Subsidized Crop Insurance and Technological Change in U.S. Crop Production

by

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ABSTRACT

SUBSIDIZED CROP INSURANCE AND TECHNOLOGICAL CHANGE IN U.S. CROP PRODUCTION

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Innovation in the agricultural sector will determine our ability to consistently sustain high yields and feed nine billion people by 2050. Most of the world's agricultural crop production is produced under heavily subsidized crop insurance, so understanding the impact that subsidized insurance has on technological change is important. In the United States, insurance premium subsidies increased from 30 percent to 60 percent between 1994 and 2000. In this thesis, I compare the rates of technological change in the lower and upper tails of crop yield distributions before and after the subsidy change by modelling corn, soybean, and winter wheat yields as a mixture of two normal distributions. My results indicate that higher subsidies increase the rates of technological change in both tails of the yield distribution, with the increase being greater in the lower tail. These results can be used to inform the design of business risk management programs.

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Chapter 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. Technological change has historically been a major driver of yield increases and will continue to dictate our ability to sustain high yields and meet food demand. In addition, climate change will negatively impact agricultural production in North America due to changing weather patterns and events, and so, again, technological change will be important in building yield resiliency and meeting global food demand. The majority of agricultural crop production in developed countries is produced under heavily subsidized crop insurance, and this may have multiple effects on technological change. First, high subsidies increase the returns to innovate, increasing the supply of innovations and the overall rate of technological change. Second, high subsidies decrease financial risk, potentially incentivizing the adoption of high-risk high-reward technologies at the expense of competing risk-reducing technologies. In the United States, subsidies on crop insurance premiums were substantially increased under the 1994 Federal Crop Insurance Reform Act and the 2000 Agricultural Risk Protection Act. In this thesis, I use these policy changes as a natural experiment to empirically investigate the effect that the increased subsidies had on the rates of technological change in corn, soybean, and winter wheat production in the United States.

Meeting the world's growing food demand and feeding over nine billion people by 2050 is a major challenge for global agriculture (Godfray et al., 2010; Pretty et al., 2010; McKenzie and Williams, 2015). One of the main ways to address this challenge is agricultural innovation[1] – a solution that has been working well historically, especially over the past century. Technological advancements in fertilizer, herbicides and pesticides, farm machinery, irrigation, and seed genomics have 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). Such advances lead 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). 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), as well as 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. Thus, agricultural innovation will continue to play a dominant role in meeting growing food demand. In addition, because the United States is a major global exporter of corn and soybeans, innovation in these production sectors will influence the ability to stay internationally competitive.

Technological change will also determine our ability to sustain high yields in the face of a changing climate. Numerous studies conducted over the past 20 years all suggest that climate change will have a major impact on crop production in North America. The impact will not be uniform across all regions. Southern production regions, such as the

[1] I use the terms "innovation" and "technological change" interchangeably.

Midwest and the southern states, are likely to experience substantial decreases in crop yields due to the increased frequency of extreme heat and drought conditions (Schlenker and Roberts, 2009; Lobell et al., 2013, 2014). For example, Schlenker and Roberts (2009) find that while moderate heat is essential for optimal crop yields, persistent temperatures above 30 degrees Celsius (86 degrees Fahrenheit) significantly damage corn and soybean production and may cause yield reductions of 30 to 80 percent under a range of climate change scenarios by the end of the 21st century. Northern production regions, such as Canada, will likely benefit from warmer temperatures and longer growing seasons (Weber and Hauer, 2003; Cabas, Weersink, and Olale, 2010; Gaudin et al., 2015). However, despite the warmer climate, the variability in temperature and precipitation from year to year will increase, with potentially wetter springs, drier summers, and more frequent abnormal precipitation events (Gaudin et al., 2015). This increased variability in weather will negatively affect average crop yields and year-to-year yield variability in regions such as Ontario and the Midwest (Cabas, Weersink, and Olale, 2010; Schlenker and Roberts, 2009). As such, the ability of the agricultural production sector to sustain high yields will be largely influenced by the extent of technological change and adaptation to this changing climate. However, Burke and Emerick (2016) found limited adaptation among major crops in the United States over the past 60 years.

Most of the world's agricultural crop production is produced under heavily subsidized crop insurance. In the United States and Canada, administrative and operating costs are fully absorbed by the government in most cases, and subsidies on crop insurance premiums are around 60 percent on average (Glauber, 2013; Ker et al., 2017; Rosa, 2018). In addition, Rude and Ker (2013) have shown that 45 percent of business risk management program payments remain with the producers, demonstrating that producers benefit from the subsidized programs. In countries in the European Union where crop insurance is subsidized by government, subsidies on premiums range from 30 percent to 70 percent on average (e.g. 46 percent in Austria, 49 percent in Spain, 64 percent in Italy, and 65 percent in France) (Bielza et al., 2007; Enjolras and Sentis, 2011). In Brazil, premium subsidies are almost 50 percent (Lavorato and Braga, 2018), and in China subsidies range from 50 to over 80 percent (Wang et al., 2011).

In the United States, the Federal Crop Insurance Program is a fundamental component of domestic farm policy. Since its establishment in 1938 under the Agricultural Adjustment Act, it grew from a small supplementary low-participation program covering only a few crops to the major national agricultural support program it is today (Rosa, 2018). Subsidies on crop insurance premiums were first implemented in 1980 when the insurance program underwent significant changes under the Federal Crop Insurance Act. Under this Act, premium subsidies at the 65 percent coverage level were set at 30 percent (Glauber, 2004, 2013; Rosa, 2018). In 1994, the crop insurance program underwent even greater changes under the Federal Crop Insurance Reform and Department of Agriculture Reorganization Act. Enrollment in the insurance program was made mandatory to be eligible for payments under other federal farm support programs. The 1994 Act also introduced catastrophic coverage level (CAT) covering losses exceeding 50 percent of an average yield. The Federal Crop Insurance Corporation paid 100 percent of the CAT premium, with farmers paying only a small administrative fee (Rosa, 2018). At the same time, premium subsidies on buy-up coverage – coverage levels above 50 percent of yield – were increased to just over 40 percent at the 65 percent coverage level. Further increases in the premium subsidies occurred under the Agricultural Risk Protection Act of 2000, with subsidies increasing to 60 percent (Glauber, 2004, 2013; Rosa, 2018). The main goal of the increased subsidization in both the 1994 and the 2000 Acts was to increase farmer participation in the insurance program.

Participation in the Federal Crop Insurance Program increased substantially since its introduction, especially following the 1980 and 1994 Acts. Percent of eligible acres enrolled in the program grew from only 12 percent in 1980 to over 86 percent 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. Although participation in the crop insurance program decreased slightly after the eligibility requirement was repealed in 1996, enrollment in the program continued to grow, particularly after premium subsidies were further increased in the 2000 Act (Rosa, 2018). From 2007 to 2016, the total net cost of the crop insurance program was $72 billion – the second largest outlay in the farm bill (nutrition being the largest). Of the $72 billion, 60 percent ($43 billion) was direct benefits to farmers (Rosa, 2018).

Because the crop insurance program is a vital part of agricultural production in the United States and because innovation will be pivotal in meeting increased food demand at affordable prices, understanding and quantifying the impact that subsidized insurance has on technological change is important. Economic theory suggests that highly subsidized insurance may potentially have two effects on technological change: an income effect and a risk effect.

Income effect: Subsidization makes insurance cheaper for farmers, increasing the amount of income that they are able to spend on new technologies and resulting in an increased rate of technological change. In addition, seeing that producers now have a greater willingness to adopt new technologies, agricultural R&D firms increase innovation activity and expand the set of technologies available to farmers, which also increases the rate of technological change. This overall positive effect of higher subsidies on the rate of technological change can be called the income (or wealth) effect.

Risk effect: With crop insurance, farmers do not have to worry about lower yields because they will be compensated for yield losses. This potentially creates an incentive to reduce the use of risk-reducing technologies and instead adopt riskier technologies that can produce higher yields. Because high premium subsidies make insurance cheaper, producers may be inclined to increase coverage and rely more on insurance, making the willingness to accept greater risk stronger. This increased adoption of high-risk high-reward technologies at the expense of competing risk-reducing technologies can be called the risk or the moral hazard effect.

The following figures illustrate the risk effect. Figure 1.1 shows a hypothetical yield distribution for corn produced under a low-risk technology. On average, the yield achieved with this technology is not very high – only 120 bushels per acre. However, the variability, i.e. riskiness, is not large: there is a chance of having lower than average yields or higher than average yields, but these probabilities are not very high. Conversely, Figure 1.2 shows an example of a corn yield distribution produced under a high-risk technology. This (hypothetical) technology is able to produce higher average yields than the low-risk technology – around 140 bushels per acre. However, the possibility of a lower than average yield is fairly high, as seen from the thick lower tail. Assume that the two technologies are competing: the adoption of one technology precludes the adoption of the other technology. A risk-averse producer choosing between these two technologies may prefer the low-risk one (Figure 1.1). Now assume that crop insurance is available. What insurance essentially does is cut off the lower tail, as shown in Figure

1.3. In this new situation, a risk-averse producer choosing between the two technologies may be more willing to adopt the riskier one because they can now achieve higher yields and not have to worry about the lower tail anymore. Insurance has essentially reduced their income variability, because now they will be compensated for yield losses. High premium subsidies make insurance cheaper and encourage greater participation in insurance programs, and so this risk effect – substitution away from risk-reducing technologies towards competing high-risk technologies – may be more prominent under higher subsidization.

