An Analysis of Cover Crops and Yield Risk: A Parametric Moment Based Approach

AN ANALYSIS OF COVER CROPS AND YIELD RISK: A PARAMETRIC MOMENT BASED APPROACH

by

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LAND ACKNOWLEDGEMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

DEDICATION

To my family

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ABSTRACT

The potential benefits of cover crops have been highlighted in the literature, yet there is a limited understanding of their impact on crop yield risk. This study investigates the impact of cover crop adoption on crop yield risk. Specifically, a parametric moment-based approach is utilized to evaluate how cover crops affect the moments of crop yield distribution (i.e., mean yield, yield variance, skewness, and kurtosis). For this study, we utilize a unique county-level panel dataset containing information on cover crop adoption rates, corn and soybean yields, and weather variables. The dataset spans the period from 2005 to 2018 and covers three main corn and soybean production regions in the United States (US) Central Corn Belt (CCB)(i.e., Illinois, Indiana, and Iowa). Along with the parametric moment-based estimation method, several robustness checks in the empirical analysis (e.g., recently developed instrumental variable procedures, long-difference approach, and alternative empirical specifications) are employed. Our estimation results indicate that the counties with higher cover crop adoption tend to lower the production risk.

Keywords: Cover crops, Yield risk, Production Risk, Moment-based approach

INTRODUCTION

Inherited risk in production, rising production costs, climate change, and growing environmental consciousness have increased the interest in the potential benefits of cover crops in crop production. Due to the on-farm economic benefits and off-farm environmental benefits, farmers are encouraged to adopt sustainable practices that can mitigate the adverse impact of farming (e.g., chemical and fertilizer runoff, soil compaction, and erosion). Cover crops—typically legumes, grasses, or brassicas—are thought of as such practices that provide many benefits to the farm operation such as boosting soil productivity, improving the climate resilience of cash crops, reducing soil erosion levels, suppressing weeds, reducing fertilizer usage, improving nutrient cycling (Snapp et al., 2005; Myers and Watts, 2015; Wittwer et al., 2017; Kaye and Quemada, 2017; Myers et al., 2019; Giri et al., 2020; Hunter et al., 2021; Rejesus et al., 2021; Chen et al., 2022; Aglasan et al., 2023b; Won et al., 2023). Cover crops, typically non-commodity crops, cover the soil in the "off" period between the growing seasons of the cash crop (e.g., winter months) primarily for the purpose of protecting and improving the soil in between periods of regular crop production (Schnepf et al., 2006; Arbuckle and Roesch-McNally, 2015)

Despite elevated interest through agronomic discussions, government payments, and policy incentives, such as the USDA's Environmental Quality Incentives Program (EQIP) and the Risk Management Agency's Pandemic Cover Crop Program, cover crop adoption remains relatively low, accounting for only around 4.7% of cropland area according to the 2022 Census of Agriculture (AgCensus). This low adoption rate highlights the importance of further research to better understand the potential benefits of cover crops to integrate them more into mainstream agricultural practices. There is a growing literature that has documented the impacts of cover cropping on mean yields for a variety of cash crops (e.g., among others, Munoz et al., 2014; Belfry et al., 2017; Marcillo and Miguez, 2017; Blanco-Canqui et al., 2020). In general, the literature indicates that cover crops increase mean crop yield. For example, Miguez and Bollero (2005) finds that winter cover crops resulted in a 21% increase in corn yield. Furthermore, Munoz et al. (2014) illustrates the beneficial influence of cover crop biomass on increasing corn yields. It's worth noting, however, that some existing literature presents opposite results. For instance, in their review of cover crop studies, Abdalla et al. (2019) analyzed 106 studies across 372 sites, finding an average yield reduction of 4 percent due to cover crop adoption. Furthermore, Leslie et al. (2017) suggests that cover crops do not yield any positive effects on soybean yield. Moreover, Deines et al. (2023) demonstrates that cover crops negatively affect both corn and soybean yields.

Although there is a larger body of research on the analysis of cover cropping impacts on crop yields, there is little research investigating the effects of cover crops on crop yield risk (Duzy et al., 2014; Smith et al., 2014; Florence et al., 2019; Anderson et al., 2020; Leuthold et al., 2020). These predominantly field-level studies use the coefficient of variation (CV) and/or the yield variance to measure the impact of cover crops on yield risk or yield variability (yield risk is often called 'yield stability' by agronomists). Note that the existing literature on the effects of cover crops on mean yield and yield risk is mostly based on field-level studies usually for a narrower geographical area (i.e., specific locations) and for shorter time periods. In the limited research on cover crop-yield risk literature, it is worth noting that there exists mixed results. Some studies indicate that cover crops increase crop yield risk (see, for example, Li et al. (2019)).

In light of these discussions, this study investigates whether counties with higher cover crop adoption rates experience lower corn and soybean yield risk in three US Central Corn Belt (CCB) states (i.e., Illinois, Indiana, and Iowa). In particular, parametric moment-based estimation procedures (see Antle, 1983; Antle and Goodger, 1984; Chavas, 2004) are employed to estimate stochastic production functions. This analysis aims to examine the relationship between cover crop adoption rates and all four moments of the yield distribution (e.g., mean, variance, skewness, kurtosis) for both corn and soybean. To achieve this aim, we utilize a large-scale dataset containing information on corn and soybean yields. These yield data are then merged with satellite-based data on cover crop adoption percentage by county. Along with county-level data on weather variables, we construct a comprehensive county-level panel dataset covering the years 2005 to 2018 for the following CCB states:

Illinois, Indiana, and Iowa. To estimate the effect of cover crops on all four moments of the yield distribution, linear panel fixed effects (FE) models that can help address potential endogeneity due to time-invariant unobservables is employed. Several robustness checks using alternative empirical specifications and alternative estimation methods (e.g., the moment-based instrumental variable (IV) procedure and the kinky least squares (KLS) method) are employed to validate the strength of the results from the linear panel FE models and address other identification issues.

Findings from this study suggest that counties with higher cover crop adoption rates tend to have lower yield risk measured by variance, skewness, and kurtosis of yield (e.g., the variance and kurtosis of yields decrease). Hence, we provide empirical evidence that cover crops reduce year-to-year temporal variability of yields and decrease the likelihood of extreme events in the tails of the yield distribution. Our study contributes to the literature by specifically examining the risk reduction benefits of cover cropping with a parametric moment-based empirical approach, thereby offering additional insights into the advantages of cover cropping for the agricultural sector.

DATA

The unique county-level panel data used in this study come from several sources and are discussed in turn below. The data spans the period from 2005 to 2018 and covers the following states in the US Midwest: Illinois, Indiana, and Iowa. These 'I' states constitute the heart of the Corn Belt, known for high-yielding, commercial-scale agriculture primarily focused on maize-soybean rotation (Green et al., 2018; Deines et al., 2023). The main dependent variables of interest in this study—the county-level corn and soybean data on yields—for the same period (i.e., from 2005 to 2018) are drawn from the National Agricultural Statistics Service (NASS) database. The main independent variable of interest of this study—the county-level cover crop adoption—is sourced from the Operational Tillage Information System (OpTIS), a satellite-based system developed by ReGrow Ag® for the period 2005–2018.[1] OpTIS generates timely, spatially comprehensive, and accurate annual data on the adoption of winter cover crops by utilizing multi-temporal optical satellite observations from various platforms.[2] In OpTIS, a crop year extends from November 1 of the preceding year to October 31 of the year when the subsequent main (or cash) crop is planted. For example, the 2005 crop year extends from November 1, 2004, to October 31, 2005. The cover crop adoption data corresponds to the winter months following the harvest of the previous year's main crop and preceding the planting of the subsequent main crop. Therefore, the OpTIS cover crop adoption data for the crop year 2005 reflects cover crops detected by the satellites beginning in November 2004, after the fall harvest of the main crop in 2004.

