Warming Temperatures, Planting Density, and Crop Insurance Losses in US Corn Production

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August 12, 2025

Abstract

In the face of increased frequency of weather extremes and higher climatic variability, understanding the effects of warming temperatures on crop production risk is important. Given that corn planting density (i.e., plants per acre) has steadily increased over the years in the United States (US), this has prompted debate as to how higher planting densities may have influenced corn production losses and downside yield risk over time, especially in the presence of a warming climate. This study examines whether higher planting densities increase crop insurance losses due to warming temperatures. To achieve this objective, we utilize county-level data on crop insurance production losses, planting density, weather, and other control variables for the period 1997 to 2015 in the Central Corn Belt (CCB) states of Illinois, Indiana, and Iowa. Results from linear fixed effects econometric models and a number of robustness checks suggest that the impact of extreme heat on crop insurance losses becomes more severe as planting density rates increase. Nonetheless, for counties with high adoption rates of genetically-modified rootworm resistant (GM-RW) corn, we also find that the magnitude of crop insurance losses due to extreme heat decreases as planting density rate rises.

Keywords: Plant density, Climate change effects, Corn resilience, Yield risk

JEL Classification Numbers: Q10, Q16, Q19

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Production agriculture is considered one of the most vulnerable to climate change because it depends on favorable weather conditions to achieve satisfactory yield outcomes. There is a large literature that has demonstrated the large negative impacts of climate change and warming temperatures on mean crop production yields (see, among others, Schlenker and Roberts 2006; Schlenker and Roberts 2009; Roberts, Schlenker, and Eyer 2012; Lobell et al. 2013; Tack, Barkley, and Nalley 2015; D'Agostino and Schlenker 2016; Tack, Barkley, and Hendricks 2017). Aside from studies that examine the mean yield effects of climate change and warming, there is also a number of previous studies that have investigated the impact of climate change and warming temperatures on crop yield risk (i.e., its effects on yield variability and higher moments of the yield distribution) (Chen, McCarl, and Schimmelpfennig 2004; Chen and Chang 2005; Isik and Devadoss 2006; McCarl, Villavicencio, and Wu 2008; Kim and Pang 2009; Barnwal, Kotani et al. 2010; Boubacar 2010; Tack, Harri, and Coble 2012; Attavanich and McCarl 2014; Ray et al. 2015; Urban et al. 2012; Urban, Sheffield, and Lobell 2015; Tack, Coble, and Barnett 2018; Chavas et al. 2019; Connor and Katchova 2020; Perry, Yu, and Tack 2020). Most of these papers indicate that climate change and warming temperatures increase yield risk (and also simultaneously decrease mean yields).

There is growing scientific consensus that prolonged periods of extreme temperatures and dry weather are becoming more common globally due to climate change (Walthall et al. 2013; Cook, Ault, and Smerdon 2015; Stocker 2014), and therefore management practices that can help minimize the effects of warming temperatures on crop production have increasingly become an important topics of discussion in agriculture. Since most farmers are risk-averse (Chavas and Holt 1996), they typically view the climate change impacts on inter-annual yield variability and/or yield risk—particularly, downside risk—as at least as important as the direct effect of climate change on mean yields.

In particular, Lobell et al. (2014) and Ortiz-Bobea, Knippenberg, and Chambers (2018) have strongly indicated that crop yields and farm productivity in the United States (US) are increasingly becoming more sensitive to higher temperatures. This implies that crop yield response to extreme heat events (e.g., droughts) are becoming larger

such that year-to-year variability (or yield risk) from global warming has increased. The Lobell et al. (2014) study is of particular interest because they hypothesized that the rise in planting density over time (i.e., higher plant populations per acre) may be the main factor contributing to the increased sensitivity of US corn yields (though they did not prove this using observational data). Note that, from 1964-2016, average US corn planting densities have more than doubled, from about 14,000 plants/acre to around 30,000 plants/acre (Wang et al. 2021). Hence, even with recent technological and varietal improvements in their study period, Lobell et al. (2014) suggests that the increase in planting density can still exacerbate the yield-risk-increasing effect of warming temperatures. This implication supports the notion that higher planting density magnifies the impacts of warming events on crop insurance losses (i.e., to the extent that downside yield risk can be can be represented by crop insurance losses (Goodwin and Piggott 2020; Perry, Yu, and Tack 2020; Aglasan, Goodwin, and Rejesus 2022).

The objective of this study is to empirically examine how higher planting densities influence the impact of warming events on crop insurance losses for corn in the US Midwest. Hence, we provide insight into whether increases in planting density contributes to larger downside risks due to warming. In addition, we investigate how adoption of genetically-modified corn varieties with the rootworm resistance trait (GM-RW) affects the interrelationships between planting density, warming, and crop insurance losses. To accomplish these objectives, we construct a long-run, county-level panel data set from 1997 to 2015 with information on crop insurance losses, planting density levels, GM-RW adoption rates, input expenditures (i.e., fertilizer and chemicals), and weather variables, for the following US Central Corn Belt (CCB) states: Illinois, Indiana, Iowa. Traditional linear panel fixed effects (FE) econometric models with a number of interaction terms are developed and estimated to determine how increasing planting density levels affect crop insurance losses due to detrimental warming events (like drought). A variety of robustness checks are also conducted using different empirical specifications and alternative estimation procedures (e.g., a correlated random effects (CRE) probit model and a recently developed moment-based instrumental variable (IV) model) to validate the

strength of the results from the linear panel FE models, and address other identification issues. Results from the linear panel FE models and a variety of robustness checks suggest that the impact of extreme heat on crop insurance losses becomes more severe as planting density rates increase. However, for counties with high adoption rates of GM-RW corn, we find that the magnitude of crop insurance losses due to extreme heat decreases as planting density rate rises.

There are now a number of studies that have examined the "triple" interactions between mean crop yields, poor growing environments (i.e., low moisture conditions), and planting densities. For example, Van Averbeke and Marais (1992), Assefa et al. (2016), and Assefa et al. (2018), find that the negative mean yield effects of low moisture (or extreme heat) events is further exacerbated when planting densities are high. These studies argue that higher planting densities result in more intense inter-plant competition for limited moisture and nutrients under extreme heat environments, which in turn leads to larger mean yield reductions due to warming temperatures. In contrast, Carter et al. (2018) find that higher planting density do not necessarily magnify the negative mean yield effect of low moisture and extreme heat events. The authors attribute their result to improved canopy development at higher planting densities, which helps trap moisture in the ground and can potentially improve yield performance.

In addition, Chavas, Shi, and Lauer (2014), Chavas and Shi (2015), and Wang et al. (2021) investigate the "quadruple" interactions among mean crop yields, poor growing environments (i.e., low moisture conditions), planting densities, and adoption of GM varieties. Chavas, Shi, and Lauer (2014) and Chavas and Shi (2015) suggest that the negative marginal yield effect of poor growing conditions (e.g., warming temperatures) at higher planting densities tend to be smaller if GM varieties are used. Wang et al. (2021) finds that reduction in mean crop yields due to warming temperatures are exacerbated at higher planting densities. Moreover, Wang et al. (2021) shows that the marginal yield effect of increasing planting density is less negatively affected by warming when GM-RW varieties varieties are used. These studies are part of the literature that explores how complex interactions between genotype (G), growing environment (E), and management

(M) practices influence crop yield outcomes (i.e., the so-called G × E × M literature).

In light of the previous studies discussed, we contribute to the literature in a couple of ways. First, to the best of our knowledge, there has been no study that explored the "quadruple" interrelationship between crop insurance losses, warming temperatures, planting density, and GM crop adoption. Past literature focused on how warming temperatures affect mean yields (rather than crop insurance losses), and the role that planting density and/or GM variety choices play in this context. Since the crop insurance loss measure we use in the study—the loss cost ratio (LCR) (i.e., the ratio of indemnities over insured liabilities)—is considered a valid downside risk measure (Goodwin and Piggott 2020; Perry, Yu, and Tack 2020; Aglasan, Goodwin, and Rejesus 2022), we extend the G × E × M literature by evaluating how the downside-risk-increasing effects of warming temperatures (i.e., "E") are influenced by planting density (i.e., "M") and GM variety (i.e., "G") choices.[1]

Second, much of the previous literature that has examined the role of planting density and warming temperatures in US corn production have utilized plot-level experimental data with limited geographical scope and/or time-scales (perhaps with the exception of Lobell et al. 2014 and Assefa et al. 2018, though these two studies do not specifically explore issues related to yield risk and GM crop use). For example, Chavas and Shi (2015) and Wang et al. (2021) only use experimental plot data from Wisconsin for the period 1990-2010 to investigate the impacts of planting density and GM varieties on corn yields under a warming environment. Arguably, more policy relevant insights can be gleaned from an analysis of data based on actual farmer behavior, even if the farmer data is at a higher level of aggregation (e.g., county-level). Nonetheless, given that the present study uses aggregated data from actual farmers, it serves as a complement to previous studies that have used plot-level field experiment data to explore the interactions among yield outcomes, warming conditions, planting densities and/or varietal choices.

[1]The LCR as a downside risk measure gives direct information about the cost of providing a given level of risk protection when shortfalls in yields or revenue occurs. The LCR also has the advantage of theoretically embodying the higher moment risk variables (e.g., variance, skewness, and kurtosis) in one single risk indicator, rather than having separate measures for each of the higher moments of the yield distribution (as is done in Shi, Chavas, and Lauer 2013 and Wang, Rejesus, and Aglasan 2021). This simplifies our empirical specification and estimation procedure.

Data and Descriptive Statistics

The panel data used in this study comes from a variety of 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 the 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.[2] We utilized the publicly available Summary of Business (SOB) data from the Risk Management Agency (RMA), which has county-level information on indemnities and liabilities (among other crop insurance related variables). The LCR data we use spans the period 1997 to 2015 and geographically covers all counties in Illinois, Indiana, and Iowa.

One of the main explanatory variables of interest in our empirical analysis is a measure of average corn planting density at the county-level. We utilize data from GfK Kynetec for our planting density variable and for other variables reflecting adoption of various GM corn varieties. The GfK Kynetec data contain information on corn seed traits, planting density, and acres planted for each seed trait in a given county and year. Each year, GfK Kynetec conducts surveys throughout the US of randomly sampled farmers and collect information about decisions pertaining to seed and pesticide choices. From these surveys, county-level aggregates (i.e., averages) of the acres planted to particular GM crops and planting density can be calculated. We have county-level averages of planting density and GM corn adoption for the period 1997–2015.

