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Do Cover Crops Reduce Production Risk?

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Abstract

This study examines whether cover crop adoption reduces production risk. A crop insurance loss measure is used as the main measure of downside production risk. To achieve this objective, we utilize a county-level panel data set with information on cover crop adoption rate, crop insurance production losses, and weather variables. The data covers the main corn and soybean production regions in the Midwestern United States (US) for the period 2005 to 2018. We employ linear fixed effects econometric models and a number of robustness checks in the empirical analysis (i.e., including a fractional regression approach, recently developed instrumental variable procedures, and alternative empirical specifications). The estimation methods used take advantage of the panel nature of the data to address various specification and endogeneity issues. Our estimation results suggest that counties with higher cover crop adoption tend to have lower crop insurance losses (and thus have lower downside production risk).

Keywords: Cover crops, Crop insurance losses, Production risk, Yield risk, Panel data, Moment-based instrumental variable (IV), KLS estimation

JEL Classification Numbers: C01, Q10, Q16, Q18, Q19

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1 Introduction

Cover crops — typically legumes, brassicas, or grasses — are defined as plants grown primarily to cover the soil in between periods of regular cash crop production (Arbuckle and Roesch-McNally, 2015). In other words, cover crops are planted to cover the soil in the 'off' period between the growing seasons of the main cash crop (e.g., winter months in the United States (US)). The main purpose of planting these cover crops is to enhance soil health, and these are not usually meant to be harvested. Aside from its direct soil health improving effects (e.g., improved soil quality and soil organic matter), previous studies have shown that planting cover crops can also provide a number of other on-field and off-field benefits, such as: reducing fertilizer applications, improving nutrient cycling, decreasing soil erosion, reducing sediment runoff, preventing nutrient leaching, sequestering carbon, provide habitat for beneficial insects and pollinators, and increased resilience to adverse weather events (Malone et al., 2014; Kaye and Quemada, 2017; Myers et al., 2019; Giri et al., 2020; Hunter et al., 2021; Rejesus et al., 2021).

The potential productivity and environmental benefits from the use of cover crops have spurred the agricultural industry's recent interest in this practice and fueled the push to further encourage its use. However, only around 4% of all U.S. cropland acres is planted in cover crops based on the 2017 Census of Agriculture (AgCensus) (Zulauf and Brown, 2019). This relatively low adoption rate have prompted research to further understand how cover crops affect farm profits, average cash crop yields, and the variability in cash crop yields (i.e., production risk). For example, there have been numerous studies that examined the impact of cover crops on mean yields (e.g., a non-exhaustive list includes Munoz et al., 2014; Belfry et al., 2017; Marcillo and Miguez, 2017; Blanco-Canqui et al., 2020). Although much of this literature suggest that cover crops has the potential to increase mean cash crop yields, there are some studies that found little or no evidence of any positive effect of cover crops on mean cash crop yields. There are even studies that found that cover crops negatively impacts subsequent cash crop yield (Reddy, 2001; Tonitto et al., 2006; Burgess et al., 2014; Kaspar and Bakker, 2015; Leslie et al., 2017).

As alluded to above, much of the previous studies have focused on the effects of cover crops on the mean yield of the subsequent cash crop. However, only a handful of studies have paid attention to the impacts of cover crops on yield variability or production risk (i.e., also called 'yield stability' by agronomists). Agronomic studies focusing on the impacts of cover crops on yield stability generally use the coefficient of variation (CV) and/or the yield variance as their main metric to measure year-to-year cash crop yield variability (Duzy et al., 2014; Smith et al., 2014; Florence et al., 2019; Anderson et al., 2020). These predominantly field-level studies indicate that cover crops can help farmers reduce yield risk (i.e., lower variance and decrease CV) by improving soil health. Additionally, in their county-level analysis, Aglasan et al. (2021) show that cover crops can reduce production risk through increased resilience to damaging extreme weather events (e.g., drought, flood). On the other hand, note that there are studies that have shown that cover crop can also increase yield risk (i.e., see Li et al. (2019) where they indicated that cover crops reduce maize and tomato yield stability).

The objective of this study is to examine whether planting cover crops reduce downside risk in the production of the subsequent cash crop. A crop insurance loss measure is used as the main variable that represents downside production risk. Specifically, we explore whether counties with higher cover crop adoption rates are more likely to have lower crop insurance losses, which implies that these counties have smaller downside production risk. We construct a long-term panel data set for counties in twelve US Midwest staes to accomplish our study objective. The panel data was constructed by first by first utilizing the Summary of Business (SOB) crop insurance database from the Risk Management Agency (RMA). This data set has information on the amount of crop insurance indemnities and liabilities, along with other pertinent crop insurance variables. We then merge this crop insurance data with novel satellite-based cover crop adoption data at the county-level. Together with county-level data on weather-related variables, we then create a county-level panel data set from 2005 to 2018, for counties in the following twelve Midwestern states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, Oklahoma, South Dakota, and Wisconsin. With the panel data set developed, we are able to estimate linear panel fixed effects (FE) models that can help address potential endogeneity due to time-invariant unobservables. We also employ a number of robustness checks using different empirical specifications and alternative estimation procedures (e.g., a correlated random effects (CRE) probit model, a recently developed moment-based instrumental variable (IV) model, and a new "external-IV-free" estimation approach) to verify the strength of the results from the linear panel FE models, and address other identification or specification issues.

