) < 0 \\ 0 & \text{otherwise.} \end{cases}$$

As with the renters, comparing (12) with (9) reveals that the price premium has an ambiguous effect on the share of owners who adopt CC; adding a premium increases the mean profits but also the variance of profits. For small premiums, the net effect may be to increase $\hat{\kappa}^{o,prem}$ and, hence, the share of owners who adopt the sustainable practice. However, as the premium gets larger, the utility losses from increased variance may swamp the utility gains from greater mean profits. Note also that the second condition in (13) is more likely to hold as v increases. This implies that the premium is more likely to attract relatively less risk-averse farmers. We explore this in our simulation later.

The total area of CC adopted in each period under the premium is

(14) $$a^{prem} = [(1-\rho)\Omega^{o,prem} + \rho\Omega^{r,prem}]n.$$

4.3 Lump-Sum Subsidies

Next, consider the effect of a lump-sum subsidy per unit of land area, denoted η, paid to sustainable farmers to encourage CC adoption. Again, the subsidies are needed only for the first period of adoption and are the same for renters and owners. The renter farm's utility from conventional production is still $u^{c,r,*}$, defined as before. If the farmer adopts CC, utility is

$$u^{s,r,sub} = p\mu_1^s + \eta - (w^c + w^s) - \kappa p^2 \sigma_1^s$$

As before, renter farmers that adopt CC in period 1 will maintain sustainable production in period 2. Recall that we allow for $\sigma_1^s \geq \sigma^c$. This implies the share of renters who adopt CC will be case-specific. When $\sigma_1^s > \sigma^c$, the proportion of renters who adopt is $\Phi^{r,sub} = G(\hat{\kappa}^{r,sub})$, where

(15) $$\hat{\kappa}^{r,sub} = \frac{p(\mu_1^s - \mu^c) + \eta - w^s}{p^2(\sigma_1^s - \sigma^c)} = \frac{\Delta E(\pi^{r,sub})}{\Delta V(\pi^{r,sub})}.$$

When $\sigma_1^s = \sigma^c$, the proportion is

$$\begin{cases} 0 & \text{if } \Delta E(\pi^{r,sub}) < 0 \\ 1 & \text{otherwise.} \end{cases}$$

Intuitively, all renters will adopt as long as mean profits increase since there is no additional yield risk from adopting CC in this case.

For an owner farmer, the present value of expected utility from adopting CC given the price premium is

$$u^{s,o,sub} = p\mu_1^s + \eta - (w^c + w^s) - \kappa p^2 \sigma_1^s + \delta[p\mu_2^s - (w^c + w^s) - \kappa p^2 \sigma_2^s].$$

The farm adopts CC if $u^{s,o,sub} \geq u^{c,o,*}$. The critical value of κ is

(16) $$\hat{\kappa}^{o,sub} = \frac{\eta + \sum_t \delta^{t-1}[p(\mu_t^s - \mu^c) - w^s]}{\sum_t \delta^{t-1} p^2 [\sigma_t^s - \sigma^c]} = \frac{\Delta E(\pi^{o,sub})}{\Delta V(\pi^{o,sub})},$$

and the share of owners that adopt is $\Omega^{o,sub}$ and equal to

$$(17) \qquad \begin{cases} 1 & \text{if } \Delta E(\pi^{o,sub}) \geq 0,\ \Delta V(\pi^{o,sub}) \leq 0 \\ G(\hat{\kappa}^{o,sub}) & \text{if } \Delta E(\pi^{o,sub}) > 0,\ \Delta V(\pi^{o,sub}) > 0 \\ [1 - G(\hat{\kappa}^{o,sub})] & \text{if } \Delta E(\pi^{o,sub}) < 0,\ \Delta V(\pi^{o,sub}) < 0 \\ 0 & \text{otherwise.} \end{cases}$$

Comparing (15) and (16) with the corresponding conditions under a premium (expressions (11) and (12), respectively) reveals that the lump sum subsidy will induce greater adoption than the premium if $\sigma_1^s > \sigma^c$ and $p\mu_1^s + \eta = (p + v)\mu_1^s$; that is, assuming the increase in mean profits is the same across both instruments, the lump sum subsidy will induce greater adoption since the subsidy does not increase the variance of farmer profits like the premium does. The effect of the subsidy is ambiguous if $\sigma_1^s = \sigma^c$ given the bang-bang nature of the adoption decision in this case.

