Decomposing Moral Hazard in Prevented Planting

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Abstract

Prevented planting (PP) provision of the US Federal Crop Insurance Program (FCIP) indemnifies when the adverse weather or field condition prevents the insured from planting. We explore empirical relationships between weather and PP using two different datasets, observational and experimental, to assess whether moral hazard behavior exists in PP provision in the US FCIP. Overall, we find that observed PP is more sensitive to weather than PP occurrence in experimental data. Our finding implies that producers with crop insurance and PP provision tend to react more responsively to adverse weather than they would otherwise, indicating a form of moral hazard behavior.

Keywords: Prevented Planting, Risk Preference, Crop Insurance, Moral Hazard
JEL Codes: Q10, Q14, Q18

1 Introduction

Prevented planting (PP) provision, which indemnifies when the adverse weather or field condition prevents the insured from planting, has been part of the Federal Crop Insurance Program (FCIP) since the 1994 Federal Crop Insurance Reform Act. Since its inception, there has been a longstanding concern about whether this policy is effectively monitored and implemented (USDA-OIG, 2024). In particular, the weak incentive compatibility between insurance payouts and planting crops has provoked concern about farmers' strategic behaviors, such as fraudulent claims (Jin et al., 2005; Rejesus et al., 2003) or decisions to forgo planting altogether (Wu et al., 2020; Kim and Kim, 2018). A significant challenge in examining whether and to what extent the policy causes welfare loss has been the absence of an effective way to disentangle economic incentives for PP from weather-related factors. The existing literature attests to the moral hazard in PP by documenting the positive effect of the insurance coverage or market conditions on the observed PP indemnity payments (Wu et al., 2020; Boyer and Smith, 2019; Kim and Kim, 2018). However, it is unclear whether these empirical findings isolate economic incentives from weather and agronomic conditions.

The objective of this paper is to explore empirical relationships between weather and PP to assess whether there exists moral hazard behavior caused by PP provision in the US FCIP. Since moral hazard is defined as any behavioral changes of the insured, which potentially increase insurance payout, à la Ramaswami (1993), we approach this problem by examining potential differences in the likelihood and degree of PP that is observed in insurance data and experimental data, which serve as counterfactuals for the absence of PP provision.

Therefore, we first uncover the empirical relationship between weather variables and the likelihood and magnitude of PP. More importantly, we document this relationship using two different datasets, where one is observational data of crop insurance claims from USDA RMA and the other is a set of experimental data. By statistically establishing the potential difference in weather-PP linkages between these two datasets, one can infer the presence of moral hazard. In other words, the experimental dataset serves as a benchmark of what would have been in the

absence of crop insurance (and PP provision), and the comparison to the observed crop insurance claim serves as a measure of moral hazard.

Our contribution is largely twofold. Whether and to what extent moral hazard exists in crop insurance has been a long-lasting question (e.g., Horowitz and Lichtenberg, 1993; Ramaswami, 1993; Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Yu and Hendricks, 2020). While theoretical discussion is rich, documenting its empirical evidence and establishing their causality are known to be challenging due to the possible endogeneity in insurance choices (Tack and Yu, 2021). We provide a novel empirical approach by comparing observational insurance data and experimental data (field trial data) where the experimental data serve as counterfactuals. While Yu et al. (2025) leverages field trial data to support the results estimated from on-farm observations and the underlying assumptions, we directly use field trial data as counterfactuals. We also contribute to the growing literature of PP provision in the US FCIP (e.g., Kim and Kim, 2018; Boyer et al., 2023; Won et al., 2024; Turner et al., 2025). Prior to 2003, PP claims have been less than 10% of the total FCIP indemnity (Kim and Kim, 2018), and their importance grew to about 27% in 2020 (Won et al., 2024), implying greater economic and policy importance of the program. We provide important economic estimates on the likelihood and magnitude of moral hazard in the context of PP provision.

2 Data

To empirically identify potential moral hazard in the Prevented Planting provision, we rely on two complementary data sources that isolate agronomic from economic drivers of planting behavior: (i) detailed data on corn and soybean variety trials from the Farmers' Independent Research of Seed Technologies (FIRST), and (ii) on-farm planting data from the Risk Management Agency (RMA) "cause-of-loss" (COL) dataset. We further incorporate county-level final planting dates for PP claims from the USDA Actuarial Information Browser and daily weather data from the PRISM (parameter-elevation regressions on independent slopes

model) dataset to account for agronomic timing constraints.

2.1 Experimental Planting: FIRST data

We exploit unique information on planting dates from extensive field trials conducted by FIRST, a professional seed testing network (www.firstseedtests.com). Because the primary goal of FIRST is to assess the yield potential of commercial seed varieties under optimal agronomic conditions, planting decisions in this context reflect only environmental and operational feasibility—unaffected by insurance incentives or strategic behavior. This feature is crucial for isolating agronomic drivers of prevented planting. The trials follow a standardized randomized block design, with tested varieties cultivated under uniform farming conditions within each station, such as planting date, tillage system, crop rotation, soil type, and seed density (see Lee et al., 2024).

Our sample consists of year-station-level observations for corn and soybeans, where a station is defined by its geographic location at the township level, following the definition in Lee et al. (2024). In some cases, multiple plots are observed within the same year and location. As shown in Figure 1, the dataset includes 504 corn stations and 368 soybean stations, spanning 259 and 201 counties, respectively, over the period 2002–2023. The broad geographic coverage across major crop-producing regions in the Midwest allows us to examine planting timing as determined primarily by weather-related factors. For example, in 2019 – a widely recognized year for PP due to an exceptionally wet planting season – the FIRST dataset still includes 154 corn stations and 104 soybean stations. Figure 2 shows that while planting was delayed for the majority of plots, they were eventually planted.

2.2 Observed Planting: RMA COL data

Observed planting decisions and indemnities recorded in the USDA Risk Management Agency's (RMA) Cause of Loss (COL) dataset reflect real-world responses to adverse weather within an institutional setting where indemnification is contingent on reporting prevented planting. In

contrast to the FIRST trial data, these administrative records capture behavior shaped by both agronomic constraints and economic incentives. The COL dataset provides detailed aggregates of crop insurance indemnity payments and indemnified acreage by county, year, crop, insurance plan, stage, and cause of loss, allowing us to isolate payments attributed to prevented planting [1].

