Measuring the Impact of Hurricane Incidence on Crop Insurance Premium Rates in the Mississippi Delta

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Abstract

Hurricanes are the most destructive natural disasters in the United States. The exposure of agricultural production systems to hurricanes varies between regions in contrast to global risks like commodity price volatility and international trade policies. The regional differences in hurricane exposure may lead to heterogeneity in crop insurance premium rates. This work aims to measure the impact of hurricane incidence on crop insurance premium rates for crops grown in the Mississippi Delta. We leverage a county-month panel of insurance losses spanning 2002-2021 from the USDA-RMA, and daily data from the NOAA National Hurricane Center, to construct novel measures for hurricane treatment assignment under a Difference-in-Differences identification strategy. We find hurricane incidence results in increases to crop insurance premium rates in treated counties relative to untreated counties. The way in which hurricane treatment is measured matters with a conservative measure of treatment producing effects exhibiting downward attenuation bias and suggest a preferred measure which accounts for the dynamic changes in the scope of a hurricane over its life. We also find hurricane incidence to result in heterogeneous treatment effects between crops which provide implications for HIP-WI insurance availability and catastrophic loading in premium rating.

Keywords: Crop Insurance, Premium Rating, Climate Change, Difference-in-Differences

JEL Codes: Q12, Q18, Q54

1 Introduction

Hurricanes are the most destructive natural disasters in the United States. In 2021 alone, hurricanes caused $145 billion in total damages to commercial and personal property, making it the third most costly hurricane season on record and the seventh straight year in which 10 or more one-billion-dollar events occurred (NOAA Office for Coastal Management, 2022). Furthermore, due to the well documented relationship between increasing sea surface temperatures and greater hurricane incidence in the Atlantic Ocean basin, these catastrophic events are likely to increase in frequency and magnitude in the coming years due to climate change (Webster, et al., 2005; Trenberth, 2005; Emanuel, 2005). Despite the scale and urgency of this threat, relatively little attention has been given to measuring how hurricanes impact the riskiness of U.S. crop production.

In contrast to global risks like commodity price volatility and international trade policies, exposure to extreme weather like hurricanes varies across regions (Hardaker, Lien, and Anderson, 2015). For example, multiple hurricanes occasionally strike the same area during a single hurricane season (NOAA National Hurricane Center, 2022). One of the primary ways in which crop producers manage the risk of hurricanes is by purchasing crop insurance. The price producers pay per dollar of liability for crop insurance, known as a premium rate, varies geographically as a function of the regional riskiness in agricultural production (Biram, et al., 2022). As such, an increase in the frequency of hurricanes could drive up premium rates. To illustrate this possibility, we display county-level base premium rates with the paths of hurricanes which made landfall in our study area, the Mississippi Delta region, between 2002 and 2021 in Figure 1. In addition to region-specific risks including local climate and catastrophic weather events, variation in crop insurance premium rates can also be driven by heterogeneity in farm-level characteristics such as soil type (Chen and Chang, 2005; Miller, Tack, and Bergtold, 2020; Tsiboe and Tack, 2021). Therefore, to understand the implications of increasing hurricane incidence and magnitude on the riskiness of crop production, the impact of hurricanes must be disentangled from these alternative sources of risk.

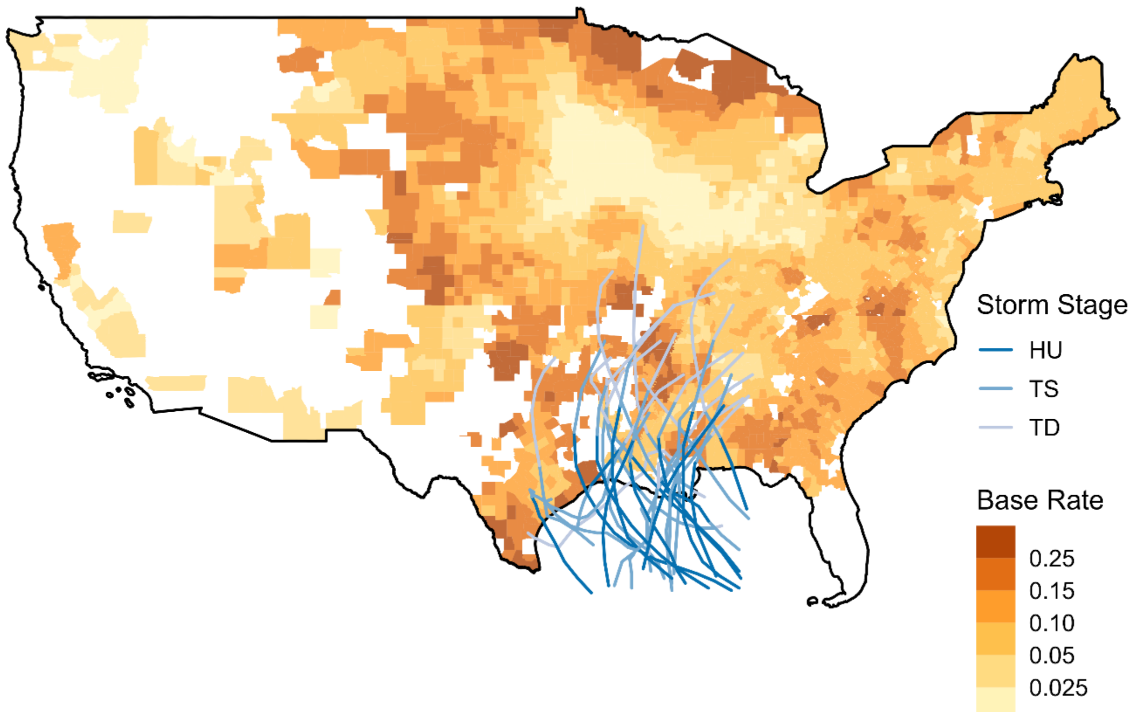

Figure 1. Spatial Relationship Between Average Corn Crop Insurance Base Premium Rates and Hurricane Incidence in the Mississippi Delta Region (2002-2021) This figure gives the county-specific base premium rates averaged across both irrigated and nonirrigated corn and the 6-hour storm tracks for hurricanes to make landfall in the Mississippi Delta region over the period 2002-2021. We note the base premium rate is interpreted as the amount of actuarially fair premium paid per dollar of purchased liability. (Source: USDA-RMA and NOAA National Hurricane Center, 2022)

In this paper, we measure the impact of hurricane incidence to on-farm damages for crops grown in the Mississippi Delta region (i.e., Arkansas, Louisiana, and Mississippi), an area which has experienced 30 hurricanes and tropical storms spanning 2002-2021 (see Figure 2). Previous works relevant to this question fall into two veins of literature which include the implications of climate change on increased tropical storm incidence and the impact of this incidence on crop yield variability. Prior research has measured the impacts of climate change on hurricane frequency and intensity through changes in maximum wind speeds and simulating storm tracks (Boose et al, 2004; Emanuel et al., 2005; Jagger and Elsner, 2006). Boose et al. (2004) estimate maximum sustained wind speeds and reconstruct hurricane storm tracks to model hurricane damages as a function of wind speeds. Emanuel et al. (2005) produce synthetic hurricane tracks to assess hurricane risk and damages using a power dissipation index based on a maximum wind speed. In the area we study, Jagger and Elsner (2006) show that among hurricanes making landfall in the United States, hurricanes with the greatest wind speeds are experienced in the Gulf of Mexico with category 4 and 5 hurricanes estimated to strike at least once every 10 years.

