

Weather Effects on Trend, Variance and Distribution of Crop Yield

Tian Yu

Department of Economics

Iowa State University

515-294-2241

yutian@iastate.edu

Bruce A. Babcock

Department of Economics

Iowa State University

515-294-6785

babcock@iastate.edu

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Introduction

FAVORABLE WEATHER CONDITIONS for dryland crop production, including a proper amount of heat and rainfall during the growing season, are critical factors determining yield outcomes. Weather conditions however, are randomly distributed across regions and over time, thus influencing the temporal and geographical patterns of measured crop yield. Failure to account for weather factors when estimating crop yield distributions, time trends or productivity gains can lead to spurious conclusions regarding technology improvement, yield risk and skewness of yield. This paper addresses some limitations in the literature that result from not taking into account weather, and proposes an approach to incorporate weather into modeling yield.

A Yield Model with Weather Factors

Using panel data of county-level weather and corn yield, we estimate the following model:

$$Y = \beta_0^a + \beta_1^{CRD}T + \beta_2 \min(0, (Temp - \theta_1)) + \beta_3 Temp + \beta_4 \max(0, (Temp - \theta_u)) + \beta_5 \min(0, (Rain - \lambda_1)) + \beta_6 Rain + \beta_7 \max(0, (Rain - \lambda_u)) + \beta_8 D_{93} + \varepsilon$$

Y , T , $Temp$, $Rain$ and D_{93} denote corn yield, time, temperature, rainfall and a year-1993-dummy variable respectively. The marginal effect of temperature within the pre-set range of “normal temperature,” $[\theta_l, \theta_u]$, is measured by β_3 . β_2 and β_4 capture possibly different yield responses in cold and hot conditions. In general, rainfall in-

creases corn yield while heat reduces corn yield. Yield responds differently to temperature changes in cold and hot conditions, and rainfall effects are non-linear as well (see Figure 1).

We extend the model by specifying time-varying weather effects: $\beta_4 = \gamma_1 + \delta_1 T$ and $\beta_5 = \gamma_2 + \delta_2 T$. Corn has become less susceptible to excessive heat and/or drought in most states over time.

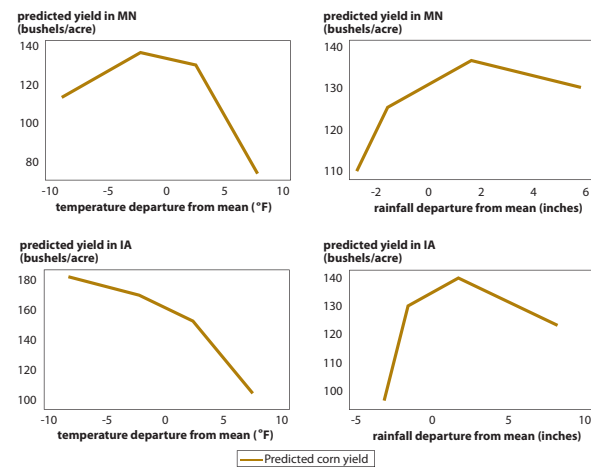


Figure 1: Impacts of temperature and rainfall on corn yield in Iowa and Minnesota

Weather Effects on Yield Trend

Without considering weather, yield trend estimates will be inflated (underestimated) in situations of improving (worsening) weather. The second row in Table 1 shows that the bias is positive in all states during 1980-2008, implying an improving climate trend. One might “discover” temporal/geographical

patterns of technology change, which were really a result of random weather patterns in the sample (see rows 3 to 6 in Table 1).