We also incorporate RMA Summary of Business (SOB) data, which provides corresponding exposure metrics—total liabilities and total insured acres at the same unit of aggregation. Following Won et al. (2024), we use these sources to construct two normalized indicators of prevented planting risk: PP-Loss Cost Ratio (PP-LCR) and PP-Loss Acres Ratio (PP-LAR). The indemnity-based PP-LCR is defined as the ratio of total PP-related indemnities to total liabilities, while the acre-based PP-LAR captures the proportion of total insured acres associated with PP-related indemnities.

We estimate our primary regressions separately for PP-LCR and PP-LAR (in percentage form) over the 2002–2023 crop years for corn and soybeans, matched at the county–year level to the nearest FIRST trial station. We further disaggregate by insurance plan (YP, RP, RPHPE). By using both monetary- and acreage-based measures, we account for the influence of county size and insured exposure, thereby improving comparability across counties and years. These measures accurately capture the intensity of PP events across space and time while mitigating biases from variations in county size or acreage under insurance.

2.3 Variable Definitions and Summary Statistics

To isolate prevented planting (PP) outcomes attributable solely to agronomic constraints rather than economic incentives, we construct a variable called *Trial PP*, defined as an indicator equal to one if a FIRST trial plot was planted after the county-specific final reporting date for PP and zero otherwise. As shown in Figure 3, each county has a designated final reporting date – available from the USDA Actuarial Information Browser – for filing PP claims for corn and soybeans (Schnitkey et al., 2022). We treat planting after this cutoff as a proxy for conditions

[1] Refer to Table **??** for a complete listing of the stage codes applied to classify PP indemnities and the associated insured acreage.

that, under the presence of insurance, could have triggered a PP claim. This classification serves as a benchmark to compare behavior in a context free from insurance incentives. Thus, *Trial PP* functions not as a general measure of delayed planting, but as a counterfactual indicator of potential PP behavior in the absence of insurance coverage. To ensure geographic comparability, we match each county to the nearest FIRST station based on county-level centroids to minimize spatial measurement error, assuming that agronomic conditions at the station and within the county are sufficiently similar for meaningful comparison.

Similar to Won et al. (2024), we use daily temperature and precipitation data for April and May to construct growing degree days (GDD: DD 10–29°C), cooling degree days (CDD: DD 0–10°C), excess heat degree days (HDD: DD >29°C), and total precipitation (mm). For the yield estimation, we compute GDD, HDD, total precipitation, and vapor pressure deficit (VPD) – a temperature-based measure of atmospheric dryness – over the entire growing season (March through September), based on the approach in Lee et al. (2022). County-level weather variables are then constructed by aggregating 2.5×2.5-mile grid data using cropland-weighted averages, as is standard in the literature (Schlenker and Roberts, 2009).

Table 1 reports summary statistics for the key variables. Notably, we observe descriptive evidence of a substantial difference between on-farm PP from the RMA-COL data and Trial PP, suggesting that economic incentives play a significant role in PP decisions.

3 Model

3.1 Validity of Trial PP

To validate our Trial PP variable, we conduct two complementary analyses: (1) estimating the relationship between prevented planting loss measures and experimental PP, and (2) assessing yield responses to Trial PP within the experimental sample. The first analysis evaluates whether Trial PP captures meaningful variation in on-farm PP observed in the RMA-COL data, while the second examines whether Trial PP affects yield outcomes – providing evidence of agronomic,

rather than economic, incentives underlying planting behavior.

As in Won et al. (2024), we first estimate the responsiveness of county-level prevented planting loss measure, PP_{it} – measured as PP-LCR, and PP-LAR (both in percentage terms) – to experimental prevented planting and weather variables. Given a crop (either corn or soybeans) for county i and year t, the estimation equation is specified as:

$$PP_{it} = \alpha \cdot I\{\text{Trial PP}\}_{it} + \mathbf{w}'_{it}\boldsymbol{\beta} + \xi_i + \xi_t + \xi_{j[i]} + \varepsilon_{it} \tag{1}$$

where $I\{\text{Trial PP}\}_{it}$ is a proxy for the occurrence of experimental prevented planting, and $\mathbf{w}'_{it} = [\text{GDD}_{it}, \text{HDD}_{it}, \text{CDD}_{it}, \text{PPT}_{it}, \text{PPTsq}_{it}]$ is a vector of weather variables in April–May. County fixed effects ξ_i (e.g., soil quality), year fixed effects ξ_t (policy chnages), and insurance program fixed effects $\xi_{j[i]}$ (program-specific structural differences in PP incentives) are also included to control for unobserved confounding factors; and ε_{it} is the idiosyncratic error term.

Previous studies (Chen and Miranda, 2007; Kim and Kim, 2018) emphasize the importance of weather conditions at planting time. The three degree-day variables control for the nonlinear effects of temperature, while precipitation and its square capture the role of moisture availability. As most prevented planting losses result from excess moisture (Won et al., 2024; Lee and Abatzoglou, 2023), these controls are particularly important.

Note that α is the coefficient of primary interest. A significantly positive estimate on $I\{\text{Trial PP}\}_{it}$ would indicate a meaningful correlation between our two primary data sources and provide evidence of residual, weather-driven PP not captured by the other controls.

For the second component of validating Trial PP, we estimate a crop yield model following Lee et al. (2022): given a crop (corn or soybeans), for trial site i and year t,

$$yield_{it} = \delta \cdot I\{\text{Trial PP}\}_{it} + f(\mathbf{W}_{it}; \boldsymbol{\theta}) + \tau \cdot trend_t + \phi_i + \varepsilon_{it} \tag{2}$$

Here, the weather vector $\mathbf{W}_{it} = [\text{GDD}, \text{HDD}, \text{VPD}, \text{VPD}^{\text{Jul,Aug}}, \text{PPT}, \text{PPTsq}]$ captures condi-

tions over the entire growing season (March through September).[2] A significantly negative estimate of δ would indicate that Trial PP is associated with lower yield outcomes, suggesting that it captures meaningful agronomic constraints that influence PP decisions. While such effects may also be relevant to economic considerations, the Trial PP measure remains insulated from moral hazard incentives by construction.