With regards to GM crop adoption, we are particularly interested in the number acres planted to GM corn varieties with the rootworm resistant trait (GM-RW). GM corn varieties may have a single trait (e.g., corn that is only herbicide tolerant) or they may have multiple "stacked" traits (e.g., corn with herbicide tolerance plus, say, resistance to corn rootwoorm and European corn borer, has three traits). GM-RW is of interest in our context because the root architecture of these varieties are thought to be more

[2]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.

robust than those without this trait (Goodwin and Piggott 2020).[3] Therefore, varieties with this specific trait is sometimes considered more resilient to extreme heat events. As such, we construct a GM-RW variable from the GfK Kynetec data set that represents the proportion of total acres in the county planted to GM corn varieties with at least one RW trait (i.e., regardless if the GM corn is single-trait or multiple-trait)

The other set of important independent variables included in our empirics are weather-related covariates. The first set of weather variables we consider are degree day measures for the corn growing season (i.e., May to September) that have been used in the literature to allow for non-linearities in the effect of temperature on yield outcomes (see, e.g., Ritchie and Nesmith 1991; Schlenker and Roberts 2006; Schlenker and Roberts 2009).[4] A degree day measure is typically defined as the number of degrees that the daily mean temperature is above a threshold (or is within a range) per day, accumulated over a defined period of time (say, summed over a month or over a growing season). The GDD range we use are between 8°C (the lower threshold) and 29°C (for the upper threshold). On the other hand, the HDD threshold used is above 29°C. The GDD and HDD measures used are summed over the May to September growing season. We also consider a weather variable that represent accumulated precipitation (in mm) summed over the growing season. A squared precipitation term is also included to account for potential non-linearity in the precipitation effect. We primarily utilize data from the "Parameter-Elevation Regression on Independent Slopes Model" (PRISM) for calculating the GDD, HDD, and precipitation measures used in this study. PRISM is a gridded 4km resolution data set, which can then be aggregated to obtain county averages. The PRISM data has been widely used in previous climate change studies (e.g., Schlenker and Roberts 2009).

Another weather variable considered in this study (i.e., primarily in our robustness

[3]Though it should be noted here that, if there is no rootworm infestation, the root balls of crops with rootworm resistant traits should theoretically have the same robustness as other varieties without rootworm resistant traits. However, when there is rootworm infestation, it is reasonable to theoretically expect that crops with rootworm resistant traits should be healthier and more robust than those without the trait.

[4]Note that some previous climate econometric studies use the months from May to September as the growing season time frame, while some use May-August as the growing season time frame. However, we believe that the preponderance of studies mainly use the May-September period, and we use this time frame here.

checks) is the Palmer Z drought index, which has also been used in a number of past climate studies (e.g., Xu et al. 2013 among others). This index variable is standardized to the local climate and measures relative dryness or wetness relative to local norms. Positive index values typically represent wetness and negative values typically indicate dryness. As such, we categorize the Palmer Z drought index into the following groups: normal, wet, and dry. That is, we have three dummy variables for Palmer Z index that represent normal, wet, and dry conditions.[5] Data on the drought index are derived from the National Climatic Data Center (NCDC). Note that the drought indices from NCDC are aggregated at the climate division level. Hence, counties in our data set falling in one climate division have the same drought index values.

In addition to the weather variables mentioned above, we also control for other observable factors that can potentially influence crop insurance outcomes at the county-level. For example, we account for the level of inputs used (i.e., fertilizer and chemicals) and average crop insurance coverage levels for the county. To control for input use, we specifically utilize county-level input expenditure data (per acre) on the fertilizer and chemical expenditures. Input expenditure data were collected from the the Bureau of Economic Analysis.[6] We use RMA SOB data to calculate the average county-level coverage level variable.[7] Summary statistics for all the variables used in this research are presented in Table 1. Supplementary figures that shows trends of these variables over time are presented in the Appendix (See Appendix Figures A.5-A.9).

Empirical Framework

This study employs a linear panel data model, with interactions and county fixed effects, to investigate how planting density influence the impact of high temperature stress on

[5]Note that dummy for Palmer Z dry equals one if Palmer Z values are less than or equal to -1.25. Palmer Z wet dummy equals one if Palmer Z values are above 1. Values are between -1.25 and -1 represents normal Palmer Z).

[6]Note, however, that the expenditure data used here represents expenditures not only for corn, but for all crops in the county. The data can be accessed from: https://www.bea.gov/regional/.

[7]County average coverage level is created by weighting each possible coverage level by the associated acres insured at each coverage level. That is, to get the average county-level coverage level, we multiply each coverage level with associated insured acres, then we divide this multiplication by total insured acres in a county.

crop insurance losses. More formally, consider the following empirical specification:

$$LCR_{it} = \beta_1 PD_{it} + \beta_2 GDD_{it} + \beta_3 HDD_{it} + \beta_4 precip_{it} + \beta_5 precip_sq_{it} + \gamma_{12}(GDD_{it} \times PD_{it}) + \gamma_{13}(HDD_{it} \times PD_{it}) + \eta X_{it} + \alpha_i + \delta t + \varepsilon_{it} \quad (1)$$

where LCR_{it} represents LCR in county i and year t, PD_{it} is county-average planting density level (in '000 plants per acre), GDD_{it} is the growing degree day measure, HDD_{it} is the harmful degree day measure, $precip_{it}$ represents precipitation (in mm), $precip_sq_{it}$ is the squared precipitation term, X_{it} is a vector of control variables (i.e., including: (i) the GM-RW variable (i.e., a proportion between zero and 1.0) (ii) county-level expenditures on fertilizer and chemicals (in $ per acre), and (iii) average county-level crop insurance coverage level (i.e., a decimal between 0 and 1.0)), t is a linear time trend (i.e., to capture the technological advances over time), and ε_{it} denotes the idiosyncratic error term for county i in year t. The β, γ, η, α, and δ terms are parameters to be estimated. Specifically, α_i is the county fixed effects to control for unobserved time-invariant county level factors that impact crop insurance performance. Note that the weather variables included in equation (1) are consistent with empirical specifications used in previous studies that analyze nonlinear effects of weather on crop yield outcomes (Ritchie and Nesmith 1991; Schlenker and Roberts 2006; Schlenker and Roberts 2009; Tack, Harri, and Coble 2012; Annan and Schlenker 2015; Lusk, Tack, and Hendricks 2018).

A traditional linear panel fixed effects (FE) model is the main empirical strategy utilized to estimate equation (1). Robustness checks are also conducted to show that estimation results from equation (1) are robust to a variety of other alternative specifications, such as: including a non-linear trend (instead of a linear time trend),[8] and clustering SEs at the agricultural crop-reporting districts (CRD) (rather than at the county) (i.e., more on these in the robustness checks below). Note that we also use alternative estimation methods (i.e., the correlated random effects (CRE) probit method and

[8]Note that the use of linear or non-linear time trends above are consistent with previous climate change econometric studies in agriculture (see Tack, Harri, and Coble 2012; Tack, Barkley, and Nalley 2015; Tack, Barkley, and Hendricks 2017). As an alternative, year fixed effects could have been used instead of time trends (which some consider as more flexible because it picks up non-time-trend unobservables). However, this flexibility sometimes come at the cost of soaking up a lot of the variation across time such that most parameter estimates for the variables of interest become statistically insignificant. This is the main reason for utilizing linear and non-linear time trends in our empirical specification.

the Lewbel moment-based IV approach) to verify the results from our main estimation method—the linear panel FE model.

Given the primary objective of this study, the main parameter of interest in equation (1) is γ_{13}. This parameter allows one to infer whether higher planting densities exacerbate the losses associated with HDD. For ease of interpretation and to better asses how planting density affects the LCR response to extreme heat, we calculate the marginal effect of LCR with respect to HDD, evaluated at different planting density values. Based on equation (1), the partial derivative of LCR with respect to HDD can be expressed as follows:

$$\frac{\partial LCR_{it}}{\partial HDD_{it}} = \beta_3 + \gamma_{13} PD_{it} \tag{2}$$

A priori, we theoretically expect β_3 to be positive (i.e., extreme heat increases losses). If γ_{13} is positive (negative), then higher planting densities further increase (decrease) the effect of extreme heat on crop insurance losses.

This study also aims to determine how adoption of GM-RW corn varieties affects the magnitude of high temperature losses at different planting densities. Therefore, we consider another empirical model that adds the following terms: a double interaction term for planting density and GM-RW, double interaction terms for GM-RW and the degree day variables, and triple interaction terms for planting density, GM-RW, and the degree day variables. That is, we add the following expression on the right-hand side of equation (1):

$$\begin{aligned} \eta_{22}(PD_{it} \times GM_{it}) + \gamma_{22}(GDD_{it} \times GM_{it}) + \gamma_{23}(HDD_{it} \times GM_{it}) + \\ \psi_{122}(GDD_{it} \times PD_{it} \times GM_{it}) + \psi_{123}(HDD_{it} \times PD_{it} \times GM_{it}) \end{aligned} \tag{3}$$

where GM_{it} is the GM-RW variable for county i in year t. In this case, the specific parameter of interest is ψ_{123} as it shows how high temperature losses at different planting densities are influenced by GM-RW adoption. We also calculate the marginal effect of LCR with respect to HDD, but now at different levels of planting density and GM-RW adoption. The partial derivative of LCR with respect to HDD for the specification that adds equation (3) to the right-hand side of equation (1) is:

$$\frac{\partial LCR_{it}}{\partial HDD_{it}} = \beta_3 + \gamma_{13} PD_{it} + \gamma_{23} GM_{it} + \psi_{123} PD_{it} \times GM_{it} \tag{4}$$

Casual identification in our empirical model primarily relies on the control of unobserved heterogeneity through county level fixed effects. The county-level fixed effects account for unobserved time-invariant variables that potentially affects both the LCR outcome and the main independent variables of interest (e.g., planting density). Heterogeneous soil quality can be regarded as an unobservable variable that potentially affects model identification in our context. However, heterogeneous soil quality that varies across counties can be reasonably assumed as time-invariant since soil quality generally do not change much from year to year. Hence, the potential endogeneity due to this effect is absorbed by the county fixed effects. Unobserved management ability is also one potential unobservable that may cause identification issues. However, unobserved ability is typically assumed to be time-invariant and the county-fixed effects takes care of this as well. Including linear time trends in the specification also helps facilitate identification. This accounts for other time-varying unobserved factors (i.e., technological changes) that similarly affects each county in the sample.[9] Additionally, we cluster standard errors by county to account for heteroscedasticity and potential year-to-year correlations within each county.

To further verify the stability and strength of the results from the linear FE model, we conduct several robustness checks where: (1) we estimate an alternative specification that includes a non-linear trend (instead of a linear time trend), (2) we use a two-way clustering procedure by county and by year (rather than just a one-way clustering by county), (3) we cluster SEs at the CRD level rather than at the county level, (4) we estimate our model without input expenditure and coverage level variables control variables, (5) we consider the LCR for the YP policy (i.e., excluding the data from the RP policies) and for the RP policy (i.e., excluding the data from the YP policies) separately, (6) we utilize the Palmer Z drought index variables instead of using the precipitation terms.