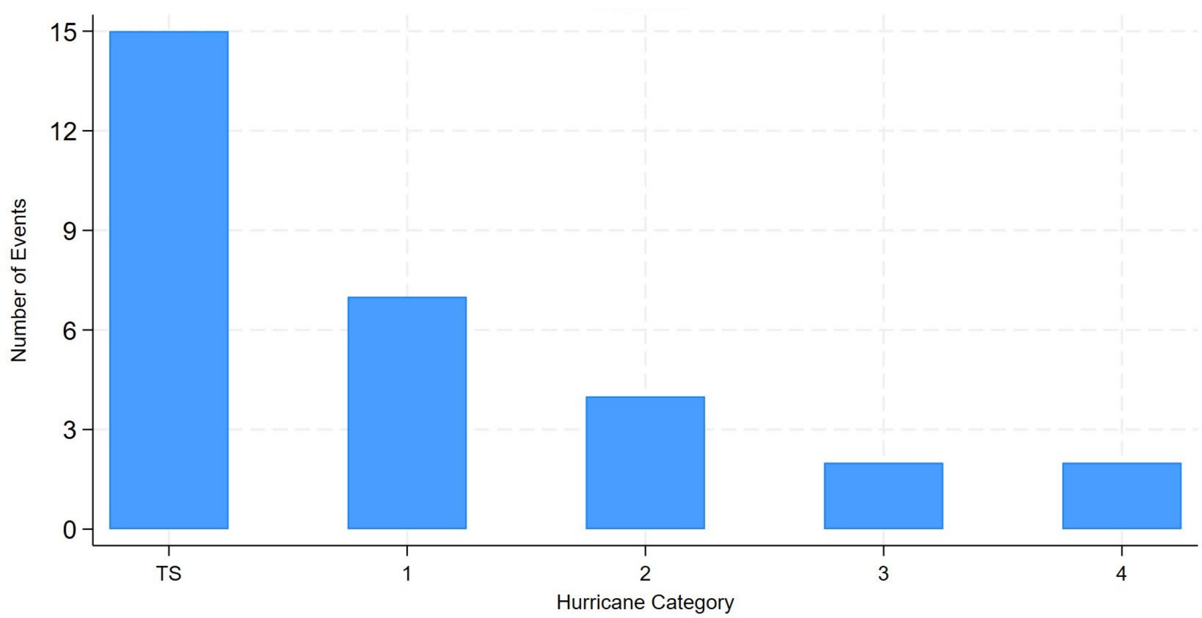

Figure 2. Frequency of Hurricane Events to Make Landfall in Louisiana and Mississippi (2002-2021)
Source: NOAA National Hurricane Center (2022)

Other relevant research considers the impacts of climate change and extreme weather on mean yields and yield variability. In general, warmer temperatures tend to be associated with decreased yields in corn, cotton, and soybeans (Schlenker and Roberts, 2009) and rice (Peng et al., 2004). In addition to reducing mean yields, climate change also increases yield variability (McCarl et al., 2008; Tack et al., 2012) which has been found to reduce producer welfare (Chen and McCarl, 2009; Strobl, 2012; Fuss et al., 2015). A few works have considered the impacts of tropical storms on rice production in the Pacific Ocean basin and find rice production to be most vulnerable in the heading stage (Masutomi et al., 2012; Blanc and Strobl, 2016). To our knowledge, there is only one other paper which specifically explores the implications of increased hurricane incidence for crop insurance premia (Chen and Chang, 2005). Chen and Chang (2005) estimate a crop yield response function and show increases in air temperature and levels of precipitation have raised yield variability and lowered yields of rice, corn, and adzuki beans grown in Taiwan.

Our contributions to the growing literature on the impacts of climate change on yield variability are twofold. The first contribution is methodological whereby we use a quasi-experimental approach to quantify the impact of hurricanes to on-farm damages in the Mississippi Delta using four different measures of hurricane treatment. The outcomes in our analyses are monthly crop losses attributed to specific causes of loss recorded at the county level in the USDA-RMA Summary of Business and Cause of Loss datasets spanning 2002-2021. Our Difference-in-Differences (DiD) framework compares the change in these monthly outcomes for treated counties which experienced tropical storm and hurricane force winds to control counties which did not. To determine the treatment and control counties, we use the daily HURDAT2 data from the NOAA National Hurricane Center and create four different indicators assigning hurricane treatment.

The second contribution is empirical in that we find the estimated impacts are sensitive to the type of hurricane treatment measure used and that impacts are heterogeneous between crops.

The first measure most conservatively assigns treatment likely leaving out treated counties and results in a 0.075 percentage point increase in county mean loss-cost ratios. The second measure assigns treatment to considerably more counties likely capturing untreated counties and results in a 0.05 percentage point increase in county mean loss-cost ratios. Using our preferred treatment measure, which dynamically accounts for the hurricane wind field extent over the life of each hurricane, we find hurricane incidence results in up to a 1.5-percentage point increase in mean loss-cost ratios (LCR) for yield and revenue insurances across crops predominantly grown in the region. We consider a fourth hurricane measure using the Hurricane Insurance Protection – Wind Index (HIP-WI) trigger file constructed by RMA, which assigns treatment to counties adjacent to treated counties under our preferred measure and find an impact similar to our preferred measure. This main result is robust to the causes of loss included in the LCR and additional months of losses accounting for potential delayed loss reporting error by insurance adjusters.

We find heterogeneous impacts between crops, with cotton experiencing the greatest increase of 4-percentage points in the mean LCR. Results suggest that crop choice may make certain regions especially vulnerable to tropical storms, and even though tropical storms may become more frequent everywhere, certain regions may experience greater impacts due to crop choice and proximity to the coast. Prior climate change research highlights how production of certain crops may improve given climate change predictions (Spencer and Polachek, 2015). We find results for the crop-specific regressions to be robust to the causes of loss included in the LCR. Finally, we use our estimated impacts to map the percentage of county base premium rates attributed to hurricane losses for each crop and discuss the implications for HIP-WI availability.

The remainder of the paper is organized as follows. The next section describes the sources of data used to construct hurricane wind field measures and the measure we use to represent crop insurance rates by specific causes of loss. We motivate identification of hurricane treatment effects on crop damages using DiD, discuss the assumptions necessary to conduct valid inference, and present a regression specification using a two-way fixed effects (TWFE) estimator. The fourth section provides main findings and discussion from regressions linking county specific LCRs to hurricane incidence. The last section concludes and provides implications of the estimated treatment effects of hurricane incidence on crop insurance premium rates.

2 Data and Variable Construction

We use data spanning 2002-2021 on county-level indemnities and liabilities from RMA to construct a measure of crop insurance premium rates and use daily historical hurricane tracker data from NOAA spanning the same period to construct a measure assigning hurricane treatment. We use the RMA Summary of Business (SOB) to obtain data on liabilities which will provide the information needed to form the sample by which we assign hurricane treatment. Data on cause-specific indemnities from the RMA Cause of Loss (COL) are used to construct cause-specific Loss-Cost Ratios (LCRs), the ratio of indemnities to liabilities used to model crop insurance premium rates (Coble, et al., 2010). NOAA's HURDAT-2 and Wind Field Advisory data contain latitude and longitude coordinates for the center of hurricanes, or centroids, at six-hour time points. These data sets also include information on the length of wind field radii in each hurricane quadrant (i.e. NE, SE, SW, or NW). We use the radii indicating the maximum distance that experienced one-minute sustained wind speeds of 34-knots per hour for a given wind field to construct the hurricane treatment measure.

