The Fingerprint of Climate on 65 Years of Increasing and Asymmetric Crop Yield Volatility in the Corn Belt

Tor Tolhurst, Agricultural and Resource Economics, University of California Davis (tolhurst@primal.ucdavis.edu)

Alan Ker, Department of Food, Agricultural and Resource Economics, University of Guelph, (aker@uoguelph.ca)

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Abstract

Crop yields have increased at impressive rates since 1930s and rightly received the lion's share of the attention in the crop productivity literature. However, increases in average yields fail to capture changes in the higher moments of the yield crop distribution, changes which may have larger and more immediate implications for food sufficiency, security, sovereignty, and sustainability. We use a comprehensive data set—covering roughly 80% of national corn production and 70% of national soybean production—on county-level corn and soybean yields in the Corn Belt from 1951–2015 to examine changes in yield volatility over time and space. We document our findings in two empirical regularities. First, the volatility of corn and soybean yields increased by factors of 2.5 and 2.0, respectively, roughly commensurate with increases in average yields. Second, this increase in volatility has been asymmetric across the tails for both crops, with the lower tail getting considerably longer. Third, roughly one quarter of the spatial variation in volatility is explained by the spatial variation in climate trends. Fourth, realized trends in climate variables are differentially correlated across corn quantiles but not soybean quantiles. These four regularities have yet to be empirically documented; can not be identified when analyzing average yield data; present a serious and increasing challenge to the livelihood of rural populations; and depict a more complete picture of the evolving relationship between crop yields, innovation, and climate.

Keywords: attribution, crop yields, innovation, productivity, risk, volatility.

1 Introduction

Despite impressive gains in crop productivity since the 1930s (Duvick, 1977; Duvick and Cassman, 1999; Cassman, 1999; Hafner, 2003; Lobell, Schlenker, and Costa-Roberts, 2011; Ray et al., 2012), concerns that yields will be flat, declining, or at best, subject to diminishing marginal returns have persisted (Ladha et al., 2003; Peng et al., 2004; Brisson et al., 2010; Finger, 2010; Lin and Huybers, 2012; Ort and Long, 2014). Stagnant crop productivity would make ensuring a safe and secure food supply at relatively reasonable and stable prices a challenge (Roberts and Schlenker, 2009; Godfray et al., 2010; Tilman et al., 2011; Zilberman, 2014). This challenge could easily be exacerbated by any number of circumstances: a growing population with evolving preferences, higher demand for non-food agricultural products (e.g. biofuels), and adapting to an uncertain future climate. A more thorough understanding of the relationship between crop yields, climate and innovation would lessen the burden of this challenge now and for future generations.

The effect of climate and innovation on yields is complex. While the vast majority of scientific inquiry has focused on *average* or *mean* yields, this summarising measure nonetheless misses critical intricacies. Yield volatility measures the year-to-year deviations from average yields; these deviations may in fact be more influenced by innovation and a changing climate than average yields. Furthermore, deviations have notably asymmetric implications: low yields have far greater negative consequences for farmers (and countries) relative to the positive consequences of high yields. For subsistence farmers, lack of effective risk management to mitigate low yield outcomes has been found to be the most important impediment to social and economic development (Karlan et al., 2014). Governments in developed countries provide large subsidies to mitigate the economic consequences of low yields: in the U.S. alone, federal government outlays to the crop insurance program totalled \$70 billion since 2004 and are trending upwards (United States Department of Agriculture Risk Management Agency, 2015). With this in mind, we offer a more complete picture of yield volatility, paying special attention to the lower tail of the yield distribution.

Using a comprehensive data set—with counties covering between 79.0–86.1% of national corn and 62.2–76.8% of national soybean production since 2001—we document four broad empirical regularities in the Corn Belt over the past 65 years. First, we find widespread evidence of increasing year-to-year volatility in both corn and soybean yields. Second, and more nuanced, the increase in yield volatility is not even across the tails of the distribution: more often than not, the spread between the lower quantiles is far greater than the upper quantiles. To examine the influence of climate trends on yield volatility, the final two regularities focus on Iowa (relatively homogeneous and historically the country's largest corn and soybean producer). Third, spatial variation in climate trends account for roughly one-quarter of the spatial variation in yield volatilities for both corn and soybean. Fourth, the magnitude of climate effects varies greatly across yield quantiles. Perhaps most interestingly—and inconsistent with extrapolating findings for average yields to the tails of the distribution—the fourth regularity implies yield responses to climate trends are consistently larger at lower quantiles for corn while conversely, yield responses are relatively uniform across all quantiles for soybeans. These findings suggest future changes in climate will have a greater impact on the lower tail of the corn yield distribution, but a relatively consistent impact across the entire soybean distribution. Differential responses to a changing climate will require different mitigation strategies and should influence public risk management policies and research funding priorities.

2 Data

2.1 Yield Data

To measure yield volatility we obtained county-level corn and soybean daya from the from the United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) online database. The data, at the lowest level of aggregation that are publicly available with high temporal and spatial coverage, are based on the the County Agricultural Production Survey which NASS conducts to collect acreage and production estimates for state and federal programs at the end of the harvest season. The stated purpose of the survey is to generate data with sufficient sample size for county-level analysis and the stated target of the survey is all farms in each state. The USDA relies on this data for a variety of purposes pertinent to yield volatility. For example, the USDA Farm Services Agency uses it to administer disaster assistance programs and the USDA Risk Management Agency uses it to determine crop insurance premiums and payments.

Specifically, we collected all available county-level data from 1951–2015 for 13 contiguous states which account for the vast majority of national corn and soybean production: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. All of these states produced over 200 million bushels of corn and 88 million bushels of soybean in 2015. In terms of rank, these 13 states include the top 12 corn producers (Kentucky ranked 14th behind Texas) and eight soybean producers (all fall into the top 15 with our data set excluding Arkansas at 9 and Mississippi at 11). For convenience of analysis, we delineate the data set into two regions which we term the Inner (IL, IN, IA, MO, and OH) and Outer (KS, KY, MI, MN, NE, ND, SD, and WI) Corn Belt. We removed all counties with more than 5% of their sample missing (i.e four or more missing observations) or

Table 1: Summary statistics of yield data, 1951–2015, corn and soybeans.