Aside from our main estimation method—the linear FE estimation procedure, we also utilize two other estimation strategies as robustness checks, such as: fractional regression approach for unbalanced panel data (CRE probit) and an "external-instrument-free"

[9]Note that we also examine the use of a quadratic trend specification in our model to account for nonlinear technological change, and the results are similar with a linear time trend.

moment-based instrumental variable (IV) approach (Lewbel 2012). CRE probit method allows us to account for the fractional nature of our dependent variable (LCR), while the Lewbel IV procedure can help further sharpen identification by addressing possible residual endogeneity due to time-county varying unobservables.

The linear panel FE model has desirable properties (i.e., accounting for time-invariant unobservables), however it does not directly account for fractional outcomes. Our dependent variable—LCR is bounded between zero and one. It can be argued that the fractional nature of this outcome variable might require some other estimation method since predictions from the traditional FE can be outside the range of zero and one, and the "incidental parameters" problem for nonlinear models may occur (e.g., inconsistency does not go away as number of cross-sectional units increase with a fixed time dimension). Thus, as a robustness check, we also estimate equation (1) using the fractional regression method developed by Wooldridge (2019) for unbalanced panel data (i.e., the correlated random effects (CRE) probit model). Similar to the linear panel FE model, the CRE probit approach accounts for potential endogeneity due to unobserved heterogeneity. It also 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). Wooldridge (2019)'s CRE probit approach builds on the Mundlak-Chamberlain mechanism for controlling unobserved heterogeneity in panel data, and models county fixed effects as a linear function of the county-level averages of control variables (Mundlak 1978). Wooldridge (2019)'s CRE probit method also controls for unobserved heterogeneity in fractional response models by including time averages of control variables and the number of time periods available for each cross-sectional unit.

A moment-based IV procedure is also used as another robustness check in this study (See Lewbel 2012). Although we believe that the use of county fixed effects and time trends likely account for the major sources of potential endogeneity, it is still possible that there are other unobserved variables that vary both in space and in time that can threaten model identification. The methods discussed above, linear FE and CRE probit, have their own advantages given the panel data and/or fractional outcomes, but they do not deal

with the aforementioned potential residual endogeneity due to time-varying and county-varying unobservables. Traditional IV methods (i.e., two-stage least squares (2SLS)) are the typical approach to control for time-county-varying unobservables that potentially affect both the outcome and the main independent variables (e.g., planting density in our case). We believe that external instruments are not available that are correlated with the potentially endogenous planting density variable (PD) but uncorrelated with the outcome variables (LCR_{it}). In other words, we cannot find external IVs satisfying the traditional IV exclusion restrictions. Thus, to deal with the issue of endogeneity due to time-county-varying unobservables, we utilize an moment-based IV model, which does not rely on having exogenous external IVs (i.e., "external-instrument-free") (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 on the observable covariates) to identify the coefficients of the endogenous variables in the main equation, even in the absence of valid external instruments that satisfy exclusion restrictions. According to Lewbel (2012), the model is identified if the error terms in the first-stage equations are heteroscedastic, and a subset or all of the exogenous variables in the second-stage equation (i.e., equation (1)) are uncorrelated with the covariance between the first-stage error term and the error term in the second-stage equation. In this case, the residuals from the first-stage equation multiplied by each of the exogenous covariates in mean-centered form can serve as valid instruments.

We use the Breusch-Pagan (BP) test to validate the presence of heteroscedasticity in our first-stage regressions (Breusch and Pagan 1979). The BP test rejects the null hypothesis of homoscedasticity (e.g., BP test statistic is 6349.64 and the p-value < 0.0001 for equation (1) with no interaction terms) and supports the use of the moment-based IV approach of Lewbel (2012) as an alternative estimation procedure to potentially address residual endogeneity due time and county-varying unobservables. In addition to the BP test, we also implemented a set of diagnostic tests (i.e., Hansen J test, Kleibergen-Paap rk LM test, and Cragg-Donald Wald F statistic) to assess the strength of the Lewbel

(2012) IV approach.[10] Overall, the preponderance of the diagnostic tests support the use of the Lewbel (2012) moment-based IV.

Results and Discussion

Our main estimation results are reported in Table 2. The estimates presented in the second to fourth columns of Table 2 are results from different model specification runs. Model 1 (second column) do not include any of the interaction terms in equation (1). Model 2 (third column) is the full specification in equation (1), while Model 3 (fourth column) shows results from the specification where the expression in (3) above is added to the right-hand side of equation (1) (i.e., adding the GM-RW double and triple interaction terms).

For all three models, the parameter estimate for planting density by itself is positive and statistically significant (at the 5% level). In general, this implies that higher planting densities are associated with larger crop insurance losses (and greater production risk) when the planting density interactions are assumed to be zero.[11] This is largely consistent with insights from Lobell et al. (2014) and Ortiz-Bobea, Knippenberg, and Chambers (2018) that corn yields in the Midwest US are increasingly becoming more sensitive to heat events. In addition, the parameter estimates for the all the weather variables are also statistically significant, and have signs that are consistent with previous literature

[10]The calculated test statistics and associated p-values for the Kleibergen-Paap rk LM test indicate that we can reject the null hypothesis that model is underidentified (e.g., the associated p-values < 0.001 for all regression runs in Table A.8). The Cragg-Donald Wald F statistic tests the overall strength of the IV's used in the Lewbel (2012)'s IV approach. This "IV strength" tests suggests that we can reject the null hypothesis that the IVs used are weak. Note that to reject the null hypothesis that the IVs used are weak, one needs to compare the magnitudes of the Cragg-Donald Wald F statistic relative to the Stock-Yogo critical values. Sanderson and Windmeijer (2016) suggest that if the Cragg-Donald Wald F statistic are greater than the Stock-Yogo critical values, then one can reject the null hypothesis that the IVs used are weak. Lastly, the Hansen J test assessing the validity of all IVs used in the moment-based IV procedure (p-value > 0.05) in column 1 in Table A.8 suggests that one can not reject the null hypothesis that all IVs used in the moment-based IV procedure are valid. Note that for column 2 and 3, the Hansen J test (p-value s< 0.01) suggests that one can not reject the null hypothesis (i.e., this means that at least one IV used in the estimation is not valid). Nevertheless, Baum and Lewbel (2019) points out 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).

[11]For ease of interpretation, all interaction terms are centered. Note that centering does not change the meaning of the model or the predictions that are made but it might make the results more easily interpretable.

(see, e.g., Annan and Schlenker 2015). Notably, our results verify that high temperatures (as represented by the HDD variable) typically lead to higher crop insurance losses, while moderate temperatures (as represented by GDD) reduce crop insurance losses. On the other hand, the estimates from the two precipitation terms suggest that it has a U-shaped relationship with crop insurance losses (e.g., additional rainfall is beneficial to a point, but too much (i.e., floods) would lead to losses).

With regards to the control variables, the estimates associated with the coverage level and fertilizer/chemical expenditure variables are positive and statistically significant (at the 1% level). The positive coverage level variable is consistent with expectation that higher insurance coverages might trigger large indemnity payments more often.[12] On the other hand, the fertilizer and chemical expenditure parameter suggest that more expenditures on these input can result in higher losses (and higher production risk). Although this result seem counterintuitive, Horowitz and Lichtenberg (1993) point out that fertilizer and chemical inputs can be risk-increasing (and can lead to more losses).

Marginal Effect of Warming at Different Planting Densities

Model 2 (third column) in Table 2 presents the results of the full specification in equation (1) (i.e., the specification with interaction terms for planting density and the weather variables). The results from Model 2 (Table 2) indicate that the HDD variable leads to higher crop insurance losses.[13] Moreover, the parameter estimate of the interaction term for planting density and HDD is 0.021 (significant at the 1% level).

To get a a more accurate estimate of the effect magnitudes, we calculate the marginal impact of HDD at different planting density levels using the expression in equation (2) (Table 3). We show the effect of a one unit increase (i.e., 100 °C increase) in HDD when the following planting densities are used: 26, 29, 32, and 35 (in '000s of plants per acre). All marginal effect estimates are positive and statistically significant (at the 0.1% level), and the important thing to note is that the insurance loss magnitudes increases

[12] In addition, it is possible that higher coverage levels lead to more moral hazard incentives such that producers do not exert optimal management effort and results in more frequent larger losses.

[13] Note that with the centered variables, the main effect of HDD is the effect of HDD on the LCR at the average planting density (i.e., has a score of zero on the centered planting density variable).

as one increases planting density from 26,000 to 35,000 plants per acre (i.e., LCR increases from 0.244 at 26,000 plants per acre to 0.436 at 35,000 plants per acre). A visual representation of this upward sloping planting density effect on crop insurance losses is depicted in Figure 1. This pattern is consistent with the hypothesis that higher planting densities may result in more intense inter-plant competition for the limited moisture available in high-temperature environments, such that it leads to larger crop insurance losses (Van Averbeke and Marais 1992; Assefa et al. 2016; Assefa et al. 2018; Wang et al. 2021). Therefore, the results here indicate that increasing planting densities may lead to higher overall production risk (specifically downside risk) in unfavorably warm environments (relative to environments with more moderate temperatures). This result also support insights in Lobell et al. (2014) that higher planting densities may be the main factor influencing the increased sensitivity of corn yields to heat events in the US Midwest.

Marginal Effect of Warming at Different Planting Densities and GM-RW Adoption

The last model run in Table 2 (see the column for Model 3) allows one to investigate how the loss impact of warming at different planting densities are affected by the type of corn variety used. In this case, the main parameters of interest are those associated with the triple interaction terms that includes PD, GM-RW, and the weather variables. All the triple interaction effects are statistically significant, which validates the importance of how varietal choice (GM-RW in this case) interacts with planting density and the weather.

To facilitate interpretation, we calculate the marginal effects of HDD on crop insurance losses at different levels of planting density and GM-RW adoption using the expression in (4) (see Table 4). Moreover, the calculated marginal effects in Table 4 are graphically presented in Figure 2. For counties with low levels of GM-RW adoption, the marginal effect of HDD increases at higher planting densities. This result is consistent with the trend in Figure 1. However, for counties with high GM-RW adoption (at 0.45 and 0.6), we

find that the marginal impact of HDD on losses decreases as planting density increases.[14]

This latter finding is important since it implies that heat related losses at higher planting densities are reduced if the predominant variety used has the GM-RW trait. This outcome implies that corn varieties with GM traits (especially GM-RW hybrids) may be more efficient in utilizing nutrients and moisture even under intensified inter-plant competition when planting densities and temperatures are high. Moreover, the GM-RW results based on the triple interactions support the idea that the use of GM varieties may have facilitated increases in planting density over time. Perhaps the root structure of GM-RW varieties are indeed more robust such that it becomes more resilient to extreme heat even at higher planting densities.

