Cover Crops and Interactions with Corn and Soybean Yields: Evidence from Satellite data in Indiana

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Abstract

This study explores the effect of planting cover crops to corn and soybeans on their yields in terms of mean effects and resilience to extreme wet and dry weather events. We combine OpTIS data and non-irrigated yield data reported by the RMA to carry out the study. Based on fixed effects and IV free estimates, we are able to show that cover crops do not have a significant positive impact on mean yields. However, we find that mean yields for both corn and soybeans are more resilient to both extreme wet and extreme dry conditions than for corn and soybeans acres not planted to a cover crop. Specifically, we find that planting both corn and soybeans to a cover crop reduces yield damage by roughly 0.7 percentage points when either extreme dry or extreme wet conditions occur, compared to acres for both crops not planted to a cover crop. Additional sensitivity analyses using IV free methods show that our results hold for 70% of the allowable range of endogenous correlation but the effect goes away if endogenous correlation is less that -0.4.

1 Introduction

To mitigate the increasing negative environmental impacts of crop production (e.g., chemical runoff, soil erosion) adopting conservation practices in farming has become a very important policy and research focus. However, the interest of farmers in adopting conservation practices is highly dependent on the potential on-farm benefits that these practices bring (Lee et al. 2018). Planting cover crops is one such practice which can minimize negative externalities of farming on the environment, and at the same time contribute to factors that promote crop resilience and productivity (Bergtold et al. 2012); Myers and Watts 2015; Wittwer et al. 2017). Cover cropping involves the planting of crops–generally legumes, grasses, or brassicas to cover the soil in the fallow period between the regular growing seasons of main cash crop. They are typically planted in the winter months. Cover crops have gained policy attention for their numerous environmental benefits such as reducing the loss of nutrient and mineral from soils, increasing water infiltration and retention (Kaspar et al. 2001) among other features. They have also been shown to have large scale environmental benefits through their ability to decrease soil loss and minimize externalities associated with modern, intensive agricultural production. Kaye and Quemada 2017 consider cover cropping as a climate-smart farming practice that can provide protection to crops against adverse weather events such as droughts and floods.

Despite all the potential benefits of cover crops, their rate of adoption has remained low in the United States (U.S.). According to the 2017 U.S. Census of Agriculture only 3.9 % of total cropland acres are planted to cover crops (Zulauf and Brown, 2017). The low adoption rates of cover crops nationally have prompted numerous studies to understand how well any benefits of cover crops translate to the farm environment. To this end, economists have investigated the impact planting covers have on crop yields, on farm profits and on yield and farm income risk. Consistent findings suggest that short term use of cover crops are associated with lower, or more volatile benefits than continuous long term use of the practice. However, studies by Boyer et al. [2018], analyzing field experiment data, suggest that uncertainty of the net benefits of cover crops exist even over a longer term period of use.

Some questions remain in light of these studies, such as whether findings will persist even in a farm environment. Additionally, while studies such as Boyer et al. [2018] have looked at the effect of cover crops on the variance of the yield distribution, questions still exist on how the yield of crops planted to a cover crop may perform in the presence of extreme risk events such as excess moisture or excess dry conditions. While many studies have claimed that cover crops can improve resiliency of farms against excessive dry and wet conditions (USDA, 2019; Myers and Watts 2015), these claims mostly rely on case studies of farmers obtained by interviewing them or through farm surveys. Quantitative empirical research to understand the true impact of cover crops on farm profitability and crop resiliency is lacking, especially on major crop production regions in the U.S. This study contributes to the existing literature in this regard. We attempt to shed some light on these fundamental questions that remain on the on-farm benefits of cover crops. To our knowledge, this paper is the first to investigate crop commodity yield resilience on commercial farms, planted to cover crops. Crop yields and cover crop observations for this study were collected from RMA actuarial data and the OpTIS satellite dataset respectively. Additionally, another contribution of this study is the utilization of a unique data set which encompasses a large crop production region and extends for a long time period. Most of the previous studies on the farm benefits of cover crops are limited to small regions and few years of data only. Therefore, our study contributes to the literature by being one of the first to analyse the on-farms benefits of cover crops along with their impact on farm resilience by utilizing a novel data set.

Findings from this study suggest no significant yield increasing effect occurs for corn and soybean yields when planted to a cover crop. However, we find increased yield resilience when corn and soybeans are planted to a cover. Our estimates suggest that both crops can have as much as a 5 percent decrease in damages due to drought and 7 percent decrease in damages due to excess moisture. In general, we consistently find that cover crops may actually protect row crops from the adverse impacts of extreme weather events. Hence, the empirical findings from this study provide validity to the numerous claims made by previous studies regarding the resiliency to unfavorable weather events provided by cover crops to the crop environment. Overall, our findings provide important insights on the potential benefits gained by adopting cover crops that can help policy makers design policies on conservation payment such that they are more effective in encouraging farmers to adopt cover crops to enhance farm resilience.

2 Background and Data

The empirical setting for this study is agricultural production in the State of Indiana. Based on the 2017 US Census of Agriculture, Indiana is the third-ranked state in terms of cover crop acreage (936,118), just behind Texas and Iowa. In Indiana, cover crops are planted close to row crop harvest in the fall, and are left to overwinter until they are either naturally winter-killed by harsh winter weather or terminated/killed using herbicides in the spring. Several species of plants can be used as cover crops, and the mix of cover crops can be catered to fit the particular needs of the farmer. Common plant species used as cover crops in Indiana include annual ryegrass, fall-seeded cereals, late summer-seeded spring oats, and legumes planted in the late summer or early fall for nitrogen fixation (Mannering et. al., 2000; Lira and Tyner, 2018).

2.1 Data Description

For this study we use county level panel data set spanning from 2006 to 2015, obtained from a variety of sources which are discussed below. As mentioned earlier, this paper investigates the effect of planting cover crops on crop yield which makes mean crop yield our main dependent variable. Our study focuses on two crops–corn and soybeans, in the state of Indiana. The county level mean yield data for the two crops is obtained from the US Department of Agriculture (USDA) National Agricultural Statistics Service (NASS).

County level data for our main independent variable (i.e., cover crop acreages) are drawn from the Operational Tillage Information System (OPTIS) developed by Dagan Inc.®, Applied Geosolutions (AGS). Remotely sensed (satellite-based) data of conservation practices in agricultural systems is produced by OPTIS, which also includes the data of cover crops planted in winter. The OPTIS calculations are performed and validated at the farm-field scale while also maintaining the privacy of individual producers by aggregating the results at the county level or higher (Hagen et al. 2020). In this study, the county-level OPTIS cover crop acreage data covers 83 counties in the state of Indiana.

To validate the cover crop adoption data from OpTIS, comparisons were done with photo and roadside survey information collected for many representative counties at the field level (see Hagen et al. [2020] for more details on the validation procedure). Hagen et al. [2020] suggest that the validation analysis performed on the full OpTIS data (in over 30 counties across twelve states on 1195 fields) showed that the remote sensing based OPTIS cover crop adoption data is 87.9 accurate. It is important to note that regardless of the relatively high accuracy of the OpTIS cover crop adoption data based on field level validation, there are still known differences between the OpTIS estimated cover crop adoption acres vis-'a-vis other aggregate cover crop data sets (i.e., like those from the Census of Agriculture (AgCensus) and data collected by the Environmental Working Group (EWG)) (Hagen et al. 2020). Differences in the data collection methods are likely responsible for the discrepancies in the estimates of cover crop adoption rate among these data sets. For example, the AgCensus data is obtained from the survey of complete census of growers and likely records their intent to grow cover crops, and/or whether they have planted cover crops already at the time of survey. So, a record of adoption in the AgCensus can mean that a farmer responded that he/she planted (or intend to plant) cover crops in the winter. However, it is likely that due to some unfavorable weather condition, cover crops couldn't properly establish in the field such that it can be detected by the satellites. In a case like this, AgCensus will register a cover crop but OPTIS won't. Despite these potential differences, Hagen et al. [2020] reports that the OPTIS data is still highly correlated with both the AgCensus and EWG data.

