The Impact of Crop Insurance Participation on Landscape Complexity

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The Impact of Crop Insurance Participation on Landscape Complexity

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Abstract

This study explores how increased participation in the Federal Crop Insurance Program likely influences county-level landscape complexity. We utilize 2008-2018 county-level panel data with information on landscape complexity, crop insurance participation, and a number of weather variables to achieve the study objective. We apply linear fixed effect models, fixed effect instrumental models, and a number of robustness checks in the empirical analysis (i.e., two "external-instrument-fre" estimation procedures and a variety of alternative empirical specifications). Our estimation methods take advantage of the panel nature of the data to address various specification and endogeneity issues. Our results suggest that counties with greater crop insurance participation, especially at the intensive margin, tend to have lower landscape complexity. The finding underscores the idea that governmental policies aimed at helping farmers manage risk may inadvertently influence rural landscape diversity and sustainable agricultural systems.

Keywords: ecosystem service, landscape diversity, risk management
JEL classification: Q15, Q18, Q57

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1 Introduction

Greater landscape complexity has been shown to bolster ecosystem services essential for agricultural resilience in the face of climate change (Duarte et al., 2018; Verhagen et al., 2016; Gaudin et al., 2015; Renard, Mahaut, and Noack, 2023). Diverse cropping systems and rotations, which enhance the complexity of rural landscapes, have been shown to improve yield stability under drought and heat stress (Renard, Mahaut, and Noack, 2023; Altieri, Funes-Monzote, and Petersen, 2012; Abson, Fraser, and Benton, 2013; Christman et al., 2024; Fabri et al., 2024), while various vegetative features such as cover crops and riparian buffers have been shown to mitigate flooding (Antolini et al., 2020; Verhagen et al., 2016). However, agricultural intensification has simplified landscapes globally. Over half of the US land area is used for agricultural use, with two-thirds dedicated to only three crops: corn, soybean, and wheat (Bigelow and Borchers, 2017). This reduction in landscape complexity can adversely affect ecosystem services, including water quality, pollination, and carbon storage (Duarte et al., 2018).

Crop insurance is an important safety net for US farmers to manage climate risks. There have been arguments in the literature that the relationship between crop insurance and on-farm diversification can be either positive (Knapp et al., 2021) or negative (Falco et al., 2014), making the connection between crop insurance and landscape complexity largely an empirical question. For example, insurance participation may discourage farmers from diversifying their crops to manage risk (Knapp et al., 2021), as they already rely on insurance to mitigate their risks. This, in turn, can potentially lead to decreased landscape complexity and diminished ecosystem services. Conversely, insured farmers may be incentivized to cultivate riskier crops or plant new crops on marginal lands (Yu and Sumner, 2018), which could then enhance landscape complexity.

This study addresses the question of how increased participation in the Federal Crop Insurance Program likely influences county-level landscape complexity. Specifically, we assess whether counties with greater insurance participation exhibit increased or decreased compo-

sitional complexity (i.e., the number of land cover types) and configurational complexity (i.e., more diverse spatial arrangement of land covers). To accomplish this objective, we construct a county-level panel dataset with rich information on crop insurance participation, landscape complexity, and weather conditions for the 2008-2018 period. Panel fixed effects (FE) models and fixed effects instrumental variable (FE-IV) models are the primary approaches used to examine the effect of crop insurance participation on landscape complexity at the county level. We believe that these estimation strategies allow us to sufficiently account for potential unobserved confounders (i.e., due mainly to time-invariant unobservables) and to reasonably identify the effects of crop insurance participation on landscape complexity. We also conduct several robustness checks using alternative empirical specifications and estimation methods (i.e., two "external-instrument-free" estimation procedures).

Most previous studies in this literature have examined how participation in crop insurance affects land use decisions and their consequences. Specifically, many studies have explored the effects of crop insurance on a variety of farm inputs and farm outcomes (e.g., effects on crop specialization, fertilizer and pesticide usage, acreage responses, enrollment in the Conservation Reserve Program (CRP), and cover crops) (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Wu, 1999; Goodwin, Vandeveer, and Deal, 2004; Weber, Key, and O'Donoghue, 2016; Walters et al., 2012; Claasen, Langpap, and Wu, 2017; DeLay, 2019; Connor, Rejesus, and Yasar, 2022). These studies find mixed responses to increasing crop insurance participation. We contribute to the literature by examining how risk management policies influence land use patterns by directly estimating the relationship between various crop insurance participation measures and landscape complexity using county-level panel data. To the best of our knowledge, no other study has examined the aforementioned relationship using panel data. A reduced form regression that directly evaluates the effects of crop insurance participation on landscape complexity is important to ascertain the overall effect of crop insurance through all potential mechanisms rather than inferring the effects based only on the impact of crop insurance on particular farmer decisions (i.e., its impact

on land use or crop choices). Direct estimation of the landscape complexity response to crop insurance also bypasses the added complexity of constructing structural multi-equation models that incorporate all possible farm decisions influenced by crop insurance.

The second main contribution of this study is our use of a novel county-level data set that allows us to quantitatively analyze the relationship between crop insurance participation and landscape complexity over a wider geographical scope (i.e., the whole continental US) and over a longer time-series coverage (i.e., 2008-2018), which in turn enhances the external validity of our findings. Much of the existing agronomic and ecological studies that explore how landscape complexity affects ecosystem services and agricultural resilience are typically limited to specific field locations and short time periods, which might constrain their external validity. Only a few studies have used county-level data rather than field-scale data to examine landscape complexity in the context of agricultural production (Burchfield, Nelson, and Spangler, 2019; Nelson and Burchfield, 2021). However, these studies do not explicitly analyze the landscape complexity from a risk management perspective. We are able to merge new publicly available crop insurance data with county-level landscape complexity data that allow us to examine the effects of crop insurance participation on landscape complexity.

Our empirical results show that counties with higher crop insurance participation, especially based on an intensive margin measure (e.g., higher average coverage), have lower compositional complexity (lower Shannon diversity index) and lower configurational complexity (higher contagion). Insurance participation at the intensive margin may influence farmer behavior by discouraging diverse and spatially heterogeneous cropping systems, thereby reducing landscape complexity. However, the effect of extensive margin participation measures tends to weak. These findings underscore the idea that governmental policies aimed at helping farmers manage risk may inadvertently influence rural landscape diversity and sustainable agricultural systems.