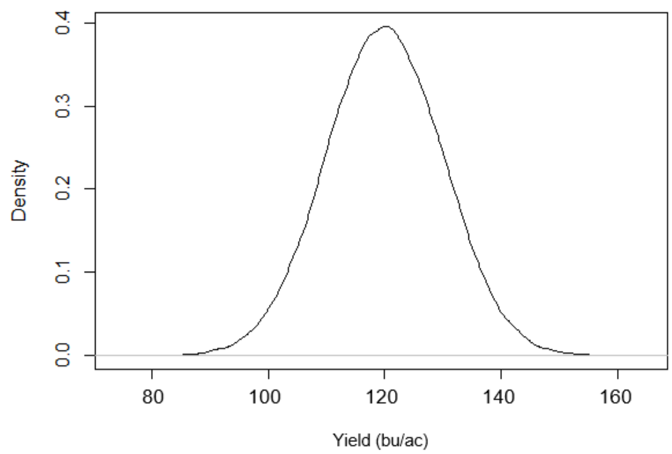


Figure 1.1: Hypothetical corn yield distribution for a low-risk technology.

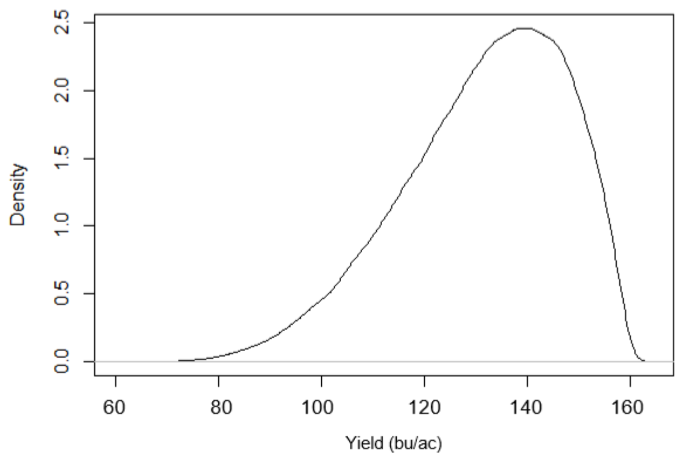


Figure 1.2: Hypothetical corn yield distribution for a high-risk technology.

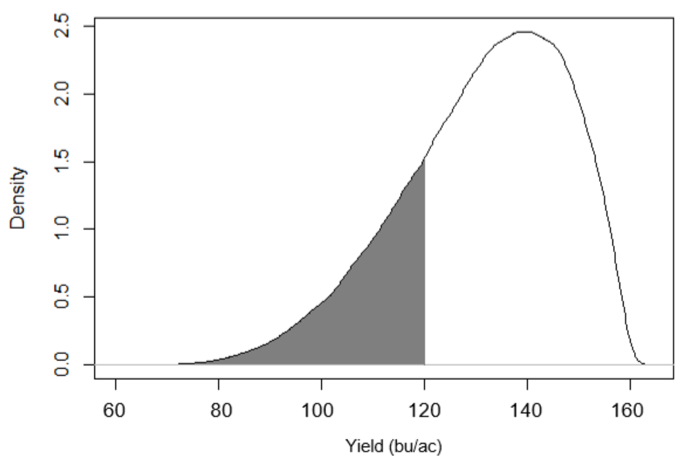


Figure 1.3: Hypothetical corn yield distribution for a high-risk technology with insurance.

As was already mentioned, government subsidies on crop insurance premiums in the United States increased substantially – from 30 percent to 60 percent – following the Crop Insurance Reform Act of 1994 and the Agricultural Risk Protection Act of 2000. These policy changes represent a unique natural experiment which can be used to analyze differences in the rates of technological change before and after the subsidy increase and to test for the presence of the income and risk effects. To the best of my knowledge, no literature has yet looked at this question.

Technological change can affect the crop yield distribution in different ways, and these changes may not necessarily be uniform throughout all parts of the distribution. While the income effect is likely to be consistent across the yield distribution, the risk effect can create heterogeneity in technological change between different parts of the distribution. Thus, when analyzing the effect of increased subsidies on technological change, it is important to measure technological change in a way that would account for this heterogeneity; otherwise, it will not be possible to measure the risk effect.

The primary objective of my thesis is to empirically estimate the effect of the increased crop insurance premium subsidies on the rates of technological change in crop production in the United States. To account for and measure the potentially heterogeneous effect of these changes on different parts of the yield distribution, I use a mixture model to estimate the rates of technological change in the lower and upper tails of crop yield distributions. I focus on corn, soybean, and winter wheat yields, which are the major economically significant crops in the United States. Figure 1.4 illustrates my research question. Using a mixture model, I will estimate two rates of technological change corresponding to the two mixture components – lower and upper. The two components essentially measure the different rates of technological change in "poor-year" yields and "good-year" yields. I want to empirically estimate whether there has been any change in these two rates of technological change after the subsidy increases (represented by the vertical dashed line in Figure 1.4): Have the rates stayed the same or have they increased or decreased? Was the direction of the effect the same in both components or different?

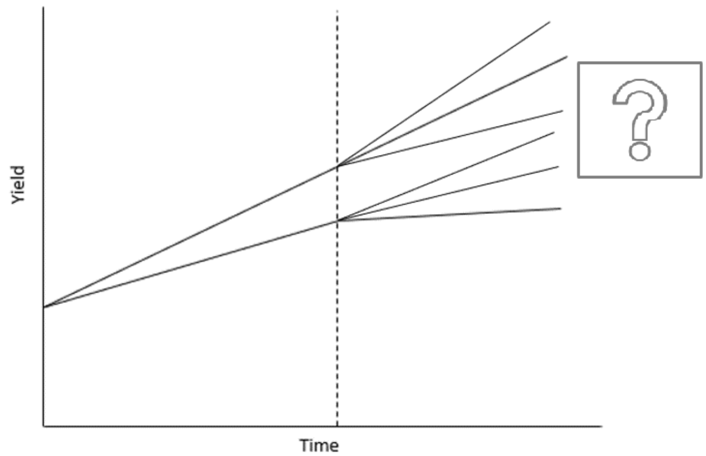


Figure 1.4: My thesis research question.

The remainder of this thesis proceeds as follows. In Chapter 2, I provide an overview of crop production in the United States, summarize technological advancements over the past century, and review the existing literature on crop insurance and choice of technologies with a focus on adaptation to climate change. In Chapter 3, I describe the data that I used in my analysis and outline my empirical approach and crop yield model. In Chapter 4, I present the results of my empirical analysis and then discuss the economic implications of these results in the context of my research question in Chapter 5. I conclude with Chapter 6, in which I briefly summarize my results and emphasize the implications of my research. Supplemental information and results which are not thoroughly discussed within the thesis but may be of interest to readers are available in the Appendix.

Chapter 2 Literature Review

2.1 Crop Production in the United States

The United States is a major global producer of numerous field crops. It leads the world's corn and soybean production and is the largest global exporter of corn and second-largest exporter of soybeans (Ort and Long, 2014; United States Department of Agriculture, 2018). In 2017, total grain corn production in the United States was over 14.4 billion bushels valued at $48.5 billion. Total soybean production in the same year was 4.4 billion bushels valued at $41 billion dollars (National Agricultural Statistics Service, 2019). Over 90 million acres and over 80 million acres are planted annually to corn and soybeans, respectively. The majority of corn and soybean production is concentrated in the Midwest Corn Belt states – Illinois, Indiana, Iowa, South Dakota, Nebraska, Ohio, Minnesota, and Wisconsin (Green et al., 2018). Illinois, Iowa, and Indiana account for nearly half of corn production every year (National Agricultural Statistics Service, 2019). Figures 2.1 and 2.2 illustrate the geographical spread of corn and soybean production in the United States in 2017. Note how the production of both crops is concentrated in the Corn Belt area.

