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The Effect of Climate on Crop Insurance Premium Rates and Producer Subsidies

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The likely impacts of climate change in the U.S. include damages to agricultural production resulting from increased exposure to extreme heat (Schlenker and Roberts 2006, 2009; Urban et al. 2012; Fisher et al. 2012). However, there remains considerable uncertainty regarding associated impacts on the performance of the Federal Crop Insurance Program (FCIP), which covered roughly 280 million acres and $116 billion in liabilities in 2012 (FCIC 2012a). These impacts would likely extend beyond the agricultural sector as the heavily subsidized program has averaged over $6.4 billion in taxpayer-sponsored subsidy payments to producers over the last three years (FCIC 2012a).

Here we utilized nearly 40,000 county-level corn yield observations spanning 1950-2005 to predict the effect of a 1°C uniform increase in temperature on crop insurance premium rates and subsidies for the Group Risk Plan. We found a statistically significant increase in premium rates, which is primarily driven by increased exposure to extreme heat. These increases induce large increases in subsidy payments, the incidence of which is spread disproportionately across the U.S. Corn Belt. The implied increase in annual tax payer burden could be as high as $923 million depending on how these findings extrapolate to other crop insurance policies. These results suggest that warming presents an even greater challenge than implied by previous studies.

Corn is the most intensively insured crop in the FCIP with more than 81 million insured acres and $53 billion in liabilities in 2012, and is the biggest driver of total FCIP subsidy payments as the $2.7 billion paid to producers represents 39 percent of all program subsidies (FCIC 2012a,b). The political motivation for this subsidy is to increase FCIP enrollment as farmer participation levels are below those desired by policy-makers (Knight and Coble 1997). Empirical research has consistently found that meeting this objective requires heavy subsidization as insurance demand is largely insensitive to small price changes (Coble and

Barnett 2012; Goodwin 1993; Barnett and Skees 1995; Coble et al. 1997; Barnett et al. 2005; Shaik et al. 2008).

The Federal Crop Insurance Act of 1980 reduced farm dependence on *ex post* disaster assistance, which was previously provided by the federal Disaster Payments Program (Barnett 2000). This Act was coupled with a shift toward a more private-sector oriented program as sales and servicing of policies is conducted by privately owned companies. However, substantial public sector influence remains in the form of government-set premium rates, administrative and operating expense compensation for private sellers, and subsidy payments to producers to induce policy purchases (Coble and Barnett 2012; Coble and Knight 2002).

The key components of any crop insurance policy are the coverage level, guarantee, indemnity, premium, and subsidy. The coverage level is a value between 0.5 and 0.9 that is used to calculate the policy's guarantee, which establishes the threshold below which indemnities are triggered. Essentially, the insured unit/farm receives an indemnity payment if the realized *ex post* production outcome is below the guarantee, and receives nothing otherwise. The premium is the purchase price of the policy, and the subsidy is the amount of this price covered by the government.

Figure 1a plots total FCIP premiums and subsidies over the last ten years, and the stability of the pair plot across years (Fig 1b) demonstrates a stable, proportional relationship between subsidies and premiums. Indeed, the producer paid net-premium (premium less subsidy) is simply the product of the premium and a subsidy factor that is set by the government. This relationship implies a percentage change in premium necessarily equals a percentage change in subsidy, and is confirmed in the data as a regression of log subsidy on log premium generates an r-squared of 0.997 and a parameter estimate of 1.04.

In response to the Intergovernmental Panel on Climate Change findings, many studies have analyzed the effects of climate on the agricultural sector including Schlenker and Roberts (2006, 2009), Urban et al. (2012), Fisher et al. (2012), Lobell and Asner (2003), Lobell et al. (2011), Lobell et al. (2011), Mendelsohn et al. (1994), Pongratz and Lobell (2012), and Schlenker et al. (2005, 2006, 2007). Overall, studies have found that U.S. agriculture will likely not see major impacts over at least the next few decades, but findings vary considerably across contexts (Beach et al. 2010). While farmland value and/or profitability studies suggest relatively minor short-term implications, research focusing on crop yields has found much larger effects (Beach et al. 2010). Initial yield studies focused primarily on mean impacts, however more recent studies have included higher order moments of the crop distribution (Tack et al. 2012).

With the exception of a recent USDA Risk Management Agency report (see Beach et al. 2010), no study has focused on estimating the effects of warming temperatures on the FCIP. While the scope of this report is quite large and covers a range of crops insurance products, the empirical approach assumes that premium rates remain constant and offers no guidance regarding subsidy effects. These shortcomings represent major knowledge gaps as premium rates capture the inherent riskiness of crop production and would thus likely increase under warming as exposure to extreme heat increases. Furthermore, given the proportional relationship between subsidies and premiums, these rate increases would in turn drive up subsidy payments to producers.

Here, we introduce an approach for measuring the impacts of alternative climates on FCIP premium rates and subsidies, which utilizes a rich dataset of historical yield and weather outcomes previously utilized in Schlenker and Roberts (2006, 2009). FCIP premium rates predictions from our model are made using the historical data, and then compared with

predictions based on simulating a 1°C uniform increase in daily temperatures. These comparisons are used to explore whether premium rates and producer subsidies are affected by warming.

Empirical Model

We use a Moment Based Maximum Entropy model to link weather outcomes to crop yields, which is the preferred approach for analyzing climate impacts on yield distributions (Tack et al. 2012). We assume that corn yields follow a Beta distribution as most of the empirical literature in agricultural economics over the past decade has used the beta distribution to model crop yields (Babcock et al. 2004). The Beta distribution is the maximum entropy solution under a specific set of moment constraints, so by regressing the sample moments on a set of regressors one can then predict the moments for different subsets of the data. These predicted moments can then be used to estimate densities using the principle of maximum entropy.

The first step of the Moment Based Maximum Entropy Model is the estimation of a linear moments model using regression analysis. The Beta probability density function is the Maximum Entropy solution under moment constraints defined by $\mu_1 \equiv E\left[\ln(Y)\right]$ and $\mu_2 \equiv E\left[\ln(C-Y)\right]$ where Y is the underlying random variable (corn yield) defined on the positive support $(0, C]$. To ensure that the support contains all reasonable values for corn yields, we fix the upper value of the support at $C \equiv 1.5\max\{y\}$ where $\max\{y\}$ denotes the maximum yield contained in the historical yield sample. The regression equations are defined by

$$\begin{aligned} \ln(y) &= \mathbf{X}'\boldsymbol{\beta}_1 + \varepsilon_1 \\ \ln(C-y) &= \mathbf{X}'\boldsymbol{\beta}_2 + \varepsilon_2 \end{aligned} \tag{1}$$

where the set of regressors $\mathbf{X}$ contains low, medium, and high temperature exposure, precipitation, precipitation squared, county-level fixed effects, and a trend to account for changes in technology over time.

Parameter estimates for the moments model given by (1) are estimated using OLS. For the baseline climate scenario, we predict the two Beta-defining moments according to $\hat{\mu}_j = \bar{\mathbf{X}}'\hat{\boldsymbol{\beta}}_j,\ j = 1,2$ where $\bar{\mathbf{X}}$ is the sample average of the regressors. We do the same for the warming scenario, except the temperature variables in $\mathbf{X}$ are recalculated in accordance with a 1°C uniform increase in daily minimum and maximum temperatures as in Tack et al. (2012). We modify publicly available Matlab code for univariate maximum entropy density estimation from Wu (2003) to reflect the use of a Beta distribution, and use the predicted moments to estimate baseline and warming densities $\hat{f}^0(y \mid \mathbf{X} = \bar{\mathbf{X}}^0)$ and $\hat{f}^1(y \mid \mathbf{X} = \bar{\mathbf{X}}^1)$ for each county in the data. A more detailed discussion of the Moment Based Maximum Entropy model is provided in Tack et al. (2012)

Data

This study focuses on the U.S. Corn Belt, one of the most intensive corn growing regions in the world, which produced 7.8 billion bushels of corn (nearly 75 percent of total U.S. production) in 2012. We include all counties in Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Nebraska, Ohio, and Wisconsin, which represented 77 percent of FCIP corn liabilities in 2012 (FCIC 2012b). This region has a fairly homogenous April to September growing season, and previous research indicates that warming will have large negative effects on yields (Schlenker and Roberts 2006, 2009).

The dataset combines yield data from the National Agricultural Statistics Service with the best available historical temperature and precipitation data, and contains 39,200 observations spanning 700 counties from 1950-2005. We utilize the same low, medium, and high temperature degree day measures as Schlenker and Roberts (2009). Exposure to 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. The precipitation variable is measured 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 2006, 2009; Tack et al. 2012), and a summary of the data is provided in Table 1 and Figure 2.