The OpTIS data undergo calculation and validation on a farm-field level, prioritizing the confidentiality of individual producers by only disclosing spatially aggregated findings on

[1] ReGrow Ag® developed the OpTIS system that enables the use of satellite images to estimate the adoption of winter cover crops over time. The company partnered with several organizations, like the Conservation Technology Information Center (CTIC), in order to develop OpTIS.

[2] Cover crop adoption is assessed using a time series of the Normalized Difference Vegetation Index (NDVI). Subsequently, each pixel is categorized into one of two classes: (1) no cover crop—where less than 30% of the field exhibits green cover during winter, and (2) cover crop—where at least 30% of the field area displays green cover in the winter.

broader scales such as county, watershed, and state levels (Hagen et al., 2020). Additionally, for validation purposes, the OpTIS data is rigorously compared with field-level photos and roadside survey data gathered from various representative counties spread across the Corn Belt region (see Hagen et al., 2020 for detailed validation methodologies). Through this validation process, Hagen et al. (2020) concluded that the satellite-based cover crop adoption data demonstrated a fairly high accuracy rate (87.9%). OpTIS data is accessible for all counties within the states of Illinois, Indiana, and Iowa, providing complete statewide coverage.[3]

Following the collection of winter cover crop adoption data, we proceeded to gather information on various weather variables. Weather data were sourced from the 'Parameter Elevation Regression on Independent Slopes Model' (PRISM) climate dataset. PRISM, a gridded dataset with a resolution of 4 km, has been extensively employed in prior climate change research (e.g., Schlenker and Roberts, 2006, 2009; Annan and Schlenker, 2015; Ortiz-Bobea, 2021; Wang et al., 2021) and is considered one of the premier sources of weather and climate-related data in the US. The relevant weather variables used in the study encompass the number of growing degree days (GDD) (8-29°C), heating degree days (HDD) (above 29°C), precipitation, and a squared precipitation term. The degree day measures provide information about the number of days a crop is exposed to certain temperature ranges and allow for capturing the nonlinear relationship between temperatures and yield. Note that the degree day and precipitation variables are aggregated over the May to September growing season months (Schlenker and Roberts, 2009). The county-level aggregates of these weather variables are then merged with the NASS and OpTIS datasets to produce the final data set used in this study.

Table 1 presents summary statistics for all variables utilized in the empirical analysis. The average cover crop adoption percentage per county over our data period stands at 3.18%. Throughout the study period, the county-average cover crop adoption rate is 3%. The average corn yield is 165 bushels per acre (bu/acre) and the average soybean yield is 50 bu/acre. Figures 1 and 2 show trends of yield variables over time. Figure 3 illustrates

[3] It's also important to note that we specifically concentrate on the 'I' states to align with one notable paper in the literature (i.e., (Deines et al., 2023)).

the average yearly cover crop adoption, indicating an upward trend over time, particularly notable in the last three years (2016–2018). Figure 4 shows trends in the weather variables used in this study.

EMPIRICAL FRAMEWORK

3.1 Parametric Moment-based Estimation Method

To investigate the relation between cover crops and yield risk, we use the parametric moment-based framework of Antle (1983) and Antle and Goodger (1984) for estimating stochastic production functions for corn and soybean. Let's represent the crop production process with the stochastic production function:

$$y = \mu(X) + \varepsilon, \tag{3.1}$$

where y is crop (i.e., corn or soybean) yield; X is a vector of control variables, which includes cover crop adoption and weather variables; and ε is the idiosyncratic error term (which is mean zero conditional on the explanatory variables).

Our analysis assessing the risk linked with any element in X relies on a moment-based approach by evaluating the mean, variance, skewness, and kurtosis of crop yields. The first moment, representing the mean yield can be expressed as $M_1(X) = E[\mu(X)]$. The higher moments of the production function (i.e., variance, skewness, and kurtosis) that characterize the associated risk exposure are expressed as:

$$\hat{\varepsilon}^i = [y - \mu(X)]^i = M_i(X) + u_i, \quad \forall i = 2, 3, 4 \tag{3.2}$$

where $\hat{\varepsilon}^i$ is the i^{th} power of the predicted residuals from the regression specified in Equation (3.1), $M_i(X)$ is the i^{th} moment function, and u_i is the error term. Equation (3.7) represents the variance of y, $M_2(X)$ when $i = 2$, the skewness of y, $M_3(X)$ when $i = 3$, and the kurtosis of y, $M_4(X)$ when $i = 4$.

Control variables in the vector X affect the variance, skewness, and kurtosis of yield (i.e., $M_2(X)$, $M_3(X)$, and $M_4(X)$, respectively). For instance, x_1 can increase, maintain neutrality, or decrease variance (i.e., $\partial M_2/\partial x_1 > 0$, $= 0$, or < 0, respectively). Similarly, a particular variable in X can induce an increase, exhibit neutrality, or cause a decrease in skewness, and the same applies to kurtosis. A negative (positive) skewness indicates a distribution skewed to the left (right), with negative skewness suggesting a higher exposure to downside risks, such as unexpected low yield or crop failure. Conversely, high kurtosis may suggest a higher likelihood of extreme events in the tails of the yield distribution. In other words, in the context of crop yield, lower kurtosis implies a more uniform distribution of yields, reducing rare events in the tails of the yield distribution. Notably, equation (3.7) surpasses the conventional mean-variance approach commonly employed in past studies. This extension becomes particularly relevant in scenarios where exposure to downside risk (i.e., asymmetric risk effects).

Antle (1983)'s Linear Moment Method (LLM) is employed to estimate equations (3.1) and (3.7). In this approach, the moments of the yield distribution are assumed to be parametric linear functions of independent variables, such as:

$$y = X\beta_1 + \varepsilon, \tag{3.3}$$

$$\hat{\varepsilon}^i = X\beta_i + u_i, \quad \forall i = 2, 3, 4 \tag{3.4}$$

It is important to note that equations (3.3) and (3.4) demonstrate heteroscedasticity, necessitating the use of heteroscedasticity-robust standard errors in the estimation process. Given the absence of endogeneity issues, one can straightforwardly estimate equations (3.3) and (3.4) using ordinary least squares (OLS), along with heteroscedasticity-robust standard errors.