	Yield (bu./ac.)				Acreage (000s acres)						
	Min.	Mean	Max.	S.D.	Min.	Mean	Max.	S.D.	Obs.	Units	NA(%)
					Corn (1951–2015)						
All	0.3	98.2	236.0	41.9	0.5	75.5	397.0	57.1	52845	813	0.8
Corn Belt	0.3	105.2	236.0	40.0	0.7	85.9	397.0	59.4	27430	422	0.6
IL	9.0	109.3	236.0	41.7	6.0	114.5	397.0	75.0	6370	98	0.5
IN	22.2	107.7	214.9	37.2	4.6	67.9	185.9	31.9	5525	85	0.5
IA	18.3	112.2	209.6	41.5	7.0	123.4	339.5	49.2	6435	99	0.1
MO	0.3	87.3	209.7	37.3	0.7	36.4	151.5	26.4	4615	71	1.8
OH	32.0	104.2	200.0	35.6	5.5	51.4	139.0	27.0	4485	69	0.3
Outer	3.5	90.6	224.0	42.6	0.5	65.6	369.5	52.9	25415	391	1.1
KS									0	0	
KY	16.0	89.6	199.1	37.3	1.6	22.8	94.7	17.9	3315	51	0.9
MI	18.6	92.0	198.8	35.0	3.7	50.5	160.0	30.9	2925	45	0.5
MN	16.1	101.1	207.4	43.6	5.8	106.9	305.0	59.4	4225	65	0.4
NE	6.2	101.9	224.0	46.8	1.4	84.6	265.9	57.1	5590	86	0.5
ND	8.0	60.9	160.5	35.1	0.5	30.0	365.5	39.8	2340	36	6.7
SD	3.5	67.3	193.8	40.7	0.5	76.8	369.5	46.4	3185	49	0.9
WI	22.0	98.7	194.2	33.2	2.0	58.6	253.0	39.8	3835	59	0.3
					Soybean (1951–2015)						
All	2.5	32.0	73.1	11.0	0.1	63.0	541.0	51.3	42640	656	0.6
Corn Belt	2.5	34.2	73.1	10.2	0.1	75.3	329.0	46.8	27625	425	0.5
IL	7.0	35.7	73.1	10.3	5.0	96.5	329.0	57.2	6305	97	0.3
IN	10.0	35.3	64.6	10.0	2.7	55.7	127.5	28.0	5655	87	0.5
IA	7.3	36.7	64.1	10.2	2.1	91.2	274.0	41.9	6370	98	0.1
MO	2.5	28.6	55.8	8.7	0.5	61.2	319.0	44.8	5135	79	1.6
OH	10.0	33.6	62.2	9.6	0.1	62.9	150.5	36.7	4160	64	0.4
Outer	3.0	27.9	61.7	11.1	0.1	44.9	541.0	52.2	15015	231	0.7
KS	3.0	24.4	60.0	10.5	0.1	29.6	151.3	27.8	3510	54	1.1
KY									0	0	
MI	7.0	29.5	56.9	9.9	0.5	43.1	140.0	30.9	2145	33	0.3
MN	7.0	29.9	61.7	11.2	0.2	85.1	290.5	61.4	4290	66	0.3
NE									0	0	
ND	7.0	24.4	41.4	8.6	0.4	132.7	541.0	131.0	260	4	4.6
SD	4.0	25.9	56.9	11.0	0.1	51.1	186.0	48.5	1625	25	1.3
WI	7.0	29.5	59.5	11.5	0.1	13.2	106.3	16.8	3185	49	0.5

with less than 5,000 acres of production in 2011, leaving 813 counties for corn and 656 counties for soybean. Summary statistics for the sample and subsets of the sample by region and state are reported in table 1.

2.2 Climate Data and Agronomic Metrics

Daily data for all weather stations within Iowa were downloaded from the National Oceanic and Atmospheric Administration database for 1955–2012. Raw weather station data was spatially interpolated to county centroids based on distance-weighted averages of observations from individual weather stations within Iowa. This data is used to estimate county-level yield trends separately for each crop for a total of 99 corn and 98 soybean county-level trend coefficient estimates. Dubuque county soybean is excluded from the analysis due to an incomplete yield history. We do not directly control for irrigation because production of these field crops is primarily, if not exclusively rainfed: for corn (soybean): 11,051 acres (6,556) were completely irrigated, 100,470 (43,081) partly irrigated, and 13,597,887 (9,251,957) no irrigation.

We examine potential changes in climate through three agronomic metrics—growing degree days (GDD), harmful degree days (HDD), and vapor pressure deficit (VPD)—as well as precipitation (PCP). GDD is a nonlinear agronomic metric which measures daily accumulated exposure to temperatures that are beneficial for plant growth based on daily minimum and maximum temperatures. HDD is an analogous measure but for temperatures exceeding the optimum, which tend to be harmful for plant growth. Specifically, a trigonometric sine curve approximation with multiple temperature thresholds is used to calculate GDD and HDD Schlenker and Roberts (2009). Intuitively, temperatures below the threshold do not contribute to plant growth, temperatures between the lower and upper threshold contribute positively, and temperatures above the upper threshold contribute negatively. We use an upper temperature threshold of 29°C for corn and 30°C for soybean based on Schlenker and Roberts (2009) and assume a lower temperature threshold of 10°C. VPD is also a nonlinear agronomic metric based on daily minimum and maximum temperature; however its purpose is to proxy for plant water demand based on diurnal temperature variation Roberts and Schlenker (2009). High VPD is associated with hot and dry conditions when water demand will be high, whereas low VPD is associated with cool and cloudy conditions which provide less solar radiation for photosynthesis. Vapor pressure at temperature T in degrees Centigrade is $VP(T) = 0.6107 \exp^{A}$ where $A = 17.269T/(T+237.3)$ and VPD is simply the difference between the vapor pressure at the daily maximum and minimum temperature Lobell et al. (2014); Ort and Long (2014). For corn and soybeans all climate variables are calculated on a daily basis over a fixed 214 day growing season from April 1 to October 1. Then, in order to correspond with the annual yield data (i.e. one observation per year), daily GDD, HDD, VPD, and precipitation are annualized by summing over the 214 days of the growing season. Following Roberts, Schlenker, and Eyer (2012); Lobell et al. (2014) we also include a separate metric for July-August (July 1 to August 31) VPD and precipitation because the magnitude and direction of these coefficients may change over different portions of the growing season. For instance, relatively dry and high VPD conditions may facilitate planting and plant growth throughout the growing season except during the hot and dry months of July-August, when insufficient moisture or excessive VPD could be harmful. These metrics are denoted VPDJA and PCPJA, respectively. VPDJA is responsible for roughly 30 to 40% of the VPD accumulated over the growing season, whereas PCPJA accounts variously from roughly 10 to 50% of the total rainfall accumulated over the growing season.

3 Methods

Our empirical approach follows what has remained the predominant view in the literature since at least Botts and Boles (1958) and Day (1965) onwards. In brief, we view yield realizations as an annual draw from an unknown latent probability distribution. Changes in both production processes and climate can alter the location, scale, and shape of this probability distribution over time. The conditional mean (i.e. location) of the latent distribution is estimated with a trend line. We then interpret (the magnitude of) deviations from the estimated conditional mean as volatility. The goal of this manuscript is to estimate how the scale and shape of the probability distribution, which determine volatility, has changed over time. Note we do not impose a particular form on the scale and shape of the probability distribution in any way unless otherwise noted.[1] Rather, we are examining how the upper moments are changing over time empirically.

Estimation of the time conditional mean is clearly an important assumption of our manuscript. Thus, we considered four different detrending specifications: linear, cubic, median (conditional quantile regression at the median), and nonparametric (local lines regression). All four approaches led to identical conclusions, so we report results from linear detrending in the body of the manuscript and from the alternative specifications in the supplemental appendix.[2] The residuals from the detrending process are the basis for the analysis that follows. The remainder of this section is divided into two subsections. The first describes a number of ways we used to measure yield volatility over time. The second describes the methods used to estimate the contribution of

[1]Given our data is at the county-level, we are interested in modeling the county-level distribution; however, this viewpoint is general and could be as easily applied to different levels of aggregation. For a more thorough examination of the literature on modeling the probability distribution of crop yields over time see Tolhurst and Ker (2015).