The present study contributes to the literature in a couple of ways. First, to the best of our knowledge, our study is the first to empirically investigate whether cover crops reduce overall production risk using long-term data for a major agricultural region in the US. In this study, we use the loss cost ratio (LCR) — the ratio of indemnities over liabilities — as the main crop insurance loss variable. One advantage of using LCR as the outcome of interest is that it is also considered a measure of downside production risk (Goodwin and Piggott, 2020; Aglasan et al., 2020; Perry et al., 2020). This loss measure gives straightforward information about the cost of providing a given level of risk protection when shortfalls in yields or revenues occurs. As such, it is an excellent representation of downside production risk. In addition, given that the US federal crop insurance program is an important cornerstone of US agricultural policy (i.e., the program covers around $100 billion in liabilities annually), better understanding of how cover crops influence LCR may have important implications for how RMA can improve program design in the presence of soil health conservation practices like cover crops (Connor et al., 2021).

Second, our study also makes a contribution by specifically investigating the impact of cover crop use on 'overall' production risk (i.e., by using a crop insurance loss variable that is determined by all causes of loss). This is in contrast to a recent study by Aglasan et al. (2021) where the focus is on the effect of cover crop adoption on crop insurance losses due specifically to weather-related causes like drought or floods. The third contribution of this study is the development and utilization of a unique longitudinal data set that allows one to assess the relationship between cover crop adoption and crop insurance losses for relatively large geographical region and over a fairly long period of time. In comparison, much of the past agronomic literature on the cash crop yield stability effects of cover crops only considers a single location and only for shorter periods of time (e.g., one or two years). Moreover, to date, only a few studies have used the LCR variable from the RMA as a downside risk indicator for agricultural economics research (Goodwin and Piggott, 2020; Aglasan et al., 2020, 2021; Perry et al., 2020), and studies that have utilized remotely sensed, satellite-based cover crop data has also been limited (Seifert et al., 2018; Chen et al., 2021; Connor et al., 2021; Park et al., 2022).

Findings from this study suggest that counties with higher cover crop adoption tend to have lower crop insurance indemnity payments. These results suggest that cover crops can help reduce downside production risk, and implies that cover crops decreases year-to-year yield variation of the subsequent cash crop. We believe that our empirical results help inform current policy debates about how government conservation programs can support broader adoption of cover crops. Inferences from the study may also have important ramifications for the future structure of the US crop insurance program.

2 Data

The county-level panel data set was constructed based on information collected from various sources, and are discussed in turn below. As mentioned in the previous section, the main dependent variable of interest is the LCR. We specifically use LCR calculated from the two most popular crop insurance plans that constitute the majority of policies in the US — the Yield Protection (YP) plan and the Revenue Protection (RP) plan.[1] The main source for the crop insurance data is the Summary of Business (SOB) of the RMA, which has county-level information on indemnities and liabilities (among other crop insurance related variables). The LCR data we use spans the period 2005 to 2018 and geographically matches the US Midwestern states covered by the cover crop adoption data: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio,

[1] YP was previously called the Actual Production History (APH) policy in the early years of the crop insurance program. YP protects insureds against yield shortfalls. RP, on the other hand, insures against low prices, low yields, or both. Note that RP plan also includes Revenue Protection with Harvest Price Exclusion (RPHPE)

Oklahoma, South Dakota, and Wisconsin (more on this data below).

Our main independent variable of interest in the study — county-level cover crop adoption rates — are drawn from the Operational Tillage Information System (OpTIS) developed by Regrow Ag®.[2] OpTIS provides satellite-based information of conservation practices in agricultural systems, including the planting of winter cover crops over large agricultural areas. OpTIS produces accurate, timely and spatially comprehensive annual data of cover crop adoption using information from multiple satellite based (i.e., remotely-sensed) observations. The county-level OpTIS cover crop adoption data utilized in this study covers 645 counties over 12 States in the US Midwest—Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, Oklahoma, South Dakota, and Wisconsin. Note that the OpTIS cover crop data are validated at the farm-field scale, and are spatially aggregated at the county level or higher (Hagen et al., 2020). Moreover, validation of the OpTIS cover crop adoption data was mainly done through comparisons with photo and roadside survey information collected at the field level for several representative counties (see Hagen et al., 2020 for more details on the validation procedure). Furthemore, the validation procedures in (Hagen et al., 2020) indicate that the OpTIS data have fairly high accuracy rates (89%) and relatively low false positive rates.

Despite the the relatively high accuracy levels of the OpTIS data (based on comparisons with field data), it is important to note that there are still known discrepancies between the OpTIS-estimated cover crop adoption rate vis-à-vis other aggregate cover crop data sets (i.e., like those from the AgCensus) (Hagen et al., 2020).[3] The differences in the cover crop adoption estimates among these datasets likely stem from the different methods used to collect the data. For example, the AgCensus relies on surveys of the complete census of growers and likely captures their intent to grow cover crops, and/or whether they indeed planted cover crops at the time of the survey. But even if AgCen-

[2]Regrow Ag is a geospatial analysis company that partnered with the Conservation Technology Information Center (CTIC) to create OpTIS based on satellite imagery back dated going back to 2005. This effort was funded by USDA, Monsanto, John Deere, Soil Health Partnership, the Indiana Soybean Alliance and Indiana Corn Marketing Council.

[3]We do not utilize the county-level AgCensus cover crop adoption data because of the limited number of years it is available. For example, the cover crop adoption data from the AgCensus were only available in 2012 and 2017. Hence, the AgCensus data does not allow for statistical analysis over a longer period of yearly time-periods, while the OpTIS data does.

sus captures this as adoption, it could be that the cover crop did not establish properly such that it was not detected by the remote sensing procedures used to develop OpTIS. Nonetheless, Hagen et al. (2020) finds that the OpTIS data is still highly correlated with the AgCensus data. In addition, this data has some track record of being used in past research studies published in peer-reviewed agricultural economics journals (e.g., Chen et al., 2021; Connor et al., 2021; Park et al., 2022).