Wheat is the third-largest field crop in the United States in terms of production after corn and soybeans. Although wheat exports have been declining over the past couple of decades due to increased competition from Russia, the European Union, and Canada, wheat continues to be an economically significant crop for U.S. agriculture (United States Department of Agriculture, 2018). In 2017, more than 1.7 billion bushels

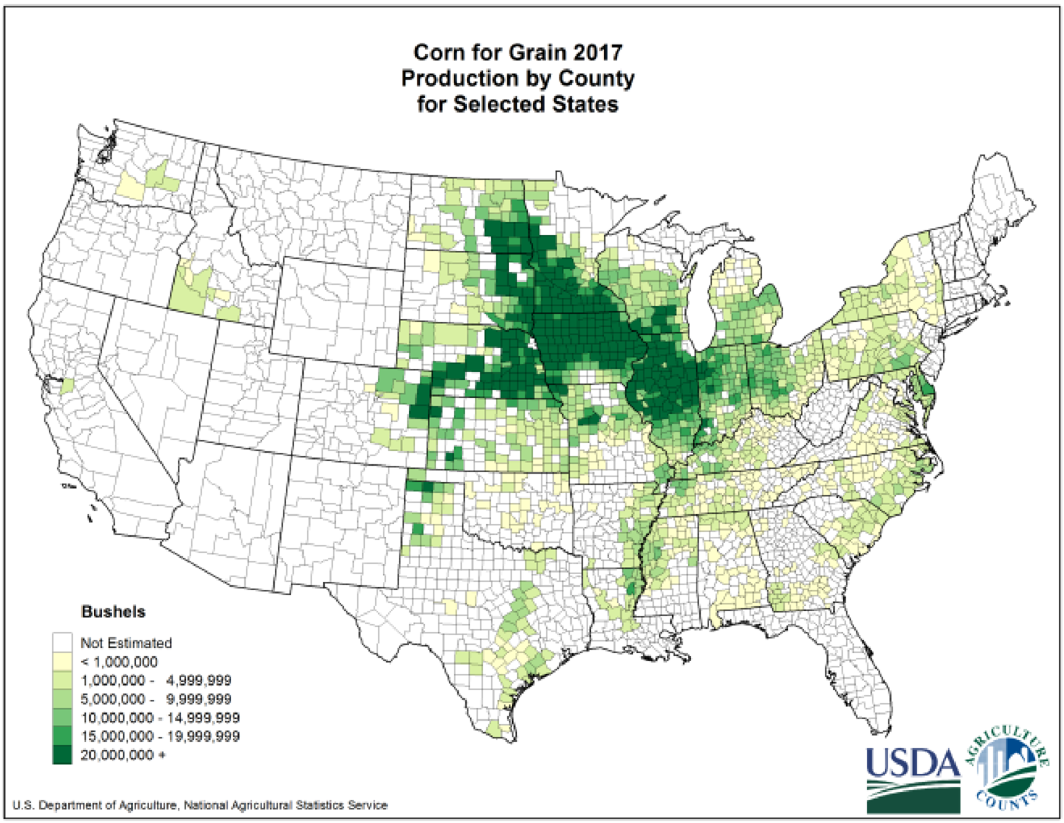


Figure 2.1: Grain corn production by county for selected states in the United States in 2017. Source: National Agricultural Statistics Service (2019).

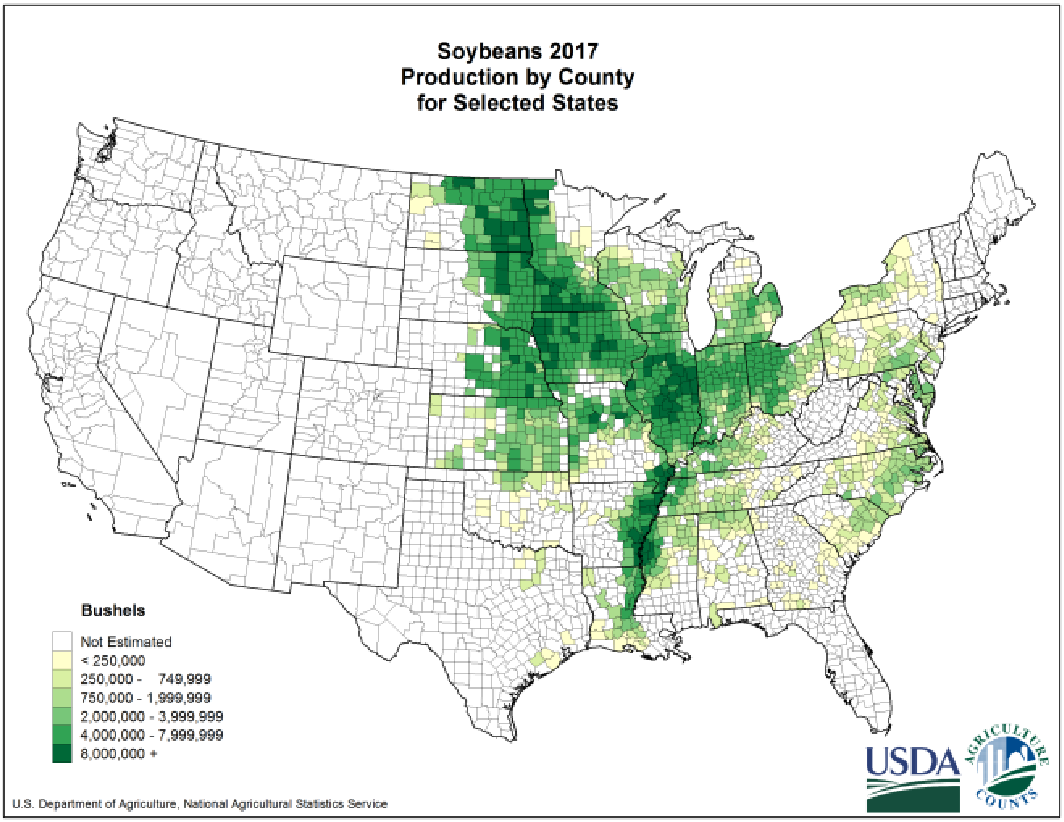


Figure 2.2: Soybean production by county for selected states in the United States in 2017. Source: National Agricultural Statistics Service (2019).

of wheat were produced and valued at over $8.1 billion, with Kansas, Montana, and North Dakota being the largest wheat-producing states (National Agricultural Statistics Service, 2019). The three major crops – corn, soybeans and wheat – account for about 70 percent of acreage enrolled in the Federal Crop Insurance Program and 70 percent of claim payments (Congressional Budget Office, 2017).

2.2 Agricultural Innovation

Over the past century, average crop yields all around the world have increased dramatically. In the United States specifically, average corn yields have increased from around 20 bushels per acre in the 1920s to over 170 bushels per acre today, as seen in Figure 2.3 (National Agricultural Statistics Service, 2019). The increase in average soybean and winter wheat yields over the past 90 years has also been steady. Soybean yields increased from approximately 11 bushels per acre to over 50 bushels per acre, and winter wheat increased from 15 bushels per acre to about 50 bushels per acre (Figure 2.3). Technological advancements in the agricultural sector have been the main driver of this growth. Fertilizer, herbicides and pesticides, farm machinery, irrigation, seed genomics, and other agricultural innovations have allowed producers to substantially increase agricultural yields, often without the need to bring more land into production (Alston, Beddow, and Pardey, 2010; Piesse and Thirtle, 2010; Pisante, Stagnari, and Grant, 2012; Wright, 2012). Plant breeding and development of high-yielding crop varieties, particularly rice and wheat, have lead to large productivity gains in both developed and developing counties during the Green Revolution (Evenson and Gollin, 2003; Tilman, 1998). The discovery of the Haber-Bosch process for the production of nitrogen fertilizer from atmospheric nitrogen at the beginning of the twentieth century, as well as the

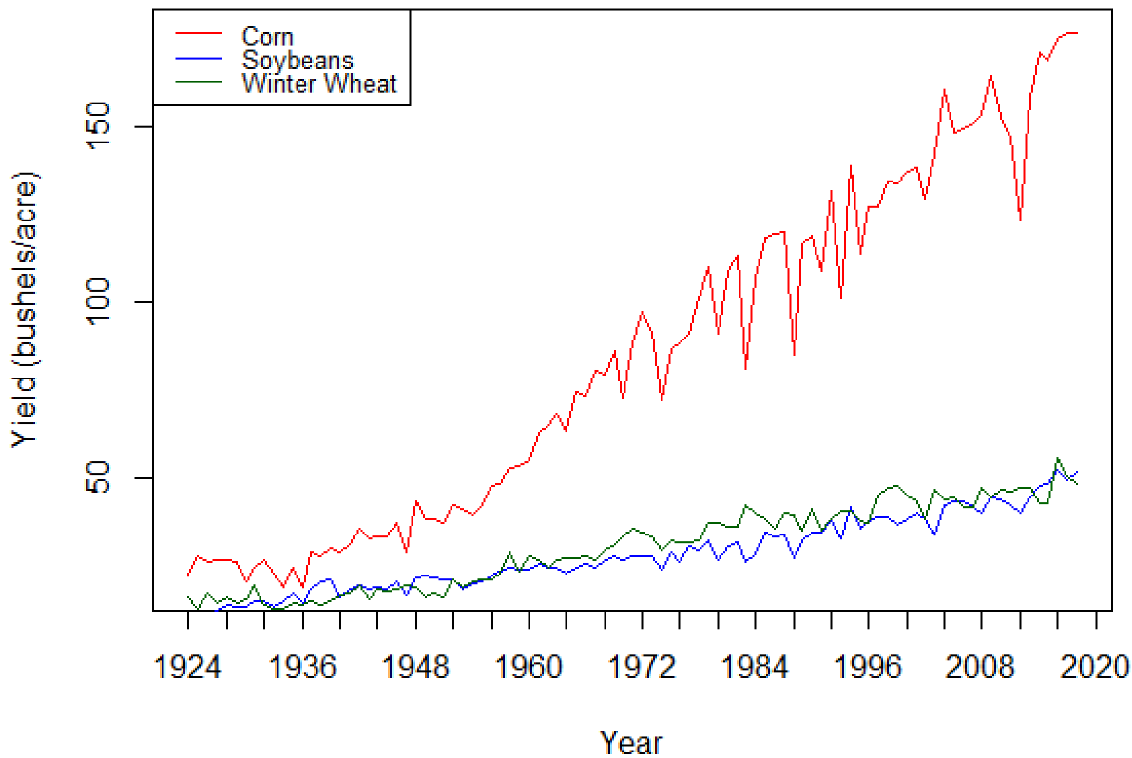


Figure 2.3: Corn, soybean and winter wheat average yields (bushels per acre) in the United States from 1924 to 2018. Source: historical yield data, National Agricultural Statistics Service (2019).

development and increased use of other synthetic fertilizers, has been paramount in increasing crop yields and feeding the growing global population (Tilman, 1998; Pisante, Stagnari, and Grant, 2012). Along with the development of irrigation systems, these advancements have substantially increased crop productivity and have allowed for the intensification as opposed to extensification of agricultural production (Godfray et al., 2010; Foley et al., 2011; Mueller et al., 2012; Pisante, Stagnari, and Grant, 2012).