Furthermore, note that the change in the present value of profit variance is independent of η. Assume this change is negative (which is the case in our numerical example). Given our assumptions about the distribution of y_t^s and the incremental production costs, the change in the mean of profits for small values of η is likely to be negative, too. This implies that the third condition in (17) will hold, and hence the lump sum subsidy will attract relatively risk-averse farmers—i.e., farmers with $\kappa \geq \hat{\kappa}^{o,sub}$. This is intuitive; since subsidies increase the mean of profits without changing the variance, farmers who receive the greatest disutility from risk will adopt CC first under this instrument. These compositional effects contrast with those of the premium, which initially attracts the least risk-averse farmers.

The total area of CC adopted in each period under the subsidies is

$$(18) \qquad a^{sub} = [(1 - \rho)\Omega^{o,sub} + \rho\Omega^{r,sub}]n.$$

4.4 Green Insurance

The final type of incentive we consider is green insurance, through which the RP or another agent may offer to share the risk in the farmers' yield in the first period following CC adoption. For simplicity, we consider a basic form of yield insurance which fully covers the loss in yield under a trigger level, $\gamma \in \left(\underline{y}_1^s, \bar{y}_1^s\right]$ common to both types of farmers. If a farm experiences a yield $y_1^s < \gamma$, it receives compensation from the RP equal to $p(\gamma - y_1^s)$. The means and variances of conventional and period-2 sustainable yields stay the same as before. However, the indemnity changes the mean and variance of yield for the sustainable farm in the first period after adopting CC to

$$\check{\mu}_1^s(\gamma) = \gamma + \int_{\gamma}^{\bar{y}_1^s} (y - \gamma) h_1^s(y) dy$$

and

$$\check{\sigma}_1^s(\gamma) = \int_{\gamma}^{\bar{y}_1^s} (y - \check{\mu}_1^s)^2 h_1^s(y) dy + \int_{\underline{y}_1^s}^{\gamma} (\gamma - \check{\mu}_1^s)^2 h_1^s(y) dy,$$

respectively. Note that for any γ, $\check{\mu}_1^s(\gamma) > \mu_1^s$ and $\check{\sigma}_1^s(\gamma) < \sigma_1^s$.

A sustainable renter farmer's utility under the indemnity is $u^{s,r,ins} = p\check{\mu}_1^s(\gamma) - w^c - w^s - \kappa p^2 \check{\sigma}_1^s(\gamma)$. A conventional renter farmer has utility $u^{c,r,*}$, defined as before. The critical value of the risk aversion parameter in this case is

(19) $$\hat{\kappa}^{r,ins} = \frac{p[\check{\mu}_1^s(\gamma) - \mu^c] - w^s}{p^2[\check{\sigma}_1^s(\gamma) - \sigma^c]} = \frac{\Delta E(\pi^{r,ins})}{\Delta V(\pi^{r,ins})}.$$

The share of renters who adopts is

(20) $$\begin{cases} 1 & \text{if } \Delta E(\pi^{r,ins}) > 0,\ \Delta V(\pi^{r,ins}) < 0 \\ G(\hat{\kappa}^{r,ins}) & \text{if } \Delta E(\pi^{r,ins}) > 0,\ \Delta V(\pi^{r,ins}) > 0 \\ 1 - G(\hat{\kappa}^{r,ins}) & \text{if } \Delta E(\pi^{r,ins}) < 0,\ \Delta V(\pi^{r,ins}) < 0 \\ 0 & \text{otherwise.} \end{cases}$$

The critical value of κ for an owner farmer is $\hat{\kappa}^{o,ins}$, given by (9) after substituting $\check{\mu}_1^s(\gamma)$ and $\check{\sigma}_1^s(\gamma)$ for μ_1^s and σ_1^s, respectively.

Comparing (19) with the analogous conditions for the other two incentives, and holding the change mean profits the same, the green insurance would generate the greatest level of adoption since it reduces profit variance, conditional on adoption. Furthermore, if the change in profit variance from adoption is negative (consistent with our numerical example), then for small values of γ, the third condition in (20) is likely to hold. This implies the green insurance will have similar compositional effects as the lump-sum subsidy.