Empirical Results

The Federal Crop Insurance Corporation (FCIC) currently lists 17 different insurance plans available to producers, the most popular of which are farm-based policies in that indemnities are triggered by farm level outcomes. As an alternative, the FCIC also offers the Group Risk Plan (GRP) and the Group Risk Income Protection plan, both of which are triggered by county level outcomes. The GRP program has received much attention as it has the potential to mitigate the adverse selection and moral hazard problems that are associated with farm-based policies (Barnett et al. 2005; Deng et al. 2007; Harri et al. 2011). Thus, we focus on the GRP program here.

Moments of the Beta Distribution

The effects of temperature and precipitation on the characterizing moments of the Beta distribution are summarized in Table 2. We include all three degree day measures of temperature, a quadratic formulation for precipitation, state-specific trends, and county fixed effects. The parameters are estimated using OLS with standard errors clustered by year to account for arbitrary patterns of spatial correlation among the residuals. The r-squared values suggest that a large portion of the variation in the dependent variables is explained by the regressors, thus implying a reasonable level of fit. Consistent with previous findings, exposure to extreme heat is the biggest driver of yield response among the temperature variables, and precipitation has the standard inverted-U effect on log yields. Importantly, weather affects the yield distribution through both of the characterizing moments as nearly all variables are statistically significantly different from zero across both equations.

Proper identification of weather effects in this data requires accounting for gradual trends in yields due to technology changes. 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 et al. 2011).

We account for nonlinear technological change by modeling the trend component in each year $t = 1, ..., T$ as

(2) $$trend_t = \alpha_0 t + \theta_1 \sin(2\pi\tilde{t}) + \theta_2 \cos(2\pi\tilde{t}) + \theta_3 \sin(4\pi\tilde{t}) + \theta_4 \cos(4\pi\tilde{t})$$

where $\tilde{t} \equiv t / T$. This approach utilizes a set of functionally flexible trigonometric functions to nest the more commonly used linear technological change model defined by $\boldsymbol{\theta} = \mathbf{0}$, and we allow for the trend parameters α_0 and $\boldsymbol{\theta}$ to vary by state to capture potential differences in technological change. We find that both extensions are warranted as the p-value for a Wald test

of constant coefficients across states is 0.000, and the largest p-value for state-specific Wald tests of the null hypothesis $\boldsymbol{\theta} = \mathbf{0}$ is 0.061.

Baseline and Warming Densities

The effects of warming are measured relative to historical climate, which is constructed as the sample average of the weather variables within each county. These averages are used to predict county-specific moments, which in turn generate county-specific baseline densities. Conversely, to construct densities for the warming scenario, we first modify the underlying temperature data so that the daily minimum and maximum values are increased by 1°C. These changes are aggregated up to the county-year level for all observations, and used to construct new low, medium, and high degree day measures. Next, we calculate sample averages of the new temperature variables within each county, predict the associated moments, and then estimate the corresponding warming densities.

The baseline and warming densities are reported for the largest producing counties within each state in Supplementary Figures S1-S9. The legend in each figure includes both the mean,

(3) $$M^s \equiv E(y^s) = \int_0^C y\hat{f}^s(y \mid \mathbf{X} = \overline{\mathbf{X}}^s)dy,\ s = 0 \text{ (baseline) and 1 (warming)},$$

and downside risk, where downside risk is measured as the partial variance below the mean,

(4) $$D^s \equiv Var^-(y^s) = \int_0^{M^s} (y - M^s)^2\, \hat{f}^s(y \mid \mathbf{X} = \overline{\mathbf{X}}^s)dy,\ s = 0 \text{ (baseline) and 1 (warming)}.$$

It is clear that the magnitude of the warming effect varies by state, but the general pattern is a decrease in the mean coupled with an increase in downside risk.

Figure 3 provides kernel density plots for the county-level effects of warming on mean yield for the full sample (Fig 3a), western region (Iowa, Minnesota, Missouri, and Nebraska; Fig

3b), and eastern region (Illinois, Indiana, Michigan, Ohio, and Wisconsin; Fig 3c). The acreage-weighted average impacts across panels a-c are -4.23%, -4.61%, and -3.76%, so the reduction in mean yields is roughly one percentage point higher on average for the eastern versus western region. While negative on average, nearly ten percent of the counties in the sample have positive impacts. Unsurprisingly, these positive impacts are concentrated among the northern states of Michigan, Minnesota, and Wisconsin, with just over 65 percent of all Wisconsin counties experiencing an increase. The estimated densities and associated findings are consistent with previous findings in the literature.

GRP Rate Effects

The estimated densities are used to quantify the effect of warming on per-acre actuarially fair premium rates for GRP insurance policies. The estimated rates for coverage levels $cov \in [.5,.9]$ are calculated as the ratio of expected indemnity over liability for each county,

(5) $$rate_{cov}^{s} = E(indemnity_{cov}^{s}) / liability_{cov}^{s},$$

where

(6) $$\begin{aligned} E(indemnity_{cov}^{s}) &= \int_0^{y_{cov}} [(y_{cov} - y) / cov] \hat{f}^{s}(y \mid \mathbf{X} = \overline{\mathbf{X}}^{s}) dy, \\ liability_{cov}^{s} \equiv y_{cov}^{s} &= covE^{s}(y) = cov \int_0^{C} y \hat{f}^{s}(y \mid \mathbf{X} = \overline{\mathbf{X}}^{s}) dy. \end{aligned}$$

The factor $1/cov$ in the expected indemnity calculation reflects the "disappearing deductible" that is built into GRP contracts (Barnett et al. 2005).

Acreage-weighted rate averages for the baseline and warming scenarios are reported in Figure 4. Panels a-c plot the calculated GRP rates against coverage levels, while panels d-f report corresponding pair plots constructed as the ratio of the warming rate over the baseline rate. The implied percentage change in rates is simply $100(ratio - 1)$, and for the entire sample warming

increases premium rates between 9-30 percent (Fig. 4d). The rate increases are much larger for low coverage levels, which is consistent with an increased frequency of large-scale crop loss under warming. However, these averages mask a considerable amount of regional heterogeneity as the ratios are much smaller in the western region (Fig. 4e) relative to the eastern region (Fig. 4f).

To evaluate the uncertainty around these impacts, 95 percent confidence intervals are constructed for the ratios in Figure 4d based on a block bootstrapping routine that is robust to spatial correlation. For each of 999 bootstrap iterations, we first construct a bootstrap sample by sampling with replacement whole years from the data. Importantly, block sampling whole years preserves any spatial correlations across counties inherit in the data. Each bootstrap sample is used to re-estimate the parameters of the regression model, which are then used to predict the moments for the baseline and warming scenario for the largest producing county in each state. These moments are then used to re-estimate the Beta densities and calculate the corresponding premium rate ratios, which are in turn acreage-weighted to construct sample averages as in Figure 4d. For each coverage level, this generates 1000 premium rate ratios, which are sorted from smallest to largest. The 25th and 975th ordered observations represent the lower and upper bounds for a 95 percent confidence interval. The constructed interval for each coverage level does not span a ratio of one, which implies that the estimated rate increases are statistically significantly different from zero.

Recalling that the distinction between baseline and warming scenarios is driven by changes in the degree day variables, we evaluate the relative importance of each temperature variable using an analysis of variance. We regress GRP rate differences on differenced temperature variables using pooled OLS, the results of which are reported in Table 3. Model (1)

yields an r-squared of 0.001, so coverage level fixed effects alone do not explain much of the variation in rate differences. The next three models demonstrate the relative importance of changes in high temperature as model (4) generates the largest r-squared increase. The next two models demonstrate the relative importance of adding low versus medium temperature to the model, and the results of model (7) show that 24.3 percent of the variation in rate differences is explained by the combination of all temperature variables. Interestingly, nearly all the remaining variation is explained by the inclusion of county fixed effects, which suggests that the effects of warming on crop insurance will be highly localized even after changes in temperature patterns have been taken into account.

