Insurance Subsidies, Technological Change, and Yield Resiliency in Agriculture

Anna Chemeris and Alan P. Ker[1]

Department of Food, Agricultural and Resource Economics

University of Guelph

First Draft: June 18, 2019

Abstract

Innovation in the agricultural sector will determine our ability to reduce food insecurity and feed nine billion people by 2050. Concomitantly, most of the world's agricultural crop production is produced under heavily subsidized insurance. Changes in food security will be largely driven by the nexus of innovation, climate change, and the policy institutions under which production agriculture operates. In the United States, crop insurance subsidies increased from 30% to 60% between 1994 and 2000, bringing about a significant increase in program participation. We use this increase as a natural experiment (event) to empirically estimate the impact of insurance subsidies on rates of technological change and measures of yield resiliency in corn (maize) yields. Our event results indicate that subsidies caused an increase in the rates of technological change and, more surprisingly, an increase in yield resiliency measures. However, point identification fails if there exist any confounding variables. Therefore, we use the spatial heterogeneity in our estimated event parameters to identify causal effects from three sources: introduction of genetically modified seeds, changing climate, and insurance subsidies themselves. Quite interestingly, the increase in the rates of technological change dissipates and the yield resiliency effect is reversed (consistent with theory). Furthermore, we find that the positive effects of genetically modified seeds dominate the effects from both changing climate and increased subsidies.

Keywords: insurance subsidies, technological change, yield resiliency, changing climate

Institute for the Advanced Study of Food and Agricultural Policy
Working Paper 2019.8

[1]Alan Ker - corresponding author, aker@uoguelph.ca. Professor, Department of Food, Agricultural and Resource Economics, OAC Research Chair in Agricultural Risk and Policy, Director, Institute for the Advanced Study of Food and Agricultural Policy, University of Guelph. Anna Chemeris, M.Sc. Student, Department of Food, Agricultural and Resource Economics, University of Guelph.

1. Introduction

One of the biggest challenges facing global agriculture today is feeding the world's growing population – an estimated nine billion people by 2050 – as well as ensuring food security (Godfray et al., 2010; Pretty et al., 2010; McKenzie and Williams, 2015). Technological advancements in fertilizer, herbicides and pesticides, farm machinery, irrigation, and seed genomics have historically allowed producers to substantially increase agricultural yields, often without the need to bring more land into production (Evenson and Gollin, 2003; Godfray et al., 2010; Piesse and Thirtle, 2010; Pisante, Stagnari, and Grant, 2012; Wright, 2012; McKenzie and Williams, 2015).[2,3] Technological change will undoubtedly determine our ability to increase or sustain high yields. However, food security will also be affected by the institutions under which production agriculture (the farm sector) operates.

Much of production agriculture in developed countries is produced under heavily subsidized insurance and has been for the past 20-25 years. Moreover, crop insurance appears to be the main avenue by which governments will continue to funnel monies into their production agriculture sectors. In the United States and Canada, administrative and operating costs are fully absorbed by the government and subsidies on crop insurance premiums are around 60% on average (Glauber, 2013; Ker et al., 2017; Rosa, 2018). In countries in the European Union, subsidies on premiums range from 30% to 70% on average (for example, 46% in Austria, 49% in Spain, 64% in Italy, and 65% in France) (Bielza et al., 2007; Enjolras and Sentis, 2011). In Brazil, premium subsidies are almost 50% (Lavorato and Braga, 2018), and in China subsidies range from 50% to over 80% (Wang et al., 2011). These subsidies have generated significant transfers of public monies to the production agriculture sectors in each of these countries. With respect to the U.S. crop insurance program, the total net cost between 2007 and 2016 was \$72 billion – the second largest outlay in the farm bill (nutrition being the largest). Of the \$72 billion, 60% (\$43 billion) was direct benefits to farmers (Rosa, 2018). Unlike past transfers to farmers via price supports or direct payments,

[2] Such advances led to an over six-fold increase in corn yields and over three-fold increases in soybean and wheat yields in the United States over the past century (Alston, Beddow, and Pardey, 2010; Piesse and Thirtle, 2010; National Agricultural Statistics Service, 2019).

[3] Additional proposed ways to address the global food challenge include reducing food waste (Godfray et al., 2010; Parfitt, Barthel, and MacNaughton, 2010; Foley et al., 2011) and reducing the overconsumption of calories and animal-based protein sources, particularly beef (Godfray et al., 2010; Foley et al., 2011; Ranganathan et al., 2016). However, both of these solutions could be challenging to implement because of increasing global wealth: both food waste and meat consumption tend to increase with higher incomes.

insurance subsidies can have a risk substitution effect as well as a wealth effect.[4] Given that much of the world's crop production is produced under heavily subsidized crop insurance, subsidies may very well have an impact on food security and adaptation to a changing climate.

The significance of food security has – unsurprisingly – spawned numerous studies on the interactions between technological change in yields, yield resiliency, insurance subsidies, and climate change. With respect to yield resiliency and climate change, Schlenker and Roberts (2009), Lobell et al. (2013), Lobell et al. (2014), Tack, Barkley, and Hendricks (2017), and Tack, Coble, and Barnett (2018) suggest that crop yields will experience a substantial decrease due to the increased frequency of extreme heat and drought conditions. Others have considered the connection between insurance subsidies and climate change. For example, Annan and Schlenker (2015) found that subsidies disincentivized producers in mitigating the effects of a changing climate. Finally, a few studies have considered the effects of genetically modified (GM) seeds on yield resiliency. For example, Goodwin and Piggott (2019) find that GM advances have led to greater yield resiliency and suggest that the somewhat dire predictions from the climate literature are not empirically warranted.[5]

In this manuscript, we use institutional changes in the U.S. crop insurance program to identify the effects of insurance subsidies on the rates of technological change in yields and the various measures of yield resiliency. Both the rates of technological change and yield resiliency play important roles in overcoming food insecurity. We require two methodological innovations to identify these effects. First, insurance subsidies would be expected to have heterogeneous effects between the upper and lower tails of the yield distribution. To accommodate this, we use mixture methods which let the data define the number of possibly heterogeneous and asymmetric yield responses to institutional

[4]Many suggest that moral hazard – using fewer risk-mitigating measures than without insurance – is a serious problem for crop insurance (Chambers, 1989; Miranda, 1991). Empirically, Babcock and Hennessy (1996) and Smith and Goodwin (1996) find that crop insurance decreases chemical input use. Antón et al. (2012) and Di Falco et al. (2014) suggest that subsidized crop insurance may be a lower-cost substitute for on-farm adaptation measures. There appears to be a consensus that increased subsidies will lead to increased risk as measured in the lower tail of the yield distribution, i.e. subsidies should decrease yield resiliency. With respect to a wealth effect, Kirwan (2009) shows that the vast majority of insurance subsidies remains with the producer and is not predominately captured by land values. This finding is contradicted by Goodwin, Mishra, and Ortalo-Magne (2011) who conclude that land-owners capture the majority of the benefits from agricultural policy. With respect to Canada, Rude and Ker (2013) show that 45% of business risk management program payments remains with the producers. There does not appear to be a consensus in the literature that increased subsidies would lead to increased on-farm wealth. Nevertheless, increased wealth would lead to higher and quicker adoption rates of new technologies and, in turn, more innovations. In other words, subsidies should increase the rates of technological change in yields.

[5]The first genetically modified crops – corn, soybeans, cotton, and canola – became commercially available in the United States in 1996 and were rapidly and widely adopted by U.S. farmers (Fernandez-Cornejo et al., 2014). These crops have traits that give them resistance to certain insects (Bt trait), as well as tolerance to herbicides such as glyphosate (HT trait) which makes weed control easier. GM crop varieties can have either one of the traits (Bt or HT) or both (stacked varieties) (Fernandez-Cornejo et al., 2014; McFadden et al., 2019). In 2013, 90% of total corn acres in the U.S. were planted to genetically modified hybrids (Fernandez-Cornejo et al., 2014).

changes. Moreover, this approach then allows us to introduce a set of yield resiliency measures not previously considered. Second, we can only point identify the institutional changes if there are no confounding events. Changing climate and the introduction of GM seeds are possible confounding events. To establish identification, we subsequently model the spatial heterogeneity in our event parameters as a function of total subsidies (instrumented by 1995 premium rates), adoption of GM seeds, and changing climate. These two methodological innovations allow us to exploit heterogeneity (within the yield distribution and across space) for identification purposes.