In addition to data on cover crop adoption, we utilize the "Parameter-Elevation Regression on Independent Slopes Model" (PRISM) data to produce county-level weather variables that are used as additional covariates in the empirical model.[4] PRISM is a gridded 4km resolution data set, which has been widely used in previous climate change studies (e.g., Schlenker and Roberts, 2006, 2009; Annan and Schlenker, 2015; Wang et al., 2021), and is considered world-wide as one of the highest-quality spatial climate data sets currently available. The relevant weather variables utilized in the study include: the number of growing degree days (GDD) (8-29°C) and harmful degree days (HDD) (above 29°C), precipitation, and precipitation squared. All degree days and precipitation used in this analysis are accumulated over the May to September growing season (Schlenker and Roberts, 2009).

Brief descriptions of the variables used in this study, as well as the corresponding summary statistics, are presented in in Table 1. The county-average cover crop adoption rate for our data is around 3.30% in the study period. In Figure A.1, we show average yearly cover crop adoption for our data and it shows an increasing trend over time, most especially in the last three years of the data (2016 to 2018). A map of the study area that depicts the spatial distribution of cover crop adoption in 2005 and 2018 are also shown in Figures A.2 and A.3, respectively. Figure A.4 depicts change in cover crop adoption rate between 2005 and 2018 for each county in our study area. The higher adoption counties tend to be in the southern portion of our study area. The average yearly LCRs over all counties in the data are also shown in Figure A.5. Lastly, trends in the weather variables used in this study are shown in Figure A.6

[4]PRISM was developed by the Spatial Climate Analysis Service at Oregon State University.

3 Empirical Specification and Estimation Strategies

For our main estimation procedure, this study employs a linear panel FE model to investigate how cover crop adoption affects downside production risk (as represented by the LCR). We regress LCR on cover crop adoption rate, HDD, GDD, precipitation, precipitation squared, and a linear time trend. More formally, we estimate the following empirical specification:

$$LCR_{it} = \beta_1 CC_{it} + \boldsymbol{\beta_w} \boldsymbol{W_{it}} + \lambda T_t + \alpha_i + \varepsilon_{it}, \tag{1}$$

where LCR_{it} represents the LCR (%) in county i and year t; CC_{it} denotes the cover crop adoption variable (% of planted crop acres with cover crops) in county i and year t; $\boldsymbol{W_{it}}$ is a vector of weather variables (e.g., GDD, HDD, precipitation, and precipitation squared); T_t is a linear time trend; α_i are county fixed effects that control for unobserved time-invariant factors at the county-level; and ε_{it} denotes the idiosyncratic error term for county i in year t. β_1 in equation (1) is the main parameter of interest and represents the impact of cover crop adoption on downside production risk. Note that the weather variables we use as controls are consistent with previous studies that analyze nonlinear effects of weather on crop yield outcomes (see, e.g., Schlenker and Roberts, 2006, 2009; Annan and Schlenker, 2015).

Given the panel nature of our county-level dataset, as mentioned above, a traditional linear fixed effects (FE) model is the main empirical strategy utilized to estimate equation (1). The FE model allows us to address endogeneity due to time-invariant unobservables. In particular, the county fixed effects account for unobserved time-invariant variables that potentially affect both dependent variable (LCR) and the main independent variable of interest (i.e., cover crop adoption rate). We argue that the overall soil quality of the county is one of the main unobservables that can be correlated with the dependent variable and the main independent variable, which may then cause endogeneity issues. However, the overall soil quality is considered roughly time-invariant in our county-level context, and is absorbed by the county fixed effects. In addition to the overall soil quality, unobserved management ability is another unobservable variable that potentially affects model identification. However, unobserved management ability is typically assumed to be time-invariant and the county-fixed effects take care this potential endogeneity as well. We also include linear time trends in the specification to sharpen identification. The time trend accounts for other unobserved factors affecting LCR of all counties the same way over time (i.e., technological growth). To facilitate proper inference, we also use standard errors clustered by county to account for potential year-to-year correlations within a county.

To further check robustness of our main results from the linear FE model in equation (1), we also estimate several alternative empirical specifications. For the first alternative specification, we include additional crop insurance related covariates as controls on the right-hand side of the equation. Since our outcome variable — LCR — is a crop insurance measure, one can argue that crop insurance related variables are relevant controls. Hence, we explore a specification where crop insurance participation (i.e., ratio of insured acres over planted acres) and county-average crop insurance coverage levels are included as control variables in equation (1). The idea is to avoid omitted variable bias by including these crop insurance variables in the specification. However, the disadvantage of including these variables in the specification is that some researchers may argue that these confounders may be endogenous. For the second alternative specification, we use "acres" planted to cover crops as the main independent variable (rather than % cover crop adoption), and then include planted crop acres (i.e., for all available crops) as a control variable in the specification. Including planted acres in this alternative specification allows us to control for potential scale effects (i.e., bigger counties naturally having larger cover crop acres).

In addition to the traditional linear FE estimation procedure, we also utilize three other estimation strategies as robustness checks. The first procedure is a fractional regression approach for unbalanced panel data, and the other two strategies are: (i) a recently developed moment-based instrumental variable (IV) approach, and (ii) an "external-IV-free" estimation approach. The fractional regression method allows us to account for the fractional nature of the dependent variable, while the moment-based IV and external-

IV-free procedures can help further sharpen identification by addressing possible residual endogeneity due to time-county varying unobservables in the error terms.