[2]In fact, trends in the data look quite linear and indeed, even the more flexible forms tend to give a very linear fit.

innovation and weather trends to yield volatility patterns over space.

3.1 Measuring Yield Volatility

Yield Volatility Index. As a nonparametric first pass to measure yield volatility, we constructed a yield volatility index by dividing deviations from trend into five subsets of 13 years (1951–1963, 1964–1976, 1977–1989, 1990–2002, and 2003–2015). The volatility index is the standard deviation of detrending residuals in the given time period, normalized such that the first period equals 100.[3]

Timewise Non-Constant Volatility Test. We derived a timewise non-constant volatility (i.e. heteroskedasticity) test following Park (1966). Assume the variance of detrending residuals follows the structure:

$$Var_{\hat{e}_{i,t}}(t) = \sigma_i^2 t^{\beta_i} \exp \nu_{i,t} \tag{1}$$

where $\hat{e}_{i,t}$ are the residuals from detrending for county i indexed at time t, σ_i^2 is a time independent variance at the county-level, and $\nu_{i,t}$ is a well-behaved error term. Then a county-level coefficient of non-constant volatility, β_i, can be estimated in log-log form using least squares regression by plugging in $\hat{e}_{i,t}^2$ for $Var_{\hat{e}_{i,t}}$ and α_i for σ_i^2:

$$\ln \hat{e}_{i,t}^2 = \ln \alpha_i + \beta_i \ln t + \nu_{i,t} \tag{2}$$

$\hat{\beta}_i$ parametrizes the degree of non-constant yield volatility for a given county. We can use this estimated heteroskedasticity coefficient $\hat{\beta}_i$ as a dependent variable in the attribution model presented in section 3.2. Furthermore, we could test for non-constant yield volatility using a t-test under a null hypothesis of constant volatility $H1.\, \hat{\beta}_i = 0$;

[3]See supplemental appendix for a formal definition.

non-decreasing volatility $H2.\, \hat{\beta}_i \leq 0$; or non-increasing volatility $H3.\, \hat{\beta}_i \geq 0$.[4]

Quantile Regression. We examine if changes in the yield distribution go beyond the first two moments using conditional quantile regression. Coefficients are estimated using linear programming methods as the solution to the optimization problem:

$$\hat{\beta}_i^\tau \equiv \arg\min_{\beta^\tau \in \Re} \sum_t \rho_\tau(y_{i,t} - t\beta_i^\tau) \tag{3}$$

where $\hat{\beta}_i^\tau$ are the estimated coefficients at quantile τ and $\rho_\tau(\cdot)$ is a tilted absolute value function with the τth sample quantile as the solution. Specifically, we estimated unique conditional quantile functions for each crop-county combination across $\tau = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ using the `quantreg` package in `R`. For an overview of quantile regression see Koenker and Hallock (2001).

Two Trend Mixture Model. As another means of testing if the higher moments of the yield distribution have changed over time we estimated the two trend mixture model of Tolhurst and Ker (2015). Specifically, assume yield from county i at time t follows a mixture of two normals

$$y_{i,t} \sim \lambda_i \mathcal{N}(\mu_i^u(t), \sigma_i^{u2}) + (1 - \lambda_i)\mathcal{N}(\mu_i^\ell(t), \sigma_i^{\ell 2}) \tag{4}$$

with time dependent component $\{\mu_i^u(t), \mu_i^\ell(t)\}$, but time independent mixture weights λ_i and component variances $\{\sigma_i^{u2}, \sigma_i^{\ell 2}\}$. Using deterministic time trends for the time

[4]However, as shown in the supplementary appendix, the power of this test tends to be low (not surprising given our sample size is fairly small for a test of the second moment). As a robustness check for this specification we also estimated the model $Var_{\hat{e}_{i,t}}(t) = \sigma_i^2 \mathbb{E}[y_{i,t}]^{\beta_i} \exp \nu_{i,t}$ with $\mathbb{E}[y_{i,t}] = \hat{y}_{i,t}$ per Harri et al. (2011) which leads to qualitatively identical results, though a slightly different interpretation of β_i, presented in the supplementary appendix.

dependence in the means gives:

$$y_{i,t} \sim \lambda_i \mathcal{N}(\alpha_i^u + \beta_i^u t, \sigma_i^{u2}) + (1 - \lambda_i) \mathcal{N}(\alpha_i^\ell + \beta_i^\ell, \sigma_i^{\ell 2}) \tag{5}$$

which can be estimated using the EM algorithm with weighted least squares in the component trends. For convenience of interpretation (and without loss of generality) assume $\alpha_i^u + \beta_i^u t \geq \alpha_i^\ell + \beta_i^\ell t$ so that superscript u is the upper component and ℓ the lower component. The parameters of this model are estimated for each crop-county combination using the robust starting value procedure detailed in Ker, Tolhurst, and Liu (2016).[5] In addition to using the estimated parameters for the analysis, we impose the functional form to compute the variance of $y_{i,t}$ as a function of time t:

$$Var_{y_{i,t}}(t) = \lambda_i \sigma_i^{u2} + (1 - \lambda_i)\sigma_i^{\ell 2} + \lambda_i(1 - \lambda_i)\left(\alpha_i^u - \alpha_i^\ell + (\beta_i^u - \beta_i^\ell)t\right)^2 \tag{6}$$

and plugging in the parameter estimates we can examine changes in the upper moments over time. Note this is the lone exception where we impose form on the scale and shape of the yield distribution; however, the functional form is quite flexible. For instance, with one set of parameters the distribution of $y_{i,t}$ could: begin as symmetric and unimodal, become asymmetric and unimodel in the middle of the sample, and be asymmetric (or symmetric) and bimodal at the end of the sample.

3.2 Yield Volatility Attribution Model

The contribution of innovation and climate on yield trends is estimated using the cross-sectional model of Lobell and Asner (2003a), which regresses yield trend coefficients against climate trend coefficients. For $i = 1, 2, \ldots, k$ counties let $((dc_1, dy_1), \ldots, (dc_k, dy_k))$ be a sequence of county-level yield and climate trends where, with j climate variables,

[5] Also included in the supplemental appendix.