Producer Subsidy Effects

Per-acre premiums for the GRP contract are the product of the liability, premium rate, and the subsidy factor,

(7) $$premium_{cov}^{s} = liability_{cov}^{s} \times rate_{cov}^{s} \times sf_{cov}^{s}.$$

This implies that the per-acre subsidy is proportional to the expected indemnity since

(8) $$\begin{aligned} subsidy_{cov}^{s} &= premium_{cov}^{s}\Big|_{sf=0} - premium_{cov}^{s} \\ &= liability_{cov}^{s} \times rate_{cov}^{s} - liability_{cov}^{s} \times rate_{cov}^{s} \times sf_{cov}^{s} \\ &= liability_{cov}^{s} \times rate_{cov}^{s} \times (1 - sf_{cov}^{s}) \\ &= E(indemnity_{cov}^{s}) \times (1 - sf_{cov}^{s}), \end{aligned}$$

which in turn implies that the percentage in subsidy to equal to the percentage change in expected indemnity since

(9) $$\begin{aligned} \frac{subsidy_{cov}^{1} - subsidy_{cov}^{0}}{subsidy_{cov}^{0}} &= \frac{E(indemnity_{cov}^{1}) \times (1 - sf_{cov}) - E(indemnity_{cov}^{0}) \times (1 - sf_{cov})}{E(indemnity_{cov}^{0}) \times (1 - sf_{cov})} \\ &= \frac{E(indemnity_{cov}^{1}) - E(indemnity_{cov}^{0})}{E(indemnity_{cov}^{0})}. \end{aligned}$$

Acreage-weighted average subsidy impacts are plotted against coverage levels in Figure 5, and range from 4.9 to 32.8 percent for the full sample (Fig. 5a). Interestingly, the subsidy incidence varies across regions as the percentage increase is nearly twice as large for eastern producers across all coverage levels (Fig. 5b). The reason for this disproportionate increase is that warming generates a more risky production environment in the east, as evidenced by the rate difference pair plots in Figures 4e and 4f.

We combine the results from Figure 2 with 2012 FCIP subsidy data to measure the implied impact U.S. taxpayers, which are reported in Table 4. Column 1 provides subsidy payments by coverage level for the corn Group Risk Program, which totaled $5 million dollars in 2012. The level increase in subsidy payment is rather small at $300,000 since the majority of acreage in this program is enrolled at the highest coverage level. However, if the findings here extrapolate to other corn-based insurance policies offered by the FCIP, which is likely given that the majority of other policies are farm-based and thus inherently more risky, the level impact becomes just over $300 million dollars. Furthermore, but perhaps less realistic, if these findings extrapolate to the other crops covered by the FCIP then the level impact is nearly $1 billion.

Conclusion

This research focused on two components of a standard FCIP contract, the premium rate and the producer subsidy. Premium rates essentially capture the cost of the crop insurance coverage, which is positively correlated with yield risk. Previous research has linked warming to increased yield risk, which in turn suggests that warming will also increase premium rates. Our empirical analysis confirms this hypothesis, and provides estimates of premium rate changes and implied subsidy effects under a $1^{o}C$ warming scenario.

These increased premium rates imply increased crop insurance subsidies and the associated taxpayer burden of the program. Whether these results hold beyond the crop and insurance policy considered in this study is a question for future research to address, and will probably depend on the degree to which other crop policy premium rates respond to increased exposure to extreme heat. This represents the major limitation of this research, however the findings provide a benchmark for future research that expands the scope of insurance instruments.

The FCIP represents the most widely used risk protection policy instrument in the U.S., and current debate on the extension of the Farm Bill suggests that the next wave of agricultural policy will provide an even greater emphasis on this type of protection. As such, the findings reported here should benefit policy makers, as well as the academic community. The FCIP is a highly subsidized program as the government currently covers over fifty percent of the insurance cost. This subsidy is directly proportional to the cost of insurance by design, so that a percentage change in premium will generate an equal percentage change in subsidy. This implies that as premium rates increase the taxpayer burden increases as well. 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.

As a final note, the structure and performance of the FCIP is of great interest globally. In particular, the public/private nature of the FCIP is attractive to agrarian-based developing countries as the cost of risk protection is at least partly offset by private companies. This interest might lessen if the subsidization required to induce participation increases under climate change.

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Tables

Table 1 | Yield and Weather Data: 1950-2005

Variable	Sample Mean (s.d.)	Min	Max	Obs
All Years				
Cotton Yield (bushels per acre)	92.90 (35.73)	0.041	200.0	39,200
Low Temperature (degree days)	1,706 (56.86)	1,433	1,825	39,200
Medium Temperature (degree days)	1,645 (255.5)	8,48.3	2,496	39,200
High Temperature (degree days)	21.67 (21.76)	0.000	240.4	39,200
Precipitation (centimeters)	55.98 (13.59)	14.18	126.9	39,200

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

Table 2 | Regression results for corn yield moments

	1	2
Dependent variable:	**ln(Yield)**	**ln(C-Yield)**
Low Temperature	0.0123	-0.0351**
	[0.0308]	[0.0153]
Medium Temperature	0.0329**	-0.0000213
	[0.0138]	[0.00621]
High Temperature	-0.872***	0.258***
	[0.0956]	[0.000436]
Precipitation	1.55***	-0.624***
	[0.383]	[0.177]
Precipitation Squared	-0.0137***	0.00549***
	[0.00292]	[0.00138]
County Fixed Effects	Y	Y
State Trends	Y	Y
N	39,200	39,200
R-sq	0.849	0.834

Notes: Table shows results of regressing ln(yield) and ln(c-yield) on temperature and precipitation. Parameter estimates and standard errors scaled up by a factor of 100. 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% levels.

Table 3 | R-squared results for regressions of premium rate difference

Dependent variable: Premium Rates Differences due to Warming								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Diff Low Temperature	N	Y	N	N	Y	N	Y	Y
Diff Med Temperature	N	N	Y	N	N	Y	Y	Y
Diff High Temperature	N	N	N	Y	Y	Y	Y	Y
Coverage Level FE	Y	Y	Y	Y	Y	Y	Y	Y
County FE	N	N	N	N	N	N	N	Y
R-squared	0.001	0.088	0.007	0.211	0.234	0.232	0.243	0.989

Notes: Table shows results of regressing estimated premium rate differences on combinations of differenced temperature variables and county fixed effects. Coverage level fixed effects are included in all regressions.

Table 4 | Subsidy outlay and warming impacts, 2012

Cov Level	(1) GRP Corn	(2) All Corn	(3) All All
50	--	53.9	441
55	--	4.75	36
60	--	40.2	276
65	0.249	138	600
70	0.133	551	1,694
75	0.073	906	2,178
80	0.146	646	1,117
85	0.442	268	454
90	3.99	69.7	146
Total	5.033	2,677	6,942
Impact	0.307	304	923

Notes: Table shows the 2012 subsidy levels in million dollars for various insurance policies and coverage levels. GRP corn refers to the Group Risk Plan for corn, All Corn refers to all insurance policies for corn, and All All refers to all insurance policies for all crops.

Figures

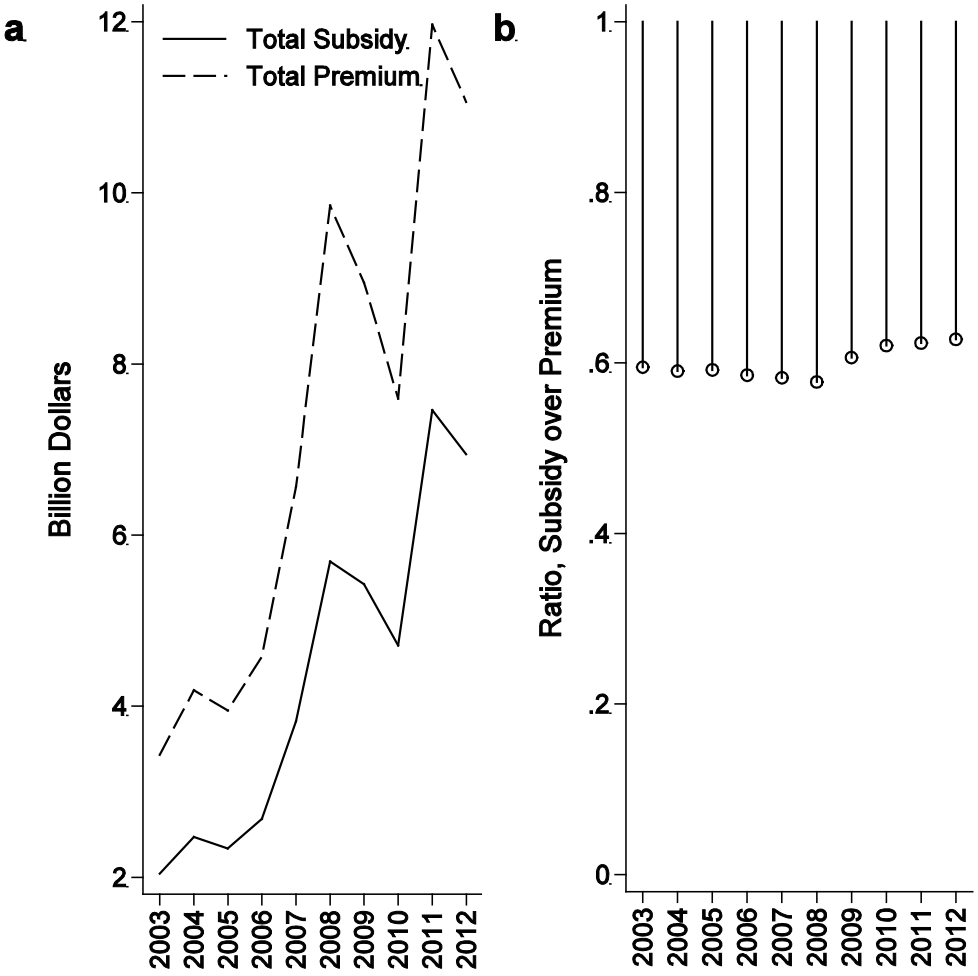

Figure 1 | Insurance premiums and subsidies for the Federal Crop Insurance Program, 2002-2012. a, The total dollar value of subsidies and premiums for all policies. **b**, A pair plot of these values measured as the ratio of subsidies over premiums.

