Warming temperatures will likely induce higher premium rates and government outlays for the US crop insurance program

Running Title: Warming Effects on U.S. Crop Insurance

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Abstract. Likely climate change impacts include damages to agricultural production resulting from increased exposure to extreme heat. Considerable uncertainty remains regarding impacts on crop insurance programs. We utilize a panel of U.S. corn yield data to predict the effect of warming temperatures on the mean and variance of yields, as well as crop insurance premium rates and producer subsidies. While we focus on corn, we demonstrate that the subsidy impacts are likely to carry over to other major program crops. We find that warming decreases mean yields and increases yield risk on average, which results in higher premium rates. Current legislation sets producer subsidy payments as a percentage of the premium, so we simulate the impact of a 1°C warming scenario and find that annual subsidy payments will likely increase by as much as $850 million, representing a 13% increase relative to current levels. This estimate increases to 2.2 billion (34%) under a 2°C warming scenario. We also find evidence of extensive spatial heterogeneity of the premium rate effects. Our results indicate that the program level effects of climate change will increase both the cost of obtaining insurance for producers, as well as the governmental outlay required to subsidize this purchase.

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Introduction

A large and growing literature has documented that climatic variables exert economically meaningful and statistically significant influences on a variety of economic outcomes (Dell, Jones, and Olken, 2014). However, very little research has focused on the agricultural insurance sector even though this is a large and rapidly expanding component of the global agricultural economy. Agricultural insurance markets were initiated in Europe over 200 years ago and have experienced rapid expansion in the last 50 years (Smith and Glauber, 2012; Mahul and Stutley, 2010). While the U.S. crop insurance program is the world's largest with more than $100 billion of liability in place in 2015, agricultural insurance has gained increasing popularity as a government-sponsored support program in developing countries as China has become the second largest market in the world (Mahul and Stutley, 2010).

Previous research has shown that the likely impacts of climate change include damages to agricultural production resulting from increased exposure to extreme heat (Lobell, Schlenker, and Costa-Roberts, 2011; Schlenker and Roberts, 2011; Tack, Barkely and Nalley, 2015; Welch et al., 2010; Liu et al., 2016; Lobell et al., 2013; Rosenzweig et al., 2014). Overall, the literature provides evidence of strong negative effects on crop yields in response to climate change across a wide range of locations, modelling approaches, and climate predictions. Recent studies have begun focusing on yield variability as well, and some have found that inter-annual variations for corn yields will likely accompany reductions in average yields in some regions (Urban et al., 2012; Attavanich and McCarl, 2014; Ray et al., 2015; Urban, Sheffield, and Lobell, 2015). This suggests that the cost of insurance (i.e. premium rates) will likely be affected by warming temperatures as well, and any impacts to the program would naturally extend beyond the agricultural sector as the heavily subsidized program has averaged over $6.5 billion in taxpayer-sponsored subsidy payments to producers over the last three years (USDA Risk Management Agency, 2016a, 2016b). However, there remains considerable uncertainty regarding climate change impacts on the Federal Crop Insurance Program (FCIP). To date, no study has reported estimates of the marginal effect of warming on premium rates, and only a recent report prepared for the Office of Management and Budget has provided estimated subsidy impacts (Executive Office of the President of the United States, 2016). Importantly, this report does not emphasize the cross-sectional heterogeneities of the subsidy impacts that are the focus of this study.

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Our analysis utilizes just over 35,000 county-level corn yield observations spanning 1950-2015 to predict the effect of warming temperature on crop insurance premium rates and subsidies for the Area Yield Protection (AYP) plan of the FCIP. Under a 1°C warming scenario, we find a statistically significant decrease in mean yield and increase in both yield risk and premium rates, which in turn imply increases in producer subsidy payments. We show that historical loss cost ratios for AYP corn are highly correlated with those for all corn crop insurance products as well as those for all crops in general. Thus, we extrapolate our findings to these other products and find that the increase in annual tax-payer burden could potentially be as high as $0.85 ($2.2) billion annually under a 1°C (2°C) warming scenario. We also find evidence suggesting extensive cross-sectional heterogeneity of warming effects across counties. Overall, our results indicate that the program level effects of climate change will increase both the cost of obtaining insurance for producers, as well as the governmental outlay required to subsidize this purchase.

The reported impacts correspond to a very specific counterfactual: what are the marginal effects of warming temperatures on crop insurance premium rates and subsidies under current technology and fixed production locations? As in previous work we focus on uniform shifts in temperature while holding precipitation fixed to estimate this marginal effect, *ceteris paribus* (Liu et al., 2016). This approach provides an answer to important policy questions as premium rate changes reflect changes in the cost of obtaining insurance from the producer's perspective while subsidy levels capture the financial burden of governmental support for the program. While modeling producer adaptations, or future changes in agricultural policy that might arrive in response to climate change concerns, are beyond the scope of this study, the estimates provided here are a crucial first step toward a more general decision-theoretic framework that is capable of addressing these additional dimensions.

A related study identifies extreme heat sensitivities across insured versus uninsured acreage in the US corn belt and concludes that these differences reduce producers' incentives to engage in costly adaptation to climate change (Annan and Schlenker, 2015). Another study focused on producers in Italy and finds that crop insurance demand increases with weather risk exposure, thereby implying a tradeoff between insurance purchases and adaptation (Di Falco et al., 2014). A recent

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USDA Risk Management Agency report (Beach et al., 2010) analyzed the effect of a large number of alternative climate change scenarios on the U.S. crop insurance portfolio. While the scope of this report is large, it does not report changes in premium rates nor does it discuss implied subsidy effects. A more recent report prepared for the Office of Management and Budget for the President (Executive Office of the President of the United States, 2016) provides subsidy impacts under alternative global warming scenarios, however it does not provide estimates for changes in premium rates. Neither report provides insight into the relevant geographical heterogeneities that we find evidence of here.

Background

Corn is the most intensively insured crop in the FCIP, and is the biggest driver of total subsidy payments as the $2.24 billion paid to corn producers in 2015 represented 37 percent of all program subsidies in that year (USDA Risk Management Agency, 2016a, 2016b). The subsidy is politically motivated to increase program enrollment as research has consistently found that crop insurance demand is largely insensitive to small price changes (Knight and Coble, 1997; Coble and Barnett, 2013; Goodwin, 1993; Barnett and Skees, 1995; Coble et al., 1997; Barnett et al., 2005; Shaik et al., 2008; Woodard, 2016). The most popular insurance products are unit-level policies where indemnities are triggered by yield or revenue shortfalls at the unit (generally, farm or sub-farm) level, referred to as Yield Protection (YP) and Revenue Protection (RP), respectively. The FCIP also offers area-level products for which indemnities are triggered by shortfalls at the county level, referred to as Area Yield Protection (AYP) and Area Revenue Protection (ARP), repesctively.[1] The aim of the AYP and ARP products is to mitigate adverse selection and moral hazard problems, diminish transaction costs, and reduce rate inaccuracies that are associated with unit-level products (Deng, Barnett and Vedenov, 2007; Harri et al., 2011). We focus our analysis on the AYP program, but also present a method for extending our findings to other insurance products and crops.

[1] The names of crop insurance products have changed over time which can create confusion when reading the scholarly literature. For example, in many articles the product now called YP is called by its previous name of Actual Production History (APH). Revenue Assurance (RA), Crop Revenue Coverage (CRC), and Income Protection (IP) were all predecessors of the current RP product. AYP was previously called the Group Risk Plan (GRP) while ARP was called Group Risk Income Protection (GRIP).

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The key components of a crop insurance policy are the coverage level, guarantee, indemnity, premium, and subsidy. The coverage level is a percentage of the expected yield (revenue) that is used to calculate the policy's guarantee, which establishes the threshold below which indemnities are triggered. An indemnity is paid only if the realized yield (revenue) is less than the guarantee. The premium is the purchase price of the policy, and the subsidy is the amount of this price covered by the government. Figure S1 in the Supplementary Material plots total FCIP premiums and subsidies since 2001 (panel A), which demonstrates a stable proportional relationship between subsidies and premiums (panel B). In fact, the producer paid net-premium (premium less subsidy) is simply the product of the gross premium and one minus a subsidy factor that is set by the government. A stable subsidy factor thus implies that a percentage change in premium necessarily induces a percentage change in subsidy.[2]

Data and Empirical Model

This study focuses on the U.S. corn belt, which we define to include all counties in Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Nebraska, Ohio, and Wisconsin. This region is one of the most intensive corn growing regions in the world, producing 10.2 billion bushels of corn (75 percent of total U.S. production) in 2015. The region also represented 77 percent of FCIP corn liabilities in 2015 (USDA Risk Management Agency, 2016a, 2016b).

Data

The dataset combines yield data from the National Agricultural Statistics Service (NASS) with the best available historical temperature and precipitation data, and contains 35,772 observations spanning 542 counties from 1950-2015. Exposure to low temperature is measured in degree days between 0°C and 9°C; medium temperature is measured in degree days between 10°C and 29°C; and high temperature is measured in degree days above 29°C. Precipitation is measured as cumulative rainfall in centimeters, and all weather variables are calculated as growing season aggregates across the months April-September. This approach is consistent with previous research analyzing the nonlinear effects of weather on crop yields (Schlenker and Roberts, 2009; Tack,

[2] Subsidy percentage varies with producer choices of coverage levels and unit-level versus area-level products. For unit-level products it further varies according to producer choices of unit structure. Thus, one would expect to see some variation across time in the subsidy/premium relationship as producer choices change from year to year.

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Harri, and Coble, 2012; Tack and Ubilava, 2013). There exists substantial cross-sectional and temporal variation within the data, which permits accurate identification of county-specific distributional effects of weather (Table S1 and Figure S2).

Overview of Empirical Model

We utilize regression models to estimate both the mean and variance of the conditional-on-weather yield distributions for each county. Yields are regressed on county fixed effects, trend variables, cumulative precipitation, and degree day variables as in (Schlenker and Roberts, 2009. We then use the empirical distribution of weather to construct county-specific unconditional distributions, which are a mixture of the conditionals and thus functionally flexible (Tolhurst and Ker, 2015; Woodard and Sherrick, 2011). We then simulate changes in these densities by uniformly increasing temperatures and feeding these changes through the estimated regression model. From these densities we are able to construct measures of actuarially fair premium rates and producer subsidies for each county-climate combination. We also report results for the coefficient of variation (CV), defined as the ratio of the standard deviation to the mean, as it is a normalized (i.e. unitless) measure of dispersion that easily admits comparisons across different distributions. The skewness of the distributions is reported as well to demonstrate the changing values in this curvature measure across county-climate scenarios.

Estimation of Yield Distributions

As discussed in Tack and Ubilava (2013), corn yield distributions vary both spatially and temporally due to localized growing conditions and the evolution of production technology over time. As a result, historical yield data alone are not sufficient to analyze climatic impacts as there is no single "common" distribution from which all data are sampled; rather, each historical observation is drawn from a specific location-year distribution. To address this concern, we utilize the moments-based approach of Antle (1983, 2010) to link the distribution of corn yields to location-specific factors, weather outcomes, and trend variables that account for changes in technology over time.

We first begin with a regression specification linking weather to mean crop yields for county i in state s and year t,

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(1) $y_{it} = \alpha_i + \beta_1 low_{it} + \beta_2 med_{it} + \beta_3 high_{it} + \beta_4 prec_{it} + \beta_5 prec_{it}^2 + \beta_{s7} trend_t + \beta_{s8} trend_t^2 + \varepsilon_{it}$

where α_i is a county fixed effect that controls for time-invariant factors such as soil quality, low_{it} captures exposure to low temperatures during the growing season, med_{it} captures exposure to medium temperatures, and $high_{it}$ captures exposure to high temperatures. We follow the piecewise linear approach of Schlenker and Roberts (2009) in which the low, medium, and high temperature exposures are measured using growing degree days. The strength of this approach is that is allows the marginal effect of temperature to be piecewise linear. We include a quadratic function of cumulative precipitation to allow this effect to be nonlinear as well.

Proper identification of the weather effects requires accounting for gradual trends in yields due to changing technologies. Controlling for this change is necessary to ensure that the regression model parameter estimates are not biased from common trends in the data. For example, a positive yield trend during periods of warm weather does not imply that warming is beneficial, since other factors drive the yield trend (Lobell, Schlenker, and Costa-Roberts, 2011). Thus, we include a quadratic trend specification to account for nonlinear technological change over time, and we allow these trend parameters to vary cross-sectionally across each state.