The remainder of this manuscript proceeds as follows. In section 2, we discuss the U.S. crop insurance program, the institutional changes with respect to subsidies, and the accompanying responses in program participation. We outline our data in section 3 and our empirical approach in section 4. In section 5, we discuss the estimation results. We conclude with section 6, in which we emphasize the food security implications of our results.

2. U.S. Crop Insurance Program and Identification of the Effects of Subsidies

The U.S. crop insurance program covers over 100 different crops, ranging from traditional ones like corn, soybean, cotton, and wheat to specialty crops like grass seed and sunflower. More recently, insurance programs for livestock and dairy production have also been introduced. The Congressional Budget Office estimates that spending of public monies on agricultural insurance programs will be almost $90 billion for the 2014-2023 period. Individual farm revenue and yield insurance are the predominant programs, but other programs such as shallow loss and area-yield and area-revenue insurance also exist. The insurance program is operated by the Risk Management Agency (RMA), an arm of the United States Department of Agriculture (USDA). RMA sets premium rates, subsidizes those premiums, and shares the underwriting gains and losses of the insurance contracts with private insurers. The premium rates are set to be actuarially fair with an 11% top-up for reserves; unlike in private insurance markets, there is neither a risk premium nor a premium to cover a return to capital. Program participation has increased substantially since its introduction, especially following Acts in 1980 and 1994. Percent of eligible acres enrolled in the program grew from only 12% in 1980 to over 86% in 2015, and the number of insured crops increased from 28 to 123 over this same time period (Rosa, 2018). The greatest spike in participation followed the 1994 Act, mainly because of the mandatory enrollment requirement for eligibility under other programs. Participation then decreased somewhat after this eligibility requirement was repealed in 1996 (see

Table 1). To encourage participation, particularly in buy-up coverage, Congress passed ad hoc disaster legislation in 1998, 1999, and 2000 (Glauber, 2004) and provided supplemental premium subsidies in 1999 and 2000 (Glauber, 2013). However, as seen from Table 1, program participation in buy-up only increased substantially after premium subsidies were further increased in the 2000 Act.

The Federal Crop Insurance Reform Act of 1994 and the Agricultural Risk Protection Act of 2000 represent a unique natural experiment which can be used to analyze differences in the rates of technological change and yield resiliency before and after the subsidy increase. As seen from Table 1, participation in the crop insurance program increased dramatically after the 1994 Act. Participation in buy-up coverage notably increased after the 2000 Act. Thus, in our analysis we used the 1994 Act as the start of the event.[6]

Table 1. Percentage of corn acres insured in the Federal Crop Insurance Program.

		1994	1995	1996	1997	1998	1999	2000	2001
Illinois	Total acres insured	31.6	85.6	67.0	57.8	59.6	64.2	67.1	66.7
	Insured in buy-up	30.2	36.3	31.8	24.6	21.6	16.8	54.6	55.0
Indiana	Total acres insured	21.9	72.7	48.4	44.1	45.0	51.0	59.8	57.8
	Insured in buy-up	21.5	26.1	21.1	14.4	11.1	10.2	52.0	50.7
Iowa	Total acres insured	55.6	90.2	48.8	78.5	78.2	80.2	82.9	83.7
	Insured in buy-up	52.2	58.3	20.5	16.8	15.3	11.5	74.5	75.5
Minnesota	Total acres insured	63.0	88.2	79.5	80.0	81.5	81.6	84.6	86.7
	Insured in buy-up	52.4	52.5	31.9	27.8	26.7	19.6	69.0	71.7
Ohio	Total acres insured	15.8	73.8	56.6	38.5	38.8	44.4	48.8	51.3
	Insured in buy-up	15.1	20.2	31.9	17.1	12.9	10.6	39.8	42.9
Wisconsin	Total acres insured	39.4	68.3	53.4	44.6	46.8	47.9	53.0	54.0
	Insured in buy-up	27.2	23.6	32.3	23.8	22.6	19.3	52.2	36.4
S. Dakota	Total acres insured	59.2	130.3*	91.8	91.2	87.0	97.2	89.9	103.4*
	Insured in buy-up	44.3	67.4	37.7	32.3	31.7	23.5	75.3	89.9

Notes: Numbers reported are acres insured as a percentage of total acres planted. Acres insured in buy-up are acres insured at 65% coverage or higher (i.e. above CAT coverage). Percentages were computed using USDA Risk Management Agency (RMA) Summary of Business data and USDA NASS crop acreage data. For South Dakota, percentages of acres insured in 1995 and 2001 are over 100% due to the total acreage planted as reported by USDA NASS being smaller than the acreage insured as reported by USDA RMA.

[6] We performed the analysis using year 2000 as the start of the event and the results did not change in any material way.

As discussed, we use the premium subsidy increase from 30% to 60% between 1994 and 2000 as a quasi-experiment to empirically estimate the impact of insurance subsidies on rates of technological change and measures of yield resiliency. Our approach is to compare the component specific slope parameters before and after the event using dummy variables to identify the change. However, these dummy variables identify the average effects in aggregate of any changes post 1994. For this to identify the subsidy effect, there must be no confounding variables. However, there are two possible confounding events: changing climate and the introduction of GM seeds. As a result, the estimated dummy variables do not identify the subsidy effect but instead represent the aggregated effects of changing subsidies, changing climate, and the introduction of GM seeds.

Note that we undertake our analysis for 400 counties independently and thus have 400 county-level post 1994 effects. Moreover, we expect heterogeneity in these effects because of heterogeneity in the changing subsidies, changing climate, and adoption of GM varieties. We can use this spatial heterogeneity for point identification of the effects of subsidies, changing climate, and GM seeds by using the estimated dummy variables as our response variables, and subsidies, changing climate, and adoption of GM seeds as our regressors. Specifically, we use 70% coverage level premium rates in 1995 as an instrument for total subsidies post 1994 to remove any potential issues of endogeneity due to reverse causation. Changing climate is a collider variable, as defined by Lewbel (forthcoming), and so we use the 1995-2017 trends in various climate variables. Finally, we use the 2000 state-level GM adoption rates – although GM seeds were introduced in 1996, adoption rate data begins only in 2000. Note that a reverse causation argument could be made here: increased subsidies caused increased innovation which may have led to GM seeds. However, research spending and innovation in GM technology preceded the 1994 subsidy increase by at least a decade, and so this form of reverse causation is unlikely. A self selection argument could also be made in relation to adopters knowing that they would experience the greatest gains. To minimize this potential issue, we only use the first available adoption rates (in 2000). Note that others have also exploited spatial heterogeneity to distinguish between climatic and non-climatic effects in yields (e.g. Nicholls, 1997; Lobell and Asner, 2003; Lobell and Field, 2007; Tao et al., 2008; Zhang et al., 2016; Feng et al., 2018; Kukal and Irmak, 2018).

In this secondary regression – the regression of estimated dummy variables on premium rates, climate trends, and GM adoption rates, – the conventional standard errors are biased downwards because they do not account for the fact that our response variable is estimated. We account for this using jackknife methods. The jackknife is preferable to a bootstrap in our context. First, it is well known that residual bootstraps are invalid in the presence of conditional heteroscedasticity, which we expect in the initial regressions. Second, while the wild bootstrap is robust to conditional heteroscedasticity, perturbing the sign of residuals necessarily imposes symmetry, whereas our mixture models indicate asymmetry. Third, bootstraps for spline estimates typically use residual or wild bootstraps because paired bootstraps bias the knot estimates (e.g. Wang, 1995). The jackknife circumvents these three issues. Specifically, our jackknife drops one year of the panel in each iteration, thereby maintaining robustness to the presence of spatial dependence, along the lines of Hahn and Newey (2004). The jackknife is a linear approximation to the bootstrap but is biased upwards relative to the bootstrap (Efron and Tibshirani, 1993). Given this upward bias, for comparison we also report conventional standard errors.

It is worth noting that the existing literature measures the effects of technological change on yields almost exclusively by estimating changes in productivity with respect to time. Given the vast number of technological advances in seed, machinery, inputs, and farm management technologies with varying and unknown rates of adoption, pinpointing the effect of a given technology is empirically impossible unless experimental plot data is used. As a result, technological change is measured by time and reflects not only changing technology but also its interactions with changing policy, changing climate, changing farm management strategies, etc. Therefore, consistent with the literature, we use time to model technological change and explicitly recognize that what we are capturing is technological change interacting within its production environment.