$dc_i = (dc_{i1}, \ldots, dc_{ij})^\top$. Note the yield and climate trends are observed over the same time periods. Then we estimate

$$dy_i = r_0 + dc_i^\top r_y + \varepsilon_i, \qquad i = 1, 2, \ldots, k \tag{7}$$

where r_0 is a regression constant, $r_y = (r_{y,1}, \ldots, r_{y,j})^\top$ is a j unknown parameter vector, and ε_i are random regression residuals. For climate trends we use linear trends in the agronomic metrics detailed in section 2.2.2. The resultant model explains cross-sectional variation in yield trends using cross-sectional variation in climate trends. All estimates of (7) are computed using acreage as weights (NASS planted acreage in 2011) in a weighted least squares problem with heteroskedastic standard errors clustered at the crop reporting district level.[6]

Lobell and Asner (2003a) use this model with estimates of the conditional mean as the dependent variable.[7] Instead, we used a number of different yield volatility trend measures as the dependent variable described in section 3.1: (i) the nonconstant volatility coefficient, $\hat{\beta}_i$; (ii) the positive residual coefficient analogous to (i), $\hat{\beta}_i^+$; (iii) the negative residual coefficient analogous to (i), $\hat{\beta}_i^-$; and (iv) five conditional quantile coefficients, $\hat{\beta}_i^\tau$ for $\tau = \{0.1, 0.3, 0.5, 0.7, 0.9\}$. Further, given that the relationship between asymmetry in volatility and trends in agronomic metrics is undoubtedly complex, we also considered a number of potentially interesting transformations: (v) the difference between (ii) and (iii), $\hat{\beta}_i^+ - \hat{\beta}_i^-$; (vi) the ratio of (ii) to (iii), $\hat{\beta}_i^+ / \hat{\beta}_i^-$; (vii) the difference in the two trend mixture model estimated variances evaluated at 2015 and

[6]There are 100 clusters in the corn data and 76 clusters in the soybean data. Kézdi (2004) argues approximately 50 well balanced clusters are sufficient for accurate inference. In both data sets the number of clusters range from one to 16 counties with a median of nine counties. We would argue the clusters are fairly well balanced—16 clusters is 1.96% of the corn sample and 2.44% of the soybean sample—but nevertheless include the degree of freedom correction $\frac{M}{M-1}\frac{N-1}{N-K}$ to account for the unbalanced nature of the clusters where M is the total number of clusters, N is the length of a given cluster, and K is the rank of the model.

[7]We also do this and report the results in the supplementary appendix.

1951, $\widehat{Var}_{y_{i,t}}(t)\big|_{t=2015} - \widehat{Var}_{y_{i,t}}(t)\big|_{t=1951}$; and (viii) the ratio of two the two trend mixture model estimated variances evaluated at 2015 and 1951, $\widehat{Var}_{y_{i,t}}(t)\big|_{t=2015} / \widehat{Var}_{y_{i,t}}(t)\big|_{t=1951}$.[8] Note the regression constant, r_0, estimates the climate-adjusted yield effect (i.e. when $r_y = 0$) corresponding to the given dependent variable. Thus

$$\text{Net climate effect } \equiv dy_i - dy_i|dc_i \tag{8}$$

and we can attribute the difference between the conditional and unconditional mean of dy_i to the net effect of climate on dy_i.

The model is intended to separate the impacts of climate and innovation on observed yield trends, though this attribution exercise involves some caveats. The primary concern is the interpretation of r_0 as innovation when it may be confounded with other variables. For instance, Kucharik (2008) notes the model implicitly assumes other factors which may contribute to yield trends (e.g. ozone, pests, disease) but are uniform across space would be erroneously attributed to r_0. It also should be noted that identification of the statistical model relies on historical yield data and assumes technologies adopted during the sample have not been targeted at mitigating the effects of a changing climate (also noteworthy because this approach may not be possible with future yield data).[9]

[8] Note $\widehat{Var}_{y_{i,t}}(t)\big|_{t=2015} / \widehat{Var}_{y_{i,t}}(t)\big|_{t=1951} \propto \hat{\beta}_i^u / \hat{\beta}_i^\ell$ (and analogous for difference), so we could estimate (vii) and (viii) using the estimated component trends instead; however, we do not for brevity and because $\hat{\beta}_i^\ell$ is allowed to be zero.

[9] In a survey of 1,276 Iowa farmers in 2011, 55.4% of participants did not believe climate change is occurring or believed it is a natural phenomenon and were "[far less likely to believe] that steps leading to adaptation should be pursued," (Arbuckle, Morton, and Hobbs, 2013). Implicit then, at least anecdotally, is that extensive preemptive or reactive technologies had not been widely adopted in Iowa over the sample period.

4 Results: Four Empirical Regularities

Regularity 1: Volatility increased dramatically over time throughout the Corn Belt.

Figure 1 plots changes in the yield volatility index for corn (left) and soybean (right) over time and space. The top panel presents an aggregate measure of yield volatility in 11 year bins with 1951–1963 standardized to a value of 100. For both crops yield volatility has increased steadily over time. The value of the index in the 2003–2015 implies volatility more than doubled for corn and nearly doubled for soybean. This is roughly equivalent to the increase in average yields during the time period and, as argued above, has greater economic consequences for producers in both developing and developed countries.

The bottom panel of figure 1 disaggregates these patterns to the county level. Each map shows the yield volatility index at the county level for the 2003–2015 period with increasing volatility shown in red, constant volatility yellow, and decreasing volatility green.[10] A small share of counties have experienced declining or relatively constant volatility, slightly more so for soybean: the volatility index is less than 100 in 1.6% of corn counties and 3.8% of soybean counties. Overall, yield volatility is unambiguously increasing the vast majority of counties—greater than 150 in 92.0% for corn and 80.2% for soybean. More often than not, 77.9% for corn and 51.7% for soybean, the yield volatility index more than doubled from 1951–1963 to 2003–2015.

To support the illustrations in figure 1, we conducted the timewise non-constant volatility test at the county level. At the 5% level, the null hypothesis of constant volatility ($H1$) was rejected in 60.8% of corn and 45.4% of soybean counties. In the

[10] Counties not meeting the criteria for inclusion in the data set are in gray. County-level yield volatility index is VI_{i,T_j} and aggregated yield volatility index is VI_{Pool,T_j} as formally defined in the supplementary appendix.