We follow Antle (1983) and estimate the variance of crop yields using the same specification as equation (1) except the squared error term ε_{it}^2 replaces yield as the dependent variable. Denoting by $\mathbf{x_{it}}$ the weather variables and $\mathbf{z_{t'}}$ the trend variables, the *conditional* mean and variance are defined as $\mu_{itt'} = E(y \mid \mathbf{x_{it}}, \mathbf{z_{t'}})$ and $\sigma_{itt'}^2 = E(\varepsilon_{it}^2 \mid \mathbf{x_{it}}, \mathbf{z_{t'}})$. Under current technology in year $t' = T$, these become μ_{itT} and σ_{itT}^2. We fix the trend variable at the most recent year in the data to account for modern production practices and seed varieties. These parameters represent the mean and variance conditional on the weather observed for each year in the historical data, adjusted for modern technology.

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We estimate the parameters of the mean and variance equations using ordinary least squares and then predict $\hat{\mu}_{itT}$ and $\hat{\sigma}^2_{itT}$ using these estimates. We assume that *weather-conditional* yields are lognormally distributed so that $y_i \mid \mathbf{x_{it}} \sim LN(\hat{\mu}_{itT}, \hat{\sigma}^2_{itT})$. We estimate the unconditional (i.e. weather independent) yield distribution for each county $f_i(y)$ as a mixture of these lognormals defined by

(2) $$f_i(y) = \sum_{t=1}^{T} w_t LN(\hat{\mu}_{itT}, \hat{\sigma}^2_{itT}),$$

where the t index denotes the number of sample years (i.e. weather draws) in the historical data, and $LN(\hat{\mu}_{itT}, \hat{\sigma}^2_{itT})$ is the probability density function for the lognormal distribution. We use mixture weights $w_t = 1/T$, which is consistent with using the joint empirical distribution of the weather variables to combine the lognormal mixture components. As such, the functional form of $f_i(y)$ is quite flexible and need not take on the characteristics of the underlying lognormals. For example, although lognormals are necessarily positively skewed, a mixture of lognormals need not be. This mixture does however inherit a positive support from the lognormals, a necessary characteristic for yield distributions. This would not be the case if one were to use a mixture of normals.

Mixture models have recently been used to estimate yield distributions due to their flexibility in approximating the true, unknown density function (e.g. Woodard and Sherrick, 2011; Tolhurst and Ker, 2015). One can use any set of weights they deem appropriate. Here, we use the empirical distribution of sample weather outcomes due to the long time series dimension of the data. See Woodard and Sherrick (2011) for an extensive overview of commonly used approaches for modeling yield distributions.

Although the county-specific density functions $f_i(y)$ do have closed form solutions, they are difficult to use in practice when calculating means, variances, and premium rates when there are a large number of mixture components as we have here ($T = 66$). Thus, we recover $f_i(y)$ by randomly drawing 10,000 times from each of the $T = 1,\ldots,66$ conditional distributions $LN(\hat{\mu}_{itT}, \hat{\sigma}^2_{itT})$ and pooling the $T \times 10,000 = 660,000$ draws.

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This approach can be easily modified to trace out the effect of warming temperatures on the unconditional yield distribution. For each shift s in temperature, the daily minimum and maximum temperatures become $t_{min} + s$ and $t_{max} + s$. From these we can recalculate the low_{it}, med_{it}, and $high_{it}$ temperature exposures in equation (1) and obtain new predictions for the lognormal parameters under each temperature s. The simulated draws from the *conditional* distributions generate climate-shifted unconditional distributions $f_{is}(y)$.

Figure S3 shows how the draws are used to simulate the unconditional yield distributions. Once obtained, these densities can be used to calculate the mean and variance of crop yields, as well as actuarially-fair AYP premium rates. We find that there exists a wide range of mean, variance, and skewness for the simulated densities across both counties and warming scenarios (see Results section), indicating that the proposed approach is sufficiently flexible for the current purpose.

Premium Rate Calculation

The methods used by RMA to set premium rates differ for area and farm level insurance. Area insurance uses a simulation of area yield or revenue, while farm-level insurance rates are based on weather-weighted historical loss experience for each county/crop combination (Rejesus et al., 2015). In both cases, rates are adjusted for an uncertainty load of roughly 13% to reflect loss events not previously experienced (Coble et al., 2010). However, neither approach can be used to forecast rate changes out-of-sample, as would be required to estimate the effect of warming temperatures. Instead, we focus here on actuarially fair premium rates derived from an estimated distribution of yield outcomes. This distribution is conditioned on historical weather outcomes, which permits out-of-sample forecasting across any climate scenario one might want to consider.

The estimated actuarially-fair rates for coverage levels $cov \in [0.5, 0.9]$ are calculated as the ratio of expected indemnity per acre over liability per acre for each county-climate combination,

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$$rate^s_{cov} = E(indem^s_{cov}) / liab^s_{cov},$$

$$(3) \quad E(indem^s_{cov}) = F_s(y^s_{cov}) \int_0^{y^s_{cov}} [(y^s_{cov} - y) / cov] f_s(y) dy,$$

$$liab^s_{cov} = y^s_{cov} = cov \int_0^{y^s_{cov}} y f_s(y) dy.$$

In the first line $rate^s_{cov}$ is the premium rate for coverage level cov under climate s, $E(indem)^s_{cov}$ is the expected indemnity, and $liab^s_{cov}$ is the liability. The second line defines the expected indemnity as the product of the probability of an indemnity occurring and the average indemnity paid conditional on an indemnity occurring. The factor $1/cov$ in the conditional expected indemnity reflects the "disappearing deductible" that is built into AYP contracts (Barnett, Black, and Skees, 2005). The third line defines the liability, which is simply the yield guarantee y^s_{cov} since we are assuming prices equal to unity without loss of generality. The guarantee is the product of mean yield and the coverage level. Currently, AYP and ARP coverage levels range from 70% to 90% in 5% increments. We also include coverage levels from 50-70% here in order to extrapolate our findings to YP and RP products, for which coverage levels range from 50% to 85% in 5% increments. In practice the RMA also includes a loss limiting factor in the indemnity payment which places an upper bound on the indemnity. Given that we simulate the densities $f_s(y)$, we use discretized versions to calculate the expected indemnity and liability.

Linking Subsidies to Expected Indemnities

The producer paid premium $prem^s_{cov}$ is defined as the product of one minus the subsidy factor sf_{cov} and the gross premium (i.e. price of insurance), which is itself the product of the liability times the premium rate,

$$(4) \quad prem^s_{cov} = liab^s_{cov} \times rate^s_{cov} \times (1 - sf_{cov}).$$

Note that we are allowing the subsidy factor to vary across coverage levels. RMA also varies the coverage level across area vs. unit products, as well as by the chosen structure of the unit. However, this equation holds regardless of the category, as will the result linking changes in expected

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indemnity to changes in subsidy within each category. This implies that the per-acre subsidy sub_{cov}^{s} is proportional to the expected indemnity since

$$\text{(5)}\quad \begin{aligned} sub_{cov}^{s} &= prem_{cov}^{s}\,|_{sf=0} - prem_{cov}^{s} \\ &= E(indem_{cov}^{s}) \times sf_{cov,} \end{aligned}$$

which in turn implies that the percentage change in subsidy when climate shifts from $s=0$ to $s=1$ is equal to the percentage change in expected indemnity since

$$\text{(6)}\quad \frac{sub_{cov}^{1} - sub_{cov}^{0}}{sub_{cov}^{0}} = \frac{E(indem_{cov}^{1}) - E(indem_{cov}^{0})}{E(indem_{cov}^{0})}.$$

Bootstrapping Procedure

It is important to be able to identify the uncertainty around the reported estimates, which is made difficult by the multiple dimensions of correlation inherent in the empirical framework. The estimated parameters from the mean and variance equations introduce parameter uncertainty into the simulation exercise, which in turn introduces uncertainty into the premium rate estimates. Intuitively, variation in the mean and variance of a distribution affects the shape of that distribution, which in turn affects the premium rate. Unfortunately, tracing this uncertainty through both the simulation exercise and the (nonlinear) calculation of rates is difficult in practice.

Deriving an asymptotic approximation of the variance for the rate effects is a daunting task given the multiple sources of uncertainty inherent in the modeling framework. As an alternative, we appeal to the method of bootstrapping (Efron, 1979), which is a resampling method that can be used to obtain confidence intervals around the rates in the current setting. It is important to note that even if obtaining estimates of the yield distributions did not involve multiple models, one would still have to confront the fact that rate calculations are a highly nonlinear transformation of the underlying data and parameters. For example, in a simple setting where densities were estimated directly from available data using maximum likelihood, one would still have to account for the fact that the premium rates are a nonlinear transformation of the estimated densities. Conventional techniques for statistical inference such as the delta method would likely not be applicable.

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We construct 95 percent confidence intervals using a block bootstrapping routine that is robust to spatial correlation. For each of 99 bootstrap iterations, we first construct a bootstrap sample by sampling with replacement whole years from the data. By resampling whole years, we are preserving the spatial correlation structure of the data across counties. This is in the same spirit as clustering standard errors by year in a linear regression model (Cameron, Gelbach, and Miller, 2008). Each bootstrap sample is used to re-estimate the parameters of the mean and variance equations, which are then used to construct the simulated yield densities as discussed in the main text. By running through the model entirely for each bootstrap iteration, we preserve any correlation present between the parameter estimates, simulation exercise, and rate calculations. This generates a total of 100 acreage-weighted premium rate effects, which are sorted from smallest to largest. The 2.5th and 97.5th percentiles represent the lower and upper bounds for the 95 percent confidence interval.

Warming Impacts

We measure the effects of warming relative to baseline climate, which is simulated using the historical in-sample weather outcomes within each county. Warming effects are modeled as a uniform shift in the underlying daily minimum and maximum temperatures. We consider five different warming scenarios for each of the 542 counties, +0°C (i.e. baseline) to +2°C by 0.5°C increments. Each county-level impact is weighted by its temporal average of acres harvested over the length of the sample period when aggregate results are reported.

Results

The parameter estimates for the mean and variance equations are presented in Table S2, and are consistent with previous findings as exposure to extreme heat has a large negative effect. Figure 1 provides kernel density plots for the county-specific mean, CV, and skewness across warming scenarios. There exists substantial spatial heterogeneity across counties, demonstrating the extensive flexibility in the yield modeling approach. These results indicate that we effectively relax cross-sectional and cross-climate restrictions on the functional form of the unconditional density function by mixing a large number of conditional lognormal distributions with different means and variances.

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Mean Yield and Yield Risk Impacts

We report the percentage-change in mean yield for the full sample (corn belt), southern corn belt states (Iowa, Illinois, Indiana, Missouri, Nebraska, and Ohio), and northern corn belt states (Michigan, Minnesota, and Wisconsin) in Figure S4. The acreage-weighted average impacts under 1°C warming for the full sample is -4.3%, compared to -5.4% change in the acreage-intensive southern region versus a -0.3% change in the north. While this aggregate impact is consistent with previous results (Schlenker and Roberts, 2009), we also document the existence of substantial impact heterogeneities across counties within the corn belt (Figure S5). The percentage changes in the CV are reported in Figure S6. The acreage-weighted average impact under the 1°C scenario for the full sample is 15.0%, compared to a 17.2% change in the southern region versus a 6.9% change in the north. This indicates a rather large increase in yield risk as a result of warming on average, and again we find evidence of substantial cross-sectional heterogeneity (Figure S7). These findings are consistent with those previously found in the literature (e.g. Urban et al., 2012).

Crop Insurance Premium Rate Impacts

The simulated densities are used to quantify the effect of warming on per-acre actuarially fair premium rates for AYP policies. Rates under the various climate-county combinations are reported in Figure S8 across alternative coverage levels. We report the percentage-change in premium rates at the 90% level for the full sample, southern, and northern regions in Figure S9. While positive on average, there again exists substantial cross-sectional heterogeneities as evidenced by the spatial map in Figure 2.

The aggregate estimates for the mean, CV, and premium rates effects from the 1°C warming scenario are summarized in Figure 3. We find that the acreage-weighted mean and CV impacts translate into increased premium rates under the 1°C warming scenario. The premium rate impact for the full sample is 33.3%, and is statistically significant at the 5% level. This result is driven by a larger statistically significant effect among southern corn belt states (36.4%) compared to a 22.1% change in the north. Figure S10 reports impacts under 2°C warming where we find premium rates increases of 87.3% (full), 92.3% (south), and 69.4% (north). Note that even though the mean yield impacts in the north are small, the CV and premium rate effects are large in magnitude and

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become statistically significant under 2°C warming (Figure S10). In addition, we find evidence of a nonlinear relationship between warming and premium rate impacts indicating that premium rates are increasing at an increasing rate across warming scenarios (Figure 3). We also find that exposure to extreme heat is the biggest driver of premium rate impacts (Table S3).