Although the traditional linear FE model — our main estimation method — has desirable properties (i.e., accounting for time-invariant unobservables), it does not directly account for fractional outcomes. Note that our dependent variable, the LCR is essentially bounded between zero and one. It can be argued that another estimation method to account for the fractional nature of our dependent variable might be be required. Therefore, as a robustness check, we also estimate equation (1) using the fractional regression method developed by Wooldridge (2019) for unbalanced panel data (i.e., it is also called the correlated random effects (CRE) probit model). Similar to the linear panel FE model, the fractional regression approach for panel data accounts for potential endogeneity due to unobserved heterogeneity. But it has the advantage of accounting for the non-linear nature of the outcome variable using quasi-maximum likelihood (QML) techniques (for a particular link function like probit or logit). The Wooldridge (2019) fractional regression approach builds on the well-known Mundlak-Chamberlain mechanism for controlling unobserved heterogeneity in panel data. It models county fixed effects as a linear function of the county-level averages of the model covariates (Mundlak, 1978). The Wooldridge (2019) fractional regression procedure for unbalanced panels also control for unobserved heterogeneity in fractional response models by including time averages of the covariates and the number of time periods available for each cross-sectional unit.

We also use a moment-based IV procedure as another robustness check in this study (see Lewbel, 2012). In equation (1), we account for endogeneity due to time-invariant unobservables by using of county fixed effects and time trends. However, it is possible that there may be residual endogeneity due to time and county varying unobservables that jointly influence LCR and cover crop adoption (e.g., unobserved soil conservation effort). The linear FE and CRE probit methods have their own advantages given the panel nature of the data and/or the fractional outcomes of the dependent variable, but they do not deal with the aforementioned potential residual endogeneity. The typical approach in this case is to use instrumental variable (IV) methods. Traditional IV methods control for time-county-varying unobservables that potentially affect both the outcome and the main independent variable of interest. Unfortunately, in our empirical context, strong external instruments are not available that are correlated with the potentially endogenous main independent variable (CC_{it}) but uncorrelated with the time-county unobservables remaining in the error terms. As we do not have any external IVs that can strongly satisfy these exclusion restrictions, we first utilize the Lewbel (2012)'s IV estimator, which do not require an external IV (as traditionally defined).

The Lewbel (2012) moment-based IV estimator utilizes heteroscedasticity in the error terms from the first-stage regressions (e.g., regression of the potentially endogenous variable, CC_{it}, on the observable covariates) to identify the coefficients of the endogenous variables in the main equation (even in the absence of valid instruments). Lewbel (2012) indicates that the model is identified if the error terms in the first-stage equations are heteroscedastic. In other words, a subset or all of the exogenous control variables in the first stage are correlated with the variance of the first-stage error terms, but not with the covariance between the first stage error term and the error term in the main second-stage equation (i.e., equation (1)). Then, the residuals from the first-stage equation multiplied by each of the exogenous covariates in mean-centered form can serve as valid instruments.

To validate the presence of heteroscedasticity in our first-stage regressions, we use the Breusch-Pagan (BP) test (Breusch and Pagan, 1979). The BP test rejects the null hypothesis of homoscedasticity (i.e., BP test statistic is 4070.71 and the p-value < 0.001). This supports the use of the moment-based IV approach of Lewbel (2012) as an alternative estimation procedure. In addition to the BP test, we also use other diagnostic tests to assess the strength of the Lewbel (2012) IV approach. First, we use the Kleibergen-Paap rk LM test statistic to evaluate whether IV approach used is underidentified (Kleibergen and Paap, 2006). The associated p-values and the calculated test statistics for the Kleibergen-Paap rk LM test (see the lower panel of Table A.4) indicate that we can reject the null hypothesis that model is underidentified (e.g., the test statistic = 45.89 with p-value < 0.001). Second, we use the Kleibergen-Paap rk Wald F statistic and the Cragg-Donald Wald F statistic to evaluate whether the IVs used in the estimation are weak or strong. Both tests suggests that we can reject the null hypothesis that the IVs used are weak. Lastly, we implement the Hansen J test to assess the validity of all IVs used in the moment-based IV procedure. The calculated Hansen J test statistics are large (i.e., 52.86) and have p-values less than 0.001 (see the lower panel of Table A.4). These numbers suggest that one can reject the null hypothesis that all IVs used in the moment-based IV procedure are valid (i.e., this means that at least one IV used in the estimation is not valid). Nevertheless, Baum and Lewbel (2019) indicates that it is possible for the Hansen J test to fail to support the validity of all IVs used, but the key assumptions for the moment-based IV model to work can still hold in general (i.e., especially if the heteroscedasticity condition and the other tests for IV strength still holds). Thus, given that the majority of the diagnostic tests supporting the use of the Lewbel (2012) moment-based IV, we proceed to use this as an alternative estimation approach that serve as another robustness check.

To further validate our results from the the linear FE and the Lewbel (2012) moment-based IV approaches, we also implement a recently developed "external-IV-free" approach (called "kinky least squares" (KLS) regression) by Kiviet (2013, 2020). The KLS estimation procedure also addresses possible residual endogeneity due to time-county-varying unobservables.[5] KLS can be considered as an alternative to the Lewbel (2012) moment-based IV approach (which does not require external IVs as in the traditional 2SLS procedure).

In contrast to the Lewbel IV approach, the instrument-free KLS approach first makes an assumption about the admissible degree of endogeneity in the model. Set identification of the coefficients is achieved by constraining the endogeneity correlations within reasonably narrow bounds. With the KLS approach, we do not need external instruments. Kripfganz and Kiviet (2021) indicates that asymptotically conservative inference can be performed by considering the union of confidence intervals over a grid of endogeneity correlations that the analyst assumes. This provides a set of coefficient estimates in accordance with the postulated endogeneity range. We assume that the range of resid-

[5]We direct the interested reader to the following references: Kiviet (2013, 2020) and Kripfganz and Kiviet (2021).

ual endogeneity present in our linear FE model in equation (1) would be minimal given that we already control for time-invariant and county-invariant unobservables through the county fixed effects and time trends. We also argue that the endogeneity correlations are positive such 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 soil conservation effort that may be positively correlated with cover crop adoption and crop insurance losses). Hence, it is reasonable to assume that the range of endogeneity correlation in our context is only between 0.1 to 0.2. Hence, we implement the KLS procedure to estimate equation (1), where the endogeneity correlation is assumed to be 0.1 and 0.2.