Hence, the Lobell et al. (2014) hypothesis that higher planting densities lead to increased sensitivity to heat events is not necessarily observed when the GM-RW variety is predominantly used. In general, results in this subsection suggest that the adverse risk effects of higher planting densities when there is warming can be offset by risk benefits from using GM-RW varieties in these conditions. In the context of the G $\times$ E $\times$ M concept, the "G" choice (i.e., using GM-RW varieties) can help mitigate the combined detrimental risk effects of warming (i.e., the "E" condition) and the use of higher planting densities (i.e., the "M" used).

Robustness Checks

We conduct various robustness checks to assess the strength and stability of our results. First, we consider a quadratic time trend specification instead of a linear time trend. Some argue that technological changes might be better captured with a nonlinear trend specification. For this purpose, we employ a quadratic time trend specification instead of linear time trend. Table A.1 in the Appendix presents the results of this analysis.

[14]For the data period we have, there were a large number of counties where GM-RW adoption is low (especially in the early part of the data, 1997-2008). Note that GM seed for better management of rootworm were registered in 2003. In the latter half of the data (2009-2015), significantly more counties in the "I" states now have higher levels of GM-RW adoption (compared to earlier period). Therefore, when GM-RW is not explicitly controlled for (as in Table 3 and Figure 1), the loss increasing effect of higher planting densities for counties in the early part of the data (with less GM-RW adoption) likely overwhelms the loss decreasing effect in the latter part of the data (with more GM-RW adoption).

The results from this robustness check are still consistent with our main results in the previous section when a linear time trend is used.

For the second robustness check, we carry out a robustness check that slightly alters the procedure for clustering the SEs. Note that in our main regression runs above we use one-way clustering at the county level. In the robustness check we implement here, we use a two-way clustering approach by county and year. Clustering SEs by year allows for an arbitrary form of spatial correlation across counties within each year. Thus, two-way clustering of SEs by year and county can be regarded as robust to heteroscedasticity, spatial correlation of the error terms across counties, and serial correlation of the errors within each county (Cameron, Gelbach, and Miller 2012). Results from this two-way clustering procedure (see Table A.2) are still consistent with our main results above.

Third, following the logic in our two-way clustering robustness check, we also cluster SEs at agricultural crop-reporting district (CRD) level, which controls for temporal autocorrelation and a limited form of spatial autocorrelation (i.e., between counties in the same CRD).[15] Results of the runs with CRD level clustered SEs are reported in Table A.3; and findings from this robustness check are still similar to our main model runs.

Fourth, given some concerns about potential endogeneity due to inclusion of input expenditure and coverage level variables, we re-ran our main model without these variables in the specification. Results from this robustness check can be seen in Appendix Table A.4. The parameter estimates and inferences from these estimates are still consistent with the main parameter estimates reported in the previous section.

For the fifth robustness check, we consider LCR for the YP policy (i.e., excluding the data from the RP policies) and for the RP policy (i.e., excluding the data from the YP policies) separately. Note that RP-type plans came about in the mid-1990s and have become the predominant plan for corn since the mid-2000s. Results from only for the YP losses or only for the RP losses are presented in Tables A.5 and A.6 respectively. These robustness checks produces similar results with those found in our main model.

[15]Clustering at the CRD level allows for correlation of error terms both over time and across counties in the same CRD. We basically assume that the error terms for observations in different clusters (CRD) are uncorrelated, but within CRD they can be correlated.

Sixth, we use CRE probit as an alternative estimation procedure to check whether our main results hold when the fractional nature of our the variable is directly controlled for. Results for this fractional regression runs are reported in Table A.7. Results from this alternative estimation procedure are still largely consistent with those from our linear panel FE regressions. Parameter estimates from this robustness check indicate that the insurance losses (and production risk) due to heat events increases as one increases planting density. Consistent with our base model runs, we still find that for counties with high GM-RW adoption, the marginal impact of HDD on losses decreases as planting density increases.

As another robustness check, we employ the Lewbel (2012)'s moment-based IV procedure to determine if our results from the linear panel FE model still holds when residual time and county varying unobservables are addressed using this external-IV-free procedure. Table A.8 presents the parameter estimates of this robustness check. The parameter estimates and statistical significance of the interaction terms from the moment-based IV model are still consistent with the linear panel FE results. The results from the Lewbel (2012)'s IV procedure indicates that an increase in planting density exacerbates the effects of HDD on the LCR (and production risk). Note that higher GM-RW adoption rates decrease the effects of HDD on the LCR as planting density increases.

Lastly, we conduct a robustness check where we utilize the Palmer Z drought index variables to capture moisture levels (e.g., variables to represent dryness, normal conditions, wetness), instead of using the precipitation terms. Table A.9 presents the estimation results for this specification. The marginal effects of HDD on LCR for alternative planting density levels are presented in Table A.10 and graphically depicted in Figure A.1. Moreover, marginal effects of HDD on LCR at different levels of planting density and GM-RW adoption are shown in Table A.11 and graphically depicted in Figure A.2. Results from these marginal effect calculations are still consistent with the patterns shown in the our main regression runs above.

A slightly different version of the last robustness check can also be constructed by estimating the LCR when the conditions are dry (based on the Palmer Z) for varying levels

of planting density. In this case, one considers the Palmer Z index as the main measure of warming (or low moisture environment) where an excessively dry index value represent drought conditions. The predicted LCRs when conditions are dry, for different planting densities, are reported in Table A.12 and graphically shown in Figure A.3. Moreover, the predicted LCRs in dry Palmer Z conditions, for varying levels of planting density and GM-RW adoption, are presented in Table A.13 and visually depicted in Figure A.4. The general pattern of results from these Palmer Z-based marginal effects are still consistent with our main results in the previous section.

Overall, the robustness checks conducted still support the notion that heat-related crop insurance losses (and downside production risk (under warming)) becomes larger at higher planting densities. However, additional high temperature losses (downside risks) at higher planting densities can be mitigated by adoption of corn varieties with the GM-RW trait. Thus, the sensitivity of corn yields to drought events observed in previous studies may indeed be plausibly linked to higher planting densities, but likely only when higher planting densities are used in conjunction with conventional non-GM-RW corn varieties.

Conclusions

In this study, we investigate whether the marginal impact of high temperatures on crop insurance losses becomes larger when corn is planted more densely. Furthermore, we examine how these heat-related losses at different planting densities are affected by the use of GM-RW varieties. A county-level panel data set is constructed for Iowa, Illinois, and Indiana from 1997 to 2015 with key information on crop insurance losses, planting density, and weather variables to fulfill the study objectives. The crop insurance loss variable used in the study is the loss cost ratio (LCR), which is considered a valid measure of downside production risk (Perry, Yu, and Tack 2020; Goodwin and Piggott 2020). Fixed effect econometric models are then constructed and estimated, where LCR is a function of planting density, GM-RW adoption, weather variables, input expenditures, coverage levels, and a number of interaction terms. Robustness checks are also conducted

using alternative model specifications and estimation procedures.

Findings from the primary econometric models and the robustness checks all strongly indicate that the magnitude of warming-related crop insurance losses becomes *more severe* at higher planting densities. The additional loss-increasing effect of higher planting density supports the idea that inter-plant competition for nutrients and moisture escalates under severe heat stress and higher planting densities. This intensified competition can then lead to higher losses and higher production risk. However, if the rate of GM-RW adoption is high, the effect of warming on crop insurance losses becomes *less severe* as one increases planting density levels. This indicates that the use of varieties that are potentially more resilient to warming can alleviate the loss (and/or risk) increasing effect of higher planting densities. Hence, we do not find evidence that GM varieties and higher planting densities together necessarily increase crop insurance losses, production risk, and corn yield sensitivity to warming temperatures.

Results from our study point to a couple of important implications. First, it is clear that the G $\times$ E $\times$ M concept is important when assessing the adverse impacts of climate change in agriculture. In our context, we do find that warming induced crop production losses are likely to increase with higher planting densities. But this may not be necessarily true if the GM-RW variety is the predominant variety used. Hence, this does not support the conjecture that GM varietal improvements that facilitate higher planting densities necessarily lead to higher year-to-year variability in row crop yields (see Lobell et al. 2014). Based on the evidence from this study, it is possible that warming induced risk increases over time may be attributed to higher planting densities, but it does not mean that higher planting density together with GM technology per se are the source of the risk increases. The role of planting density on the magnitude of climate-change-induced risks is more nuanced than previously thought. Second, from a farm management perspective, inferences from the present study suggest that planting density and varietal choice decisions at the start of the season should be partly conditioned on farmer expectations about the likely weather during the season, especially if one is interested in managing production risk more efficiently (Solomon, Chauhan, and Zeppa 2017). For example, if

farmer expectation is that summer season temperature is higher than normal, then based on our results it may be prudent to not increase planting density for conventional corn production (but it may be fine to maintain high planting densities if GM-RW varieties are planted).

Even though this study contributes to further understanding about the loss and downside risk impacts of warming conditions under different planting density regimes, it is important to acknowledge limitations of the empirical analysis and identify potential areas for future research. First, although we employ Lewbel (2012)'s moment-based IV procedure, causal identification in our empirical approach can be further strengthened by using valid external IVs that satisfy exclusion restrictions. Using an traditional IV methods (like two-stage least squares (2SLS)) estimation strategy maybe a fruitful avenue for future research. Second, the level of aggregation for the data used in this study is at the county-level. Yield variability (and crop insurance loss measures) naturally decreases as one moves from the a lower level of aggregation (e.g., farm level) to a higher level of aggregation (e.g., county or state level). Hence, replicating the study approach here using farm level data (perhaps using survey based farm data like the Agricultural Resource Management Survey (ARMS) data of the US Department of Agriculture) for the same (or wider) geographic area may provide new inferences. Note however that the farm-level survey data sets typically do not have the long time series required when one is interested in looking at temporal risk effects. Lastly, we only carefully examined the role of corn varieties with a specific trait (e.g., GM-RW). It would also be interesting to investigate how the warming-related losses (risks) at higher planting densities are influenced by other corn varieties with other traits. Investigating how adoption of newer varieties with actual drought-resistant traits would be an interesting research avenue to pursue. In addition, investigating how specific traits (e.g., herbicide tolerance, corn borer resistance) may influence the planting density effects would also provide new and useful insights. We leave these research directions for future work.

Acknowledgements

The authors declare no financial relationships or other potential conflicts of interest.