3.2 Detecting the existence of non-agronomic factors in PP

An effective way to demonstrate that economic factors play a substantial role in PP decisions is to reveal the discrepancy between experimental PP and on-farm PP. Following Yu et al. (2025), we construct an empirical model to test for a statistical difference between on-farm PP and Trial PP. For county i and year t, we estimate the following model:

$$I\{\text{PP}\}_{it} = g(\mathbf{w}_{it}^{g}; \boldsymbol{\beta}^{g}) + h(\mathbf{w}_{it}^{h}; \boldsymbol{\beta}^{h}) + \zeta_i + \zeta_t + \varepsilon_{it} \tag{3}$$

Here, $g(\cdot)$ represents the baseline specification of weather variables as in equation (1), while $h(\cdot)$ includes interaction terms between a data-source indicator (i.e., $I\{\text{Trial}\}$) and all weather variables, allowing coefficients to vary across data sources. County fixed effects ζ_i and year fixed effects ζ_t are incorporated.

Regarding the dependent variable, we define on-farm PP as a county-level indicator equal to one if at least one PP occurrence is observed under any insurance program code, and zero otherwise. This aggregation avoids multiple counting of PP events within the same county-year. Additionally, following Yu et al. (2025), we construct the matched Trial PP dataset by assigning each Trial PP observation to the corresponding county-year, effectively doubling the number of observations.

The key identification strategy relies on the assumption that if the two data sources – on-farm and trial – are drawn from the same data-generating process, then the parameters

[2] VPD and $\text{VPD}^{\text{Jul,Aug}}$ denote vapor pressure deficits for the full growing season and for July–August, respectively. See Roberts et al. (2013) for a detailed discussion of the agronomic relevance of these variables.

associated with $h(\mathbf{w}_{it}^h; \boldsymbol{\beta}^h)$ should not be statistically significant. This specification thus enables a direct, apples-to-apples comparison between experimental and on-farm measures of PP under comparable weather conditions.

Additionally, if significant countervailing effects are detected in the interaction terms associated with the trial data – that is, if $\boldsymbol{\beta}^h$ indicates differential weather responsiveness of PP – then one can project the implied changes in the probability gap between on-farm and trial PP outcomes under warmer or wetter conditions. To implement this, we adopt the blocked bootstrap procedure proposed by Yu et al. (2025), in which entire years are sampled with replacement $b = 1, \ldots, B$ times. In each bootstrap iteration, we re-estimate the regression model (3) and compute the change in predicted PP for the on-farm data as:

$$\Delta PP_{it}^g = g(\tilde{\mathbf{w}}_{it}^g; \hat{\boldsymbol{\beta}}^g) - g(\mathbf{w}_{it}^g; \hat{\boldsymbol{\beta}}^g) \tag{4}$$

and for the trial data as:

$$\Delta PP_{it}^h = \left[g(\tilde{\mathbf{w}}_{it}^g; \hat{\boldsymbol{\beta}}^g) + h(\tilde{\mathbf{w}}_{it}^h; \hat{\boldsymbol{\beta}}^h)\right] - \left[g(\mathbf{w}_{it}^g; \hat{\boldsymbol{\beta}}^g) + h(\mathbf{w}_{it}^h; \hat{\boldsymbol{\beta}}^h)\right] \tag{5}$$

where $\tilde{\mathbf{w}}_{it}$ denotes the counterfactual weather condition – a uniform change consisting of either a 1°C increase in April–May temperature or a 1 mm increase in precipitation. The difference $h(\mathbf{w}_{it}^h; \hat{\boldsymbol{\beta}}^h) - h(\tilde{\mathbf{w}}_{it}^h; \hat{\boldsymbol{\beta}}^h)$ thus captures the differential impact on PP probability between the on-farm and trial data under the altered weather scenario.

4 Results

In this section, we present the findings from the empirical models introduced in the previous section.

4.1 Trial PP effectively captures agronomic drivers

Regarding the validity of the trial data, as specified in equation (1), we find a statistically significant estimate for $I\{\text{Trial PP}\}$, indicating a strong correlation between on-farm PP and Trial PP. This result suggests the presence of residual weather-driven variation in PP outcomes that is not fully captured by the observed weather variables but is instead absorbed by the Trial PP indicator (Table 2). Notably, CDD, PPT, and PPTsq are consistently significant across all specifications, in line with the findings of previous studies (Won et al., 2024; Boyer et al., 2023).

Table 3 presents yield estimates based on the Trial PP indicator, controlling for weather, time trends, and fixed effects. The estimated weather coefficients broadly align with findings in the existing literature (Lee et al., 2022; Lusk et al., 2018; Roberts et al., 2013). We find that both corn and soybean yields decline significantly when Trial PP is triggered – by approximately 34 bu/acre for corn and 14 bu/acre for soybeans. These reductions correspond to roughly 17% and 26% of the FIRST sample average yields for corn and soybeans, respectively. The relative difference suggests that PP decisions may differ by crop type, potentially reflecting variation in crop development stages and agronomic sensitivity to planting disruptions.

4.2 On-farm PP is more sensitive to weather shocks

The key decomposition analysis is based on the fixed-effects model in equation (3). Table 4 reports statistically significant differences between on-farm PP and Trial PP in their responsiveness to weather variables. This finding implies that the on-farm PP decisions, at least with respect to weather shocks, differ substantially from those observed in experimental settings where economic incentives are absent. For instance, the effect of CDD on PP is largely diminished in the Trial data, as indicated by the significant interaction between CDD and the Trial data source indicator – suggesting that much of the CDD-driven variation in on-farm PP does not manifest under experimental conditions.

In fact, all interaction terms between Trial PP and weather variables – except for HDD – exhibit signs opposite to the baseline weather coefficients. This pattern suggests that on-farm

PP is more sensitive to adverse weather conditions than Trial PP. In Table 4, we further disaggregate the analysis by insurance type. Although the magnitude of the effects varies across crop types and insurance programs, the general pattern that Trial PP is less sensitive to weather shocks remains consistent.

Additionally, we assess how warming and increased precipitation affect the PP differential between on-farm and trial data. Using the bootstrap procedure described earlier with 1,000 replications, we simulate uniform changes in weather conditions and evaluate their effects. Figure 4 shows that a 1°C increase in April-May temperature reduces the gap between on-farm and Trial PP by 4.1% for corn and 3.2% for soybeans, whereas a 1 mm increase in precipitation widens the gap by 0.16% for corn and 0.15% for soybeans. Interestingly, the insurance-group-specific simulations show qualitatively similar patterns with moderate heterogeneity (Figure 5). Among the insurance types, RPHPE exhibits the most responsive PP gap to weather shocks – showing smaller reductions under warming and larger increases under additional precipitation.