The total area of CC adopted in each period under green insurance is

$$a^{ins} = \left[(1-\rho)\Omega^{o,ins} + \rho\Omega^{r,ins}\right]n. \tag{18}$$

5. Numerical Model

Our analytical results do not reveal the magnitude of the effect of these different adoption incentives. We hence turn to a numerical example to study these effects. Based on plausible parameter values, we simulate the scale and compositional effects of adoption under each incentive using a numerical model of CC adoption calibrated for corn producers in Indiana. Table 4 shows the parameter values and their sources.

[Table 4 approximately here]

We start by simulating the share of owners and renters that adopt CC under various levels of each incentive. The left panel of Figure 2 shows the effect of a price premium that ranges from \$25 to \$100/MT, or 14-57 percent of the assumed output price. Adoption among both farmer types initially increases rapidly. Among owners, adoption increases from about 20% at a premium of \$25/MT to 60% at \$50/MT. Among renters, adoption increases from about 10% to 45% for over the same range of premiums. Note that adoption among owners is everywhere greater than for renters, reflecting owners' longer time horizon and, hence, their ability to internalize the future gains from adopting CC.

Beyond ~\$50/MT, however, the premium has no additional impact on either type of farmers' adoption incentives; adoption plateaus at ~60% among owners and ~50% for renters. This reflects the increased variance from larger premiums, which begin to swamp the gains to the producer from greater mean profits, as we point out in Section 4.2.

[Figure 2 approximately here]

Figure 3 shows the compositional effects of each incentive. We summarize these compositional effects by plotting the mean of κ among adopting renter and owner farmers at each premium, subsidy, and green insurance coverage level. For a given policy instrument $i \in \{prem, sub, ins\}$, we write the conditional expectation for a type-m farmer as

$$E(\kappa|adopt, m, i) = \begin{cases} \int_{\hat{\kappa}^{m,i}}^{\infty} \kappa \frac{g(\kappa)}{\Omega^{m,i}} d\kappa & \text{if } \Delta E(\pi^{m,i}), \Delta V(\pi^{m,i}) < 0 \\ \int_{0}^{\hat{\kappa}^{m,i}} \kappa \frac{g(\kappa)}{\Omega^{m,i}} d\kappa & \text{otherwise.} \end{cases}$$

Under the premium, the mean value of κ increases with ν for both renter and owner farmers (left panel, Figure 3). This is consistent with our prediction above that the premium attracts the least risk-averse farmers.

Similarly, the middle panels of Figures 2 and 3 show the scale and compositional effects of the lump sum subsidy. In contrast to the premium, a sufficiently large subsidy induces full adoption once the mean profit becomes positive under sustainable production (i.e., at about \$200/ha for each type of farmer). Prior to this point, renters do not adopt; note that the share of renters jumps from 0 to effectively 1 at ~\$200/ha.

The composition of adopting farmers is different under the subsidy, too; the mean value of κ among adopting owners *decreases* with η, in contrast with the premium (see middle panel of Figure 3). This implies the subsidy attracts the most risk-averse owners. Among renters, the mean value of κ jumps from 0 to about 0.006 at η = \$200/ha, which is simply the mean value of κ in the population of farmers. This jump occurs as all renters adopt at this value of the subsidy.

Finally, the right panels of Figures 2 and 3 show the scale and compositional effects of the insurance indemnity. Notably, the indemnity initially attracts the most risk-averse owners *and* renters. As the indemnity increases, more and more farmers adopt CC. Once again, adoption rate of owners always stays above the rate of renters.

[Figure 3 approximately here]

We can assess the cost-effectiveness of each incentive by comparing the scale of adoption holding total expenditures on each incentive fixed. Specifically, we calculate the total expenditure given a premium of roughly 15% of the base output price. We then solve for the subsidies and indemnity levels that result in the same total expenditure. Figure 4 shows the scale of adoption under each incentive given this expenditure, relative to that under no incentive. The indemnity generates nearly double the total adoption under the subsidy and triple the total adoption of the premium given the same expenditure, making it the most cost-effective policy. The indemnity also generates proportionally greater incentives for renters to adopt; CC area is roughly split between renters and owners under an indemnity. This contrasts with the other two instruments, which generate proportionally greater effects for owners.