The OpTIS cover crop data utilized in this study spans from crop year 2006 to 2015. In the OpTIS data set, a crop year represents the time period starting from November 1 of the previous year through October 31 of the year when the subsequent cash crop is planted. For example, the 2012 crop year starts from November 1, 2011 and ends on October 31, 2012. Cover crop planted in the winter months after the harvest of the cash crop from the previous year and before planting of the subsequent cash crop is recorded in this data. Additionally, the OpTIS cover crop data is classified on the basis of the row crop planted on the previous year – which is corn and soybeans in this study. As such, the OpTIS cover crop adoption data for soybeans in crop year 2012 reflects the cover crop detected by the satellites starting in November 2011, after the harvest of soybeans in the Fall of 2011. In the present study, we specifically utilize information on: (a) the proportion of cover crop acres planted after corn, and (b) the proportion of cover crop acres planted after soybeans.

As mentioned in the previous section, we are interested in the yield performance of crops planted to a cover crop during extreme weather events such as excess moisture and excess dry conditions. As such, besides cover crop acres, our independent variables of interest are measures of excess moisture and drought conditions respectively. In this study, we construct these two variables using the Palmer Drought Severity Index (PDSI). PDSI values indicates the comparative climatic condition with respect to long-term average conditions for a region[1]. As PDSI value at a particular time is a combination of current values and past conditions, it indicates the progression of climate trends (i.e. whether it is a dry spell or a wet spell) Ding et al. [2009]. PDSI is constructed from gridded temperature and precipitation data aggregated to county level and county-level Available Water Content (AWC) of the topsoil. PDSI value ranges from 4.0 to -4.0, with a positive value indicating wet and a negative value indicating dry conditions. Increases in the absolute value of the PDSI represent increasing wet and dry conditions respectively. PDSI values more than 2 indicates moderate wet and less than -2 indicate moderate drought conditions (Palmer, 1965). However, for this study, we follow (Schoengold, Ding and Headlee, 2014) to adjust the PDSI threshold levels for excess dry and moist conditions, given that the distribution of our PDSI data doesn't fit the normal distribution centered with zero mean. To be specific, PDSI threshold values are set at -2.5 and 2.5 for drought and excess moisture respectively. In addition to the drought and excess moisture data, we also use other weather controls that also influence the yield of the cash crops we examine. Weather data utilized to construct key weather covariates were obtained from the Parameter Regression Independent Slopes Model (PRISM) climate group. Numerous studies have utilized this data source to investigate various climate change issues over the years (See Annan and Schlenker [2015] for example) and is considered as one of the best sources of weather and climate related data. The weather constructed weather covariates include precipitation (in mm), temperature (in F) growing degree days (GDD), and heating degree days (HDD).[2]

For precipitation and temperature variables, we follow the crop yield model given by Westcott and Jewison (2013) where they have found that in-season rainfall and temperature conditions for particular months highly influence the yield for corn and soybeans. Following that, we include total precipitation and mean temperature for the month of June as controls for the corn yield model and, total precipitation and mean temperature for the months of July and August combined for soybean model. We also include winter precipitation (precipitation occurring in the months January to April) to control for the wet conditions in winter months that can constrain fieldwork before planting the cash crops. It can lead to delay in planting

[1] Further background on the PDSI can be found at the National Center for Atmospheric Research (NCAR) website: `https://ncar.ucar.edu/`

[2] GDD represents the number of degree days in the season where temperature is between 10 degrees Celsius (ºC) and 29ºC. On the other hand, HDD represents the number of degree days in the season where temperature is above 30ºC. HDD essentially represents the days with temperatures potentially harmful to the cash crop, and GDD is more moderate temperatures that are not harmful to the crop.

and potentially affect crop yields. Table 1 presents the summary statistics for all the variables used in our empirical study.

3 Empirical Strategy

We estimate the effect of cover crops on crop yield at the county-level according to the following specification:

$$\tilde{y}_{it} = \beta CC_{it} + \gamma X_{it} + u_i + \tau_t + \varepsilon_{it} \quad (1)$$

where: $\tilde{y}_{it}$ is the log of average RMA detrended non-irrigated yields in county i for year t, CC_{it} is the proportion of the cash crop acres planted with cover crops in county i for crop year t, X_{it} is a vector of weather controls, u_i is a vector of county fixed effects, τ_t is a vector of year fixed effects, and ε_{it} is the idiosyncratic error term.

The vector X_{it} in equation 1 includes pre-season, within season and end of season/harvest weather controls. These weather variables are included since weather and environmental conditions before, during and at harvest can affect crop yields. The weather variables included in the specification are: precipitation (in mm), the square of precipitation, GDD (in days), and HDD (in days). Winter precipitation can delay planting, reducing yields, and may also encourage the use of cover crops under RMA prevent plant rules. As such we include the cumulative precipitation over the winter months to account for such events. Similarly, we include total precipitation and mean temperature for the month of June for corn and, the total precipitation and mean temperature for the months of July and August combined for soybean.

Additionally, we include indicators of excess moisture and drought. As previously defined, the drought and excess moisture are taken to be county/year observations where the PDSI exceeded an absolute value of two (PDSI < -2.5 for drought and PDSI $> +2.5$ for excess moisture). Of interest is the interaction of our cover crop variable with our measures of drought and excess moisture which we include in our analysis. This variable measures the effect on corn or soybean yields as the proportion of cover crops adopted changes. Hence, the variables CC_{it}, $CC_{it} * Drought$ and $CC_{it} * ExcessMoisture$ measure the average response of yields to changes the proportion of cover planted acres with cover crops. $CC_{it} * Drought$ and $CC_{it} * ExcessMoisture$ measure the performance of yields in the event of a drought or excess moisture event. Hence, CC_{it} allows us to determine the effect of cover crops on yields while $CC_{it} * Drought$ and $CC_{it} * ExcessMoisture$ allow us to assess the effect of cover crops on risk in a fashion less well investigated in the literature by investigating the impact of cover crops to specific events associated with downside risk in crop production.

3.1 Endogeneity Factors

To this point our procedures have controlled for fixed factors and year specific factors that can bias estimates in our models. These county and year specific factors are likely to be primarily related to farm management practices and annual fluctuations in external production pressures such as pest pressure. Each can also affect propensity to adopt cover crops. However, our fixed effects modelling will also account for other county fixed and year specific factors. Factors that are neither fixed at the county level nor vary uniformly across counties, remain unaccounted for in our modelling.

Bias in empirical analysis occurs when assumptions of zero correlation between regressors and the error term is violated $E(X\varepsilon) = 0$ fails. Instrumental Variables (IV) procedure is often relied upon to overcome potential bias in estimations but requires the identification of an instrument that is both strong (correlated with the dependent and endogenous variables) and satisfies the exclusion restriction (uncorrelated with unobserved factors excluded from the estimation model). It can often be difficult to identify such a variable and even then, be difficult to verify that each requirement of a good instrument is satisfied, chief among those is that correlation between the error term and included regressors has been fully eliminated. Kripfganz and Kiviet [2021] introduced a procedure that allows for the estimation of econometric models, correcting for correlation bias spanning the interval [-1,1]. According to Kripfganz and Kiviet 2021, if we have some prior knowledge about the range of endogeneity correlations for our endogenous variable, KLS confidence intervals and test procedures can produce reliable estimates.