4.3 Robustness checks

A potential source of measurement error in our analysis arises from RMA-COL observations that do not have a corresponding match in the FIRST dataset. As shown in Figure 1, a considerable number of counties remain uncovered by FIRST. While the nearest experimental station is expected to reasonably capture local planting patterns, some counties may be located too far from their matched trial site to ensure reliable comparability. To address this concern, we conduct robustness checks using a restricted subsample of RMA-COL data that includes only counties directly covered by the FIRST dataset.

Tables 6 and 7 reaffirm our main findings. Although some coefficients lose statistical significance due to the reduced sample size, we continue to find that, for both crops, CDD and PPT are key determinants of PP, and that Trial PP remains significantly less sensitive to weather shocks. However, as shown in Table 8, the insurance-specific analysis reveals that many

coefficients lose significance, even though the signs remain broadly consistent with those in Table 5. Table 8 also highlights more pronounced heterogeneity in the differential between on-farm PP and Trial PP across insurance programs, implicating that economic incentives may be an important driver of this divergence.

5 Concluding Remarks

This paper provides evidence that economic factors play a significant role in prevented planting decisions by decomposing agronomic and non-agronomic components of PP behavior. Leveraging extensive field trial data – generated under agronomic conditions and absent economic incentives – we identify a substantial divergence between on-farm PP and Trial PP. We also find that this gap narrows under warmer temperatures or reduced precipitation and widens under cooler or wetter conditions. Furthermore, we document considerable heterogeneity across insurance programs, suggesting that economic incentives embedded in insurance design may require closer scrutiny when evaluating the drivers of PP behavior.

Future research could build on this decomposition by developing a structural model that explicitly accounts for the economic drivers of PP decisions. In particular, incorporating how farmers update their expected profits and evaluate risk throughout the planting season would provide a richer understanding of the role of economic incentives. Additionally, future work may explore heterogeneous yield responses to planting disruptions across crops, as soybean yields appear more sensitive to such disruptions than those of corn.

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Tables and Figures

Table 1: Summary Statistics of Main Variables

	(1) Corn		(2) Soybeans	
	mean	sd	mean	sd
Prevented Planting (PP)	0.329	0.470	0.325	0.468
I{Trial PP}	0.035	0.183	0.026	0.159
PP LCR	1.518	6.250	0.976	4.544
PP LAR	2.186	7.792	1.339	5.435
GDD-Apr,May	307.291	76.237	309.652	75.607
CDD-Apr,May	83.358	68.451	81.070	67.445
HDD-Apr,May	0.000	0.008	0.000	0.008
PPT-Apr,May	195.839	82.708	197.951	82.568
Observations	61003		58612	
Number of states	13		13	
Number of counties	1077		1059	
Number of stations matched	489		361	

Note: The number of stations extitmatched refers to the FIRST trial stations that were matched to the RMA-COL dataset based on geographic proximity. Because some counties contain multiple stations, not all stations could be matched. The total number of unique stations in the full FIRST sample is 504 for corn and 368 for soybeans, respectively.

Table 2: RMA dependent variables

	(1) Corn PP	(2) Corn PP-LCR	(3) Corn PP-LAR	(4) Soy PP	(5) Soy PP-LCR	(6) Soy PP-LAR
I{Trial PP}=1	0.0829***	1.400***	1.872***	0.0691***	1.935***	2.329***
	(0.00966)	(0.240)	(0.295)	(0.0121)	(0.249)	(0.281)
GDD-Apr,May	-0.000445***	-0.00703***	-0.00927***	-0.000181**	-0.000504	-0.000452
	(0.0000792)	(0.00130)	(0.00161)	(0.0000820)	(0.00106)	(0.00121)
CDD-Apr,May	0.000516***	0.0119***	0.0154***	0.000545***	0.00807***	0.0114***
	(0.0000768)	(0.00142)	(0.00168)	(0.0000800)	(0.00104)	(0.00128)
HDD-Apr,May	0.473***	2.475***	3.265***	0.556***	0.719	1.243
	(0.161)	(0.626)	(0.859)	(0.178)	(1.407)	(1.443)
PPT-Apr,May	0.00259***	0.0110***	0.0139***	0.00225***	0.0129***	0.0168***
	(0.0000873)	(0.00156)	(0.00198)	(0.0000881)	(0.000974)	(0.00115)
PPTsq-Apr,May	-0.00000171***	0.00000195	0.00000821*	-0.00000166***	-0.0000154***	-0.0000195***
	(0.000000175)	(0.00000337)	(0.00000436)	(0.000000176)	(0.00000200)	(0.00000239)
Constant	-0.00920	0.392	0.589	-0.0345	-1.419***	-1.935***
	(0.0306)	(0.487)	(0.606)	(0.0320)	(0.389)	(0.454)
Observations	61002	61002	61002	58608	58608	58608
R^2	0.355	0.207	0.239	0.340	0.156	0.188

Standard errors in parentheses

Fixed effects for county, year, and insurance code (YP, RP, RPHPE) are applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Trial PP effect on yield (bu/acre)

	(1) Corn yield		(2) Soybean yield	
1{Trial PP}	-32.45***	(7.954)	-13.68***	(4.178)
GDD	0.0562***	(0.0159)	0.0310***	(0.00622)
HDD	-1.118***	(0.141)	-0.0888	(0.0595)
VPD	28.86*	(15.33)	-0.938	(6.370)
VPD-Jul,Aug	-29.42***	(9.799)	-13.55***	(3.815)
PPT	0.180***	(0.0471)	0.0101	(0.0178)
PPTsq	-0.000168***	(0.0000379)	-0.0000126	(0.0000145)
Trend	2.221***	(0.180)	0.537***	(0.0796)
Constant	80.72***	(26.97)	33.46***	(10.51)
Observations	3055		1824	
R^2	0.435		0.390	

Station fixed effects are included. Standard errors in parentheses.