We form our hurricane treatment assignment variables by considering only hurricanes and tropical storms which made landfall in Louisiana and Mississippi during years for which wind field data are available. We further filter our sample to only include hurricanes with at least one recorded six-hour time stamp in Louisiana or Mississippi to guarantee we have at least one centroid to construct a wind field treatment measure. For a list of hurricanes included in the sample, see Table 1. Using liabilities from the SOB, we construct LCRs by only preserving counties for which there is liability recorded in a given year. From here, we combine[1] the SOB and COL data to form cause[2] specific LCRs at the county and month level by summing indemnities across causes associated with hurricane incidence.

2.1 Hurricane Treatment Assignment

We construct four different measures of hurricane treatment assignment. The first treatment assignment measure is referred to as the Centroid Treatment (CT). For a given hurricane, the CT measure assigns treatment based on whether counties intersect the straight line connecting the centroids from each 6-hour timestamp within the NOAA HURDAT-2 tracker data. The second and third measures of treatment assignment rely on polygons created by connecting the points at the ends of the wind field radii. The method for creating these polygons and the resulting treatment measures is described in further detail below. For the second treatment assignment, Polygon Treatment (PT), counties are considered treated if they intersect with the path created by selecting the first polygon to intersect a county and interpolating this same polygon across all 6-hour timestamps. The third treatment measure, Interpolated Treatment (IT), allows the assignment polygons to change shape over time according to the observed wind

[1]Importantly, if a county did not report a cause of loss associated with hurricane incidence, we would record the associated LCR as a zero rather than drop the observation since this may provide information which is needed for a counterfactual in our treatment effect estimation.
[2]For this work we consider wind, excess precipitation, flood, and hurricane/tropical depression causes of loss to construct cause-specific LCRs. For a full list of the covered causes of loss see the RMA Loss Adjustment Manual (USDA-RMA, 2006).

field radii. Due to its ability to capture the dynamic nature of a hurricane, we believe the IT treatment measure is the most precise treatment assignment measure.

Last, the fourth hurricane treatment measure is called the RMA Treatment (RT) and is constructed using the HIP-WI trigger files from RMA. This measure assigns treatment to counties which triggered a HIP-WI indemnity for a given hurricane system and is like the IT measure which interpolates the path of a hurricane. However, RT assigns treatment to counties immediately adjacent to counties which triggered a HIP-WI indemnity based on an interpolation procedure and, as such, may assign treatment to counties which have not experienced weather resulting from a hurricane system. Visual representations for each hurricane treatment measure can be found in figure 3.

Interpolation Procedure for PT and IT Treatment Assignments

We construct a polygon wind field measure to assign county-level hurricane treatment using the wind field radii variables from the HURDAT-2 data. First, we calculate latitudes and longitudes for the corners of each quadrant of the wind field polygon by using the six-hour time stamps of latitudes and longitudes of the hurricane centroids and the rules of a right triangle whose legs are the same length. The longitude of each corner point in a quadrant is found by:

$$LON_{hsq}^{j} = LON_{h}^{j} + \frac{R_{hsq}^{j}}{\sqrt{2}}\left(\frac{1}{111.32*\cos\left(LAT_{t}^{j}*\frac{\pi}{180}\right)}\right) \tag{1}$$

Table 1. Hurricanes Which Made Landfall (2002-2021)

Year	Month	Name	Category
2002	August	Bertha	TS
2002	September	Isidore*	2
2002	October	Lili*	3
2003	July	Bill	TS
2004	October	Matthew*	TS
2005	July	Cindy	TS
2005	July	Dennis*	4

2005	August	Katrina*	4
2005	September	Rita*	4
2007	September	Humberto*	1
2008	September	Gustav*	4
2008	September	Ike*	3
2010	August	Five	TS
2011	September	Lee*	TS
2012	August	Isaac*	1
2015	June	Bill*	TS
2017	June	Cindy*	TS
2017	August	Harvey*	3
2017	September	Irma	4
2017	October	Nate	1
2018	September	Gordon*	TS
2019	July	Barry*	1
2019	October	Olga*	TS
2020	September	Beta*	TS
2020	June	Cristobal	TS
2020	October	Delta*	3
2020	August	Laura*	4
2020	October	Zeta	2
2021	August	Ida*	4
2021	June	Claudette	TS

*Indicates hurricane is in the sample used to estimate treatment effects

where LON_{hsq}^{j} is the longitude of a wind field corner point of hurricane event *j* at six-hour time stamp *h,* wind speed *s* for wind field quadrant q, where $q\epsilon[NE, SE, SW, NW]$. R_{hsq}^{j} is the length of a wind field radius in kilometers, and $LON_{h}^{j}$and $LAT_{h}^{j}$is the longitude and latitude of the hurricane centroid.

The second term gives us the degrees longitude, moving west or east, that is required to arrive at the corner point of a given wind field quadrant. The fraction $\frac{R_{hsq}^{j}}{\sqrt{2}}$ gives us the distance between the hurricane centroid and the new point of longitude, while the term in parentheses converts the distance to degrees longitude. The latitude of a corner point of a wind field quadrant can similarly be calculated as:

$$LAT_{hsq}^{j} = LAT_{h}^{j} + \frac{R_{hsq}^{j}}{\sqrt{2}}\left(\frac{1}{111.32}\right) \quad (2)$$

Since some hurricanes travel relatively long distances across time stamps, we observe gaps in the polygon wind fields which likely leave out treated counties. We perform an interpolation of polygon wind fields to fill these gaps between observed hurricane centroids. We define an increment, δ ,which is a constant fraction[3] of the distance between two observed hurricane centroids and create new centroids. We assume each observed wind polygon evolves smoothly over the distance between two empirical time stamps, meaning the length of the wind field radii change as a linear function of time between observed data points. Lastly, a county is assigned hurricane treatment if the interpolated wind field polygon intersects a county boundary at any point. The interpolation can be formally represented as:

$$Lat_{h+n*\delta}^{j} = \sum_{n=1}^{1/\delta} n * \delta * \left(Lat_{h}^{j} - Lat_{h-1}^{j}\right) \quad (3)$$

[3] We use $\delta = 0.025$ as our increment. This means that there will be $n = 40$ interpolated points between the observed hurricane centroids observed at different six-hour time stamps.