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Table 1: Description and summary statistics of variables

Variable Name	Description	Mean	SD	Min	Max
LCR	County avg. loss cost ratio	0.062	0.111	0.000	1.000
Planting Density	County avg. thousand plants p/a	30.025	2.738	16.000	38.965
GM-RW	County avg. adoption of GM-RW	0.260	0.317	0.000	1.000
HDD	Harmful degree days in hundred, °C	0.750	0.604	0.007	4.115
GDD	Growing degree days in hundred,°C	16.125	1.637	11.387	21.503
Precipitation	(mm) in hundred	4.402	1.110	1.401	9.196
Coverage Level	County-average	0.743	0.048	0.477	0.841
Fert.&Chemical Exp.	Per acre $ amount spent	0.121	0.034	0.044	0.389
Observations		5091	5091	5091	5091

Notes: The weather variables in this table are accumulated for growing months of May-September.

Table 2: Results from the main linear panel fixed effects model (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002***	0.002***	0.002**
	(2.63)	(2.61)	(2.53)
HDD	0.329***	0.330***	0.360***
	(21.28)	(20.06)	(19.33)
GDD	-0.287***	-0.297***	-0.344***
	(-15.74)	(-15.59)	(-15.44)
Precipitation	-0.143***	-0.140***	-0.145***
	(-14.99)	(-15.02)	(-15.56)
Precipitation Squared	0.017***	0.017***	0.017***
	(16.07)	(16.29)	(16.92)
GM-RW	-0.006	-0.009	-0.009
	(-0.83)	(-1.30)	(-1.01)
Coverage Level	0.253***	0.243***	0.225***
	(7.34)	(7.04)	(6.77)
Fertilizer&Chemical Exp.	0.529***	0.499***	0.486***
	(6.26)	(6.37)	(6.14)
Trend	-0.002***	-0.002***	-0.001***
	(-3.72)	(-2.93)	(-2.78)
PD × HDD		0.021***	0.007
		(4.48)	(1.10)
PD × GDD		-0.026***	-0.003
		(-5.89)	(-0.52)
GM-RW × HDD			0.301***
			(4.93)
GM-RW × GDD			-0.366***
			(-6.88)
PD × GM-RW			0.002
			(1.15)
PD × GM-RW × HDD			-0.091***
			(-6.02)
PD × GM-RW × GDD			0.096***
			(5.94)
Observations	5091	5091	5091
Adjusted R^2	0.406	0.414	0.429

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Marginal effects of HDD on LCR at different levels of planting density (PD)

	Estimates
PD=26	0.244***
	(9.23)
PD=29	0.308***
	(17.48)
PD=32	0.372***
	(20.59)
PD=35	0.436***
	(15.94)
Observations	5091

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the estimated marginal effects of HDD on LCR. Figure 1 depicts these results.

Table 4: Marginal effects of HDD on LCR at different levels of planting density (PD) & GM-RW adoption

	Estimates
PD=26 & GM-RW=.15	0.257***
	(9.02)
PD=29 & GM-RW=.15	0.309***
	(16.63)
PD=32 & GM-RW=.15	0.362***
	(12.99)
PD=35 & GM-RW=.15	0.414***
	(9.04)
PD=26 & GM-RW=.3	0.357***
	(10.39)
PD=29 & GM-RW=.3	0.368***
	(17.83)
PD=32 & GM-RW=.3	0.380***
	(17.34)
PD=35 & GM-RW=.3	0.391***
	(10.69)
PD=26 & GM-RW=.45	0.457***
	(10.25)
PD=29 & GM-RW=.45	0.428***
	(16.01)
PD=32 & GM-RW=.45	0.398***
	(21.56)
PD=35 & GM-RW=.45	0.368***
	(12.47)
PD=26 & GM-RW=.6	0.557***
	(9.79)
PD=29 & GM-RW=.6	0.487***
	(14.03)
PD=32 & GM-RW=.6	0.416***
	(22.02)
PD=35 & GM-RW=.6	0.346***
	(13.08)
Observations	5091

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the estimated marginal effects of HDD on LCR. Figure 2 depicts these results.

Figure 1: Marginal effect of HDD on LCR at different planting densities

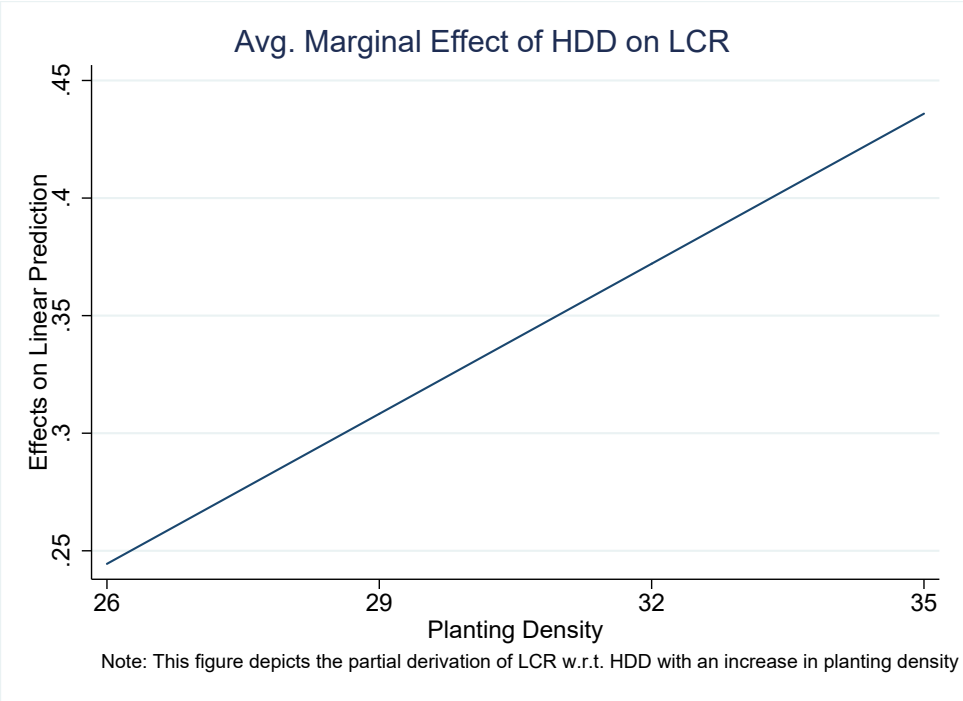
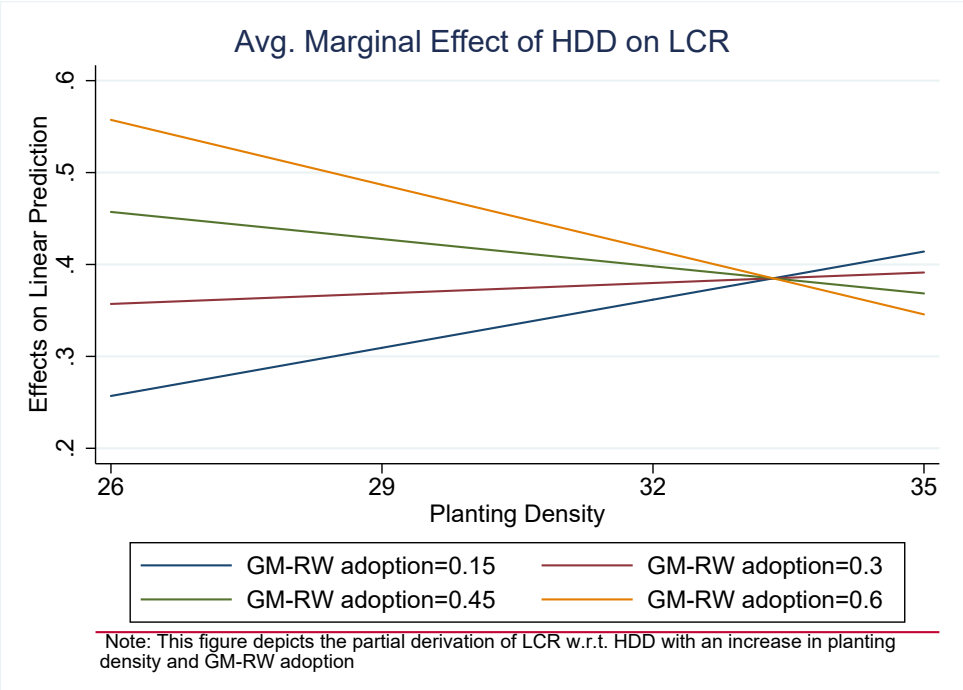


Figure 2: Marginal effect of HDD on LCR for different combinations of PD and GM-RW



Appendix

Results from the Robustness Checks

Table A.1: Results from the main linear panel fixed effects model with non-linear time trends (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002**	0.002**	0.001*
	(2.34)	(2.26)	(1.73)
HDD	0.332***	0.334***	0.365***
	(21.42)	(20.06)	(19.38)
GDD	-0.283***	-0.294***	-0.348***
	(-15.63)	(-15.37)	(-15.34)
Precipitation	-0.142***	-0.139***	-0.143***
	(-15.06)	(-15.06)	(-15.54)
Precipitation Squared	0.017***	0.017***	0.017***
	(16.08)	(16.28)	(16.87)
GM-RW	-0.008	-0.013*	-0.003
	(-1.14)	(-1.74)	(-0.29)
Coverage Level	0.221***	0.204***	0.194***
	(6.53)	(5.98)	(6.00)
Fertilizer&Chemical Exp.	0.428***	0.379***	0.367***
	(5.03)	(4.81)	(4.57)
Trend	-1.383***	-1.593***	-1.598***
	(-11.46)	(-12.45)	(-10.90)
Trend × Trend	0.000***	0.000***	0.000***
	(11.43)	(12.43)	(10.89)
PD × HDD		0.024***	0.010
		(5.01)	(1.53)
PD × GDD		-0.030***	-0.006
		(-6.72)	(-1.00)
GM-RW × HDD			0.294***
			(4.86)
GM-RW × GDD			-0.392***
			(-7.35)
PD × GM-RW			-0.003
			(-1.52)
PD × GM-RW × HDD			-0.088***
			(-5.84)
PD × GM-RW × GDD			0.104***
			(6.35)
Observations	5091	5091	5091
Adjusted R^2	0.413	0.422	0.437

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Results from the main linear panel fixed effects model with two-way clustering (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002**	0.002*	0.002*
	(2.13)	(1.94)	(1.87)
HDD	0.329***	0.330***	0.360***
	(4.62)	(4.80)	(5.15)
GDD	-0.287***	-0.297***	-0.344***
	(-3.44)	(-3.69)	(-4.19)
Precipitation	-0.143***	-0.140***	-0.145***
	(-4.70)	(-4.58)	(-4.71)
Precipitation Squared	0.017***	0.017***	0.017***
	(5.30)	(5.28)	(5.41)
GM-RW	-0.006	-0.009	-0.009
	(-0.38)	(-0.60)	(-0.50)
Coverage Level	0.253***	0.243***	0.225***
	(2.77)	(2.81)	(2.85)
Fertilizer&Chemical Exp.	0.529***	0.499***	0.486***
	(3.41)	(3.54)	(3.68)
Trend	-0.002	-0.002	-0.001
	(-1.57)	(-1.31)	(-1.32)
PD × HDD		0.021***	0.007
		(2.64)	(1.12)
PD × GDD		-0.026**	-0.003
		(-2.21)	(-0.32)
GM-RW × HDD			0.301***
			(3.02)
GM-RW × GDD			-0.366***
			(-2.85)
PD × GM-RW			0.002
			(0.54)
PD × GM-RW × HDD			-0.091***
			(-3.64)
PD × GM-RW × GDD			0.096**
			(2.41)
Observations	5091	5091	5091
Adjusted R^2	0.437	0.444	0.458

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: SEs are two-way (county and year) clustered.

