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Economic and risk analysis of sustainable practice adoption among U.S. corn growers☆

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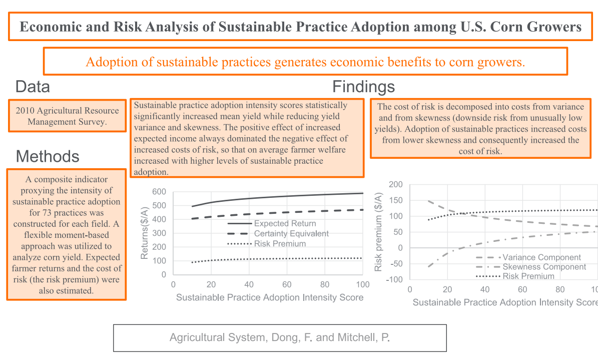
HIGHLIGHTS

- Most programs prioritize environmental benefits over economic aspects when establishing protocols for farms.
- We quantify the effects of sustainable practices on the three moments of U.S. corn yields and economic returns.
- A flexible moment-based approach is used to investigate the effects.
- Cost of risk is decomposed into costs from variance and skewness.
- Results show that sustainable practices boost mean yield, reduce yield variance and skewness, and raise expected returns.
- The study fills literature gap by assessing the economic aspects of sustainability, specifically farm income and risk cost.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Agricultural sustainability has three main pillars: a healthy environment, economic profitability, and social equity. Most programs, however, focus on environmental benefits when establishing protocols for farms, de-emphasizing or ignoring the economic and social aspects. This focus on the environmental aspects of agricultural sustainability misses the importance of economic factors that are commonly found to be key determinants of farmer adoption of best management practices. More research on the economic effects of sustainability practices on farm income and risk would improve understanding and facilitate communication with farmers about the tradeoffs and risks when using the protocols.
OBJECTIVES: Our study has two primary objectives. First, we quantify the effects of sustainable practice adoption on the mean, variance, and skewness of yield for U.S. corn farmers. Second, based on the estimated yield risk model, we quantify the effects of sustainable practice adoption on farmer returns and the cost of risk to better understand the impacts of sustainability on farmer welfare.
METHODS: Using the 2010 Agricultural Resource Management Survey, we construct a composite indicator proxying the intensity of sustainable practice adoption for 73 practices mostly intended to reduce soil erosion

☆ The findings and conclusions in this paper are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

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and improve nutrient and pest management. We use this indicator in a flexible moment-based approach to analyze field-level corn yield data. Estimation results are used to quantify expected farmer returns and the cost of risk (the risk premium). The cost of risk is decomposed into costs from variance (symmetric variation around the mean) and from skewness (downside risk from unusually low yields).
RESULTS AND CONCLUSIONS: Results indicate that substantial opportunities exist for US corn growers to increase sustainable practice adoption. Increased sustainable practice adoption significantly increased mean yield and decreased yield variance and skewness. In addition, increased adoption of sustainable practices increased expected farmer returns and, in most cases, also increased the cost of risk mostly from increased costs from lower skewness (greater downside risk). The positive effect of increased expected income always dominated the negative effect of increased costs of risk, so that on average farmer welfare increased with higher levels of sustainable practice adoption.
SIGNIFICANCE: Our study helps fill a literature gap by evaluating the economic aspects of sustainability, specifically farm income and the cost of risk. The results provide critical information for policy making and program establishing.

1. Introduction

Agricultural sustainability is among the grand challenges of our time – how to grow adequate amounts of healthy food while mitigating the negative effects of agriculture on soil, water, biodiversity, and climate in an equitable and just manner (Jordan et al., 2020). The multidimensional and highly uncertain nature of agricultural sustainability, combined with the involvement of many stakeholders who do not share a common assessment of the problems or solutions, create a complex, "wicked problem" to address (Levin et al., 2012; Iannetta et al., 2021). As a result, practical progress towards achieving even some of the many goals of agricultural sustainability has been slow and geographically varied, despite its urgency (Chaudary et al., 2018; FAO, 2020; Movilla-Pateiro et al., 2021). The emergence of climate smart agriculture and resilience in farming add to the complexity. These concepts build on and refine agricultural sustainability to address climate change and various stressors (Lipper et al., 2014; Bullock et al., 2017) and assessments and protocols to achieve these goals at least partially align with sustainability (van Wijk et al., 2020; Meuwissen et al., 2019).

Agricultural sustainability has three main objectives: a healthy environment, economic profitability, and social equity (Purvis et al., 2019). Farmers play a central role in agricultural sustainability, but all stakeholders along food supply chains have roles (Chioleau and Dourian, 2021; Wu and Huang, 2018). Though consumers around the world do not fully understand sustainability (Sánchez-Bravo et al., 2021), many still show a willingness to pay premiums for sustainably produced foods (Yue et al., 2020; Li and Kallas, 2021). Nevertheless, sustainable eco-labels continue to face several challenges and most do not generate price premiums for producers (Iraldo et al., 2020). Regardless, most multinational companies operating in food supply chains have goals to sustainably source their priority ingredients, including those from farms, and so multiple agricultural sustainability programs exist (Ambekar et al., 2019; Strube et al., 2021; Arulnathan et al., 2020).

Though agricultural sustainability has three pillars, most programs focus on environmental benefits when establishing protocols for farms, de-emphasizing or ignoring the economic and social aspects (Janker and Mann, 2020; Arulnathan et al., 2020). For example, Field to Market's FieldPrint® Calculator, the largest and most established program in the United States, generates metrics on biodiversity, energy use, greenhouse gas emissions, irrigation water use, land use, soil carbon, soil conservation and water quality (Field to Market, 2022; Strube et al., 2021). Similarly, the Cool Farm® Tool with >22,000 registered users has metrics for greenhouse gas emissions, water use, and biodiversity (Cool Farm Alliance, 2022; Kayatz et al., 2018). Neither has metrics for any of the economic or social aspects of sustainability.

This focus on the environmental aspects of agricultural sustainability misses the importance of economic and social factors that are commonly found to be key determinants of farmer adoption of best management practices (Ruzzante et al., 2021; Liu et al., 2018; Baumgart-Getz et al., 2012). Key economic factors include practice cost, adoption subsidies, farm financial capacity, and changes in income risk, while key social factors include connection to local farmer networks, access to information, and farmer environmental attitudes (Ruzzante et al., 2021; Liu et al., 2018; Baumgart-Getz et al., 2012). Arulnathan et al. (2020) note the poor balance across the three sustainability pillars in their review of nineteen protocols and they call for more holistic approaches that, among other things, communicate the tradeoffs and risks for farmers when using the protocols. More research on the economic effects of sustainability practices on farm income and risk would improve understanding and facilitate such communication.

The multidimensional nature of agricultural sustainability also creates measurement and analysis problems. To adequately quantify sustainability, sustainability metrics commonly report multiple indicators and/or use an index approach (Arulnathan et al., 2020). However, including many variables in regression analysis contributes to overfitting, correlation among regression variables often exists that biases estimated standard errors, and with many interrelated variables, results can be difficult to interpret. In addition, depending on the regressors and predicted variables, the analysis will likely need to control for endogeneity (Ruzzante et al., 2021). Addressing these analytical issues often requires key assumptions for empirical tractability.

Our study has two primary objectives. First, we quantify the effects of sustainable practice adoption on the mean, variance, and skewness of yield for U.S. corn farmers using data from the Agricultural Resource Management Survey conducted by the U.S. Department of Agriculture. Yield risk is a key contributor of income risk for crop farmers and farmers are typically averse to risk, especially to downside risk, and so managing production risk is an important factor in their decisions (Iyer et al., 2020). We use a flexible moment-based approach to estimate a stochastic production function, with special attention on the effects of farm-specific conditions. To account for the multidimensional nature of sustainability, we use the composite index of Dong et al. (2015a) as a measure of adoption intensity for farmer use of 73 production practices identified as contributing to sustainability. Because endogeneity between this adoption intensity measure and yield was indicated, we use Lewbel (2012) method to create instrumental variables.

Second, based on the estimated yield risk model, we quantify the effects of sustainable practice adoption on farmer returns and the cost of risk to better understand the impacts of sustainability on farmer welfare. We follow Di Falco and Chavas (2006) approach to decompose the farmer's risk premium into variance and skewness components. Results show that increasing the intensity of sustainable practice adoption increases mean returns for farms and in most cases also the cost of risk. The mean increasing effect empirically dominates the risk increasing effect, so that on average, farmer welfare increases with increased sustainable practice adoption. Results also show the importance of including skewness to capture the downside risk of unexpectedly low yields and returns. If the risk analysis only included yield variance, results show that increasing the intensity of sustainable practice adoption decreases the cost of risk to farms, opposite of the effect we find when yield skewness is also included.