3. Data

We obtained county-level corn yield data from the National Agricultural Statistics Service (NASS) of the USDA. The most complete data was available for the time frame of 1951 to 2017 (67 years). To be included in the analysis, the following criteria had to be met: (i) counties had to have complete 67 years of data; (ii) states had to have 25 or more counties with complete 67 years of data; and (iii) less than 10% of state acreage had to be irrigated as reported in the 2012 Census of Agriculture. Seven states met the inclusion criteria: Illinois (IL), Indiana (IN), Iowa (IA), Minnesota (MN), Ohio (OH), South Dakota (SD), and Wisconsin (WI). These seven states accounted for 62% of total corn produced in the United States in 2017. In total, our data set consisted of 414 corn counties. We focus on corn yields because corn is the most important and globally grown grain crop. It serves both as a food staple and as livestock feed. The U.S. is the largest global producer of corn; in 2018, it accounted for 366.29 million metric tonnes of the total 1107.38 million metric tonnes produced globally.

For our causal analysis, we need an estimate of the 1995 premium rates, GM adoption rates, and climate change trends. We used estimated premium rates for 1995 at the 70% coverage level as an instrument for total subsidies between 1995 and 2017. To obtain the estimated 1995 premium rates, we re-estimated the county models without the event parameters using yield data from only 1951-1994. This avoided any possible reverse causation issues. We also obtained state-level data on the adoption of GM corn from the USDA (county-level adoption data was not available). The earliest year for which adoption information was available is 2000. Summed across all GM varieties (insect-resistant, herbicide tolerant, and stacked), the percentage of corn acres planted to GM seed in 2000 was 17% in Illinois, 11% in Indiana, 30% in Iowa, 37% in Minnesota, 9% in Ohio, 18% in Wisconsin, and 48% in South Dakota.

With respect to climate data, we obtained daily temperature (in degrees Celsius) and precipitation (in millimeters) data from weather stations across the United States from the NOAA National Climate Data Center for the time frame of 1951 to 2015. This data was used to compile a data set of six climate variables: growing degree days (GDD), extreme temperature degree days (HDD), vapour pressure deficit over the entire growing season (VPD), vapour pressure deficit during July and August (VPD_{ja}), precipitation over the entire growing season (PCP), and precipitation during July and August (PCP_{ja}). These six chosen variables have the strongest relationship with yield and are most commonly used in the literature (e.g. Cabas, Weersink, and Olale, 2010; Lobell et al., 2013; Roberts, Schlenker, and Eyer, 2013; Lobell et al., 2014; Annan and Schlenker, 2015; Tolhurst and Ker, 2015; Burke and Emerick, 2016). Growing degree days measure the number of days that a crop is exposed to temperatures below the critical threshold (29 degrees Celsius for corn) and have a positive relationship with yield. Extreme temperature degree days are the number of days that a crop is exposed to temperatures above the critical threshold and thus have an inverse relationship with yield. Vapour pressure deficit can influence yield both positively and negatively, and thus its relationship with yield is an empirical question, as discussed by Roberts, Schlenker, and Eyer (2013). On the one hand, vapour pressure deficit is related to relative humidity, with a larger value implying a lack of moisture and thus having a negative impact on yield. On the other hand, vapour pressure deficit is associated with diurnal temperature variation (the difference between daily minimum and maximum temperatures) which is in turn correlated with less cloud cover and more solar radiation, therefore having a positive impact on yield (Roberts, Schlenker, and Eyer, 2013). Precipitation has a positive relationship with yield up to a particular point after which excessive precipitation starts to have a decreasing effect on yield due to waterlogging and oxygen deficiency.

4. **Mixture Models**

Studies such as Chambers (1989), Miranda (1991), Smith and Goodwin (1996), Antón et al. (2012), and Di Falco et al. (2014) argue that subsidies lead to a shifting of risk away from on-farm measures to crop insurance. While this effect would be evident in our standard measures of variance, it would result in vastly different changes in the lower and upper tails of the yield distribution. That is, shifting from on-farm risk mitigation efforts to subsidized insurance would lead to a longer lower tail in the observed yield distribution and not necessarily any effect in the upper tail. Standard metrics of variance are symmetric and thus would mute the risk substitution effect relative to more appropriate metrics that can measure differing volatility changes between the tails. A technique based on mixtures is proposed. Mixtures let the data determine the number of possibly heterogeneous yield responses to technological change, subsidies, climate change, etc. Furthermore, using mixtures generates some interesting and new measures of crop yield resiliency (discussed later).

In general, a mixture model with J components is defined as:

$$f(y_t) = \sum_{j=1}^{J} \lambda_j f_j(y_t). \tag{1}$$

Note, $f_j(y_t)$ is a continuous density and λ_k corresponds to the mixing weights where $\sum_{j=i}^{J} \lambda_j = 1$. We assume that the component densities are normal. A mixture of normals can approximate any continuous density to any desired level of error (Everitt and Hand, 1981). The number of components is chosen using information criterion across one, two, and three components ($J = 1, 2, 3$). We follow Anderson, Pittau, and Zelli (2016) and consider Akaike Information Criterion (AIC), AIC with a parameter penalty factor of two, Bayesian Information Criterion (BIC), and the Consistent Akaike Information Criterion (CAIC). In more than 95% of the counties, the number of components was two and so that was imposed for all counties.

The normal mixture model has been used by Tolhurst and Ker (2015) and Ker, Tolhurst, and Liu (2016) to model yields. Given $J = 2$ and our normality assumption, we have:

$$(2) \qquad y_t \sim \lambda N(\alpha_l + \beta_l t + \delta_l t I_{[1995,T]}(t), \sigma_l^2) + (1-\lambda) N(\alpha_u + \beta_u t + \delta_u t I_{[1995,T]}(t), \sigma_u^2)$$

In this model, λ is the probability of the lower component, $\alpha_l + \beta_l t + \delta_l t I_{[1995,T]}(t)$ is the lower component conditional mean, and $\alpha_u + \beta_u t + \delta_u t I_{[1995,T]}(t)$ is the upper component conditional mean. The lower and upper component variances are σ_l^2 and σ_u^2, respectively. The event parameters of interest are δ_l and δ_u; they represent the changes in the rates of technological change in the lower and upper components, respectively, post 1994.

As is commonly done with mixture models, we use the expectation-maximization (EM) algorithm to estimate the unknown parameters (Dempster, Laird, and Rubin, 1977). The EM algorithm solves the incomplete data problem that we do not know which component the yield realization is drawn from. If such information was known, we would simply estimate the parameters of the component distribution with the subset of data realized from the distribution with standard likelihood or moment methods. This is the maximization or M-step. The EM algorithm replaces the true unknown memberships with estimates of the expected membership recovered from the estimated conditional probabilities of component membership. This is the expectations or E-step. The process is iterated until convergence. Because local optimums can be found, the process is repeated for multiple starting membership assignments to ensure that a global optimum is found, and the maximum of the various maximized likelihoods conditional on the set of starting values is chosen. We impose two restrictions on our estimated parameters. First, $\alpha_l \leq \alpha_u$: the component conditional means processes do not cross at the beginning of the sample (this can occur because of the bunching of the data in the early period). This restriction, tested using a Likelihood Ratio test, was only rejected in a few counties and below the size of the test. Similarly, we also restrict the conditional means to not cross post 1995. Again, this was only rejected in a few counties and well below the size of the test.[7] Finally, we restrict the component variances away from zero.[8]

[7] We removed counties with a persistent crossover issue from our analysis. This resulted in the removal of 18 out of 414 (4.3%) counties.