4 Results and Discussion

Table 2 presents the results from our main model — the traditional linear panel FE regression. In Table 2, the parameter estimate for the cover crop adoption variable indicates that counties with higher cover crop adoption have statistically lower LCRs (at the 5% level of significance). Based on the results, a one percentage point cover crop adoption increase will result in approximately a 0.051 percentage points reduction in the LCR at the county-level.[6]

To better contextualize the magnitude of the estimated cover crop effect on the production risk (LCR), we conduct a simple back-of-the-envelope calculation based on 2012 crop insurance SOB data. First, let us consider the estimated impact of cover crop adoption on the LCR (i.e., 0.051 in Table 2). Given that the average LCR in 2012 is 6.68%, our 0.051 parameter estimate suggests that a one percentage point increase in cover crop adoption would likely reduce the average LCR to 6.63% (i.e., 6.68-0.051=6.63). This is equivalent to a 0.75% decrease in the LCR (i.e., (6.63-6.68)/6.68). Second, to calculate how the aforementioned 0.75% decrease in LCR translate to dollar amounts, we then consider the indemnities amounting to $10.4 billion that was observed in 2012 from our

[6]Note that we utilize the percentage form (%) of the LCR in our estimations (i.e., multiply the ratios by one hundred) for ease of interpretation.

SOB data. Assuming that liabilities (\$56.3 billion in 2012 from our SOB data) are held constant, and noting that the LCR is a ratio of indemnities over liabilities, then our estimates suggest that a one percentage point increase in cover crop adoption would reduce indemnities by 0.75%. That is, the \$10.4 billion indemnities in 2012 would have been reduced by \$78 million had there been one more percentage point of cover crop adoption in our study area (e.g., \$10.4 billion $\times$ 0.0075 = \$78 million). Thus, the foregoing calculations indicate that the dollar reduction in production loses, because of a one percentage point increase in cover crop use is not trivial.

Regarding the weather variables, the estimated effects largely follow expectations. We see the nonlinear effect of the degree days measures (i.e., heat up to a certain point is required for plant to grow well, and past this certain point damage occurs). In Table 2, we find that increased incidence of extreme heat (i.e., higher HDD) tends to increase the crop production risk, whereas GDD has a negative and statistically significant estimated coefficient (i.e., moderate temperatures reduce production risk). The parameters associated with the precipitation variables generally indicate a "U-shaped" behavior (e.g., production risk decreases as precipitation increases (from zero), but after a "turning point" higher levels of precipitation increases production risk).

To verify the strength and stability of our main linear panel FE results above, we also conduct several robustness checks where: (i) we add crop insurance related control variables on the right-hand side of equation (1), (ii) we use cover crop acres measure as the main independent variable of interest (instead of cover crop adoption percentage (%) measure), (iii) we utilize fractional regression (i.e, CRE probit) as an alternative estimation procedure to deal with the fractional nature of the LCR dependent variable, (iv) we use Lewbel (2012)'s moment based IV procedure to help deal with residual time-county varying unobservables that may cause endogeneity issues, and (v) we implement a recently developed "external-IV-free" estimation procedure, KLS regression that can serve as an alternative to the Lewbel moment based IV approach.

First, we conduct a robustness check where we include crop insurance related variables as additional controls in the specification. The linear panel FE results with additional crop insurance regressors are reported in Appendix Table A.1. The main inferences that can be drawn from these runs are still consistent with our main linear panel FE results. The signs and magnitudes of the cover crop parameter estimates for this robustness check are very similar with those found in our main linear panel FE model.

Second, we use the number of acres planted to cover crops in the county as the main independent variable of interest (instead of the percentage (%) of cropland acres with cover crops) as another robustness check. In this specification, we include planted acreage as an additional regressor to control for potential scale effects.[7] Regression results using this specification are presented in Appendix Table A.2. The main inferences based on this alternative cover crop "acres" specification still follow those observed in the main linear panel FE runs. In particular, the signs and magnitudes of the cover crop adoption coefficients, as well as the level of statistical significance, are very similar.

Third, we use CRE probit as an alternative estimation procedure to verify our results when the fractional nature of the LCR is directly controlled for. Results of this fractional regression are reported in Appendix Table A.3. The main inferences that can be drawn from this alternative estimation procedure are still consistent with those from our linear panel FE regression. The cover crop risk reduction effect holds even when using the fractional regression model.

Fourth, we employ a moment-based IV procedure as another robustness check to evaluate whether our results from the linear panel FE model still holds when residual time-county varying unobservables are addressed using this moment-based IV procedure. Parameter estimates from the moment-based IV procedure are reported in Appendix Table A.4. The results from this estimation procedure consistently indicate that cover crops reduce LCR (and downside production risk).

Lastly, we implement the KLS regression method as our final robustness check. This "external-IV-free" estimation method is an alternative to Lewbel (2012)'s moment-based IV approach. As discussed in the empirical specification and estimation strategies section,

[7] In our main specification where we use the percentage (%) of cropland acres with cover crops, the planted acreage for all available crops variable as control are not included because planted acreage are already accounted for in the percent cover crop adoption variable.

we think that the range of residual endogeneity present in our baseline specification (1) would be minimal as we already include county fixed effects and linear time trends in our main specification. Given a modest endogeneity correlation range (i.e., 0.1-0.2), we implement the KLS procedure using our baseline specification. The results of this estimation procedure are presented in Appendix Tables A.5 and A.6. The KLS regression results, where minimal residual endogeneity is assumed, still support the main conclusion that counties with higher cover crop adoption tend to have lower crop production risk.