More formally, in the model specified in equation 1, with CC_i [3] as our potentially endogenous variable, and ϵ_i as our error term, valid inference through an instruments based approach with IVs z_i requires orthogonality conditions for the instruments: $E(z_i\epsilon_i) = 0$. However, the KLS method uses a non-orthogonality condition for the endogenous variable in equation 1: $E(CC_i\epsilon_i) = \rho\sigma_1\sigma_\epsilon$, where ρ is the correlation coefficient between CC_i and ε_i, and σ_1 and σ_ϵ are the standard deviations (SD) of CC_i and ε_i respectively. As described in Kripfganz and Kiviet 2021 we can easily calculate σ_1 and σ_ϵ from equations 2 and 3 respectively.

$$\hat{\sigma}_1^2 = N^{-1}\sum\nolimits_{\imath=1}^{N} CC_i^2 \tag{2}$$

$$\hat{\sigma}_\epsilon^2(\rho) = \hat{\sigma}_{\epsilon,OLS}^2\left(1 - \rho^2\frac{\hat{\sigma}_1^2}{\hat{\sigma}_1^2 - \hat{\sigma}_{12}'\hat{\sum}_2^{-1}\hat{\sigma}_{12}}\right)^{-1} \tag{3}$$

where $\hat{\sigma}_{\epsilon,OLS}^2$ is the variance estimate from the OLS residuals. Because OLS is inconsistent when $\rho \neq 0$, the OLS variance estimate needs to be adjusted. The adjustment term is calculated using covariance estimates obtained from the endogenous variable CC_i and the vector of control variables X_i, which is utilized to obtain our KLS estimates. KLS estimates are obtained in the form of coefficients β=(β_1, β_2). The KLS estimator is asymptotically normally distributed with a variance covariance matrix, from which we obtain our estimate of variance.[4] However, we still need the value of correlation coefficient (ρ), which is not attainable without imposing additional restrictions. Instead of striving for a point estimate for ρ ($\rho = r$), it is assumed that the true value is encompassed within a set $\rho \in [r_l, r_u]$. A prior information about the magnitude or sign of the endogenous correlations will allow us to

[3] for the ease of presentation we exclude the time factor (t) for the equations for our KLS estimation procedure

[4] see Kripfganz and Kiviet 2021 for a detailed procedure to calculate the KLS estimator and the variance estimate

specify the plausible boundaries for this interval. Now we can attain the KLS estimator $\hat{\beta}(r)$ for the specified range of values $r \in [r_l, r_u]$. Now, using the variance estimates, confidence intervals can be produced.

In addition to that, we can also graph the coefficient estimates with corresponding confidence intervals for the specified range of endogeneity correlations. One example of such graph is Figure 3. This graph illuminates immediately the sign and magnitude of our coefficients when we have a prior knowledge about the degree of endogeneity. We utilize this procedure as a robustness check for our primary results. Additionally, with the use of the Indiana Tillage Transect dataset, we inspect the ability of the IV free procedure to correct for biases caused by any measurement errors in the OpTIS data.

4 Results and Discussion

4.1 Base Model and Sensitivity Analysis

Estimated parameters of linear fixed effects results with and without year fixed effects, as part of our sensitivity analysis, are presented in Table 2 and Table 3 for corn and soybeans respectively. Our results show that planting corn and soybean to a cover crop increases yields (mitigates damage) relative to the same crops not planted to a cover during extreme wet or dry conditions. That is our results indicate that a 1 percentage point increase in cover crop acreage increases crop yields during a drought ~ 0.62 percentage points for soybeans. However, during drought we do find any statistically significant effect of cover crops on crop yield for corn when we control for time variant effects. While not controlling for year specific effects, our results show that a 1 percentage point increase in cover crop acreage increases crop yields during a drought ~ 1.38 percentage points for corn, which is comparatively higher than the effect observed in soybeans. Our results further show that cover crop increase soybean yields by ~ 0.51 percentage points during extreme moisture stress conditions with a relatively stronger effect on corn showing a ~ 0.75 percentage point increase in yields.

Our results do not support a consistent and statistically strong yield increasing effect of corn or soybeans planted to cover crops. While planting soybeans to a cover crop appears to increase soybean yields in three of our four specifications, the effect goes away when accounting for the effect of the cover crops during extreme weather (moisture and dry) conditions and controlling for year specific effects. This may imply that the effect of crops planted to a cover during extreme weather years may be driving the result on the average effect rather than yield being improved unconditionally. This is an important result to note for other studies as the performance of cover crops in extreme years can affect estimates of the overall yield effect, skewing results.

Our main findings concur with previous agronomic studies suggesting that planting cover crops is a 'climate-smart' farming practice which can reduce the negative impacts of extreme weather conditions (Kahimba, F. C. et al. 2008; Kaye and Quemada 2017; Volpi et al. 2017; Basche and DeLonge 2019). Our results show that cover crops provide resiliency to corn and soybean crop against excess moisture conditions. This finding supports the common claim made by previous agronomic studies that planting cover crops enhance the water infiltration rate in soil and improves the transpiration rate, which is crucial in reducing the adverse impacts of excess moisture conditions (Kahimba, F. C. et al. 2008; Volpi et al. 2017; Basche and DeLonge 2019). Similarly, our results also demonstrate that cover crops can mitigate yield loss in corn and soybeans due to drought. As cover crops are perceived to improve the water holding capacity of soil (Basche and Edelson 2017), it provides protection to crops during dry conditions which is supported by our results. Overall, our findings provide empirical evidence that cover crops protect crops from the negative impacts of extreme weather conditions such as drought and excess moisture, maintaining consistency with previous agronomic findings. Regarding the weather controls included in our analysis, their effect on county level yield is largely on par with our expectations. The impact of degree days on crop yield is non-linear, as heat up to a certain level is beneficial for yield, and excessive heat beyond a threshold level has a damaging effect. Results in Table 2 and Table 3 show that GDD (i.e., moderate temperature) has a positive and significant effect on yield for both corn and soybeans, whereas the effect of HDD (i.e., higher temperature) on yield is negative and significant. However, for corn, we can notice in Table 2 that the coefficient for GDD is positive and significant only when the year is fixed in the model. This explains that there is some heterogeneity due to time-variant unobservables, that are not included in our model, and only after we control for the heterogeneity for corn, our estimates follow our expectations.

Our assumptions of the primary endogenous (with yield outcomes) factors affecting adoption of cover crops are farm management, soil quality and climactic factors, all of which are relatively fixed over time. Hence our fixed effects specification allows us to control for such factors. Our inclusion of year fixed effects allows us to control for year specific events which may include early season factors that affect planting dates and or encourage the use of cover crops as prescribed by RMA prevented planting rules. Nevertheless, there still remains the potential for additional time varying endogenous factors to affect our results. In light of this we we perform a few robustness checks to verify our results. First, data quality is often a concern for the OpTIS data. we perform our estimation with the use of a secondary dataset, the Indiana Tillage Transect (TT), which is a dataset produced annually from a survey administered by the Indiana State Department of Agriculture. While some measurement error likely exists in the TT data, the sources of measurement error in the TT dataset are likely to be unrelated to the sources of measurement error in the OpTIS data and reduce concern of measurement error driving our results. Second, we utilize a the recently introduced IV free regression technique called Kinky Least Squares (KLS) to inspect the behavior of our coefficient of interest under various bias correlation assumptions.

4.2 Robustness Check: Tillage Transect Comparison

Table 4 presents the results from the comparative analysis of OPTIS data and the TT data. The TT data set began tracking cover crop acres in 2014. Hence we compare the results obtained from the two data sources for 2014 and 2015.[5]. Results in Table 2 and Table 3 support the idea that cover crops do not contribute to overall yield gains once we account for potential downside risk factors and control for heterogeneity across time. However, we do find a positive and significant effect of cover crops on corn and soybean yields during

[5]Based on the definitions used for drought (PDSI < -2.5) in this study, no drought events were observed in the 2014-2015 window and so we only compare protection from excess moisture

periods of excess moisture exposure. Results in Table 4, however, are different for corn but are similar to the base model results for soybeans. For soybeans, we can see that cover crops mitigates yield loss caused by excess moisture conditions for both OPTIS and TT data but we do not find any loss mitigating effect of cover crops against excess moisture for corn in any of the two data set. Since we're using only two years of data for this comparative analysis, it is highly likely that we are not being able to capture the true effect of cover crops on crop yield and hence getting unexpected results. The incidence of excess moisture events in these two years is also very low, which also might be driving our results showing the lack of statistical significance of the resilience provided by cover crops against excess wet conditions for corn. Nevertheless, the result for soybeans provides strong support to our primary finding that planting cover crops protects crops from yield loss during extreme moisture events.