[8] Another issue with the EM algorithm in small samples is that the component probabilities tend to be biased to $1/J$. Therefore, using our parameter estimates from the EM algorithm as starting values, we subsequently maximized a penalized (in the direction of the bias) likelihood. A standard squared term in the direction of the bias was used as the penalty and 50 levels of tuning parameters were considered (the tuning parameter puts more or less weight on the penalty relative to the likelihood). This led to 50 additional sets of parameter estimates. Our chosen final estimate was the set of parameters that maximized the unpenalized likelihood from amongst the 51 sets of parameters. That is,

Recovering the Risk Substitution Effect and Yield Resiliency Measures

Yield resiliency is important in meeting future food demand at affordable and stable prices, particularly in a changing and more volatile climate. In the crop science literature, yield resiliency is typically defined as the ability of a crop to retain its productivity following environmental stresses (Holling, 1973). Methods of measuring yield resiliency include, but are not limited to, determining the plant biomass after recovery and resurrection from stress (Lukac et al., 2012; Gaudin et al., 2013; Griffiths et al., 2016) and estimating the ratio of crop productivity to severeness of stress (Simelton et al., 2009). These measures, while appropriate for plot data on yields, are not very helpful in measuring yield resiliency beyond the specific plant. There is no consensus in the climate change or agricultural economics literature on measures of yield resiliency. Nonetheless, the literature has almost exclusively found yield resiliency decreasing (as measured by some increase in mass in the lower tail) and offered a number of explanations. For example, Tack, Coble, and Barnett (2018), Lobell et al. (2014), and Burke and Emerick (2016) suggest that the changing climate has been negatively influencing yield resiliency. Ker et al. (2017) and Annan and Schlenker (2015) suggest that the decrease in resiliency was driven by high insurance subsidies. Finally, Ker et al. (2017) suggest that increases in technology have lead to increased planting densities, creating greater sensitivities to climate. In contrast to the above, Goodwin and Piggott (2019) compare corn yield responses between the droughts of 2005 and 2012 and suggest that the introduction of biotech seeds has lead to greater yield resiliency.

Our two-component normal mixture model allows us to formalize a number of yield resiliency measures with respect to changes in the yield distribution. First, we consider whether the probability of the lower component is increasing or decreasing through time. If the probability is decreasing through time, then yields are becoming more resilient. We term this measure *probability* yield resiliency. It is recovered by regressing the component probabilities within the sample against time:

$$\omega_t = \alpha_\lambda + \beta_\lambda t + \delta_\lambda t I_{[1995,T]}(t) + \nu_t \tag{3}$$

only if the penalized maximization resulted in parameter estimates that lead to an optimum with a higher likelihood than the EM algorithm were those parameters used.

where α_λ is the intercept, β_λ is the slope representing the change in the probability of a low yield over time, and δ_λ is the change in the slope after 1995. Note that *probability* yield resiliency is increasing if $\delta_\lambda > 0$.

We consider two additional measures of yield resiliency taken from the economic growth literature which uses mixtures to measure polarization/convergence between sets of countries in poverty measures. We are obviously concerned with the polarization or convergence between yields from the lower component and yields from the upper component. First, consider the following metric:

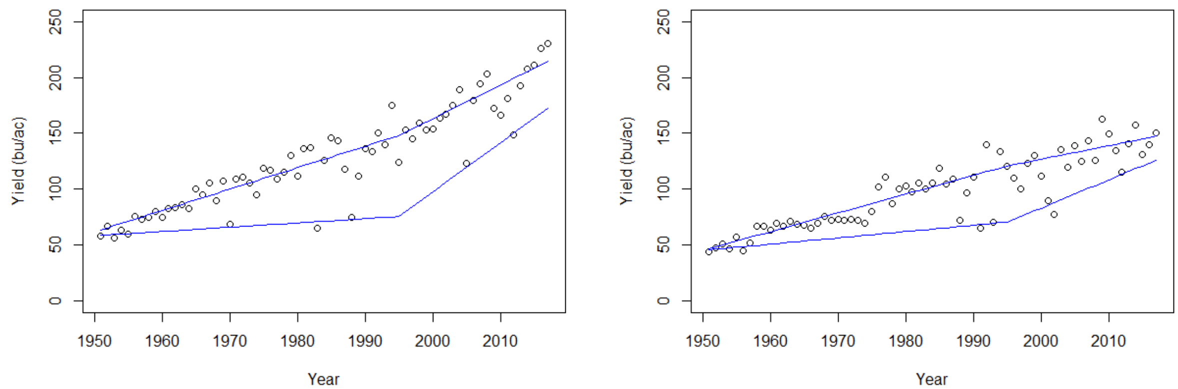
$$\theta_t = \int_{-\infty}^{\infty} min\{f_t(y), g_t(y)\}dy \tag{4}$$

where $f_t(y)$ and $g_t(y)$ are density functions. θ_t has been used to measure changes in economic polarization or convergence over time between two groups (see Anderson, Leo, and Muelhaupt, 2014; Anderson, 2010; Anderson, Pittau, and Zelli, 2016). Asymptotic properties are investigated in Anderson, Linton, and Whang (2012). Note that $\theta_t \in [1, 2]$, where $\theta_t = 1$ is indicative of complete convergence as the densities are necessarily identical and $\theta_t = 2$ is indicative of complete polarization where the densities necessarily do not overlap. As stated, we use this quantity as a measure of polarization/convergence between the upper and lower component densities of our yield mixture model over time. We consider the following two measures of yield resiliency. First, we define yield resiliency as increasing if the *rate* of polarization decreases post 1994. We define this as *marginal* yield resiliency and represent it by an indicator variable, denoted R_m, equal to 1 if $\frac{d\theta_t}{dt}|_{t=1994} < \frac{d\theta_t}{dt}|_{t=1995}$ and 0 otherwise.[9] Second, we define a stricter measure of yield resiliency, termed *absolute* yield resiliency. This measure reflects whether polarization is increasing in absolute. We define a second indicator variable, denoted R_a, equal to 1 if $\frac{d\theta_t}{dt}|_{t=1995} > 0$ and 0 otherwise. Note, if $R_m = 1$, then $R_a = 1$.

5. **Estimation Results**

In this section, we report the results of our estimation, testing, and causal effects analysis. Figures 1a and 1b illustrate two examples of the component trends from our estimated mixtures. As seen from Figure 1a, the rates of technological change (i.e. slopes) in Stark County, Illinois, are positive and have increased in both the lower and the upper components post 1995, more so in the lower component. In Medina County, Ohio (Figure 1b), the rates of technological change

[9] We necessarily define this measure as a change in the first derivative, as the second derivative is not continuous given θ_t is a piecewise linear function.



(A) Stark County, Illinois

(B) Medina County, Ohio

Figure 1. Model estimation results for two representative corn counties.

are again positive but appear to be decreasing post 1995 in the upper component and increasing in the lower component. In addition, both plots illustrate that the probability of a draw from the lower component is roughly 10-20%, and, while relatively constant across the years for Stark County, the draws appear to be increasing in frequency for Medina County. These counties are fairly representative of our overall results: pre 1995, the rates of technological change are positive in both components but noticeably higher in the upper component, and post 1995 the change in the rate of technological change in the lower component tends to be sizeable and positive while the change in the upper component tends to be smaller.

All parameter estimates from our mixture model are summarized at the state level in Table 2. There are a number of interesting results. First, we find that $\beta_u > 0$ and $\beta_l > 0$, indicating overall increases in yields from technology. Second, consistent with Tolhurst and Ker (2015) and Ker and Tolhurst (2019), we find that $\beta_u > \beta_l$ for all states, indicating an increasingly longer lower tail of the yield distribution, i.e. asymmetric heteroscedasticity and decreasing yield resiliency. Third, λ – the overall probability of the lower tail component – represents roughly 20% of the yield realizations and is spatially quite consistent.