Table 1. Comparing trend estimates from models with or without weather

	IL	IN	IA	MN	MO	OH
Bias (1980-2008)	9%	12%	12%	5%	12%	7%
Bias (1990-2002)	3%	-39%	37%	177%	-3%	-82%
Productivity growth rates during 1990-2002 (Alston et al., 2010)	1.03%	0.89%	2.37%	1.91%	1.02%	0.02%
Biased trend estimates during 1990-2002	1.48%	0.98%	2.56%	3.70%	1.59%	-0.03%
Correct trend estimates during 1990-2002	1.48%	1.56%	1.87%	2.13%	1.79%	0.76%

Yield Risk and Distribution

Risk Management Agency (RMA) recently included in Group Risk Plan (GRP) rating procedure a step to estimate a heteroskedasticity parameter b by regressing log of estimated yield variation on log of trend yield (Coble et al. 2009). We improve estimation of b in two aspects: (1) we control for random weather patterns to reduce bias in both estimated yield variation and estimated trend yield; (2) we estimate reduction in yield variation due to improved drought/heat tolerance. Table 2 presents our results.

The marginal benefit of favorable weather decreases as the growing condition gets better, which partly explains why distribution of corn yield is negatively skewed (see Figure 2). Conditional on weather, Figure 3 shows that yield residuals are mostly of normal distribution.

Table 2. Yield risk

States	Less susceptible to hot weather	Less susceptible to dry weather	b	Yield risk
IL	Yes	Insignificant	-1.54	Decreasing absolute risk
IN	Yes	Insignificant	-0.85	Constant absolute risk
IA	Insignificant	Yes	-0.11	Constant absolute risk
MI	Yes	Insignificant	2.14	Constant relative risk
MN	Yes	Insignificant	0.84	Increasing absolute risk
MO	Yes	Insignificant	0.52	Constant absolute risk
OH	Insignificant	No	0.29	Constant absolute risk
WI	Yes	Yes	1.75	Constant relative risk

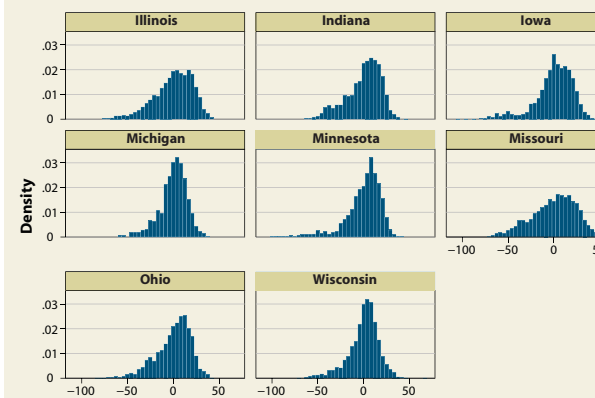


Figure 2: Histograms of residuals from regressing yield on a time trend

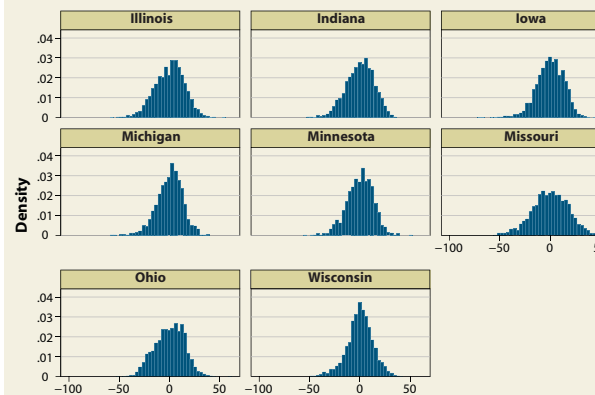


Figure 3: Histograms of residuals from regressing yield on a time trend and weather variables

Conclusion

WE ESTIMATE NON-LINEAR impacts of temperature and rainfall on corn yield. The improving climate trend from 1980 to present explains about 10% of observed yield trend. Not controlling for weather factors could lead to biased trend estimates, especially for short times series. Modeling changing drought/heat tolerance over time offers an improved estimate of the temporal heteroskedasticity parameter used in GRP rating. Decreasing marginal benefit of weather partly explains why corn yield is negatively skewed. Conditional on weather, unexplained residuals from our yield model are of normal distribution in general.

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