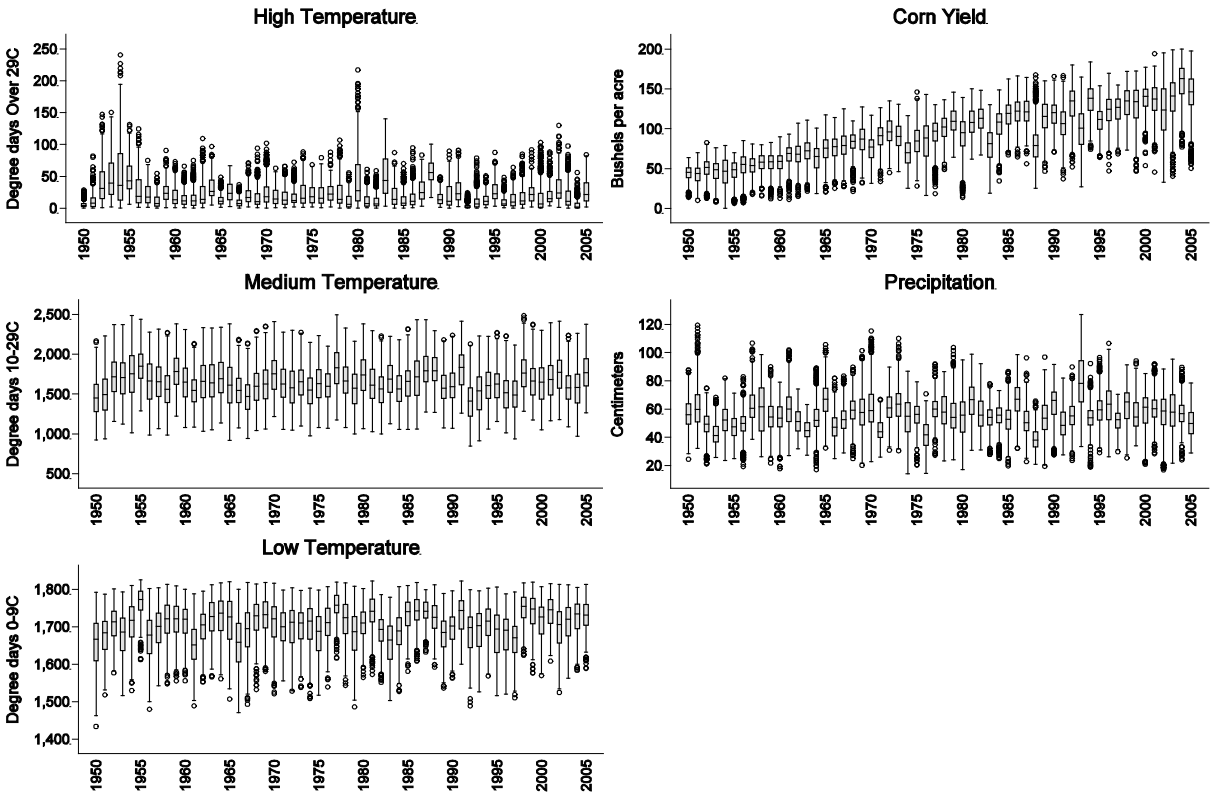

Figure 2 | Annual box plots for county level yield and weather sample data, 1950-2005. Each box is defined by the upper and lower quartile, with the median depicted as a horizontal line within the box. The endpoints for the whiskers are the upper and lower adjacent values, which are defined as the relevant quartile +/- three-halves of the interquartile range, and circles represent data points outside of the adjacent values.

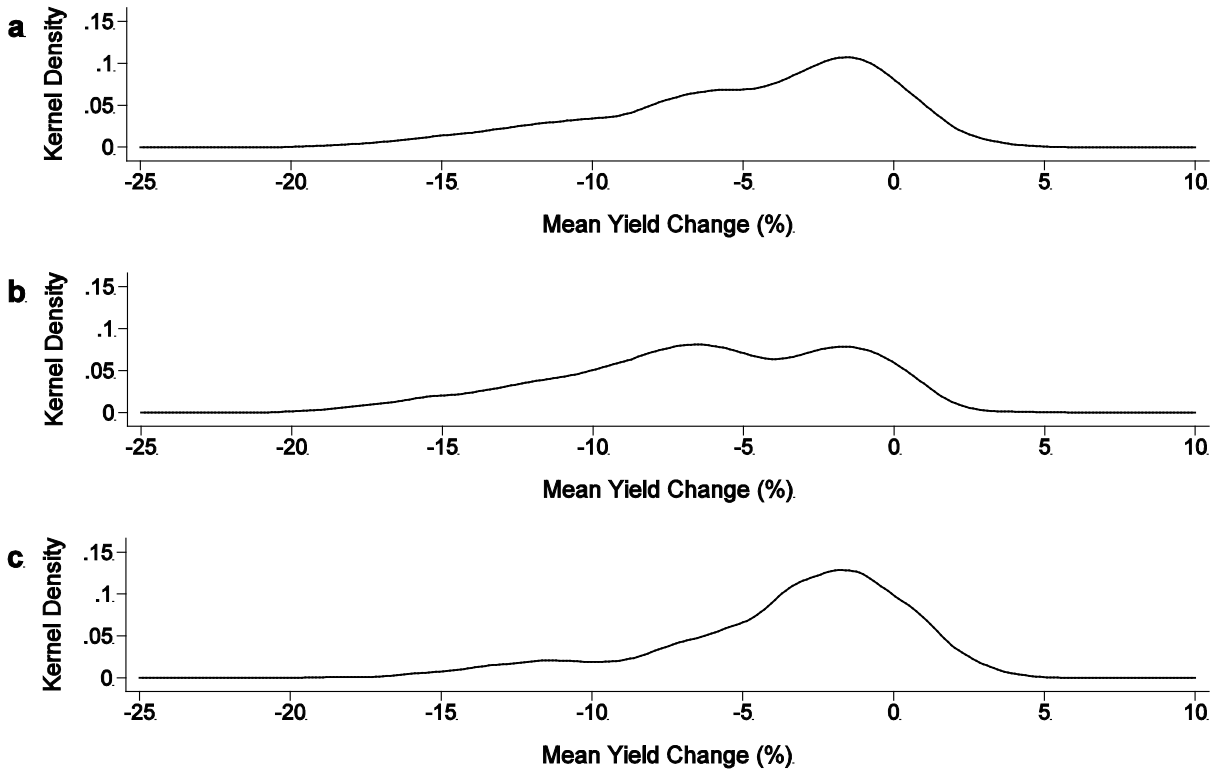

Figure 3 | Percentage change in mean yield due to warming. The percentage change in mean yield due to warming is estimated for each county in the data, and reported as kernel density plots for the full sample (**a**), western region (**b**), and eastern region (**c**). For each plot, an Epanechnikov kernel function is used with the bandwidth set at the value that would minimize the mean integrated squared error if the data were Gaussian and a Gaussian kernel was used.