Crop Insurance Subsidy Impacts

We find that warming's influence on premium rates leads to increased tax payer burden for the AYP portion of the crop insurance program since the percentage change in subsidy is equal to the percentage change in expected indemnity (see equation 6 above). We use the county-climate yield densities to calculate expected indemnities, and in turn use these to calculate the percentage change in producer subsidy under both the 1°C and 2°C warming scenarios. We then combine these percentage changes with FCIP subsidy data to measure the implied impact on U.S. taxpayers, which are reported in Table 1. Since both the expected price for corn and the level of enrollment can vary quite a bit from year to year, we use a five-year average of FCIP subsidies from 2010-2014. Focusing solely on the AYP plan for corn in column 1, the level increase in annual subsidy payment is $1.4 million under the 1°C scenario, which represents a 28% increase in total subsidy outlays. This increases to $3.1 million under the 2°C scenario, a 62% increase. Thus, warming temperatures are found to translate into economically meaningful increases to the cost of subsidizing the AYP plan.

We provide evidence that the estimated warming impacts will likely extend to other crop insurance products and have a large aggregate impact on the overall program. The cost of subsidizing the AYP plan is small relative to the overall FCIP program, which averaged $6.5 billion in annual subsidy payments from 2010-2014. As a percentage of this outlay, the AYP effects represent less than a 0.05% increase under both warming scenarios. However, it is likely that warming effects will influence subsidy levels for other crop insurance products for corn (e.g., YP and RP). To investigate this possibility, we utilize historical loss-cost ratio (i.e. indemnity payments divided by liability) data for three categories of insurance plans: (a) the AYP plan for corn, (b) all insurance plans for corn, and (c) all crop insurance plans. We restrict our attention to county-year combinations in which AYP corn plans have been offered. This results in 6,943 county-level

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observations spanning 18 years (1997-2014), 651 counties, and 24 states. Each observation contains the realized loss cost for each of the three categories.

Figure S11 plots the loss cost ratio data and shows that all three series move together, thus establishing a tight linkage between the three categories of insurance plans. Column 1 of Table S4 reports the results of regressing the loss cost for all corn policies on the loss cost for AYP corn policies. The near one-to-one relationship implies that, on average, an additional percentage point of loss cost for AYP corn is associated with an additional percentage point of loss cost for all corn policies. The strong linkage between AYP with other corn policies is not surprising. The most popular alternative policy is farm-level revenue insurance, in which the systemic yield variation captured here at the county level is a major component of producers' risk exposure.

Column 4 of Table S4 reports the results of regressing the loss cost for all crop policies on the loss cost for AYP corn policies, and again we see a strong linkage between the two. This is not surprising either as corn represents the largest share of insured value among all crops, and other major crops (soybeans, wheat, rice, and cotton) are sensitive to extreme heat (and thus, warming) (Schlenker and Roberts, 2009; Tack, Barkley, and Nalley, 2015; Lyman et al., 2013; Tack et al., 2016).

A stable loss cost relationship among these different policy categories implies that the subsidy impacts identified for AYP corn will likely extend to other crop insurance products and have a large effect on total program outlays. Since the majority of insurance purchases are at the farm level, and because farm level outcomes are more variable than aggregate county level outcomes, we increase the standard deviation of the conditional yield distributions by a factor of 2.8.[3] This has the effect of increasing the premium rates within each coverage level as one would expect since farm-level yields are less risky in the aggregate (Figure S12). We then re-calculate the percentage change in subsidies and report the implied warming effects in columns 2 and 3 of Table 1. We find that the 1°C and 2°C warming scenarios for all corn-based insurance policies imply

[3] The factor 2.8 is derived from Table 1 of (Dismukes, Arriola and Coble, 2010). They find that the coefficients of variation for US county- and farm-level corn yields are 0.136 and 0.378, respectively, which implies that farm-level yields have a standard deviation that is 2.8 (=.378/.136) times higher than county-level yields.

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level increases in annual subsidy payments of $287 million and $769 million, respectively. These increases represent an 11% and 28% increase in total subsidy outlays. Furthermore, extending these impacts to all crops covered by the FCIP implies that subsidy outlays increase by $850 million (13%) and 2.2 billion (34%) under the 1°C and 2°C scenarios.[4]

Conclusion

Our empirical analysis shows that *ceteris paribus*, a warming climate will increase crop insurance premium rates and producer subsidies, in turn increasing the associated taxpayer burden of the program. Previous studies estimating the effect of a changing climate on federal level outcomes such as GDP and per-capita income have not taken these "program effects"' into consideration (Dell, Jones, and Olken, 2014). These program effects will produce both winners and losers as these programs are largely a reallocation of resources within an economy, however it is an open question as to whether the net welfare effect is non-zero.

The FCIP represents the most widely used agricultural risk protection policy instrument in the U.S., and the most recent Farm Bill suggests that the next wave of agricultural policy will provide an even greater emphasis on this type of protection (Barnaby and Russell, 2016). As such, the findings reported here will be of interest to food and agricultural policy-makers, as well as the academic community. As current and future Federal budget deficits continue to occupy policy-makers' and the general public's attention, this connection to the more general populace outside of the agricultural sector provides a much larger scope for this research. An important dialogue regarding the structure of crop insurance subsidies is likely to occur during future farm policy debates (Coble and Barnett, 2013). The current subsidy structure is defined on a percentage basis; thus, *ceteris paribus*, a riskier farm gets more subsidy. This is inconsistent with climate change adaptation incentives. One possible modification would be to fully or partially decouple subsidy from risk levels. Another possibility would be to link subsidy to certain climate change adaptation practices. However, such linkages would need to be verifiable by an insurer or third party.

[4] Note that when we extrapolate to alternative insurance products, we are also spatially extrapolating to other production regions beyond the US corn belt. This might understate the actual impacts because the other major production regions for crops in the US (e.g. southeast, mid-south, and southern plains) are further south and are thus more likely to be adversely affected by warming.

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Given the farm-level crop insurance rating system relies on a weather-weighted 20 year moving average of loss experience (Coble et al., 2015), one may question the possibility of lags between loss experience (on average a 10-year lag) and the forecast of expected losses one or two years in advance. If temperatures are trending upward and causing more yield variability over time, the current rating process would generate premium rates that are consistently less than the actuarially fair rate. Any effort to address this problem (e.g., by modifying weights in the existing weather weighting of historical loss data) would further increase premiums and (for a given subsidy percentage) taxpayer cost.

The performance of the FCIP is of great interest globally as the public/private nature of the program is attractive to agrarian-based developing countries since the cost of risk protection is split across the two sectors. This interest might lessen if subsidization required to induce participation increases under climate change. Some studies have established a linkage between climatic variations driven by the El Nino Southern Oscillation and insurance-related outcomes (Khalil et al., 2007; Skees, Hartell, and Murphy, 2007; Carriquiry and Osgood, 2012). These studies are typically conducted in a developing county context, where severe weather events can have widespread effects beyond agricultural production. Thus, while our focus here has been on global warming and the U.S. crop insurance program, these findings will be useful in guiding insurance design and implementation - as well as assessing the net effects of climate change - in developing countries.

A potential limitation of this study is that adaptation strategies have the potential to reduce the effects found here. For example, (Ortiz-Bobea and Just, 2012) finds that re-optimizing planting dates can reduce yield reductions, and (Tack et al., 2016) suggests that future genetic enhancements could help alleviate heat stress. However, we do provide estimates of warming impacts on yield and yield risk which are crucial inputs for modeling production-based adaptation strategies. One could use the county-level estimates found here and aggregate them up to regional levels using alternative weights derived from a forecasting model of acreage shifts in order to gain a better understanding of the potential influence of adaptation. Another form of adaptation that could affect total program subsidy payments is insurance-based, in that producers could alter their choice of insurance products and/or coverage levels in response to changing premium rates. Other

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limitations include the implicit assumption that crop insurance will continue to play an important role within US agricultural policy, and that subsidy rates will remain at historical levels. The latter is an especially relevant concern given the pressures to reduce the overall cost of subsidizing agricultural production. While the form and magnitude of federal support may change in the future, more than 80 years of historical experience suggests that US policymakers are determined to provide assistance to farmers who suffer yield losses due to natural causes.

We also note that our statistical approach does not incorporate the effect of elevated atmospheric CO_2 on crop yields, which will likely benefit average yield performance and could also reduce yield variation as well. Some recent evidence suggests that ignoring these benefits leads to overstated climate change impacts (Attavanich and McCarl, 2014; Urban, Sheffield, and Lobell, 2015). These studies point to the need for a deeper physiological understanding of the nonlinear yield responses arising from interactions between the various factors influencing plant growth (Urban, Sheffield, and Lobell, 2015). The extent to which CO_2 fertilization effects might offset the increases in yield risk found here remains an open question and is a ripe area for future study.

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Tables

Table 1. Subsidy outlay and warming impacts, million USD

Coverage Level	(1) AYP Corn	(2) All Corn	(3) All All
50	--	56.8	450
55	--	5.13	37.2
60	--	34.6	262
65	0.196	129	557
70	0.099	497	1,500
75	0.078	867	1,960
80	0.114	685	1,080
85	0.384	336	504
90	4.06	95.3	170
Total Outlay	4.93	2,710	6,520
Warming Impact 1°C	1.36	287	848
Warming Impact 2°C	3.08	769	2,240

Notes: Table shows the 2010-2014 average subsidy levels in million US dollars for various insurance policies and coverage levels. AYP corn refers to the Area Yield Plan for corn, All Corn refers to all insurance policies for corn, and All All refers to all insurance policies for all crops.

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Figures

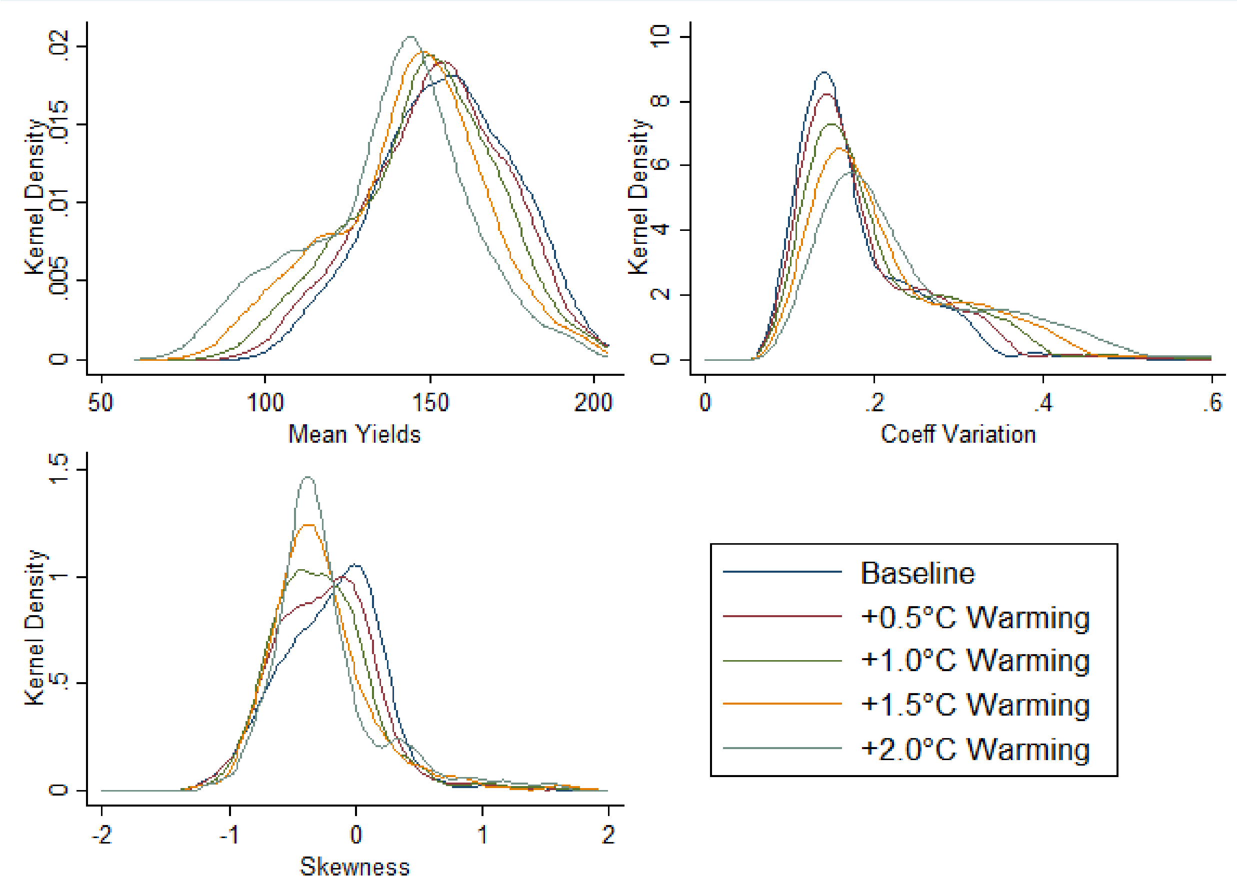

Figure 1. Heterogeneity of distributional moments for the unconditional yield distributions within and across warming scenarios. Separate yield densities are estimated for each county-climate combination in the data. The 542 county-specific mean, coefficient of variation, and skewness estimates are summarized under each warming scenario by a kernel density plot.