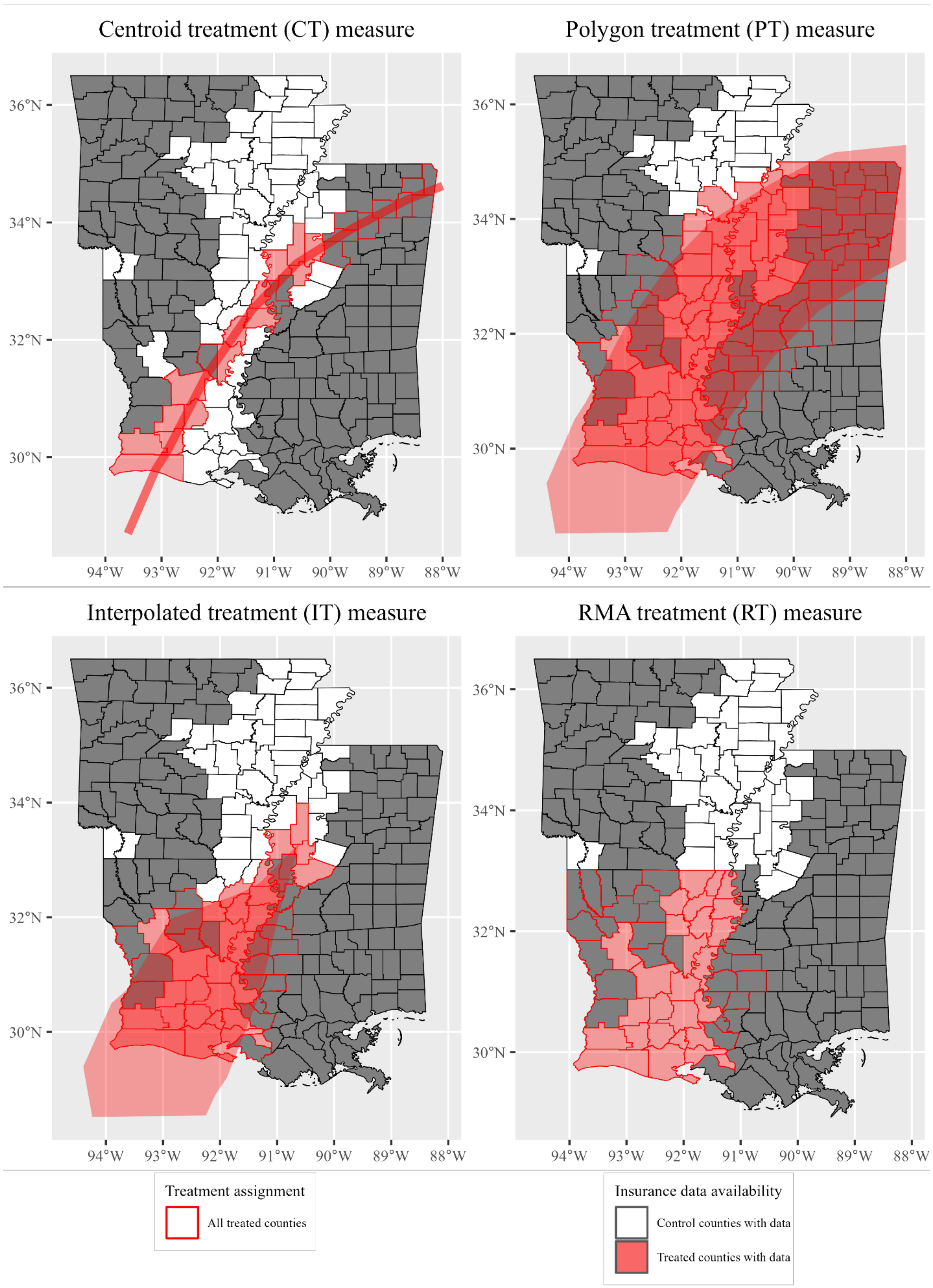
Centroid treatment (CT) measure
Polygon treatment (PT) measure
Interpolated treatment (IT) measure
RMA treatment (RT) measure
36°N
34°N
32°N
30°N
94°W
93°W
92°W
91°W
90°W
89°W
88°W
Treatment assignment
All treated counties
Insurance data availability
Control counties with data
Treated counties with data

Figure 3. County-level treatment assignment examples using Hurricane Delta The figure above gives a visual summary of the measures used to assign hurricane treatment effects. The counties which are in the sample for insurance but are untreated are given by the white fill color. The counties which are in the sample for insurance data and are treated are given by the red fill color. The red swaths overlaying the maps are the visual representations of the hurricane treatment measures which utilize the NOAA HURDAT-2 data. Counties which have the red county borders and have a grey fill color were in the hurricane treatment path but are not in the insurance sample (i.e. there is no liability data for these counties). Counties with grey fill and black borders were not treated by a hurricane and were not in the insurance sample.

2.2 Lost Cost Ratio Construction and Premium Rates

In order to evaluate the impact of hurricanes on crop insurance premium rates we follow previous studies which apply the actuarial principal that the mean of the county-level LCR is the equivalent of a premium rate (Woodard, Sherrick, and Schnitkey, 2011; Rejesus, et al., 2015; Woodard and Verteramon-Chiu, 2017). Thus, when we run regressions with LCRs as the outcome variable we arrive at a treatment effect on the premium rate. Using the data on losses associated with hurricane incidence in a given month, one can identify the impact of hurricanes on base premium rates by measuring the impact of specific hurricanes on the portion of the LCR attributed to hurricane losses. This is necessary in identifying the impact of a specific catastrophic risk event because of the multiple peril nature of contemporary crop insurance products.

We consider four different measures of LCRs which account for the different weather effects of a hurricane with each successive LCR containing more indemnities than the previous measure. The first LCR contains indemnities only recorded as a Hurricane/Tropical Depression cause of loss. The second LCR adds indemnities with a Wind cause of loss. The third LCR adds indemnities recorded as Excess Precipitation and Flooding causes of loss, while the fourth LCR contains indemnities for all recorded causes of loss.

In order to isolate losses that are only associated with a hurricane event, we sum indemnities across all losses in the months prior to the month in which a hurricane struck to create the cumulative LCR in the pre-period. The cause-specific LCR is formed by summing the indemnities by causes of loss for the specific LCR measure consider (i.e. wind vs. rain) in the post-treatment period and adding them to the pre-period cumulative LCR. Lastly, we pair hurricane-associated causes of loss in a given month with the hurricane which made landfall in the same month to arrive at a final panel dataset which gives county-level LCRs by treatment period for a given hurricane event and year.

3 Empirical Strategy

We use a Difference-in-Differences (DiD) identification strategy to isolate the treatment effects of hurricanes on crop insurance premium rates. Our approach differs from a typical DiD analysis in two ways. First, we are interested in the average effect of treatment across multiple hurricanes occurring in various years. Second, due to the seasonal nature of the LCR measures, we do not have a variable which provides a continuous index of time. To accommodate these differences, we specify the regression equation as:

$$Y_{i,p,t,h}^{C} = \eta_h * \left(d_{i,t,h} + p_{t,h} + \beta_h d_{i,t,h} p_{t,h}\right) + \lambda_i + \gamma_t + \varepsilon_{i,p,t,h} \qquad (4)$$

where $Y_{i,p,t,h}^{C}$ is the cumulative LCR specific to the causes of loss $C \epsilon [Hurricane, Hurricane + Wind, Hurricane + Wind + Rain, All\ Losses]$ in county i, period $p \in [pre, post]$, and year t for hurricane h. The η_h variable in equation 4 is a hurricane specific fixed effect. By pre-multiplying the terms in parentheses by it, we ensure the changes in outcomes over time are compared within storms and not across them.

The terms within parentheses in equation 4 constitute a standard two-period DiD analysis. The first term, $d_{i,t,h}$, is an indicator variable equal to one if insured county i is treated at any point during year t by hurricane h. Its inclusion addresses differences between treated and untreated counties that are invariant within the year that a specific hurricane occurs. The second, $p_{t,h}$, is an indicator variable equal to zero in the months before hurricane h made landfall in year t and one in the month, or months, afterward. Including $p_{t,h}$ in our regression accounts for the evolution of LCRs during the year caused by factors other than hurricanes like weather. β_h, the coefficient for the interaction of $d_{i,t,h}$ and $p_{t,h}$, is the target estimand of the treatment-effect for a given hurricane h. To recover the overall average treatment effect across all hurricanes, we calculate the average marginal effect of $d_{i,t,h}p_{t,h}$.

The final three terms in equation 4, λ_i, γ_t, and $\varepsilon_{i,p,t,h}$ are a county fixed effect, a year fixed effect, and an idiosyncratic error term, respectively. We include the county fixed effect, λ_i, to control for time-invariant confounding factors influencing losses as well as the likelihood of being treated, such as proximity to the coast and regional differences in climate. Lastly, the year fixed effect, γ_t, controls for unobserved heterogeneity which varies across years and is constant across counties, such as price levels.