One of the major recent breakthroughs in crop production has been the genetic modification (also called genetic engineering) of crops. 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. Genetically modified 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). Figure 2.4 illustrates the rapid increases in the adoption of genetically modified soybeans, cotton, and corn in the United States since their introduction. In 2013, 90 percent of total corn acres and 93 percent of total soybean acres were planted to genetically modified hybrids (Fernandez-Cornejo et al., 2014). As noted by Fernandez-Cornejo et al. (2014), the main reason for producers' such high willingness to adopt the genetically modified hybrids is yield gains. In addition to herbicide-tolerant and insect-resistant corn, drought-resistant corn (both conventionally bred and genetically modified) has been recently introduced to the U.S. markets, and the adoption of such hybrids is also rapidly growing, as seen in Figure 2.5 (McFadden et al., 2019).

2.3 Insurance and Choice of Technologies

Crop insurance reduces the financial risk faced by producers and can thus have various effects on management choices and technology adoption decisions. Numerous literature suggest that moral hazard – using fewer risk-mitigating measures than without insurance – is a serious problem for crop insurance (Chambers, 1989; Miranda, 1991). Evidence on whether crop insurance increases or decreases chemical input use varies in the literature. Some studies, such as Babcock and Hennessy (1996) and Smith and Goodwin (1996),

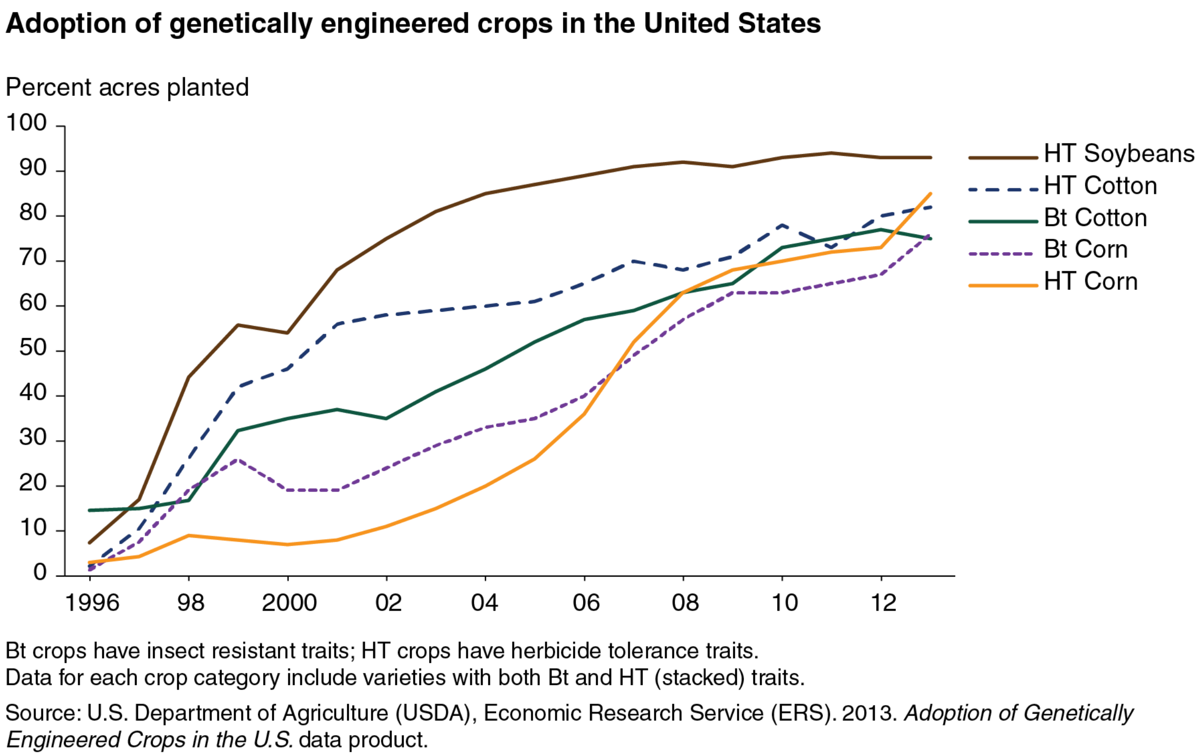
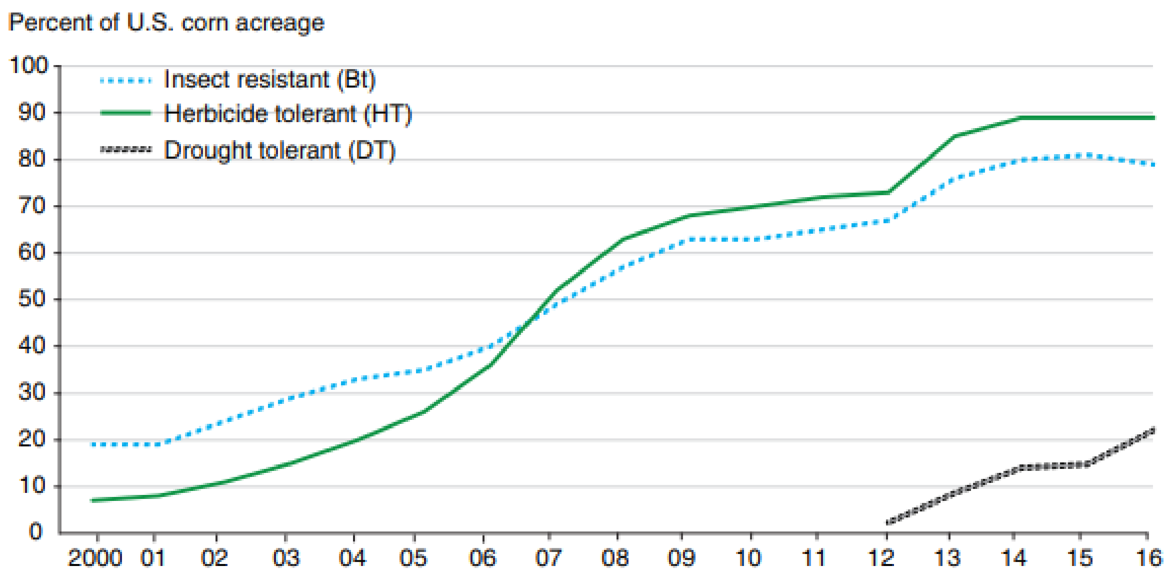


Figure 2.4: Adoption of genetically modified soybeans, cotton and corn in the United States since 1996. Source: Figure 5 from Fernandez-Cornejo et al. (2014).

Percent of U.S. corn acres planted with insect-resistant, herbicide-tolerant, and drought-tolerant hybrids, 2000-16



Note: The insect-resistant (Bt) and herbicide-tolerant (HT) lines also include acreage planted with stacked corn hybrids. Stacked hybrids contain both herbicide tolerance and insect resistance.
Source: USDA, Economic Research Service (ERS), "Adoption of Genetically Engineered Crops in the U.S." data product; USDA, ERS and National Agricultural Statistics Service, 2016 Agricultural Resource Management Survey; other sources (see Note to appendix fig. A-1).

Figure 2.5: Percent of United States corn acreage planted to insect-resistant, herbicide-tolerant, and drought-tolerant hybrids since 2000. Source: Figure 2 from McFadden et al. (2019).

suggest that crop insurance decreases chemical input use, while others suggest that insurance increases chemical use at the intensive margin (Horowitz and Lichtenberg, 1993) and the extensive margin (Wu, 1999). Crop insurance may also encourage expansion of production and the adoption of potentially harmful practices. For example, Claassen, Langpap, and Wu (2017) demonstrated that crop insurance can alter producers' incentives in two ways: expansion of production to marginal lands and switching to crops that are covered by insurance but are potentially more erosive and input-intensive. These findings are supported by other studies, such as Wu (1999), Goodwin, Vandeveer, and Deal (2004) and Miao, Hennessy, and Feng (2016). On the issue of soil erosion, however, Goodwin and Smith (2003) suggest that it is actually not the insurance program that can increase erosion (due to increased participation and expansion of production) but other government support programs. Also on the topic of environmental impacts, Walters et al. (2012) have found that subsidized crop insurance does create negative environmental impacts but they are small and are often countered by beneficial impacts also resulting from crop insurance adoption. Outside of crop insurance, studies have been finding evidence of moral hazard in other forms of agricultural insurance; for example, Roll (2019) has found evidence of moral hazard in Norwegian aquaculture. This indicates that the moral hazard issue is not unique to crop insurance. Also, from the insurance provider side, Ker and McGowan (2000) has shown that insurance companies may use weather-based adverse selection to generate excess rents.