Table A.3: Results from the main linear panel fixed effects model with CRD-level clustering (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002***	0.002***	0.002***
	(3.30)	(3.11)	(2.96)
HDD	0.329***	0.330***	0.360***
	(12.26)	(11.47)	(11.28)
GDD	-0.287***	-0.297***	-0.344***
	(-6.42)	(-6.22)	(-6.16)
Precipitation	-0.143***	-0.140***	-0.145***
	(-6.14)	(-6.31)	(-6.51)
Precipitation Squared	0.017***	0.017***	0.017***
	(6.53)	(6.79)	(7.02)
GM-RW	-0.006	-0.009	-0.009
	(-0.64)	(-1.09)	(-0.79)
Coverage Level	0.253***	0.243***	0.225***
	(5.00)	(4.68)	(4.38)
Fertilizer&Chemical Exp.	0.529***	0.499***	0.486***
	(4.13)	(4.13)	(4.12)
Trend	-0.002**	-0.002*	-0.001*
	(-2.32)	(-1.83)	(-1.75)
PD × HDD		0.021***	0.007
		(3.99)	(0.94)
PD × GDD		-0.026***	-0.003
		(-4.71)	(-0.40)
GM-RW × HDD			0.301***
			(4.07)
GM-RW × GDD			-0.366***
			(-4.61)
PD × GM-RW			0.002
			(0.75)
PD × GM-RW × HDD			-0.091***
			(-6.49)
PD × GM-RW × GDD			0.096***
			(3.42)
Observations	5091	5091	5091
Adjusted R^2	0.406	0.414	0.429

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: SEs are clustered at CRD level.

Table A.4: Results from the main linear panel fixed effects model without expenditure and coverage-level variables (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002**	0.002**	0.002**
	(2.27)	(2.22)	(2.17)
HDD	0.339***	0.339***	0.367***
	(21.79)	(20.26)	(19.35)
GDD	-0.282***	-0.293***	-0.333***
	(-15.22)	(-15.14)	(-14.93)
Precipitation	-0.135***	-0.132***	-0.138***
	(-14.59)	(-14.66)	(-15.29)
Precipitation Squared	0.016***	0.016***	0.017***
	(15.73)	(16.03)	(16.75)
GM-RW	0.021***	0.015**	0.013
	(3.32)	(2.49)	(1.59)
Trend	0.001***	0.002***	0.002***
	(3.32)	(4.08)	(3.84)
PD × HDD		0.023***	0.008
		(4.77)	(1.07)
PD × GDD		-0.028***	-0.002
		(-6.13)	(-0.25)
GM-RW × HDD			0.325***
			(5.35)
GM-RW × GDD			-0.410***
			(-7.89)
PD × GM-RW			0.003
			(1.49)
PD × GM-RW × HDD			-0.088***
			(-5.56)
PD × GM-RW × GDD			0.084***
			(5.13)
Observations	5091	5091	5091
Adjusted R^2	0.391	0.400	0.417

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Results from the main linear panel fixed effects model for only Yield Protection (YP) plans (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.001*	0.001	0.001
	(1.83)	(1.46)	(1.40)
HDD	0.204***	0.200***	0.207***
	(16.76)	(15.80)	(14.78)
GDD	-0.154***	-0.153***	-0.175***
	(-11.56)	(-11.61)	(-11.19)
Precipitation	-0.065***	-0.063***	-0.066***
	(-10.11)	(-9.90)	(-10.00)
Precipitation Squared	0.009***	0.008***	0.009***
	(12.00)	(11.92)	(11.96)
GM-RW	-0.015**	-0.014**	-0.008
	(-2.25)	(-2.16)	(-1.18)
Coverage Level	0.215***	0.222***	0.231***
	(4.92)	(5.09)	(5.15)
Fertilizer&Chemical Exp.	0.406***	0.375***	0.378***
	(5.44)	(5.43)	(5.30)
Trend	-0.001**	-0.001	-0.001*
	(-2.12)	(-1.57)	(-1.80)
PD × HDD		0.013***	0.005
		(4.20)	(1.21)
PD × GDD		-0.007*	0.000
		(-1.81)	(0.04)
GM-RW × HDD			0.158***
			(3.94)
GM-RW × GDD			-0.124***
			(-3.02)
PD × GM-RW			-0.002
			(-1.48)
PD × GM-RW × HDD			-0.037***
			(-3.43)
PD × GM-RW × GDD			0.045***
			(3.55)
Observations	5091	5091	5091
Adjusted R^2	0.278	0.285	0.293

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Results from the main linear panel fixed effects model for only Revenue Protection (RP) plans (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.003***	0.003***	0.003***
	(2.81)	(2.91)	(2.94)
HDD	0.334***	0.336***	0.368***
	(19.57)	(18.70)	(18.28)
GDD	-0.278***	-0.290***	-0.340***
	(-13.59)	(-13.57)	(-13.77)
Precipitation	-0.152***	-0.150***	-0.155***
	(-14.74)	(-14.76)	(-15.29)
Precipitation Squared	0.018***	0.018***	0.018***
	(15.86)	(16.05)	(16.70)
GM-RW	-0.002	-0.006	-0.006
	(-0.24)	(-0.79)	(-0.55)
Coverage Level	0.150***	0.148***	0.147***
	(4.70)	(4.78)	(4.81)
Fertilizer&Chemical Exp.	0.594***	0.567***	0.535***
	(6.38)	(6.55)	(6.20)
Trend	-0.002***	-0.002***	-0.002***
	(-3.17)	(-2.61)	(-2.67)
PD × HDD		0.020***	0.004
		(3.90)	(0.60)
PD × GDD		-0.028***	0.002
		(-5.10)	(0.22)
GM-RW × HDD			0.328***
			(5.15)
GM-RW × GDD			-0.451***
			(-7.53)
PD × GM-RW			0.002
			(0.93)
PD × GM-RW × HDD			-0.094***
			(-5.90)
PD × GM-RW × GDD			0.100***
			(5.59)
Observations	5091	5091	5091
Adjusted R^2	0.366	0.372	0.388

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Results form Correlated Random Effects (CRE) Approach (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002**	0.019***	0.016**
	(2.45)	(2.62)	(2.42)
HDD	0.184***	1.764***	1.836***
	(21.51)	(21.75)	(20.37)
GDD	-0.171***	-1.730***	-1.758***
	(-14.67)	(-14.79)	(-14.54)
Precipitation	-0.079***	-0.728***	-0.743***
	(-16.22)	(-16.53)	(-17.49)
Precipitation Squared	0.009***	0.088***	0.090***
	(18.08)	(19.17)	(20.86)
GM-RW	0.016***	0.086*	0.021
	(3.10)	(1.79)	(0.39)
Coverage Level	0.242***	2.105***	1.899***
	(7.34)	(7.12)	(6.54)
Fertilizer&Chemical Exp.	0.311***	2.873***	2.759***
	(4.75)	(5.30)	(5.45)
Trend	-0.002***	-0.018***	-0.014***
	(-4.78)	(-3.89)	(-3.20)
PD × HDD		0.135***	0.067***
		(7.16)	(2.64)
PD × GDD		-0.248***	-0.069*
		(-8.50)	(-1.81)
GM-RW × HDD			1.144***
			(4.73)
GM-RW × GDD			-2.482***
			(-7.30)
PD × GM-RW			0.051***
			(4.17)
PD × GM-RW × HDD			-0.210***
			(-3.39)
PD × GM-RW × GDD			0.203**
			(2.01)
Observations	5091	5091	5091

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Results form Lewbel moment-based IV Approach (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.000	0.088***	0.004
	(0.16)	(4.98)	(0.30)
HDD	0.330***	-0.217	-0.419**
	(21.34)	(-0.85)	(-2.54)
GDD	-0.287***	1.207***	-0.084
	(-15.74)	(4.23)	(-0.36)
Precipitation	-0.143***	-0.143***	-0.147***
	(-15.05)	(-14.63)	(-21.03)
Precipitation Squared	0.017***	0.017***	0.017***
	(16.14)	(15.81)	(24.14)
GM-RW	-0.004	-0.011	2.087**
	(-0.46)	(-1.39)	(1.99)
Coverage Level	0.249***	0.208***	0.221***
	(7.09)	(5.77)	(5.55)
Fertilizer&Chemical Exp.	0.530***	0.540***	0.455***
	(6.26)	(6.40)	(6.95)
Trend	-0.002*	0.000	-0.002***
	(-1.70)	(0.12)	(-3.23)
PD × HDD		0.019**	0.023***
		(2.22)	(4.01)
PD × GDD		-0.051***	-0.004
		(-5.09)	(-0.51)
GM-RW × HDD			2.668***
			(7.76)
GM-RW × GDD			-1.509***
			(-2.61)
PD × GM-RW			-0.049
			(-1.46)
PD × HDD × GM-RW			-0.078***
			(-7.04)
PD × GDD × GM-RW			0.038**
			(2.04)
Observations	5091	5091	5091
Adjusted R^2	0.370	0.362	0.390
Kleibergen-Paap rk LM statistic	38.242	145.364	1462.865
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)
Cragg-Donald Wald F statistic	43.245	57.185	56.617
(Stock-Yogo 10% max)	(11.39)	(10.70)	NA
Hansen J (or Sargan) statistic	6.340	109.105	505.169
	($p = 0.500$)	($p = 0.000$)	($p = 0.0009$)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Results from the main linear panel fixed effects model: using Palmer Z as control instead of precipitation (Dep var: LCR)