5 Conclusions

Soil health conservation advocates have long discussed the potential benefits of cover crops on farm productivity, such as improvement in soil health and increased resilience against extreme weather events like droughts and floods. However, these conclusions were largely drawn from anecdotal observations of cover crop users' experience with the practice, or short-term agronomic studies that tend to have a narrower geographic and temporal scope. Additionally, previous literature investigating the effect of cover crops on year-to-year yield variability of the subsequent cash crops has been limited and there is no data-driven consensus yet as to the impact of cover crops on downside risk.

In this study, we explore how increasing cover crop adoption in a county can affect downside production risk (as represented by a crop insurance loss measure). A county-level panel data set spanning the 2005-2018 period is constructed for a major crop production region in the US Midwest to achieve the objective of the study. We merge a novel satellite-based cover crop data set with publicly available crop insurance data to create the county-level panel data used in this study. Linear panel FE models and a number of robustness checks (i.e., using alternative specifications, fractional regression, a moment-based IV estimation approach, and the KLS approach) are then used in the empirical analysis. The empirical results in this study indicate that counties with higher cover crop adoption tend to have lower crop insurance losses (and thus lower downside production risk). Our results provide support the notion that cover crops increase yield performance and can reduce yield variability.

Inferences from the study point to several potential policy implications. First, our empirical results provide new empirical evidence on the direct impact of cover crops on production risk. Because our dependent variable, the LCR measure, is considered a valid downside risk measure (Perry et al., 2020), our finding indicating that cover crops reduce risk supports the idea behind recent premium discounts given by RMA to farmers who have historically used cover crops. Since our findings indicate that cover crops reduce incidence and magnitude of crop insurance losses, farmers who adopt cover crops in their cropping systems are likely to have lower production risks and might merit the lower premiums that are charged. Thus, we believe that findings from this study can help justify making the pilot cover crop premium discount a permanent part of the crop insurance program, and can help make it more widely available for the states covered in this study. Second, our findings augment the scientific evidence base because the analysis is based on outcomes from actual cover crop adoption by farmers rather than from controlled field experiments. Third, since we explicitly quantify the risk reduction benefits of cover crops, these benefits can be used by policy makers to further justify increasing support for federal cost-share programs in the US like the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP). The findings may also be used to encourage development of state-level cost-share programs that aim to encourage further cover crop use.

Even though the present study provides important insights regarding the downside risk effects of cover crops, it is important to recognize its limitations and discuss potentially fruitful avenues for future research. First, although we have strived to assure proper identification of the cover crop effect (using various econometric approaches), we did not use the traditional IV approach that utilize external instruments that satisfy classical exclusion restrictions (since we believe none are available). Using the traditional IV approach may be an avenue for future research. Second, although we believe that crop insurance data already allows us to separately estimate the cover crop effects on production risk and the geographical scope in this study is fairly wide (i.e., the US Midwest), future studies may also use a different data set for a different geographical area and for a longer time period to have better external validity. Using farm-level data for a large geographical region is also a potential next step to further validate the findings in this study. We leave all these potential extensions for future work.

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Table 1: Description and summary statistics of variables

Variable Name	Description	Mean	SD	Min	Max
CC adoption	Cover Crop Adoption Rate (%)	3.24	5.89	0.00	80.80
LCR	Loss Cost Ratio (%)	6.68	9.83	0.00	95.34
HDD	Heating degree days (in hundred °C)	0.33	0.31	0.00	2.58
GDD	Growing degree days (in thousand °C)	1.93	0.23	1.17	2.63
Precipitation	Precipitation ((mm) in '000)	0.53	0.14	0.10	1.16
N		8894	8894	8894	8894

Table 2: Impacts of Cover Crop Adoption on the Loss Cost Ratio (LCR): Linear Panel Fixed Effects Results

	LCR
CC adoption	-0.051**
	(-2.06)
HDD	0.303***
	(25.34)
GDD	-0.036***
	(-25.59)
Precipitation	-0.075***
	(-12.23)
Precipitation sq.	0.075***
	(13.82)
Observations	8894
Adjusted R^2	0.347
AIC	60710.184
BIC	60752.743

t statistics 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: Impacts of Cover Crop Adoption on the Loss Cost Ratio (LCR): Linear Panel Fixed Effects Results with Additional Crop Insurance Related Variables

	LCR
CC adoption	-0.045*
	(-1.83)
HDD	0.302***
	(25.61)
GDD	-0.036***
	(-26.19)
Precipitation	-0.074***
	(-12.21)
Precipitation sq.	0.074***
	(13.82)
Observations	8894
Adjusted R^2	0.350
AIC	60677.387
BIC	60734.132

t statistics 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. Parameter estimates for the crop insurance variables are also not included. In each specification, standard errors are clustered by county.

Table A.2: Impacts of Cover Crop Adoption on the Loss Cost Ratio (LCR): Linear Panel Fixed Effects Results Using "Acres" of Cover Crops

	LCR
CC acres	-0.051***
	(-3.00)
HDD	0.304***
	(25.26)
GDD	-0.036***
	(-25.56)
Precipitation	-0.074***
	(-12.11)
Precipitation sq.	0.074***
	(13.69)
Planted acres	-0.000
	(-1.36)
Observations	8724
Adjusted R^2	0.348
AIC	59507.396
BIC	59556.913

t statistics 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.3: Impacts of Cover Crop Adoption on the Loss Cost Ratio (LCR): Correlated Random Effects (CRE) Results

	LCR
CC adoption	-0.061***
	(-3.02)
HDD	0.186***
	(21.80)
GDD	-0.029***
	(-22.55)
Precipitation	-0.057***
	(-17.36)
Precipitation sq.	0.055***
	(20.14)
Observations	8894

t statistics 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: Impacts of Cover Crop Adoption on the Loss Cost Ratio (LCR): Moment-based IV Results