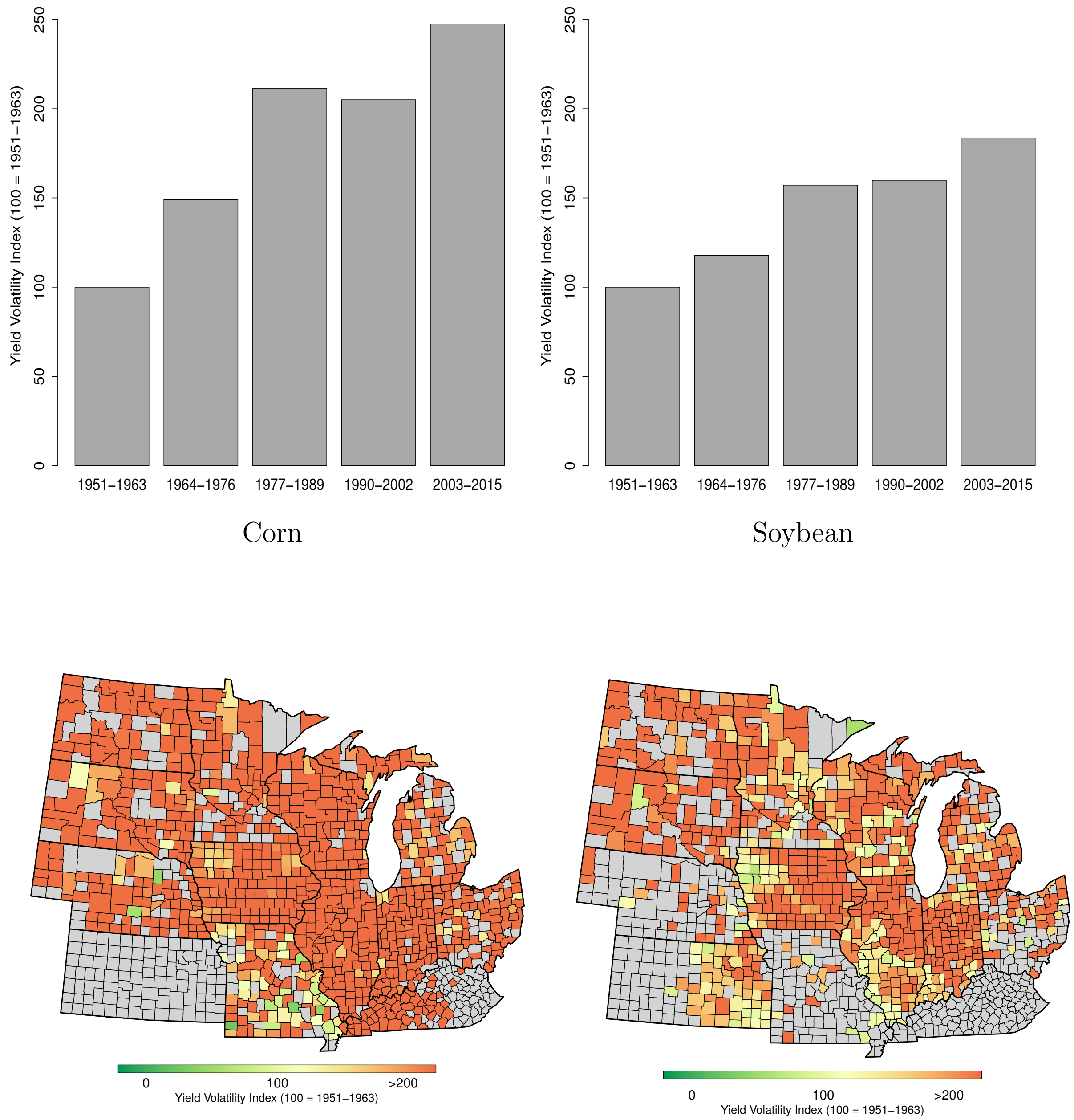

Figure 1: Increases in yield volatility index illustrated over time and space for corn (left) and soybean (right). Boxplots show the index value averaged over all counties in the sample segmented into 11 year windows. The maps illustrate the increase in in the index from 1951–1963 to 2003–2015 across counties in the sample.

overwhelming majority of counties, this non-constant volatility is increasing: using the one-sided test under the null of non-decreasing volatility ($H2$) rejected 60.0% and 45.3% of counties for corn and soybean, respectively. In contrast, under the null of non-increasing volatility ($H3$), only 0.7% and 0.2% of counties rejected the null, far below the size of the test. In light of the relatively low power of tests for changes in the second moment,[11] these results indicate increases in yield volatility has been significant and widespread throughout the Corn Belt over the past 65 years.

Next, we considered these patterns by region and state. Interestingly, we found the aggregated yield volatility index is quite a bit lower in the outer Corn Belt than the inner: the volatility index in the 2003–2015 period is 298 for the inner but only 203 for the outer. The pattern is similar for soybeans, but less dramatic: 186 for the inner and 179 for the outer. Along these lines, no corn counties had index values less than 100 in the inner region, while 3.3% of corn counties in the outer region did. For soybean the share of index values less than 100 are nearly identical for the inner and outer regions at 3.8% and 3.9%, respectively. The share of soybean counties with index values over 200 in 2003–2015 are also nearly identical at 51.7% for the inner and 51.5% for the outer; however, for corn the share is much higher in the inner region at 87.9% compared to the outer at 67.0%. The pattern of higher volatility in the inner region was also reflected in the timewise non-constant volatility test. For corn $H1$ is rejected 66.4% for the inner region and 54.7% for the outer region, $H2$ is rejected 66.4% for inner and 53.2% for the outer, and $H3$ is never rejected the inner and in 1.5% of counties in the outer region. As expected, rejection rates are also higher for soybean in the inner region but at a lower magnitude: $H1$ is rejected 46.8% for inner to 42.9% for the outer, practically identical rates for $H2$, and $H3$ is rejected in only four counties (0.2%) in the inner region and never in the outer region. In sum, we found non-constant and almost always increasing

[11]See analysis in the supplementary appendix.

yield volatility in both regions, though with increasing volatility more prevalent in the inner region of the Corn Belt than the outer.

For brevity, we summarized the results across states by focusing on the top and bottom three for each metric. We found the aggregated yield volatility index was highest for corn in Kentucky, Missouri, and Indiana, while lowest in Minnesota, Michigan, Nebraska (notably Iowa was the fourth lowest). For soybeans the highest were Wisconsin, Ohio, and Michigan with the lowest South Dakota, Missouri, and North Dakota (notably Illinois was the fourth lowest). The states with the highest share of counties with yield volatility index values greater than 200 were Kentucky (100.0%), Illinois (95.9%), and Ohio (94.2%) for corn and Wisconsin (98.0%), Michigan (69.7%), and Ohio (67.2%) for soybeans. The lowest share of counties with volatility index values below 200 were Minnesota (66.2%), Michigan (51.1%), and Nebraska (34.9%) for corn and Missouri (38.0%), South Dakota (28.0%), and North Dakota (none). As expected, these are (mostly) reflected in the timewise nonconstant volatility hypothesis test rejection rates. The highest rejection rates of $H1$ for corn were in Ohio (92.7%), Kentucky (88.2%), and North Dakota (72.2%) (Illinois fourth at 71.4%), while for soybean they were Wisconsin (83.7%), Ohio (53.1%), and Indiana (51.7%). The rejection rates for $H2$ are practically identical as for $H1$. Interestingly, all rejection rates for $H3$ were zero except for in Nebraska for corn (7.0%) and Iowa for soybean (1.0%). The lowest rejection rates for $H1$ (and $H2$) were in Michigan (48.9%), Iowa (46.5%), and Nebraska (22.1%) for corn and Illinois (36.1%), South Dakota (24.0%) and North Dakota (none) for soybean. Taken together, these results show there is considerable variation in the magnitude of volatility trends in the the Corn Belt over time; however, the pattern of increasing volatility is remarkably consistent throughout.

Finally, we also assessed the sensitivity of the estimates to detrending and bin width assumptions using the two trend mixture model. Specifically, we used the estimated parameters of the two trend mixture model and calculated the fitted variance (6) at 1951 and 2015. Examining the percentage change in volatility, we find a very similar pattern to the earlier results. The percentage change in volatility is positive in 97.7% of corn counties and 98.3$ of soybean counties.[12] Once again we see both corn and soybean volatility increased, but corn tended to do so at a higher relative rate: the volatility increased by a factor of one in 67.9% of corn counties and 68.2% of soybean counties; in over half (52.7%) of corn counties and just less than half (48.2%) of soybean counties yield volatility increased by more than a factor of two; and one quarter of corn counties increased by more than a factor of 3.7, while one quarter of soybean counties increased by more than a factor of 3.1. Further, we find a similar pattern to the earlier analysis when we consider results at the regional level for corn. Volatility in the Inner Corn Belt tended to increase faster than in the Outer: for example, in the median county volatility increased by a factor of 2.5 in the inner region compared to 1.6 in the outer. For soybean, the results are slightly different in that the outer region experienced higher volatility than the inner region; however, like the earlier results the differences between regions tends to be fairly small. For example, in the median county volatility increased by a factor of 1.9 in the inner region and 2.0 in the outer region. Overall, these results show that the finding of substantially higher yield volatility over time throughout the Corn Belt is robust to specification assumptions.