The economic importance of corn in the U.S. makes it a suitable target for empirical analysis. Corn is the most valuable crop grown by U. S. farmers. In 2021, U.S. farmers planted 37.8 million hectares of corn, producing 384 million metric tons of corn grain with a farmgate value of more than $90 billion, or >40% of the value of all U.S. crops produced in 2021 (USDA-NASS, 2022; USDA-OCE., 2022). The U.S. is also the world's largest corn producer, annually producing almost one-third of all corn globally, and the world's leading corn exporter (USDA-OCE., 2022). Given the predominate place of corn in U.S. crop production and its global importance, corn will be a key part of any successful agricultural sustainability program.

2. Conceptual framework

2.1. Moment representation of the production function

Consider a farmer who uses a vector of inputs $\boldsymbol{x}$ to produce a scalar output Q by adopting sustainable practices at the level S. The production technology is represented by $Q = Q(\boldsymbol{x}, S, \boldsymbol{e})$, where $\boldsymbol{e}$ denotes uncontrollable random factors unknown to the farmer such as weather, pests, and diseases. Since the random term $\boldsymbol{e}$ representing production uncertainty affects output, the production function is stochastic. The behavior of a farmer under production uncertainty can be defined in terms of the moments of the probability distribution of output if the range of the output is finite (Antle, 1983). In other words, a stochastic technology can be represented by a general parameterization of the moment functions. Let the stochastic output Q have a cumulative distribution $F(Q)$ and a probability density function of $f(Q)$, where the farmer knows and accurately assesses the form of $F(\bullet)$. The first and the i^{th} central moments of output Q can be represented, respectively, as

$$m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1) = \int Q dF(Q) = \int Q f(Q) dQ = \mathrm{E}[Q(\boldsymbol{x}, S, \boldsymbol{e})] \tag{1}$$

$$m_i(\boldsymbol{x}, S, \boldsymbol{\beta}_i) = \int (Q - m_1)^i dF(Q) = \int (Q - m_1)^i f(Q) dQ = \mathrm{E}\left[\{Q(\boldsymbol{x}, S, \boldsymbol{e}) - m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1)\}^i\right], \text{for } i \geq 2 \tag{2}$$

Here m_1 (the first moment) is the mean, m_i is the i^{th} central moment of output, and $\boldsymbol{\beta}_i$ is a vector of parameters in the moment functions.

Given that the variance (m_2) is a function of both inputs $\boldsymbol{x}$ and the sustainable practice adoption level S, the stochastic production function may exhibit heteroscedasticity. The sustainable practice adoption level S is variance increasing, variance neutral, or variance decreasing as $\frac{\partial m_2}{\partial S}$ is greater than, equal to or less than zero, respectively. A risk averse farmer finds a higher level of sustainable practice adoption undesirable if it creates greater output risk, i.e., if $\frac{\partial m_2}{\partial S} > 0$. As discussed by Scott and Horvath (1980), the mean and the variance cannot completely determine a distribution of returns if the distribution is asymmetric; the third and perhaps higher moments must be considered.

The third central moment (m_3) is the skewness and measures the asymmetry of the distribution around its mean. A negative skewness implies a distribution skewed to the left, and so a lower skewness implies greater exposure to downside risk. A risk averse farmer prefers a higher probability of a return greater than the expected value compared to one with a higher probability of a return less than the expected value (Scott and Horvath, 1980). As a result, a risk averse farmer prefers a positive skewness to no skewness and also to negative skewness in the distribution of returns and finds a higher sustainable practice adoption level undesirable if it increases downside risk exposure, i.e., $\frac{\partial m_3}{\partial S} < 0$. The sustainable practice adoption level S is skewness increasing, skewness neutral, or skewness decreasing as $\frac{\partial m_3}{\partial S}$ is greater than, equal to or less than zero, respectively.

The models in Eqs. (1) and (2) have the advantage of being flexible, as there are no restrictions within moments or across moments. If the moment functions in eq. (1) and (2) take the parametric form $m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1)$ and $m_i(\boldsymbol{x}, S, \boldsymbol{\beta}_i)$, respectively, where $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_\text{i}$ are each a vector of the parameter to be estimated, then with an additive error, $Q(\boldsymbol{x}, S, \boldsymbol{e}) = m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1) + \varepsilon_1$, and based on eqs. (1) and (2) we have:

$$\varepsilon_1 = Q(\boldsymbol{x}, S, \boldsymbol{e}) - m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1) \tag{3}$$

$$(\varepsilon_1)^i = m_i(\boldsymbol{x}, S, \boldsymbol{\beta}_i) + \varepsilon_i, i \geq 2 \tag{4}$$

Here, $\mathrm{E}[\varepsilon_j] = 0$ and $\mathrm{E}[\varepsilon_j \varepsilon_{j'}] = 0$ ($j = 1, 2, \ldots, n$ and $\neq j'$). Empirically, if $\boldsymbol{\beta}_1^*$ is a consistent estimator of $\boldsymbol{\beta}_1$ from a sample of observed outputs, then $\varepsilon_1^* = Q(\boldsymbol{x}, S, \boldsymbol{e}) - m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1^*)$ is a consistent estimator of $\varepsilon_1 = Q(\boldsymbol{x}, S, \boldsymbol{e}) - m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1)$, suggesting that $(\varepsilon_1^*)^i = m_i(\boldsymbol{x}, S, \boldsymbol{\beta}_i^*) + \varepsilon_i, i \geq 2$. As the first three moments can adequately approximate a distribution for many applications (Kendall and Stuart, 1977), this empirical approach has been used in several analyses (e.g., Day, 1965; Anderson et al., 1980; Di Falco and Chavas, 2009). Hence, we follow this empirical approach and specify the mean, variance, and skewness of output according to eqs. (3) and (4) as follows:

$$Q = m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1) + \varepsilon_1 \tag{5}$$

$$(\varepsilon_1)^2 = m_2(\boldsymbol{x}, S, \boldsymbol{\beta}_2) + \varepsilon_2 \tag{6}$$

$$(\varepsilon_1)^3 = m_3(\boldsymbol{x}, S, \boldsymbol{\beta}_3) + \varepsilon_3 \tag{7}$$

These equations provide an empirical framework to investigate the distribution of output with a flexible representation of the impact of the level of sustainable practice adoption.

2.2. Evaluating the cost of risk

Let a farmer's net income be $\pi = pQ(\boldsymbol{x}, S, \boldsymbol{e}) - \boldsymbol{wx}$, where p is the output price and $\boldsymbol{w}$ is a vector of input prices. Let $U(\pi)$ be the utility function that represents farmer preferences and ignore all other income sources and wealth. While the output price p is typically not known until output is sold, to help make the analysis tractable, assume that the only uncertainty in income comes from the production uncertainty $\boldsymbol{e}$. The farmer's objective is to maximize the expected utility of this income by choosing $\boldsymbol{x}$ and S:

$$\max_{x,S} \mathrm{E}[U(\pi)] = \int \mathrm{U}(pQ(\boldsymbol{x}, S, \boldsymbol{e}) - \boldsymbol{wx}) dF(Q) \tag{8}$$

Following Pratt (1964), the risk premium R measures the cost of risk, implicitly defined by $\mathrm{E}[U(\pi)] = U(\pi_1 - R)$, where π_1 is the mean of the farmer's income. The risk premium is a monetary measure of a farmer's willingness to pay to eliminate risk exposure by replacing the random net return π by its mean π_1. Thus, R is positive if the decision maker is risk averse, zero if the decision maker is risk neutral, and negative if the decision maker is risk seeking.

Following Di Falco and Chavas (2006), the risk premium R can be approximated by

$$R = R_2 + R_3 = \frac{1}{2} r_2 \pi_2 + \frac{1}{6} r_3 \pi_3 \tag{9}$$

where π_i $(i \geq 2)$ indicates the i^{th} moment of income, $r_2 = -\left(\frac{\partial^2 U/\partial \pi^2}{\partial U/\partial \pi}\right)$ is the Arrow-Pratt coefficient of absolute risk aversion, and $r_3 = -\left(\frac{\partial^3 U/\partial \pi^3}{\partial U/\partial \pi}\right)$ is the downside risk aversion parameter, both evaluated at the mean π_1. Eq. (9) decomposes the risk premium into two parts: R_2 which reflects the effect of the variance π_2, and R_3 reflecting the effect of the skewness π_3. Under risk aversion (when $r_2 > 0$), an increase in the variance of net returns tends to increase the risk premium, implying higher cost of risk bearing for farmers. Under downside risk aversion (when $r_3 < 0$), an increase in skewness, which decreases downside risk exposure, would reduce the risk premium, implying a lower cost of risk bearing. Finally, assuming a positive marginal utility in income ($\frac{\partial U}{\partial \pi} > 0$), the certainty equivalent (CE) is expected income minus the risk premium and a monetary measure of farmer welfare: $CE = \text{E}[\pi] - R = \pi_1 - R$. Under risk aversion, higher risk exposure presented as higher variance and lower skewness reduces the certainty equivalent and makes the decision maker worse off.