2 Background

2.1 Federal Crop Insurance Program

The Federal Crop Insurance Program (FCIP), introduced in 1938, was designed as a policy response to the widespread agricultural instability of the Great Depression. Since then, it has evolved into a central pillar of US farm policy, covering a wide range of crops and a vast portion of US farmland. By the 2023 crop year, the program provided coverage for over 539 million acres, with total liability surpassing $207 billion. The FCIP is administered by the Risk Management Agency (RMA) under the United States Department of Agriculture (USDA), and it is delivered through private insurance companies. Although premiums are structured to be actuarially fair, the government heavily subsidizes both the premiums paid by producers and the delivery costs, ensuring broad participation and reducing farmers' financial exposure to adverse conditions.

Participation in the FCIP grew significantly following the Federal Crop Insurance Reform Act of 1994, which introduced fully subsidized catastrophic (CAT) coverage and temporarily tied crop insurance enrollment to eligibility for other federal support. Major reforms under the Agricultural Risk Protection Act of 2000 and the 2008 Farm Act raised average premium subsidies to about 60 percent and introduced new coverage options with higher subsidies (O'Donoghue, 2014). Subsequent legislation, the 2014 Farm Bill, introduced yield exclusion options, streamlined policies for small diversified farms, and improved data sharing across USDA agencies. The 2018 Farm Bill expanded coverage to new crop types, increased subsidies for beginning farmers, and adjusted administrative fees to help control program costs. These continuing reforms have solidified the role of FCIP as a cornerstone of US agricultural policy, enabling it to evolve in response to changing production risks and market dynamics.

2.2 Landscape complexity

Landscape complexity is a multidimensional concept that captures both the variety of land cover types and the spatial structure in which they are arranged. It is typically be characterized by two key features: compositional complexity and configurational complexity. Compositional complexity refers to the number and relative abundance of distinct land cover categories within a landscape. Configurational complexity, on the other hand, reflects how these categories are spatially organized, including their shapes, proximity, and distribution patterns across the landscape (Nelson and Burchfield, 2021; Fahrig et al., 2011; Meehan et al., 2011). Changes in land use, particularly those driven by intensive agriculture, have led to the simplification of both components (Landis, 2017). Large-scale monoculture, land consolidation, and field enlargement often reduce habitat diversity and spatial heterogeneity, leading to a more uniform and less ecologically functional landscape. These shifts can compromise biodiversity and diminish ecosystem services essential to both agricultural sustainability and broader environmental health (Termorshuizen and Opdam, 2009; Bastian et al., 2014; Duarte et al., 2018).

To assess landscape complexity in empirical research, researchers use quantitative landscape metrics that capture compositional and configurational attributes (Turner, 1990; Schindler, Poirazidis, and Wrbka, 2008; Plexida et al., 2014). The Shannon diversity index (SHDI) is commonly used to assess compositional complexity, and it integrates both the richness and evenness of land cover types to provide a single, interpretable score of landscape diversity (Aguilar et al., 2015). Landscapes with a higher SHDI contain a wider mix of land cover classes, indicating a more complex and potentially resilient system. Configurational complexity, by contrast, can be evaluated using contagion, a metric that measures the degree of dispersion and interspersion of land cover patches. A high contagion value indicates a landscape where similar land covers are clustered, and the overall spatial pattern is less fragmented, indicating lower configurational complexity. Conversely, lower contagion values suggest a more intermixed and irregular landscape structure (Nelson and Burchfield, 2021).

3 Data description

The panel data used in this study are constructed from multiple sources, which are discussed in turn below. As suggested in the previous section, we are interested in the effect of crop insurance participation on landscape complexity. The dependent variables of interest are two main measures of landscape complexity. We utilize the Shannon diversity index to measure landscape compositional complexity and contagion to measure configurational complexity for agricultural land use. Specifically, we use the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) as our indicator of land cover. This dataset classifies land cover at a 30 m resolution nationwide using satellite imagery and extensive ground truth data.[1] Given its relatively high resolution, full coverage and historical availability, it is the best available data for understanding agriculture land cover across the US (Nelson and Burchfield, 2021).

After compiling the landscape complexity data, we then collect the data needed to construct several measures of crop insurance participation, our main independent variables of interest. The primary source for crop insurance participation data is from the US Department of Agriculture (USDA) Risk Management Agency (RMA) Summary of Business (SOB).[2] The dataset is based on actual administrative information from all insurance policies handled by the federal crop insurance program through the years, rather than collecting data from farm surveys. Thus, we expect that there is less measurement error. We obtain the insurance data aggregated to the county-crop level from 2008-2018. The SOB data contain information on insured acreage, coverage levels, premium amounts, and subsidies. The insurance policies included in the study are limited to only yield protection (YP), revenue protection (RP), and revenue protection with harvest price exclusion (RPHPE), since these policies comprise the majority of all insurance policies sold in the US. We also collect county-level data on major

[1]The landscape indexes from the CDL data can be obtained through the *landscapemetrics* package in R, see details in Nelson and Burchfield (2021).

[2]The county-level crop insurance data from SOB can be obtained from the following website: https://www.rma.usda.gov/SummaryOfBusiness.

crop planted acreage from the USDA National Agricultural Statistics Service (NASS) and merge them with insurance data to facilitate the calculation of crop insurance participation measures.

Based on crop insurance data from SOB, we construct three annual county-level variables to measure insurance participation. The first insurance participation measure is "insured acreage ratio" and it represents the ratio of enrolled insurance acreage over total planted acreage in each county-year. Previous studies, such as Annan and Schlenker (2015), have used this measure, but we should note that this measure does not capture the variation in coverage levels chosen for crops (i.e., this participation measure remains the same when insured acreage is constant, even if coverage level choices increase). Thus, it is considered as an "extensive margin" measure. The second crop insurance participation measure is "average coverage level," and it is calculated by taking the acre-weighted average of the coverage levels chosen in each county-year. This measure captures the variation in the amount of coverage level chosen for the enrolled acres, and it is considered an "intensive margin" measure of crop insurance participation (i.e., it captures increases in participation through higher coverage levels, even when insured acreage remains constant). The third crop insurance participation measure is "premium per acre," and it is the dollar of insurance premium spent (before subsidy) per planted acre. Premiums vary depending on both the coverage level choices and insured acreage (i.e., it captures both intensive and extensive margin effects). Weber, Key, and O'Donoghue (2016) use premium levels as a measure of crop insurance participation.

In addition to data on landscape complexity and crop insurance, we utilize several weather variables from the Parameter Regression Independent Slopes Model (PRISM) climate group to serve as controls in our empirical analysis. There are time-county varying observable factors that can influence landscape transformation. Consistent with the approach used in Schlenker and Roberts (2009), the following weather variables are utilized in our study: degree days for extreme heat ("heating degree days (HDD)"), degree days for moderate heat ("growing degree days (GDD)"), and precipitation. The two degree day measures provide

information on the number of days a crop is exposed to certain temperature ranges. We follow the method in Schlenker and Roberts (2009) to calculate HDD and GDD. We use degree days above 29°C as the measure for extreme heat and between 10-29°C as the measure of moderate heat. These temperature cutoffs have been widely used in climate econometrics literature (Annan and Schlenker, 2015; Wang et al., 2021). The degree day measures are the sums of daily exposures over the May-September growing season. The precipitation variable represents the cumulative sum of precipitation received over the May-September growing season.