	Model 1	Model 2	Model 3
Planting Density (PD)	0.002**	0.002**	0.002**
	(2.47)	(2.37)	(2.26)
HDD	0.344***	0.343***	0.378***
	(18.96)	(18.24)	(17.79)
GDD	-0.261***	-0.263***	-0.317***
	(-12.53)	(-12.46)	(-12.48)
Palmer Wet	0.046***	0.046***	0.043***
	(15.09)	(15.16)	(14.77)
Palmer Dry	0.054***	0.050***	0.048***
	(11.19)	(10.56)	(10.25)
GM-RW	-0.002	-0.003	-0.003
	(-0.31)	(-0.44)	(-0.34)
Coverage Level	0.244***	0.237***	0.224***
	(7.02)	(6.88)	(6.72)
Fertilizer&Chemical Exp.	0.492***	0.464***	0.470***
	(6.10)	(6.10)	(5.98)
Trend	-0.002***	-0.001**	-0.001**
	(-3.13)	(-2.53)	(-2.23)
PD × HDD		0.016***	0.007
		(3.18)	(1.01)
PD × GDD		-0.015***	0.002
		(-3.03)	(0.29)
GM-RW × HDD			0.217***
			(3.26)
GM-RW × GDD			-0.274***
			(-4.31)
PD × GM-RW			0.002
			(0.88)
PD × GM-RW × HDD			-0.085***
			(-5.27)
PD × GM-RW × GDD			0.105***
			(5.83)
Observations	5091	5091	5091
Adjusted R^2	0.365	0.369	0.380

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Marginal effects of HDD on LCR with different levels of planting density (PD)(using Palmer Z as control instead of precipitation)

	Estimates
PD=26	0.280***
	(9.76)
PD=29	0.327***
	(16.39)
PD=32	0.374***
	(18.41)
PD=35	0.422***
	(14.30)
Observations	5091

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the estimated marginal effects of HDD when the model specification includes Palmer-Z drought index variable instead of precipitation variables. Figure A.1 depicts these marginal effects.

Table A.11: Marginal effects of HDD on LCR with different levels of planting density (PD) & GM-RW adoption (using Palmer Z as control instead of precipitation)

	Estimates
PD=26 & GM-RW=.15	0.271***
	(9.54)
PD=29 & GM-RW=.15	0.320***
	(16.77)
PD=32 & GM-RW=.15	0.368***
	(13.30)
PD=35 & GM-RW=.15	0.416***
	(9.27)
PD=26 & GM-RW=.3	0.367***
	(10.68)
PD=29 & GM-RW=.3	0.375***
	(17.81)
PD=32 & GM-RW=.3	0.384***
	(17.49)
PD=35 & GM-RW=.3	0.393***
	(10.93)
PD=26 & GM-RW=.45	0.462***
	(10.38)
PD=29 & GM-RW=.45	0.431***
	(15.99)
PD=32 & GM-RW=.45	0.400***
	(21.38)
PD=35 & GM-RW=.45	0.370***
	(12.67)
PD=26 & GM-RW=.6	0.558***
	(9.83)
PD=29 & GM-RW=.6	0.487***
	(13.99)
PD=32 & GM-RW=.6	0.417***
	(21.65)
PD=35 & GM-RW=.6	0.347***
	(13.22)
Observations	5091

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the estimated marginal effects of HDD when the model specification includes Palmer-Z drought index variable instead of precipitation variables. Figure A.2 depicts these marginal effects.

Table A.12: Predictive margins: Predicted LCRs at Palmer Z dryness at different levels of planting density (PD)

	Estimates
PD=26	0.0534***
	(5.38)
PD=29	0.0773***
	(15.19)
PD=32	0.101***
	(15.68)
PD=35	0.125***
	(10.38)
Observations	5091

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the predicted LCRs at Palmer Z dryness for the model specification that includes the Palmer Z drought index variable instead of the precipitation variables. Figure A.3 depicts these relations.

Table A.13: Predictive margins: Predicted LCRs at Palmer Z dryness at different levels of planting density (PD) & GM-RW

	Estimates
PD=26 & GM-RW=.15	0.0701***
	(5.24)
PD=29 & GM-RW=.15	0.0791***
	(12.01)
PD=32 & GM-RW=.15	0.0882***
	(11.23)
PD=35 & GM-RW=.15	0.0972***
	(6.36)
PD=26 & GM-RW=.3	0.114***
	(4.73)
PD=29 & GM-RW=.3	0.109***
	(8.21)
PD=32 & GM-RW=.3	0.103***
	(14.56)
PD=35 & GM-RW=.3	0.0972***
	(6.74)
PD=26 & GM-RW=.45	0.159***
	(4.32)
PD=29 & GM-RW=.45	0.138***
	(6.65)
PD=32 & GM-RW=.45	0.118***
	(14.07)
PD=35 & GM-RW=.45	0.0973***
	(6.04)
PD=26 & GM-RW=.6	0.203***
	(4.09)
PD=29 & GM-RW=.6	0.168***
	(5.88)
PD=32 & GM-RW=.6	0.132***
	(12.02)
PD=35 & GM-RW=.6	0.0974***
	(4.94)
Observations	5091

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the predicted LCRs at the Palmer Z dryness for the model specification that includes the Palmer Z drought index variable instead of the precipitation variables. Figure A.4 depicts these relations.

Figure A.1: Marginal effect of HDD on LCR at different planting densities using Palmer Z instead of precipitation as controls

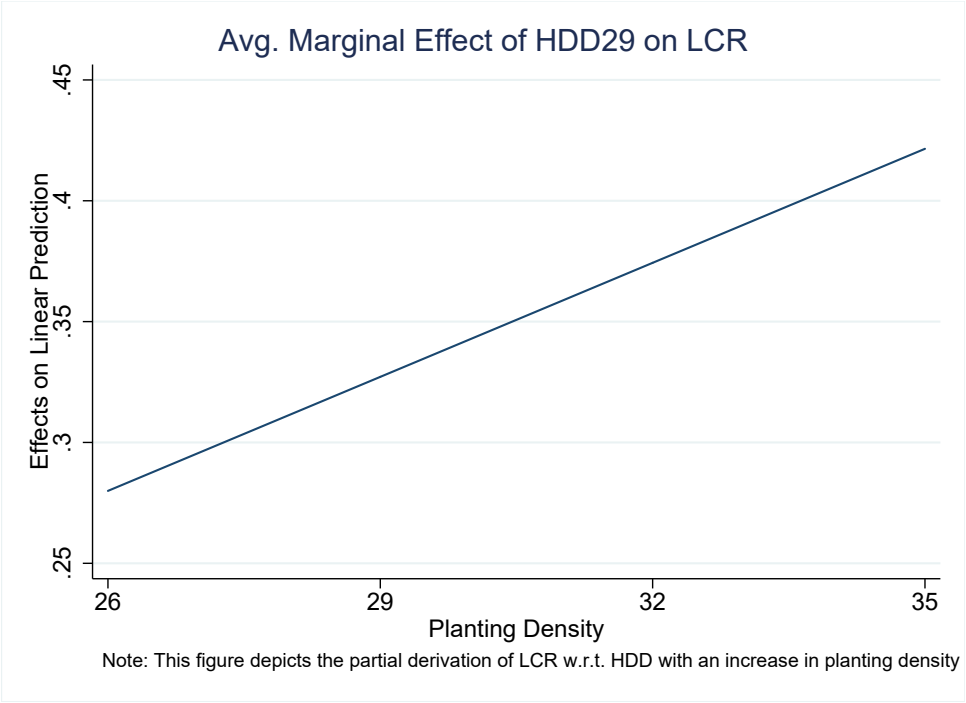


Figure A.2: Marginal Effect of HDD on LCR for different combinations of PD and GM-RW using Palmer Z is instead of precipitation as controls

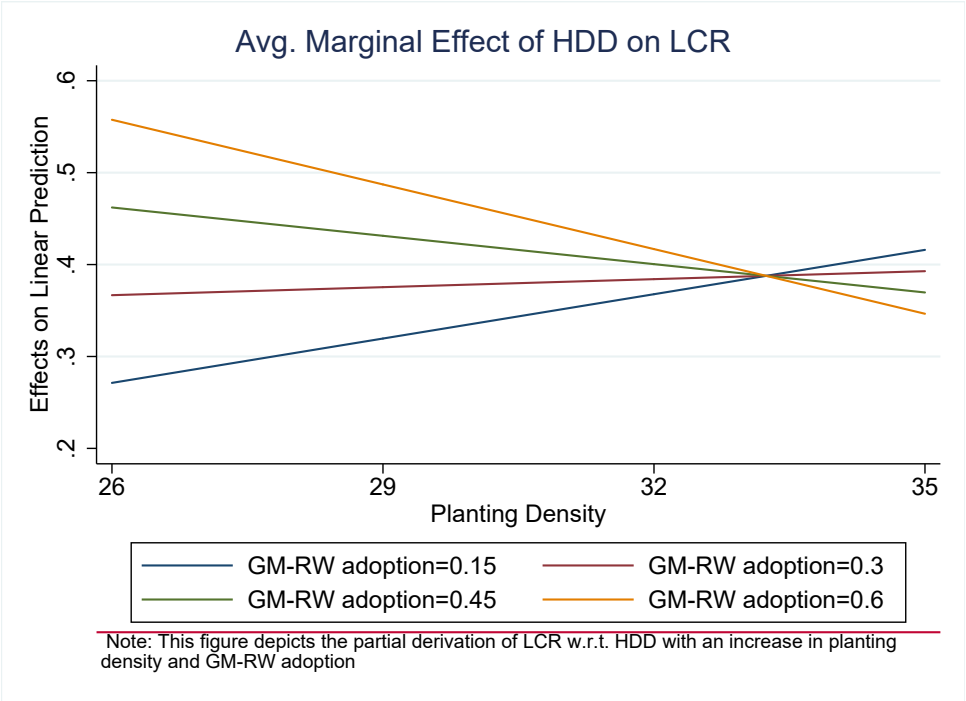


Figure A.3: Predicted LCRs at the Palmer Z dryness at different planting densities (for the specification that used Palmer Z instead of precipitation as controls)