There are two critical identifying assumptions required for our DiD approach to recover the average treatment effect on the treated (ATT) of hurricanes on crop insurance premium rates: no anticipation and common trends. The no anticipation assumption implies producers do not alter their behavior in such a way as to increase their losses in anticipation of hurricane occurrence. The common trends assumption implies that losses associated with hurricane incidence evolve the same for treated and control counties in the absence of experiencing a hurricane. We do not see any reason for these assumptions to be violated after conditioning on county fixed effects. First, hurricanes occur randomly, and producers have little warning to be able to anticipate the event. Second, county-level fixed effects account for time-invariant differences between counties and our choice of study area minimizes the possibility counties experience differential trends within a year. One reason parallel trends would be violated is if counties experience different weather or policies, but we think this is unlikely since we are considering a somewhat local impact across the Mississippi Delta region.

4 Results and Discussion

First, we present results for all indicators of hurricane treatment defined in the section above. Next, we discuss treatment effects across all crops and the robustness of our hurricane damage measure. Then, we consider treatment effect heterogeneity between crops. Finally, we discuss the implications of our results for the availability of HIP-WI insurance.

4.1 Hurricane Treatment Tradeoffs

The ATT estimates for each indicator of hurricane treatment are displayed in Figure 4. There are clear differences in estimated effects of hurricanes depending on the way in which we assign treatment. First, when the hurricane treatment assigns fewer treated units, there is a higher variance in the estimated ATT, and vice-versa (Figure 4). For example, results for the Centroid Treatment (CT) measure, which assigns treatment based on a line which connects the 6-hour timestamps of the hurricane centroid give larger confidence intervals relative to the Polygon Treatment (PT) measure, which assigns treatment based on the largest hurricane polygon to make landfall. We find the same pattern exists when comparing the interpolated hurricane treatment measure we propose (IT) and the RMA triggers (RT) based on Hurricane Insurance Protection, Wind Index insurance (HIP-WI) albeit much less so. This is because RT also considers counties adjacent to a county intersecting the hurricane field as treated, increasing the number of treated units. In contrast, IT only assigns treatment to counties which intersect with the hurricane field thereby reducing the number of treated units relative to RT.

In comparing the point estimates in figure 4, we see evidence of attenuation bias for some of our measures of hurricane treatment. For example, the broad treatment criteria for the Polygon Treatment (PT) measure produces a treated group which likely contains untreated counties by mistake. For the Centroid Treatment (CT) measure, only counties intersecting the line between centroids are assigned to the treatment group, so the control group will often incorrectly contain counties that experience significant damages. In both cases, the error in the hurricane treatment measure creates downward bias which results in ATT estimates that are small in magnitude. We believe IT to be the best hurricane treatment assignment because it correctly assigns treatment and reduces attenuation bias. This treatment measure best identifies counties which experience significant damages stemming from extreme weather that is directly and indirectly associated with hurricane systems and so assigns treatment to counties further inland regardless of the recorded wind speed.

4.2 Hurricane Impacts on Premium Rates

We first run regressions which pool observations across all crops in the sample and find there is a 1.5 percentage point increase in the mean LCR for counties in the 34-knot wind field relative to counties outside of the wind field (Figure 4). In other words, average hurricane specific LCRs for treated counties in the IT field are 1.5 percentage points higher than control counties outside of the IT field. We also perform a series of additional regressions to test that this result is robust to differences in the measure of hurricane damage. We find our main finding is robust to potential measurement error resulting from delayed reporting of causes of loss by crop insurance adjusters and to adding causes of loss other than Hurricane/Tropical Depression.

Hurricane Damage Measure Robustness

Figures 5-7 contain results using the same model as those in Figure 4 but consider different forms of measurement for the hurricane damage measure (i.e., $Y^{C}_{i,p,t}$). We find the way in which we measure hurricane damages using the county-level LCR largely does not matter. In the initial regression, we only consider losses reported by the COL in the month in which a hurricane occurred. We recognize the potential measurement error in doing this since it may not be feasible for crop insurance adjusters to report losses in the month an event occurred, thereby reducing the actual losses associated with a hurricane for a given month. We see evidence of this in the COL data as Hurricane/Tropical Storm losses are sometimes reported in months following a hurricane event, despite no storm occurring in any of the subsequent months.

We run regressions using LCRs which include 1 to 6 months of additional losses to test how delays in loss reporting by crop insurance adjusters may affect our results. These results may be observed by following the number of additional months presented along the x-axis for each hurricane treatment measure in figures 4-7. We limit the additional months to 6 because the earliest hurricane to make landfall in our sample does so in June. The estimates and overlapping confidence intervals for each hurricane treatment measure displayed in figures 4-7 suggest the impact on LCRs is largely robust to adding any number of additional months of losses.

In addition to considering the timing of reported losses, we also consider robustness to the types of losses that are reported and used to construct LCRs. While there is a cause of loss code for Hurricane/Tropical Depression, crop insurance adjusters may report losses resulting from the hurricane system using a different cause of loss code such as Wind, Excess Precipitation, or Flooding. Therefore, we test whether including Wind, Excess Precipitation, or Flooding losses in the LCR affect our results, and we consider adding all causes of loss to the LCR as a final robustness check. We find the estimated ATTs are robust to including the additional categories of hurricane-related losses in the LCR, and the ATTs are robust to the causes of loss are included which implies losses attributed to hurricanes are being accounted for correctly and insurance adjusters are not falsely categorizing losses.

4.3 Heterogeneous Treatment Effects Across Crops

We may dilute the treatment effect for specific crops if there are heterogeneous effects of hurricane and tropical storm systems by running regressions pooled across all crops in the sample. We run separate regressions for each crop and find significant variation in the ATT of being in the IT field across crops to test for heterogenous treatment effects. Results from these crop-specific regressions can be found in Appendix A. We find including additional months in the LCR used in each crop-specific regression may impact the mean ATT once there is more than one additional month included, indicating the delayed reporting of losses could impact estimated ATTs once we restrict the sample to one crop.

The ATT for corn is nearly zero and remains the same across different forms of measurement of the LCR, while the ATT for soybeans is 1.5 percentage points in the base model specification (Figure A9 and A13, respectively). However, the ATT for soybeans doubles to 3 percentage points by adding rainfall-induced losses (i.e., Excess Precipitation and Flooding) which suggests rainfall is the component of hurricane and tropical storm systems which influence losses most for soybeans (Figure A15). The ATT for corn remains the same across different forms of measurement of the LCR (Figures A9-A12). The ATT for rice is 1 percentage point and is robust to adding Wind losses and additional months of losses but appears to fall by 0.025 percentage points once 4 additional months of losses are included in the LCR. We observe the largest impacts for cotton out of the four crops considered. The ATT for cotton is nearly 3 percentage points in the base regression and is robust to adding additional months of losses and

Wind losses. In addition, we observe the ATT increases to nearly 4 percentage points once rainfall-induced losses are included in the LCR. This is largely because the boll formation, boll opening, and harvest generally occurs during July through October, which overlaps with hurricane season, making fiber loss through boll rot and fruit shedding more likely due to extreme weather (Ritchie, et al., 2007; Roughley, Smith and Allen, 2015; and Merritt, 2020).

4.4 Implications for HIP-WI Availability

We draw policy implications from the estimated ATTs by first estimating the damage component of the premium rate attributable to hurricanes across counties. We define the premium rate as the mean LCR, or the expected indemnity divided by liability (Woodard, Sherrick, and Schnitkey, 2011; Rejesus, et al., 2015; Woodard and Verteramo-Chiu, 2017). So, to determine the portion of the premium rate attributable to hurricanes, we need to determine the hurricane- induced average indemnity for each county-crop combination and the county-specific probability of receiving the loss. Then, we can calculate the expected (i.e., average) LCR by multiplying the ATT with the probability of treatment for each county-crop combination.