4.3 Robustness Check: IV Free Estimation

We perform one final analysis using the IV free estimation procedure. Rather than relying on exclusion restriction assumptions, the IV free regression allows us to investigate the range of possible coefficient estimates based on a range of allowable coefficient correlation bias assumptions.

Results from the IV free analysis suggest that a negative bias correlation would produce a positive estimate of the effect of cover crops on corn and soybean yields. The effect decreases in bias correlation and shows a negative effect of cover crops on yield if bias correlation is positive. For both corn and soybeans, a bias correlation of greater than ~ -2.0 produces a positive and significant estimate for the effect of cover crops on corn and soybean yield during times of extreme moisture. We obtain a narrower band of significance on the effect of cover crops on corn and soybean yields where a significant effect is observed at bias correlation values of greater than ~ -1.7.

Comparing densities, shown in Figure 1 and Figure 2 for tillage transect and OpTIS lends some support that significant positive bias correlation lies in our data due to measurement error. The densities show that the OpTIS data tends to underestimate observations of cover crop acres, a common issue when using satellite imagery estimates as pointed out in (). The effect is an inflation of the coefficient estimates. The tillage transect data shows that this leads to inflated (positively biased) coefficients. Compared to the tillage transect data, the OpTIS data has a greater positive skew in outcomes comparatively. Using this information, our primary assumption at this from this point in the analysis onward is that the primary bias correlation in our sample is positive (and potentially due to downward biased measurements that lead to inflated coefficient estimates). In this range the OpTIS data most closely reflect the behavior of the Tillage Transect data where the effect of cover crops on mean yields tends towards the negative. In light of this we restrict our analysis to bias estimates in the positive correlation region of the allowable range. OpTIS results more closely reflect Tillage Transect coefficients in this range. We note that for positive bias correlation, the effect of cover crops on corn and soybean yields is negative. However, the effect of cover crops and yield resistance to both drought and extreme weather increases in both magnitude and significance as positive correlation increases.

4.4 Robustness Check: Scale effects

Our primary estimates show that cover crops reduces crop stress induced by extreme weather events. Yet, it is likely that potential scale effects (larger counties have more crop acres, and seemingly have less proportion of damages during drought and/or excess moisture) might be influencing the result instead of cover crop adoption. If we can show that the size of farm acres have no effect on the yield loss for soybean and corn during abnormally dry and/or wet spells, we can easily refute the existence of scale effect of any magnitude. For that, we conduct a robustness test by utilizing an alternative specification to our base model represented in equation 1, where our dependent variable (crop yield) is the same but instead of cover crop adoption rate (CC_{it}), we keep total planted acres as our main independent variable of interest. Our other important variables of interest are the interaction terms of planted acres with excess moisture ($Plantedacres * ExcessMoisture$) and drought ($Plantedacres * Drought$). For this analysis we use normalized planted acres and cover crop acres. A positive and significant value for coefficients of the interaction terms would mean that the protection observed against yield loss attained due to cover cropping as shown by our results may not actually be true and the beneficial effect on crop yield is influenced by the increase in planted acres of cash crops. Specifically, this would imply that with or without cover crops, larger counties with larger acres planted to cash crops are more resilient to extreme dry or wet conditions. Results for the scale effect test are presented in **??**.

Our results show that increase in planted acres do not have any effects on both corn and soybean yield. During excessive wet conditions, scale effect do not exist for both crops, whereas increase in crop acres on a county level is found to reduce drought stress for both crops. Scale effect observed during drought might be due to the insufficient data for drought since we only have one extreme dry year in our dataset, which is 2012. The result for yield effects during excess wet conditions provides further validation to the loss mitigating effect of cover crops we initially find using our main FE estimation procedure.

5 Conclusion

In this paper we explored the response of county level yields of corn and soybeans planted to cover crops. We use OpTIS cover crop acre data and RMA yield data to conduct our study. Our findings suggest that cover crops do not have a statistically significant (positive) effect on corn or soybean yields. We find however, that corn and soybeans planted to a cover crop show increased resilience to exposure to drought or excess moisture conditions. Our findings are corroborated by previous studies which have found that cover crops enhance soil properties like increased water infiltration, increased soil organic matter, and higher water holding capacity (Hoorman 2009), which are the vital underlying mechanisms in soil to protect the crop against both excess dry and moist conditions. Our results show that corn and soybeans planted to a cover crop have on average a decrease of 0.7% in drought damages for both corn and soybeans and a decrease of about 0.5% in excess moisture damage. We verify these results with the use of an alternate dataset where measurement error is likely less severe. We use those results posit a suggest bound on the bias correlation and for an IV free regression. Constraining our bias correlation to be positive we confirm the findings shown from both the OpTIS and tillage transect data which show that mean yields remain relatively unaffected by cover crops but that corn and soybeans planted to a cover crops show resilience in the presence of excess moisture and dryness.

Our findings could inform policy makers to better manage extreme weather risks, which is very important in the current climate change scenario where abnormally dry and wet spells are becoming more frequent. In particular, this study shows that planting cover crops can help mitigate loss in crop yield caused by extreme weather events to some extent. In addition to providing environmental benefits, private benefits in the form of improved crop yield resiliency provided by cover crop adoption supports the continued provision of government cost-share programs like the Environmental Quality Incentives Programs (EQIP) and Conservation Stewardship Program (CSP) for producers adopting cover crops. Similarly, both on-farm and off-farm benefits gained by adopting cover crops can act as an policy instrument for the government to integrate the practice with other federally subsidized agricultural programs. For example, to farmers experiencing reduced crop yield risks during extreme weather events by growing cover crops, special discounts on crop insurance premiums can be provided.

There are some caveats in our analysis. Since this study specifically focuses on the cover crop adoption effect on crop yield in the state of Indiana only, the observed effects may not translate to other states with different climatic and crop growing conditions. We might need a data set for a longer time period and covering a wide geographical region to better estimate the effects of cover crops on crop yields during extreme weather conditions. Similarly, using other indexes to measure drought and excess moisture can also provide more validity to our estimates. Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI) have been used widely in literature to measure drought, and using them along with PDSI can potentially capture the yield losses in corn and soybeans due to excess dry/wet conditions. Furthermore, using farm-level data might help us better estimate the resiliency provided by cover crops, compared to the county-level data, considering the weather and farm related factors influencing crop yield are more homogeneous in a farm-level scenario. In addition to that, a farm-level data can also facilitate the estimation of the true effect through the comparison between a control and and a treatment group in terms of cover crop adoption.

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Table 1: Summary Statistics of Variables

	Mean	SD
Cover crop acres for corn	.0506788	.0609029
Cover crop acres for soybeans	.0601965	.0618688
Corn acres	70285.55	33227.01
Soybean acres	63363.88	26098.44
PDSI	.8600746	1.541689
GDD	159.2283	29.36898
HDD	1.880768	4.837043
July mean temperature	23.36328	2.142814
July precipitation	100.8263	51.33158
July-August mean temperature	23.05202	1.55507
July and August precipitation	92.26573	34.01799
Winter precipitation	103.7567	29.70818
Observations	828	

Table 2: Sensitivity analysis: Corn Yield

	Model 1	Model 2	Model 3	Model 4
Percent Cover Crop Acres	-0.336**	-0.0908	-0.412***	-0.188
	(0.129)	(0.131)	(0.132)	(0.137)
Excess Moisture	-0.0664***	-0.0453***	-0.0850***	-0.0838***
	(0.0197)	(0.0158)	(0.0285)	(0.0235)
Drought	-0.0228	0.0280	-0.172**	-0.0434
	(0.0684)	(0.0570)	(0.0799)	(0.0811)
Excess Moisture X Percent CC Acres			0.316	0.751***
			(0.294)	(0.283)
Drought X Percent CC Acres			1.382**	0.633
			(0.548)	(0.393)
GDD	-0.00146***	0.00552***	-0.00143***	0.00542***
	(0.000340)	(0.00126)	(0.000352)	(0.00122)
HDD	-0.0306***	-0.0221***	-0.0315***	-0.0223***
	(0.00305)	(0.00234)	(0.00312)	(0.00247)
Winter Precipitation	-0.00115***	-0.000285	-0.00112***	-0.000341
	(0.000299)	(0.000354)	(0.000305)	(0.000352)
Constant	5.819***	3.924***	5.811***	4.058***
	(0.124)	(0.349)	(0.126)	(0.328)
Observations	790	790	790	790
No. of counties	83	83	83	83
Year FE	No	Yes	No	Yes

Standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01

Table 3: Sensitivity analysis: Soybean Yield

	Model 1	Model 2	Model 3	Model 4
Percent Cover Crop Acres	0.403***	0.259**	0.314***	0.170
	(0.105)	(0.115)	(0.109)	(0.117)
Excess Moisture	-0.0332***	-0.0253**	-0.0710***	-0.0597***
	(0.00958)	(0.0100)	(0.0169)	(0.0152)
Drought	0.0427	0.0217	-0.0288	-0.0496
	(0.0474)	(0.0447)	(0.0683)	(0.0630)
Excess Moisture X Percent CC Acres			0.554***	0.508***
			(0.144)	(0.152)
Drought X Percent CC Acres			0.624*	0.619**
			(0.338)	(0.298)
GDD	0.000770***	0.00494***	0.000747***	0.00474***
	(0.000271)	(0.000747)	(0.000275)	(0.000732)
HDD	-0.0122***	-0.00923***	-0.0120***	-0.00931***
	(0.00122)	(0.00145)	(0.00122)	(0.00147)
Winter Precipitation	-0.000327**	0.000873***	-0.000366**	0.000825***
	(0.000161)	(0.000263)	(0.000162)	(0.000258)
Constant	3.902***	5.165***	3.890***	5.072***
	(0.0859)	(0.402)	(0.0850)	(0.375)
Observations	796	796	796	796
No. of counties	84	84	84	84
Year FE	No	Yes	No	Yes

Standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01

Table 4: Sensitivity Analysis: Tillage Transect Data

	OpTIS: Corn	OpTIS: Soybeans	TT: Corn	TT: Soybeans
Cover Crop Acres: OpTIS	1.197***	0.599**		
	(0.293)	(0.270)		
Excess Moisture X OpTIS CC	-0.00649	1.637***		
	(0.484)	(0.397)		
Cover Crop Acres: TT			-0.363	-0.264
			(0.257)	(0.162)
Excess Moisture X TT CC			1.245	0.664**
			(0.862)	(0.282)
Excess Moisture	-0.0981*	-0.112***	-0.186**	-0.123***
	(0.0502)	(0.0248)	(0.0716)	(0.0405)
GDD	0.0110*	0.00921***	0.00387	0.00678**
	(0.00565)	(0.00264)	(0.00581)	(0.00296)
HDD	0.159***	0.0179	0.0988*	0.0247
	(0.0447)	(0.0306)	(0.0559)	(0.0278)
Winter Precipitation	0.000387	-0.000318	0.000425	0.0000753
	(0.00163)	(0.00104)	(0.00133)	(0.00105)
Constant	4.034***	5.901***	4.011***	6.565***
	(1.121)	(0.847)	(1.279)	(1.076)
Observations	151	153	151	153
No. of counties	79	78	79	78
Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Scale effects

	Corn Model 1	Corn Model 2	Soy Model 1	Soy Model 2
Planted acres	0.214	0.250	-0.180	0.0159
	(0.160)	(0.173)	(0.109)	(0.0986)
Excess Moisture	-0.0253	-0.0246	0.0222	0.0250
	(0.0331)	(0.0380)	(0.0229)	(0.0183)
Drought	-0.276	-0.463***	-0.157	-0.166
	(0.169)	(0.161)	(0.113)	(0.126)
Excess Moisture X Planted Acres	-0.0542	-0.130	-0.0955**	-0.118***
	(0.0794)	(0.1000)	(0.0419)	(0.0415)
Drought X Planted Acres	0.845**	1.187***	0.351**	0.415**
	(0.395)	(0.358)	(0.165)	(0.183)
Percent Cover Crop Acres	0.00286	0.0497*	0.00507	0.0417**
	(0.0254)	(0.0288)	(0.0190)	(0.0188)
GDD	0.00539***	-0.000947***	0.00464***	0.000861***
	(0.00124)	(0.000314)	(0.000740)	(0.000245)
HDD	-0.0230***	-0.0321***	-0.00839***	-0.0107***
	(0.00234)	(0.00282)	(0.00133)	(0.00105)
Winter Precipitation	-0.000283	-0.00101***	0.000948***	-0.000459***
	(0.000346)	(0.000301)	(0.000256)	(0.000159)
Constant	3.974***	5.874***	5.141***	3.930***
	(0.332)	(0.107)	(0.377)	(0.0777)
Observations	790	790	796	796
No. of counties	83	83	84	84
Year FE	Yes	No	Yes	No

Standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

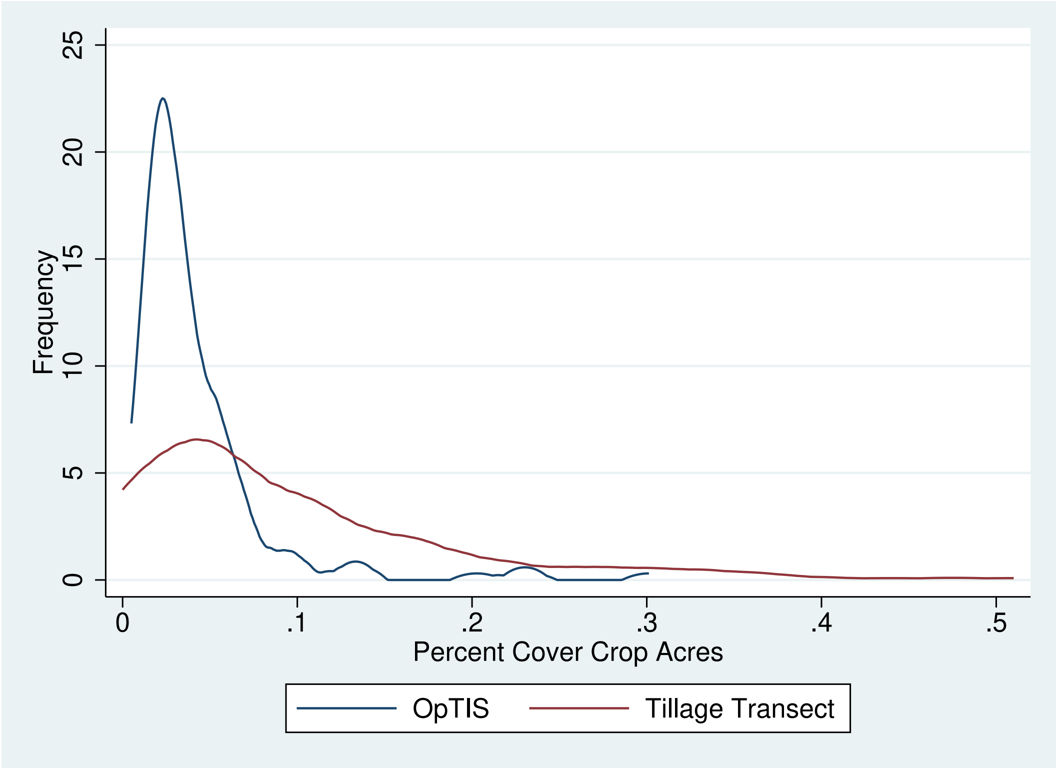

Figure 1: Kernel Density Comparing Tillage Transect and OpTIS data for Corn

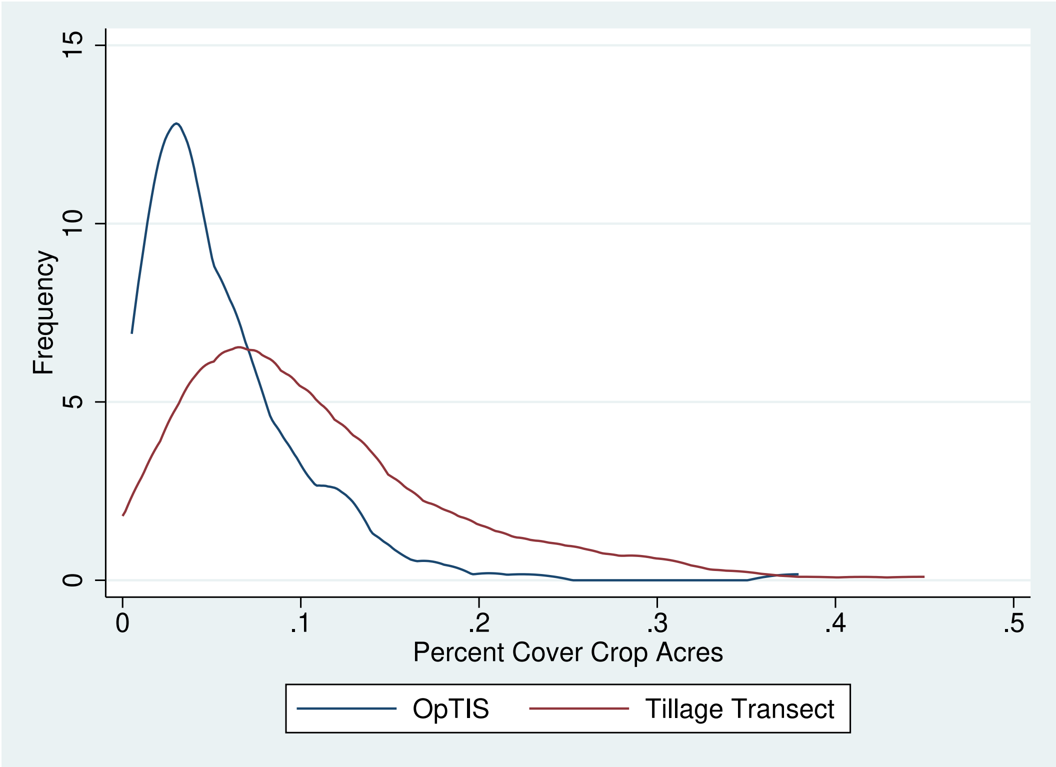

Figure 2: Kernel Density Comparing Tillage Transect and OpTIS data for Soybeans

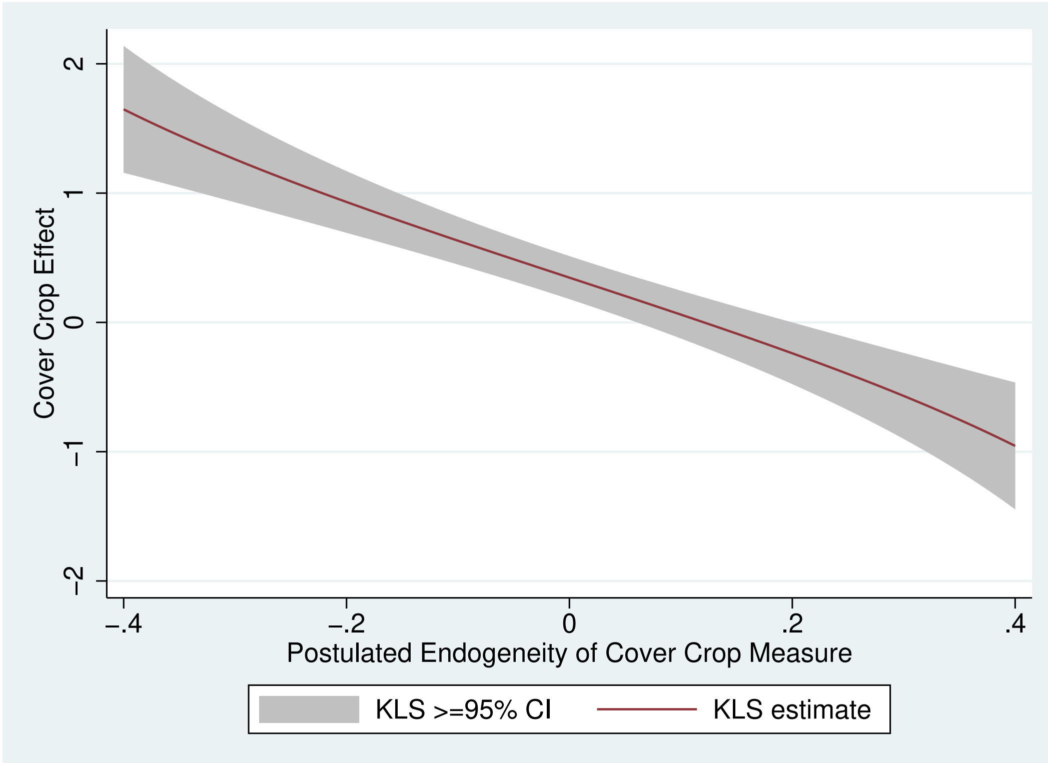

Figure 3: IV Free Regression: Effect of Cover Crops on Corn Yield

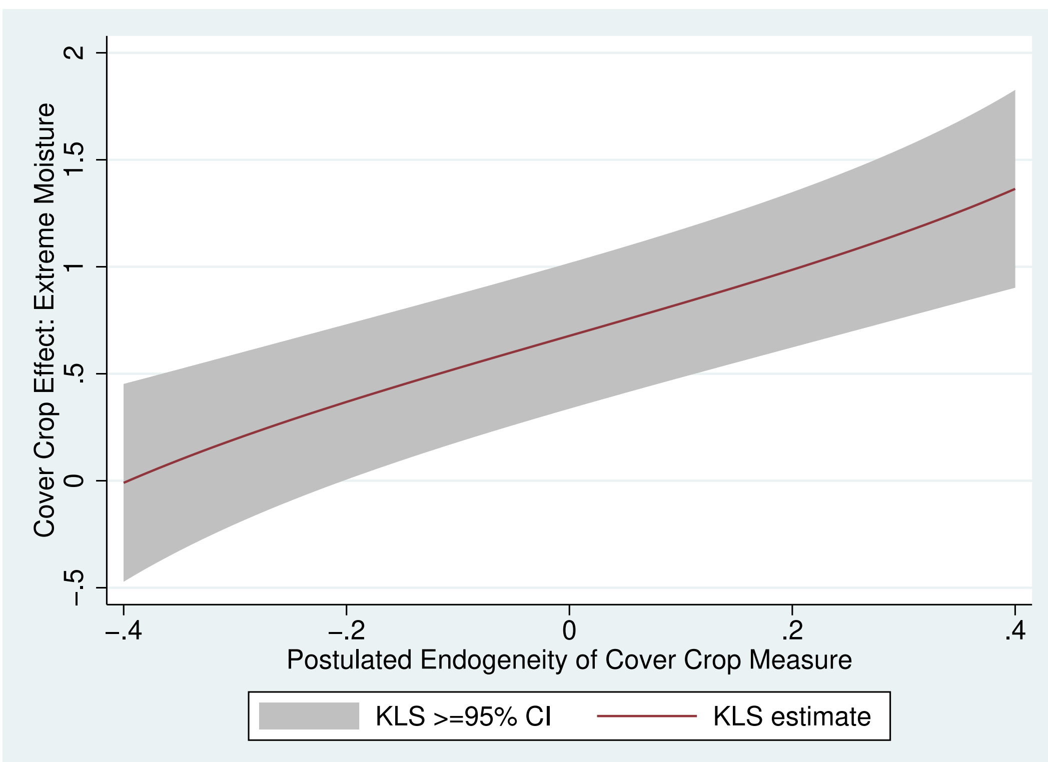

Figure 4: IV Free Regression: Effect of Cover Crops on Corn Yield under Extreme Moisture