	LCR
CC adoption	-0.162***
	(-3.76)
HDD	0.304***
	(25.30)
GDD	-0.036***
	(-25.32)
Precipitation	-0.074***
	(-12.14)
Precipitation sq.	0.074***
	(13.73)
Observations	8894
Adjusted R^2	0.294
AIC	60741.774
BIC	60784.333
Kleibergen-Paap rk LM statistic	45.89
	($p = 0.0000$)
Cragg-Donald Wald F statistic	345.75
Kleibergen-Paap rk Wald F statistic	36.91
(Stock-Yogo 15% max)	(15.09)
Hansen J statistic	52.86
	($p = 0.0000$)

t statistics in parentheses

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

Notes: County fixed effects, state-specific trends, and an overall linear time trend are included in the specification but are not reported. The Kliebergen-Paap rk LM stat, Kliebergen-Paap rk Wald stat, Cragg-Donald Wald F stat, and Hansen J stat are diagnostic tests that aim to help assess appropriateness of the IVs used and the estimation procedure. In each specification, standard errors are clustered by county.

Table A.5: Impact of Cover Crops on Weather-related Crop Insurance Losses: Kinky least-squares (KLS) IV Results (Endogeneity Correlation = 0.1)

	LCR
CC adoption	-0.331**
	(-2.20)
HDD	0.304***
	(51.19)
GDD	-0.036***
	(-31.61)
Precipitation	-0.074***
	(-19.64)
Precipitation sq.	0.073***
	(22.97)
Observations	8894

t statistics 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 Weather-related Crop Insurance Losses: Kinky least-squares (KLS) IV Results (Endogeneity Correlation = 0.2)

	LCR
CC adoption	-0.631*
	(-1.90)
HDD	0.304***
	(49.38)
GDD	-0.035***
	(-25.52)
Precipitation	-0.072***
	(-17.70)
Precipitation sq.	0.072***
	(19.69)
Observations	8894

t statistics 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.

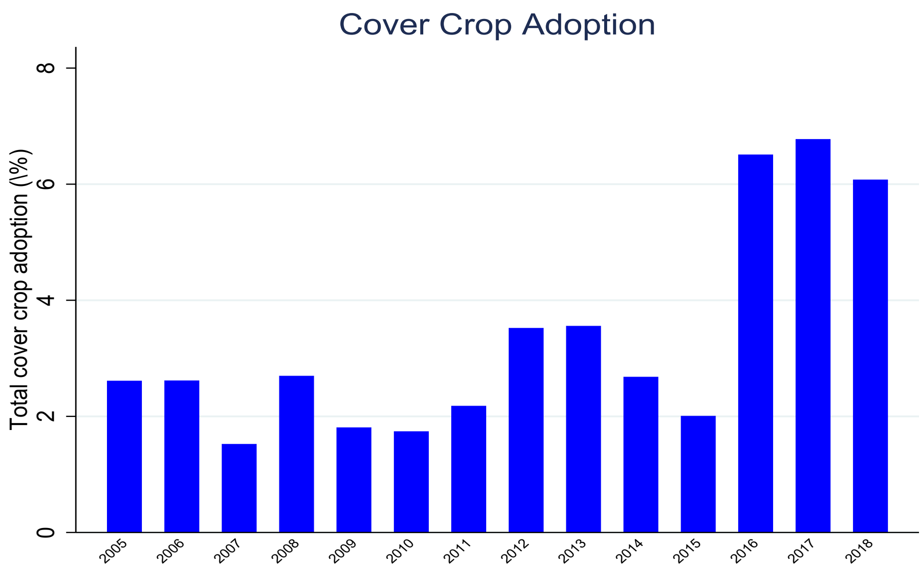

Figure A.1: County average cover crop adoption rates, 2005-2018

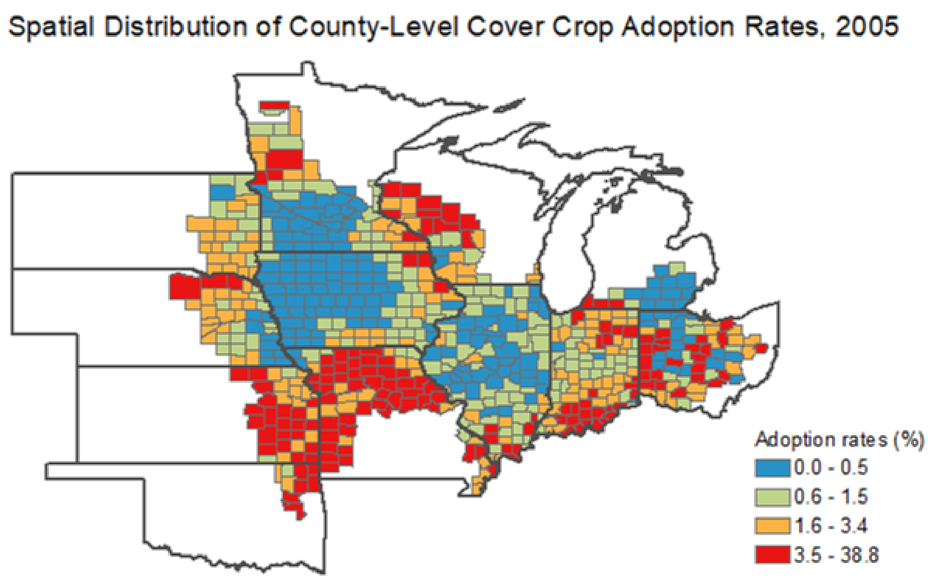

Figure A.2: Spatial distribution of the county average cover crop adoption rates, 2005