3.2 Empirical Specification

3.2.1 Main Specification and Estimation Method

We utilize a linear panel fixed effects (FE) model to estimate the county-level impact of cover crop adoption on yield risk by implementing the parametric moment-based estimation method above using the following empirical specification:

$$y_{jt} = \beta_{11}CC_{jt} + \beta_{12}HDD_{jt} + \beta_{13}GDD_{jt} + \beta_{14}Prec_{jt} + \beta_{15}Prec_{jt}^2 + \alpha_{1j} + \lambda_1 T_t + \varepsilon_{jt} \tag{3.5}$$

The dependent variable, y_{jt}, represents the corn or soybean yield (in bu/ac) for the j^{th} county in year t, with t ranging from 2005 to 2018. CC_{jt} stands for the cover crop adoption variable (percentage of planted crop acres with cover crops). HDD_{jt} denotes heating degree days (in hundred Celsius); GDD_{jt} represents growing degree days (in thousand Celsius); and

$Prec_{jt}$ denotes cumulative precipitation during the growing season (in m). T_t accounts for a linear time trend, capturing unobserved technological growth over time. α_{1j} represents county-level fixed effects, controlling for unobserved time-invariant factors at the county level, and ε_{jt} is the error term (which is mean zero conditional on the explanatory variables). Standard errors are clustered by county to account for heteroscedasticity and potentially correlated county-year observations within each county.[4]

The risk implications of cover crop adoption are assessed through the higher moments of the production function. Following Equation 3.5, the higher moments of yield are as follows:

$$\hat{\varepsilon}^i_{jt} = \beta_{i1}CC_{jt} + \beta_{i2}HDD_{jt} + \beta_{i3}GDD_{jt} + \beta_{i4}Prec_{jt} + \beta_{i5}Prec^2_{jt} + \alpha_{ij} + \lambda_i T_t + u_{jt} \quad (3.6)$$

where $i = 2, 3, 4$ refers to i^{th} power (i.e., the second, third, and fourth power) of the residual $\hat{\varepsilon}_{jt}$, representing the variance, skewness, and kurtosis of the yield distribution, respectively. The predicted higher order moments $\hat{\varepsilon}^i_{jt}$ are calculated using the estimated parameters in Equation 3.5 and the actual values of the independent variables for each county-year in the data set (i.e., predicted moments are conditional on actual values of the independent variables, including the time trend and county fixed effects). For the variance of yield ($i = 2$, $\hat{\varepsilon}^2_{jt}$ in our case), a positive (negative) parameter estimate indicates an increase (decrease) in yield variability. For the skewness of yield ($i = 3$), capturing the tail asymmetry of a yield distribution around its mean, a positive (negative) parameter estimate suggests a reduction (increase) in exposure to downside yield risks. Similarly, kurtosis (when $i = 4$) measuring thickness (fatness) in the tails of the yield distribution, a positive (negative) parameter estimate suggests an increase (decrease) in production risk associated with the corresponding variable.[5]

In this study, our objective is to assess the impact of cover crop adoption on yield risk, focusing on the parameter of interest, β_{i1}. After estimating the relevant parameters in

[4] In addition, we implemented a robustness check that clusters standard errors both by county and by year (i.e., a "two-way" clustering procedure). See Appendix Tables A.1 and A.2. Clustering standard errors by county and by year can be regarded as robust to heteroscedasticity, spatial correlation of the error terms across counties, and serial correlation of the errors within each county (Cameron et al., 2011).

[5] Note that reducing variance and increasing skewness are favorable, as they lead to reduced risk exposure due to lower variance and a decreased likelihood of unfavorable events found in the lower tail of the yield distribution resulting from higher skewness. Additionally, decreasing kurtosis is also favorable, as it might indicate a reduction in rare events in the tails of the yield distribution.

equations (3.5) and (3.6), we analyze the effect of cover crop adoption on the moments of the crop yield distribution by examining the sign and significance of β_{i1}. For example, a negative and statistically significant value for the parameter, say β_{21}, would indicate that adopting cover crops decreases yield variability. This finding suggests that farmers with higher cover crop adoption experience lower yield risk.

3.2.2 Robustness Checks: Alternative Empirical Specifications and Estimation Methods

To verify the stability and strength of our parameter estimates, we perform several robustness checks. First, we employ an alternative model specification accounting for county-level per-acre expenditure data on inputs—fertilizer and chemicals, labor, fuel, and other production costs—sourced from the Bureau of Economic Analysis (BEA). These expenditure variables serve as proxies for actual fertilizer and chemical usage and other managerial inputs, aiming to mitigate omitted variable bias and enhance identification (Park et al., 2022). It's worth noting that some scholars argue that these control variables themselves might be endogenous, potentially adding noise to the estimation. Nevertheless, we chose to include them as part of our robustness checks. For our second robustness check, we include an additional control variable representing no-till adoption in Equations (3.5) and (3.6). As with the previous alternative specification, it is argued that no-till variable may also suffer from endogeneity issues, potentially influencing the estimates and conclusions drawn from our models.

In addition to robustness checks using alternative specifications, we also evaluate the robustness of our results from the traditional linear FE estimation procedure by using three other estimation strategies. The first two are recently developed "external-instrument-free" instrumental variable (IV) approaches (i.e., one by Lewbel, 2012, and the other by Kiviet, 2013, 2020). Lastly, we employ a "long-difference" approach. The two external-instrument-free procedures can help further sharpen identification by addressing possible residual endogeneity due to time–county-varying unobservables. The long-difference approach allows us to explore the longer-term effects of cover crops.

As our first robustness check using an alternative estimation method, we utilize a moment-based IV procedure (Lewbel, 2012). While the incorporation of county fixed effects and linear time trends in equations (3.5) and (3.6) is intended to alleviate substantial sources of potential endogeneity, residual endogeneity may still persist due to unobserved variables that vary both spatially and temporally, thereby potentially threatening the model identification. For instance, unobserved cooperative extension efforts that vary across counties and time could represent one such example.

Although the linear panel FE approach employed in equations (3.5) and (3.6) leverages the advantages of panel data, there is a potential drawback in that it falls short of adequately addressing residual endogeneity stemming from unobservable factors that vary across both time and counties. Traditional instrumental variable (IV) methods, such as two-stage least squares (2SLS), are typically utilized to counteract this issue by employing IVs correlated with the potentially endogenous primary independent variable while remaining uncorrelated with the outcome variable, thus satisfying the traditional IV exclusion restrictions. However, the absence of IVs meeting these criteria necessitates the exploration of an alternative approach. Therefore, we implement a recently developed moment-based IV approach (see Lewbel, 2012) to address the potential residual endogeneity due to time-county-varying unobservables that affect county-level yield and higher-order moments, and county-level cover crop adoption rates.

The moment-based IV estimator utilizes the heteroscedasticity observed in the error terms of first-stage regressions (i.e., regression of the potentially endogenous variable on observable covariates) to estimate the coefficients of endogenous variables in the main equations even in the absence of valid instruments. As outlined by Lewbel (2012), the model is identified if the error terms in the first-stage are heteroskedastic, and a subset (or all) of the exogenous variables are uncorrelated with the covariance between the first-stage error term and the error term in the second-stage equation (e.g., equation (3.5)). Then mean-centered covariates multiplied by the residuals from the first-stage equation serve as valid instruments.[6]

[6] More formally, with Equation (3.5) as one of the main estimating equations and the cover crop adoption variable (CC_{jt}) as the potentially endogenous variable, the first-stage regression in the Lewbel (2012) approach can be written as follows:

$$CC_{jt} = \mathbf{W}'_{jt}\boldsymbol{\gamma_w} + e_{jt} \tag{3.7}$$

where, $\mathbf{W}_{jt}$ is a k-vector of weather variables (e.g., GDD, HDD, precipitation, and precipitation squared), and e_{jt} is the error term for county j in year t. In the presence of heteroscedasticity in Equation (3.7) (i.e., $Cov(\mathbf{W}'_{jt}, e^2_{jt}) \neq 0$), Lewbel (2012) has shown that $(\mathbf{W}'_{jt} - \bar{\mathbf{W}}'_{\mathbf{jt}})\hat{e}_{jt}$ can be used as a valid IV.