Adaptation to climate change is important for sustaining high agricultural productivity in the long term. However, Burke and Emerick (2016) have found limited adaptation to climate change by farmers in the United States over the past 60 years. Studies such as Antón et al. (2012) and Di Falco et al. (2014) suggest that crop insurance may be a lower-cost substitute for on-farm adaptation measures because high subsidies make insurance cheaper for producers, and so the demand for crop insurance may increase with climate change. When considering the potential ways in which agriculture can adapt to climate change, Bryant et al. (2000) noted that Canadian institutional and public policy strategies such as crop insurance programs reduce the financial risks that farmers face from climatic variability in the short term, but in the long term tend to change adaptation behaviour and reduce the incentive to adjust to changing climatic conditions. This is also true for the United States, where Annan and Schlenker (2015) looked at corn and soybean production in the United States and found that crops insured through the Federal Crop Insurance Program are more sensitive to extreme heat because farmers choose subsidized yield guarantees over costly adaptation measures. As a result, insured acres are more prone to yield losses during drought. In addition, because of the higher indemnities, the costs to the insurance program are greater than what they could have been with adaptation (Annan and Schlenker, 2015). Looking at crop yields in Ontario since 1950, Ker et al. (2017) showed that corn yield distributions are consistent with producers substituting away from competing risk-reducing technologies to crop insurance. In the Central Great Plains, Woodard et al. (2012) demonstrated that although skip-row planting of corn increases yield performance under drought conditions, the crop insurance program design distorts producer incentives and reduces the adoption of this otherwise optimal technology. Schoengold, Ding, and Headlee (2014) found that farmers may choose to substitute away from conservation tillage to government insurance as a way of managing on-farm risk. Because conservation tillage is a practice that reduces negative environmental impacts of crop production, substitution away from such practices decreases the environmental sustainability of farming.

Chapter 3 Empirical Approach

3.1 Data

I obtained county-level crop yield data from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA) for the three major crops – corn, soybeans, and winter wheat. 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 ten percent of state acreage had to be irrigated as reported in the 2012 Census of Agriculture.

For corn, 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 61.8 percent of total corn produced in the United States in 2017. Six of the corn states also met the inclusion criteria for soybeans: IL, IN, IA, MN, OH, and WI. These six states accounted for 53.9 percent of total soybean production in 2017. For winter wheat, only two states met the inclusion criteria: Kansas (KS) and Michigan (MI). They accounted for 27.7 percent of total winter wheat produced in 2017. In total, my data set consisted of 414 corn counties, 373 soybean counties, and 64 winter wheat counties.

Daily temperature (in degrees Celsius) and precipitation (in millimeters) data from weather stations across the United States was obtained 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}). The weather station data was interpolated to the county level as in Tolhurst and Ker (2015). Growing degree days, extreme temperature degree days, and vapour pressure deficit were calculated from the daily data as per Schlenker and Roberts (2009), Roberts, Schlenker, and Eyer (2013), and Tolhurst and Ker (2015).[2]

While numerous climate factors affect yield, the 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 30 degrees Celsius for soybeans) 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 relation-

[2]Growing degree days, extreme temperature degree days, and vapour pressure deficit for corn and soybeans, as well as vapour pressure deficit for winter wheat, were provided by Tor Tolhurst. Growing degree days and extreme temperature degree days for winter wheat were calculated from raw climate data using the following temperature thresholds adapted from Tack, Barkley, and Nalley (2015) and Tolhurst and Ker (2016): in Kansas, the growing season was divided into three seasons – fall (September 1 to November 30), winter (December 1 to February 28/29), spring (March 1 to May 31) – with lower and upper thresholds of 10 degrees Celsius to 17 degrees Celsius in the fall, 5 degrees Celsius to 10 degrees Celsius in the winter, and 18 degrees Celsius to 34 degrees Celsius in the spring; in Michigan, the growing season was divided into three seasons – fall (September 15 to November 30), winter (December 1 to February 28/29), spring (March 1 to June 15) – with thresholds of above 12 degrees Celsius in the fall, 3 degrees Celsius to 15 degrees Celsius in the winter, and 9 degrees Celsius to 18 degrees Celsius in the spring.

ship 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 VPD 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.

3.2 Crop Yield Model

Technological change in crop yields is frequently measured by modelling yields over time as a reduced form catch-all:

$$y_t = f(t) + \epsilon \tag{3.1}$$

In these regressions, $f(t)$ by default encompasses not only technological change but also other factors such as climate change and policy changes, among others. This makes it exceedingly difficult to decompose the estimated effect into specific technologies and to identify policy change effects. Some suggest conditioning climate out to measure the effect without climate. However, I do not want to do this for the purposes of my research question because I want to measure technological change that occurred in response to climatic changes. It would not be possible to measure this if climate is conditioned out. This leaves me with more caveats than I want to be comfortable with, but, because of the state of nature character of such event studies, this is the best available way to measure technological change in crop yields.

The common approach to modelling crop yields over time is estimating a single trend (commonly linear), testing and correcting residuals for heteroscedasticity, and then estimating a yield density parameterically (Atwood, Shaik, and Watts, 2003; Sherrick et al., 2004; Woodard and Sherrick, 2011; Zhu, Goodwin, and Ghosh, 2011), non-parametrically (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Racine and Ker, 2006), or semi-parametrically (Ker and Coble, 2003; Ker and Ergun, 2007). This single trend approach measures only the mean effect and does not capture any heterogeneity that may be present in the data. However, technological change does not always have a uniform effect on all parts of the yield distribution and moves mass all around. Numerous recent studies, such as Goodwin and Ker (1998), Ramirez, Misra, and Field (2003), Sherrick et al. (2004), Zhu, Goodwin, and Ghosh (2011), Tolhurst and Ker (2015), and Jiang (2017), have shown that crop yields over the past several decades have not been changing uniformly, and so measuring the effect only at the mean may not always be sufficient.

Because higher premium subsidies may have a non-uniform effect on technological change in different parts of the yield distribution, being able to measure this heterogeneity is important. The income effect may be consistent throughout the distribution because higher premium subsidies are likely to increase the overall rate of technological change in both the lower and the upper tails. However, the risk effect may not be uniform, because it impacts the choice of technologies that directly affect the yield outcome. If a farmer switches to a technology that helps him achieve higher yields under optimal growing conditions but at the same time increases the probability of a low yield in poor conditions, it makes sense to expect a non-uniform response in the yield distribution, because this technology affects the upper tail differently than the lower tail. To identify the possible presence of a risk effect due to increased premium subsidies, I need to measure technological change in the different tails of the yield distribution, and so the commonly used single trend yield model (which only measures the effect at the mean) is not suitable for the purposes of my research question.

An alternative approach that has been recently proposed by Tolhurst and Ker (2015) and has been used by Ker, Tolhurst, and Liu (2016), Jiang (2017) and Ker et al. (2017) is to model yields as a mixture of normal distributions:

$$y_t \sim \sum_{j=1}^{J} \lambda_j N(f_j(t), \sigma_j^2) \quad where \quad \sum_{j=1}^{J} \lambda_j = 1 \tag{3.2}$$

Here, J is the number of mixture components, each having a probability λ_j. Each mixture component represents different economic structures, and the embedded trend functions, $f_j(t)$, represent technological change under these different structures. Using this modelling approach is intuitive from an economics standpoint because the components correspond to something economically insightful. The optimal number of mixtures is data driven and can be determined using AIC or BIC. Thus far, existing literature such as Tolhurst and Ker (2015) and Jiang (2017) has shown that crop yields are estimated well with two mixtures. Because the effect of increased subsidies is likely to be heterogeneous across the different tails of the yield distribution, I can use the approach of Tolhurst and Ker (2015) to model the data generating process of yields as a mixture of two normal distributions where the component mixture parameters are functions of time. This will allow me to compare the rates of technological change in the lower and upper tails of yield distributions before and after the subsidy increase and identify the possible presence of a risk effect.

Following the methods of Tolhurst and Ker (2015), I modelled county crop yields as a two-component normal mixture:

$$y_t \sim (1-\lambda_t)N(\alpha_l + \beta_l t + \delta_l t I_{[1995,T]}(t), \sigma_l^2) + \lambda_t N(\alpha_u + \beta_u t + \delta_u t I_{[1995,T]}(t), \sigma_u^2) \quad (3.3)$$

In this model, λ_t is the probability of the upper component in year t (computed as the mean of the probabilities of each observation belonging to the upper component) and $\alpha_j + \beta_j t + \delta_j t I_{[1995,T]}(t)$, $j = \{l, u\}$ is the component conditional mean with variance σ_j^2. The parameters of interest are δ_l and δ_u; they represent the change in the slopes of the lower and upper components, respectively, after the subsidy increase. The new slopes after the policy change are $\beta_l + \delta_l$ (lower component) and $\beta_u + \delta_u$ (upper component).