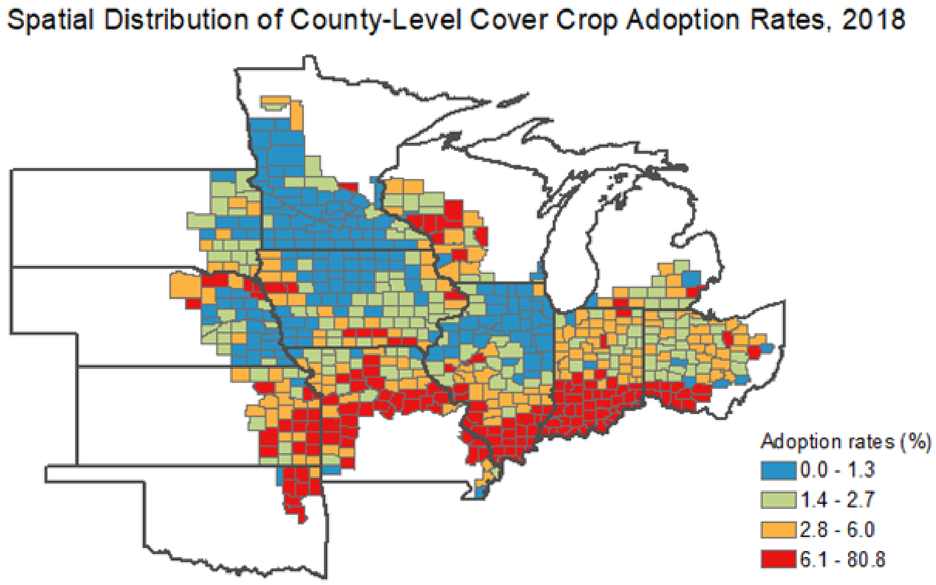

Figure A.3: Spatial distribution of the county average cover crop adoption rates, 2018

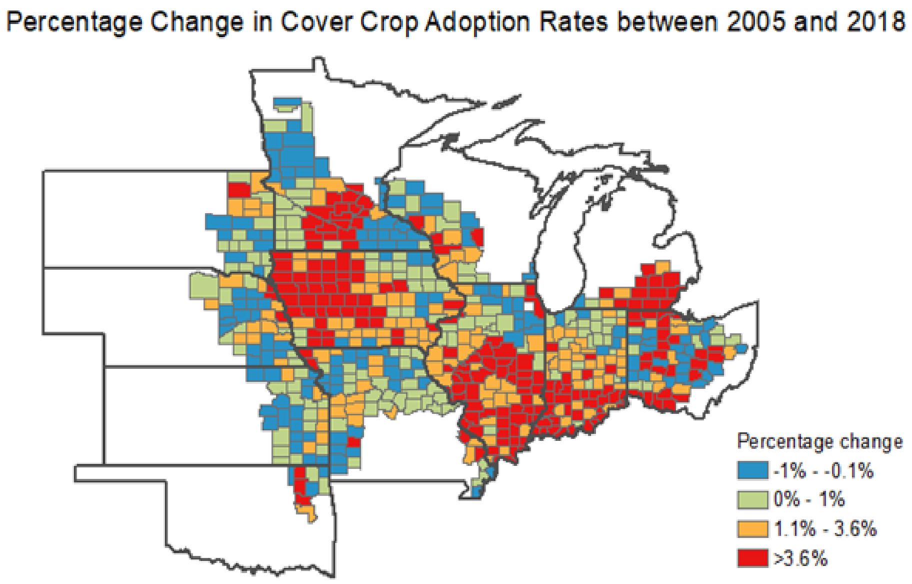

Figure A.4: Change in cover crop adoption rates between 2005–2018

Figure A.5: County average LCRs, 2005-2018

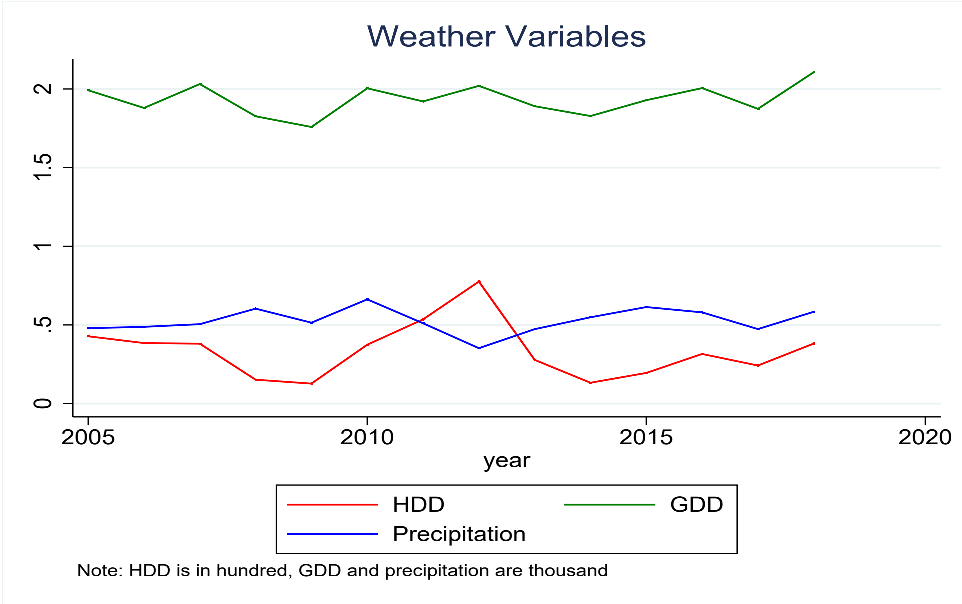

Figure A.6: County average HDD, GDD, and Precipitation variables, 2005-2018