To validate the presence of heteroscedasticity in our first-stage regressions, we utilize the Breusch-Pagan (BP) test (Breusch and Pagan, 1979). The BP test rejects the null hypothesis of homoscedasticity (i.e., the BP test statistic is 2973.96, and the p-value < 0.0001). This result supports using the moment-based IV approach of Lewbel (2012) as an alternative estimation procedure to potentially address residual endogeneity due time–county-varying unobservables. Aside from the Breusch–Pagan test, we also conducted a series of diagnostic tests to assess the robustness of the Lewbel (2012) IV approach. Firstly, we utilized the Kleibergen–Paap rk LM test to ascertain if the IV approach employed is underidentified Kleibergen and Paap (2006). The Kleibergen–Paap rk LM test rejects the null hypothesis that the IV model is underidentified. Furthermore, we employed both the Cragg-Donald Wald F statistic and the Kleibergen-Paap rk Wald F statistic to evaluate the strength of the instruments used in estimation. Both tests indicate that we can reject the null hypothesis that the IVs used are weak.

To further verify our results obtained from both the linear FE and the Lewbel (2012) moment-based IV methods, we also utilize a recently developed "external-IV-free" approach, so-called "kinky least squares" (KLS) regression by Kiviet (2013, 2020). The instrument-free KLS approach attains set identification of regression coefficients by constraining the permissible correlation of regressors with the error term within reasonable limits (Kripfganz and Kiviet, 2021). External instruments are not necessary. Instead, potential bias in non-IV, ordinary least squares (OLS) procedures (such as our baseline linear FE approach) is systematically adjusted across a spectrum of endogeneity correlations that the analyst specifies. This yields a range of coefficient estimates for varying levels of endogeneity. In our empirical analysis, we hypothesize that the residual endogeneity range in our baseline specifications (3.5) and (3.6) would be minimal, given our control for unobserved heterogeneity through county FE and time trends. Additionally, we assert that endogeneity correlations are positive, suggesting that the potentially endogenous cover crop variable is likely positively correlated with the remaining time-county-varying unobservables in the error term (i.e., unobserved extension efforts that may be positively correlated with cover crop adoption). Hence, we implement the KLS procedure to estimate Equations (3.5) and (3.6), where the endogeneity correlation is assumed to be 0.1 and 0.2.

Lastly, as our third alternative estimation method, we examine the longer-term effects of cover crops on yield risk (i.e., yield variance, skewness, and kurtosis) by utilizing the long-difference approach (see Hsiang, 2016).[7] We construct long-term variables for yield risk measures, cover crop adoption, and weather variables at two different points in time for each county. Subsequently, we calculate changes in the average yield risk measures as a function of changes in cover crop adoption and weather variables. In our long-difference approach, we divide the data into two seven-year periods; the variables are then averaged for the two periods. The first period (τ_1) spans from 2005 to 2011, while the second period (τ_2) spans from 2012 to 2018. As in the traditional linear FE model, the long-difference model is estimated by OLS.

[7]Note that if the beneficial impacts of cover crops on soil health take time to materialize fully (i.e., accumulate over time), then the estimated short-term impacts might understate the long-term benefits of continuous cover crop use on mean yield, yield variance, skewness, and kurtosis.

RESULTS AND DISCUSSION

4.1 Main Estimation Results

Our main model—linear panel FE regression—results are presented in Table 2 for corn and Table 3 for soybean. The results in Table 2 indicate that cover crop adoption for the variance and kurtosis functions are statistically significant (at the 5% significance level). However, cover crop adoption is statistically insignificant in the mean and skewness functions. It is important to note that although cover crop adoption is statistically insignificant in the mean and skewness functions, the sign of these parameter estimates is positive.[8] Negative and statistically significant parameter estimates for variance and kurtosis suggest that cover crop adoption reduces the risk associated with corn yield by diminishing year-to-year variability and the likelihood of extreme events in the tails of the yield distribution.

The findings presented in Table 3 indicate that counties with a higher adoption rate of cover crops tend to exhibit higher mean yield, lower yield variance, and lower kurtosis for soybean, all significant at the 1% level. These findings suggest that increased cover crop adoption reduces soybean yield risk. Similar to the findings in the corn regression runs, the parameter estimates indicate negative and statistically significant variance and kurtosis, along with positive but not significant skewness. However, unlike the corn case, the parameter estimate for mean yield is positive and statistically significant, suggesting that an increase in cover crop adoption leads to an increase in the mean yield of soybean.

These findings suggest that cover crop adoption significantly influences the variance and kurtosis of yield for both corn and soybeans, indicating a risk-reducing effect. These results align with the notion that cover crop adoption can enhance soil health sufficiently to mitigate production loss events and reduce yield variability. As indicated in previous literature, cover crops contribute to soil organic matter, improving nutrient cycling and soil structure; help control excess water in the soil through improved water infiltration; bolster resilience

[8]Note that an increase in skewness suggests a lower exposure to downside risks.

to extreme weather events (such as droughts or floods); control pest and diseases; and mitigate soil erosion levels (Pathak and Diaz-Perez, 2007; Steenworth and Belina, 2008; Basche and DeLonge, 2019; Chen et al., 2021; Won et al., 2023; Aglasan et al., 2023b). These factors collectively can contribute to a decreased probability of yield losses and year-to-year variability.

With regard to the weather variables presented in Tables 2 and 3 that serve as controls in our baseline models, the estimated effects generally follow a priori expectations. Specifically, we observe a nonlinear effect of the degree days measures, suggesting that optimal plant growth requires heat up to a certain threshold, beyond which damage occurs. While the negative impact of HDD (e.g., yield-reducing and risk-increasing effects) is statistically significant for corn (i.e., parameter estimates of HDD are significant for the mean, variance, skewness, and kurtosis of corn yields), the impact of HDD is only statistically significant on mean yield for soybean, although the parameter sign follows the expected direction. Parameter estimates for GDD exhibit positive and statistically significant coefficients for mean yield and skewness for both corn and soybean; and negative, statistically significant coefficients for variance and kurtosis for corn, indicating that moderate temperatures reduce production risk. The parameters associated with the precipitation variables generally demonstrate a "U-shaped" behavior (e.g., mean yield increases and risk reduces as precipitation increases, but after a certain point, higher levels of precipitation decrease mean yield and increase risk measures).

4.2 Robustness Check Results: Alternative Empirical Specifications and Estimation Methods

As discussed in the robustness checks section, we assess the strength and stability of our main linear panel FE results by conducting several robustness checks that consider alternative empirical specifications and estimation methods. First, we estimated an empirical specification with additional county-level per-acre expenditure variables—fertilizer and chemicals, labor, fuel, and other production costs. The results of this robustness check are presented in Tables A.3 and A.4. The main conclusions drawn from these runs remain consistent with our main linear panel FE results. The signs and magnitudes of the cover crop parameter estimates for this robustness check closely mirror those found in our main linear panel FE model, indicating the risk reduction effects of cover crops.