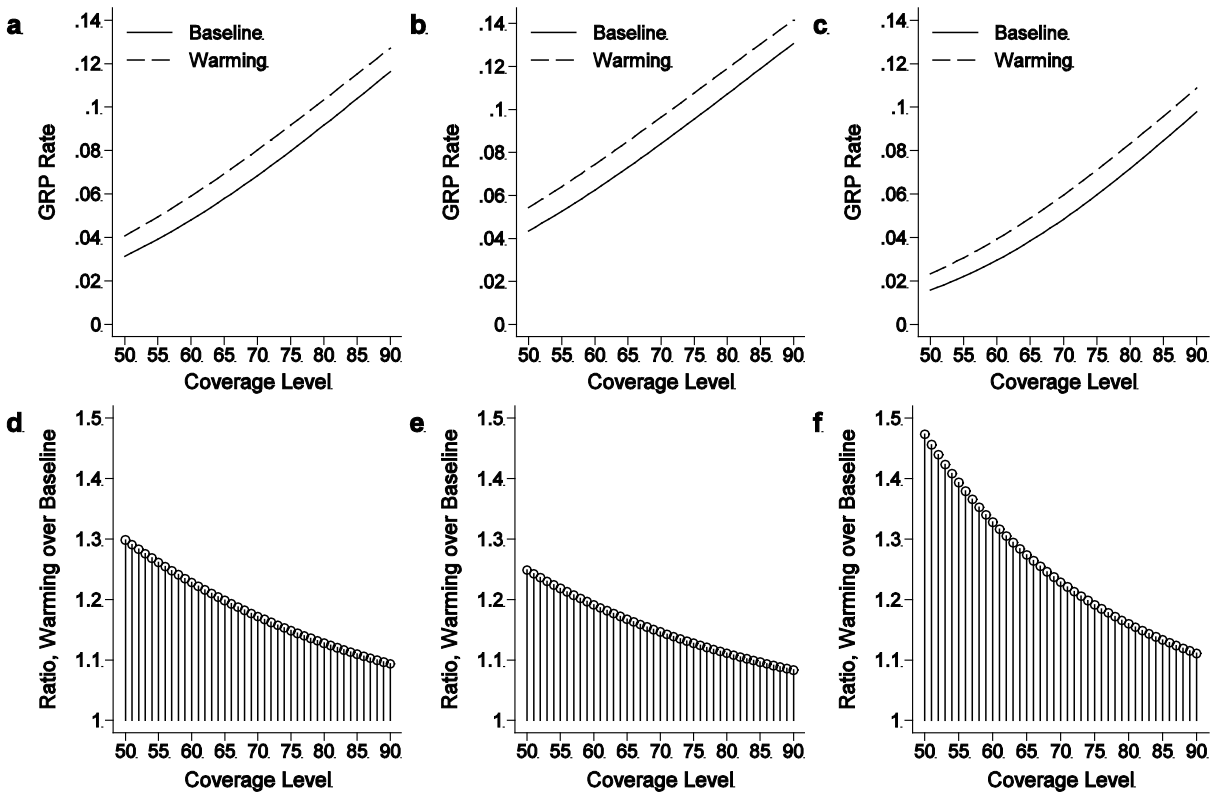

Figure 4 | Actuarially fair Group Risk Plan premium rates for baseline and warming scenarios. a-c, Estimated premium rates plotted against coverage levels for baseline and warming scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. Rates are calculated for each county in the data, and then acreage-weighted averages are constructed for the full sample (a), western region (b), and eastern region (c). **d-f**, Pair plots of these values measured as the ratio of the warming rate over the baseline rate for the full sample (d), western region (e), and eastern region (f).

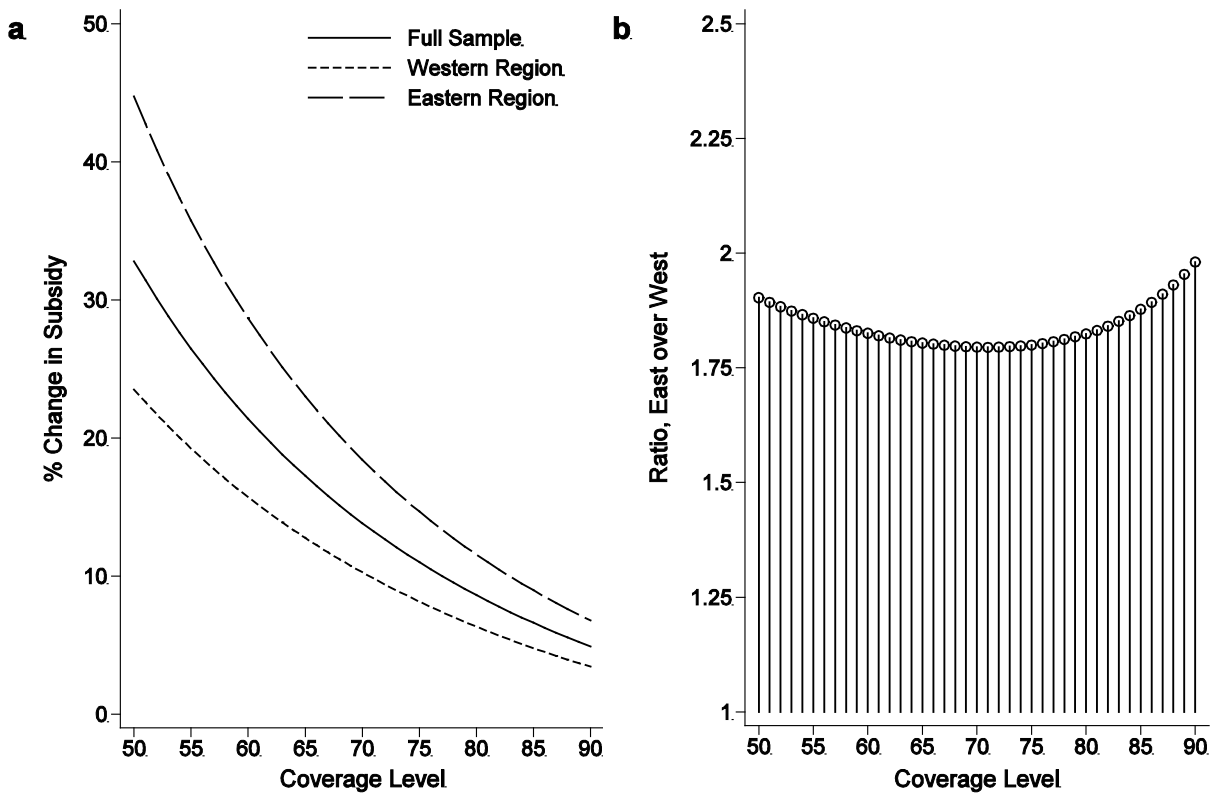

Figure 5 | Percentage change in Group Risk Plan subsidies due to warming. a, Estimated percentage changes in producer subsidies due to warming plotted against coverage levels. Percentage changes are calculated for each county in the data, and then acreage-weighted averages are constructed for the full sample, western region, and eastern region. **b**, A pair plot of the regional impacts, measured as the percentage change in the eastern region over the percentage change in the western region.

Supplementary Figures

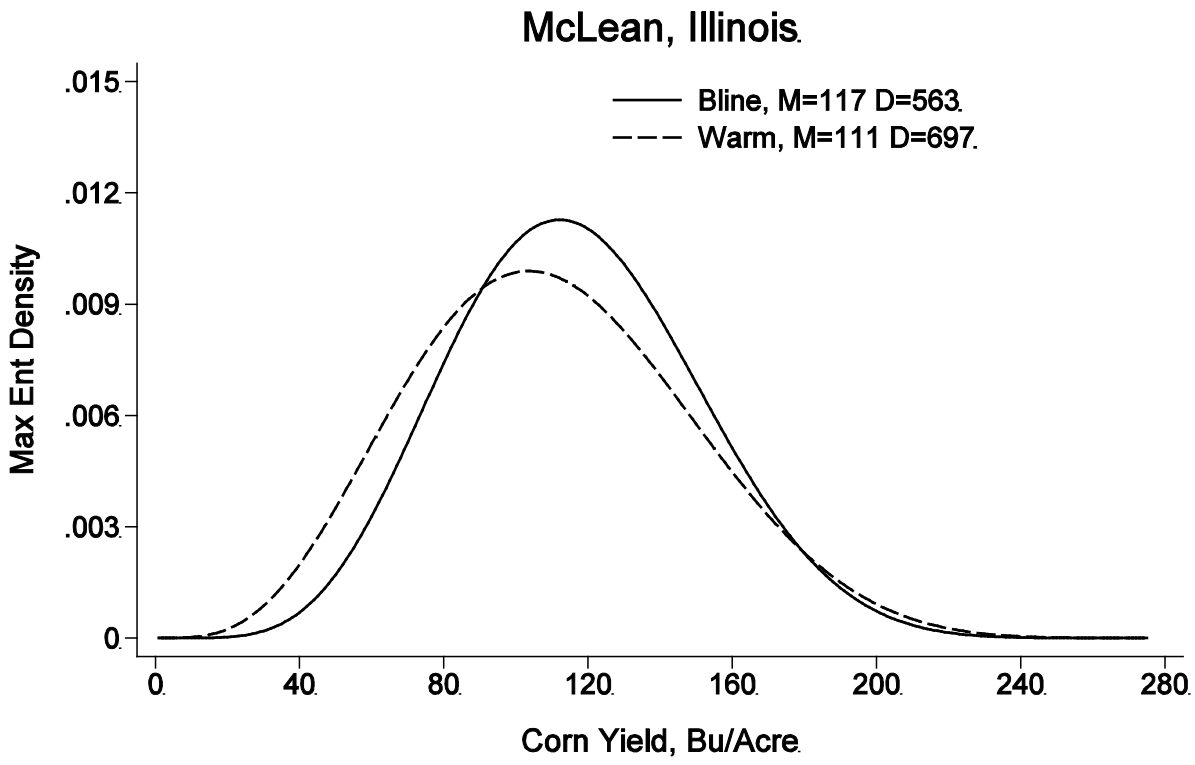

Figure S1 | Maximum entropy corn yield distributions for baseline and warming scenarios: McLean, Illinois. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