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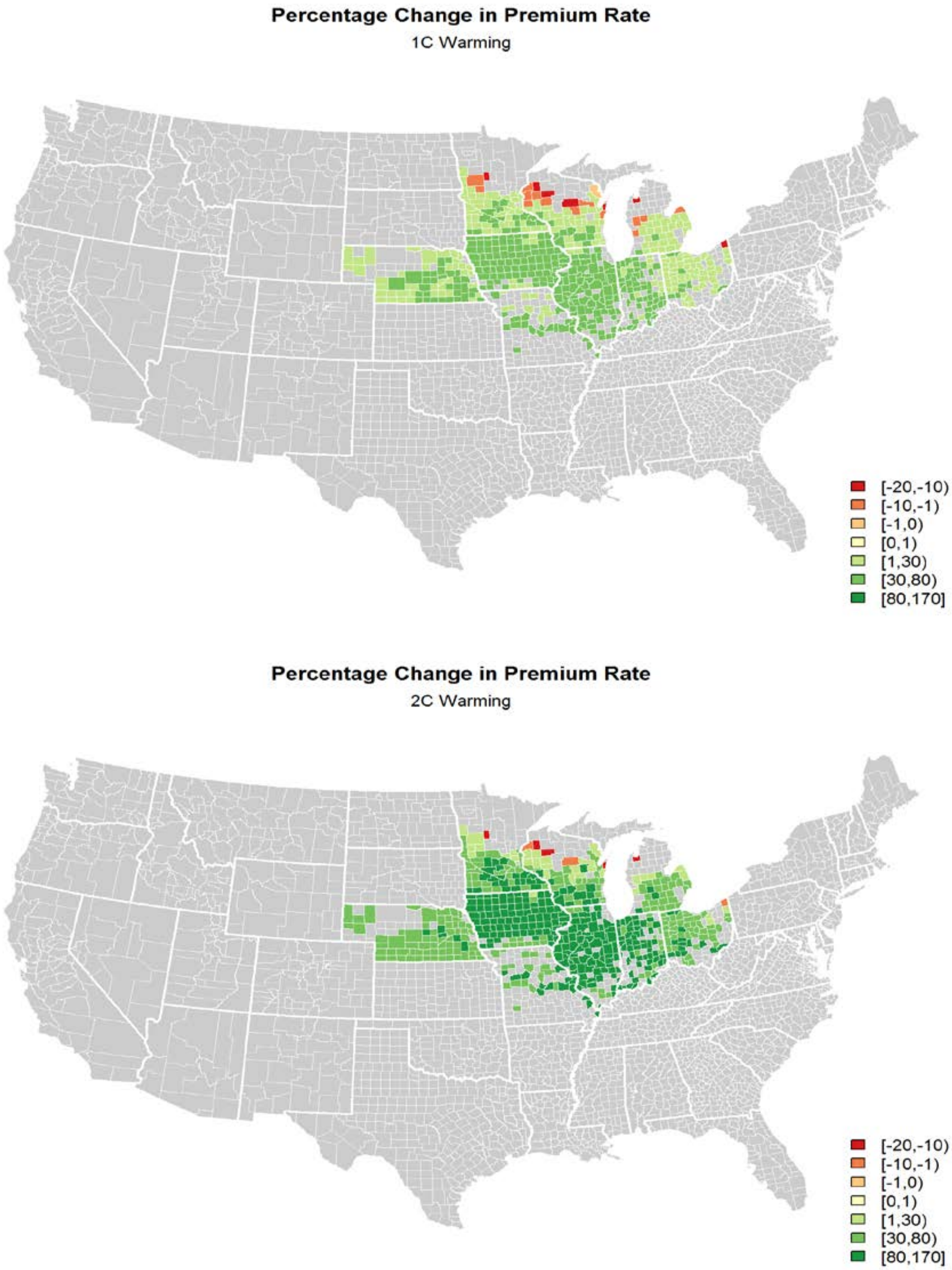

Figure 2. Spatial representation of premium rate impacts under warming. Separate yield densities are estimated for each county-climate combination in the data, and then used to calculate changes in premium rates for the 90% coverage level across warming scenarios.

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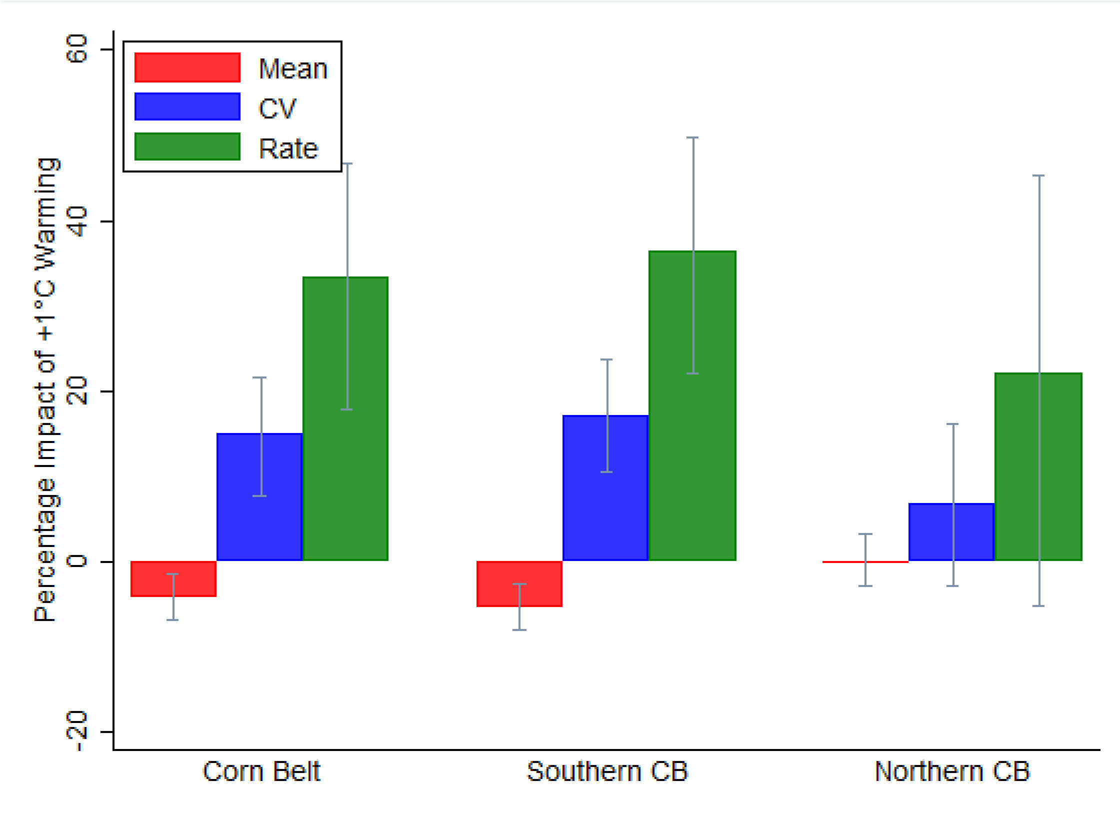

Figure 3. Aggregate and regional warming effects on mean, coefficient of variation (CV), and premium rates (90% coverage level). Impacts are expressed as a percentage change due to 1°C warming relative to baseline (historical) climate. The 542 county-specific impacts are acreage-weighted for the full sample of corn belt states, and also broken out across southern versus northern corn belt states. 95% confidence intervals are constructed from a spatially robust bootstrapping routine described in the text.

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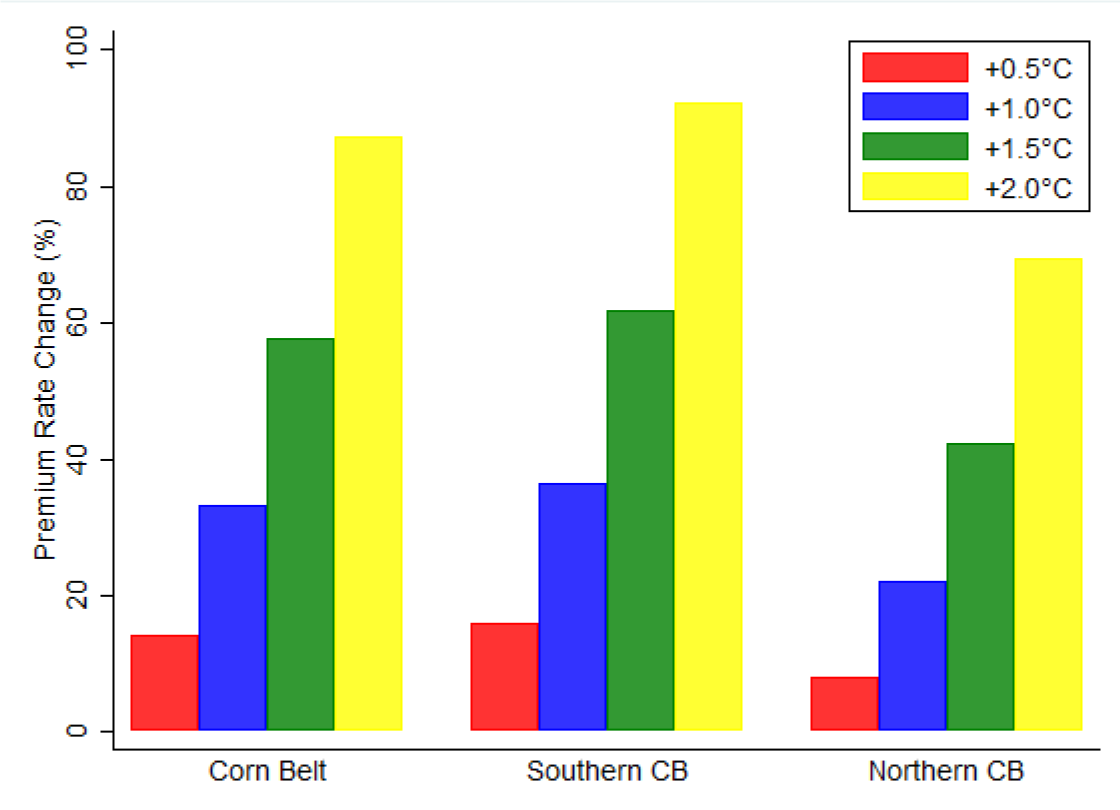

Figure 4. Aggregate and regional effects on premium rates at a 90% coverage level for alternative warming scenarios. Impacts are expressed as a percentage change relative to baseline (historical) climate. The 542 county-specific impacts for each warming scenario are acreage-weighted for the full sample of corn belt states, and also broken out across southern versus northern corn belt states. 95% confidence intervals are constructed from a spatially robust bootstrapping routine described in the text.

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Supplementary Material for Online Publication: Warming temperatures will likely induce higher premium rates and government outlays for the US crop insurance program

January 20, 2017

This document contains supplementary material for the article "Warming temperatures will induce higher premium rates and government outlays for the US crop insurance program." Sections S1 and S2 provide supplementary tables and figures, respectively.