Secondly, we extend our baseline specification in Equations (3.5) and (3.6) by incorporating no-till variable as an additional control variable. The main findings from this regression (presented in Tables A.5 and A.6) remain consistent with our base model.

In addition to testing robustness with alternative specifications, we further validate the strength of our findings by employing alternative estimation methods. For our first alternative estimation method, we utilize the Lewbel (2012) moment-based IV procedure. The parameter estimates from this robustness check are presented in Tables A.7 and A.8. The results of this approach which aims to address residual time–county-varying unobservables are still consistent with those obtained from our primary model. Specifically, the parameter estimates indicate that counties with higher levels of cover crop participation exhibit statistically lower yield risk.

Additionally, we utilize the KLS regression by Kiviet (2013, 2020). The results obtained from the KLS approach under assumed endogeneity correlations of 0.1 and 0.2 are presented in Tables A.9, A.11, A.10, and A.12. Our findings are fairly consistent with those of our main model, especially for the assumed endogeneity correlations of 0.1, indicating that counties with higher cover crop acres tend to experience lower yield risk. This consistency suggests that the findings of our baseline model are robust, even when subjected to modest levels of residual endogeneity arising from time–county-varying unobservables. However, some variations are observed in specific estimates for both main crops. In the case of corn, the sign of the mean yield exhibits alterations, while for soybean, the sign of mean yield and skewness is altered, and mean yield also loses significance in the cover crop adoption estimates.

Lastly, we conduct a long-difference analysis (see Hsiang, 2016). This approach allows us to assess whether the longer-term utilization of cover crops yields. The results of this analysis are presented in Table A.13 and Table A.14. The long-difference analysis provides evidence suggesting that an increase in cover crop adoption over the longer term period reduces yield risk. Compared to the findings of the short-term base model (refer to Tables 2 and 3), the long difference model demonstrates more substantial results, particularly for corn mean yield.

CONCLUSION

Conservation groups, agronomists, and agriculture-related government agencies advocate for cover cropping as a sustainable practice offering numerous benefits to soil and farmers, including risk reduction. These claims about risk reduction benefits are typically grounded in farmers' past experiences and short-term agronomic field studies. In this study, we aim to examine the impact of cover crop adoption on yield risk. To achieve this objective, we employ a parametric moment-based empirical approach, as outlined by Antle (1983). In particular, we investigate the relationship between cover crop adoption and the moments of crop yield distributions (i.e., mean, variance, skewness, and kurtosis of corn and soybean yields). We construct a county-level panel dataset by integrating novel satellite-based information on cover crop adoption with publicly accessible information on corn and soybean yields, and weather variables. The dataset spans three states in the Central Corn Belt from 2005 to 2016. Our empirical analysis employs traditional linear panel fixed effects (FE) models and various robustness checks, including a moment-based instrumental variable (IV) model, a KLS approach, and a long-difference approach.

Results from our empirical analysis indicate that a higher level of cover crop adoption tends to decrease crop yield risk, as measured by variance, skewness, and kurtosis. Specifically, our findings demonstrate that counties with higher cover crop adoption exhibit lower variance and kurtosis in both corn and soybean yields. The insights from our study offer valuable insights for both farmers and policymakers. To the best of our knowledge, this study is one of the first to explore how adoption affects yield risk, employing higher-order moments of crop yields and county-level data information on cover crop adoption. We strongly believe that our findings contribute to strengthening the empirical evidence base in this field.

While the empirical findings from our study contribute to enhancing our understanding of the impact of cover cropping on crop yield risk, it is essential to acknowledge the study's limitations and highlight promising opportunities for future research. Firstly, our empirical approach primarily relies on a traditional parametric moment-based methodology. Although this approach has been widely used in various agricultural economics studies, recent research has explored more flexible econometric approaches for investigating higher moment yield effects. For instance, studies by Tack et al. (2012) and Li et al. (2021) have employed entropy-based and non-parametric approaches, respectively. Aglasan et al. (2023a) incorporate crop insurance measures as a risk indicator in their analysis. Utilizing these advanced methodologies and employing alternative risk measures may offer further insights into the risk effects of warming under crop insurance. Secondly, despite our efforts to control for all sources of endogeneity, further investigation of this issue using alternative instruments and instrumental variable (IV) approaches may also be warranted. We leave this for future research.