To evaluate the risk premium for empirical analysis, we assume constant relative risk aversion utility, a common form of risk preferences for farmers (Di Falco and Chavas, 2006):

$$U(\pi) = \begin{cases} \dfrac{\pi^{1-\theta} - 1}{1-\theta} & \text{for } \theta \geq 0 \text{ and } \theta \neq 1 \\ ln(\pi) & \text{for } \theta = 1 \end{cases} \tag{10}$$

where θ measures the degree of relative risk aversion. Consequently, $r_2 = \frac{\theta}{\pi_1}$ and $r_3 = -\frac{\theta(\theta+1)}{\pi_1^2}$ when both are evaluated at the mean π_1, so that the risk premium becomes

$$R = R_2 + R_3 = \frac{\theta}{2\pi_1}\pi_2 + \frac{-\theta(\theta+1)}{6\pi_1^2}\pi_3 \tag{11}$$

Chavas and Holt (1996) estimate that the relative risk aversion coefficients for U.S. corn-soybean growers range between 5.1 and 7.2, while Bontems and Thomas (2000) estimate the coefficient for U.S. crop farmers to be 3.7. Based on these empirical results, we use $\theta = 4$ for the base case to represent the level of risk aversion of U.S. corn growers, and then vary the value for sensitivity analysis.

2.3. Farm sustainability measurement

Two issues arise when using information on farmer practice adoption to measure sustainability for empirical analysis. First, the multidimensional nature of sustainability implies that farmer adoption information is needed for many practices to adequately capture sustainability, but including too many variables leads to overfitting when using regression. Second, because farmers often adopt related practices together, measures of individual practice adoption tend to be highly correlated, creating multicollinearity among the variables used for regression analysis. To address these problems, we use the approach developed by Dong et al. (2015a) to generate a composite index that measures the intensity of sustainable practice adoption for each farm.

The practice adoption data for a single farm contains numerous variables (our analysis has 73 practices) that are highly correlated and often discrete (e.g., binary “Yes” or “No”). The Dong et al. (2015a) method begins with polychoric principal component analysis (PCA) with a non-negativity constraint on individual elements of the principal vectors, which transforms the categorical and correlated variables describing sustainable practice adoption into a smaller number of non-negative, uncorrelated continuous principal components. Next, the Dong et al. (2015a) method uses common-weight data envelopment analysis (DEA) on these principal components to generate a single composite indicator for each farm. DEA requires continuous and nonnegative variables and correlated, high dimensional data reduce the discrimination power of the DEA and introduces bias (Dyson et al., 2001), hence the need for polychoric, non-negative PCA to pre-process the adoption data. Also, common-weight DEA finds the set of common weights for all farms, instead of choosing farm-specific weights, and so has higher discriminating power than basic DEA. The outcome is a weight for each practice, which depends on the PCA weights for all practices and the DEA weights for all principal components. Furthermore, a composite index score is calculated for each farm by multiplying the weight of each practice by the farm's adoption of that practice, and then summing over all practices. The resulting composite index is a number ranging from 0 to 100 used as the measure of the sustainable practice adoption level S in the yield moment equations, with higher values indicating a high adoption intensity.

Endogeneity (or co-determination) also likely arises when using this measure S for practice adoption intensity as a regression variable to estimate yield moments because factors that remain unobserved by the analyst likely simultaneously affect both yield and the adoption intensity score. As a result, we test for endogeneity using the Sargan-Hansen test, evaluating several potential instruments as reported in the estimation section. We also use Lewbel (2012) method to supplement the instruments to improve the estimation efficiency and robustness when external instruments are weak or unavailable.

3. Data

The data used in this study are constructed from the USDA's 2010 Agricultural Resource Management Survey (ARMS) Phase II Corn Production Practices and Cost Reports, covering a cross-section of U.S. corn operations, the survey collected information on production practices, input costs, resource use, and financial conditions of farms in 19 states (USDA ERS, 2022). As conventional and organic production are significantly different in the utilization of production practices, we only use data from conventional corn growers. Keeping only observations without missing values gave a total of 1787 farms in the final data set.

To construct the sustainable practice adoption intensity indicator S, we used farmer responses to 73 questions in the ARMS data, selected as sustainable practices based on corn production guides and promoted by extension faculty and industry professionals (e.g., Laboski and Peters, 2012; Cullen et al., 2014). Practices were related to reducing soil erosion, improving nutrient, pest, and water management, and protection of beneficial organisms (see Appendix A for the complete list). Thus, though the ARMS was not specifically designed to collect data on sustainable practice adoption, and so the practices available in the survey are not exhaustive, the 73 practices used for this analysis provide good coverage of many key areas in agricultural sustainability. Available practices were generally consistent with sustainable agricultural practices defined in the 1977 Farm Bill (National Agricultural Research, Extension, and Teaching Policy Act of 1977 (7 U.S.C.3103(19)) 1977) and reaffirmed in the 1990 Farm Bill (Food, Agriculture, Conservation, and Trade Act of 1990, Public Law 101–624). Selected practices enhance environmental quality and the natural resource base, make efficient use of nonrenewable and on-farm resources, and integrate natural biological cycles and controls into crop production. For example, increased farmer use of soil testing and improved timing of nitrogen application has helped to increase average nitrogen fertilizer efficiency by 36% for corn in the past two decades (Cassman et al., 2002; Frink et al., 1999). Planting cover crops and reducing tillage not only reduces soil erosion, slows the spread of weeds, and maintains soil moisture, but also increases nutrient-use efficiency by reducing nitrogen leaching and volatilization and erosional losses of nutrients (Tilman et al., 2002; Wegner et al., 2018; Kim et al., 2020). Crop rotations improve pest control and increase nutrient-use efficiency (Tilman et al., 2002; Baligar et al., 2001; Dias et al., 2015). Almost all responses available in the ARMS for sustainable practice adoption are indicator variables equal to 1 if the farmer adopted the practice and 0 if not (see Appendix A).

Corn yield is the dependent variable in Eq. (5), $Q = m_1(\boldsymbol{x}, S, \boldsymbol{\beta}_1) + \varepsilon_1$. The covariate vector $\boldsymbol{x}$ includes the nitrogen application rate (*Nitrogen rate*, kg/ha), seed application rate (*Seeding rate*, seeds per ha), and if manure was applied (*Manure use*, equal to 1 if yes and 0 otherwise). In addition, an indicator variable (*Planted Late*) equal to 1 if the planting date fell in the last 15th-percentile of the state (and 0 otherwise) was included to indicate a shorter than typical growing season for corn. A county-level soil quality variable *County Soil Quality* based on the Land Capability Classes (LCCs) was included to proxy field soil quality. Land is classified into eight LCCs (I to VIII) based on soil characteristics and land properties (e.g., soil texture, soil depth, soil permeability, water-holding capacity, and slope) by the USDA Natural Resources Conservation Service (NRCS) (Klingebiel and Montgomery, 1961). Only LCCs I-IV are suitable for crop production, with class I indicating more productive land needing fewer management practices to maintain its productivity and class IV indicating low productivity land needing more management practices to remain productive (Wiebe, 2003; Oluwatosin et al., 2006). We use total hectares in a county in LCC's I and II divided by the total hectares in a county in LCCs I to IV to approximate the probability of a field having good soil quality. LCC acreage data were obtained from the National Resource Inventory database collected by USDA NRCS. Two additional variables related to the land characteristics of the field are included as they may directly affect crop yield – whether the land had been classified as "highly erodible" by the NRCS and whether it contains a wetland. Classification as highly erodible implies that the land has the potential to experience erosion at an excessive rate due to its specific soil properties.

To capture regional differences, indicator variables were constructed based on which Farm Resource Regions the farm was in (USDA-ERS, 2000). These regions are defined based on farm, soil, and climate characteristics rather than state boundaries. The eight regions in the data set were Heartland, Northern Crescent, Northern Great Plains, Prairie Gateway, Eastern Uplands, Southern Seaboard, Fruitful Rim, and Basin and Range. Since there were only three field observations in the Basin and Range region, they were combined with observations in the Prairie Gateway region, for a total of seven regions.

The ARMS data set also contains corn price (dollars per bushel) and input costs. Farmer net returns were calculated as the difference between revenue (yield multiplied by price) and variable cost based on the input information in the ARMS data. We include two major inputs (nitrogen and seed) in the variable costs. By normalizing the price of corn to 1, the variance and skewness of π are the same as the corresponding variance and skewness of yield $Q(\boldsymbol{x}, S, \boldsymbol{e}, \boldsymbol{\beta}_1)$ (Kim et al., 2020).

ARMS has a complex survey design including stratification, clustering, dual frames, and unequal probability sampling (National Research Council, 2007). To account for the survey design, we utilize the survey weights provided by USDA NASS to expand the sample to represent the population and generate population estimates in the statistical analysis. With the survey weights applied to the sample observations, the weighted sample represents approximately 1,427,716 corn fields totaling 29.83 million hectares in the United States.