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Section S1 Supplementary Tables

Table S1: Yield and Weather Data: 1950-2015

Variable	Sample Mean	Std Dev	Min	Max	Obs
Corn Yield (bushels per acre)	104.5	41.1	0.96	236.0	35,772
Low Temperature (degree days)	1,701	54.7	1,445	1,821	35,772
Medium Temperature (degree days)	1,615	236.6	879.0	2,447	35,772
High Temperature (degree days)	19.2	20.1	0.00	214.3	35,772
Precipitation (centimeters)	57.0	13.5	12.0	126.2	35,772

Notes: Values reported for temperature and precipitation variables correspond to the April through September growing season. Low temperature measures degree days between $0°C$ and $9°C$; medium temperature measures degree days between $10°C$ and $29°C$; and high temperature measures degree days above $29°C$.

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Table S2: Regression Results for Mean and Variance of Corn Yields

Variable	Log Yield	Log Sq Res
Low Temperature	0.00039	-0.0014
	[0.00026]	[0.0021]
Medium Temperature	0.00028	-0.0008
	[0.00012]***	[0.0008]
High Temperature	-0.0088	0.0096
	[0.00078]***	[0.0040]***
Precipitation	0.0139	-0.0931
	[0.0042]***	[0.0183]***
Precipitation Squared	-0.00012	0.0008
	[0.00003]***	[0.0001]***
County Fixed Effects	Y	Y
State Quadratic Trends	Y	Y
N	35,772	35,772
R-Squared	0.866	0.111

Notes: Table shows results of regressing log yield and the log of squared residuals on weather, county fixed effects and state-specific quadratic trends. Predicted values for yield levels obtained from the first regression are used to construct residuals for the second equation. Weather variables are aggregated for the months April-September. Clustered standard errors by year are in brackets. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

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Table S3: R-squared results for regressions of premium rate difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Diff Low Temperature	N	Y	N	N	Y	N	Y
Diff Med Temperature	N	N	Y	N	N	Y	Y
Diff High Temperature	N	N	N	Y	Y	Y	Y
Coverage Level FE	Y	Y	Y	Y	Y	Y	Y
R-squared	0.036	0.395	0.455	0.846	0.890	0.887	0.895

Notes: Table shows results of regressing estimated premium rate differences on combinations of differenced temperature variables and coverage level fixed effects.

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Table S4: Regression Results for Loss Cost Ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable:	Lcost crn	Lcost crn	Lcost crn	Lcost all	Lcost all	Lcost all
Lcost AYP crn	1.007	1.014	0.987	0.706	0.701	0.691
	[0.051]***	[0.054]***	[0.055]***	[0.027]***	[0.031]***	[0.030]***
County FE	N	Y	Y	N	Y	Y
Year FE	N	N	Y	N	N	Y
Observations	6,943	6,943	6,943	6,943	6,943	6,943
Num counties	651	651	651	651	651	651
Num years	18	18	18	18	18	18
R-squared	0.594	0.688	0.739	0.480	0.601	0.693

Notes: Table shows results of regressing loss cost ratios (i.e. paid indemnities divided by received premiums) for all corn policies (Lcost crn) and all crop policies (Lcost all) against loss cost ratios for the AYP corn (Lcost AYP crn) policies. Standard errors clustered by year in brackets. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

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Section S2 Supplementary Figures

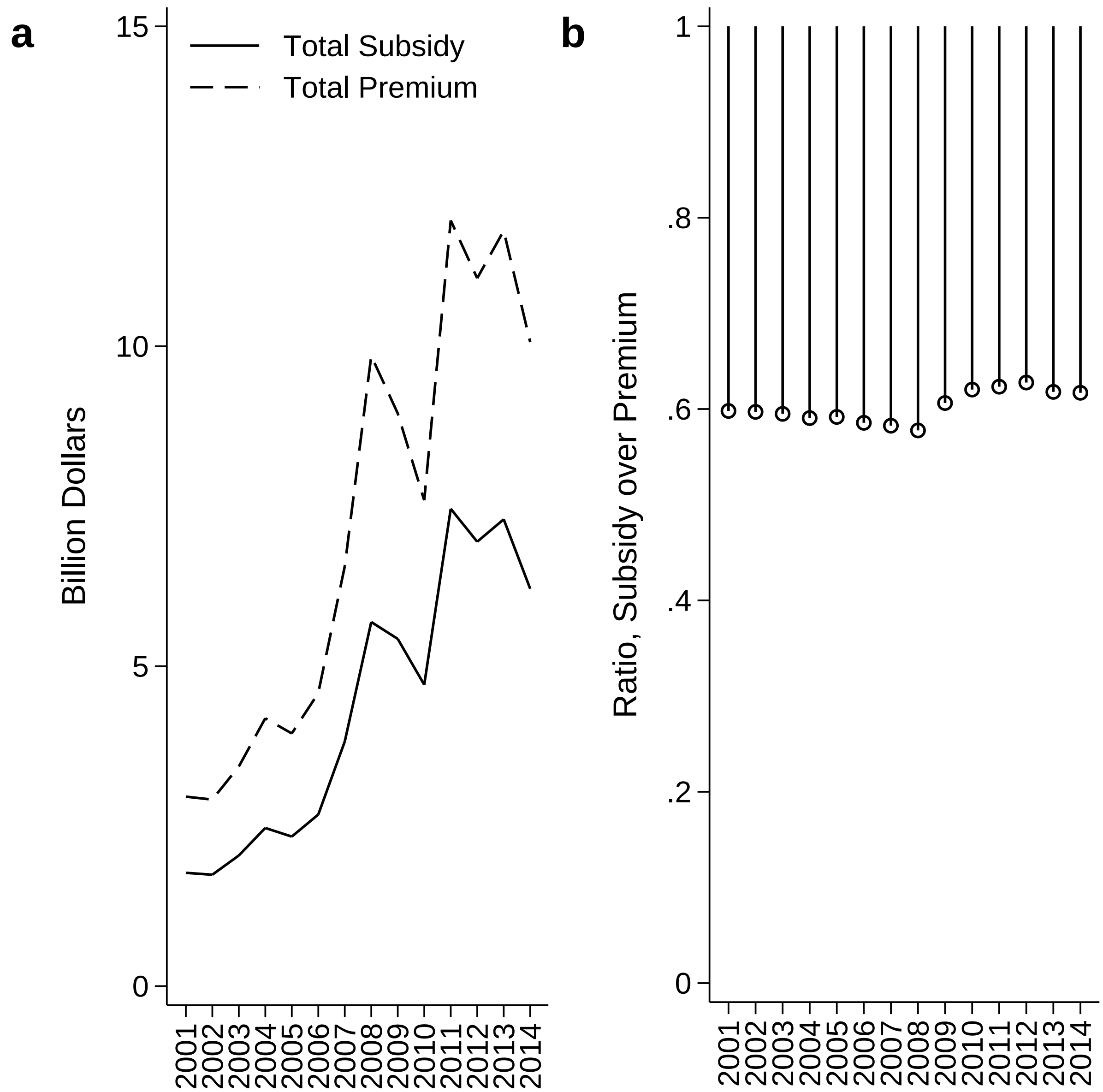

Figure S1: Insurance premiums and subsidies for the Federal Crop Insurance Program, 2001-2014. (a) The total dollar value of subsidies and premiums for all policies. (b) A pair plot of these values measured as the ratio of subsidies over premiums.

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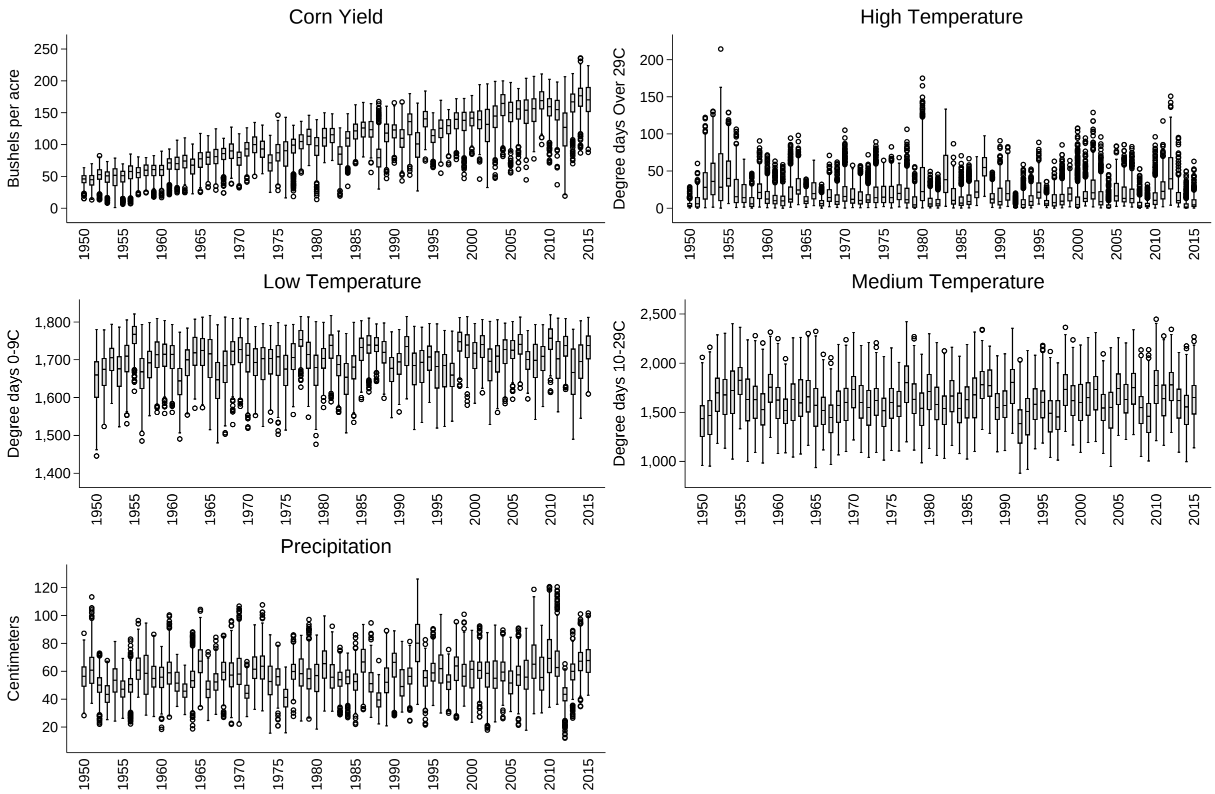

Figure S2: Annual box plots for county level yield and weather sample data, 1950-2015. Each box is defined by the upper and lower quartile, with the median depicted as a horizontal line within the box. The endpoints for the whiskers are the upper and lower adjacent values, which are defined as the relevant quartile ± three-halves of the interquartile range, and circles represent data points outside of the adjacent values.

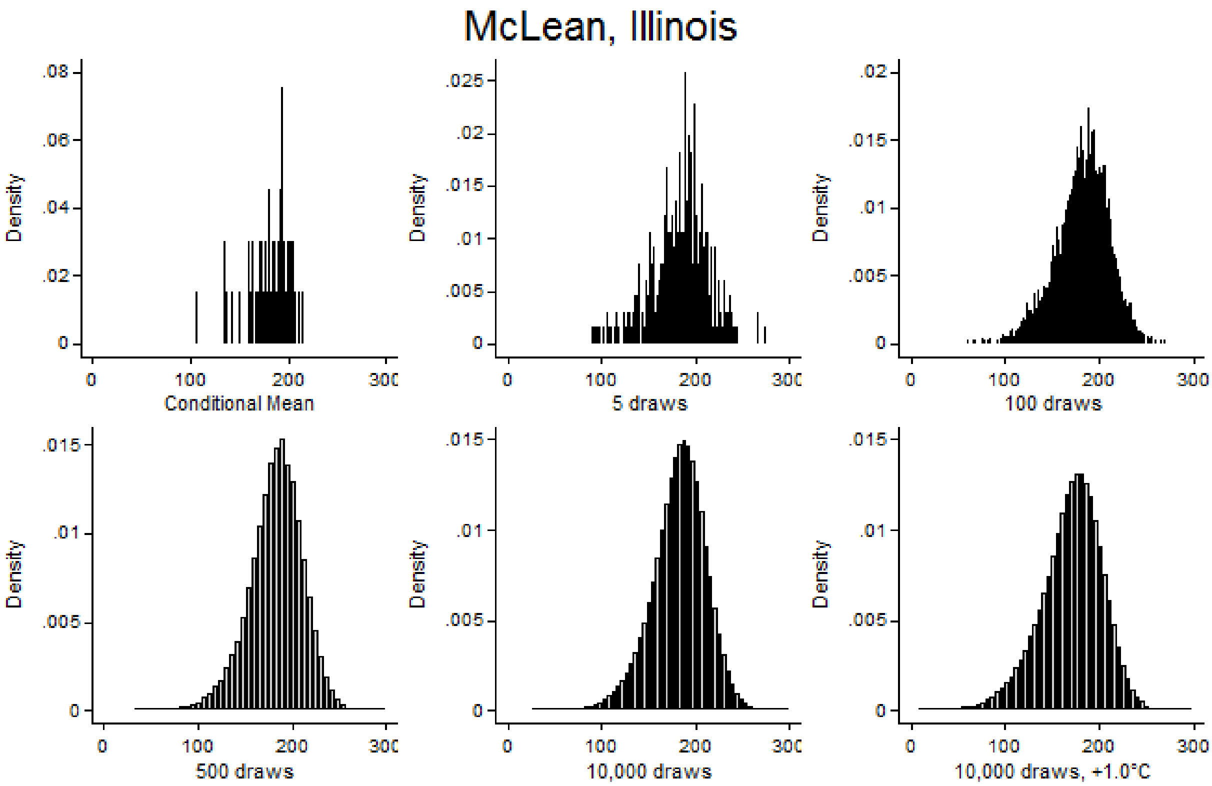

Figure S3: Simulation of yield densities. The first panel (upper left) shows the conditional mean estimates as a histogram for the 66 years of weather data. Each mean has its own lognormal distribution around it. As we draw from these 66 distributions, we empirically identify the unconditional distribution. We use 10,000 total draws from each of the 66 distributions. The draws are taken independently to mimic the year-to-year independence of weather outcomes. The final (lower right) graph shows a similar simulation outcome for the $1°C$ warming scenario, where most of the yield mass has shifted left.