We merge the county-level aggregates of these weather variables together with landscape complexity measures and crop insurance participation to generate the panel data set. Descriptive statistics of the main variables used in the empirical analysis are summarized in Table 1. Figures 1 and 2 present the spatial distribution of landscape complexity across counties in the US based on the two indexes (i.e., Shannon diversity index and contagion). Landscape complexity varies greatly in the spatial dimension. Compositional complexity is generally higher in the northern and southeastern regions, while configurational complexity is lower in the central region of the US.

4 Empirical methods

4.1 Baseline specification and estimation strategy

For our main empirical specification, we employ a linear panel data model with various fixed effects. We separately regress landscape complexity indexes on crop insurance participation measures, HDD, GDD, precipitation, precipitation squared, year fixed effects, and county fixed effects. More formally, we estimate the following empirical specification:

$$LC_{it} = \beta_0 + \beta_1 Ins_{it} + \mathbf{W_{it}}\delta + \alpha_t + \gamma_i + \varepsilon_{it} \tag{1}$$

where LC_{it} represents one of the landscape complexity indicators (i.e., SHDI and contagion) in county i and year t, Ins_{it} the crop insurance measures (i.e., insured acreage ratio, average

coverage level, and premium per acre), $\mathbf{W_{it}}$ is the set of weather variables (i.e., HDD, GDD, precipitation, precipitation squared), α_t represent year fixed effects, γ_i represents county fixed effects, and ε_{it} is the idiosyncratic error term. The coefficient of interest is β_1. Note that the weather variables used as controls are consistent with previous studies that analyze nonlinear effects of weather on crop yield outcomes (Schlenker and Roberts, 2009; Annan and Schlenker, 2015).

Considering the panel nature of our dataset, we first utilize a traditional linear panel fixed effects (FE) model to estimate equation (1). Using this estimation strategy allows us to better account for potential unobserved confounders caused by unobserved linear-additive county-specific unobservables. For example, location-specific geographic conditions that are largely time-invariant, such as topography and soil type, would be likely correlated to crop insurance choices and landscape complexity. Furthermore, the year fixed effects are included to capture the time-specific shocks that affect all counties in the same manner, such as macroeconomic shocks that could affect landscape complexity. To facilitate proper inference, we also use standard errors clustered by county to account for potential year-to-year correlations within a county (Cameron, Gelbach, and Miller, 2011).

Notwithstanding the desirable properties of the traditional linear panel FE model, one disadvantage of this approach is the potential presence of residual endogeneity (even after controlling for unobserved heterogeneity and including a number of relevant controls in the specification). The typical approach to address this issue is applying instrumental variable (IV) based panel FE models (IV-FE) to control for the potential presence of residual endogeneity, which might come from time-varying and county-varying unobservables affecting both the outcome (LC_{it}) and the main independent variable of interest (Ins_{it}). We follow the general "subsidy change" IV approach that has been utilized in recent literature where a valid external instrument was needed for a crop insurance-related variable (Connor and Katchova, 2020; Connor, Rejesus, and Yasar, 2022; DeLay, 2019; Miao, 2020; Yu and Sumner, 2018). Specifically, we apply 1-year lagged premium subsidy rate as the main IV

for crop insurance participation variable. This premium subsidy rate IV is calculated by using the total premium subsidies for all insurance policies divided by the total premium of these policies. The premium subsidy rate is a valid IV in our empirical context because (i) it is correlated with insurance participation, (ii) it is determined by the crop insurance policy change rather than other channels (Miao, 2020), and (iii) previous year subsidy rate is predetermined for the current year.

4.2 Robustness checks: Alternative specifications

To assess the robustness of the baseline linear FE model in equation (1), we estimate several alternative empirical specifications: (i) We include a measure of irrigation use at the county level. (iv) We extend the analysis to only consider counties east of the 100th meridian where farming is predominantly non-irrigated. (iii) We incorporate the shares of corn, soybeans, and wheat among total planted acres as three additional control variables. (iv) We examine the effect of crop insurance participation in the previous year on landscape complexity.

The alternative empirical specifications considered above serve as robustness checks for several reasons. First, because irrigation may influence farmers' decisions on crop insurance participation and land use choices, we introduce an irrigation variable into equation (1) to sharpen identification. However, this approach carries potential drawbacks, as some researchers may argue that such controls could be endogenous "bad controls," potentially adding noise to the estimation. Second, we extend our analysis to only consider counties east of the 100th meridian, where farming is predominantly non-irrigated (Annan and Schlenker, 2015), to provide a useful contrast to the base model for the whole US, as irrigation generally does not typically play a significant role in this region. Third, we add the shares of major crops (corn, soybeans, and wheat) among planted acres for all crops as three control variables to better capture farmers' decisions and reduce potential omitted variable bias. By including the proportions of these crops, we can identify whether observed changes in landscape complexity are driven by strategic shifts to particular crops rather than by crop

insurance choices alone. This approach prevents us from overattributing landscape complexity to crop insurance decisions when crop choices may be at play, thereby allowing us to more clearly differentiate between the effects of crop choices and insurance participation changes. Finally, we examine the impact of prior crop insurance participation, as farmers' past experience may influence their production choices in the following year and, in turn, affect patterns of landscape complexity.

4.3 Robustness checks: Alternative estimation procedures

To further validate our results of IV-FE model, we apply additional robustness checks by using an alternative IV as the interaction of continuous rating parameter and the mean of the subsidies for 65% and 75% coverage levels. Specifically, we follow the IV procedures proposed by Tsiboe and Turner (2023), which primarily relies on the current rating framework used by RMA (i.e., continuous rating). The main idea is that premium rates in the federal crop insurance program are determined via exogenously set rating parameters. Hence, the parameters can be used to generate exogenous variations in premium rates that farmers face when making crop insurance decisions. Following Tsiboe and Turner (2023), we adopt the strategy where the instruments are determined by the interaction of the continuous rating parameter calculated by RMA's "continuous rating formula" and the mean of instruments in Yu and Sumner (2018) (i.e., mean of the subsidies for 65% and 75% coverage levels). Note that there is a direct mechanical link between the continuous rating formula and individual premium rates, making the above interaction term inappropriate as an instrument when using premium per acre as crop insurance participation measure.