[Figure 4 approximately here]

6. Discussion and Conclusion

Promoting BMPs, including growing CC, is a major way of enhancing the sustainability of agricultural production. Adopting BMPs can have long-run effects on the distribution of crop yields. We show that the way in which adoption incentives interact with these effects can influence the success of conservation programs, both in terms of the scale of adoption (i.e., how many farmers adopt) and the composition of adopting farmers (i.e., the characteristics of the farmers who adopt). In particular, different incentives may attract relatively risk-averse or risk-neutral farmers to adopt, depending on how the incentive affects the variance in addition to the mean of farmer returns.

Our findings are important because prior work shows that farmer risk preferences may be correlated with other characteristics important to policymakers. For instance, Roe (2015) finds that crop farmers and farmers who are older, female, have lower incomes or live in remote areas are relatively less risk-tolerant. Many of these farmers may also be less likely to adopt conservation practices (Prokopy et al., 2019). Hence, understanding the relationship between incentive type and adoption decisions among heterogeneous farmers is important for optimally designing conservation incentives.

Our results contrast with prior work in some key ways. In one of the only other studies we are aware of that compares the cost-effectiveness of various BMPs, Palm-Forster et al. (2017) use economic experiments with farmers to show that green insurance is less cost-effective than other incentives, including cost-shares, tax credits, and price premiums for sustainable outputs. However, this is due to farmers' perceptions of relatively higher transactions costs under this incentive, which we do not account for. They also find that premiums are not cost-effective, but this is due to the inability to spatially target premium revenues to ecologically-sensitive areas rather than the risk effects we study here.

Our results are timely in that agribusinesses including Truterra, Nutrien, and others are increasingly involved in supporting the adoption of best management practices through the development "vertical coordination" programs. Under these programs, downstream firms provide incentives such as technical assistance and direct payments to upstream firms, especially agricultural producers, to support BMP adoption. In return, the downstream firms track BMP adoption data at the farm level and use it to quantify progress in attaining sustainability goals and capture consumer willingness to pay for sustainably-produced food (Apostolidis and McLeay 2019). So far, existing vertical coordination programs only offer cost-shares or other lump-sum payments along with technical assistance for adoption. To our knowledge, none of these existing programs offer incentives that share risks to farmers that are caused by deviating from the conventional farming practices (à la green insurance). Still, the novelty of these vertical coordination programs suggest there is considerable leeway in how downstream firms managing vertical coordination programs can design conservation incentives, and our results here may inform their decisions in that regard.

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Appendix 1. Plots of Mean Yields

Following column (4) of Table 2, we plot the estimated yield of CC plots and the mean yield of control plots at the mean values of variables in the OLS model. To be specific, we compute the average value of each variable in X, including the precipitation and temperature variables, in equation (3) by state and denote the mean values by $\overline{X_S}$ for state S. Then we rely on the coefficients estimated to find the predicted yield of CC plots for a particular state:

$$\widehat{y_{S,t}^{s}} = \hat{\alpha} + \widehat{\beta_1}t + \widehat{\beta_2}t^2 + \hat{\alpha}_X\overline{X_S} + \hat{\alpha}_S S,$$

where t is the number of years growing CC.

By varying t from 1 to 7 years, we are able to plot the estimated y^s based on OLS outcomes. We limit t in 1 to 7, because we have only a few observations for $t > 7$ in the sample for OLS estimation. We focus on the three states with relatively large numbers of observations: Missouri (158), Indiana (83), and Iowa (32). In Figure A1, we plot a horizontal line indicating the mean yield of control plots in each state ($\overline{y_S^c}$) and a corresponding curve showing the estimated mean yield of CC plots ($\widehat{y_{S,t}^{s}}$).

Though the mean yields of control plots differ quite considerably across states, the relative magnitudes of mean CC yields demonstrate similar patterns over the years of CC. Specifically, compared with the mean yield of control plots in a given state ($\overline{y_S^c}$), $\widehat{y_{S,t}^{s}}$ in the state always starts at the lower level when $t = 1$. As the number of CC years increases, the yield of CC plots gradually catches up and finally surpasses $\overline{y_S^c}$ at the third or the fifth year.

[Figure A1 approximately here]

Appendix 2. Alternative Production Function Estimation

In Section 3.2, we cut the range of CC years into three segments to incorporate the bell-shaped trajectory of yield as captured by the OLS estimates. Alternatively, we estimate the MLE model by searching for one optimal cut in the length of CC years to separate the 15 years into two segments. It turns out that the optimal cut falls at the fourth year (i.e., presented by the indicator d_1), creating two segments of 1-3 year and 4-15 years.