Focusing on the estimates of our event parameters (δ_l, δ_u, and δ_λ), we also find a number of interesting results. First, in four of the seven states we find that $\delta_l > \delta_u$, in contrast to our pre-1995 slope coefficients where $\beta_u > \beta_l$ (but note that δ_l and δ_u are measured as changes relative to those pre-1995 slopes (i.e. β_u and β_l) rather than absolute measures). These results suggest a decreasing longer lower tail and increasing yield resiliency post 1994. Second, the boxplots in

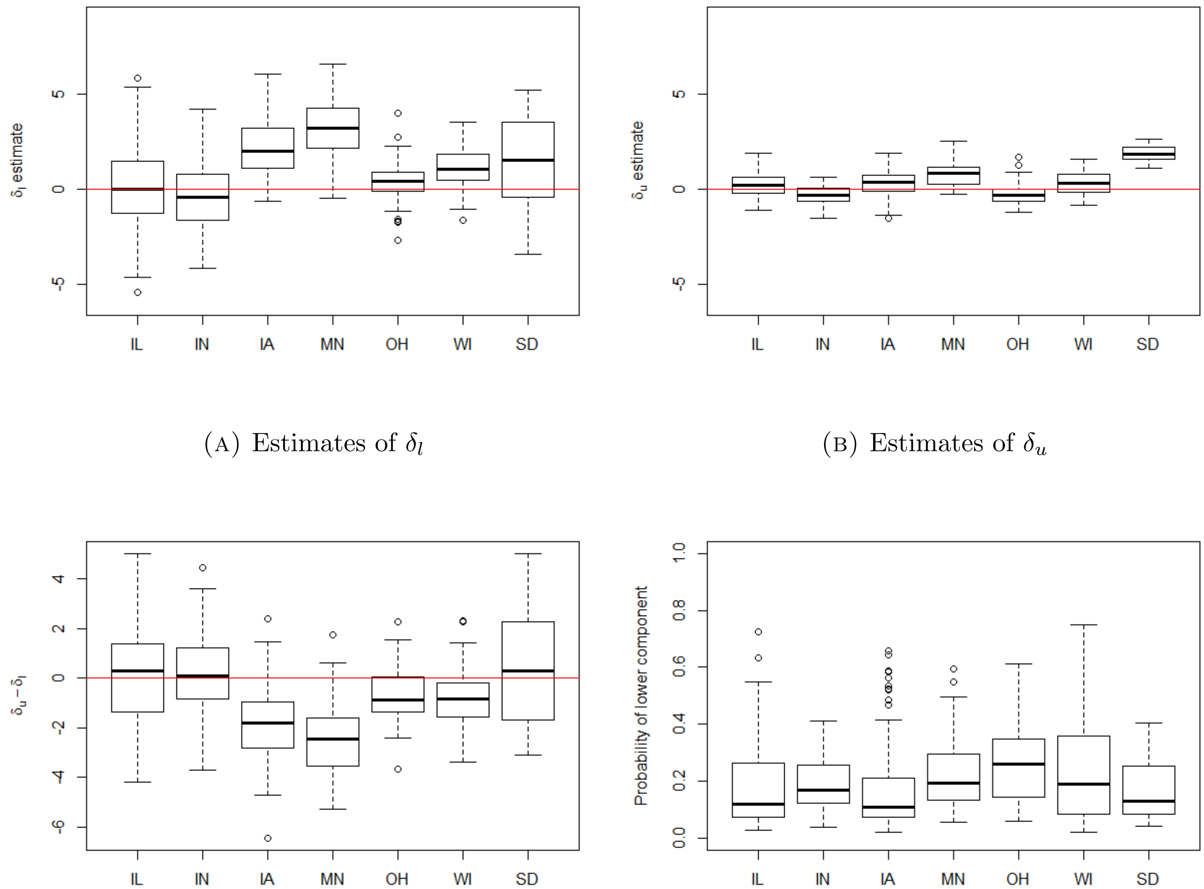
Table 2. Corn mean parameter estimates.

	Illinois	Indiana	Iowa	Minnesota	Ohio	Wisconsin	S. Dakota
λ	0.188	0.196	0.178	0.230	0.270	0.240	0.171
α_u	53.614	50.548	51.298	40.342	48.977	51.464	18.939
α_l	48.602	49.081	46.800	38.775	48.245	48.584	18.124
β_u	1.935	1.966	2.035	1.997	1.926	1.627	1.540
β_l	0.963	1.099	0.964	0.925	1.108	0.833	0.669
δ_u	0.291	-0.280	0.351	0.786	-0.209	0.358	1.904
δ_l	0.056	-0.526	2.148	3.198	0.433	1.102	1.445
σ_u	12.034	10.124	10.533	8.719	8.381	8.225	12.129
σ_l	10.902	11.730	11.505	11.086	11.293	8.372	6.208
δ_λ	-1.422	-0.708	-0.841	-0.103	-0.939	-0.501	-0.156

Figure 2 illustrate much greater variability in our estimates of δ_l versus δ_u. This is because the lower component has much less mass (and yield realizations), and, therefore, estimates of the lower component parameters necessarily tend to have greater uncertainty. Third, δ_λ is very small for all states, indicating very little change between pre and post 1994 regarding the probability of a draw from the lower tail component and suggesting little change in yield resiliency as defined by the probability of a draw from the lower tail component. The estimates of δ_l and δ_u are presented in more detail in the boxplots in Figures 2a and 2b. Similarly, our measures of risk and yield resiliency, $\delta_u - \delta_l$ and δ_λ, are presented in Figures 2c and 2d. Other than the probability of a draw from the lower component (λ), we definitely see heterogeneity across the states in our estimated parameters. The appendix geographically illustrates the event parameter estimates. Particularly interesting is that both δ_l and δ_u are higher in the northwest and systemically decrease as you move southeast. Interestingly, we see that $\delta_u - \delta_l$ (where a greater difference suggests increasing volatility or decreasing yield resiliency) is increasing as you move from the northwest to the southeast. We do not see any significant geographical clustering of the probability of a draw from the lower tail (λ). Conversely, we do see δ_λ decreasing as we move from the northwest to southeast.

5.1. *Testing*

The results of our hypothesis tests are given in Table 3. Overall, about one-third of all counties rejected the null hypothesis that either one of the δ_j's or both are zero. In over 80% of these counties across all states, the change in the rate of technological change in both components was positive, and was greater in the lower component (i.e. $\delta_l > \delta_u$). This is strong evidence of increasing yield resiliency post 1994 as measured by the lower component mean converging to the upper



(A) Estimates of δ_l

(B) Estimates of δ_u

(C) $\delta_u - \delta_l$

(D) Probability of a low yield, λ

FIGURE 2. Estimates of δ_j and the probability of a low yield for corn counties by state. Red line at zero in (A)-(C) is drawn for reference to make it easier to distinguish between positive and negative values.

component mean. Indiana and Ohio somewhat differ from this overall average, with δ_u's in many of their counties being significantly negative. With respect to the probability of a draw from the lower component, none of the estimated δ_λ parameters were significantly different from zero. This suggests no change in yield resiliency as measured solely by a decreasing probability of a yield draw from the lower tail component. Overall, these results indicate very strong changes in the parameters of the mixture models post 1994. In most event studies, these changes would be attributed to the event effect, i.e. the increases in subsidies.

Table 3. Test Results: Number of Rejections.

State	N	$\delta_l = 0$	$\delta_u = 0$	$\delta_l = \delta_u$	$\delta_\lambda = 0$
Illinois	71	23	18	19	0
Indiana	60	13	12	14	0
Iowa	86	33	28	29	0
Minnesota	51	34	26	28	0
Ohio	57	7	12	9	0
Wisconsin	48	15	19	13	0
S. Dakota	23	12	23	14	0
Total	396	137	138	126	0

Notes: Some counties were removed due to convergence issues, so the number of counties used for testing does not add up to the 414 counties initially included in the data set.

5.2. *Causal Effects*

As discussed, we take these event parameter estimates ($\delta_l, \delta_u, \delta_u - \delta_l, \delta_\lambda$) and model them as functions of a changing climate, the subsidy instrument, and GM adoption rates. Note that δ_l and δ_u, which represent changes in the component slopes, represent more location-type measures of yields, while $\delta_u - \delta_l$ and δ_λ can be considered more yield resiliency measures and arguably more important for issues of the effect of subsidies on year-to-year food security. We also consider two additional measures of yield resiliency: *marginal* yield resiliency, denoted by $R_m \in \{0, 1\}$, where $R_m = 1$ represents a decreasing rate of polarization between the lower and upper component of the yield distribution, and *absolute* yield resiliency, denoted by $R_a \in \{0, 1\}$, where $R_a = 1$ represents increasing convergence of the lower component to the upper component.

Table 4 reports the results.[10] The results are notable. First, with respect to our two location measures (δ_l and δ_u) and climate, we find that an increasing *GDD* is positive and significant (under conventional standard errors) on the upper component slope but insignificant on the lower component slope, while an increasing *HDD* is insignificant on the upper component slope but negative and significant on the lower component slope, all as expected. With respect to the premium rates – our instrument for subsidies – we find that the slope coefficients are positive (which is consistent with a wealth effect) but very insignificant. We find that GM seeds are positive and very significant.