We estimate the base model from equation 4 by regressing the county-level LCR on hurricane treatment and controls for each crop in the sample to determine the county-specific indemnity. We use the ATT from each crop-specific regression as the average hurricane-induced indemnity in each county. Next, we obtain a sample estimate of the probability of treatment by constructing a sample of the IT treatment variable from 2002-2021 for each county. The sample estimate of the probability of treatment is found by counting the number of years a county is assigned treatment and dividing this number by the total number years in the sample (i.e., 20 years). Last, we multiply the ATT from each crop-specific regression and the sample estimate of probability of treatment for each county to arrive at the estimated damage component of the premium rate attributable to hurricanes.

Results from this exercise are displayed in figures 8-11 which show the estimated portion of the county-level base premium rate attributable to hurricane damages. We calculate this portion by taking the ratio of the estimated damage component from the exercise above and the county-level base premium rate from RMA. For the base premium rate, we take the sum of the county-level reference rate and fixed rate following standard RMA actuarial procedures in estimating premium costs (Coble, et al., 2010).

We observe the portion of the base premium rate attributable to hurricane damage is greatest in counties closer to the coast and that the magnitude to which hurricane damages impact base premium rates decreases for counties further from the coast. This is expected because hurricane systems lose power as they move inland, so coastal areas are more likely to be affected by the early stages of the storm with stronger wind speeds and heavier rainfall. However, while small in comparison to the counties near the coast, the damages experienced by inland counties producing cotton and soybeans are comparable to counties eligible to enroll in HIP-WI. Furthermore, we observe the county-level availability of risk protection offered by HIP-WI crop insurance may limit the ability for a farm located in further inland to mitigate hurricane related losses.

We use the HIP-WI eligibility file provided by USDA-RMA to determine which counties are eligible to purchase HIP-WI products. The dark black lines in figures 8-11 separate counties eligible to purchase HIP-WI products, south of the line, from those which are not, north of the line. Across the four crops considered, there is no discernible difference between counties immediately north and south of the HIP-WI eligibility line. This suggests counties at least immediately above the line should be eligible to purchase HIP-WI to protect against the weather-related losses associated with hurricane and tropical storms. Therefore, we recommend USDA-RMA consider offering HIP-WI to counties immediately above the line highlighted in the figures below.

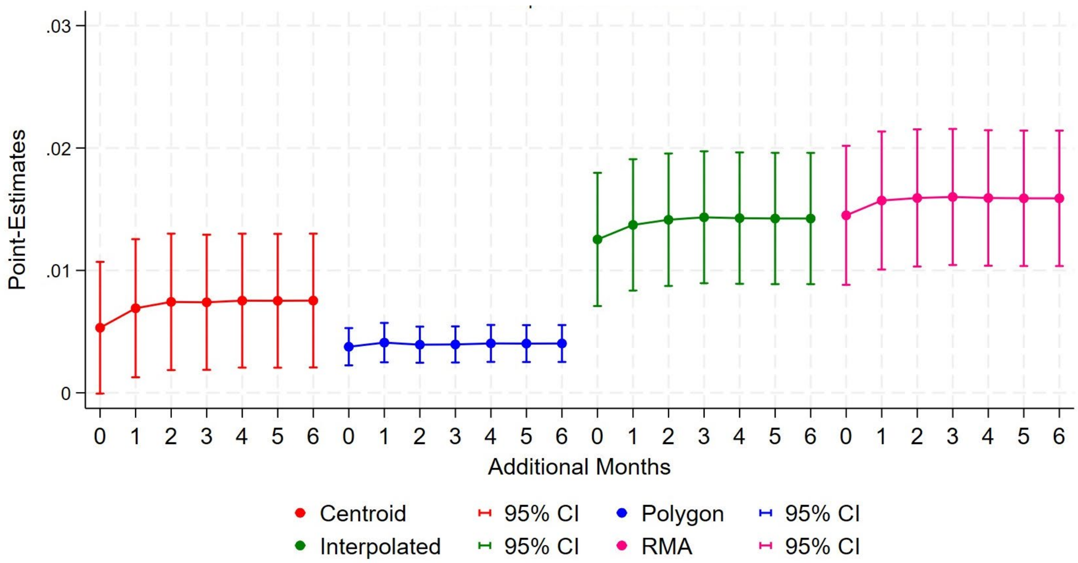

Figure 4. ATT of Hurricane Incidence on County-Level LCRs (All Crops)
These regressions use the hurricane damage measure which only considers losses with Hurricane/Tropical Depression cause code.

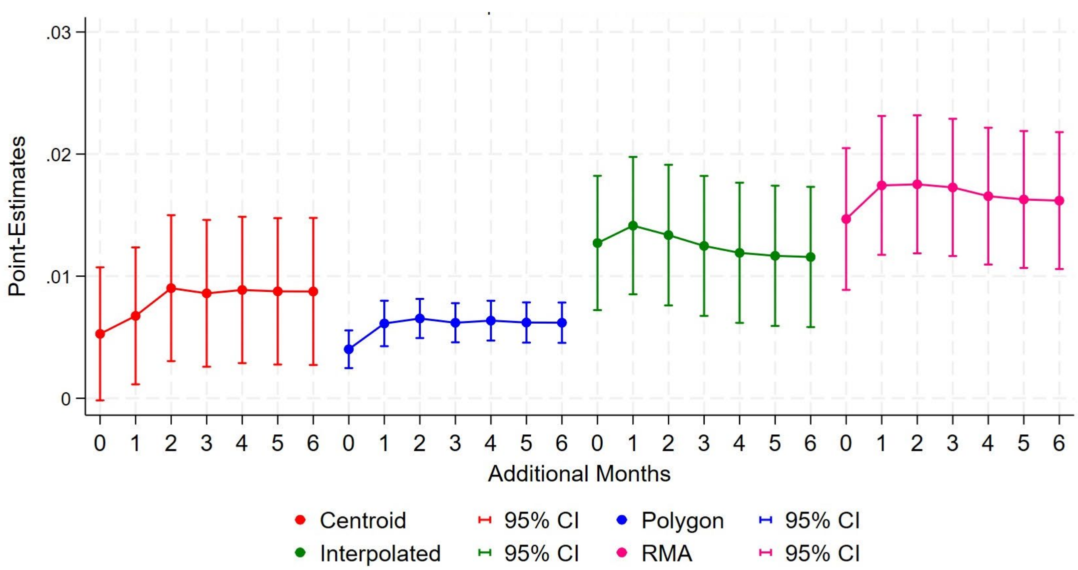

Figure 5. ATT of Hurricane Incidence on County-Level LCRs (All Crops)
These regressions use the hurricane damage measure which only considers losses with Hurricane/Tropical Depression and Wind cause codes.