FIGURES AND TABLES

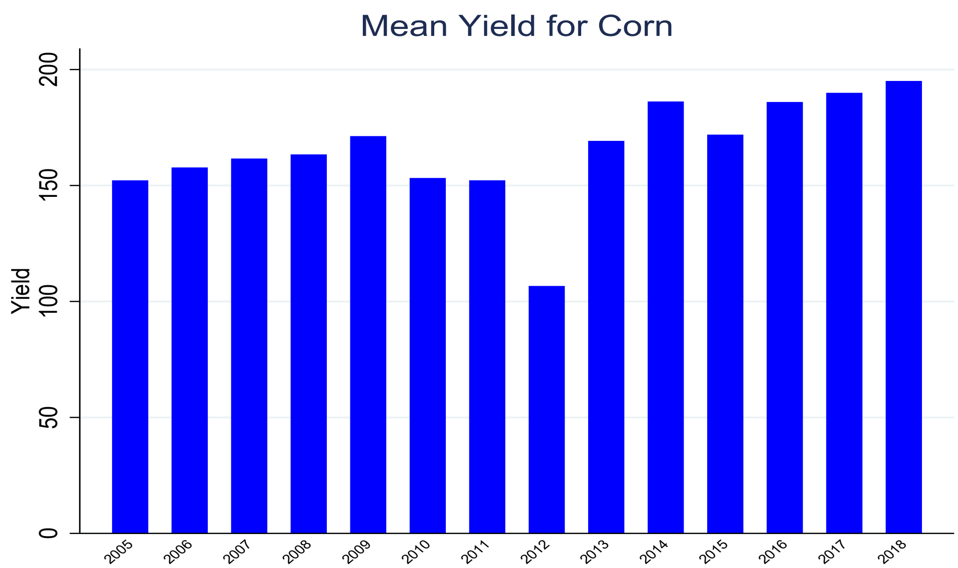

Figure 1: Corn Yield, 2005-2018

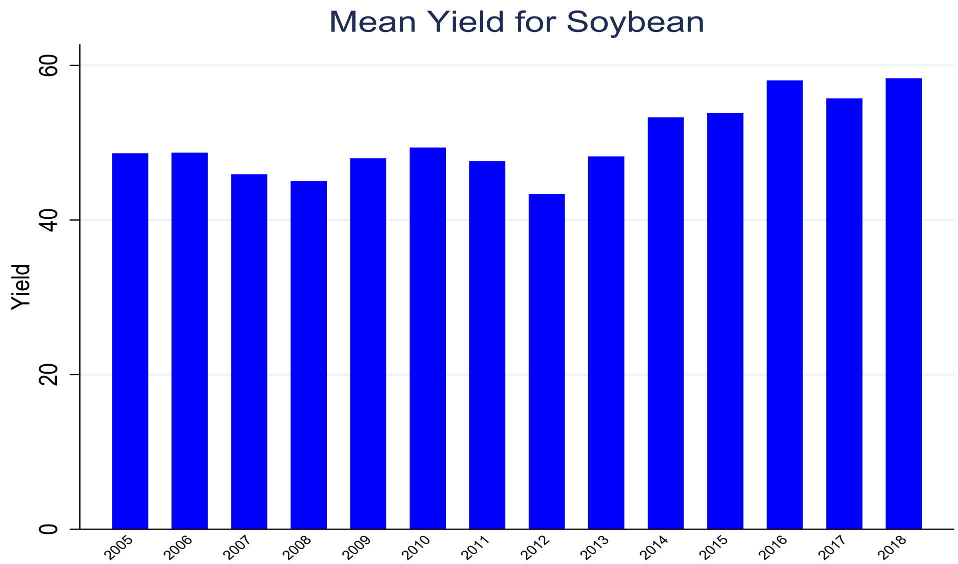

Figure 2: Soybean yield, 2005-2018

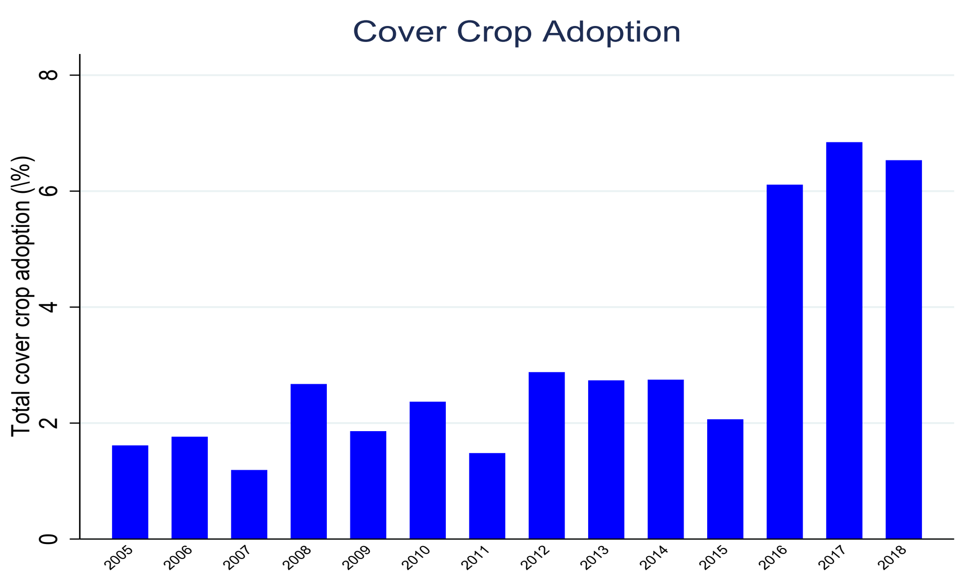

Figure 3: County average cover crop adoption rates, 2005-2018

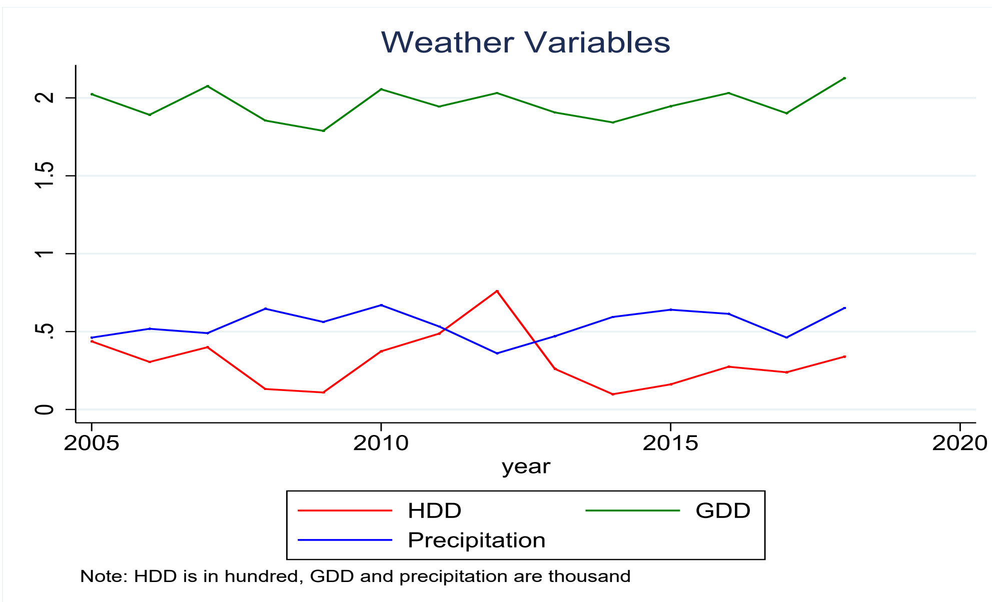

Figure 4: County average HDD, GDD, and Precipitation variables, 2005-2018

Table 1: Description and summary statistics of variables

Variable Name	Description	Mean	SD	Min	Max
Corn Yield	Total Corn Yield (bu/acre)	165.148	31.151	19.000	246.700
Soybean Yield	Total Soybean Yield (bu/acre)	50.166	7.777	19.000	80.400
Cover crop adoption	Percent of cropland acres planted with cover crops (%)	3.009	6.123	0.000	66.900
HDD	Heating degree days (in hundred °C)	0.318	0.246	0.005	1.64
GDD	Growing degree days (in thousand °C)	1.957	0.183	1.361	2.525
Precipitation	Precipitation ([mm] in'000)	0.547	0.142	0.196	1.146
N		3851	3851	3851	3851

Table 2: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.126	-5.418**	231.228	-22475.226**
	(0.095)	(2.237)	(176.100)	(10615.197)
HDD	-1.196***	5.747***	-148.095***	12541.451***
	(0.032)	(0.816)	(52.918)	(2737.460)
GDD	0.092***	-0.248***	14.321***	-702.276***
	(0.004)	(0.079)	(4.993)	(223.643)
Precipitation	0.167***	-1.814***	-26.984	-3240.420***
	(0.015)	(0.375)	(20.456)	(860.081)
Precipitation sq.	-0.179***	1.867***	15.250	3515.712***
	(0.014)	(0.331)	(18.822)	(787.376)
Observations	3851	3851	3851	3851
Adjusted R^2	0.634	0.079	0.008	0.031
AIC	32213.050	57275.830	88507.456	119820.589
BIC	32250.586	57313.367	88544.992	119858.126

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table 3: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Soybean Yield

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.094***	-0.331***	1.985	-39.125***
	(0.019)	(0.091)	(1.484)	(11.947)
HDD	-0.172***	0.040	-0.452	4.964
	(0.006)	(0.038)	(0.487)	(5.829)
GDD	0.024***	-0.004	0.178***	0.504
	(0.001)	(0.006)	(0.068)	(0.864)
Precipitation	0.040***	-0.073***	0.394	-7.544**
	(0.003)	(0.025)	(0.333)	(3.810)
Precipitation sq.	-0.037***	0.050**	-0.226	5.238
	(0.003)	(0.021)	(0.295)	(3.347)
Observations	3851	3851	3851	3851
Adjusted R^2	0.507	0.017	0.006	0.011
AIC	22109.482	35772.701	55129.367	73391.397
BIC	22147.019	35810.238	55166.904	73428.933

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

APPENDIX

Table A.1: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield (Two-Way, "County-Year" Clustering of Standard Errors)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.126	-5.418*	231.228	-22475.226*
	(0.178)	(2.970)	(239.893)	(11631.144)
HDD	-1.196***	5.747***	-148.095	12541.451**
	(0.138)	(1.610)	(165.761)	(4947.484)
GDD	0.092***	-0.248	14.321	-702.276
	(0.017)	(0.185)	(17.788)	(493.585)
Precipitation	0.167***	-1.814**	-26.984	-3240.420
	(0.042)	(0.883)	(41.151)	(2018.044)
Precipitation sq.	-0.179***	1.867**	15.250	3515.712**
	(0.035)	(0.737)	(36.653)	(1694.834)
Observations	3851	3851	3851	3851
Adjusted R^2	0.720	0.074	-0.022	0.025
AIC	32215.050	57277.830	88509.456	119822.589
BIC	32258.842	57321.623	88553.248	119866.382

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county and by year.