4. Estimation of moment functions

The specification of the mean function in Eq. (5) plays a crucial role as its error term ε_1 is utilized to estimate the parameters of the higher moments in Eqs. (6) and (7). To determine the most suitable model, we conducted tests on both linear and nonlinear functional forms. For the nonlinear model, we opted for the linear-log form, which uses untransformed yield with covariates expressed in logarithms (Di Falco and Chavas, 2009).[1] Akaike's information criterion was 12,253.69 and 12,154.12 for the linear and the linear-log forms, respectively, and the respective Bayesian information criterion was 12,340.34 and 12,240.69. Based on these values, we selected the linear-log model for the yield function.

In crop production, endogeneity arises when factors known to farmers but unknown to econometricians simultaneously affect input use rates, practice adoption, and output. More specifically, information feedback can occur because information that becomes available in earlier stages may affect the input and practice adoption decisions in later stages. For example, farmers may adjust the frequency of field scouting after wet weather delays an herbicide application or they may change the split nitrogen fertilizer application rate based on early season rainfall amounts. These feedback effects would become part of the error term in the production function, and as a result, in our analysis crop input use and adoption of sustainable practices are potentially endogenous (co-determined) with corn yield.

The heteroskedastic robust endogeneity test uses the difference between the Sargan-Hansen statistics of two equations with potentially endogenous variables treated as endogenous and exogenous, respectively. The test was conducted on the sustainable practice adoption intensity and production inputs (nitrogen and seeds) in the yield equation. Effective instrumental variables are those that have a casual effect on the endogenous variables, affect the outcome variable only through the endogenous variables, and have no confounding effects on the outcome variable. One potential instrumental variable for the sustainable practice adoption level is land ownership. Previous studies have identified a significant impact of land ownership on the adoption of sustainable practices, but the findings remain mixed. Some studies have revealed positive effects (Parker et al., 2007; Haghjou et al., 2014; and Turinawe et al., 2015), while others have found negative effects (e.g., Reimer et al., 2013; Varble et al., 2016). We do not assume positive or negative effects of sustainable practices adoption on crop yield, but include the variable and examine its effects. Also, we assume land ownership does not directly affect crop yield, but only indirectly does so through adopted practices. In addition, the prices for nitrogen and seed are included as instrumental variables for inputs, given that individual farmers are always considered as price takers in the market.

To deal with potentially weak instruments, we adopt Lewbel (2012) method to supplement the instruments to improve the estimation efficiency and robustness. Lewbel's method uses a heteroscedastic covariance to generate instrumental variables when external instruments are weak or unavailable. We apply the two-step generalized method of moments (GMM) to generate efficient continuously updated estimates of the coefficients and consistent heteroscedasticity-robust estimates of the standard errors (Baum et al., 2010; Baum and Schaffer, 2012). The heteroskedastic robust endogeneity test rejects the null hypothesis that the sustainable practice adoption intensity and input uses of nitrogen can be treated as exogeneous, with $\chi^2(1)$ values of 4.043 (p-value $=$ 0.044) and 3.903 (p-value $=$ 0.048), respectively.

5. Results and economic implications

The histogram of the farm sustainable practice adoption intensity scores (S) shows that the adoption of sustainable practices in U.S. corn production shows substantial variation among farmers (Fig. 1). For the

[1] We excluded transformed yield, such as the logarithm of yield, from the model tests since yield and transformed yield could have different distributions. This exclusion is particularly relevant when dealing with a lognormal distribution for yield, as taking the logarithm could lead to a skewness of zero, rendering our analysis of higher moments infeasible. Consequently, using the logarithm of the yield variable does not align with our objective of examining the higher moments of yield.

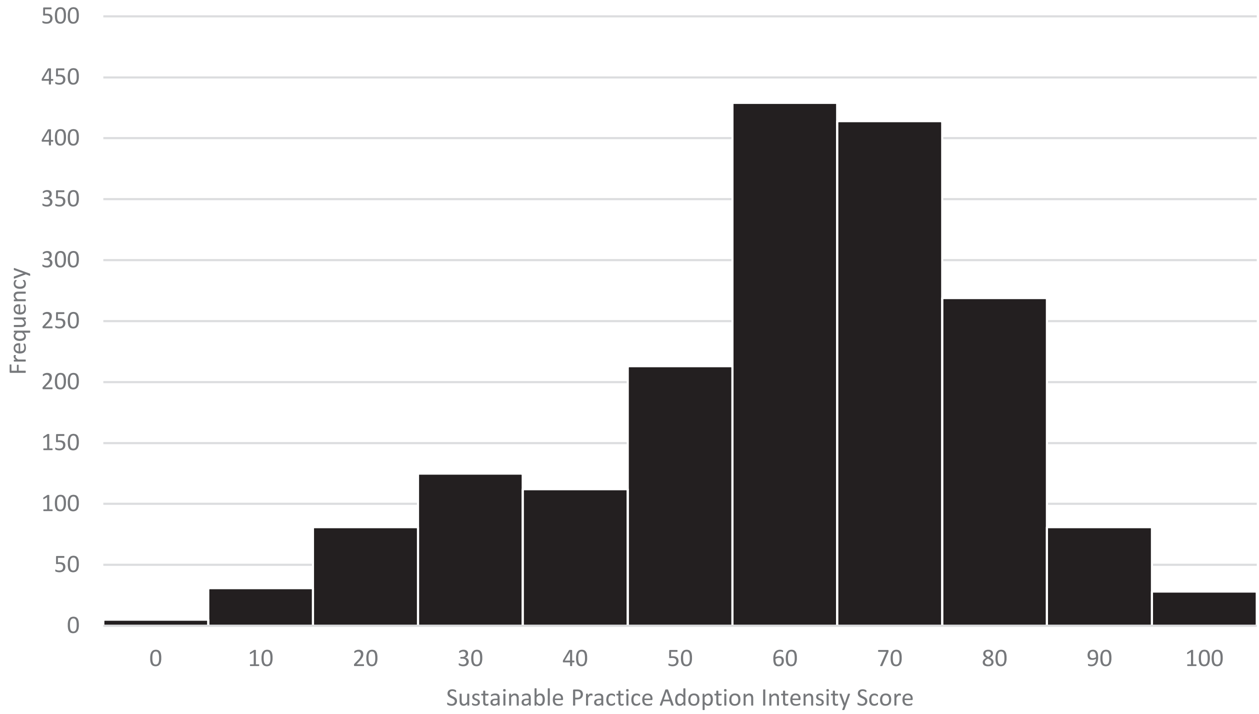

Fig. 1. Histogram of sustainable practice adoption intensity scores for U.S. corn farms.

1787 farms, the average score is 54.2 with a standard deviation of 18.0. While over half of the farms have a score ranging between 50 and 75, many have scores <20 or >90. These results suggest that the sustainability score likely has sufficient variation for use as a regressor. After applying the USDA NASS survey weights to the farm sustainable practice adoption intensity scores to represent the population, the median score for the population is 57.7, the 10th percentile 26.3, and the 90th percentile 74.1.

The method of Dong et al. (2015a) enables calculation of practice weights to assess the specific contributions of each practice to sustainable practice adoption intensity scores. These practice weights are not measures of the environmental, social, or economic importance of the practice, but are derived by the DEA-PCA process to most differentiate farms from one another. As a result, while the practices listed in Appendix A are undeniably crucial for sustainability, those practices commonly used by most farms in the population analyzed exhibit minimal variation, and so receive lower weights as they do not help differentiate farms (Dong et al., 2015a). Practices receiving the most weight are those used by a few farms who not only use these rarely adopted practices, but also use the commonly adopted practices.

For the farms examined here, the ten practices with the highest weights in rank order are:

1. Using a variable rate applicator for lime application on the field.
2. Rotating crops over the past three years specifically to manage pests.
3. Employing floral lures, attractants, repellants, pheromone traps or other biological pest controls on the field.
4. Applying or releasing beneficial organisms (insects, nematodes, fungi) to manage pests.
5. Using no-till or minimum tillage specifically to manage pests.
6. Plowing down crop residue specifically to manage pests.
7. Growing trap crops (excluding fallow) to help manage insects in the field.
8. Planting crops other than corn in the field during the last four years.
9. Applying herbicides before or after weeds emerged based on weed scouting from the previous or current year, rather than following routine treatments.
10. Implementing structures for soil erosion control.

Table 1
First-Stage Estimation Results.