In addition to the traditional IV approach, we apply two alternative estimation strategies to assess the robustness of the baseline model results. They are recently developed "external-instrument-free" instrumental variable (IV) methods (i.e., one by Lewbel (2012) and the other by Kiviet (2013, 2020)), which can help further address identification issues by dealing with possible residual endogeneity due to time–county varying unobservables. The

first moment-based IV procedure is also known as a heteroskedasticity-based IV approach (Lewbel, 2012). The moment-based IV estimator exploits heteroscedasticity in the error terms of the first-stage regressions (e.g., the regression of the potentially endogenous variable on the observable covariates) to identify the coefficients of the endogenous variables in the main equation, even in the absence of valid external instruments. According to Lewbel (2012), identification is achieved if the error terms in the first-stage regression (i.e., crop insurance participation as a function of exogenous variables in the main equation) exhibit heteroscedasticity, and a subset or all of the exogenous variables in the second-stage equation are uncorrelated with the covariance between the error terms in the first and second stages. In this case, the residuals from the first-stage regression, multiplied by the mean-centered exogenous covariates, serve as valid instruments.

Formally, with equation (1) as the main estimating equation and the crop insurance participation variable as the potentially endogenous variable, the first-stage regression in the Lewbel (2012) approach is:

$$Ins_{it} = \mathbf{X_{it}}\theta + \mu_{it}, \tag{2}$$

where $\mathbf{X_{it}}$ represents all the exogenous variables. Lewbel (2012) has shown that $(\mathbf{X_{it}} - \mathbf{X})\mu_{it}$ can be used as a valid IV in a standard 2SLS approach if there is heteroscedasticity in equation (2) (i.e., $Cov(\mathbf{X_{it}}, \mu_{it}^2) \neq 0$). To confirm the presence of heteroscedasticity, we employ the Breusch-Pagan (BP) test (Breusch and Pagan, 1979). The BP tests reject the null hypothesis of homoscedasticity in all crop insurance participation specifications. Specifically, the BP test statistics are 1175.68, 321.66 and 19902.13 for the models using three insurance participation measures, respectively, with p-values of 0.000 in all cases. The test results above support the use of the moment-based IV approach by Lewbel (2012) as an alternative estimation strategy to address residual endogeneity due to time- and county-varying unobservables.

In addition to the Breusch-Pagan (BP) test, we conduct a series of diagnostic tests to evaluate the validity and strength of the Lewbel (2012) IV approach. First, we employ

the Kleibergen-Paap rk LM test statistic to assess potential underidentification in the IV model (Kleibergen and Paap, 2006). The resulting test statistics and corresponding p-values suggest that we can reject the null hypothesis of underidentification. Second, we examine the strength of the instruments using the Kleibergen-Paap rk Wald F statistic. These tests indicate that we can reject the null hypothesis that the IVs used are weak. Finally, we apply the Hansen J test to evaluate the overall validity of IVs. Across all model specifications, the Hansen J test statistics are large with p-values below 0.01. These 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, as noted by Baum and Lewbel (2019), 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. Given that the majority of diagnostic tests support the appropriateness of the Lewbel (2012) IV approach, we retain this method as a robustness check in our empirical analysis.

To further validate our results, we also employ a recently developed "external-instrument-free" estimation method, known as the "kinky least squares" (KLS) regression proposed by Kiviet (2013, 2020). Similar to Lewbel's approach, the KLS method addresses potential residual endogeneity arising from time-county-varying unobservables, but it does so without relying on external instruments. We also argue that the endogeneity correlations are positive in our context such that the potentially endogenous crop insurance participation variable is likely positively correlated with the residual time-county-varying unobservables in the error term (i.e., unobserved extension or outreach effort that may be positively correlated with crop insurance participation).

The KLS approach establishes assumptions about the permissible degree of endogeneity within the model and achieves set identification of the coefficients by constraining endogeneity correlations within specified bounds. By selecting a range of endogeneity correlation values, the researcher can generate sets of coefficient estimates that reflect the assumptions

made about the underlying level of endogeneity. Kripfganz and Kiviet (2021) suggest that asymptotically conservative inference can be performed by considering the union of confidence intervals over a grid of such endogeneity correlations (e.g., 0.1, 0.2, 0.3, and so forth). Thus, we estimate the KLS model at assumed endogeneity correlations ranging from 0 to 1 in 0.1 increments. If the KLS estimates at small to moderate levels of assumed endogeneity (e.g., say, between 0.1 and 0.3) remain consistent with our baseline linear FE results, this suggests that our baseline findings are generally robust. In other words, a small to moderate degree of residual endogeneity does not alter the key inferences drawn from the linear FE model. Thus, if modest levels of assumed endogeneity fail to overturn our baseline conclusions, we have greater confidence in the overall robustness of our results.

5 Results and discussions

5.1 Baseline results

The results from the linear panel fixed effects (FE) regressions of landscape complexity as a function of crop insurance participation are presented in Tables 2. The FE-IV results are presented in Table 3. The results from FE and FE-IV models are consistent. For the compositional complexity (SHDI) regressions, the parameter estimates for coverage level suggest that counties with higher crop insurance participation at the intensive margin have statistically lower landscape compositional complexity (lower SHDI) and lower configurational complexity (higher contagion) (at the 1% significance level). However, no statistically significant relationship is observed between crop insurance participation at extensive margin, measured by insured acreage ratio, and landscape complexity (for both SHDI and contagion). For premium per acre, which considers both extensive and intensive margins of insurance participation, the estimated coefficients are not statistically significant.

These findings suggest that increasing crop insurance participation at the intensive margin likely has more significant landscape diversity reduction effects, which suggests that

buying higher coverage levels of insurance may discourage farmers from diversifying their crops to manage risk, as they already rely on insurance to mitigate their risks. On the other hand, the increasing insurance participation at the intensive margin does not significantly affect the landscape diversity. Insured farmers may be incentivized to cultivate riskier crops or plant new crops on marginal lands, which could then enhance landscape complexity. But this effect is not strong. Overall, the effect of intensive margin insurance participation appears to be dominant among the two directional effects mentioned above. Given the belief that farmers face various risks in a changing environment, the findings highlight important policy implications, including considering the unintended effects of risk management policies and maintaining or enhancing landscape diversity in rural areas.