Table 4: Weather effect on the county-level PP likelihood by crop

	(1) Corn PP	(2) Soybean PP
GDD-Apr,May	-0.000582***	-0.000427***
	(0.0000737)	(0.0000717)
HDD-Apr,May	0.0473	0.156
	(0.210)	(0.269)
CDD-Apr,May	0.00143***	0.00153***
	(0.0000735)	(0.0000737)
PPT-Apr,May	0.00348***	0.00323***
	(0.000108)	(0.000106)
PPTsq-Apr,May	-0.00000260***	-0.00000249***
	(0.000000205)	(0.000000205)
1{Trial}=1×GDD-Apr,May	0.000663***	0.000399***
	(0.0000358)	(0.0000353)
1{Trial}=1×HDD-Apr,May	2.307***	1.350***
	(0.711)	(0.385)
1{Trial}=1×CDD-Apr,May	-0.00150***	-0.00154***
	(0.0000454)	(0.0000431)
1{Trial}=1×PPT-Apr,May	-0.00387***	-0.00304***
	(0.000115)	(0.000107)
1{Trial}=1×PPTsq-Apr,May	0.00000425***	0.00000234***
	(0.000000251)	(0.000000224)
Constant	0.0218	0.00426
	(0.0281)	(0.0283)
Observations	45920	44152
R^2	0.497	0.502

Standard errors in parentheses

Fixed effects for county and year are applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Weather effect on the PP likelihood by crop & insurance program

	(1) Corn PP, YP	(2) Corn PP, RP	(3) Corn PP, RPHPE	(4) Soy PP, YP	(5) Soy PP, RP	(6) Soy PP, RPHPE
GDD-Apr,May	-0.000745***	-0.000533***	-0.000290***	-0.000301***	-0.000384***	-0.000282***
	(0.0000686)	(0.0000753)	(0.0000865)	(0.0000670)	(0.0000735)	(0.0000872)
HDD-Apr,May	0.214	0.245	-0.0122	0.149	0.396	-0.0878
	(0.241)	(0.215)	(0.106)	(0.270)	(0.261)	(0.0969)
CDD-Apr,May	0.00104***	0.00139***	0.000510***	0.00117***	0.00148***	0.000850***
	(0.0000748)	(0.0000762)	(0.0000969)	(0.0000764)	(0.0000766)	(0.000100)
PPT-Apr,May	0.00222***	0.00312***	0.00190***	0.00183***	0.00293***	0.00183***
	(0.000110)	(0.000114)	(0.000146)	(0.000114)	(0.000107)	(0.000143)
PPTsq-Apr,May	-0.00000125***	-0.00000200***	-0.000000926***	-0.000000730***	-0.00000213***	-0.00000150***
	(0.000000236)	(0.000000226)	(0.000000319)	(0.000000250)	(0.000000212)	(0.000000306)
1{Trial}=1×GDD-Apr,May	0.000776***	0.000608***	0.000409***	0.000441***	0.000441***	0.000197***
	(0.0000333)	(0.0000363)	(0.0000428)	(0.0000331)	(0.0000354)	(0.0000426)
1{Trial}=1×HDD-Apr,May	2.425***	1.696***	2.216***	1.223***	0.607*	1.510***
	(0.569)	(0.563)	(0.511)	(0.345)	(0.346)	(0.249)
1{Trial}=1×CDD-Apr,May	-0.000812***	-0.00143***	-0.000379***	-0.000788***	-0.00148***	-0.000424***
	(0.0000456)	(0.0000469)	(0.0000569)	(0.0000442)	(0.0000444)	(0.0000583)
1{Trial}=1×PPT-Apr,May	-0.00255***	-0.00320***	-0.00217***	-0.00156***	-0.00256***	-0.00178***
	(0.000114)	(0.000119)	(0.000144)	(0.000110)	(0.000110)	(0.000138)
1{Trial}=1×PPTsq-Apr,May	0.00000265***	0.00000308***	0.00000240***	0.000000312	0.00000175***	0.00000198***
	(0.000000265)	(0.000000264)	(0.000000330)	(0.000000247)	(0.000000234)	(0.000000306)
Constant	0.00968	-0.0137	-0.0303	-0.0817***	-0.0460	-0.0129
	(0.0266)	(0.0288)	(0.0336)	(0.0272)	(0.0287)	(0.0352)
Observations	45492	45288	31298	43390	43868	30002
R^2	0.308	0.455	0.308	0.313	0.441	0.313

Standard errors in parentheses

Fixed effects for county and year are applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Robustness check with subsample - RMA dependent variables

	(1) Corn PP	(2) Corn PP-LCR	(3) Corn PP-LAR	(4) Soy PP	(5) Soy PP-LCR	(6) Soy PP-LAR
I{Trial PP}=1	0.113***	4.247***	6.556***	0.178***	4.237***	5.186***
	(0.0310)	(0.839)	(1.115)	(0.0478)	(1.094)	(1.179)
GDD-Apr,May	-0.000275	-0.00872***	-0.00848**	0.000336	0.00311	0.00433
	(0.000264)	(0.00314)	(0.00393)	(0.000365)	(0.00406)	(0.00470)
CDD-Apr,May	0.00122***	0.00690**	0.0116***	0.00173***	0.0122***	0.0171***
	(0.000247)	(0.00299)	(0.00352)	(0.000310)	(0.00378)	(0.00410)
HDD-Apr,May	1.913	8.546*	11.31*	0.578	3.823*	5.707**
	(2.260)	(4.594)	(6.128)	(1.167)	(2.085)	(2.887)
PPT-Apr,May	0.00199***	0.00575	0.00689	0.00173***	0.00841**	0.00940**
	(0.000290)	(0.00434)	(0.00510)	(0.000367)	(0.00336)	(0.00442)
PPTsq-Apr,May	0.000000176	0.00000448	0.0000111	9.61e-08	-0.00000600	-0.00000291
	(0.000000611)	(0.00000937)	(0.0000112)	(0.000000782)	(0.00000777)	(0.0000103)
Constant	-0.112	1.449	0.852	-0.289**	-2.801**	-3.681**
	(0.0958)	(1.135)	(1.404)	(0.129)	(1.378)	(1.608)
Observations	8203	8203	8203	5098	5098	5098
R^2	0.442	0.279	0.325	0.439	0.371	0.389

Standard errors in parentheses

Fixed effects for county, year, and insurance code (YP, RP, RPHPE) are applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Robustness check with subsample - Weather effect on the county-level PP likelihood by crop