The estimation results are reported in Table A1. Patterns shown in Table 3 stay robust. For example, column (1) suggests that the mean yield of CC plots is lower than the mean of conventional plots in the first three years, but becomes weakly larger in the second segment. Columns (4) and (6) suggest that the variance in yield of CC plots is indifferent from that of conventional plots in the first segment and falls significantly lower in the second segment.

[Table A1 approximately here]

Table 1. Summary Statistics of Variables for Estimation

	Mean	SD	Min	Max	No. obs.
Yield, conventional	9.67	4.47	0.78	18.72	430
Yield, with cover crop	9.10	4.44	0.59	18.85	430
Weather variables					
Precipitation	16.03	5.33	3.92	25.12	316
Average temperature in May	64.02	4.29	52.14	71.44	316
Average temperature in June	72.43	2.59	63.99	74.54	316
Average temperature in July	74.21	2.15	65.96	78.77	316
Soil quality variables					
CC biomass	1.01	0.71	0	4.89	430
Field slope	2.52	1.24	0.5	3.5	292
Nitrogen applied	104.08	97.15	0	295	430
CC tenure	2.92	2.78	1	15	430

Source: Our yield dataset, Web Soil Survey, and Prism Climate Group.
Note: CC stands for cover crop.

Table 2. Estimation Outcomes using the OLS Model

Independent variable	(1) y^c	(2) y^s	(3) y^s	(4) y^s
Weather variables				
Precipitation	-0.10***	-0.02	-0.05	-0.06*
	(0.04)	(0.04)	(0.03)	(0.03)
Avg. temp. May	0.17	0.29***	0.07	0.08*
	(0.10)	(0.10)	(0.05)	(0.05)
Avg. temp. June	0.03	0.01	-0.03	0.12
	(0.18)	(0.18)	(0.13)	(0.14)
Avg. temp. July	-0.29***	-0.35***	-0.35***	-0.45***
	(0.10)	(0.10)	(0.09)	(0.10)
Soil quality variables				
CC biomass	0.15	0.30		
	(0.27)	(0.26)		
Field slope	0.15	0.70*		
	(0.39)	(0.39)		
Nitrogen applied	0.002	-1.03*		
	(0.63)	(0.61)		
CC years		-0.09	-0.03	0.52**
		(0.09)	(0.08)	(0.22)
CC years, squared				-0.04***
				(0.02)
Constant	21.96	19.89	35.75***	30.75***
	(13.40)	(13.38)	(8.95)	(9.06)
State FE	Yes	Yes	Yes	Yes
R^2	0.74	0.78	0.79	0.79
No. observations	292	292	316	316

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard error in the parentheses. Nitrogen is scaled by dividing 100.

Table 3. Estimation Outcomes using the ML Model

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$E(y^c)$	$Var(y^c)$	$E(y^s)$	$Var(y^s)$	$E(\Delta y)$	$Var(\Delta y)$
d_1			2.86***	-0.50*	-1.14***	-2.20***
			(0.55)	(0.21)	(0.18)	(0.21)
d_2			1.34*	-0.79**	0.67***	0.35
			(0.62)	(0.30)	(0.20)	(0.30)
Constant	9.67***	2.99***	8.39***	2.99***	0.75***	1.87***
	(0.22)	(0.07)	(0.24)	(0.08)	(0.14)	(0.08)
χ^2	-		96.92		40.27	
No. obs.			430			

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard error in the parentheses.

Table 4. Numerical Model Parameters and Functions

Parameter/Function	Value	Description	Source
n	2,186,235	Corn area planted, Indiana 2020 (ha)	USDA NASS (2021)
μ^c	9.67	Mean conventional yield	Own estimate
μ_1^s	8.92	Mean sustainable yield—period 1	Own estimate
μ_2^s	10.06	Mean sustainable yield—period 2	Own estimate
σ^c	3	Variance of conventional yields	Own estimate
σ_1^s	3.03	Variance of sustainable yield—period 1	Own estimate
σ_2^s	2.5	Variance of sustainable yield—period 1	Own estimate
δ	0.975	Rate of time preference	Assumption
ρ	0.45	Share of rented farmland	Bigelow et al. (2016)
w^c	1,390.61	Conventional corn production costs ($/ha)	Swanson et al. (2018)
w^s	69.16	Incremental costs of sustainable production	Swanson et al. (2018)
p_1, p_2	175.19	Corn price, Indiana 2020 ($/MT)	USDA NASS (2021)
$G(\kappa) = 1 - e^{-\theta\kappa}$	——	Distribution of risk aversion parameter, κ	Assumption
θ	154.49	Risk aversion distribution parameter	Own calculation