Regarding the weather variables considered as controls, the estimated county-level effects align closely with expectations. Specifically, we observe a nonlinear effect of the degree days measures (i.e., crop growth requires a certain level of heat, up to a threshold, for optimal development. Beyond this threshold, damage to the crops occurs). In Table 2, we find that increased incidence of extreme heat (i.e., higher HDD) tends to lower both compositional and configurational complexity, whereas GDD has a negative and statistically significant estimated coefficient for compositional complexity. Concerning the precipitation variables, the parameters generally exhibit a "U-shaped" pattern of behavior for compositional complexity. For example, as precipitation increases from zero, landscape compositional complexity tends to increase initially. However, after reaching a certain "turning point," higher levels of precipitation contribute to a decrease in compositional complexity.

5.2 Robustness check results: Alternative specifications

As previously mentioned, we evaluate the robustness and stability of our base model results by performing several robustness checks with alternative empirical specifications. First, we include a measure of irrigation use at the county level, as irrigation can influence both crop insurance participation and landscape complexity, addressing potential omitted variable

bias. The results for this robustness check are presented in Table A.1. The SHDI and contagion results in Table A.1 remain consistent with those from the linear panel FE and FE-IV models. Second, we extend the analysis to counties east of the 100^{th} meridian, where farming is predominantly non-irrigated, as irrigation generally does not play a significant role in influencing crop production in this region. The results in Table A.2 are consistent with those when we include the irrigation use variable and still indicate that an increased coverage level of crop insurance can significantly reduce landscape complexity.

In addition, we include the shares of three major crops (corn, soybeans, and wheat) among total planted acres as additional control variables (A.3) to capture any influence from shifts in crop choices on landscape patterns. Including this measure helps us determine whether the observed effects of landscape complexity (SHDI and contagion) might be confounded by strategic crop adaptations. After controlling the crop share variables, the crop insurance measures largely retain consistent signs and significance levels as in our baseline models. This finding implies that the relationship between crop insurance participation and landscape complexity is not merely a reflection of farmers' decisions to concentrate on particular major crops; instead, crop insurance appears to have an independent effect on landscape complexity beyond what can be explained by shifts in crop composition.

Finally, we examine the effect of crop insurance participation in the previous year on landscape complexity. The results presented in Table A.4 show that increasing crop insurance participation in the previous year at both intensive and extensive margins will lower both compositional complexity (lower SHDI) and configurational complexity (higher contagion). Farmers are protected by crop insurance in the previous year, this previous protection experience may induce to have less incentive to diversify the crop production and lower the landscape complexity due to potential moral hazard.

5.3 Robustness check results: Alternative estimations

Aside from robustness to alternative specifications, we evaluate whether our findings hold even when the main empirical specification is estimated using alternative approaches. First, we apply alternative IV as the interaction of continuous rating parameter and the mean of the subsidies for 65% and 75% coverage levels following Tsiboe and Turner (2023). The results for this FE-IV model are presented in A.5. The estimates from this robustness check still largely coincide with our results from the baseline regressions that increased coverage level of crop insurance tends to lower landscape complexity. We also find the negative effect of the insured acreage ratio on landscape complexity (lower SHDI and higher contagion).

In addition, we apply the Lewbel (2012) moment-based IV procedure as an additional robustness check to assess whether the results from the baseline model hold when accounting for residual time- and county-varying unobservables. The parameter estimates from this IV procedure are presented in Table 4. When considering the intensive margin insurance participation, the results from the moment-based IV model are consistent with those of the baseline model for SHDI. The estimates show that counties with higher crop insurance participation with all three measures tend to lower compositional complexity (lower SHDI). However, for contagion runs, only a higher premium per acre tends to have lower configurational complexity (higher contagion).

Finally, we employ the KLS regression method as an additional robustness check. This external-instrument-free estimation technique offers an alternative to Lewbel's (2012) moment-based IV approach. We implement KLS at 0.1 increments from 0.1 onward and find that under positive endogeneity levels (e.g., 0.1, 0.2, 0.3). When considering the endogeneity level of 0.1, the signs and significance of the crop insurance participation measures remain consistent with our previous models. In other words, our findings hold firm even when modest levels of endogeneity are assumed. The results seem somewhat weak when taking higher endogeneity levels (Tables A.6 and A.7). These KLS results reinforce the notion that our baseline model estimates are robust and likely can withstand modest residual endogeneity

from unobservables in the error term.

6 Conclusions

This study examines the impact of crop insurance participation on landscape complexity. To achieve this objective, we construct a unique county-level panel dataset spanning 2008 to 2018 by merging a novel dataset on landscape complexity with publicly available crop insurance participation and weather data. Empirical analysis is conducted using linear panel fixed-effects models and fixed-effects instrumental models, as well as various robustness checks in the empirical analysis. The findings of our empirical analysis suggest that counties with higher crop insurance participation tend to have lower compositional complexity (lower Shannon diversity index) and lower configurational complexity (higher contagion), with more consistent evidence for intensive margin of crop insurance participation. Insurance participation at the intensive margin may influence farmer behavior by discouraging diverse and spatially heterogeneous cropping systems, thereby reducing landscape complexity. These findings underscore the idea that governmental policies aimed at helping farmers manage risk may inadvertently influence rural landscape diversity and sustainable agricultural systems.

The findings from our study point to the following policy implications. While crop insurance programs effectively reduce financial risk for farmers, they may unintentionally promote simplified and homogeneous cropping systems, leading to declines in both compositional and configurational landscape complexity. This reduction in diversity can weaken ecosystem services such as pollination, pest regulation, and resilience to extreme weather. To address these unintended consequences, policymakers might consider incorporating conservation incentives or landscape diversification benchmarks into insurance frameworks to avoid ecological trade-offs. Without such adjustments, well-intentioned support mechanisms could erode progress toward sustainable land-use patterns and environmental stewardship in agricultural regions.

While our research represents a step forward in understanding the relationship between

crop insurance participation and landscape complexity, it is essential to acknowledge that this study is still ongoing, and there are several limitations and areas that warrant future investigation. First, our current analysis focuses on one main index for each of the two features of landscape complexity, namely compositional complexity and configurational complexity. To gain a more comprehensive understanding, future studies may examine the impact of crop insurance participation on landscape complexity by incorporating alternative indicators of landscape complexity (Nelson and Burchfield, 2021). Second, this paper specifically concentrates on insurance and landscape data in the continental US or in counties east of the 100th meridian, which we believe provides an overall relationship between crop insurance participation and landscape complexity. However, we also recognize the importance of exploring the heterogeneity of crop insurance effects on landscape complexity across different regions of the US. We leave all these suggested research directions in the future.