	Nitrogen Equation		Sustainable Practice Adoption Intensity Equation	
	Mean		Variance	
Variable	Estimate	Std. Error	Estimate	Std. Error
Nitrogen Price	−0.376**	0.153	0.228	0.147
Land Ownership	−0.093***	0.029	−0.053**	0.026
Planted late	−0.053	0.040	0.023	0.046
Seeding Rate	0.856***	0.105	−0.016	0.087
Manure use	−0.298***	0.046	−0.086***	0.031
County soil quality	−0.007	0.033	0.040*	0.024
Northern Crescent	−0.322***	0.054	−0.133***	0.038
Northern Great Plains	0.005	0.147	0.085	0.144
Prairie Gateway	0.025	0.071	−0.012	0.049
Eastern Uplands	−0.436***	0.105	−0.215**	0.093
Southern Seaboard	0.036	0.100	−0.001	0.074
Fruitful Rim	−0.197	0.689	−0.071	0.282
Age	−0.048	0.075	−0.019	0.050
College	0.015	0.034	0.095***	0.027
Highly Erodible Land	0.027	0.038	0.094**	0.038
Wetland	0.252	0.199	0.102	0.137
Intercept	1.820***	0.523	4.309***	0.383

Note: *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

The majority of these practices involve use of cultural (non-chemical) methods for pest management and are closely associated with more advanced integrated pest management strategies. The remaining practices involve precision use of lime to improve nutrient use efficiency, lengthening the corn rotation beyond the typical two-year corn-soybean rotation, and installing structures like grassed waterways or terraces to reduce soil erosion. Farms that adopt several of these practices, as well as use most of the common practices, have high sustainable practice adoption intensity scores. Conversely, farms with low scores have limited adoption of these practices and could increase their scores by implementing these more highly-weighted practices.

The first-stage estimation results are reported in Table 1. As anticipated, farms reduced nitrogen application rates in response to higher nitrogen prices and when they applied manure. Regional differences in nitrogen application were also observed. Compared to the Heartland, farms in the Northern Crescent and Eastern Uplands applied less nitrogen. Additionally, our analysis revealed that farmers applied less nitrogen if they owned the crop field.

Consistent with some previous studies (Reimer et al., 2013; Varble et al., 2016), we found lower sustainable practice adoption intensity for fields operated by farmers who owned the land. The negative relationship between land ownership and sustainable practice adoption intensity suggests that land ownership may present unique challenges or disincentives for implementing sustainable practices. Furthermore, in addition to regional differences, we found that farmers with a college degree tended to have higher sustainable practice adoption intensity, implying that higher education levels correlate with a greater awareness and understanding of sustainable agricultural practices, leading to increased adoption. The link between highly erodible fields and increased adoption intensity suggests that farmers with land susceptible to erosion may be more motivated to adopt sustainable practices to mitigate soil loss and preserve long-term productivity.

Efficient and consistent heteroscedasticity-robust estimation results from the two-step GMM for the yield mean, variance, and skewness equations are reported in Table 2. A delete-a-group jackknife method recommended by NASS and National Research Council (Kott, 2001; Dubman, 2000; National Research Council, 2007) using the 30 replicate weights provided in the ARMS data set is used to calculate the standard errors of estimated parameters. As noted by the National Research Council (2007) and MacDonald and Wang. (2011), jackknife procedures are more conservative as they produce larger variance estimators than classical inference procedures. For comparison purposes, we report ordinary least squares (OLS) estimation results in Appendix B, although OLS estimation is biased given the endogeneity issue.

For the yield mean, the coefficient for the sustainable practice adoption intensity score was positive and statistically significant, suggesting that adoption of sustainable practices on average increased mean yield. With the linear-log model, the parameter 9.27 implies that yield would increase by 0.927 bushels (equivalent to 25.23 kg) if the sustainable practice adoption intensity score increased by 10%. For the variance of yield, the coefficient for the sustainable practice adoption intensity score was negative and statistically significant, implying that as the intensity of sustainable practice adoption increased, the variance of corn yield decreased. In other words, increasing the adoption intensity of sustainable practices reduced the variability of corn yield around its mean, promoting more stable yield outcomes. The coefficient for skewness of yield was also negative and statistically significant, indicating that as the adoption intensity increased, the downside risk of corn yield also increased. Thus, in this case, a higher degree of sustainable practice adoption intensity increased the likelihood of experiencing below-average yields, indicating an elevated risk of unfavorable yield outcomes. If our empirical analysis had only used variance to account for risk, we would have concluded that sustainable practice adoption decreased risk, but by also accounting for yield skewness, we find evidence that sustainable practice adoption increased downside yield risk. Including both the variance and skewness provides a more nuanced view of the impacts of sustainable practice adoption on risk, suggesting both positive and negative effects depending on the types of risk examined.

The adoption of sustainable practices often involves a shift away from synthetic inputs, such as fertilizers, pesticides, and herbicide, towards organic or agroecological methods that emphasize natural inputs, integrated pest management, and crop rotation. While these alternative approaches promote ecological balance and minimize environmental impacts, they can introduce greater variability in input availability and effectiveness. This increased variability can lead to a higher probability of crop failure, resulting in increased yield skewness (Snapp et al., 2005; Tillman et al., 2004; Peigné et al., 2007). Furthermore, sustainable practice adoption can make production more sensitive to environmental conditions such as fluctuations in weather patterns and pest pressures. Unlike conventional practices that rely on intensive inputs to mitigate risks, sustainable practices may have less built-in resilience, resulting in higher yield skewness due to their vulnerability to variable environmental factors. Additionally, the adoption of sustainable practice requires famers to employ more intricate management techniques and acquire greater knowledge and skills. During the transition period, farmers may face challenges in effectively implementing these practices, which can contribute to increased yield skewness (Dong, 2022).

The adoption of certain practices has the potential to reduce yield variance and/or increase yield skewness. However, the index of sustainable practice adoption intensity averages across all 73 practices based on the practice weights. Additionally, the regression analysis coefficient estimate represents the average effect of this adoption intensity on yield moments across all farm fields in the dataset. Hence, the

Table 2
Estimation results for yield moment functions.

	Mean		Variance		Skewness	
Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Sustainable practice adoption intensity	9.27*	5.39	−364**	186	−48,100***	15,400
Seeding rate	74.1***	15.5	2930***	710	−16,700*	96,30
Planted late	−20.6***	4.36	206	291	−1700	35,500
Nitrogen rate	6.33	5.93	−297	204	15,200	21,200
Manure use	14.56***	5.24	−87.2	199	−17,800	21,800
County soil quality	12.7***	3.68	−405**	188	−16,800	19,300
Northern Crescent	0.865	5.19	−176	302	−3690	28,900
Northern Great Plains	−9.04*	5.31	−338	303	32,500	35,000
Prairie Gateway	−4.14	6.71	607*	330	12,200	34,700
Eastern Uplands	−2.23	10.8	−17.4	500	19,300	43,300
Southern Seaboard	−62.4***	8.90	1190**	478	71,000	54,800
Fruitful Rim	−25.4***	5.44	−72.2	430	−28,600	52,900
Age	−10.1*	5.73	94.6	425	7820	44,000
College	0.785	4.06	268	231	−19,300	34,400
Wetland	−7.18	14.35	769*	452	39,900	61,600
Highly Erodible Land	−3.73	3.54	−52.3	263	−2880	36,800
Intercept	−116.**	56.2	−6560*	3,45	618,000*	360,000
R^2	0.29		0.05		0.03	

Note: *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

coefficient estimates in Table 2 reflect the combined positive and negative effects on the yield moments from the adoption of these practices in the fields during that specific year. Overall, for these data, as sustainable practice adoption increased, on average, mean yield increased, and both the variance and skewness of yield decreased.

Soil quality was measured with the proportion of cropped land in the county in land capability classes I and II. The coefficient for land quality was positive and significant for the yield mean and negative and significant for the yield variance, and insignificant for the yield skewness. Consistent with expectations, these results suggest that yield for corn grown in areas with high quality soils are on average higher and less variable, with no consistent differences in downside risk.

As expected, planting the crop late had negative effects on the mean yield due to the shorter growing season, but had no significant effect on yield variance and skewness. Higher nitrogen application rates increased mean yield and reduced yield variance and downside risk exposure, although all the effects were not statistically significant. The insignificant effect of nitrogen on yield might be because the nitrogen application rate had already reached the threshold and its yield increasing effect had leveled off (Lu et al., 2019; Wang et al., 2018; Franzluebbers, 2018). The indicator variable for manure use increased mean yield, suggesting that manure use is beneficial on average for corn production, but did not affect yield risk as measured by the variance and skewness of yield.

Significant regional differences existed in corn yield. The Heartland (the primary U.S. corn production region) was the indicator variable not included, so that estimation results are relative to this region. Consistent with expectations, the Northern Great Plains, the Southern Seaboard and Fruitful Rim all had lower average yields than the Heartland. In addition, corn yields in the Prairie Gateway and Southern Seaboard had higher yield variance compared to the Heartland.

As a robustness check, we conducted tests using the linear functional form for the mean. By comparing the results obtained from this alternative specification with our main findings, we verified the consistency of our findings and robustness of our conclusions.

5.1. Economic implications

Figs. 2 and 3 illustrate how sustainable practice adoption affects expected returns and various measures of income risk for a moderately risk-averse farmer. Plots use the estimated yield moment functions and assume that farmer preferences exhibit constant relative risk aversion for a moderately risk averse farmer ($\theta = 4$). Fig. 2 plots expected returns (revenue minus variable costs), the certainty equivalent, and the risk premium over a range of sustainable practice adoption intensity scores (S). Fig. 3 decomposes the risk premium into the variance component (R_2) and the skewness component (R_3) based on Eq. (11) over the same range of sustainable practice adoption intensity scores. The values plotted in Figs. 2 and 3 also depend on the other regression variables, which were held constant for the base case: the field was in Heartland, not planted late, did not apply manure, and used the survey average nitrogen application and seeding rate, with farmer's age, input and output prices set at survey means.