[12] Of the 19 corn counties where the fitted variances indicate decreasing volatility, there was one in each of Illinois, Kentucky, and Michigan, two in Wisconsin, six in Nebraska, and eight in Minnesota. Of the 11 soybean counties where the fitted variances indicate decreasing volatility there were two of each in Iowa, Michigan, and Ohio, and the remaining five were in Illinois.

Regularity 2: Increases in volatility over time were not symmetric across the distribution.

Beyond the increase in volatility considered above, one may be concerned with the changes in the shape of the distribution, especially in the relative length of the distribution's tails. Figure 2 gets at how the shape of the corn (left) and soybean (right) yield distribution has changed over time. The top panel reproduces the top panel of figure 1 but with separate volatility index values for positive (blue) and negative (orange) detrending residuals. The bar heights are standardized such that the positive residuals in the 1951–1963 bin are 100. For both crops it is clear that: (a) the index values on both signed residuals increased substantially; (b) this increase was steady over time; and, perhaps most importantly, (c) the index value of the negative residuals is always higher than the index value for the positive residuals. In the first bin the value of the negative residual index was 128.7 for corn and 116.3 for soybeans. In contrast, the value of the negative residual index was 1.5 times the value of the positive residual index for corn and 1.4 times for soybeans. The values of the index suggest negative residuals increased by a factor of 2.8 for corn and 2.0 for soybeans, while positive residuals increased by factors of 2.3 and 1.6, respectively. These results imply volatility has increased asymmetrically throughout the Corn Belt in the past 65 years; in particular, the lower tail has gotten relatively longer than the upper tail, which is important because lower tail realizations are arguably more important to agricultural producers.

The bottom panel of figure 2 plots a representative county (Adair county, Iowa) of corn and soybean yields with conditional quantile trend fitted lines at the 10th, 30th, 50th, 70th, and 90th quantiles. The conditonal quantile trend lines clear shows a pattern of greater spread in the coefficients at higher quantiles for both corn and soybean. This pattern is indicative of non-uniform changes in yield volatility: a lower

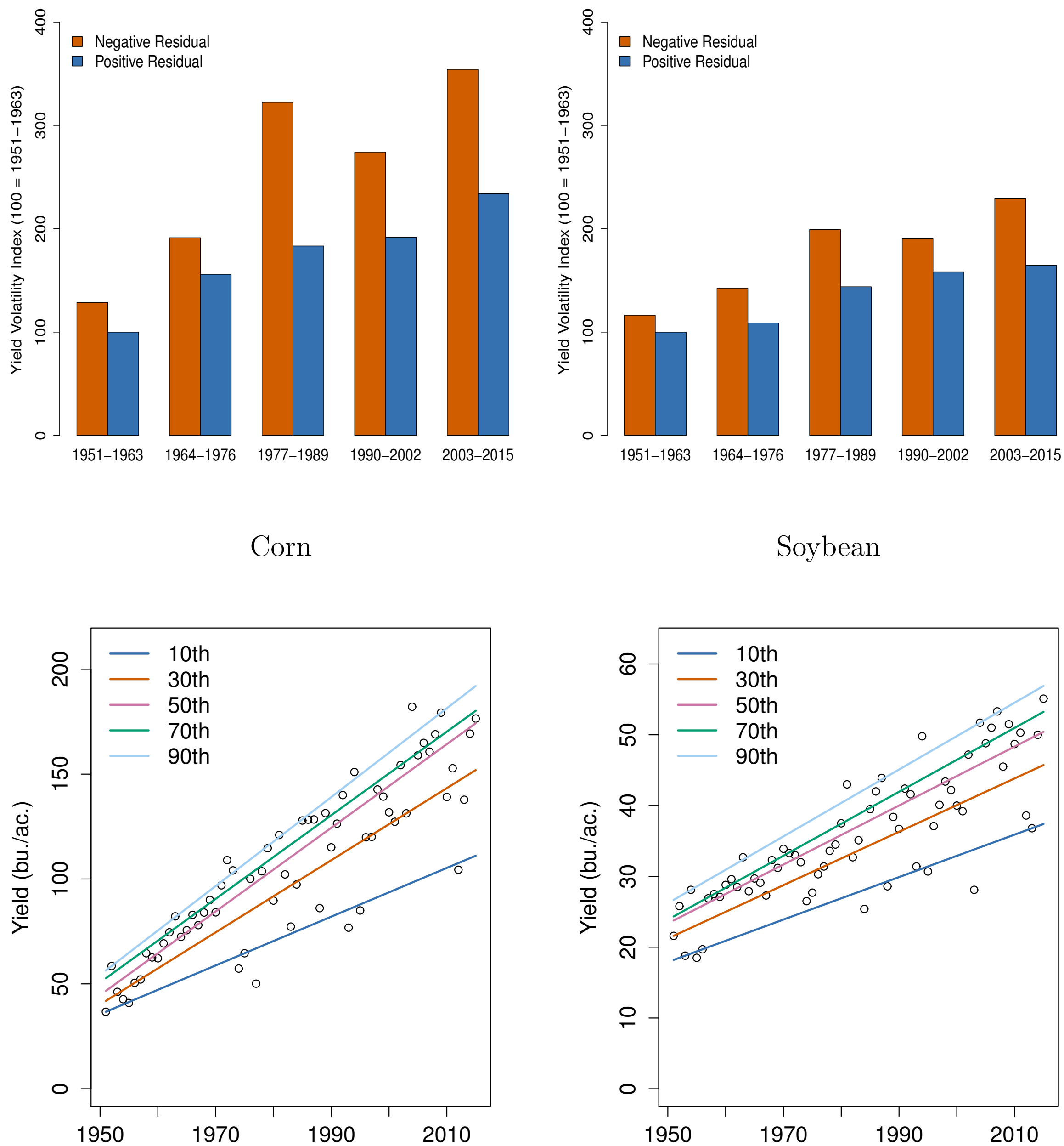

Figure 2: Pattern of changes in yield distribution over time. Top: Modified boxplots from fig. 1 for corn (left) and soybean (right) where the index is calculated separately for negative (orange) and positive (blue) residuals. Bottom: conditional quantile trend fitted lines for a representative county (Adair, IA) of corn (left) and soybean (right). The more rapid growth in orange bars suggests a widening lower tail, which is reflected in the increasing spread in the quantile trend lines.

rate of technological change in lower quantiles necessarily implies increasing dispersion and therefore increasing volatility over time.

The bottom panel of figure 1 disaggregates these patterns to the county level. Each map shows the yield volatility index at the county level for the 2003–2015 period with increasing volatility shown in red, constant volatility yellow, and decreasing volatility green.[13] A small share of counties have experienced declining or relatively constant volatility, slightly more so for soybean: the volatility index is less than 100 in 1.6% of corn counties and 3.8% of soybean counties. Overall, yield volatility is unambiguously increasing the vast majority of counties—greater than 150 in 92.0% for corn and 80.2% for soybean. More often than not, 77.9% for corn and 51.7% for soybean, the yield volatility index more than doubled from 1951–1963 to 2003–2015.