With respect to our yield resiliency measures, we find an increasing *HDD* causing an increase in $\delta_u - \delta_l$ and therefore decreasing yield resiliency. The other three measures of yield resiliency –

[10]Not all counties in the crop yield data could be paired up with climate data due to missing data in the climate data set. This required the removal of 7 counties.

Table 4. Event Parameter Regressions.

	Location measures		Resiliency measures			
	δ_l	δ_u	$\delta_u - \delta_l$	δ_λ	R_m	R_a
ΔGDD	0.152	0.252**	0.101	0.244*	0.029	-0.022
ΔHDD	-2.598***	0.304	2.902***	0.074	-0.242*	-0.224
ΔVPD	0.506	-0.382	-0.888	-0.834**	-0.173	-0.090
ΔVPD_{ja}	-1.514*	-0.268	1.246	0.580	0.168	0.297
ΔPCP	0.038	-0.027**	-0.065*	-0.046***	0.002	-0.004
ΔPCP_{ja}	-0.200***	0.023	0.223***	-0.007	0.002	-0.000
$Rates_{1995}$	0.004	0.148	0.145	0.205	-0.136**	-0.170**
GM_{2000}	0.074***	0.033***†	-0.040***	0.013**	0.009***	0.016***
R^2	0.344	0.407	0.260	0.157	0.130	0.165
Wald test overall	***	***†††	***	***	***	***
Wald test climate	***	***	***	***	***	***

Note : Statistical significance is indicated by *, ** and *** for the 10%, 5% and 1% levels under conventional standard errors. Statistical significance is indicated by †, †† and ††† for the 10%, 5% and 1% levels under jackknife standard errors. For joint significance, it was necessary to construct the jackknife covariance matrix using Shao (1992).

δ_λ, R_m and R_a – are increasing in greater yield resiliency, and we would therefore expect opposite signs to $\delta_u - \delta_l$, which decreases with greater yield resiliency. Not surprisingly, we do find opposite signs for most parameters but also very little significance. We only find *HDD* decreasing yield resiliency as measured by R_m. Note that $Rates_{1995}$ appear to cause a decrease in yield resiliency as measured by R_m, R_a and $\delta_u - \delta_l$, but are only significant for the first two measures based on the polarization/convergence of the mixture components. These results are consistent with other findings in the literature (e.g. Lobell, 2014). Finally, as expected, GM seeds adoption increases yield resiliency by all four measures and is statistically significant with all four measures.

Most interestingly, our initial event analysis would suggest significant wealth effects in terms of increased rates of technological change and significant perverse risk effects in terms of increased (not decreased) yield resiliency, both caused by increased subsidies. In fact, this is not the case. When we account for confounding events such as a changing climate and the introduction of GM seeds, we see a very different result. Increased subsidies had little to no effect on the increased rates of technological change and did, in fact, decrease, not increase, yield resiliency. Both results are consistent with literature. Goodwin, Mishra, and Ortalo-Magne (2011) indicate that the majority of income transfers is capitalized into land. Second, Annan and Schlenker (2015) find that insurance subsidies decrease mitigation efforts, thereby decreasing yield resiliency.

As mentioned earlier, the conventional standard errors are biased downwards as they do not account for the response variable being estimated. When we account for this using jackknife standard errors, only the GM seed effect remains significant in the δ_u equation. The differences in the standard errors are non-trivial, with jackknife standard errors increasing by 500-600% relative to the conventional ones in most cases. The standard errors are reported in the appendix. Note that while the conventional standard errors are biased downwards, the jackknife standard errors are biased upwards, and so the true unknown standard errors lie somewhere in between.

6. **Conclusions**

This manuscript is among the first to consider the nexus of insurance subsidies, changing climate, and GM seeds on measures of both technological change and yield resiliency. This is important because innovation in the agricultural sector will determine our ability to feed nine billion people by 2050, and, concomitantly, most of the world's agricultural crop production is produced under heavily subsidized insurance. We used the subsidy increase in the U.S. crop insurance program in the mid to late 1990s as a quasi-natural experiment or event analysis. We could expect to see both a wealth and a risk (or decrease in yield resiliency) effect.

The results of the event analysis indicate that subsidies have a positive wealth effect and a decreasing risk substitution effect or increasing yield resiliency effect. The latter is inconsistent with theory and the literature of Chambers (1989), Miranda (1991), Smith and Goodwin (1996), Antón et al. (2012), and Di Falco et al. (2014). The former is also surprising in that the increase in subsidies simply replaced other methods of transfers to the crop production sector (e.g. direct payments, price supports) rather than causing an influx of greater monies.

Identification in event studies is vulnerable to confounding events. The two possible confounding events are changing climate and the introduction of GM seeds. We subsequently model our event parameters as functions of the 1995 premium rates (an instrument for subsidies), changing climate parameters, and GM adoption rates in 2000. Interestingly, we find that the initial wealth effect dissipates and the risk substitution or yield resiliency effect reverses. Increased subsidies do not cause an increase in rates of technological change in the component and overall means. We also find that increased subsidies caused a decrease rather than an increase in yield resiliency. These results are consistent with theory.

We find that the rates of technological change in yields and the resiliency of yields are decreasing because of climate change, primarily an increase in the number of harmful degree days or days of excessive heat (as found by Annan and Schlenker (2015)). However, we do find that the introduction of GM seeds has dominated the subsidy and climate change effects, such that the overall rates of technological change have increased and yield resiliency has increased (as found by Goodwin and Piggott (2019)). It is unknown what effect will dominate in the future. It is likely that subsidies will not experience any further increases and that the adoption of GM seeds is now at nearly 100%. However, climate does appear to be continuing to change, suggesting that yield resiliency and the rate of change in yields may decrease in the future unless technology can keep up. These possible outcomes will have implications for food security, the cost of risk management programs (as noted by Tack, Coble, and Barnett (2018)), and feeding 9 billion people in 2050. In some sense, our results coalesce what may appear to be disparate findings in the literature.

References

Alston, J.M., J.M. Beddow, and P.G. Pardey. 2010. "Global Patterns of Crop Yields and Other Partial Productivity Measures and Prices." In J. M. Alston, B. A. Babcock, and P. G. Pardey, eds. *The Shifting Patterns of Agricultural Production and Productivity Worldwide*. Ames, Iowa: The Midwest Agribusiness Trade Research and Information Centre, Iowa State University, chap. 3, pp. 39–61.

Anderson, G. 2010. "Polarization of the Poor: Multivariate Relative Poverty Measurement Sans Frontiers." *Review of Income and Wealth* 56:84–101.

Anderson, G., T.W. Leo, and R. Muelhaupt. 2014. "Measuring Advances in Equality of Opportunity: The Changing Gender Gap in Educational Attainment in Canada in the Last Half Century." *Social Indicators Research* 119:73–99.

Anderson, G., O. Linton, and Y.J. Whang. 2012. "Nonparametric Estimation and Inference about the Overlap of Two Distributions." *Journal of Econometrics* 171:1–23.

Anderson, G., M.G. Pittau, and R. Zelli. 2016. "Assessing the Convergence and Mobility of Nations Without Artificially Specified Class Boundaries." *Journal of Economic Growth* 21:283–304.

Annan, F., and W. Schlenker. 2015. "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat." *American Economic Review* 105:262–266.

Antón, J., S. Kimura, J. Lankoski, and A. Cattaneo. 2012. "A Comparative Study of Risk Management in Agriculture under Climate Change." *OECD Food, Agriculture and Fisheries Papers, OECD Publishing*, pp. 89.

Babcock, B.A., and D.A. Hennessy. 1996. "Input Demand under Yield and Revenue Insurance." *American Journal of Agricultural Economics* 78:416–427.

Bielza, M., J. Stroblmair, J. Gallego, C. Conte, and C. Dittmann. 2007. "Agricultural Risk Management in Europe." In *101st EAAE Seminar "Management of Climate ERisks in Agriculture"*. Berlin, Germany, p. 22.

Burke, M.B., and K. Emerick. 2016. "Adaptation to Climate Change: Evidence from U.S. Agriculture." *American Economic Journal: Economic Policy* 8:106–140.

Cabas, J., A. Weersink, and E. Olale. 2010. "Crop Yield Response to Economic, Site and Climatic Variables." *Climatic Change* 101:599–616.

Chambers, R.G. 1989. "Insurability and Moral Hazard in Agricultural Insurance Markets." *American Journal of Agricultural Economics* 71:604–616.