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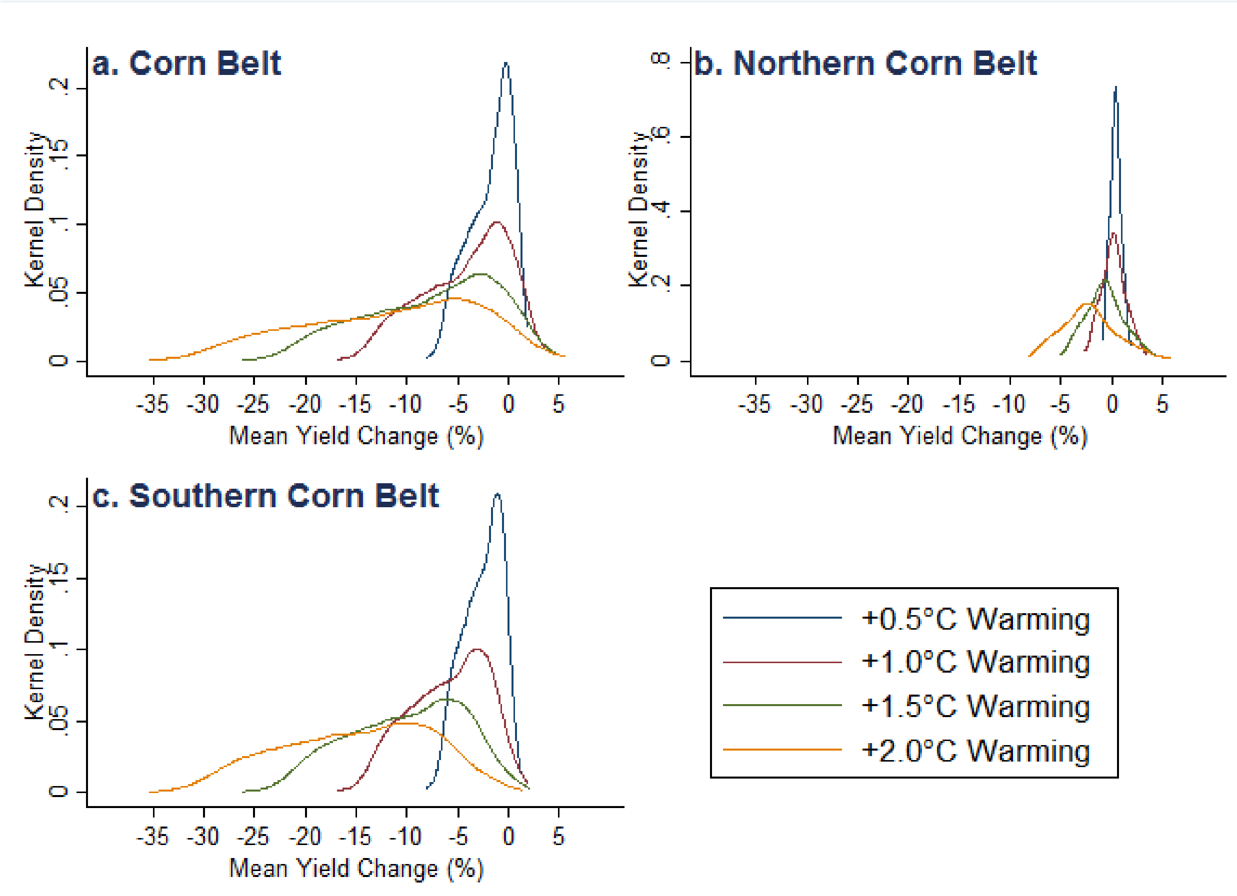
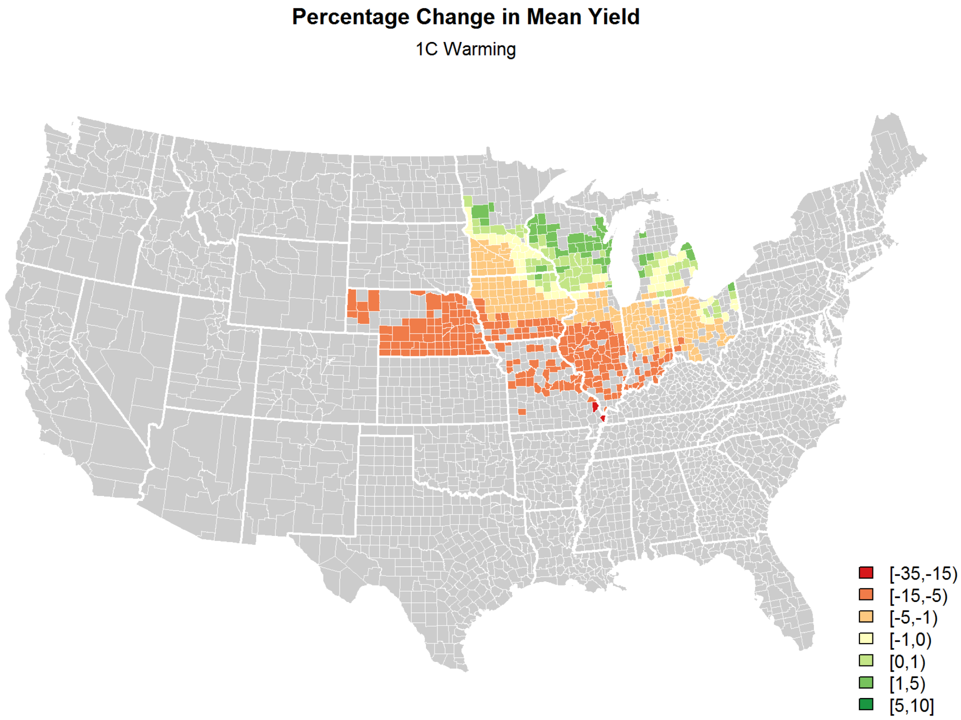


Figure S4: Percentage change in mean yield due to warming. The mean yield estimates from Figure 1 are expressed as a percentage of baseline for each county-climate combination. The 542 county-specific impacts are summarized under each warming scenario by a kernel density plot. We report plots for the full sample of corn belt states (a), northern corn belt states (b), and southern corn belt states (c).



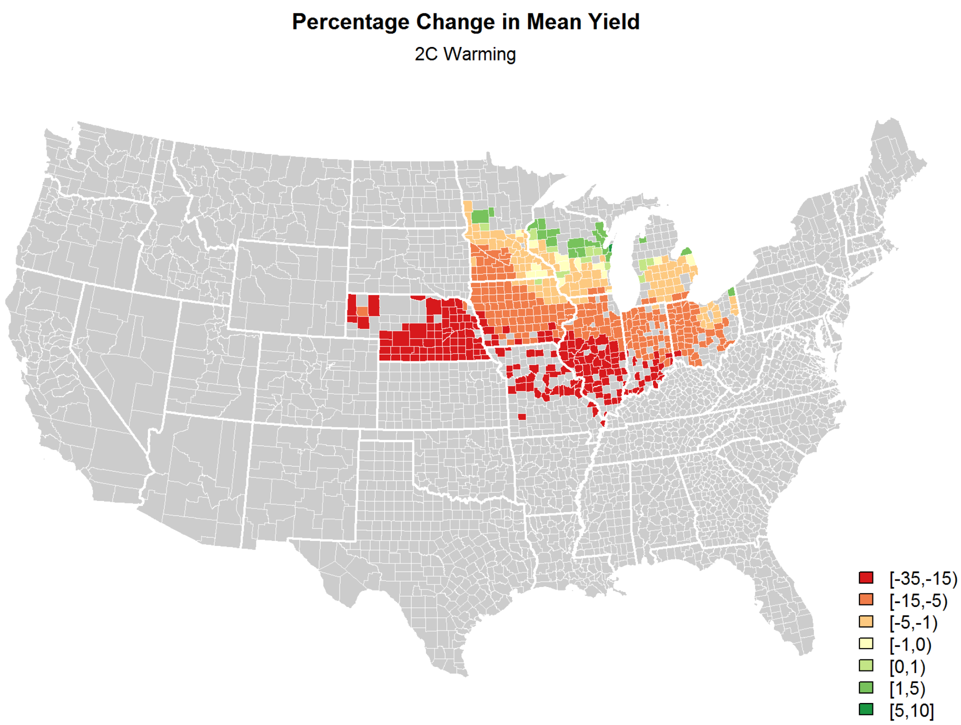


Figure S5: Spatial representation of mean yield impacts under warming. The mean yield estimates from Figure S4 are reported for each county.

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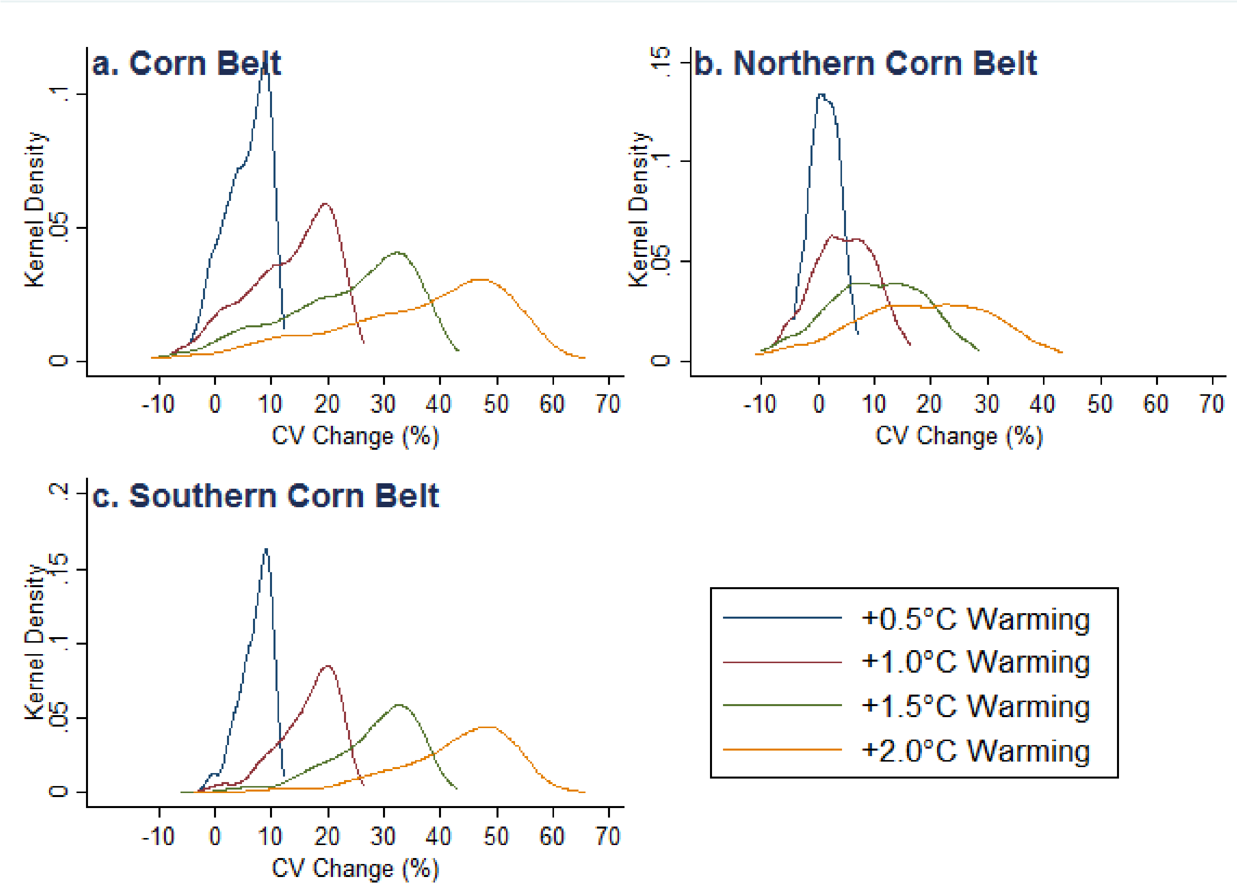

Figure S6: Percentage change in the coefficient of variation (CV) due to warming. The CV estimates from Figure 1 are expressed as a percentage of baseline for each county-climate combination. The 542 county-specific impacts are summarized under each warming scenario by a kernel density plot. We report plots for the full sample of corn belt states (a), northern corn belt states (b), and southern corn belt states (c).