Crop insurance premium subsidy increases occurred twice: in 1994 under the Federal Crop Insurance Reform Act and in 2000 under the Agricultural Risk Protection Act. As seen in Figure 3.1, participation in the crop insurance program increased dramatically after the 1994 Act.[3] Participation also increased after the 2000 Act, but this increase was less dramatic. Thus, for the purposes of my analysis I used 1994 as the year of a major policy change.[4] To account for the time that it may take for producers to react to the policy change, I allowed for a one-year lag and used the year 1995 as the particular point in time at which the premium subsidy increase had occurred.

As was done by Tolhurst and Ker (2015) and is commonly done with mixture models, I used the expectation-maximization (EM) algorithm to estimate the unknown parameters of my model (i.e. λ, α, β, δ, and σ^2). In the maximization step, the algorithm

[3] It is interesting to note that the spike in participation in 1995 was followed by a dip in 1996. This happened because the mandatory requirement to be enrolled in crop insurance to be eligible for payments under other support programs was repealed in 1996.

[4] I also performed the same analysis for 2000, but the results turned out to be very similar (nearly identical).

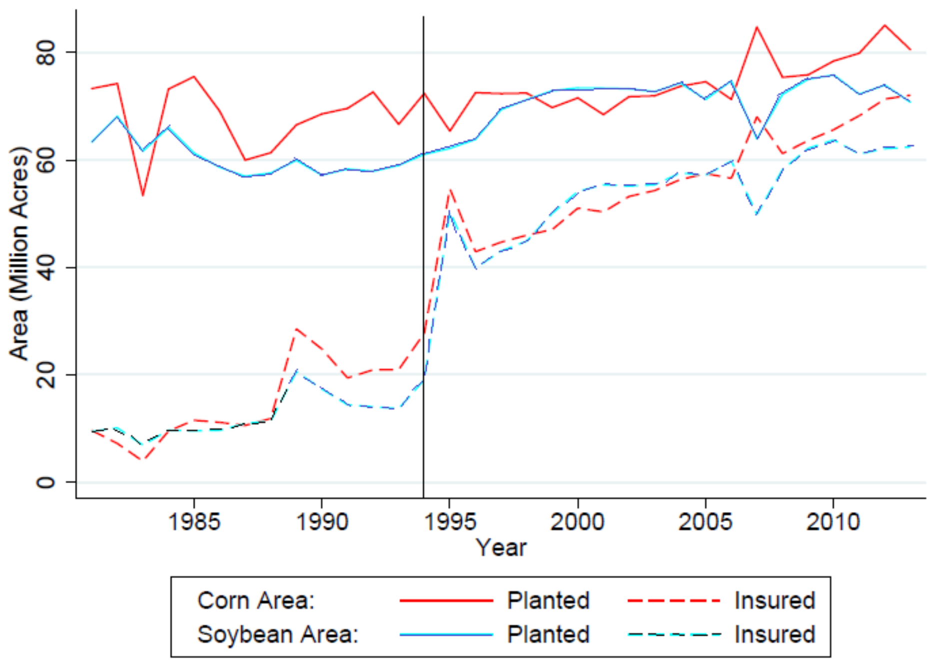


Figure 3.1: Corn and soybean acreage insured under the Federal Crop Insurance Program. Vertical line indicates the passing of the 1994 Federal Crop Insurance Reform Act. Source: edited version of Figure A1 from Annan and Schlenker (2015).

begins with starting weight values and performs a weighted estimation for each mixture component. The weights are then updated in the expectations step. The maximization and expectation steps are repeated until the parameter estimates converge. This process is repeated for multiple starting values to ensure a global optimum for the likelihood is found, and the maximum of the maximized likelihoods is chosen. In essence, this is simply a missing membership problem.

To prevent the upper and lower mixture components from crossing over, I restricted the intercept of the lower component to equal that of the upper component ($\alpha_l = \alpha_u$) whenever a crossover was occurring. This eliminated crossovers in the early part of the sample period, where the two components are close together, but did not prevent components from crossing over after 1995. This is because the slopes were allowed to change after 1995, and the algorithm was really only using 23 data points (1995-2017) to estimate the two mixture components. To address this crossover issue, I artificially deflated the likelihood of the parameters that were producing the crossover so that the EM algorithm would find a different set of parameters with a maximized likelihood but no crossover. In a similar way, I restricted the algorithm to choose non-negative intercepts and σ_l no less than ten percent of σ_u.[5] The artifical deflation of the likelihood eliminated crossovers and negative intercepts in most cases but not all. In essence, this is really a model specification issue, since these crossovers results do not have an economic (or a plant physiology) interpretation and occur mainly because of the low number of data points available for estimation. I removed the counties with a persistent crossover issue from my analysis.[6]

[5]When the variance of the lower component is very small, the algorithm may not be able to estimate the lower component if there are no low yield data points later in the sample period.

[6]This resulted in the removal of 16 corn counties, 27 soybean counties, and 11 winter wheat counties – a total of 54 out of 851 counties (6%) across all three crops.

Another issue with the EM algorithm in small samples is that the component probabilities tend to be biased to $1/J$ – in my two-component mixture, λ_j tends to be biased to 0.5. To address this, I modified the maximum likelihood procedure and added a penalty function to check optimality. A penalty value equal to $P(\lambda) = h * ((1-\lambda) - 0)^2$, where h is a tuning parameter ranging from 1 to 50, was subtracted from the likelihood. The magnitude of the penalty increased the further away from zero the probability of the lower component $(1-\lambda)$ moved. In this penalized algorithm, the optimized parameters from the EM algorithm were used as starting values, and optimal tuning parameters were chosen by maximizing the non-penalized likelihood. I checked optimality by comparing the penalized maximum likelihood to the EM algorithm maximum likelihood and chose the parameters[7] with the higher likelihood. Interestingly, the penalized likelihood approach found a higher optimum than the EM algorithm in many cases.

3.3 Probability of a Low Yield

To investigate whether the probability of a low yield has been changing over time and whether or not this probability changed after the subsidy increase, I modelled the probability of a low yield (i.e. the probability of a data point belonging to the lower component) obtained from model 3.3 as a function of time:

$$(1-\lambda_t) = \alpha_\lambda + \beta_\lambda t + \delta_\lambda t I_{[1995,T]}(t) \tag{3.4}$$

[7] In addition to the restrictions on crossovers, negative intercepts, and small lower variance, a fourth restriction was added to the penalized algorithm: λ_t had to be positive and less than one (because it is a probability). This restriction was not applicable in the EM algorithm because λ_t was calculated as an average of probabilities, but in the penalized algorithm parameter estimates could take on any values unless restrictions were imposed.

Here, $(1 - \lambda_t)$ is the probability of a low yield, α_λ is the intercept of the probability of a low yield regressed on time, 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. In this model, the parameter of interest is δ_λ, as it measures whether the policy change – increased subsidies – affected the probability of a low yield in any way.

3.4 Hypothesis Testing

To address my research question, I tested whether there was a change in the rates of technological change in the upper or lower tails of the yield distribution after the subsidy increase and, if there was a change, whether this change was positive or negative. In model (3.3), the parameters of interest are δ_l and δ_u, representing the change in the rate of technological change after 1995 in the lower and upper tails, respectively. I tested the following sets of hypotheses:

$$\text{Hypothesis Test 1} \quad H_0: \ \delta_l = 0$$
$$H_a: \ \delta_l \neq 0 \quad \longrightarrow \delta_l < 0 \text{ or } \delta_l > 0$$

Under this hypothesis, I am testing whether a change in the rate of technological change had occurred in the lower component, i.e. whether δ_l is significantly different from zero. Using the results of this hypothesis test, I can look at whether the change was positive or negative. Under the income effect, I would expect the change to be positive, i.e. the rate of technological change would increase with higher subsidies, $(\delta_l > 0)$.

$$\text{Hypothesis Test 2} \quad H_0: \ \delta_u = 0$$
$$H_a: \ \delta_u \neq 0 \quad \longrightarrow \delta_u < 0 \text{ or } \delta_u > 0$$

Similar to the first test, here I am looking at whether a change in the rate of technological change had occurred in the upper component and whether the change was positive or negative. Again, the income effect would suggest that this change would be positive and there would be an increase in the rate of technological change with higher subsidies ($\delta_u > 0$).

Hypothesis Test 3 $\quad H_0: \ \delta_l = \delta_u$

$\qquad H_a: \ \delta_l \neq \delta_u \quad \longrightarrow \delta_l < \delta_u$ or $\delta_l > \delta_u$

In this hypothesis test, I am looking at whether the change in the rate of technological change was different between the lower and the upper components. In the presence of a risk effect, I would expect the change in the rate of technological change in the upper component to be higher than that in the lower component, i.e. δ_u to be greater than δ_l.

Hypothesis Test 4 $\quad H_0: \ \delta_l = 0, \ \delta_u = 0$

$\qquad H_a: \ \delta_l \neq 0, \ \delta_u \neq 0 \quad \longrightarrow \delta_l < 0, \ \delta_u < 0$ or $\delta_l > 0, \ \delta_u > 0$

Here, I am looking at whether a change in the rate of technological change had occurred in both the lower and the upper components (as opposed to just one component as in Tests 1 and 2). I can also look at whether these changes were positive or negative. Again, as with Tests 1 and 2, I would expect to see an overall increase in the rate of technological change with higher subsidies ($\delta_l > 0$, $\delta_u > 0$).