Dempster, A.P., N.M. Laird, and D.B. Rubin. 1977. "Maximum Likelihood from Incomplete Data Via the EM Algorithm." *Journal of the Royal Statistical Society: Series B (Methodological)* 39:1–38.

Di Falco, S., F. Adinolfi, M. Bozzola, and F. Capitanio. 2014. "Crop Insurance as a Strategy for Adapting to Climate Change." *Journal of Agricultural Economics* 65:485–504.

Efron, B., and R. Tibshirani. 1993. *An Introduction to the Bootstrap*. New York: Chapman and Hall.

Enjolras, G., and P. Sentis. 2011. "Crop Insurance Policies and Purchases in France." *Agricultural Economics* 42:475–486.

Evenson, R.E., and D. Gollin. 2003. "Assessing the Impact of the Green Revolution, 1960 to 2000." *Science* 300:758–762.

Everitt, B., and D. Hand. 1981. *Finite Mixture Distributions*. London: Chapman and Hall.

Feng, P., B. Wang, D.L. Liu, H. Xing, F. Ji, I. Macadam, H. Ruan, and Q. Yu. 2018. "Impacts of Rainfall Extremes on Wheat Yield in Semi-arid Cropping Systems in Eastern Australia." *Climatic Change* 147:555–569.

Fernandez-Cornejo, J., S. Wechsler, M. Livingston, and L. Mitchell. 2014. "Genetically Engineered Crops in the United States."

Foley, J.A., N. Ramankutty, K.A. Brauman, E.S. Cassidy, J.S. Gerber, M. Johnston, N.D. Mueller, C. O'Connell, D.K. Ray, P.C. West, C. Balzer, E.M. Bennett, S.R. Carpenter, J. Hill, C. Monfreda, S. Polasky, J. Rockström, J. Sheehan, S. Siebert, D. Tilman, and D.P. Zaks. 2011. "Solutions for a Cultivated Planet." *Nature* 478:337–342.

Gaudin, A.C.M., S. Westra, C.E.S. Loucks, K. Janovicek, R.C. Martin, and W. Deen. 2013. "Improving Resilience of Northern Field Crop Systems Using Inter-Seeded Red Clover: A Review." *Agronomy* 3:148–180.

Glauber, J.W. 2004. "Crop Insurance Reconsidered." *American Journal of Agricultural Economics* 86:1179–1195.

—. 2013. "The Growth of the Federal Crop Insurance Program, 1990-2011." *American Journal of Agricultural Economics* 95:482–488.

Godfray, H.C.J., J.R. Beddington, I.R. Crute, L. Haddad, D. Lawrence, J.F. Muir, J. Pretty, S. Robinson, S.M. Thomas, and C. Toulmin. 2010. "Food Security: The Challenge of Feeding 9 Billion People." *Science* 327:812–818.

Goodwin, B.K., A.K. Mishra, and F. Ortalo-Magne. 2011. "The Buck Stops Where? The Distribution of Agricultural Subsidies." *National Bureau of Economic Research* 16693.

Goodwin, B.K., and N.E. Piggott. 2019. "Has Technology Increased Agricultural Yield Risk? Evidence From the Crop Insurance Biotech Endorsement." *American Journal of Agricultural Economics*, pp. .

Griffiths, C.A., R. Sagar, Y. Geng, L.F. Primavesi, M.K. Patel, M.K. Passarelli, I.S. Gilmore, R.T. Steven, J. Bunch, M.J. Paul, and B.G. Davis. 2016. "Chemical Intervention in Plant Sugar Signalling Increases Yield and Resilience." *Nature* 540:574–578.

Hahn, J., and W. Newey. 2004. "Jackknife and Analytical Bias Reduction for Nonlinear Panel Models." *Econometrica* 72:1295–1319.

Holling, C. 1973. "Resilience and Stability of Ecological Systems." *Annual Review of Ecology and Systematics* 4:1–23.

Ker, A.P., B. Barnett, D. Jacques, and T. Tolhurst. 2017. "Canadian Business Risk Management: Private Firms, Crown Corporations, and Public Institutions." *Canadian Journal of Agricultural Economics* 65:591–612.

Ker, A.P., and T.N. Tolhurst. 2019. "On the Treatment of Heteroscedasticity in Crop Yield Data." *American Journal of Agricultural Economics* aaz004.

Ker, A.P., T.N. Tolhurst, and Y. Liu. 2016. "Bayesian Estimation of Possibly Similar Yield Densities: Implications for Rating Crop Insurance Contracts." *American Journal of Agricultural Economics* 98:360–382.

Kirwan, B.E. 2009. "The Incidence of U.S. Agricultural Subsidies on Farmland Rental Rates." *Journal of Political Economy* 117:138–164.

Kukal, M.S., and S. Irmak. 2018. "Climate-Driven Crop Yield and Yield Variability and Climate Change Impacts on the U.S. Great Plains Agricultural Production." *Scientific Reports (Nature Publisher Group)* 8:1–18.

Lavorato, M., and M. Braga. 2018. "Assessing the Effects of Premium Subsidies on Crop Insurance Demand: An Analysis for Grain Production in Southern Brazil." In *30th International Conference of Agricultural Economists*. Vancouver, Canada, p. 19.

Lewbel, A. forthcoming. "The Identification Zoo: Meanings of Identification in Econometrics." *Journal of Economic Literature*, pp. .

Lobell, D.B. 2014. “Climate Change Adaptation in Crop Production: Beware of Illusions.” *Global Food Security* 3:72–76.

Lobell, D.B., and G.P. Asner. 2003. “Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields.” *Science* 299:1032.

Lobell, D.B., and C.B. Field. 2007. “Global Scale Climate-Crop Yield Relationships and the Impacts of Recent Warming.” *Environmental Research Letters* 2:014002.

Lobell, D.B., G.L. Hammer, G. McLean, C. Messina, M.J. Roberts, and W. Schlenker. 2013. “The Critical Role of Extreme Heat for Maize Production in the United States.” *Nature Climate Change* 3:497–501.

Lobell, D.B., M.J. Roberts, W. Schlenker, N. Braun, B.B. Little, R.M. Rejesus, and G.L. Hammer. 2014. “Greater Sensitivity to Drought Accompanies Maize Yield Increase in the U.S. Midwest.” *Science* 344:516–519.

Lukac, M., M.J. Gooding, S. Griffiths, and H.E. Jones. 2012. “Asynchronous Flowering and Within-Plant Flowering Diversity in Wheat and the Implications for Crop Resilience to Heat.” *Annals of Botany* 109:843–850.

McFadden, J., D. Smith, S. Wechsler, and S. Wallander. 2019. “Development, Adoption, and Management of Drought-Tolerant Corn in the United States.” *United States Department of Agriculture*, pp. 45.

McKenzie, F.C., and J. Williams. 2015. “Sustainable Food Production: Constraints, Challenges and Choices by 2050.” *Food Security* 7:221–233.

Miranda, M.J. 1991. “Area-Yield Crop Insurance Reconsidered.” *American Journal of Agricultural Economics* 73:233–242.

National Agricultural Statistics Service. 2019. “Quick Stats.”

Nicholls, N. 1997. “Increased Australian Wheat Yield due to Recent Climate Trends.” *Nature* 387:484–485.

Parfitt, J., M. Barthel, and S. MacNaughton. 2010. “Food Waste Within Food Supply Chains: Quantification and Potential for Change to 2050.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 365:3065–3081.

Piesse, J., and C. Thirtle. 2010. “Agricultural R&D, Technology and Productivity.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 365:3035–3047.

Pisante, M., F. Stagnari, and C.A. Grant. 2012. "Agricultural Innovations for Sustainable Crop Production Intensification." *Italian Journal of Agronomy* 7:300–311.

Pretty, J., W.J. Sutherland, J. Ashby, J. Auburn, D. Baulcombe, M. Bell, J. Bentley, S. Bickersteth, K. Brown, J. Burke, H. Campbell, K. Chen, E. Crowley, I. Crute, D. Dobbelaere, G. Edwards-Jones, F. Funes-Monzote, H.C.J. Godfray, M. Griffon, P. Gypmantisiri, L. Haddad, S. Halavatau, H. Herren, M. Holderness, A.M. Izac, M. Jones, P. Koohafkan, R. Lal, T. Lang, J. McNeely, A. Mueller, N. Nisbett, A. Noble, P. Pingali, Y. Pinto, R. Rabbinge, N. Ravindranath, A. Rola, N. Roling, C. Sage, W. Settle, J. Sha, L. Shiming, T. Simons, P. Smith, K. Strzepeck, H. Swaine, E. Terry, T.P. Tomich, C. Toulmin, E. Trigo, S. Twomlow, J.K. Vis, J. Wilson, and S. Pilgrim. 2010. "The Top 100 Questions of Importance to the Future of Global Agriculture." *International Journal of Agricultural Sustainability* 8:219–236.