	(1) Corn PP	(2) Soybean PP
GDD-Apr,May	-0.000699**	-0.0000902
	(0.000283)	(0.000390)
HDD-Apr,May	4.229	-1.201
	(2.947)	(2.646)
CDD-Apr,May	0.00159***	0.00210***
	(0.000256)	(0.000301)
PPT-Apr,May	0.00362***	0.00229***
	(0.000324)	(0.000431)
PPTsq-Apr,May	-0.00000211***	-0.000000251
	(0.000000624)	(0.000000844)
1{Trial}=1×GDD-Apr,May	0.000582***	0.000196
	(0.0000990)	(0.000132)
1{Trial}=1×HDD-Apr,May	-1.531	2.460
	(3.045)	(2.614)
1{Trial}=1×CDD-Apr,May	-0.00157***	-0.00205***
	(0.000124)	(0.000131)
1{Trial}=1×PPT-Apr,May	-0.00324***	-0.00190***
	(0.000313)	(0.000412)
1{Trial}=1×PPTsq-Apr,May	0.00000226***	2.29e-08
	(0.000000698)	(0.000000936)
Constant	-0.0255	-0.0773
	(0.0978)	(0.132)
Observations	5792	3664
R^2	0.555	0.549

Standard errors in parentheses

Fixed effects for county and year are applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Robustness check with subsample - Weather effect on the PP likelihood by crop & insurance program

	(1) Corn PP, YP	(2) Corn PP, RP	(3) Corn PP, RPHPE	(4) Soy PP, YP	(5) Soy PP, RP	(6) Soy PP, RPHPE
GDD-Apr,May	-0.000427*	-0.000636**	-0.000387	-0.000147	-0.0000881	0.000249
	(0.000252)	(0.000281)	(0.000273)	(0.000348)	(0.000391)	(0.000387)
HDD-Apr,May	-4.257**	4.920*	-2.291**	-1.527	-0.927	-0.0328
	(1.857)	(2.594)	(0.938)	(1.066)	(2.656)	(1.333)
CDD-Apr,May	0.00127***	0.00151***	0.000715***	0.00183***	0.00217***	0.000635*
	(0.000260)	(0.000259)	(0.000271)	(0.000313)	(0.000305)	(0.000334)
PPT-Apr,May	0.00112***	0.00304***	0.000833**	0.000924**	0.00198***	0.000644
	(0.000380)	(0.000324)	(0.000418)	(0.000431)	(0.000440)	(0.000518)
PPTsq-Apr,May	0.00000172**	-0.00000102	0.00000145	0.00000203**	5.90e-08	0.000000913
	(0.000000861)	(0.000000633)	(0.000000947)	(0.000000962)	(0.000000883)	(0.00000119)
1{Trial}=1×GDD-Apr,May	0.000462***	0.000526***	0.0000502	0.000172	0.000201	-0.000234*
	(0.0000995)	(0.0000982)	(0.000109)	(0.000123)	(0.000132)	(0.000142)
1{Trial}=1×HDD-Apr,May	6.205***	-2.407	3.797***	2.458**	1.965	0.417
	(1.824)	(2.737)	(0.900)	(1.052)	(2.621)	(1.322)
1{Trial}=1×CDD-Apr,May	-0.000777***	-0.00163***	-0.000269**	-0.00100***	-0.00205***	-0.000219
	(0.000130)	(0.000125)	(0.000135)	(0.000146)	(0.000134)	(0.000157)
1{Trial}=1×PPT-Apr,May	-0.00115***	-0.00261***	-0.000770**	-0.000342	-0.00159***	-0.000167
	(0.000346)	(0.000313)	(0.000371)	(0.000414)	(0.000419)	(0.000477)
1{Trial}=1×PPTsq-Apr,May	-0.00000116	0.00000104	-0.000000706	-0.00000259***	-0.000000350	-0.00000109
	(0.000000847)	(0.000000700)	(0.000000903)	(0.00000100)	(0.000000961)	(0.00000118)
Constant	-0.0503	-0.0165	0.0336	-0.154	-0.0822	-0.110
	(0.0883)	(0.0976)	(0.0978)	(0.119)	(0.134)	(0.134)
Observations	5782	5792	4834	3656	3662	2878
R^2	0.377	0.535	0.330	0.377	0.516	0.323

Standard errors in parentheses

Fixed effects for county and year are applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: FIRST trial station locations