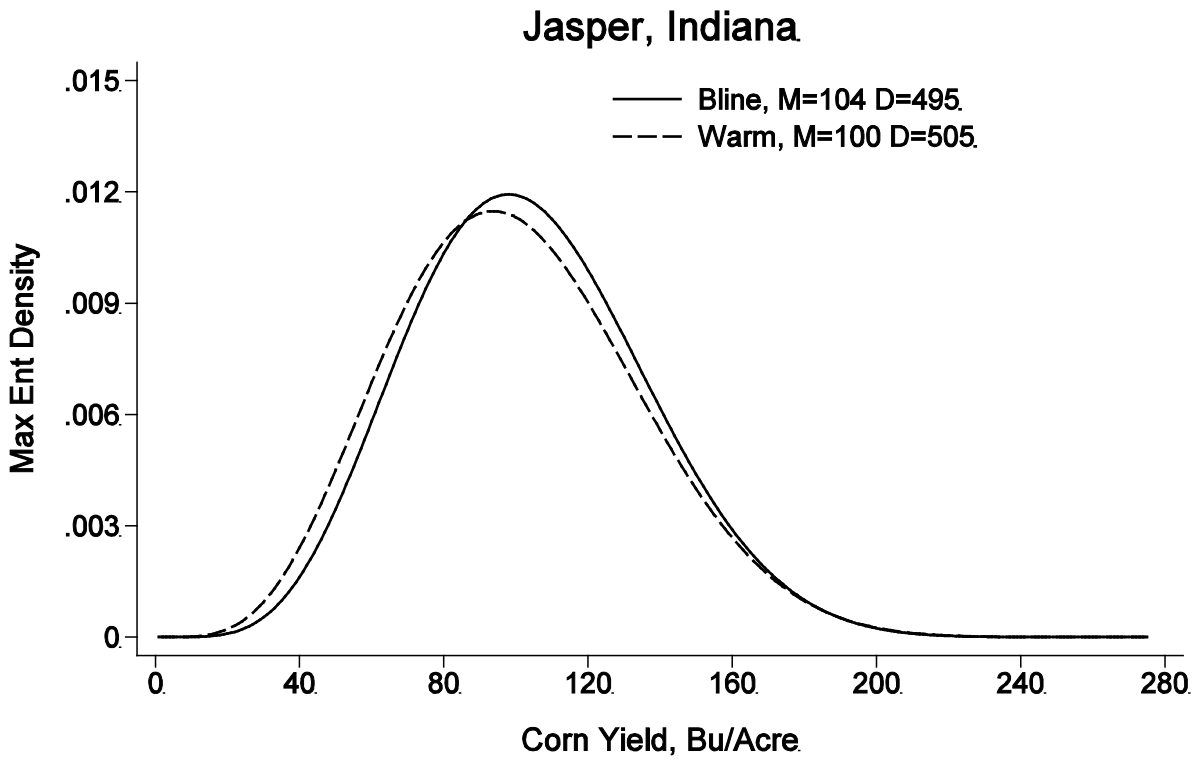

Figure S2 | Maximum entropy corn yield distributions for baseline and warming scenarios: Jasper, Indiana. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

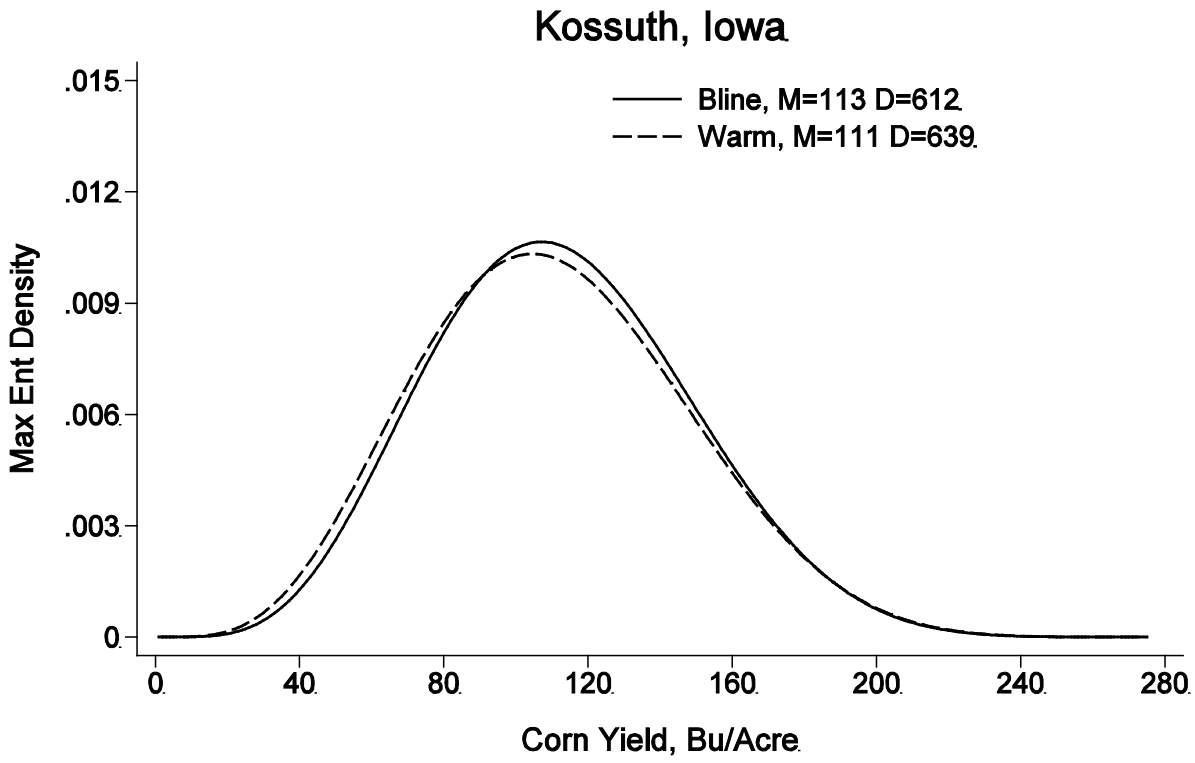

Figure S3 | Maximum entropy corn yield distributions for baseline and warming scenarios: Kossuth, Iowa. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