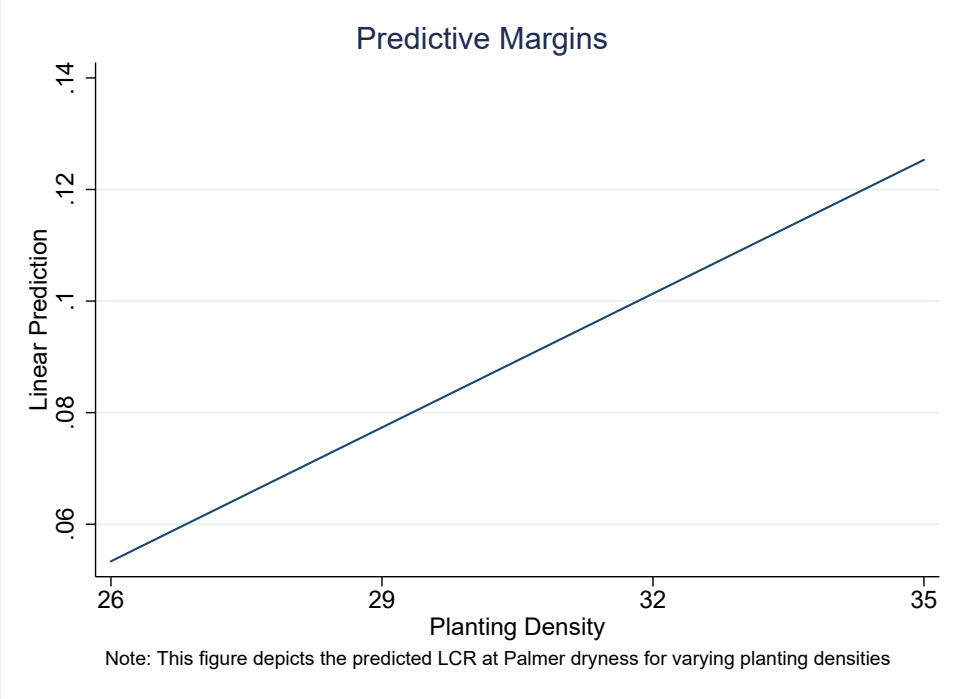


Figure A.4: Predicted LCRs at the Palmer Z dryness at different combinations of PD and GM-RW (for the specification that used Palmer Z instead of precipitation as controls)

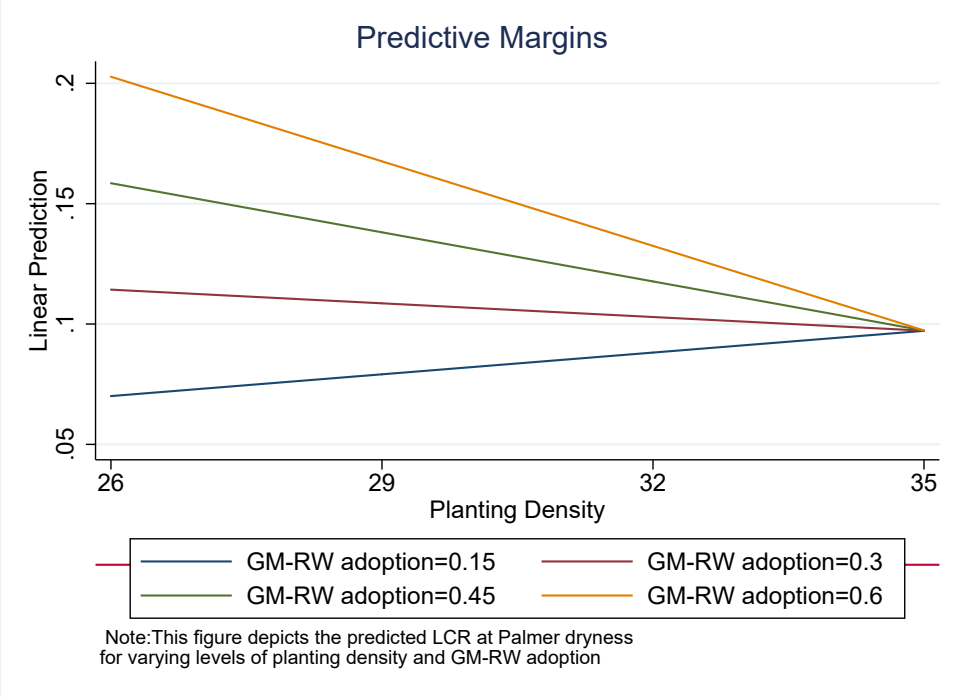


Figure A.5: Planting Density Change

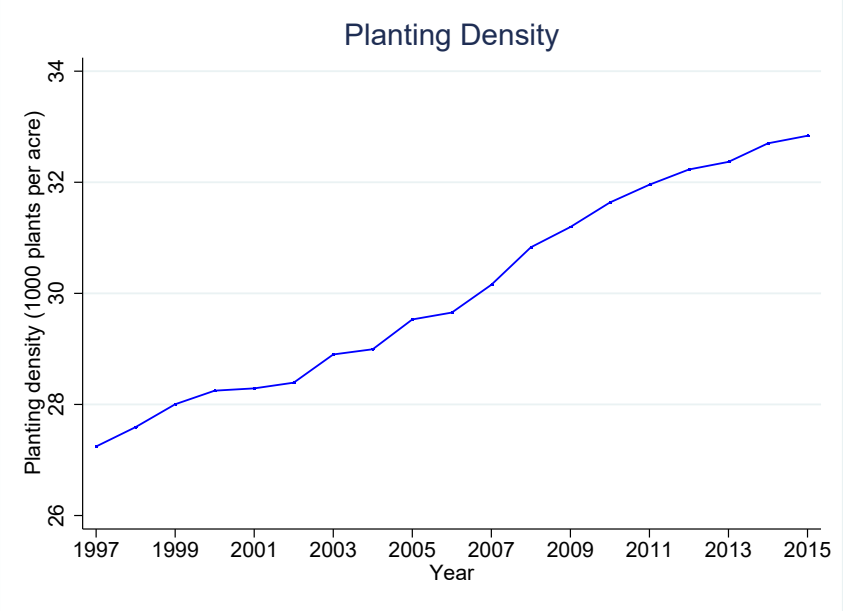


Figure A.6: Loss Cost Ratio Change

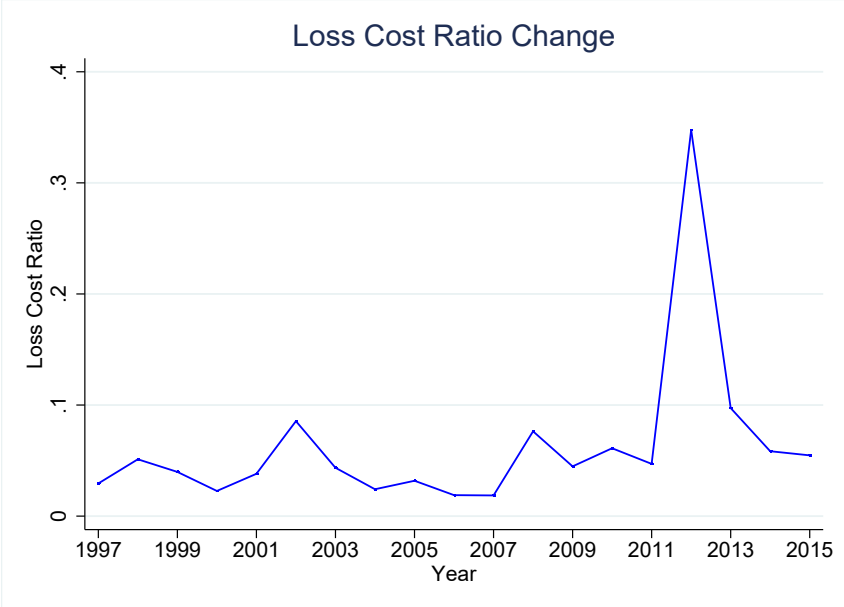


Figure A.7: GM Corn Varieties Adoption Rate

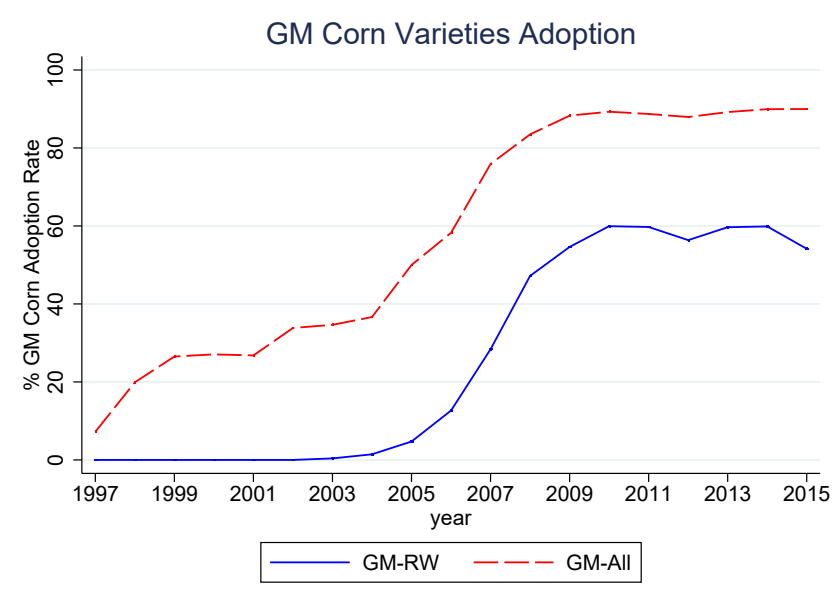


Figure A.8: Weather Variables

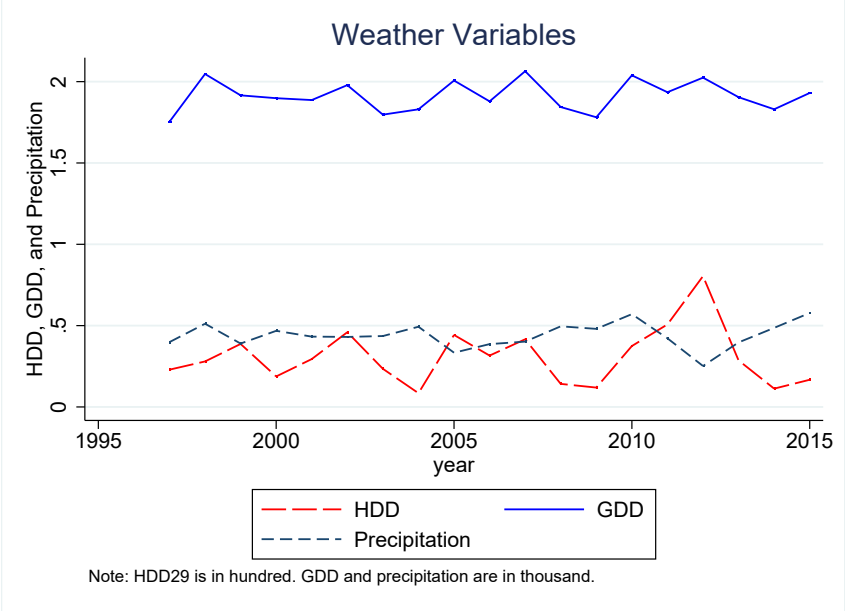


Figure A.9: Palmer Z Drought Index