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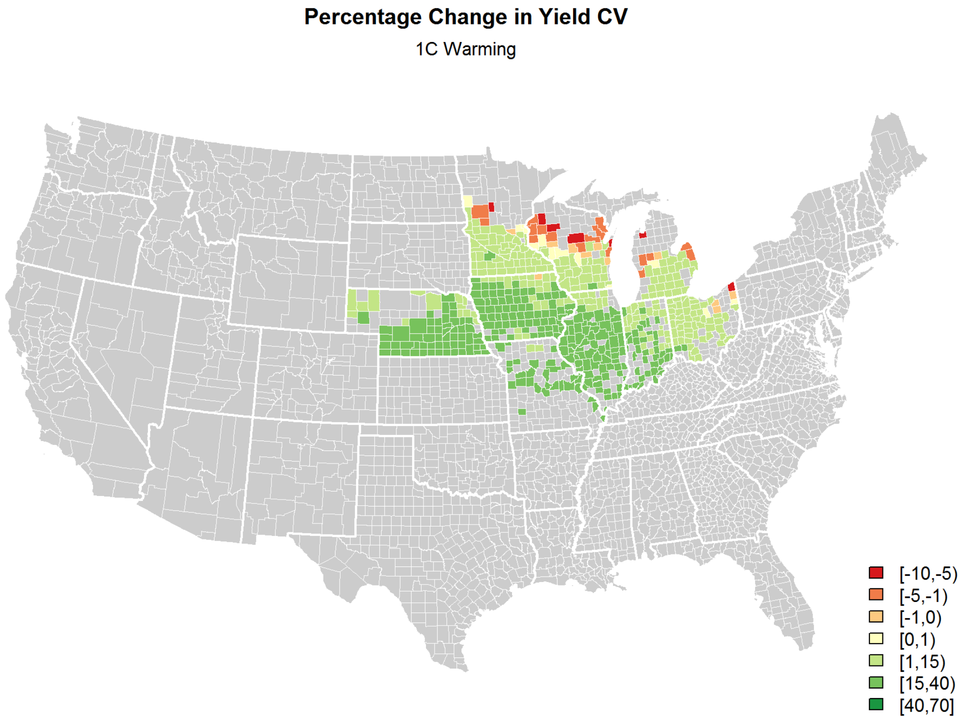

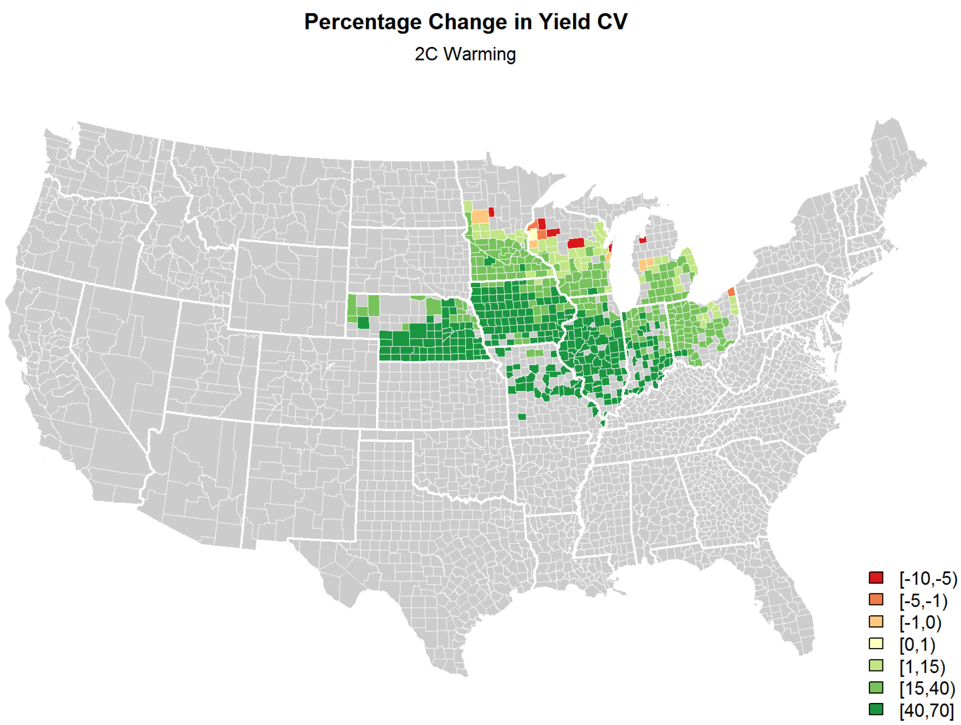

Figure S7: Spatial representation of yield coefficient of variation (CV) impacts under warming. The yield CV estimates from Figure S6 are reported for each county.

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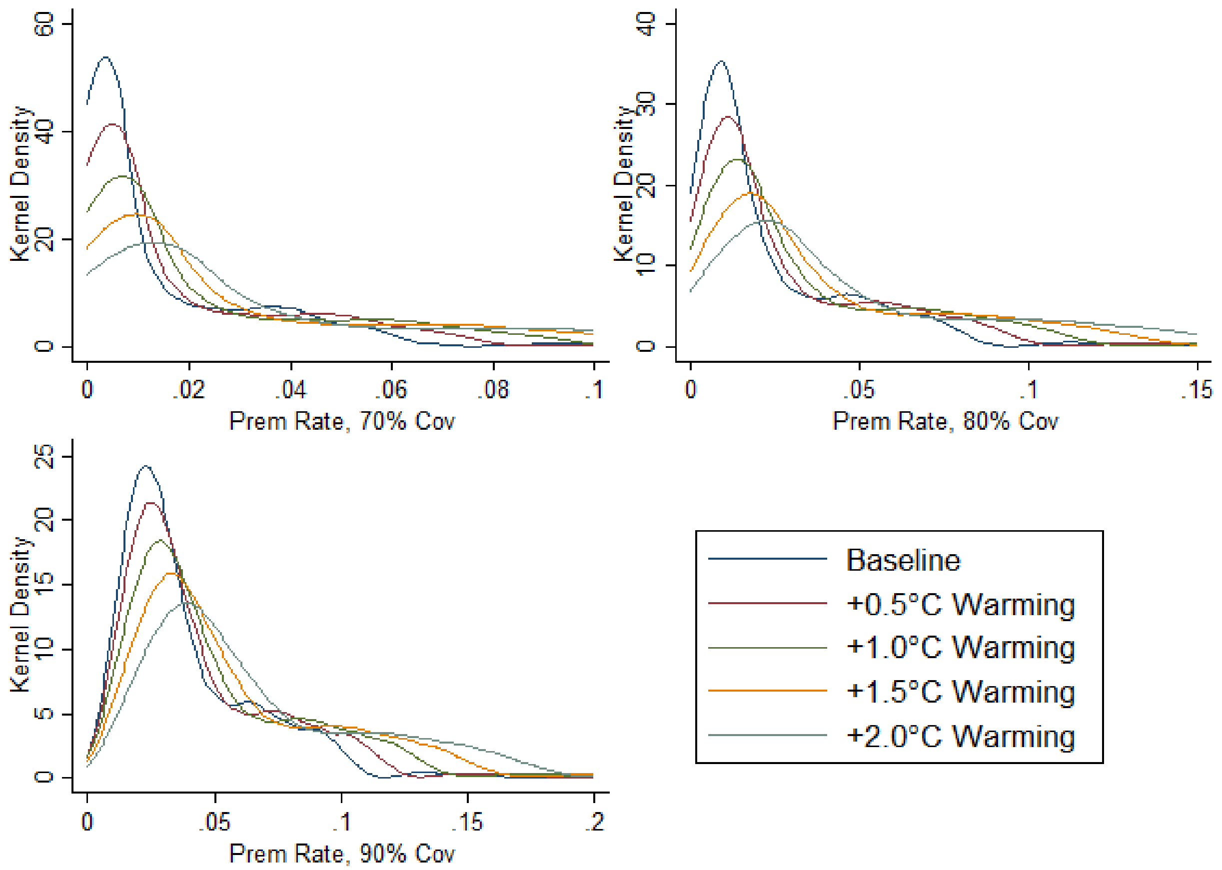

Figure S8: Heterogeneity of premium rates for the unconditional yield distributions within and across warming scenarios. Separate yield densities are estimated for each county-climate combination in the data. Within each coverage level, the 542 county-specific premium rates estimates are summarized under each warming scenario by a kernel density plot.

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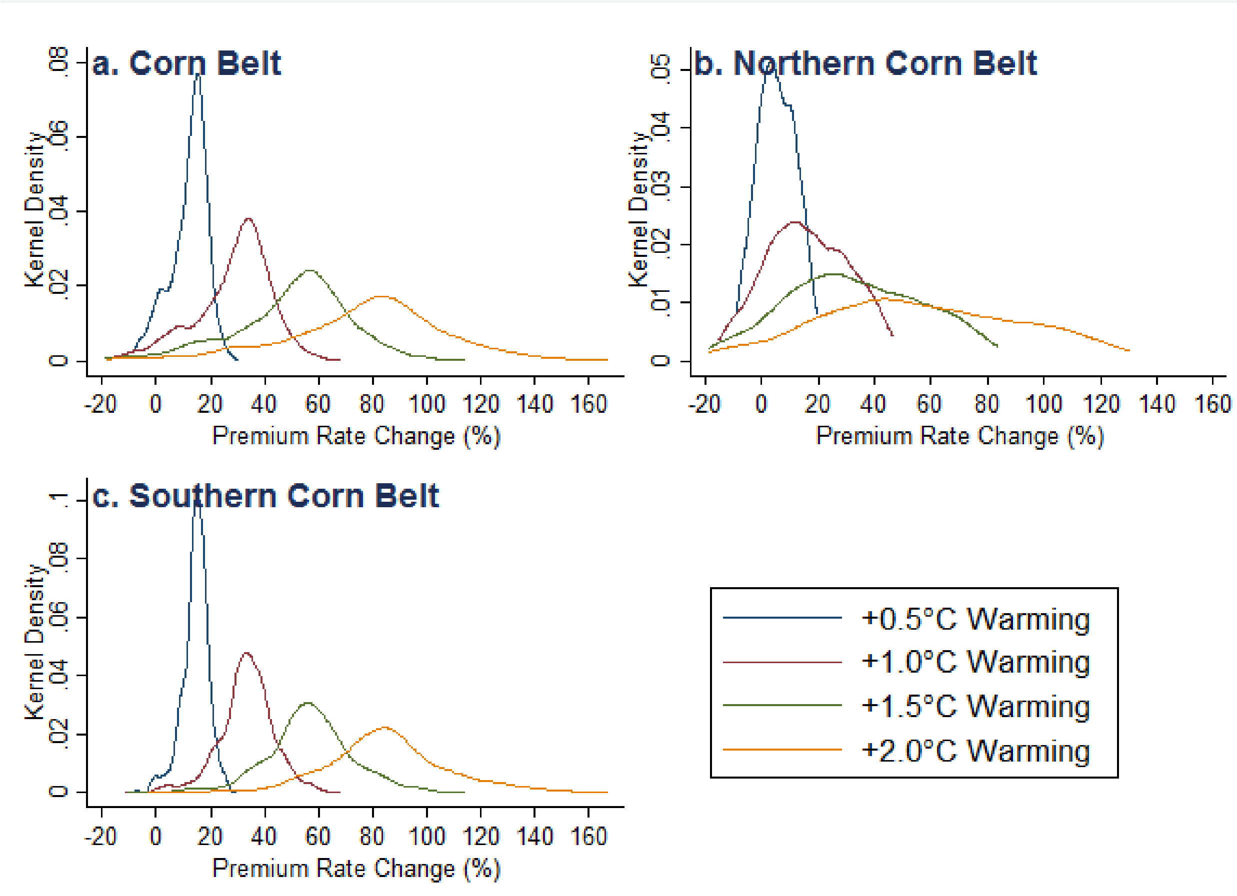

Figure S9: Percentage change in premium rates due to warming. The premium rate estimates under a 90% coverage level from Figure S9 are expressed as a percentage of baseline for each county-climate combination. The 542 county-specific impacts are summarized under each warming scenario by a kernel density plot. We report plots for the full sample of corn belt states (a), northern corn belt states (b), and southern corn belt states (c).