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Figure 1: Spatial variation in landscape compositional complexity across counties in the United States. Values presented are the average across all years (2008-2018) for Shannon Diversity Index (SHDI)

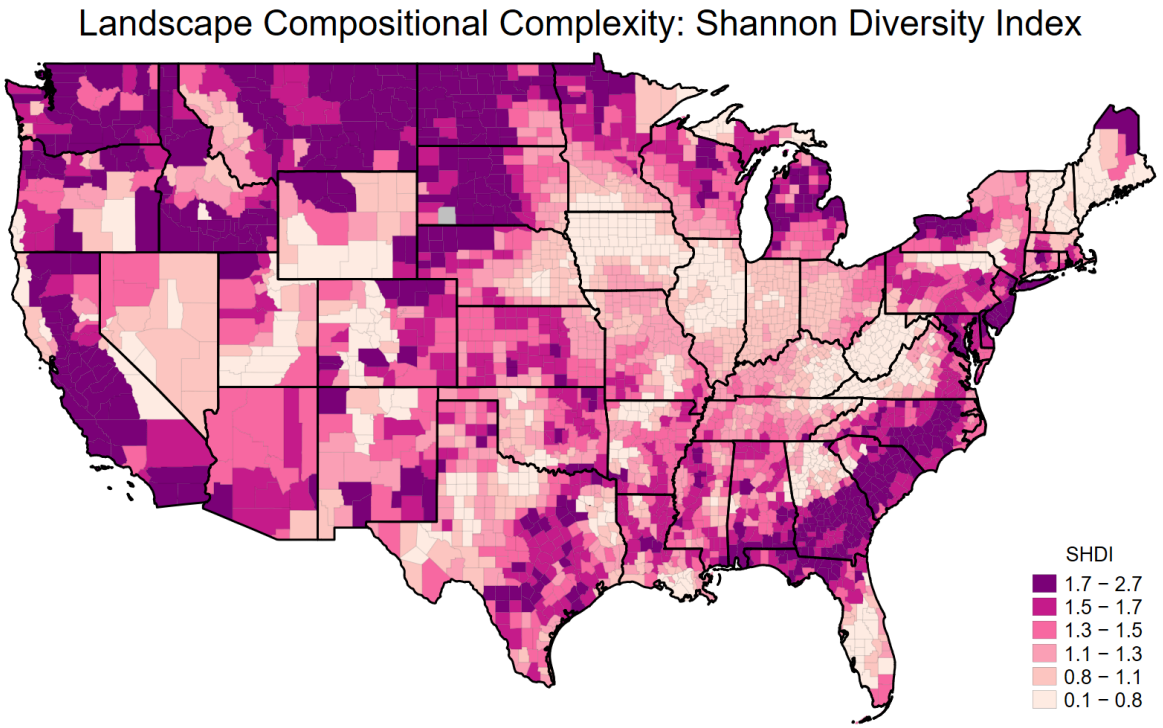


Figure 2: Spatial variation in landscape configurational complexity across counties in the United States. Values presented are the average across all years (2008-2018) for Contagion (CONTAG)

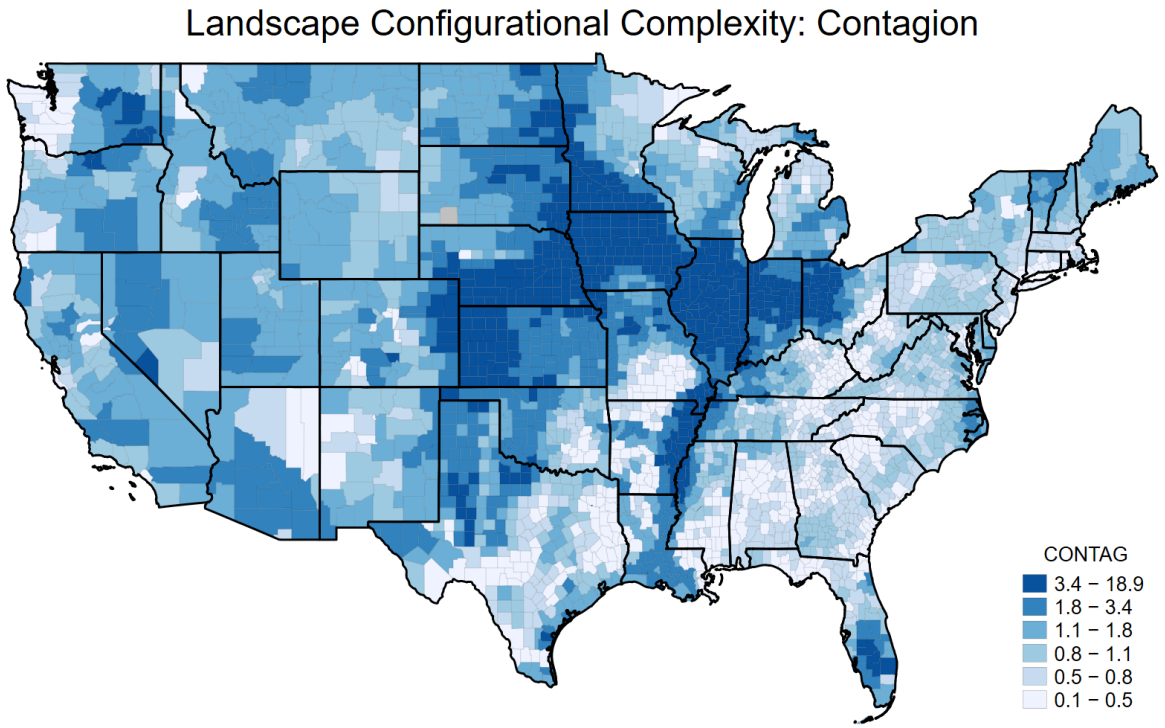


Table 1: Descriptive statistics

Variable	Description	Obs	Mean	St. Dev.	Min	Max
Shannon diversity index	Landscape compositional complexity index	19,716	1.34	0.39	0.08	2.82
Contagion	Landscape configurational complexity index	19,716	72.22	7.83	47.83	97.67
Insured acreage ratio	The ratio of insured acres over total planted acres	19,707	0.77	0.31	0.00	1.00
Coverage level	Average coverage level weighted by insured acres	19,716	0.68	0.08	0.50	0.84
Premium per acre	The ratio of premium amount over total planted acres ($100 per acre)	19,707	0.88	3.40	0.00	155.21
HDD	Heating degree days (in hundred °C)	19,716	0.67	0.74	0.00	6.84
GDD	Growing degree days (in thousand °C)	19,716	2.21	0.50	0.87	3.48
Precipitation	Precipitation (in thousand mm)	19,716	0.58	0.21	0.00	1.87

Table 2: The effect of crop insurance participation on landscape complexity: Linear panel fixed effects (FE) model