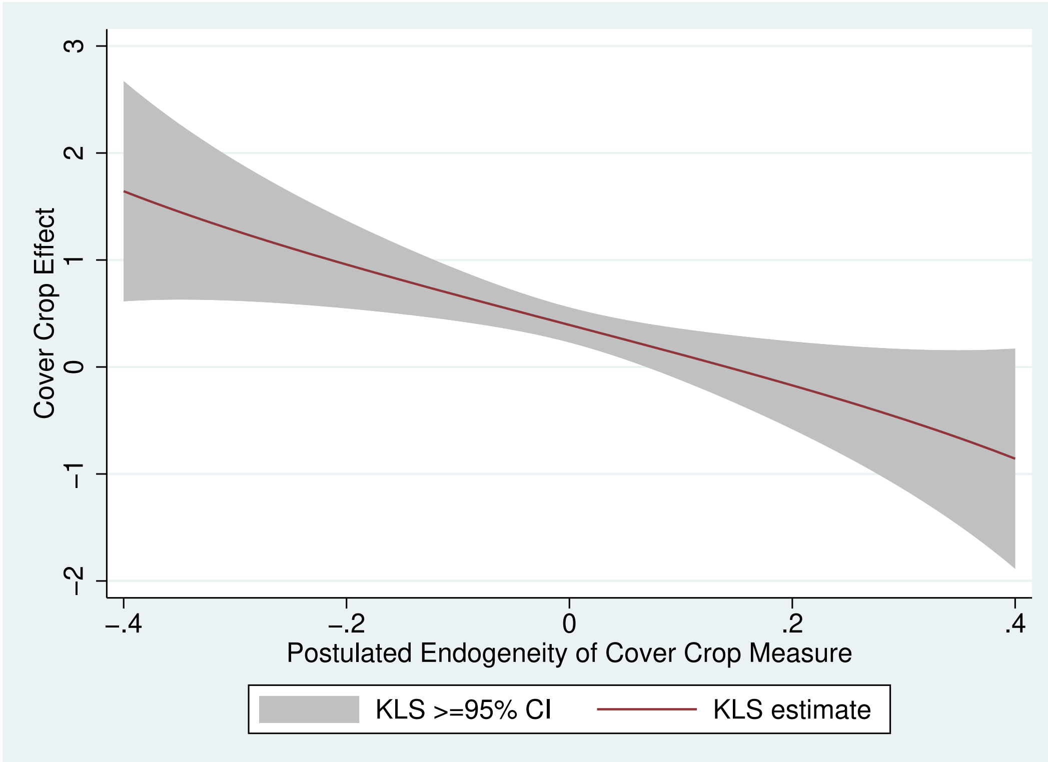

Figure 5: IV Free Regression: Effect of Cover Crops on Corn Yield

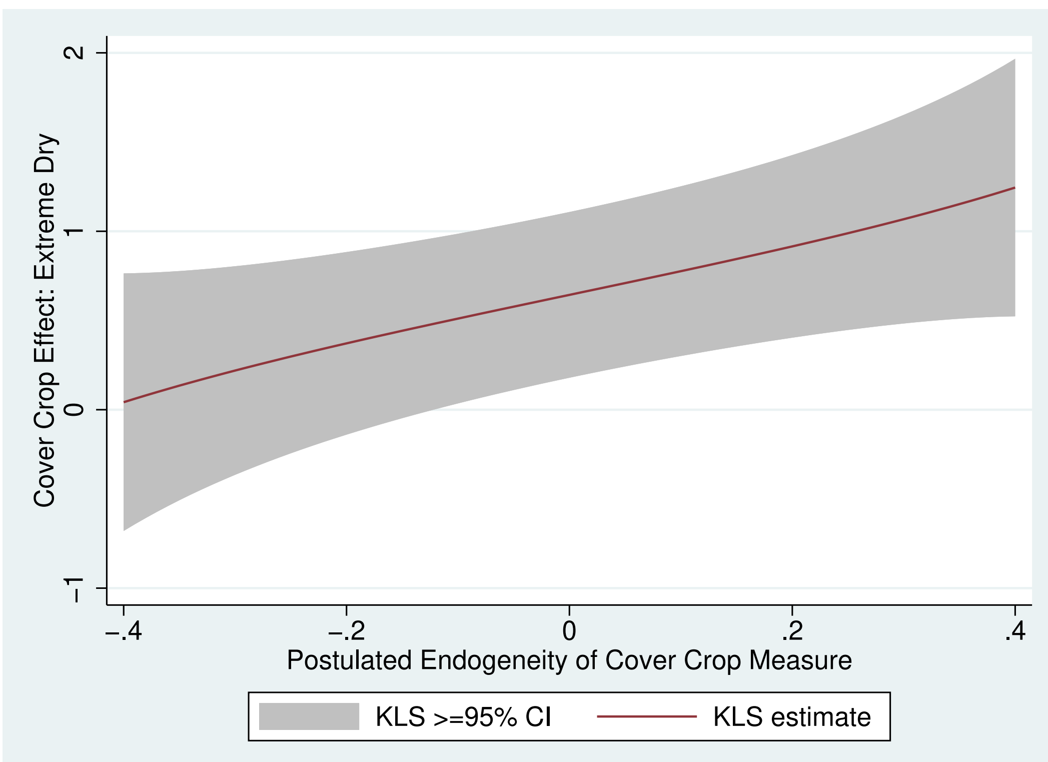

Figure 6: IV Free Regression: Effect of Cover Crops on Corn Yield under Extreme Dry