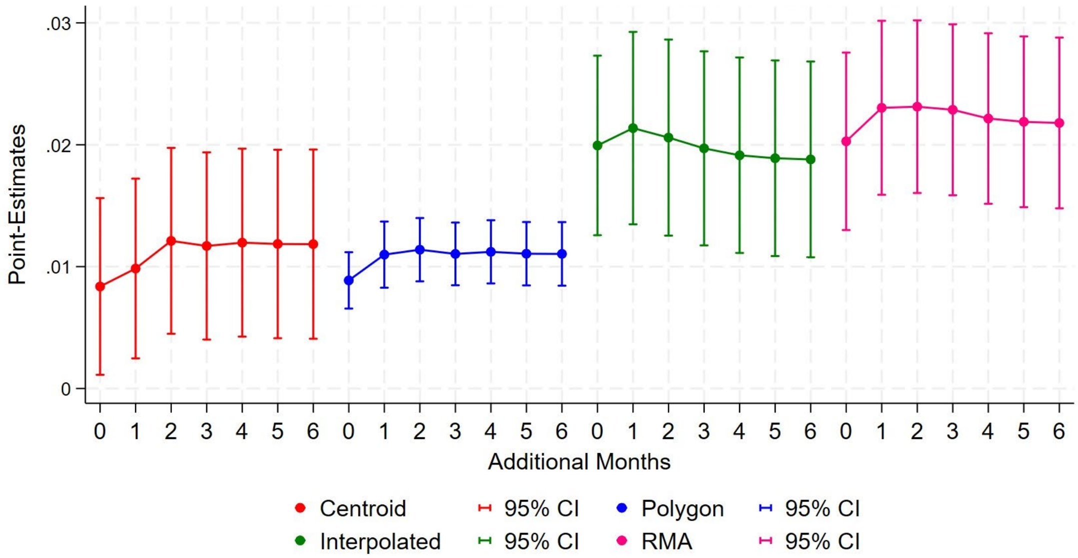

Figure 6. ATT of Hurricane Incidence on County-Level LCRs (All Crops)
These regressions use the hurricane damage measure which only considers losses with Hurricane/Tropical Depression, Wind, Excess Precipitation, and Flooding cause codes.

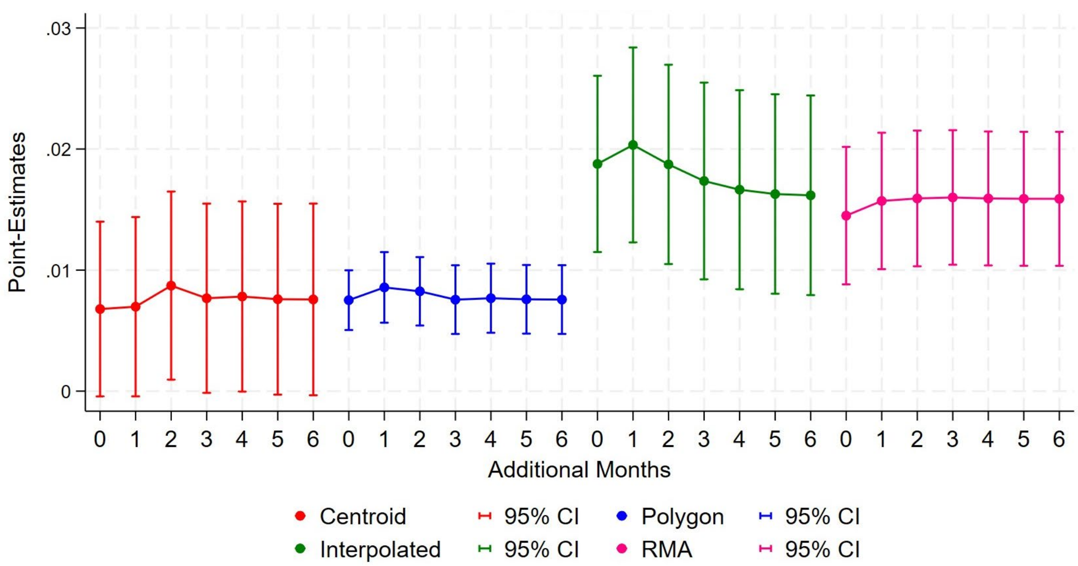

Figure 7. ATT of Hurricane Incidence on County-Level LCRs (All Crops)
These regressions use the hurricane damage measure which only considers losses with all cause codes.

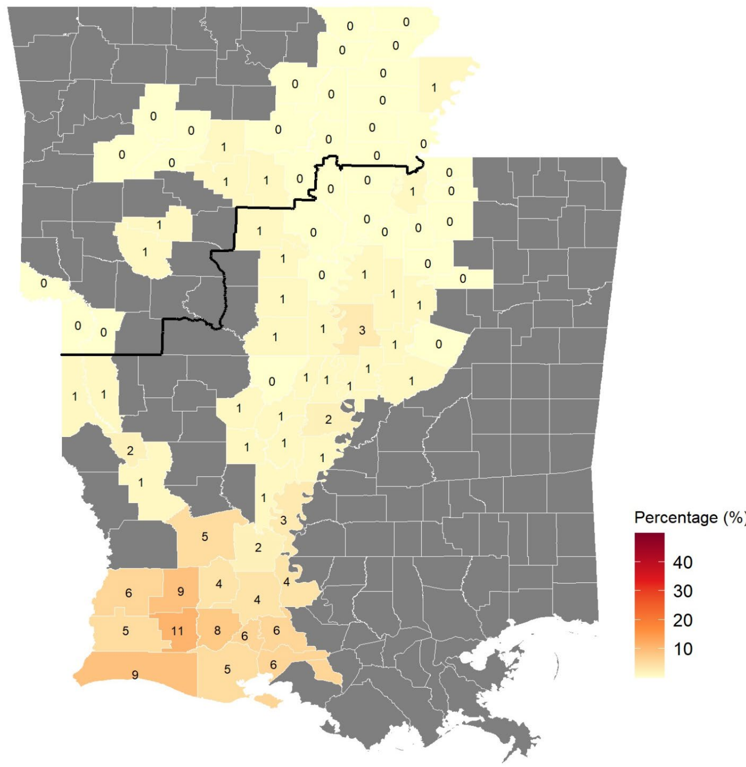

Figure 8. Hurricane Damages as a Portion of the County Base Rate (Rice)
These results are from regressions estimating hurricane premium rates which includes losses for Hurricane/Tropical Depression, Wind, Excess Precipitation, and Flood causes of loss. County-level base premium rates are for the 2022 insurance year and come from USDA-RMA Actuarial Data Master.

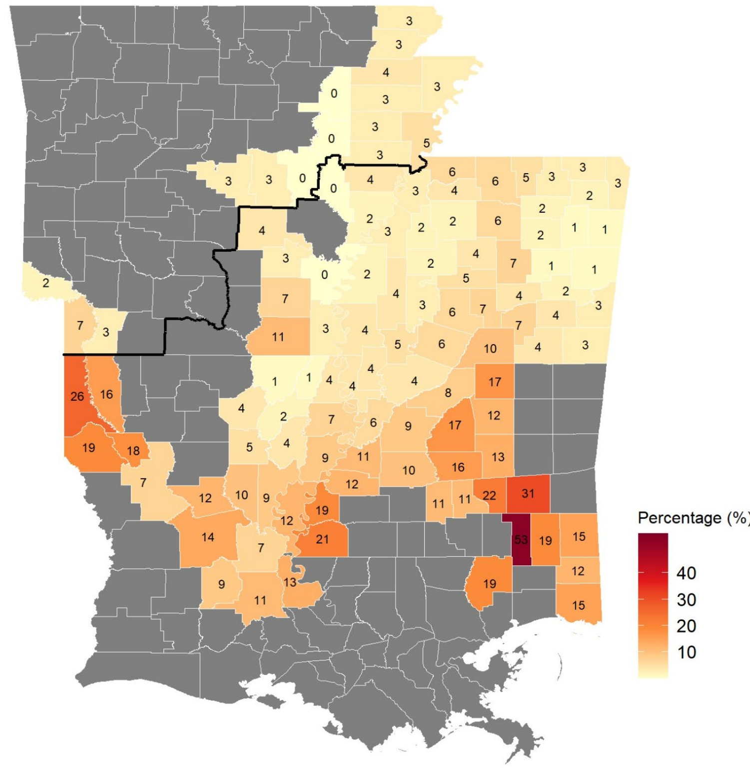

Figure 9. Hurricane Damages as a Portion of the County Base Rate (Cotton)
These results are from regressions estimating hurricane premium rates which includes losses for Hurricane/Tropical Depression, Wind, Excess Precipitation, and Flood causes of loss. County-level base premium rates are for the 2022 insurance year and come from USDA-RMA Actuarial Data Master.