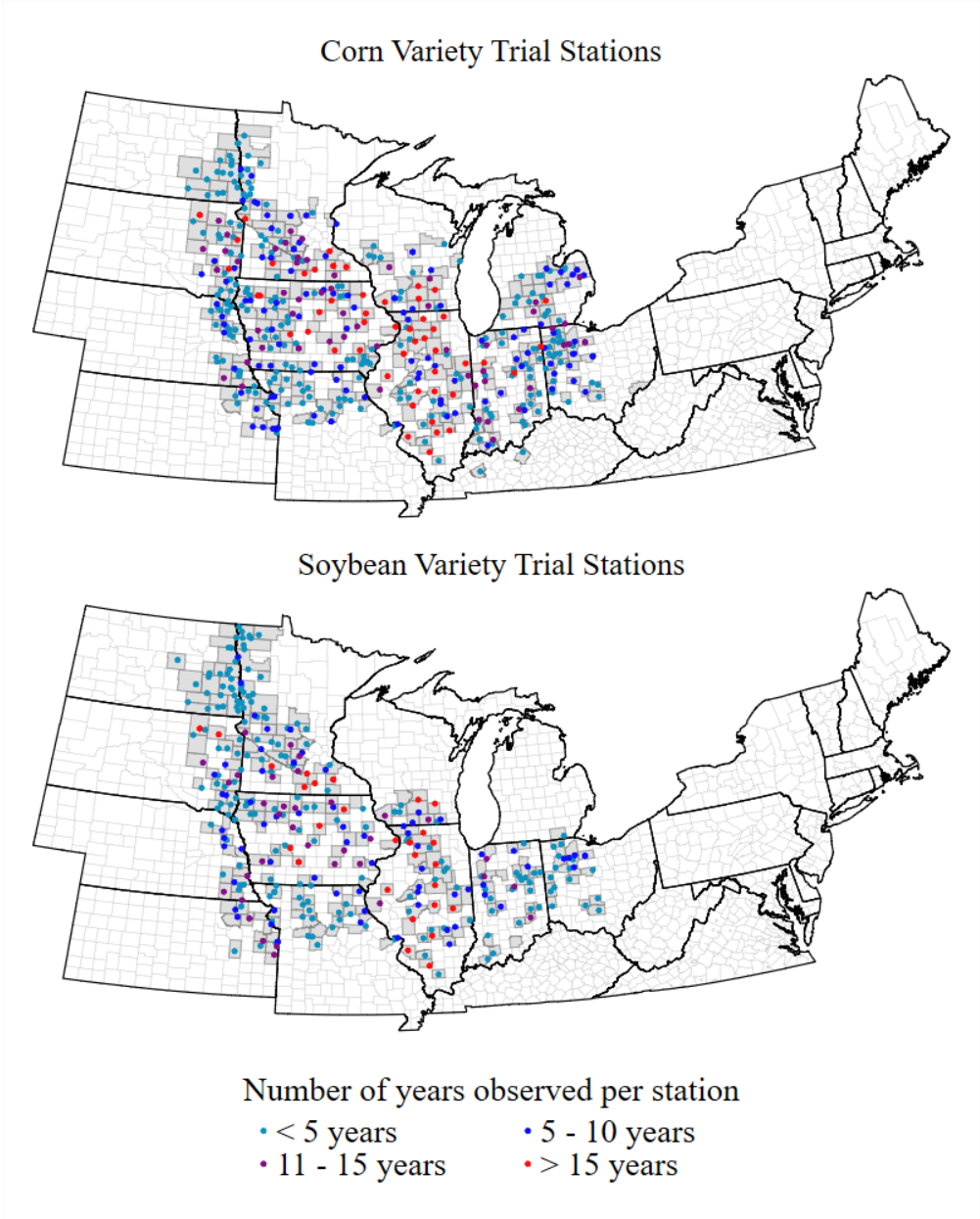


Figure 2: Planting timing differences between years in FIRST trial

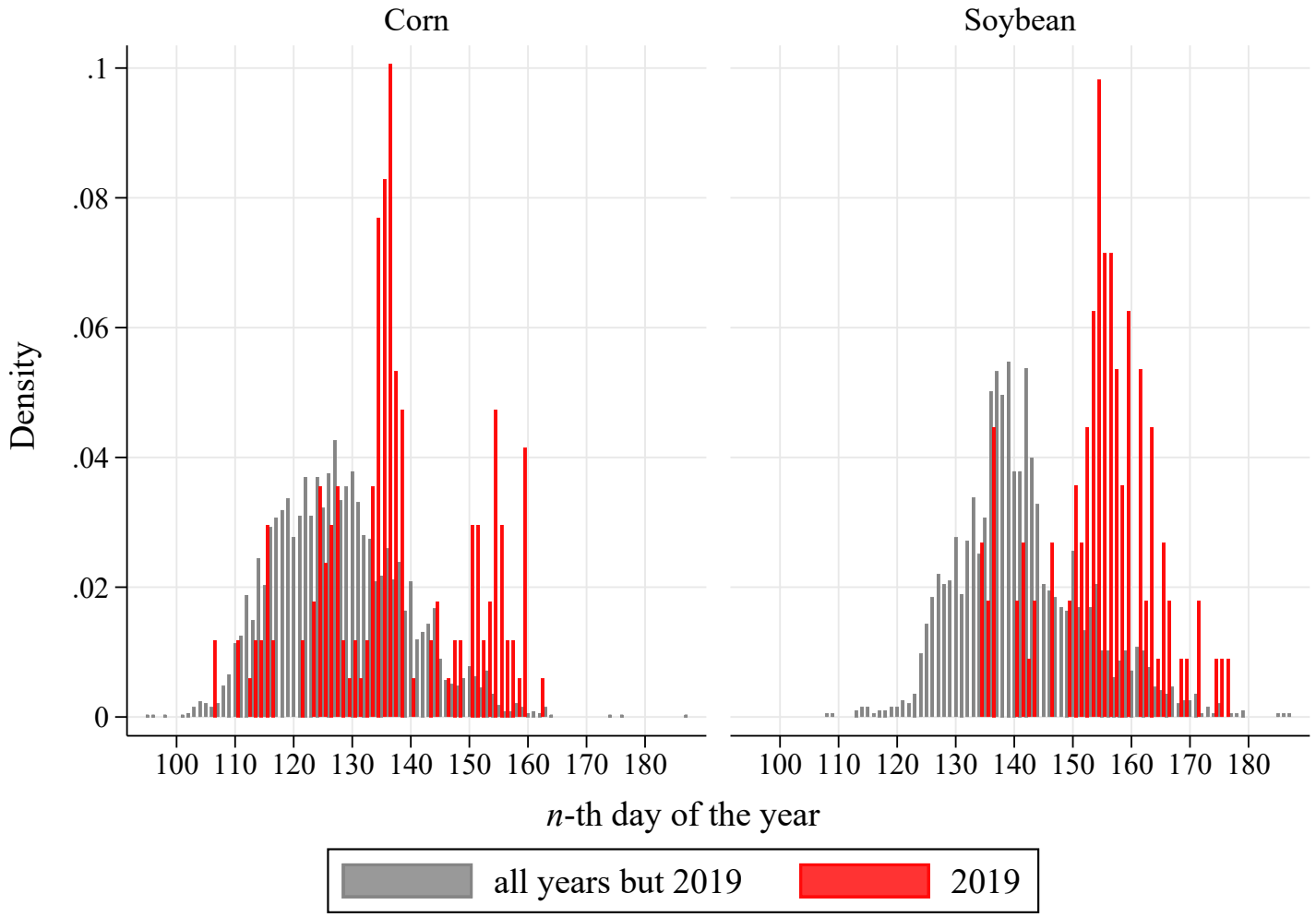


Figure 3: Final dates to file PP