Several key trends are apparent in Fig. 2. Higher sustainable practice adoption increases expected returns, suggesting that on average, increasing the adoption intensity for these sustainable practices increases mean yield and thus expected returns. The risk premium measures the perceived cost of risk to farmers in terms of a reduction in expected returns. In Fig. 2, as the sustainable practice adoption level increases, the risk premium increases, suggesting that on average, increased adoption of these sustainable practices increases the cost of risk to farmers.

Overall, the risk premium reduces the perceived value of corn production by 18% to 20% over the range of the sustainability scores, with the curve becoming less responsive at higher levels of practice adoption. Finally, the certainty equivalent (the sum of expected returns and the risk premium) aggregates the income effect from expected returns and the risk effect from the risk premium to measure farmer welfare as sustainable practice adoption varies. The income-increasing effect of sustainable practice adoption dominates the risk-increasing effect, so that farmer welfare increases with sustainable practice adoption. For example, suppose a farmer adopted some of the previously noted top ten practices that they were not using to increase their average practice adoption score by 20 points (e.g., by reducing tillage specifically to manage pests and growing trap crops to help manage insects). If they were at the survey mean of 54, adding 20 points would move them into the top 10% of farmers in terms of adoption intensity and (with the other regression variables held constant for the base case) average farmer welfare as measured by the certainty equivalent would increase by 2.4%.

Fig. 3 again plots the risk premium (on a different scale), and its decomposition into its variance and skewness (downside risk) components based on Eq. (11). The variance component is larger and slowly decreases as the sustainable practice adoption intensity score increases,

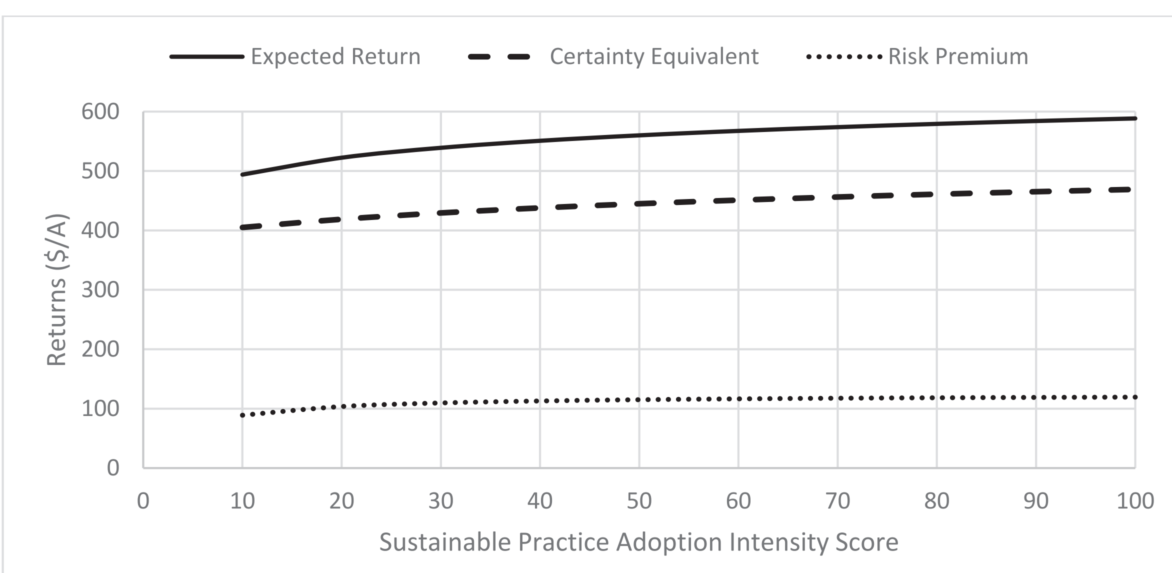

Fig. 2. Expected returns, certainty equivalent and the risk premium over a range of sustainable practice adoption intensity scores with moderate risk aversion.

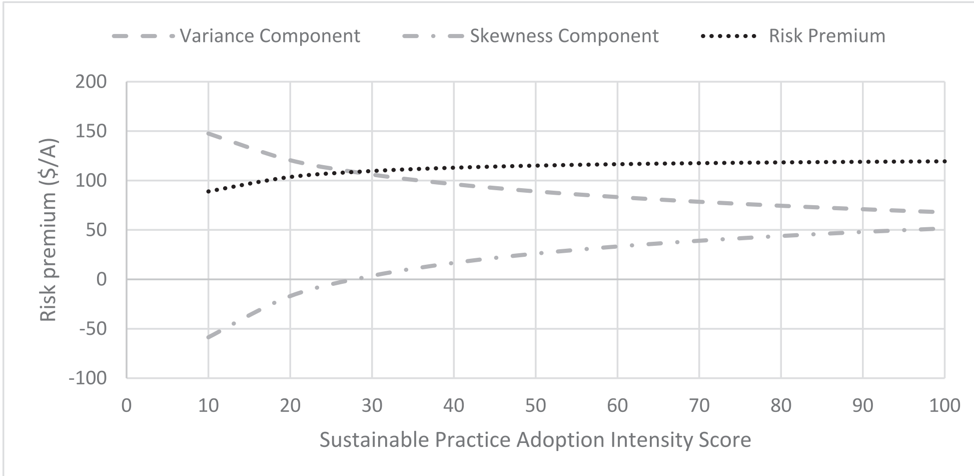

Fig. 3. Risk premium and its decomposition into variance and skewness components over a range of sustainable practice adoption intensity scores with moderate risk aversion.

while the skewness component is smaller and increases with the adoption intensity score. Overall, the increase in the skewness component exceeds the decrease in the variance component, so that the cost of risk as measured by the risk premium increases as the adoption intensity score increases.

These results demonstrate the importance of accounting for downside yield risk in the analysis of the cost of risk from increased sustainable practice adoption, not just the variability of yield. If the analysis had only accounted for the effect of the variance on the cost of risk, it would conclude that increasing sustainable practice adoption would decrease the cost of risk. However, including the effect of both the variance and the skewness provides a more comprehensive characterization of the cost of risk to farmers when increasing their use of sustainable practices. We find that increased adoption of sustainable practices on average increases the cost of risk for farmers because it increases the cost of downside risk more than it decreases the cost of yield variability. Thus, for example, if a farmer increased their sustainable practice adoption score from the survey mean of 54 to 74 to move into the top 10% of farmers, the cost of risk would increase by 1.9% for the base case. However, if the analysis only included the variance effect, this same change would have the opposite effect and decrease the cost of risk by 11.2%.

For sensitivity analysis, we first examine the robustness of these results to the risk aversion parameter θ. As the risk aversion parameter θ increases, expected returns remain unchanged, but intuitively, we would expect the cost of risk (the risk premium) to increase and the certainty equivalent to decrease. This outcome is the case empirically for the results in Table 2 over most parametrizations of the model within the ranges of the observed data. As the risk aversion parameter varies, the risk premium and certainty equivalent curves in Figs. 2 and 3 shift as expected, but the shapes and relationships among the curves remain largely the same. For example, increasing the risk aversion parameter θ from 4 to 6.5 (to change from a relatively moderate to a high level of risk aversion) increases the risk premium from 80% to almost 100% for adoption intensity scores exceeding 50, with the risk premium reducing the perceived value of corn production by 30% to 40%. Also, moving from a score of 54 to 74 increases the risk premium by 6.2%, compared to 1.9% when θ is 4.

As risk aversion increases, the risk premium generally increases as well. However, for the assumed constant relative risk aversion utility function in Eq. (10), the risk premium can become negatively sloped in the risk aversion parameter θ. For the base case and the coefficients in Table 2, this outcome occurs when sustainable practice adoption intensity scores are relatively low in combination with higher than average nitrogen application rates and/or lower than average seeding rates. For example, with a nitrogen application rate of 195 kg/ha and a seeding rate of 11,190 seeds/ha (compared to respective survey averages of 139 kg/ha and 12,430 seeds/ha), and an adoption intensity score of 10, the risk premium begins to decrease as the risk aversion parameter θ increases above 2.7. With an adoption intensity score of 20, the risk premium does not begin to decrease until the risk aversion parameter increases above 6. Nonetheless, the results still suggest that almost all risk averse farmers will find that increased adoption of sustainable practices increases their cost of risk in most cases, primarily due to increased downside risk as illustrated in Figs. 2 and 3.