Ranganathan, J., D. Vennard, R. Waite, P. Dumas, B. Lipinski, and T. Searchinger. 2016. "Shifting Diets for a Sustainable Food Future." Working paper No. Installment 11 of Creating a Sustainable Food Future, World Resources Institute, Washington, DC.

Roberts, M.J., W. Schlenker, and J. Eyer. 2013. "Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change." *American Journal of Agricultural Economics* 95:236–243.

Rosa, I. 2018. "Federal Crop Insurance: Program Overview for the 115th Congress." Working paper, Congressional Research Service.

Rude, J., and A. Ker. 2013. "Transfer Efficiency Analysis of Margin-Based Programs." *Canadian Journal of Agricultural Economics* 61:509–529.

Schlenker, W., and M.J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change." *Proceedings of the National Academy of Sciences* 106:15594–15598.

Shao, J. 1992. "Jackknifing in Generalized Linear Models." *Annals of the Institute of Statistical Mathematics* 44:673–686.

Simelton, E., E.D. Fraser, M. Termansen, P.M. Forster, and A.J. Dougill. 2009. "Typologies of Crop-Drought Vulnerability: An Empirical Analysis of the Socio-Economic Factors that Influence the Sensitivity and Resilience to Drought of Three Major Food Crops in China (1961-2001)." *Environmental Science and Policy* 12:438–452.

Smith, V.H., and B.K. Goodwin. 1996. "Crop Insurance, Moral Hazard, and Agricultural Chemical Use." *American Journal of Agricultural Economics* 78:428–438.

Tack, J., A. Barkley, and N. Hendricks. 2017. "Irrigation Offsets Wheat Yield Reductions from Warming Temperatures." *Environmental Research Letters* 12:114027.

Tack, J., K. Coble, and B. Barnett. 2018. "Warming Temperatures Will Likely Induce Higher Premium Rates and Government Outlays for the U.S. Crop Insurance Program." *Agricultural Economics* 49:635–647.

Tao, F., M. Yokozawa, J. Liu, and Z. Zhang. 2008. "Climate-Crop Yield Relationships at Provincial Scales in China and the Impacts of Recent Climate Trends." *Climate Research* 38:83–94.

Tolhurst, T.N., and A.P. Ker. 2015. "On Technological Change in Crop Yields." *American Journal of Agricultural Economics* 97:137–158.

Wang, M., P. Shi, T. Ye, M. Liu, and M. Zhou. 2011. "Agriculture Insurance in China: History, Experience, and Lessons Learned." *International Journal of Disaster Risk Science* 2:10–22.

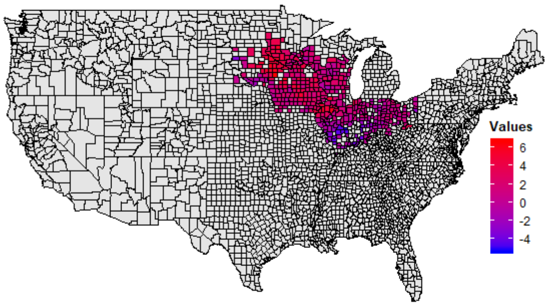
Wang, S. 1995. "Optimizing the Smoothed Bootstrap." *Annals of the Institute of Statistical Mathematics* 47:65–80.

Wright, B.D. 2012. "Grand Missions of Agricultural Innovation." *Research Policy* 41:1716–1728.

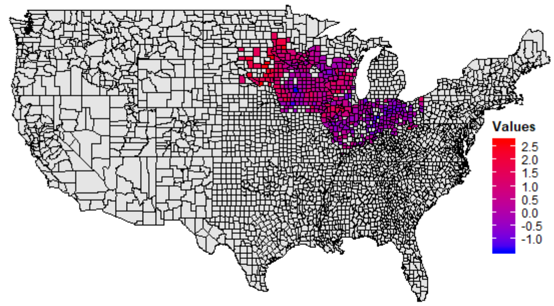
Zhang, Z., X. Song, F. Tao, S. Zhang, and W. Shi. 2016. "Climate Trends and Crop Production in China at County Scale, 1980 to 2008." *Theoretical and Applied Climatology* 123:291–302.

Appendix

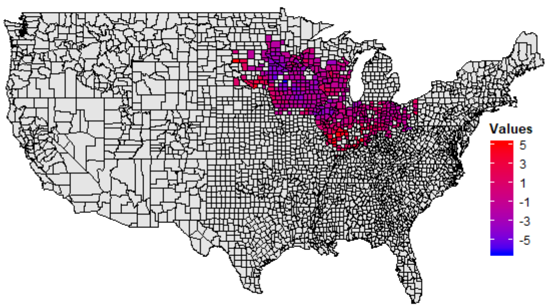
Maps



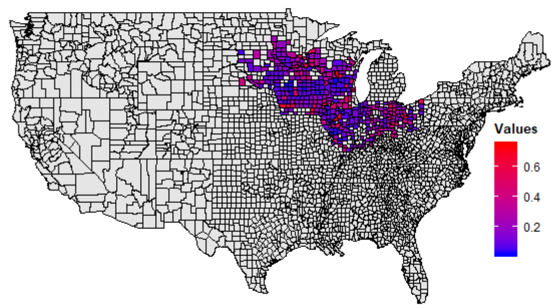
(A) δ_l



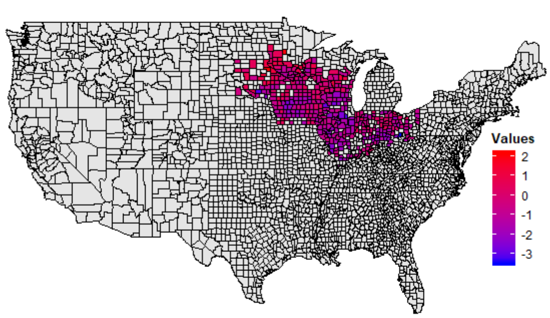
(B) δ_u



(C) $\delta_u - \delta_l$



(D) λ



(E) δ_λ

FIGURE 3. Changes in the rates of technological change in the lower (δ_l) and upper (δ_u) components after 1995, $\delta_u - \delta_l$, probability of a low yield (λ), and change in the probability of a low yield (δ_λ).

Standard Errors

Table 5. Conventional and Jackknife Standard Errors.

		Location measures		Resiliency measures			
		δ_l	δ_u	$\delta_u - \delta_l$	δ_λ	R_m	R_a
ΔGDD	SE_{conv}	0.287	0.100	0.274	0.138	0.071	0.075
	SE_{jack}	1.244	0.348	1.233	1.499	0.230	0.208
ΔHDD	SE_{conv}	0.535	0.186	0.511	0.257	0.132	0.140
	SE_{jack}	2.142	0.524	2.363	2.111	0.468	0.405
ΔVPD	SE_{conv}	0.776	0.270	0.741	0.373	0.191	0.204
	SE_{jack}	2.084	0.777	2.372	3.331	0.642	0.587
ΔVPD_{ja}	SE_{conv}	0.894	0.311	0.854	0.429	0.220	0.235
	SE_{jack}	3.402	1.081	3.127	2.404	0.721	0.617
ΔPCP	SE_{conv}	0.036	0.013	0.035	0.017	0.009	0.010
	SE_{jack}	0.156	0.034	0.147	0.058	0.033	0.032
ΔPCP_{ja}	SE_{conv}	0.069	0.024	0.066	0.033	0.017	0.018
	SE_{jack}	0.217	0.076	0.198	0.193	0.070	0.073
Rates	SE_{conv}	0.261	0.091	0.249	0.125	0.064	0.068
	SE_{jack}	1.287	0.558	1.191	0.585	0.222	0.214
GM	SE_{conv}	0.011	0.004	0.010	0.005	0.003	0.003
	SE_{jack}	0.061	0.017	0.060	0.029	0.015	0.017