Table A1. Estimation Outcomes using the ML Model with Two Segments

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$E(y^c)$	$Var(y^c)$	$E(y^s)$	$Var(y^s)$	$E(\Delta y)$	$Var(\Delta y)$
d_1			3.44***	-0.72***	-0.85***	-1.91***
			(0.41)	(0.17)	(0.17)	(0.17)
Constant	9.67***	2.99***	8.39***	2.99***	0.75***	1.87***
	(0.22)	(0.07)	(0.24)	(0.08)	(0.14)	(0.08)
χ^2	-		70.48		24.42	
No. obs.			430			

Note: *** p<0.001, ** p<0.01, * p<0.05. Standard error in the parentheses.

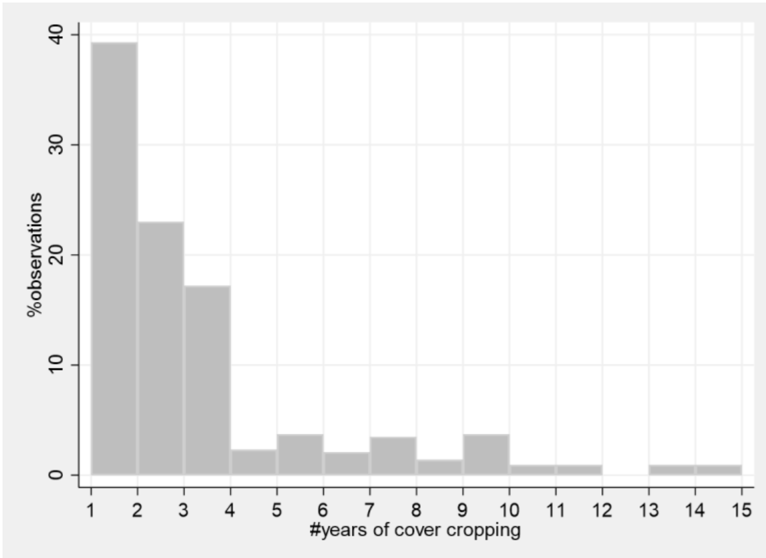


Figure 1. Distribution of Cover Cropping Years in the Sample

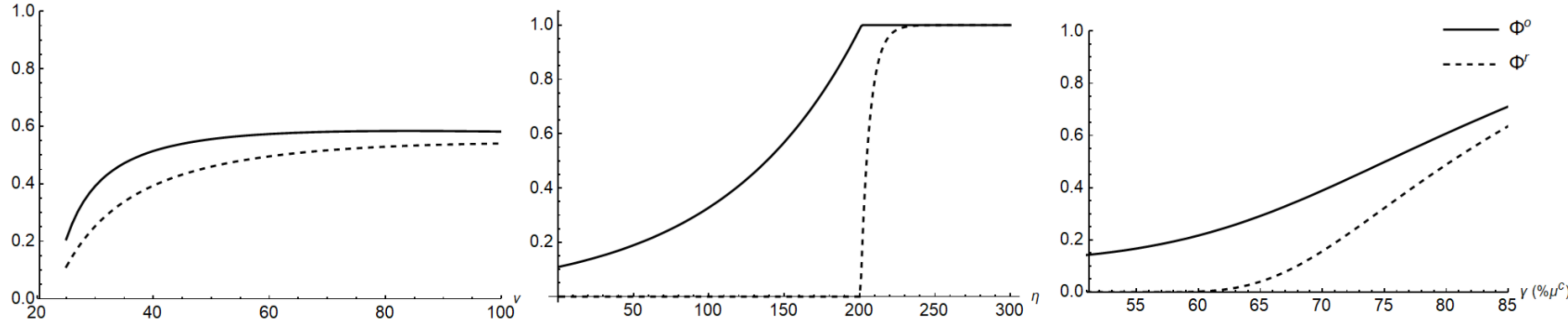


Figure 2. Share of owners (solid line) and renters (dotted line) adopting under different levels of the price premium (in $/MT; left panel), subsidy (in $/ha; middle panel), and yield insurance coverage (trigger level as a percentage of mean conventional yield; right panel).