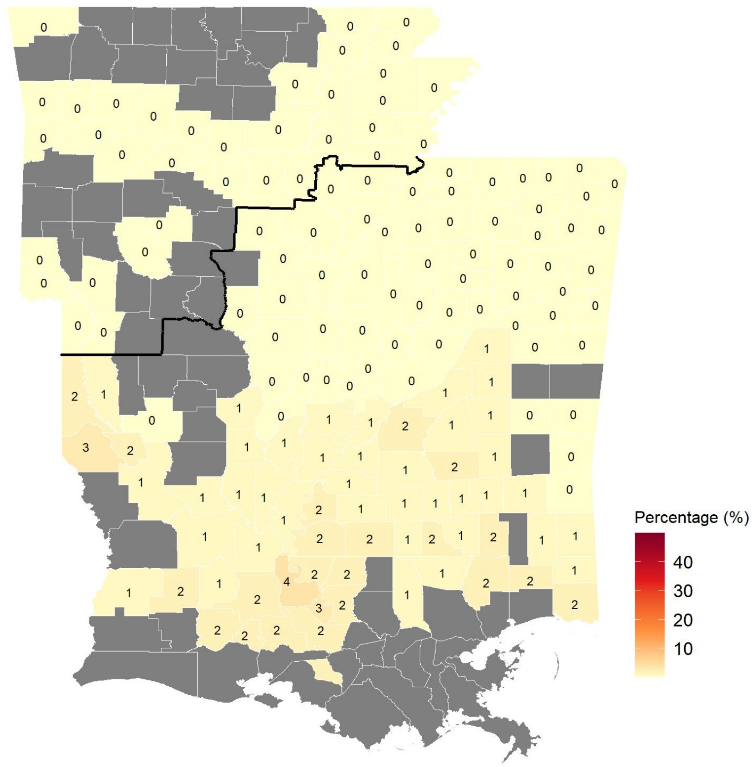

Figure 10. Hurricane Damages as a Portion of the County Base Rate (Corn)
These results are from regressions estimating hurricane premium rates which includes losses for Hurricane/Tropical Depression, Wind, Excess Precipitation, and Flood causes of loss. County-level base premium rates are for the 2022 insurance year and come from USDA-RMA Actuarial Data Master.

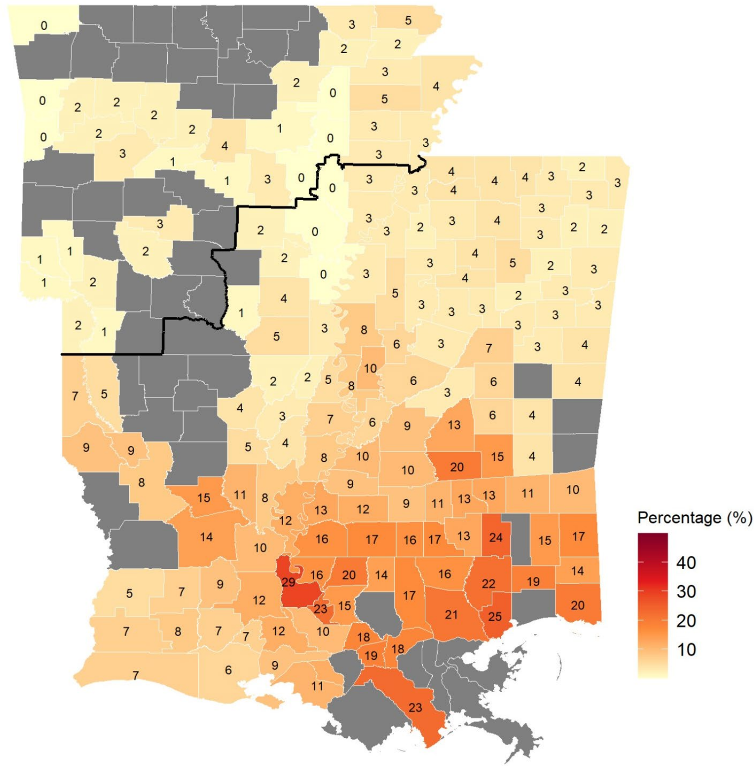

Figure 11. Hurricane Damages as a Portion of the County Base Rate (Soybeans)
These results are from regressions estimating hurricane premium rates which includes losses for Hurricane/Tropical Depression, Wind, Excess Precipitation, and Flood causes of loss. County-level base premium rates are for the 2022 insurance year and come from USDA-RMA Actuarial Data Master.

5 Conclusion

We have estimated the impact of hurricane incidence on crop insurance premium rates for 21 storms which made landfall in the Mississippi Delta in the last twenty years. We leverage county-level panel data on indemnities and liabilities by cause of loss in each month spanning 2002-2021 from RMA and daily hurricane best track data from the NOAA to construct a measure representative of crop insurance premium rates and a novel measure for hurricane treatment assignment. Under a DiD identification strategy, we find that hurricanes result in increases to crop insurance premium rates for yield and revenue insurances for major crops grown in the region. We find the way in which hurricane treatment is measured matters, and measures which fail to account for the hurricane wind field tend to underestimate the impact of hurricane incidence on crop insurance premium rates. We also find estimated impacts to be greatest for soybeans and cotton with hurricane incidence accounting for up to 29% and 53% of county base premium rates, respectively. Findings are largely robust to losses included in the hurricane damage measure, as well as the number of additional months of losses included in the damage measure.

Our findings align with previous studies which find decreases in mean yields and increases in yield variability caused by more frequent catastrophic weather events result in a fall in producer welfare and have implications for crop insurance premium rates (Chen and Chang, 2005). Since premium rates are based on a 20-year farm-level loss history (Coble, et al., 2010), the increasing frequency of hurricanes and other catastrophic weather events will likely increase yield losses leading to increased premium rates. RMA has begun to address this increased risk with the introduction and recent expansion of the area product Hurricane Insurance Protection – Wind Index (HIP-WI), but introducing a single-peril area insurance product has not necessarily provide the coverage desired by producers. For example, Stacked Income Protection (STAX) designed for cotton has relatively high subsidy rates at 80% across all coverage levels yet few producers enroll in it (Yehouenou, et al, 2021). Similar to Chen and Chang (2005), our results suggest an extreme weather loading factor may be worthwhile to consider in the base premium rate calculation for the most popular plans of multi-peril insurance available (i.e. Yield Protection and Revenue Protection) rather than only introduce a new product.

One limitation of this work is primarily concerned with measurement of hurricane treatment. One way we could improve the treatment assignment measure would be to include wind speed and consider the climatology of hurricanes. We currently ignore variables which comprise a hurricane wind profile such as wind pressure and vertical shear which drive the intensity and direction of a hurricane. This analysis could also be built upon by including empirical state and climate division catastrophic loading factors to allow for comparison with the hurricane impacts we consider here. It is possible the hurricane effects we measure here may be included in a such a catastrophic loading factor, but since there is a specified range for the loading factor as it stands, future work should consider the magnitude by which the estimated effects here compare to that of current loading factors. With an ever-changing climate, measuring the impact of hurricanes and other extreme weather events on agricultural production is of the utmost importance as we improve the ability of producers to manage extreme weather risk.

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