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.012			-0.064		
	(0.008)			(0.175)		
Coverage level		-0.147***			3.001***	
		(0.045)			(1.015)	
Premium per acre			-0.000			0.008
			(0.000)			(0.006)
HDD	-0.055***	-0.055***	-0.055***	0.909***	0.890***	0.904***
	(0.007)	(0.007)	(0.007)	(0.160)	(0.159)	(0.159)
GDD	-0.036*	-0.038**	-0.035*	-0.311	-0.270	-0.321
	(0.019)	(0.019)	(0.019)	(0.450)	(0.454)	(0.449)
Precipitation	0.125***	0.132***	0.120***	1.013	0.734	0.989
	(0.043)	(0.043)	(0.043)	(1.035)	(1.041)	(1.036)
Precipitation sq.	-0.000**	-0.000***	-0.000**	-0.000**	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19707	19716	19707	19707	19716	19707
Adjusted R^2	0.095	0.096	0.095	0.062	0.063	0.062

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table 3: The effect of crop insurance participation on landscape complexity: FE-IV model

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	6.586			-217.814		
	(13.096)			(430.994)		
Coverage level		-0.536***			17.755***	
		(0.129)			(3.052)	
Premium per acre			0.394			-13.029
			(0.945)			(31.159)
HDD	-0.439	-0.049***	-0.133	13.655	0.755***	3.533
	(0.769)	(0.005)	(0.200)	(25.320)	(0.129)	(6.585)
GDD	0.485	-0.048***	-0.644	-17.330	0.295	20.004
	(1.037)	(0.018)	(1.480)	(34.128)	(0.427)	(48.795)
Precipitation	-2.940	0.183***	0.216	102.417	-0.850	-1.926
	(6.134)	(0.036)	(0.386)	(201.864)	(0.846)	(12.729)
Precipitation sq.	0.000	-0.000***	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16831	16836	16831	16831	16836	16831
Adjusted R^2	-69.226	-0.021	-101.188	-143.055	-0.086	-209.435

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses. (iii) The IV is the subsidy rate in the previous year.

Table 4: The effect of crop insurance participation on landscape complexity: Moment-based IV model

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.016*			0.033		
	(0.009)			(0.214)		
Coverage level		-0.155***			0.050	
		(0.056)			(1.352)	
Premium per acre			-0.001**			0.023***
			(0.000)			(0.008)
HDD	-0.054***	-0.072***	-0.055***	0.904***	0.367*	0.901***
	(0.007)	(0.008)	(0.007)	(0.160)	(0.220)	(0.159)
GDD	-0.036*	0.241***	-0.035*	-0.310	8.515***	-0.345
	(0.019)	(0.076)	(0.019)	(0.450)	(2.519)	(0.449)
Precipitation	0.127***	0.392***	0.120***	0.976	9.088***	0.989
	(0.043)	(0.084)	(0.043)	(1.030)	(2.554)	(1.035)
Precipitation sq.	-0.000**	-0.000***	-0.000**	-0.000**	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19707	19716	19707	19707	19716	19707
Adjusted R^2	-0.011	0.004	-0.011	-0.048	-0.024	-0.048
AIC	-29896.541	-28716.142	-29892.826	94164.186	97018.690	94167.986
BIC	-29778.210	-28597.804	-29774.495	94282.517	97137.028	94286.317
Kleibergen-Paap rk LM statistic	986.204	754.147	38.207	986.204	753.976	38.207
	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.000)
Kleibergen-Paap rk Wald F statistic	1234.821	1072.151	50.224	1234.821	1070.635	50.224
(Stock-Yogo 15% max)	25.61	25.61	25.61	25.61	25.61	25.61
Hansen J statistic	133.348	123.616	34.157	148.593	134.366	46.170
	(p=0.000)	(p=0.000)	(p=0.000)	(p=0.001)	(p=0.000)	(p=0.000)

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table 5: The effect of crop insurance participation on landscape complexity: Kinky least squared model (endogeneity correlation = 0.1)

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.170**			3.617*		
	(0.083)			(1.926)		
Coverage level		-1.344**			30.872**	
		(0.651)			(15.151)	
Premium per acre			-0.006**			0.128**
			(0.003)			(0.062)
HDD	-0.047***	-0.048***	-0.054***	0.733***	0.739***	0.879***
	(0.006)	(0.006)	(0.005)	(0.150)	(0.146)	(0.118)
GDD	-0.037**	-0.055***	-0.028	-0.281	0.124	-0.497
	(0.017)	(0.020)	(0.017)	(0.394)	(0.454)	(0.398)
Precipitation	0.185***	0.234***	0.120***	-0.393	-1.632	0.989
	(0.045)	(0.064)	(0.032)	(1.053)	(1.497)	(0.742)
Precipitation sq.	-0.000***	-0.000***	-0.000***	-0.000	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19707	19716	19707	19707	19716	19707

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Appendix

Table A.1: The effect of crop insurance participation on landscape complexity: Linear FE model with irrigation variable

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.012			-0.068		
	(0.008)			(0.175)		
Coverage level		-0.146***			3.007***	
		(0.045)			(1.015)	
Premium per acre			-0.000			0.008
			(0.000)			(0.006)
HDD	-0.055***	-0.055***	-0.055***	0.906***	0.887***	0.902***
	(0.007)	(0.007)	(0.007)	(0.159)	(0.159)	(0.158)
GDD	-0.037*	-0.039**	-0.036*	-0.327	-0.286	-0.337
	(0.019)	(0.019)	(0.019)	(0.450)	(0.454)	(0.450)
Precipitation	0.124***	0.131***	0.119***	0.993	0.711	0.967
	(0.043)	(0.043)	(0.043)	(1.036)	(1.043)	(1.037)
Precipitation sq.	-0.000**	-0.000***	-0.000**	-0.000**	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Irrigation	-0.000	-0.000	-0.000	-0.005	-0.006	-0.005
	(0.000)	(0.000)	(0.000)	(0.008)	(0.009)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19707	19716	19707	19707	19716	19707
Adjusted R^2	0.095	0.096	0.095	0.062	0.063	0.062

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.2: The effect of crop insurance participation on landscape complexity in counties east of the 100th meridian: Linear FE model

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	0.004			-0.267		
	(0.010)			(0.226)		
Coverage level		-0.222***			5.237***	
		(0.051)			(1.186)	
Premium per acre			-0.001*			0.009
			(0.000)			(0.006)
HDD	-0.049***	-0.048***	-0.049***	0.890***	0.850***	0.881***
	(0.007)	(0.007)	(0.007)	(0.175)	(0.175)	(0.174)
GDD	-0.014	-0.007	-0.011	-0.706	-0.951	-0.844
	(0.029)	(0.029)	(0.029)	(0.667)	(0.673)	(0.681)
Precipitation	0.180***	0.200***	0.181***	0.137	-0.428	0.006
	(0.049)	(0.049)	(0.048)	(1.219)	(1.238)	(1.213)
Precipitation sq.	-0.000***	-0.000***	-0.000***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16113	16113	16113	16113	16113	16113
Adjusted R^2	0.111	0.113	0.111	0.065	0.068	0.065