The remaining sensitivity analysis focuses on how conclusions qualitatively change for assumptions different from the base case. Changes that increase only the cost of production (seed price, nitrogen price, wage rate, labor use) do not change the yield moments, but decrease expected returns, and leave the variance and skewness components unchanged, and so the risk premium increases, and the certainty equivalent decreases. Decreasing the price of corn also leaves the yield moments unchanged and expected returns decrease, but the variance of returns also decrease and the skewness increases (becomes less negative). As a result, both the cost of risk (the risk premium) and the certainty equivalent decrease because the mean effect from the expected returns dominates. However, the overall conclusions illustrated in Figs. 2 and 3 remain unchanged – expect returns and the certainty equivalent both continue to increase as adoption of sustainable practices increases, so farmer welfare is higher with higher adoption, even though the cost of risk (the risk premium) increases.

Changing regression variables from the base case changes the yield moments as indicated in Table 2. However, with regression variables within the ranges of the observed data, the qualitative conclusions evident in Figs. 2 and 3 remain unchanged. As the sustainable practice adoption score increases, the variance component decreases and the skewness component increases, with the skewness component dominating, so that the risk premium increases (Fig. 3). In the meantime, expected returns increase. Even though the cost of risk as measured by the risk premium increases, with the expected returns effect dominating, farmer welfare as measured by the certainty equivalent increases as a farmer adopts more sustainable production practices (Fig. 2).

The only exception arises for the Southern Seaboard due to its coefficients in Table 2. Expected returns and the risk premium increase in sustainable practice adoption as in Fig. 2, but the yield mean is so small and the yield variance so large that expected returns and the risk premium are similar in magnitude. As a result, the certainty equivalent is quite low over a wide range of sustainable practice adoption intensity scores, suggesting that farmers will find little value for these practices. Furthermore, because the cost of risk from the variance component remains high, the certainty equivalent actually decreases as adoption intensity increases (unlike in Fig. 2), implying that farmers would be worse off with higher adoption of sustainable practices. These results suggest more careful examination of specific sustainable practices and their applicability to the Southern Seaboard region before incentivizing widespread adoption.

6. Discussion and conclusion

Using Di Falco and Chavas (2009) moment-based approach, we quantified the effects of sustainable practice adoption on the mean, variance and skewness of yield and farmer returns in US corn production and the cost of risk. To capture the multidimensional nature of agricultural sustainability and still be empirically tractable, we combined Dong et al. (2015a) index of sustainable practice adoption intensity with instrumental variables to control for endogeneity, augmented by Lewbel (2012) method to generate instrumental variables using a heteroscedastic covariance restriction.

Our empirical results indicate several conclusions. First, the analysis of sustainable practice adoption intensity found an average score of 54, much lower than for other analyses. We hypothesize that the average score was lower because the ARMS respondents were a random sample from the corn grower population, not a convenience sample (Dong et al., 2015b) or a sample from the sub-population of larger commercial growers (Dong et al., 2016). We hypothesize that our results are more representative of the actual distribution of sustainable practice adoption among farmers, which suggests substantial opportunities exist for US corn farmers to improve their adoption of sustainable production practices.

Second, we found that the sustainable adoption intensity score significantly increases mean corn yield and thus expected farmer returns, suggesting that increased adoption of such practices is beneficial for corn growers. In terms of risk effects, we found a significant positive effect on the variance of yield and a significant negative effect on the skewness of yield, suggesting that increased use of sustainable production practices decreases variance but increases downside risk for corn growers. These results also indicate the importance of including skewness in analyses of risk. If our analysis had only included the variance of yield, we would have incorrectly concluded that sustainable practice adoption reduced yield risk.

Third, we found that increasing the intensity of sustainable practice adoption increased expected farm income and, in most cases, also increased the cost of risk to farmers. Overall, however, the effect of increased expected income dominated the effect of increased costs from risk, so that on average farmer welfare increased with higher levels of sustainable practice adoption. For a sense of the relative importance of sustainable practice adoption on expected income, the cost of risk, and the welfare of corn growers, with a moderate level of risk aversion typical of most farmers, the cost of risk reduced farmer welfare by 18%–20% over the range of adoption intensity scores. Also, increasing the practice adoption score to move from the survey mean to the top 10% of farmers in terms of adoption intensity increased expected income by 2.3%, the cost of risk by 1.9%, and farmer welfare by 2.3%. These results suggest that risk plays a role in sustainable practice adoption, but that many other economic (cost, subsidies) and social factors (networks, access to information, environmental attitudes) do as well, a common finding in meta-analyses (Ruzzante et al., 2021; Liu et al., 2018; Baumgart-Getz et al., 2012).

Overall, our results indicate that adoption of sustainable practices generates economic benefits to corn growers. The increased adoption of practices aimed at reducing soil erosion, enhancing nutrient, pest, and water management, and preserving beneficial organisms leads to higher expected farm income and welfare. However, it is important to note that the adoption of these practices often comes with an additional cost of risk. Farmer concerns regarding the increased risk associated with sustainable practice adoption are valid and can hinder their adoption. Therefore, implementing programs and policies that mitigate these risks can contribute to increasing sustainability. One example of such a risk mitigation strategy is the utilization of multiperil crop insurance, which is widely available. Farmers who adopt more sustainable practices can leverage this insurance to offset some of the financial losses resulting from below-average yields and increased yield skewness. By having insurance coverage in place, farmers have a reliable mechanism to limit the adverse impact of low yields, stabilize their income, and ensure their financial viability. Consequently, this promotes the widespread adoption of sustainable practices and ensures the resilience in agricultural systems.

There are several limitations in our analysis that suggest avenues for future research. First, our analysis does not estimate the long-term effects of sustainable practice adoption. For example, investing in cover crops and soil conservation structures to improve soil health and reduce erosion likely generates cumulative and long run yield gains and can reduce future expenses for nutrients, irrigation, and energy (e.g., Wegner et al., 2018; Araya et al., 2022). By using cross-sectional data from a single year, our study does not capture these benefits, but a dynamic analysis using panel-data could. However, obtaining such data from a wide range of farms likely will be difficult. Additionally, our analysis did not account for the costs for adopting new practices to increase the intensity of sustainable practice adoption, as such cost data were unavailable, and so actual farmer returns are likely lower than estimated here.

While agricultural practices and adoption rates change over time, influenced by policies, technical advancements, and changes in farmers' awareness and attitudes, our analysis using 2010 data still has value. Despite notable increases in no-till and cover cropping in recent years, mainly driven by national and state programs, adoption rates of many other sustainable practices, especially those given the highest weights in our analysis, have not changed much due to factors such as economic constraints, lack of knowledge, and need for long-term commitments by farmers (LeBude et al., 2017; Stetkiewicz et al., 2018; Grasswitz, 2019; Deguine et al., 2021). Hence, our analysis still has value, especially in regions where the pace of adoption has been slower. Nevertheless, the analysis could be repeated with more recent data to identify trends in practice adoption intensity and impacts on yield moments, particularly as programs have shifted to focus on other practices.

Our study suggests potential future research avenues. The practice adoption intensity score is a single index number aggregating over 73 practices. Creating sub-indices for groups of practices targeting specific outcomes (e.g., reduced soil erosion, more efficient nutrient use, enhanced biodiversity) could assess how these practice groups differentially affect expected returns. Also, the practice adoption intensity score could be used to explore the impacts of increased adoption intensity on more than just the cost of risk as examined here. For example, Won et al. (2023) has shown that cover crop adoption shifts yield distributions to reduce crop insurance indemnities, particularly after long-term use, while Chen et al. (2023) show that the yield benefits of no-till can be capitalized into land values. Similarly, Sawadgo and Plastina (2021) estimate the impact of cost share programs on cover crop adoption and the associated public cost for reducing nitrogen loads. Rather than focusing on single practices like these studies, utilizing the adoption intensity score for sets of practices (e.g., sustainability, climate smart agriculture or herbicide resistance management) could be used to investigate their effects on crop insurance indemnities, land values, and the costs of programs addressing nitrogen loads, soil erosion, and greenhouse gas emissions.

7. Significance

Farmers have a vital role to play for achieving national and global agricultural sustainability goals by adopting sustainable production practices. Though agricultural sustainability has three pillars (healthy environment, economic profitability, social equity), the primary attention of most established protocols and analyses of agricultural sustainability focus on practices to generate environmental benefits, often minimalizing or even ignoring the social and economic aspects of sustainability. To help fill this gap, our study focused on the economic aspects of sustainability, specifically farm income and the cost of risk. Our study reveals substantial economic benefits exist for US corn farmers to improve their adoption of sustainable production practices. In addition, our analysis showed the importance of including skewness (the downside risk of unexpectedly low yields and returns) in analyses of risk. If only the variance of yield had been included, we would have incorrectly concluded that sustainable practice adoption decreased yield risk. Moreover, our study provides important information on the cost of risks by separately estimating costs from variance and from skewness and identifying a critical impediment to adoption of sustainable practices.

Declaration of Competing Interest

None.

Data availability

The data that has been used is confidential.