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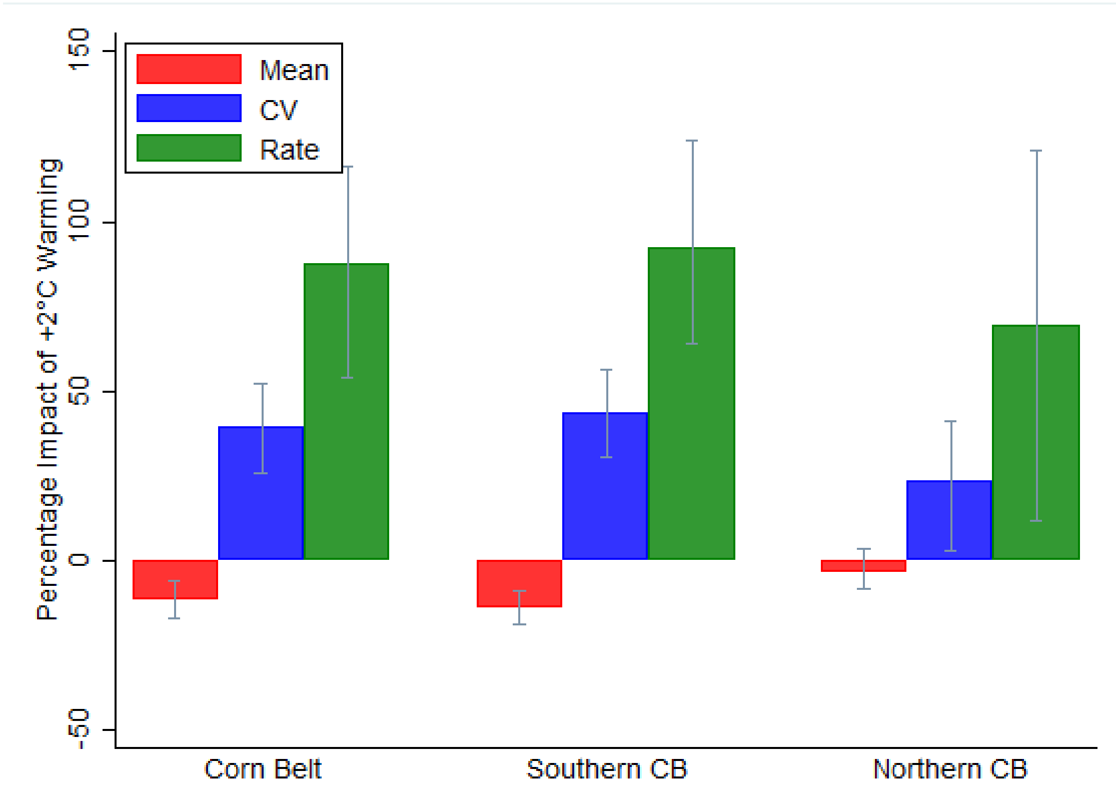

Figure S10: Aggregate and regional warming effects on mean, coefficient of variation (CV), and premium rates at a 90% coverage level. Impacts are expressed as a percentage change due to $2°C$ warming relative to baseline (historical) climate. The 542 county-specific impacts are acreage-weighted for the full sample of corn belt states, and also broken out across southern versus northern corn belt states.

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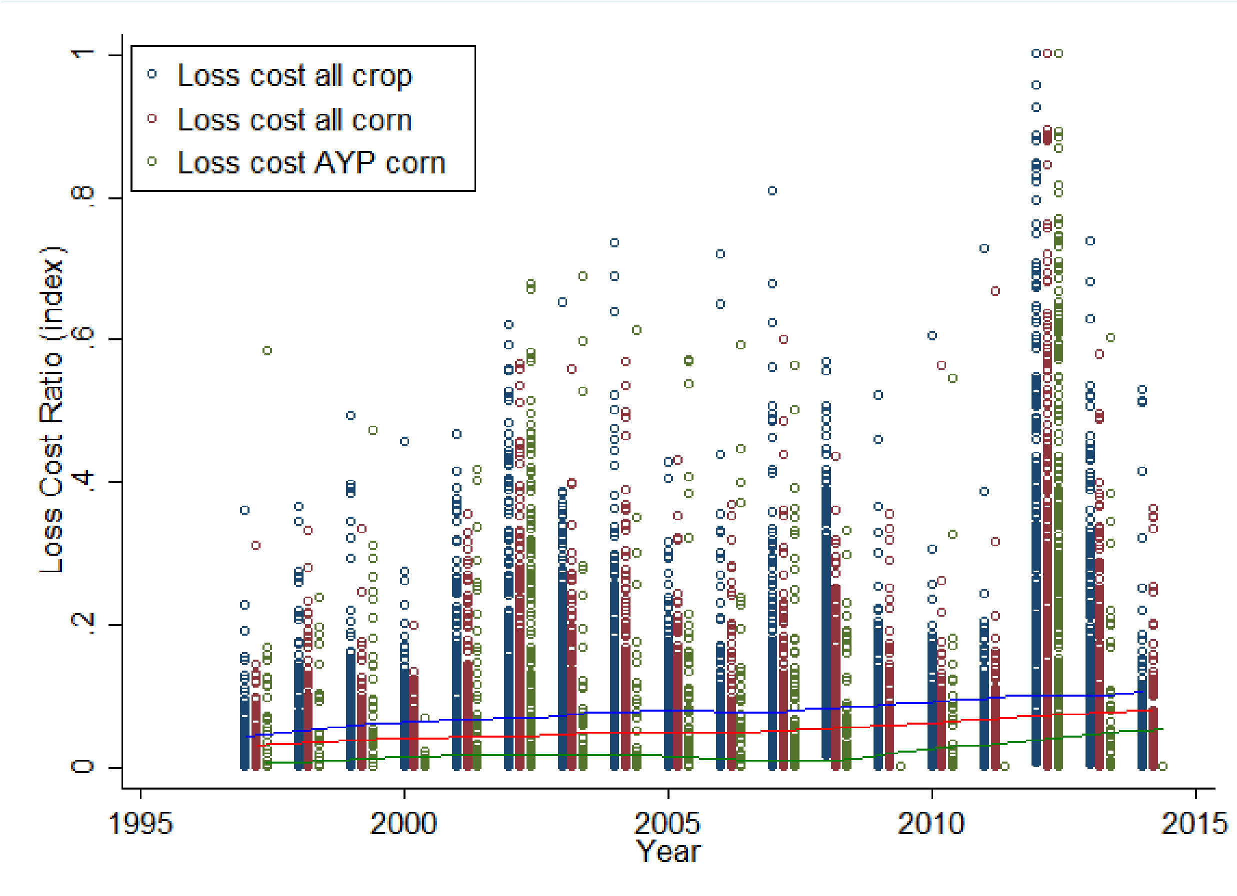

Figure S11: Historical loss cost ratios for all crop policies, all corn policies, and AYP corn policies over time. Each series is converted to an index by dividing by the maximum value within that series. Points denote observed values, the fitted lines are derived from a local polynomial trend regression for each series.

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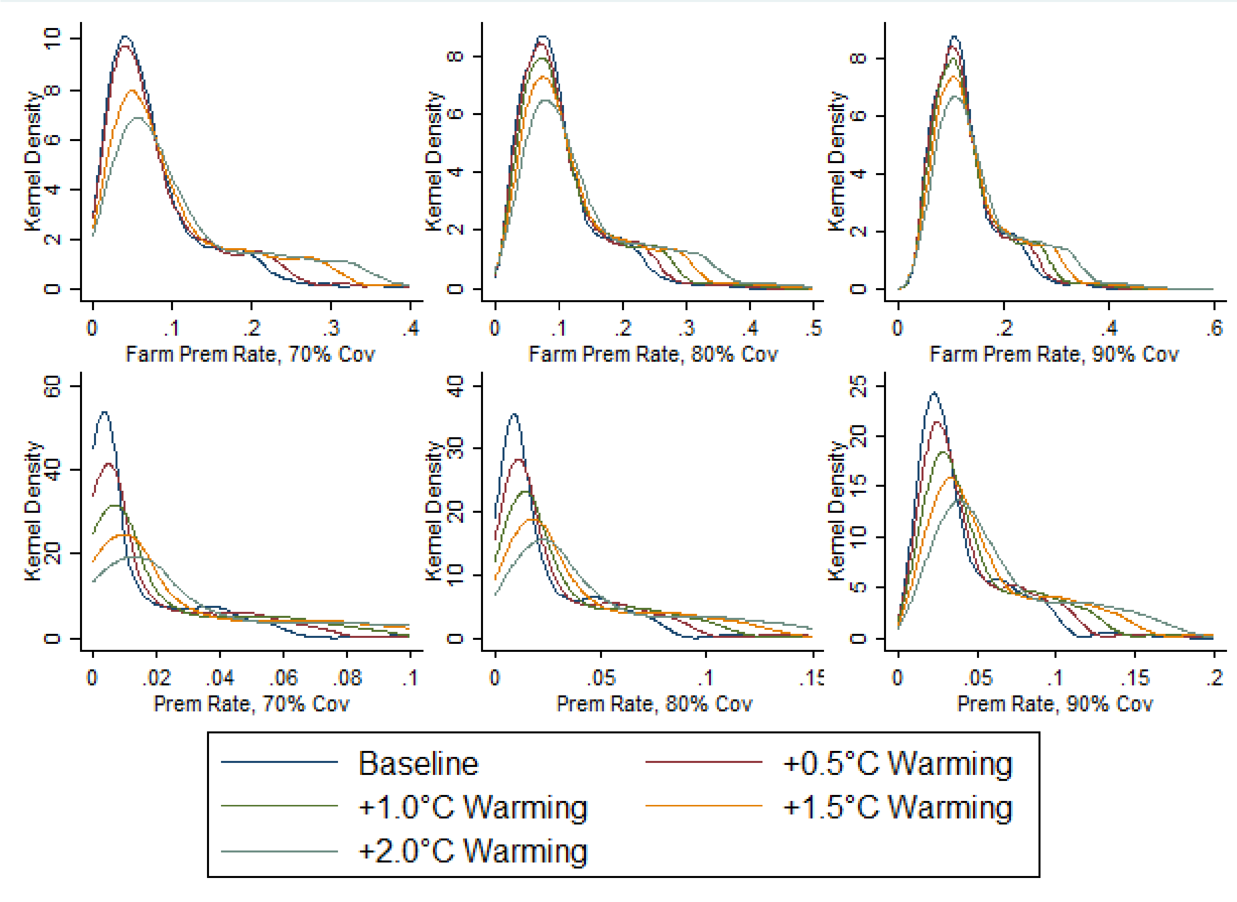

Figure S12: Heterogeneity of both farm- and county-level premium rates for the unconditional yield distributions within and across warming scenarios. The top row are the farm-level rates derived from increasing the variance of the unconditional yield distributions, while the bottom row are the county-level rates from Figure S8. Separate yield densities are estimated for each county-climate combination in the data. Within each coverage level, the 542 county-specific premium rates estimates are summarized under each warming scenario by a kernel density plot.

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