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.3: The effect of crop insurance participation on landscape complexity: Linear FE model with crop share measures

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.025*			-0.395		
	(0.014)			(0.337)		
Coverage level		-0.264***			7.230***	
		(0.059)			(1.345)	
Premium per acre			-0.008			-0.330
			(0.010)			(0.325)
HDD	-0.063***	-0.061***	-0.063***	0.965***	0.913***	0.948***
	(0.010)	(0.010)	(0.010)	(0.237)	(0.237)	(0.236)
GDD	-0.145***	-0.164***	-0.148***	2.529***	2.759***	2.586***
	(0.032)	(0.033)	(0.033)	(0.742)	(0.745)	(0.755)
Precipitation	0.045	0.058	0.042	4.416***	3.977***	4.345***
	(0.064)	(0.064)	(0.064)	(1.509)	(1.506)	(1.503)
Precipitation sq.	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corn share	-0.228***	-0.235***	-0.228***	3.775***	3.901***	3.844***
	(0.045)	(0.045)	(0.045)	(0.999)	(1.015)	(0.998)
Soybean share	0.119***	0.110**	0.121***	-4.896***	-4.578***	-4.860***
	(0.043)	(0.043)	(0.042)	(0.952)	(0.977)	(0.947)
Wheat share	-0.005	-0.005	-0.004	0.236	0.198	0.311*
	(0.006)	(0.006)	(0.007)	(0.145)	(0.138)	(0.171)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7909	7909	7909	7909	7909	7909
Adjusted R^2	0.163	0.166	0.162	0.102	0.107	0.102

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.4: The effect of previous crop insurance participation on landscape complexity: Linear FE model with previous insurance participation measures

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.033***			0.491***		
(lag 1)	(0.008)			(0.165)		
Coverage level		-0.285***			6.716***	
(lag 1)		(0.042)			(0.886)	
Premium per acre			-0.000			-0.002
(lag 1)			(0.000)			(0.008)
HDD	-0.051***	-0.051***	-0.053***	0.854***	0.838***	0.881***
	(0.007)	(0.007)	(0.007)	(0.160)	(0.159)	(0.160)
GDD	-0.035*	-0.045**	-0.031*	-0.198	0.079	-0.251
	(0.018)	(0.018)	(0.018)	(0.432)	(0.433)	(0.430)
Precipitation	0.159***	0.157***	0.141***	0.258	0.161	0.513
	(0.047)	(0.047)	(0.047)	(1.172)	(1.169)	(1.154)
Precipitation sq.	-0.000***	-0.000***	-0.000***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16881	16883	16881	16881	16883	16881
Adjusted R^2	0.109	0.112	0.107	0.069	0.073	0.068

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.5: The effect of crop insurance participation on landscape complexity: FE-IV model with alternative IV

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.693***			14.338***		
	(0.071)			(1.578)		
Coverage level		-2.817***			58.170***	
		(0.254)			(5.723)	
Premium per acre			−−			−−
HDD	-0.022***	-0.040***	−−	0.219	0.590***	−−
	(0.008)	(0.006)		(0.176)	(0.145)	
GDD	-0.042*	-0.076***	−−	-0.181	0.517	−−
	(0.024)	(0.021)		(0.527)	(0.477)	
Precipitation	0.386***	0.360***	−−	-4.513***	-3.973***	−−
	(0.053)	(0.045)		(1.175)	(1.023)	
Precipitation sq.	-0.000***	-0.000***	−−	0.000***	0.000***	−−
	(0.000)	(0.000)		(0.000)	(0.000)	
Year fixed effects	Yes	Yes	−−	Yes	Yes	−−
County fixed effects	Yes	Yes	−−	Yes	Yes	−−
Observations	19649	19657	−−	19649	19657	−−
Adjusted R^2	-0.835	-0.438	−−	-0.751	-0.395	−−

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses. (iii) The IV is the interaction of continuous rating parameter and the mean of the subsidies for 65% and 75% coverage levels, following the IV procedures proposed by Tsiboe and Turner (2023). (iv) Results using premium per acre as the measure of crop insurance participation are not reported due to a mechanical link between the continuous rating formula and individual premium rates. This connection makes the interaction term in (iii) not appropriate as an instrument when using premium per acre as crop insurance participation measure.

Table A.6: The effect of crop insurance participation on landscape complexity: Kinky least squared model (endogeneity correlation = 0.2)

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.351*			7.840*		
	(0.204)			(4.759)		
Coverage level		-2.926			67.705	
		(2.034)			(47.347)	
Premium per acre			-0.011*			0.255*
			(0.006)			(0.132)
HDD	-0.038***	-0.040***	-0.053***	0.532**	0.541*	0.854***
	(0.011)	(0.013)	(0.005)	(0.260)	(0.291)	(0.123)
GDD	-0.039**	-0.077**	-0.020	-0.246	0.644	-0.682
	(0.018)	(0.035)	(0.019)	(0.424)	(0.815)	(0.442)
Precipitation	0.255***	0.368**	0.120***	-2.007	-4.759	0.990
	(0.085)	(0.177)	(0.033)	(1.990)	(4.117)	(0.760)
Precipitation sq.	-0.000***	-0.000*	-0.000***	0.000	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19707	19716	19707	19707	19716	19707

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.7: The effect of crop insurance participation on landscape complexity: Kinky least squared model (endogeneity correlation = 0.3)

	Compositional complexity			Configurational complexity		
	SHDI	SHDI	SHDI	Contagion	Contagion	Contagion
Insured acreage ratio	-0.602			13.669		
	(0.477)			(11.093)		
Coverage level		-6.572			152.584	
		(11.166)			(259.959)	
Premium per acre			-0.017*			0.395*
			(0.010)			(0.225)
HDD	-0.027	-0.020	-0.052***	0.254	0.084	0.825***
	(0.024)	(0.061)	(0.006)	(0.549)	(1.417)	(0.133)
GDD	-0.041*	-0.128	-0.011	-0.198	1.843	-0.886*
	(0.021)	(0.161)	(0.023)	(0.498)	(3.741)	(0.529)
Precipitation	0.350*	0.678	0.120***	-4.235	-11.965	0.990
	(0.187)	(0.950)	(0.034)	(4.342)	(22.112)	(0.794)
Precipitation sq.	-0.000*	-0.000	-0.000***	0.000	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19707	19716	19707	19707	19716	19707

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.