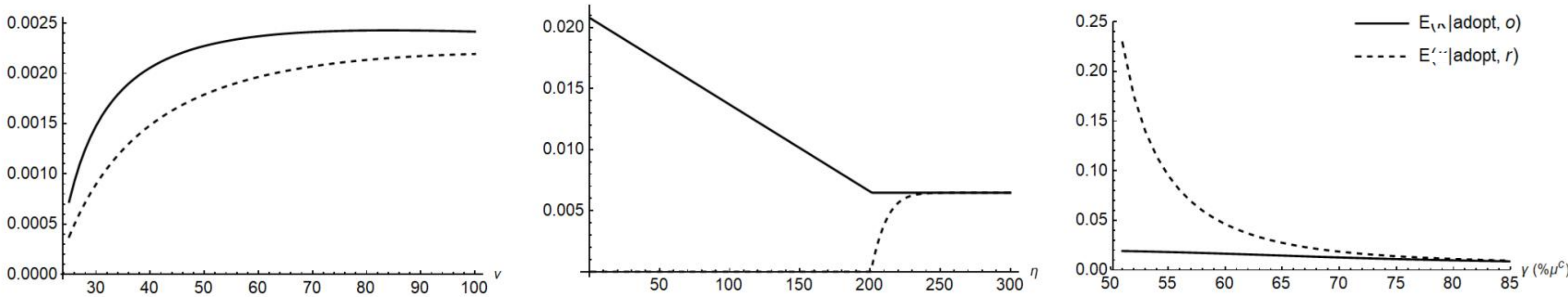


Figure 3. Mean Level of Risk Aversion (κ) among adopting owners (solid line) and renters (dotted line) under different levels of the price premium (in $/MT; left panel), subsidy (in $/ha; middle panel), and yield insurance coverage (trigger level as a percentage of mean conventional yield; right panel).