To capture this we estimated conditional quantile regression trends at the 10th, 30th, 50th, 70th, and 90th quantiles. The bottom panel of figure 2 illustrates a prevalent pattern in corn and soybean county plots: the narrow (and relatively constant) space between the upper quantiles suggests a relatively short and fixed upper tail, while the wider (and widening) space between the lower quantiles suggests an increasingly long lower tail. In fact, this pattern occurs in 74.9% of corn and 66.0% of soybean counties.

In sum, this pattern suggests that technological innovations have: (a) shifted mass upwards significantly and uniformly in the middle to upper part of the yield distribution; (b) shifted mass upwards moderately in the higher part of the lower tail of the yield distribution; and (c) had a relatively small effect on the extreme lower tail of the yield distribution where, as we see in empirical regularity 4, is relatively more dependent on climate.

[13] Counties not meeting the criteria for inclusion in the data set are in gray. County-level yield volatility index is VI_{i,T_j} and aggregated yield volatility index is VI_{Pool,T_j} as formally defined in the supplementary appendix.

Regularity 3: Changes in climate were correlated with changes in volatility.

In this section we estimate the contributions of climate and innovation to yield volatilities in Iowa via Lobell and Asner (2003a); that is using yield volatility trend coefficients as opposed to yield trend coefficients as our dependent variable as discussed earlier. We restrict the analysis (and regularity 4) to Iowa for a number of reasons: (a) the relatively homogeneous topography of Iowa reduces the possibility of climate interpolation errors; (b) we do not need to directly control for irrigation because production of corn and soybean in Iowa is almost exclusively rainfed with only 0.81% of Iowa corn and 0.53% of Iowa soybean acreage fully or partly irrigated in 2012 (2012 U.S. Census of Agriculture); (c) there is a complete yield history for corn and nearly complete yield history for soybean (all but Dubuque county); (d) 99.2% and 88.0% of the corn and soybean observations, respectively, report more than 25,000 harvested acres in any given year; and (e) the value of agricultural production in Iowa is the second largest in the U.S. (behind California), corn and soybeans are Iowa's two largest crops, and historically the state of Iowa is the largest producer of corn and soybeans by acreage, production and value in the country. In fact, Iowa produced 17% and 14% of total national corn and soybean production, the value of which exceeded $9.6 and $5.5 billion, respectively, in 2013 NASS (2015).

Overall, as reported in table 2, changes in climate variables explain roughly one-quarter of the spatial variation in yield volatilities: 26.1% for corn and 28.6% for soybean. Unlike mean yields where the directional impact of certain climate variables is arguably well-known, there is no established directional impact of climate variables on yield volatility coefficients. Interestingly, trends in GDD were broadly favourable and were significantly correlated with lower levels of yield volatility in both crops, while

Table 2: Contributions of Innovation and Climate to Yield Volatility Trends

	Corn	Soybean
Constant	0.762^{***}	0.346^{**}
	(0.112)	(0.153)
GDD	-0.072^{**}	-0.119^{***}
	(0.036)	(0.040)
HDD	1.328^{**}	3.324^{***}
	(0.536)	(0.680)
VPD	-0.465	0.408
	(0.318)	(0.405)
PCP	0.026	0.125^{*}
	(0.050)	(0.067)
VPDJA	0.925	-1.725
	(0.913)	(1.151)
PCPJA	-0.082	-0.150
	(0.092)	(0.119)
n	99	98
r^2	0.261	0.286
F	5.411^{***}	6.061^{***}

the opposite was true for HDD. VPD was negatively correlated with yield volatility trends for corn but positively correlated for soybeans, though neither were statistically significant. This pattern was reversed for VPD_{JA}, with a positive correlation in corn and negative correlation in soybean, though again neither were statistically significant. While growing season precipitation was positively correlated with yield volatility in both crops (and significant at the 10% level for soybean), July-August precipitation was negatively correlated with yield volatility. The F-statistics demonstrate that spatial variations in climate trends explain spatial variations in yield volatility trends to a statistically significant degree (both $p < 0.01\%$). Consistent with the first empirical regularity, the constant coefficients are positive and statistically significant, indicating innovations have induced higher yield volatility over time. By comparing the constant in the climate regression to the average while not conditioning on climate variables indicates the directional effects of climate on yield volatility. Given the average yield volatility trend coefficients of 0.389 for soybean and 0.583 for corn, the regression results indicate that changes in climate induced volatility in soybean and reduced volatility in corn (see *Methods* for caveats of this attribution approach).

Regularity 4. Changes in climate were asymmetrically correlated across quantile trend coefficients.

The literature has yet to consider whether climate and innovation have differential impacts across the yield distribution. That is, do climate and innovation have identical impacts across the lower tail, mean, and upper tail of the yield distribution? To answer this question, we repeat the analysis in regularity 3 and estimate the contributions of climate and innovation to yield trends across various quantiles using Lobell and Asner (2003a) with yield quantile trend coefficients as the dependent variable (*Methods*). The results are summarized in table 3. With corn the response of yield quantile trends to changes in climate trends is consistently higher at lower quantiles. GDD and growing season VPD are unambiguously positive and statistically significant determinants of yield quantile trends, where the effects are generally strongest on the lower quantiles. That is, counties with higher GDD and VPD trends experienced higher yield trends in the lower quantiles. July-August PCP was positively and significantly correlated with the middle yield quantile trends, but did not have significant effects on the extreme lower or upper quantile trends. In contrast, the effect of growing season PCP trends was ambiguous and never statistically different from zero. The effects of HDD and July-August VPD were unambiguously negative and statistically significant. Despite acting in a different direction, similar to GDD and growing season VPD the magnitude of HDD and July-August VPD effects were progressively higher at lower quantiles.

Soybean illustrates an interesting contrast to corn because the response of yield

Table 3: Contributions of Innovation and Climate to Yield Quantile Trends

	Corn						Soybean				
Quantile	10th	30th	50th	70th	90th	Quantile	10th	30th	50th	70th	90th
Constant	1.22***	1.69***	1.83***	1.99***	2.08***	Constant	0.43***	0.45***	0.47***	0.46***	0.51***
	(0.14)	(0.07)	(0.06)	(0.05)	(0.07)		(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
GDD	0.12***	0.07***	0.05***	0.05***	0.01	GDD	0.04***	0.03***	0.02***	0.01**	0.02**
	(0.034)	(0.019)	(0.015)	(0.015)	(0.016)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HDD	−2.02***	−0.90***	−0.67***	−0.60**	−0.34	HDD	−0.63***	−0.35***	−0.07	0.07	0.13
	(0.44)	(0.27)	(0.21)	(0.24)	(0.25)		(0.13)	(0.12)	(0.11)	(0.10)	(0.12)
VPD	1.24***	0.78***	0.56***	0.29**	0.46***	VPD	−0.08	0.14**	0.16**	0.24***	0.12**
	(0.37)	(0.20)	(0.16)	(0.14)	(0.16)		(0.08)	(0.07)	(0.06)	(0.05)	(0.06)
PCP	0.01	−0.03	0.00	−0.01	0.02	PCP	−0.03**	−0.02*	−0.01	−0.00	−0.00
	(0.05)	(0.03)	(0.02)	(0.02)	(0.03)		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
VPDJA	−2.30**	−1.68***	−1.16**	−0.55	−0.93**	VPDJA	0.42*	−0.21	−0.34*	−0.57***	−0.31*
	(1.08)	(0.57)	(0.46)	(0.44)	(0.46)		(0.23)	(0.21)	(0.19)	(0.16)	(0.18)
PCPJA	0.08	0.12**	0.08*	0.13***	−0.01	PCPJA	0.09***	0.07***	0.05**	0.04**	0.06***
	(0.10)	(0.05)	(0.04)	(0.05)	(0.04)		(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
n	99	99	99	99	99	n	98	98	98	98	98
r^2	0.46	0.45	0.41	0.31	0.19	r^2	0.25	0.35	0.30	0.37	0.33
F	13.1***	12.6***	10.7***	6.93***	3.61***	F	5.09***	8.32***	6.52***	8.78***	7.30***