To carry out the hypothesis testing, I used the likelihood ratio test:

$$LR = -2(lnL_{restricted} - lnL_{unrestricted}) \tag{3.5}$$

To construct the test statistic, I calculated two log-likelihoods: one for the unrestricted model and one for the restricted model (model with restrictions from the null hypothesis). Under the null hypothesis, the LR test statistic follows a chi-square distribution with the degrees of freedom equal to the number of restrictions. In Tests 1, 2 and 3 there is one restriction, and in Test 4 there are two restrictions. Thus, for the one-restriction tests the appropriate critical test value at the five percent significance level is 3.841 and for the two-restriction test it is 5.991.

Because I am simultaneously performing hypothesis tests across multiple counties, the true probability of type I error is no longer at five percent. To counter this, I also applied the Holm-Bonferroni method for multiple testing to Tests 1 to 4 (Holm, 1979). This method is likely to be overly conservative in my case because it assumes that all hypothesis tests are independent whereas my counties are in fact spatially correlated, but it can nevertheless provide a useful way to gauge the significance of my test results. To obtain the Holm-Bonferroni significance, I first ordered the LR test statistics from largest to smallest and then compared each of those test statistics to the Holm-Bonferroni critical test value, computed as $\frac{\alpha}{n-j}$, where α is the significance level (0.05), n is the number of counties (number of LR test statistics), and j is the location of each LR in the ordered list, $j \in [0, n-1]$. If the largest LR was greater than the corresponding Holm-Bonferroni critical value, I counted this county as rejecting the null hypothesis at the Holm-Bonferroni five percent significance level, then compared the second-largest LR to the corresponding Holm-Bonferroni critical value, and so on down the ordered list until the LR was no longer greater than the corresponding Holm-Bonferroni value. This procedure provided me with a (overly conservative) count of the number of hypothesis test rejections at the Holm-Bonferroni five percent significance level, which I could compare to the number of rejections at the non-adjusted five percent significance level. Using these two methods allowed me to obtain a lower and an upper bound on the number of rejections to gauge the significance of my hypothesis test results across multiple counties.

Within the context of the probability of a low yield model (equation 3.4), I tested whether the probability of a low yield has changed over time (Test 5) and whether the subsidy increase affected this probability (Test 6). I performed these tests using a regular t-test.

Hypothesis Test 5 $\quad H_0: \ \beta_\lambda = 0$

$\qquad\qquad\qquad\qquad H_a: \ \beta_\lambda \neq 0 \quad \longrightarrow \beta_\lambda < 0 \text{ or } \beta_\lambda > 0$

Hypothesis Test 6 $\quad H_0: \ \delta_\lambda = 0$

$\qquad\qquad\qquad\qquad H_a: \ \delta_\lambda \neq 0 \quad \longrightarrow \delta_\lambda < 0 \text{ or } \delta_\lambda > 0$

Tests 5 and 6 focus on estimated parameters from a model in which the independent variable $(1 - \lambda_t)$ is itself an estimated regressor. To correct for the estimated regressors, I also computed jackknife standard errors to assess the statistical significance of β_λ and δ_λ compared to the outcomes of the regular t-test in Tests 5 and 6. To obtain jackknife estimates, I re-estimated the model $T = 67$ times, dropping one year of observations in each iteration to end up with 67 parameter estimates.[8] I then computed the jackknife estimator of the standard error as

$$SE_{jack} = \sqrt{\frac{T-1}{T}\sum_{t=1}^{T}(\hat{\theta}_{-t} - \bar{\hat{\theta}})^2} \tag{3.6}$$

where $\hat{\theta}_{-t}$ is the parameter β_λ or δ_λ estimated without year t and $\bar{\hat{\theta}}$ is the mean of all of those parameters, $\bar{\hat{\theta}} = \frac{1}{T}\sum_{t=1}^{T}\hat{\theta}_{-t}$. I performed t-tests using these jackknife standard errors to test the significance of β_λ and δ_λ while accounting for estimated regressors.

[8] Due to computational difficultly, I did not include the penalized maximum likelihood algorithm in the jackknifing procedure, so these results are based only on the EM algorithm outcomes.

3.5 Climate Attribution Model

As mentioned previously, it is not desirable to condition out climate in the mixture model if the interaction between technology and climate and the change that occurred in response to climatic changes is to be measured. A different way that numerous studies have been using to distinguish between climatic and non-climatic effects is attribution models. In these models, the time aspect is conditioned out and the remaining spatial variation is instead used to measure climatic and non-climatic effects. The non-climatic effects capture changes from technology and management, and well as other spatial factors such as soil characteristics. Literature that has used this attribution model approach to measure the impact of climate trends on yield trends include Nicholls (1997), Lobell and Asner (2003), Lobell and Field (2007), Tao et al. (2008), Zhang et al. (2016), Feng et al. (2018), and Kukal and Irmak (2018).

I followed the attribution model approach to investigate how much of the change in the rate of technological change after 1995 was driven by the policy effect, and if any of this change is attributable to climate change. The estimated δ_l and δ_u parameters from model 3.3 were modelled as a function of historical climate trends:

$$\delta_l = Innovation + \gamma \Delta Climate + \epsilon \tag{3.7}$$

$$\delta_u = Innovation + \gamma \Delta Climate + \epsilon \tag{3.8}$$

Here, $Innovation$ is the mean yield trend, assumed to be constant, $\Delta Climate$ is historical climate trends, γ is the response coefficients associated with the climate trends, and ϵ is the residuals. The climate trends were obtained by regressing each of the six climate variables (GDD, HDD, VPD, VPD_{ja}, PCP, PCP_{ja}) on time and taking the estimated slope coefficient. With time conditioned out, models 3.7 and 3.8 are estimating how much of the remaining (non-temporal) variation is explained by non-climatic changes in average yields (i.e. technological change) and how much is attributable to climatic change. If the estimated changes in the rates of technological change after 1995 were not driven solely by changes in climate, I would expect the coefficients on the climate trends to be insignificant. The null hypothesis to be tested is thus H_0: $\gamma = 0$. Not being able to reject this null hypothesis would imply that the changes in mean yields after 1995 were driven by non-climatic changes – e.g. the increased subsidies. This hypothesis test was performed using a t-test. Because δ_l, δ_u, and the climate trends are estimated parameters, I calculated jackknife standard errors to correct for this presence of estimated regressors in the attribution model.

In a similar way, the estimated δ_λ parameters from the probability of a low yield model (3.4) were regressed on the climate trends:

$$\delta_\lambda = Innovation + \gamma \Delta Climate + \epsilon \tag{3.9}$$

Here, the null hypothesis to be tested is again H_0: $\gamma = 0$. This hypothesis test assesses how much of the change in the probability of a low yield after 1995 is attributable to climatic changes. As with the previous two models, non-significant γ would imply that any changes in the probability of a low yield were not driven solely by climatic trends. Because δ_λ is an estimated regressor, I calculated jackknife standard errors to use in the t-test.

Chapter 4 Estimation Results

In this chapter, I report the estimation results of my empirical model and hypothesis testing for each crop, as well as the climate attribution model results. I focus on the estimates of δ_l and δ_u, the probability of a low yield over time model, and the hypothesis test results. I then discuss the economic significance and implications of these results in relation to my research question in Chapter 5. All parameter estimates from the county crop models are summarized by state and crop in the Appendix in Tables 7.1 to 7.15.

4.1 Corn

The estimates of δ_l and δ_u for corn counties summarized by state are shown in the boxplots in Figures 4.1 and 4.2. The estimates are both positive and negative in all states except South Dakota, where the estimates of δ_u are positive in all counties. It is interesting to note that the variation in the estimates both within and across states is greater for δ_l compared to δ_u. The estimates of δ_u within states are clustered near or around zero (South Dakota being an exception) within the range of -2 to 2, and the estimates across states are fairly similar (Figure 4.2). Conversely, estimates of δ_l vary more within states, with variations as large as from -5 to 5 in some states. Variability in δ_l estimates across states is also larger than for δ_u estimates (compare Figures 4.1 and 4.2). The spatial distribution of these estimates is illustrated in the maps in Figures 7.1 and 7.2 in the Appendix.

Figures 4.3a and 4.3b illustrate two examples of the corn county model estimation

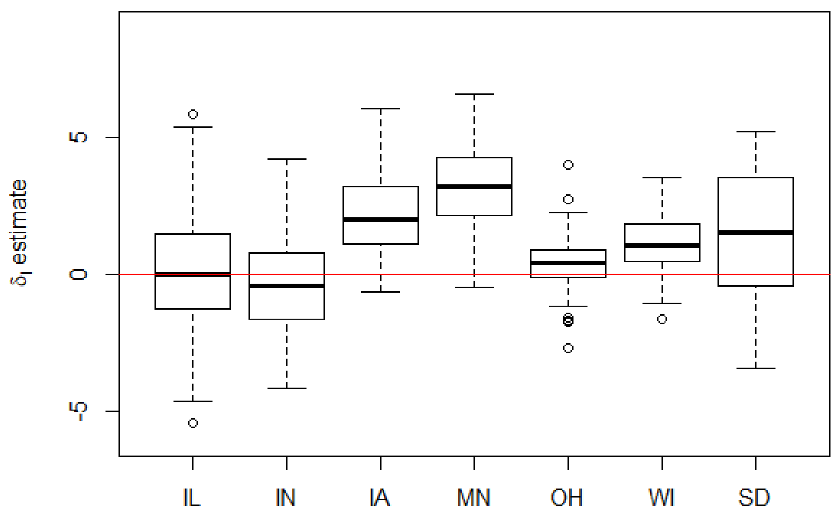


Figure 4.1: Estimates of δ_l for corn counties by state. Red line at zero is drawn for reference to make it easier to distinguish between negative and positive values.