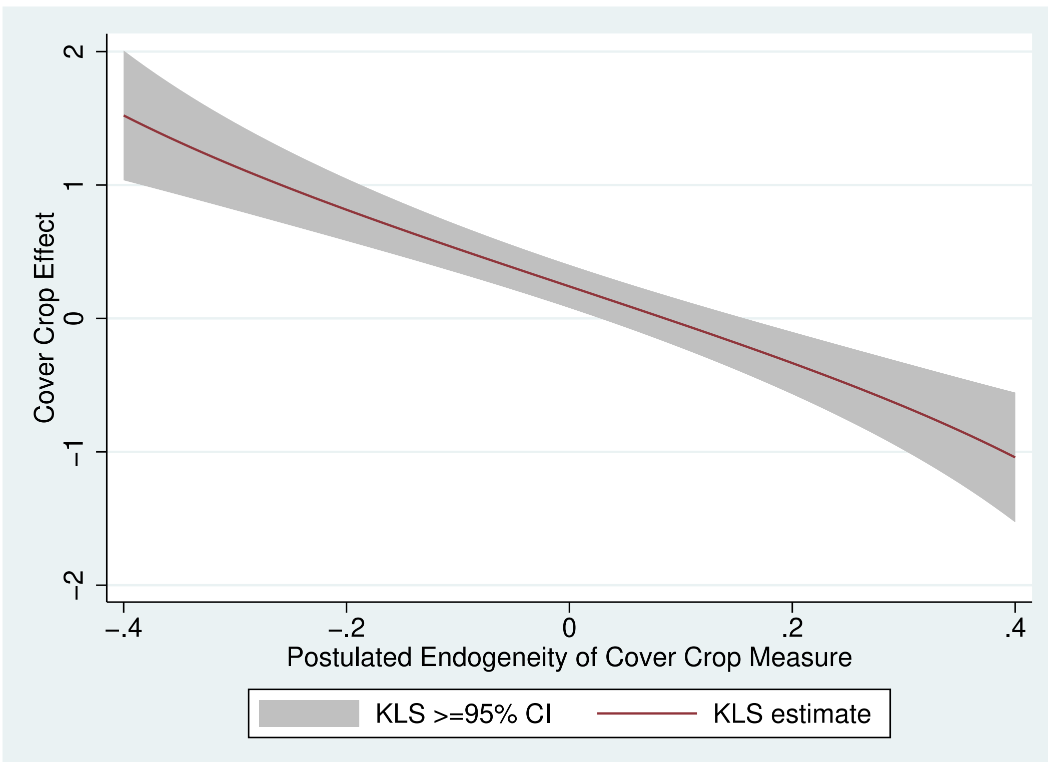

Figure 7: IV Free Regression: Effect of Cover Crops on Soybean Yield

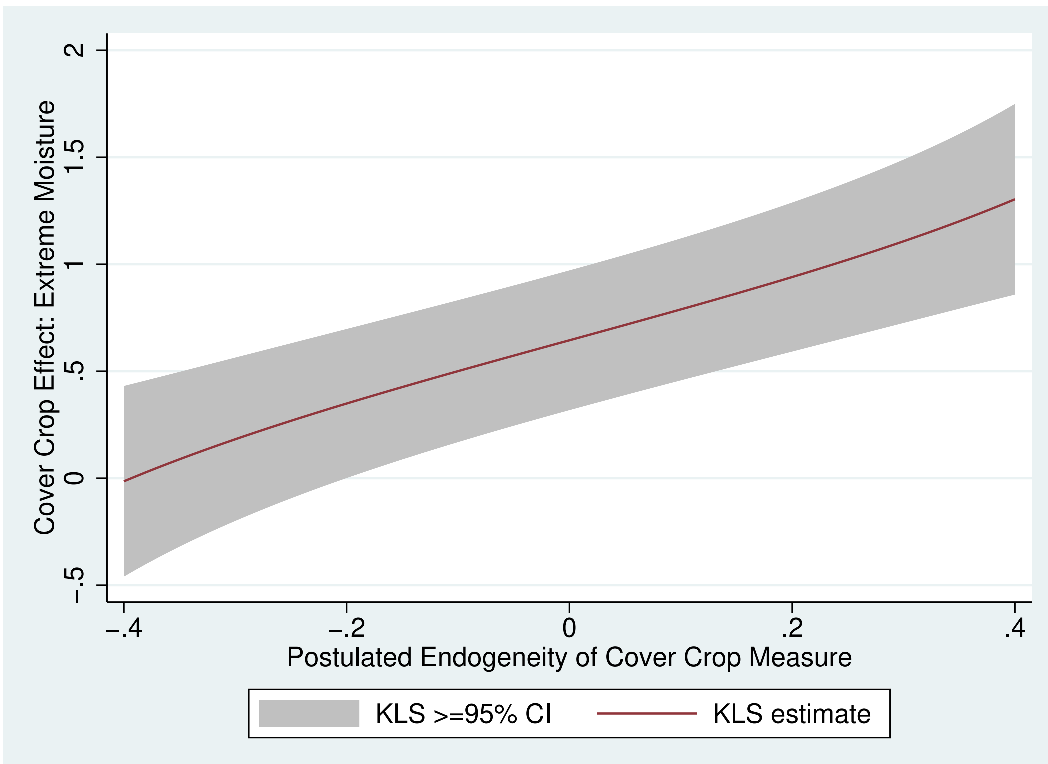

Figure 8: IV Free Regression: Effect of Cover Crops on Soybean Yield under Extreme Moisture

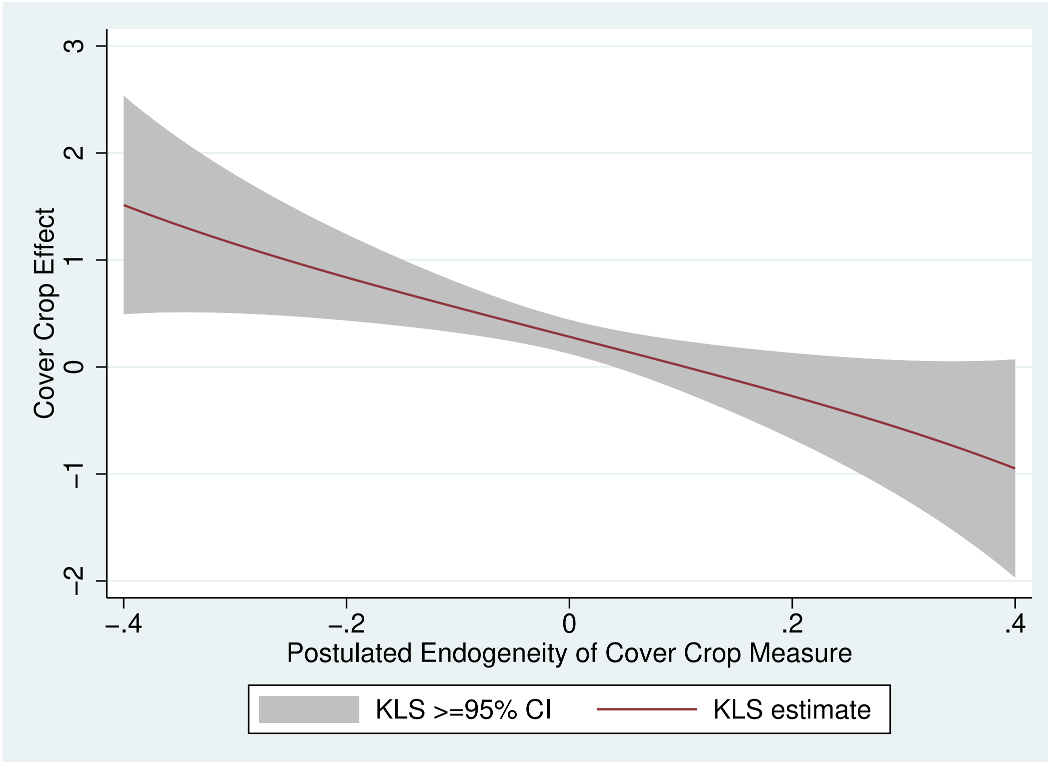

Figure 9: IV Free Regression: Effect of Cover Crops on Soybean Yield

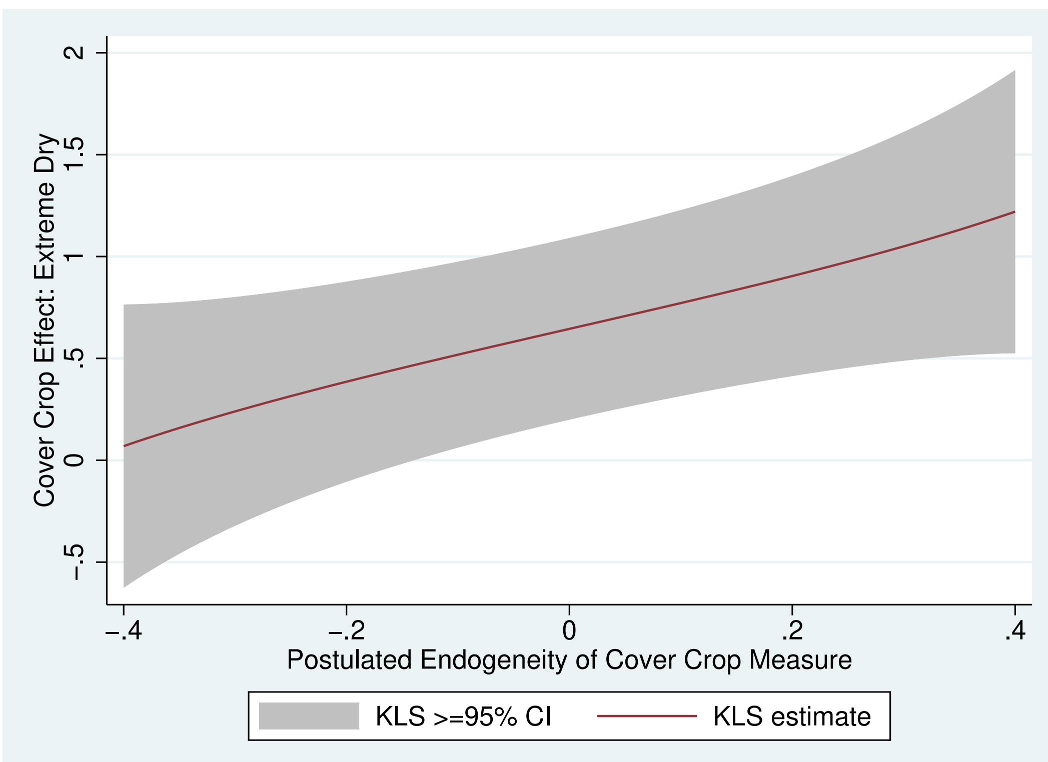

Figure 10: IV Free Regression: Effect of Cover Crops on Soybean Yield under Extreme Dry