Table A.2: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Soybean Yield (Two-Way, "County-Year" Clustering of Standard Errors)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.094**	-0.331***	1.985	-39.125***
	(0.038)	(0.113)	(2.220)	(13.209)
HDD	-0.172***	0.040	-0.452	4.964
	(0.016)	(0.066)	(0.840)	(7.342)
GDD	0.024***	-0.004	0.178	0.504
	(0.004)	(0.012)	(0.232)	(1.463)
Precipitation	0.040***	-0.073	0.394	-7.544
	(0.011)	(0.061)	(0.742)	(6.649)
Precipitation sq.	-0.037***	0.050	-0.226	5.238
	(0.009)	(0.051)	(0.614)	(5.568)
Observations	3851	3851	3851	3851
Adjusted R^2	0.674	0.036	-0.042	0.019
AIC	22111.482	35774.701	55131.367	73393.397
BIC	22155.275	35818.494	55175.160	73437.189

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county and by year.

Table A.3: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield (Alternative Estimation Specifications: Managerial Input Expenditures)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	-0.030	-5.059*	303.388	-27720.133*
	(0.088)	(2.589)	(192.739)	(14243.791)
HDD	-1.104***	5.756***	-147.171**	13752.127***
	(0.032)	(0.849)	(59.302)	(3473.556)
GDD	0.074***	-0.233***	16.520***	-899.881***
	(0.004)	(0.085)	(5.765)	(311.470)
Precipitation	0.169***	-1.850***	-20.757	-2972.028***
	(0.015)	(0.356)	(19.959)	(797.544)
Precipitation sq.	-0.178***	1.875***	10.132	3332.022***
	(0.013)	(0.317)	(18.278)	(742.182)
Fertilizer & chemical	-216.088***	-437.911	2616.402	-2325396.298*
	(41.572)	(376.305)	(36011.977)	(1187606.447)
Seed	-26.697	1103.820	61917.474	-3596937.799
	(68.760)	(1003.519)	(71825.064)	(3596696.155)
Labor	56.285*	-936.952*	-5486.532	-1575891.643
	(31.053)	(476.641)	(31148.508)	(1251960.698)
Production	7.111	201.970**	1094.170	643832.852
	(5.226)	(102.150)	(8007.001)	(433379.312)
Observations	3851	3851	3851	3851
Adjusted R^2	0.651	0.079	0.008	0.028
AIC	32034.773	57211.581	88591.697	120283.312
BIC	32097.333	57274.141	88654.257	120345.873

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.4: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Soybean Yield (Alternative Estimation Specifications: Managerial Input Expenditures)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.049***	-0.334***	3.455**	-45.208***
	(0.018)	(0.104)	(1.631)	(16.954)
HDD	-0.144***	0.065*	-0.566	9.146
	(0.007)	(0.037)	(0.526)	(5.588)
GDD	0.018***	0.003	0.146**	1.139
	(0.001)	(0.006)	(0.061)	(0.905)
Precipitation	0.042***	-0.085***	0.456	-8.654**
	(0.003)	(0.025)	(0.343)	(4.176)
Precipitation sq.	-0.037***	0.060***	-0.294	6.283*
	(0.003)	(0.021)	(0.302)	(3.622)
Fertilizer & chemical	-93.200***	-17.758	3631.248	-34478.408
	(23.853)	(64.265)	(3254.604)	(27349.760)
Seed	65.586*	108.867	-3998.424	49920.846
	(36.152)	(88.477)	(4545.489)	(37108.421)
Labor	1.463	-85.842*	1714.495	-23776.662
	(14.538)	(47.420)	(1825.786)	(17155.391)
Production	-0.669	8.850	-197.325	3144.802
	(1.996)	(8.411)	(234.066)	(2472.891)
Observations	3851	3851	3851	3851
Adjusted R^2	0.549	0.024	0.021	0.022
AIC	21763.436	35517.289	55382.803	74643.258
BIC	21825.997	35579.850	55445.364	74705.819

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.5: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield (Alternative Estimation Specifications: No Till)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.104	-5.216**	237.242	-22558.672**
	(0.094)	(2.213)	(181.756)	(11059.548)
No till adoption	-0.115***	-1.029	-16.622	-1352.462
	(0.031)	(0.722)	(40.327)	(2105.690)
HDD	-1.197***	5.839***	-157.942***	13064.916***
	(0.032)	(0.828)	(54.208)	(2845.670)
GDD	0.091***	-0.270***	14.627***	-767.661***
	(0.004)	(0.082)	(5.240)	(244.003)
Precipitation	0.169***	-1.765***	-27.065	-3109.645***
	(0.015)	(0.376)	(20.337)	(862.508)
Precipitation sq.	-0.181***	1.825***	15.221	3403.136***
	(0.014)	(0.332)	(18.752)	(786.969)
Observations	3851	3851	3851	3851
Adjusted R^2	0.636	0.080	0.008	0.033
AIC	32200.000	57243.457	88452.434	119745.868
BIC	32243.793	57287.250	88496.227	119789.660

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.6: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Soybean Yield (Alternative Estimation Specifications: No Till)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.087***	-0.376***	1.967	-44.610***
	(0.019)	(0.100)	(1.552)	(13.735)
No till adoption	-0.041***	-0.018	0.150	-7.035
	(0.009)	(0.044)	(0.590)	(5.151)
HDD	-0.173***	0.052	-0.400	6.338
	(0.006)	(0.038)	(0.497)	(6.049)
GDD	0.023***	-0.006	0.164**	0.234
	(0.001)	(0.006)	(0.067)	(0.869)
Precipitation	0.041***	-0.068***	0.392	-6.776*
	(0.003)	(0.025)	(0.320)	(3.598)
Precipitation sq.	-0.037***	0.046**	-0.213	4.538
	(0.003)	(0.021)	(0.283)	(3.137)
Observations	3851	3851	3851	3851
Adjusted R^2	0.510	0.019	0.006	0.012
AIC	22085.233	35738.735	55089.013	73399.804
BIC	22129.025	35782.527	55132.806	73443.596