Note: Robust standard errors in parentheses. Statistical significance indicated at the *-10%, **-5%, and ***-1% levels, respectively.

quantile trends to changes in climate trends is fairly constant over quantiles. GDD trends are positively and significantly correlated with yield trends across all quantiles with slightly higher effects on the lower quantiles than the median or upper quantiles. The effects of GDD trends are relatively constant over the median and upper quantiles. HDD has a strong negative and significant effect on the lower tail, but a positive and insignificant effect on the upper tail. Growing season VPD and July-August PCP have fairly consistent positive and significant effects across quantiles (with the exception of VPD's effect on the 10th quantile which is negative and insignificant) suggesting counties with higher VPD and July-August PCP had uniformly higher yield trends. Growing season PCP has a statistically negative effect on the lower tail trends, but its effect on the median and upper tail is not statistically different from zero. While the pattern of effects is not as consistent for soybean as for corn, the magnitude (and sometimes even the direction) of the effects are not equivalent across yield quantile trends; that is, there are differential climate contributions across quantiles. This is especially reflected with July-August VPD, which has a positive and significant effect on the 10th quantile, but negative and significant effects on the median and upper tail trends.

We can also use these estimated models to test some interesting hypotheses about the contributions of climate and innovation to yield quantile trends (*Methods*). The F-statistics reported in table 3 show the inclusion of the climate trend variables jointly improves the fit of the model. In other words, climate trend variables are statistically significant determinants of yield quantile trends; however, this does not speak to the net effect of these climate trends. By comparing the regression model constants (or climate-adjusted yield trends per Lobell and Asner (2003a)) to the average conditional quantile trends, we infer the average net effect of climate on respective yield quantile trends and present the results in table 4. For corn the climate-adjusted yield trends

Table 4: Net climate effect across conditional quantile trends

	Corn		Soybean	
Quantile	Effect	p-Value	Effect	p-Value
10	+0.2628	0.0291	−0.0450	0.0807
30	+0.1479	0.0203	−0.0076	0.3942
50	+0.1467	0.0903	+0.0079	0.3631
70	+0.0709	0.0880	+0.0340	0.0479
90	+0.1042	0.0574	+0.0181	0.1819

Note: Net climate effect in annual bushels per acre.

are consistently lower than the conditional quantile trends across quantiles implying observed changes in climate have shifted yield trends upwards. Once again, we see climate has had the largest effect on the lower tail of the distribution. The results for soybean are more ambiguous: climate has had a negative effect on the lower tail (though neither are statistically different from zero at the 5% level) but a positive effect on the median and upper tail.

Overall, spatial variations in climate trends explain 19% to 46% of the spatial variation in yield quantile trends for corn and 25% to 37% for soybeans. Interestingly, the explanatory power of the model steadily decreases at higher quantiles for corn, implying changes in climate disproportionately affect the lower tail (as expected but yet to be empirically documented). In an interesting contrast, explanatory power does not follow a consistent pattern across soybean conditional quantiles, likely reflecting the plant's plasticity and lower responsiveness to climate and management Vega et al. (2001). It is also clear the response of yield trends to differences in climate trends are not constant over quantiles. That is, the probability and magnitude of low yield outcomes are impacted by changing climate differently than average yield outcomes; considering climate effects *only* at the mean would be misleading.

5 Concluding Remarks

Due to the importance of agricultural production and the unknown impacts of climate change, substantial research efforts have been directed towards a better understanding of the complex relationship between weather outcomes and crop yields (Lobell and Asner, 2003a; Peng et al., 2004; Kucharik, 2008; Schlenker and Roberts, 2009; Lobell, Schlenker, and Costa-Roberts, 2011; Osborne and Wheeler, 2013; Lobell et al., 2014; Ray et al., 2015). While these research efforts have led to important advancements in knowledge, the literature has focused almost exclusively on *average* yields. While useful, the effect of climate on yield volatility has been largely ignored. This is problematic for multiple reasons: (i) changing climate and innovation are likely to impact yield volatility more than average yields; (ii) yield volatility is likely to impact year-to-year food supply more than average yields; and thus (iii) yield volatility is likely to have greater and more immediate economic consequences than average yields.

We focus on the volatility of yield outcomes as measured by the overall dispersion in the tails. The first regularity finds significant increases in the year-to-year volatility of corn and soybean yields throughout the Corn Belt. The second empirical regularity demonstrates that the increased volatility observed in the first regularity is not spread evenly across the tails of distribution: more often than not, the lower quantiles shifted upwards slower than the upper quantiles (recall figure 2). Our results in the third empirical regularity suggest one-quarter of the spatial variation in yield volatility coefficients can be explained by variation in trends in climate variables. Interestingly, the net effect of observed climate trends has had a *volatility-reducing effect* during the sample period. The findings in the fourth empirical regularity are not only inconsistent with extrapolating findings for average yields to the tails of the distribution, but are also arguably the most interesting. The response of corn yield quantile trends to changes in climate trends is consistently higher at lower quantiles; in contrast for soybean the response of yield quantile trends to changes in climate trends is fairly constant over quantiles.

During the study period there were a number of notable advancements in technology that may explain our findings: self-pollinating hybrids; ongoing germplasm heterosis and specialization in conventional breeding (Duvick, 2005); genetic traits for pest resistance and herbicide tolerance complemented by advances in nutrition, weed and pest management (Qaim and Zilberman, 2003); earlier planting dates (Kucharik, 2006); and more recently, the increasingly sophisticated and adopted precision agriculture (Mulla, 2013). Interestingly, gains in average corn yields per acre have been driven by the ability of newer hybrids to tolerate higher plant populations, which means potential yield per acre is highly dependent on high plant populations (Tollenaar and Wu, 1999; Echarte et al., 2000; Sangoi et al., 2002); however, higher plant populations have a range of adverse consequences for corn yield stability (Tollenaar and Lee, 2002; Tokatlidis and Koutroubas, 2004). While average corn yields roughly doubled, so too did plant populations and volatility. However, the mechanism for increasing soybean yield volatility is undoubtedly different, as soybean has the ability to produce relatively constant yields across different plant populations (Carpenter and Board, 1997). Most importantly, understanding the causes of the prevalence and magnitude of increases in yield volatility suggest an important question for future research with important implications for a range of fields.

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