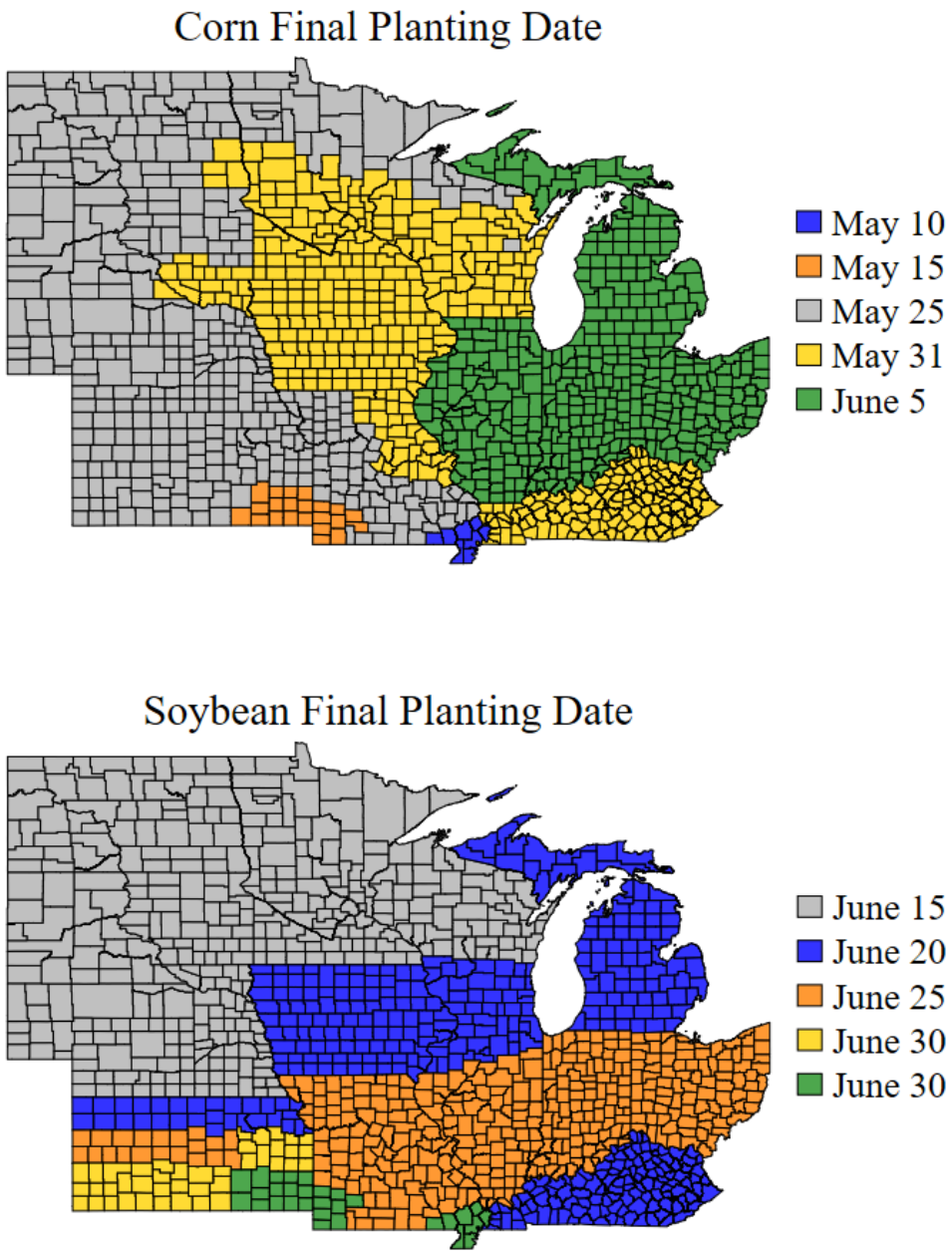


Figure 4: Weather impacts: on-farm vs experimental trial

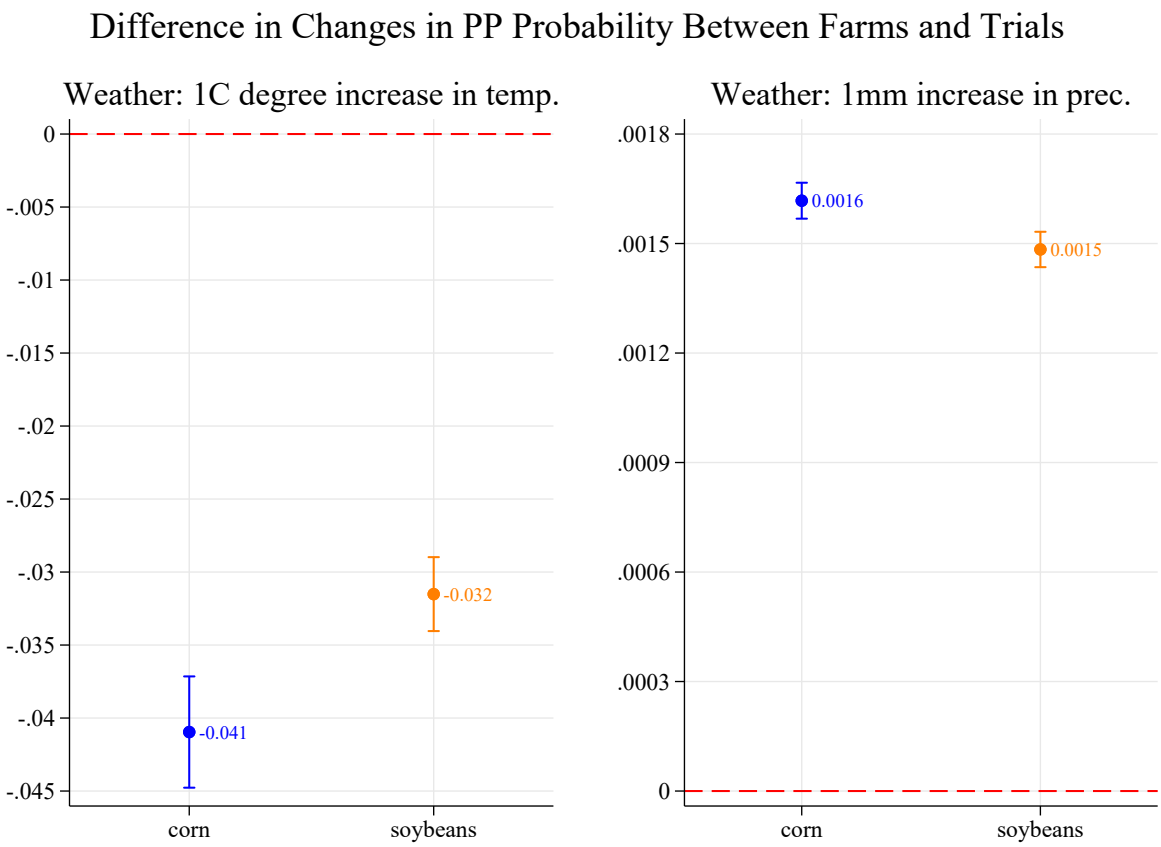


Figure 5: Weather impacts by insurance: on-farm vs experimental trial