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.7: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield (Lewbel's Moment Based-IV Approach)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.147	-10.217***	276.009	-36913.043*
	(0.146)	(3.357)	(300.640)	(19359.686)
HDD	-1.195***	5.699***	-147.504***	12329.268***
	(0.032)	(0.807)	(51.652)	(2605.290)
GDD	0.092***	-0.230***	14.154***	-639.926***
	(0.004)	(0.079)	(4.813)	(199.225)
Precipitation	0.167***	-1.802***	-27.255	-3203.769***
	(0.015)	(0.373)	(20.478)	(860.371)
Precipitation sq.	-0.179***	1.850***	15.569	3458.855***
	(0.014)	(0.330)	(18.864)	(791.002)
Observations	3851	3851	3851	3851
Adjusted R^2	0.604	0.002	-0.074	-0.050
AIC	32213.155	57276.503	88491.788	119790.183
BIC	32250.691	57314.040	88529.325	119827.720

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.8: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Soybean Yield (Lewbel's Moment Based-IV Approach)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.062**	-0.489***	1.201	-65.565***
	(0.024)	(0.131)	(2.183)	(22.130)
HDD	-0.172***	0.041	-0.515	5.272
	(0.006)	(0.038)	(0.492)	(5.913)
GDD	0.024***	-0.004	0.182***	0.529
	(0.001)	(0.006)	(0.068)	(0.870)
Precipitation	0.040***	-0.074***	0.397	-7.639**
	(0.003)	(0.025)	(0.334)	(3.826)
Precipitation sq.	-0.037***	0.050**	-0.231	5.252
	(0.003)	(0.021)	(0.296)	(3.364)
Observations	3851	3851	3851	3851
Adjusted R^2	0.466	-0.062	-0.075	-0.070
AIC	22112.719	35795.343	55169.504	73461.511
BIC	22150.256	35832.880	55207.041	73499.047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.9: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield(Kinky Least Squares(KLS) with Correlation = 0.1)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	-0.532	-19.893**	13.493	-91239.845**
	(0.358)	(9.855)	(601.079)	(39745.653)
HDD	-1.205***	5.091***	-155.519***	12715.474***
	(0.022)	(0.613)	(36.821)	(2370.833)
GDD	0.095***	-0.129	16.994***	-469.193
	(0.004)	(0.105)	(6.314)	(407.744)
Precipitation	0.168***	-1.735***	-22.088	-3053.098**
	(0.012)	(0.337)	(20.241)	(1301.610)
Precipitation sq.	-0.182***	1.758***	10.801	3285.160***
	(0.010)	(0.282)	(16.931)	(1089.141)
Observations	3851	3851	3851	3851
Adjusted R^2				
AIC	.	.	.	.
BIC	.	.	.	.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.10: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield (Kinky Least Squares(KLS) with Correlation = 0.2)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	-1.244	-31.990	92.589	-165975.803
	(0.796)	(24.876)	(1645.117)	(126591.540)
HDD	-1.214***	4.575***	-173.842***	13775.872***
	(0.025)	(0.784)	(50.951)	(3837.947)
GDD	0.098***	0.043	26.643***	268.177
	(0.005)	(0.153)	(10.018)	(759.861)
Precipitation	0.170***	-1.551***	-15.814	-2520.816
	(0.013)	(0.402)	(26.023)	(1951.130)
Precipitation sq.	-0.184***	1.579***	7.184	2913.390*
	(0.011)	(0.344)	(22.273)	(1672.518)
Observations	3851	3851	3851	3851
Adjusted R^2				
AIC	.	.	.	.
BIC	.	.	.	.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.11: Impact of cover crops on mean, variance, skewness and kurtosis of soybean yield (Kinky Least Squares(KLS) with correlation = 0.1)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	-0.083	-1.515***	-2.261	-216.847***
	(0.096)	(0.587)	(7.385)	(82.426)
HDD	-0.174***	0.047	-0.830*	7.542
	(0.006)	(0.037)	(0.460)	(5.100)
GDD	0.025***	-0.002	0.193**	0.744
	(0.001)	(0.006)	(0.079)	(0.874)
Precipitation	0.041***	-0.078***	0.408	-7.898***
	(0.003)	(0.020)	(0.253)	(2.805)
Precipitation sq.	-0.038***	0.051***	-0.252	5.125**
	(0.003)	(0.017)	(0.211)	(2.346)
Observations	3851	3851	3851	3851
Adjusted R^2				
AIC	.	.	.	.
BIC	.	.	.	.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.12: Impact of cover crops on mean, variance, skewness and kurtosis of soybean yield (Kinky Least Squares(KLS) with correlation = 0.2)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	-0.275	-2.375*	-0.293	-432.382*
	(0.214)	(1.425)	(18.443)	(231.722)
HDD	-0.177***	0.072	-1.295**	15.796**
	(0.007)	(0.045)	(0.581)	(7.253)
GDD	0.025***	0.004	0.219*	1.217
	(0.001)	(0.009)	(0.114)	(1.421)
Precipitation	0.041***	-0.078***	0.448	-7.502**
	(0.003)	(0.023)	(0.298)	(3.712)
Precipitation sq.	-0.038***	0.048**	-0.286	4.537
	(0.003)	(0.020)	(0.255)	(3.175)
Observations	3851	3851	3851	3851
Adjusted R^2				
AIC	.	.	.	.
BIC	.	.	.	.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.13: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Corn Yield (Long-Difference Regression with Two Periods: 2005-2011 and 2012-2018)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.142*	-1.613***	-5.576	-1059.736***
	(0.076)	(0.556)	(17.683)	(365.706)
HDD	-0.270**	0.254	-98.490***	915.231
	(0.114)	(0.938)	(32.939)	(602.973)
GDD	0.172***	0.226***	-2.478	32.695
	(0.007)	(0.068)	(2.203)	(49.570)
Precipitation	0.129***	0.514	-8.366	522.140
	(0.043)	(0.347)	(14.640)	(329.840)
Precipitation sq.	-0.124***	-0.243	3.387	-301.188
	(0.032)	(0.237)	(9.770)	(215.342)
Observations	829	829	829	829
Adjusted R^2	0.778	0.132	0.025	0.070
AIC	5742.641	9120.390	15039.553	20013.410
BIC	5766.242	9148.711	15067.874	20041.731

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

Table A.14: Impact of Cover Crops on Mean, Variance, Skewness and Kurtosis of Soybean Yield (Long-Difference Regression with Two Periods: 2005-2011 and 2012-2018)

	Mean Yield	Variance	Skewness	Kurtosis
CC adoption	0.040*	-0.138**	-3.183***	-7.022**
	(0.023)	(0.067)	(0.798)	(2.983)
HDD	-0.012	-0.220**	-5.229***	-8.711*
	(0.040)	(0.106)	(1.089)	(4.706)
GDD	0.044***	0.054***	-0.191***	2.724***
	(0.002)	(0.011)	(0.070)	(0.713)
Precipitation	0.062***	0.007	0.404	1.631
	(0.013)	(0.033)	(0.357)	(1.504)
Precipitation sq.	-0.055***	-0.006	-0.399	-1.490
	(0.010)	(0.023)	(0.266)	(1.084)
Observations	829	829	829	829
Adjusted R^2	0.665	0.089	0.122	0.066
AIC	4066.828	5709.096	9698.845	12485.143
BIC	4090.429	5737.417	9727.167	12513.464

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: County fixed effects and a linear time trend are included in the specification but are not reported above. In each specification, standard errors are clustered by county.

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