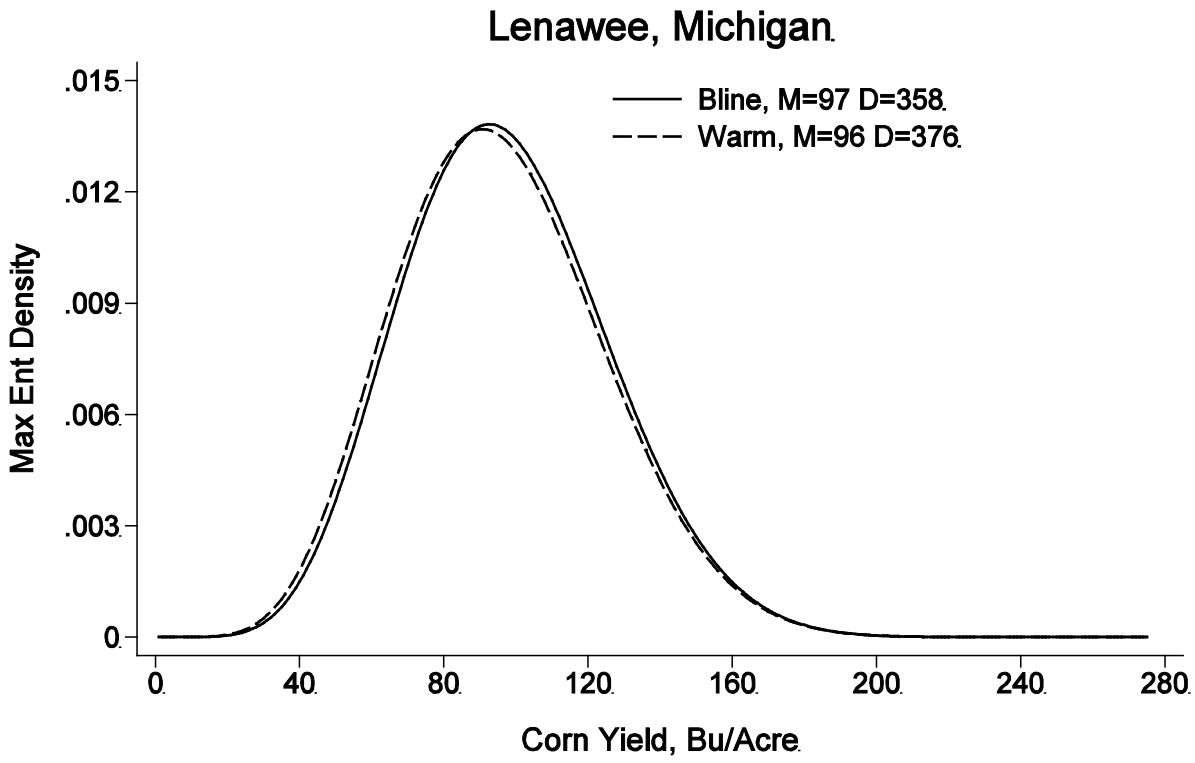

Figure S4 | Maximum entropy corn yield distributions for baseline and warming scenarios: Lenawee, Michigan. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

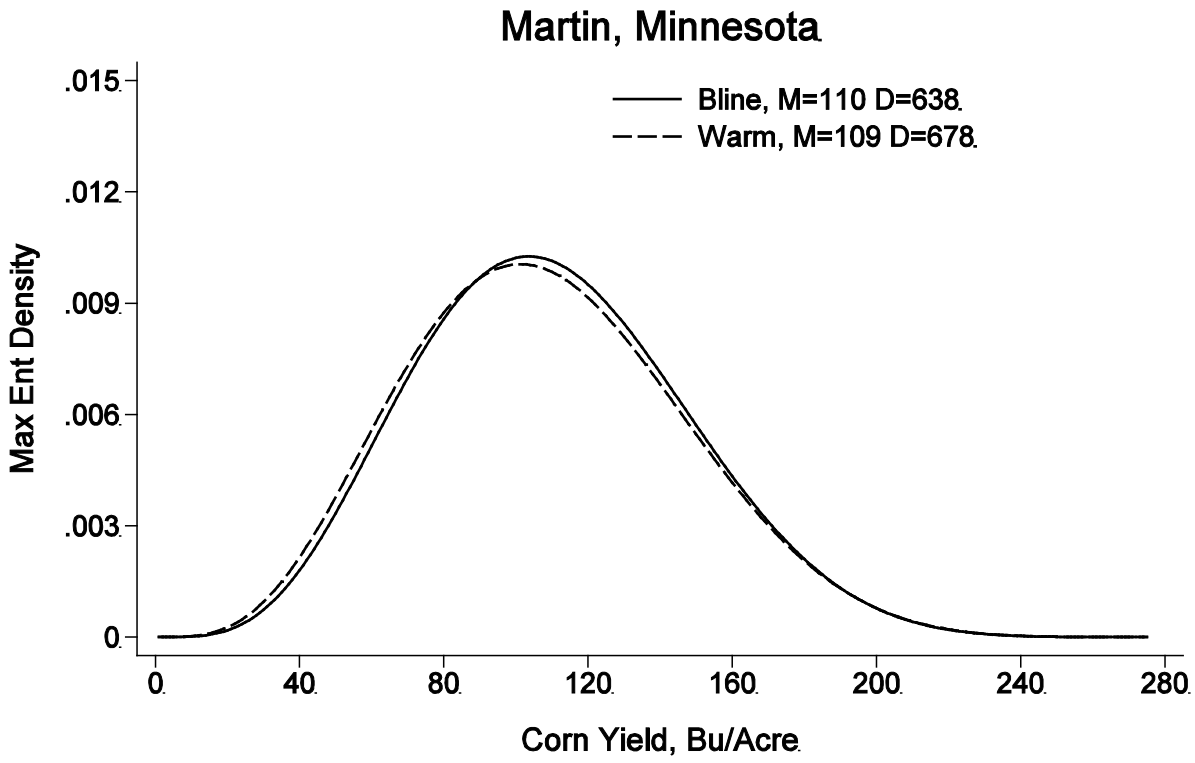

Figure S5 | Maximum entropy corn yield distributions for baseline and warming scenarios: Martin, Minnesota. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

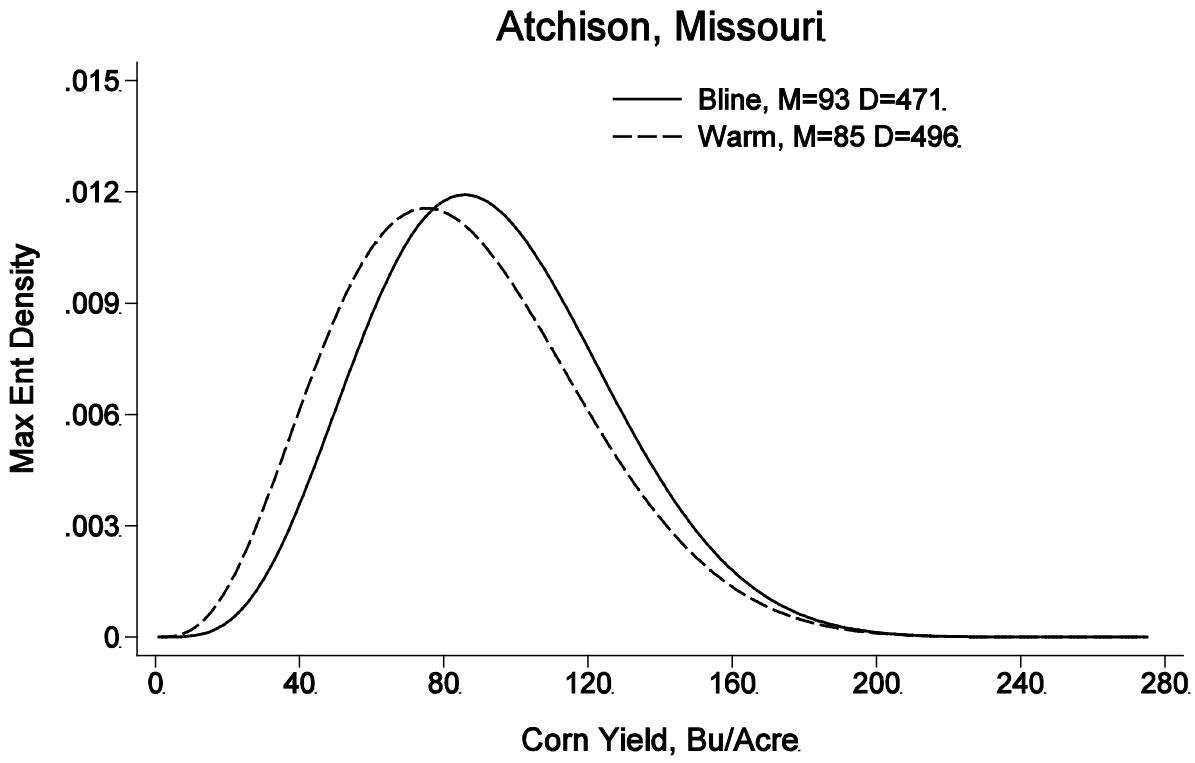

Figure S6 | Maximum entropy corn yield distributions for baseline and warming scenarios: Atchison, Missouri. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