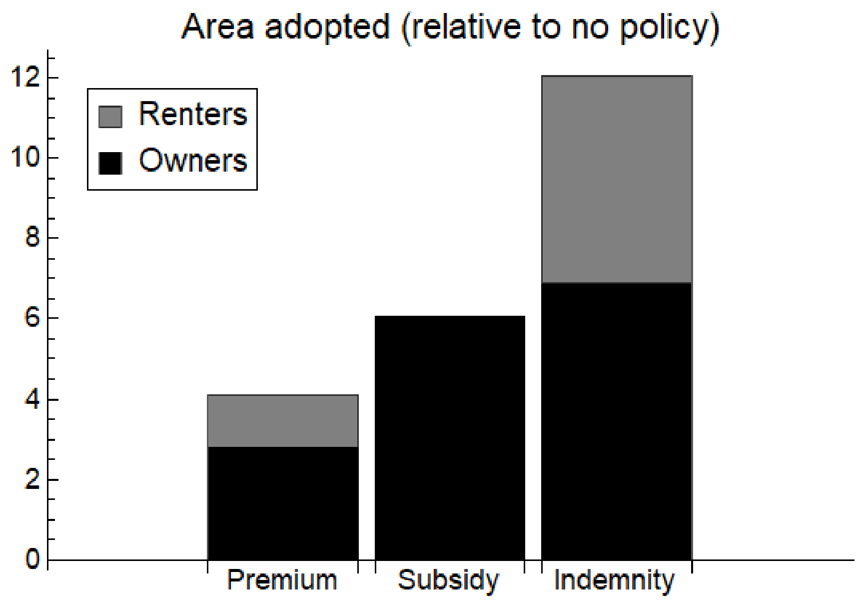
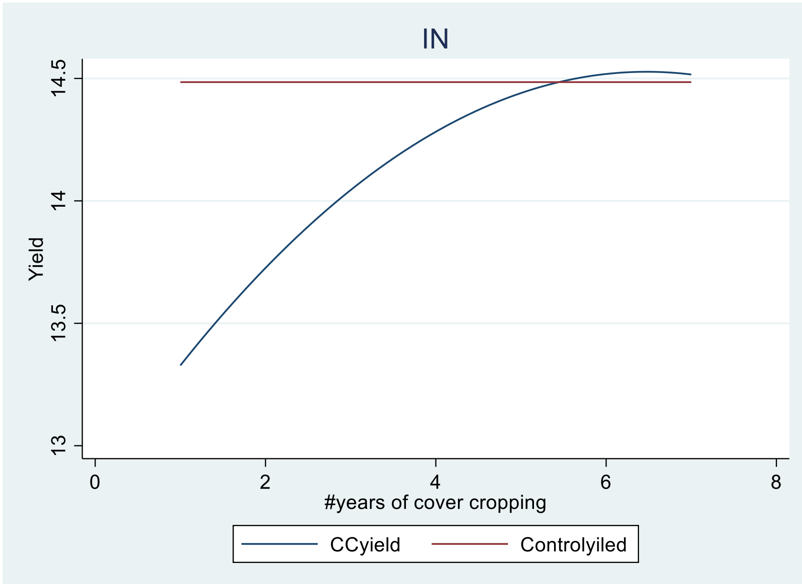
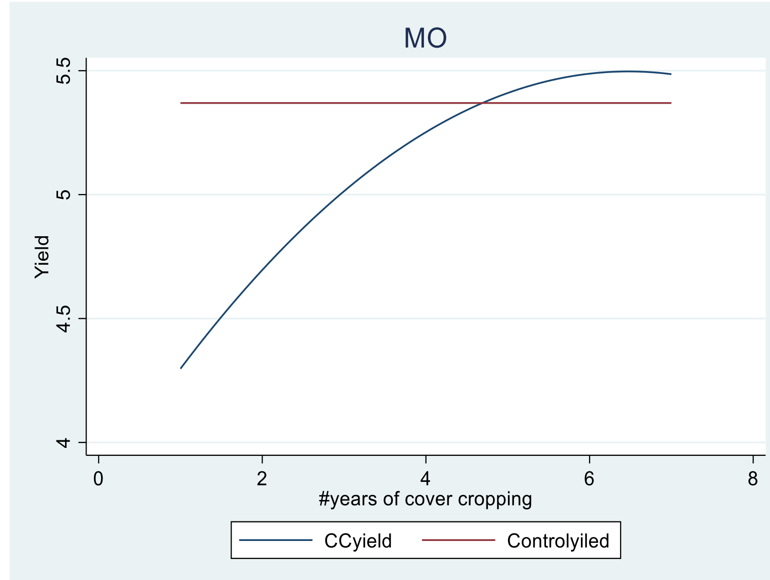


Figure 4. Cover crop area adopted under each instrument as a proportion of the area adopted in the absence of any policy, holding total policy expenditures constant.





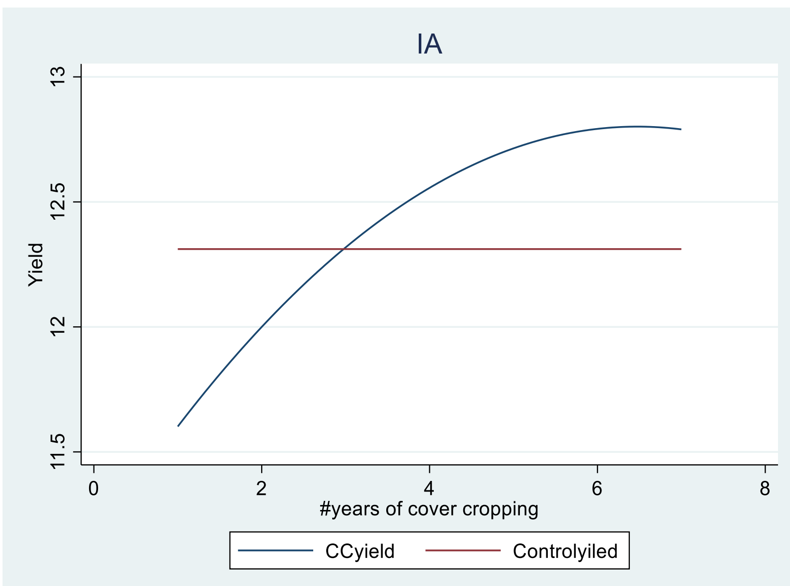


Figure A1. Estimated Yield with Cover Crops and Mean Yield without Cover Crops