Appendix A. Sustainable practices in corn production

Farmer responses to the following 73 questions from the ARMS were used to measure farmer adoption for sustainable practices (https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/questionnaires-and-manuals/#2010).

1. During 2010, did a written conservation plan specifying practices to reduce soil erosion cover this field?
2. During 2010, did a written comprehensive nutrient management plan specifying practices for applying both fertilizer and manure cover this field?
3. During 2010, did a written pest management plan to implement Integrated Pest Management (IPM) practices to control weeds, insects, and/or plant diseases cover this field?
4. During 2010, did a written irrigation water management plan specifying practices for applying or conserving irrigation water cover this field?
5. In 2010, did your land-use practices for this field include structures for soil erosion control?
6. In 2010, did your land-use practices for this field include structures for storm water runoff control/handling?
7. In 2010, did your land-use practices for this field include filter strips or other conservation buffers?
8. In 2010, did your land-use practices for this field include contour farming and strip cropping?
9. In 2010, did your land-use practices for this field include conservation tillage/no-till?
10. How many years in the last 4 years other crops (other than corn) were planted in the field?
11. How many seasons in last 4 years was a cover crop planted in this field?
12. How many seasons in last 4 years was this field no-tilled?
13. Was a soil test for phosphorus performed on this corn field in 2009 or 2010 for the 2010 crop?
14. Was a soil test for nitrogen performed on this corn field in 2009 or 2010 for the 2010 crop?
15. Was the amount of nitrogen you decided to apply to this field based on

a. Results of a soil or plant tissue test? b. Crop consultant recommendation?
c. Fertilizer dealer recommendation? d. Extension service recommendation?
e. Contractor recommendation?

16. Was a plant tissue test or leaf analysis for nutrient deficiency performed on this field for the 2010 crop?
17. Of the manure applied to this field, was any tested for nutrient content prior to application?
18. Was the application rate of commercial nitrogen fertilizer on this field reduced due to manure application?
19. Was nitrogen requirement of the crop the basis used to determine manure application rate?
20. Was phosphorus requirement of the crop the basis used to determine manure application rate?
21. Were weather data used to assist in determining either the need or when to make pesticide applications?
22. Were any biological pesticides such as Bt (*Bacillus thuringiensis*), insect growth regulators, need or other natural/biological based products sprayed or applied to manage pests in this field?
23. Were pesticides with different mechanisms of action rotated or tank mixed for the primary purpose of keeping pests from becoming resistant to pesticides?
24. Were herbicides applied before/after weeds emerged on this cornfield based primarily on weed scouting from the previous/current year, instead of routine treatments of what weeds are usually present?
25. Were the insecticides applied to this corn field based primarily on scouting for insect infestation?
26. Was this corn field scouted for weeds?
27. Was this corn field scouted for diseases?
28. Was this corn field scouted for insects or mites?
29. Were written or electronic records kept for this field to track the activity or numbers of weeds, insects or diseases?
30. Were scouting data compared to published information on infestation thresholds to determine when to take measures to manage pests in this field?
31. Did you use field mapping of previous weed problems to assist you in making weed management decisions?
32. Did you use the services of a diagnostic laboratory for pest identification or soil plant tissue pest analysis for this field for the specific purpose of managing or reducing the spread of pests in this field?
33. Did you plow down crop residue for the specific purpose of managing or reducing the spread of pests in this field?
34. Did you remove/burn down crop residue for the specific purpose of managing or reducing the spread of pests in this field?

35. Did you rotate crops in this field during the past 3 years for the specific purpose of managing or reducing the spread of pests in this field?
36. Did you maintain ground covers, mulches, or other physical barriers for the specific purpose of managing or reducing the spread of pests in this field?
37. Did you choose crop variety because of specific resistance to a certain pest for the specific purpose of managing or reducing the spread of pests in this field?
38. Did you use no-till or minimum till for the specific purpose of managing or reducing the spread of pests in this field?
39. Did you plan planting locations to avoid cross infestation of pests for the specific purpose of managing or reducing the spread of pests in this field?
40. Did you adjust planting or harvesting dates for the specific purpose of managing or reducing the spread of pests in this field?
41. Did you clean equipment and field implements after completing field work to reduce the spread of pests for the specific purpose of managing or reducing the spread of pests in this field?
42. Did you adjust row spacing, plant density or row directions for the specific purpose of managing or reducing the spread of pests in this field?
43. Did you maintain a beneficial insect or vertebrate habitat for the specific purpose of managing or reducing the spread of pests in this field?
44. Did you plant earlier or later to avoid weeds for the specific purpose of managing or reducing the spread of pests in this field?
45. Were any beneficial organisms (insects, nematodes, fungi) applied or released in this field to manage pests?
46. Were floral lures, attractants, repellants, pheromone traps or other biological pest controls used on this field?
47. Was a trap crop (excluding fallow) grown to help manage insects in this field?
48. Were water management practices such as irrigation scheduling, controlled drainage, or treatment of retention water used on this field to manage for pests or toxic producing fungi and bacteria?
49. Did you change timing of, reduce application rate of, or eliminate a pesticide application to protect beneficial organisms?
50. Did you change to an alternative pesticide, biocontrol, or non-pesticide practice to protect beneficial organisms?
51. Other than pesticide applicator training, have you attended any training session on pest identification and management since October 1, 2009?
52. Did you hire any technical or consultant services for nutrient recommendations/management service?
53. Did you hire any technical or consultant services for soil or tissue sample collection?
54. Did you hire any technical or consultant services for pest control recommendations/management service?
55. Did you hire any technical or consultant services for pest scouting?
56. Did you hire any technical or consultant services for irrigation management service (i.e. irrigation scheduling)?
57. Did you hire any technical or consultant services for yield map or remote sensing map development/interpretation?
58. Was there (or will there be) a yield map produced from the harvest using information from the yield monitor on the harvest equipment for this corn field?
59. Did you use the yield monitor information to monitor crop moisture content to determine need for crop drying?
60. Did you use the yield monitor information to add/improve tile drainage?
61. Did you use the yield monitor information to add/improve irrigation equipment/irrigation water application?
62. Did you use the yield monitor information to conduct in-field experiments (such as compare fertilizer applications, seed varieties, herbicides, pesticides, etc.)?
63. During 2009 or 2010, was the information collected from a GPS device used to produce a map of the soil properties (such as nitrate levels, PH, soil type, etc) of this field?
64. Was a guidance or auto-steering system (connected to GPS) used with any machine operation on this field?
65. Did you use a variable rate applicator for nitrogen applications?
66. Did you use a variable rate applicator for phosphorus applications?
67. Did you use a variable rate applicator for potash applications?
68. Did you use a variable rate applicator for lime applications?
69. Did you use a variable rate applicator for manure applications?
70. Was a variable rate applicator used on this field for seeding?
71. Was a variable rate applicator used on this field for pesticide applications?
72. Is the run-off from this field retained at the end of the field, reused to irrigate on the farm, collected in evaporation ponds on the farm, or is there no run-off?
73. Did you use nitrification inhibitors (such as *N-serve*), urease inhibitors (such as *Agrotain*), chemical-coated fertilizers (such as sulfur-coated urea and polymer-coated urea) or other inhibitors to slow the breakdown of nitrogen on this field?

Appendix B. OLS estimation results

	Mean		Variance		Skewness	
Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Sustainable practice adoption intensity	3.579	3.755	−231.811	163.527	−15,100.860	12,058.840
Seeding rate	71.649***	11.927	2864.511***	739.132	−161,032.000*	94,001.710
Planted late	−10.806	50.262	182.523	303.628	−46,394.860	37,713.620
Nitrogen rate	8.777	9.527	−329.068**	142.372	−499.983	15,521.990
Manure use	7.730	31.049	−70.961	172.456	19,883.200	20,332.300
County soil quality	7.929	29.959	−423.573***	141.400	5781.749	16,709.080
Northern Crescent	−3.726	17.903	−169.379	286.102	14,032.060	26,652.430
Northern Great Plains	−12.210	26.502	−496.266*	265.938	40,125.470	30,429.730
Prairie Gateway	−1.338	17.007	514.285	314.208	−3582.400	32,940.580
Eastern Uplands	−14.405	67.967	−164.739	428.535	60,371.060*	33,687.300
Southern Seaboard	−41.888	100.134	1373.988**	588.408	−72,294.590	58,020.990

(*continued on next page*)

(*continued*)

	Mean		Variance		Skewness	
Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Fruitful Rim	−32.087	20.512	−91.856	409.164	−25,668.620	50,113.320
Age	−13.017	22.950	48.291	424.703	33,809.320	44,998.590
College	1.093	4.418	207.003	251.624	−20,015.100	33,381.950
Wetland	−2.200	28.255	583.418	512.504	14,173.890	60,552.500
Highly Erodible Land	−3.496	4.224	−53.195	256.569	−9563.340	36,112.490
Intercept	−89.648**	44.683	−6451.385*	3743.070	455,193.000	360,178.200
R^2	0.29		0.06		0.02	

Note: *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

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