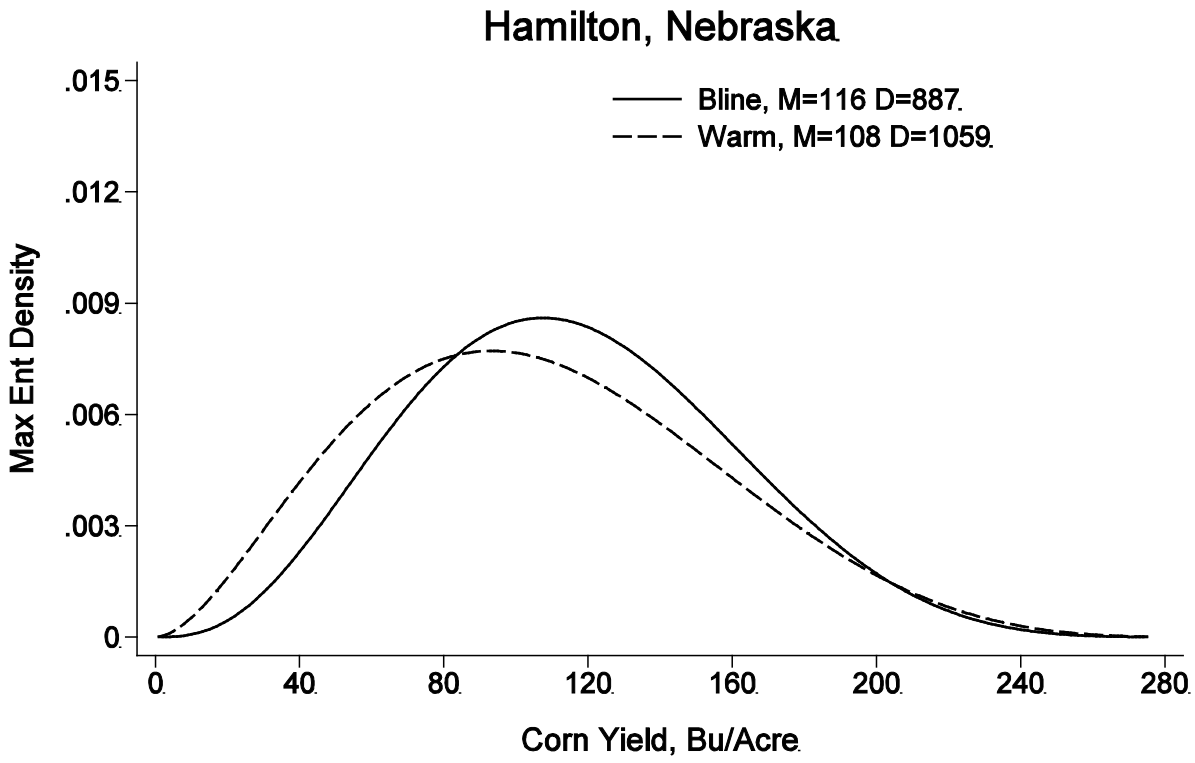

Figure S7 | Maximum entropy corn yield distributions for baseline and warming scenarios: Hamilton, Nebraska. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

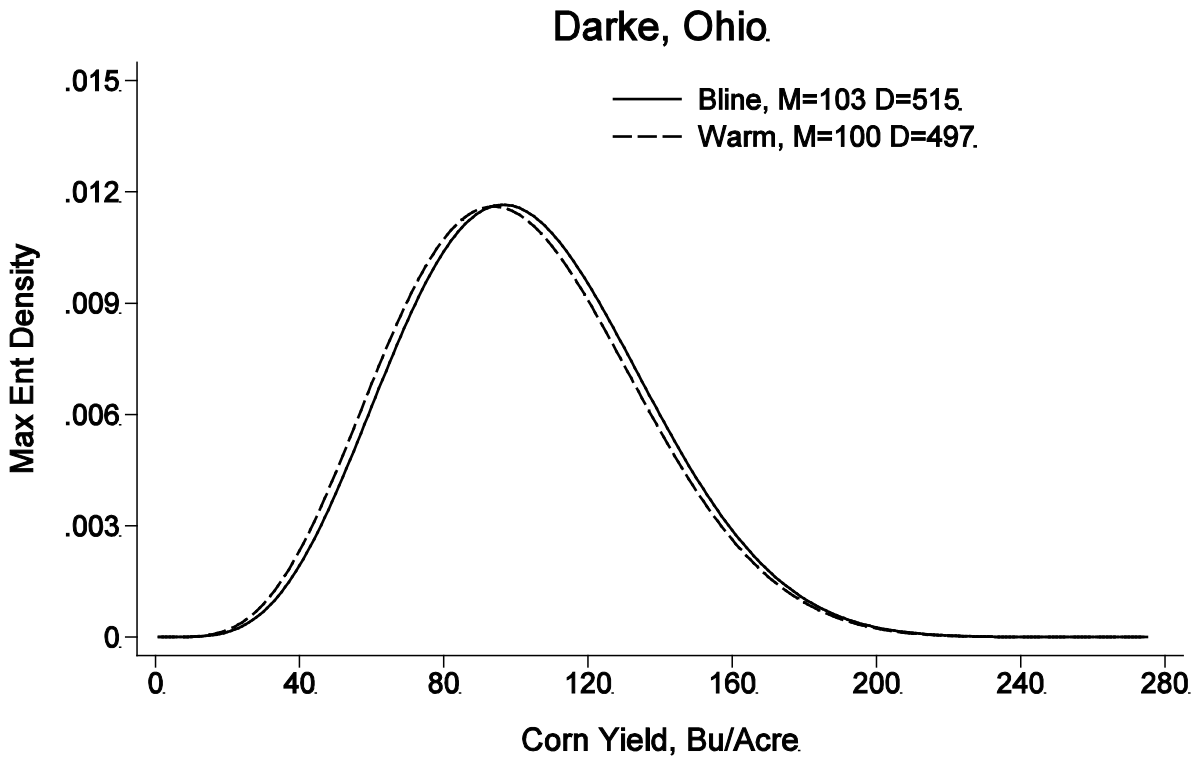

Figure S8 | Maximum entropy corn yield distributions for baseline and warming scenarios: Darke, Ohio. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.

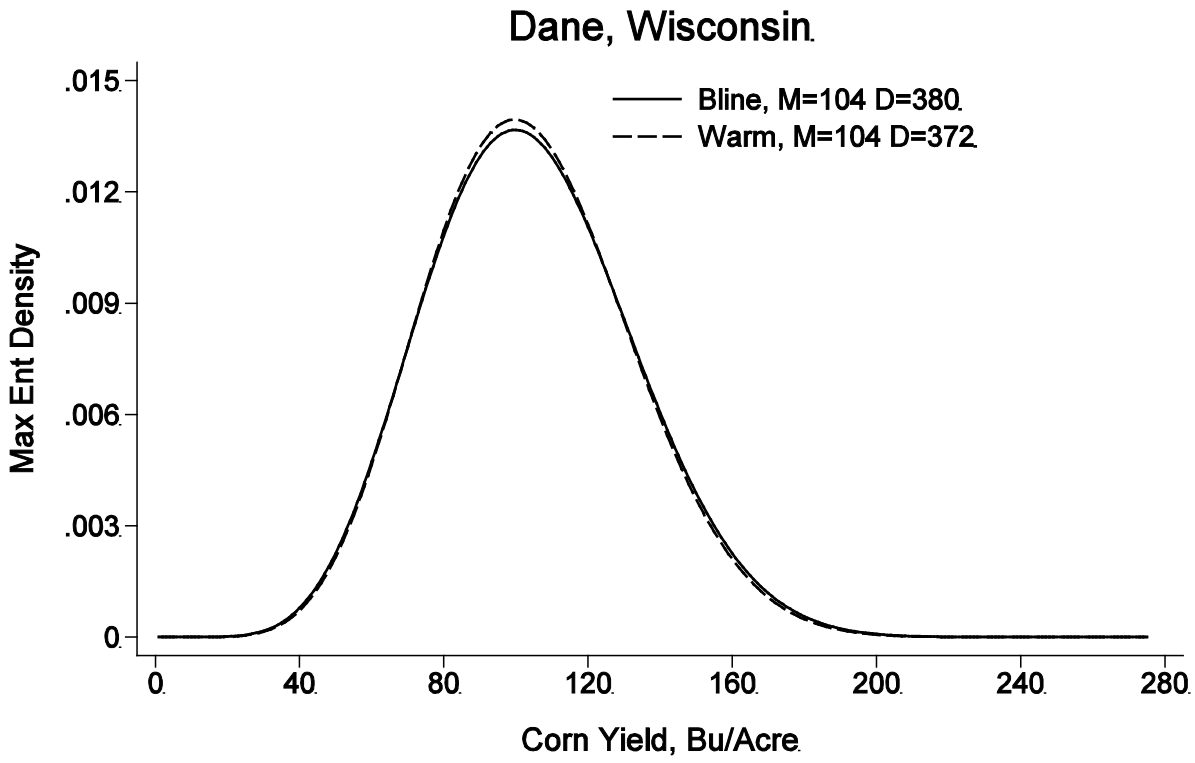

Figure S9 | Maximum entropy corn yield distributions for baseline and warming scenarios: Dane, Wisconsin. Densities are estimated using the Moment Based Maximum Entropy for the baseline (Bline) and warming (Warm) scenarios. The baseline scenario holds temperature variables fixed at the sample average of the data, while the warming scenario simulates these averages for a uniform 1°C increase in daily minimum and maximum temperatures. The legend includes the mean (M) and downside risk (D) for each density, where downside risk is measured as the partial variance below the mean.