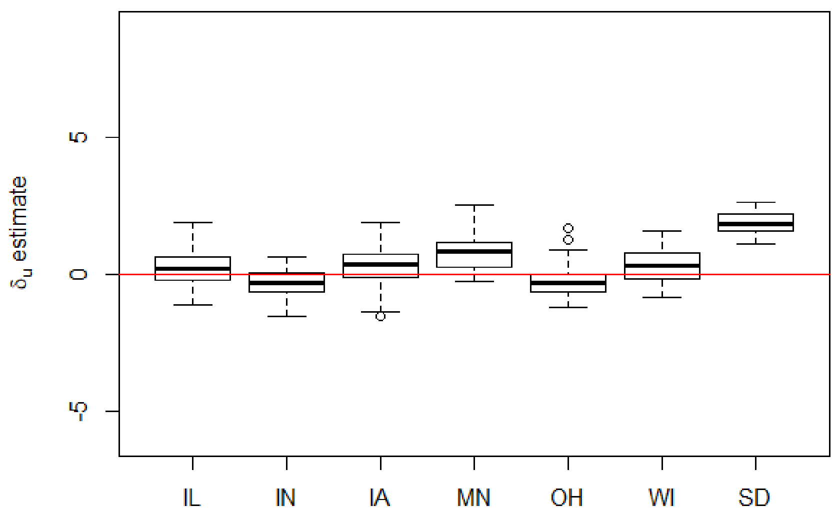
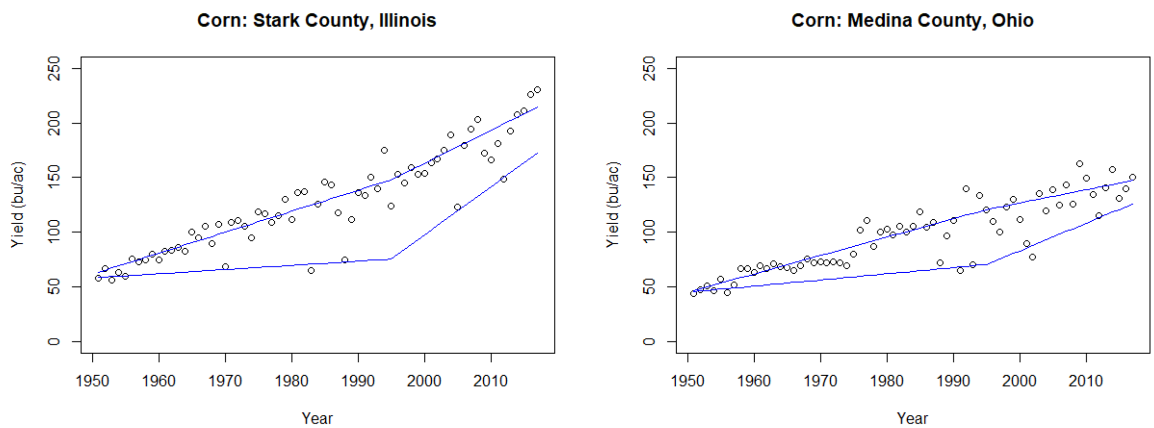


Figure 4.2: Estimates of δ_u for corn counties by state. Red line at zero is drawn for reference to make it easier to distinguish between negative and positive values.



(a) Stark County, Illinois **(b)** Medina County, Ohio

Figure 4.3: Corn model estimation results for two representative counties. Note the changes in the slopes of both components after 1995.

results. As seen from Figure 4.3a, the rates of technological change (i.e. slopes) in Stark County, Illinois, increased in both the lower and the upper components after the subsidy increase in 1995, more so in the lower component. In Medina County, Ohio (Figure 4.3b), the rate of technological change after 1995 increased in the lower component, but slightly decreased in the upper component. These counties are representative of the overall corn model results: in general, the lower component experienced a greater change than the upper component and was positive.

The probability of a low yield, $(1 - \lambda_t)$, in the corn model is shown in Figure 4.4 (also mapped in Figure 7.7 in the Appendix). In most corn counties, this probability is below 0.5, with the majority of estimates falling between 0.1 and 0.4.

The results of the hypothesis tests are given in Table 4.1. Overall, about one-third of all corn counties rejected the null hypothesis that either one of the δ_j's or both are zero. On average, the change in the rate of technological change in both components was positive, and was greater in the lower component (i.e. $\delta_l > \delta_u$). Indiana and Ohio

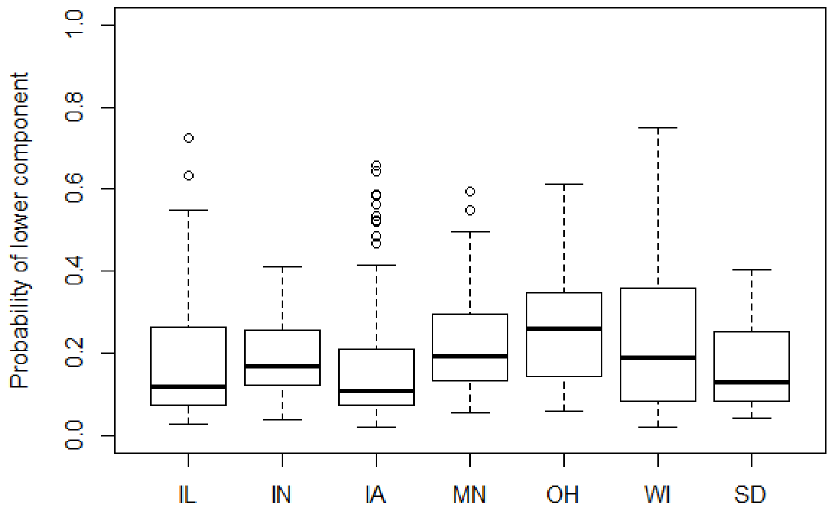


Figure 4.4: Probability of a low yield, $(1 - \lambda_t)$, for corn counties by state.

somewhat differ from this overall average, with δ_u's in many counties being significantly negative. In the probability of a low yield model, none of the estimated δ_λ parameters were significantly different from zero.

4.2 Soybeans

The estimates of δ_l and δ_u for soybeans are summarized in Figures 4.5 and 4.6, and the spatial distribution of these estimates is mapped in Figures 7.3 and 7.4 in the Appendix. As seen from the boxplots in Figures 4.5 and 4.6, the estimates of δ_l and δ_u are both positive and negative in all states. Similar to the corn model results, the variation within states is greater for the δ_l estimates as compared to the δ_u estimates. The δ_l estimates across counties within states are fairly spread out, spanning a range of -1 to 1.5 in some

Table 4.1: Corn – number of hypothesis test rejections and direction of estimated effect.

State	N	$\delta_l = 0$	$\delta_u = 0$	$\delta_l = \delta_u$	$\delta_\lambda = 0$
Illinois	71	23 (6); 11	18 (9); 16	19 (2); 10	0 (0); 0
Indiana	60	13 (1); 6	12 (4); 1	14 (1); 8	0 (0); 0
Iowa	86	33 (5); 33	28 (5); 25	29 (5); 5	0 (0); 0
Minnesota	51	34 (7); 34	26 (7); 26	28 (6); 0	0 (0); 0
Ohio	57	7 (1); 4	12 (1); 4	9 (1); 2	0 (0); 0
Wisconsin	48	15 (3); 14	19 (3); 18	13 (3); 1	0 (0); 0
S. Dakota	23	12 (2); 10	23 (19); 23	14 (3); 9	0 (0); 0
Total	396	137 (25); 112	138 (48); 113	126 (21); 35	0 (0); 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 included in the corn data set. First number is the number of rejections under each hypothesis. Number in parentheses is Holm-Bonferroni significance under multiple testing. Number after semicolon is the number of rejections for (i) $\delta_l \leq 0$; (ii) $\delta_u \leq 0$; (iii) $\delta_l \geq \delta_u$; (iv) $\delta_\lambda \geq 0$. Tests (i), (ii), and (iii) carried out by likelihood ratio test and Test (iv) by t-test. Test (iv) used jackknife standard errors to account for estimated regressor.

states, whereas the δ_u estimates are more closely clustered around zero within a range of -0.5 to 0.5. The variation across states is not as great as with the corn model estimates, but the difference in estimation results across states is still evident from the boxplots.

Figures 4.7a and 4.7b illustrate the estimation results for two representative soybean counties. In Warren County, Indiana (Figure 4.7a), the rates of technological change have increased in both the lower and upper components after 1995, with the increase being greater in the lower component. In Renville County, Minnesota (Figure 4.7b), there has been no change in the rate of technological change after 1995 in the upper component but an increase in the lower component.

The probability of the lower component for soybean counties is summarized in Figure 4.8 and mapped in Figure 7.8 in the Appendix. Similar to corn, the probability of a low yield for different soybean counties is below 0.5, with the majority of estimates ranging

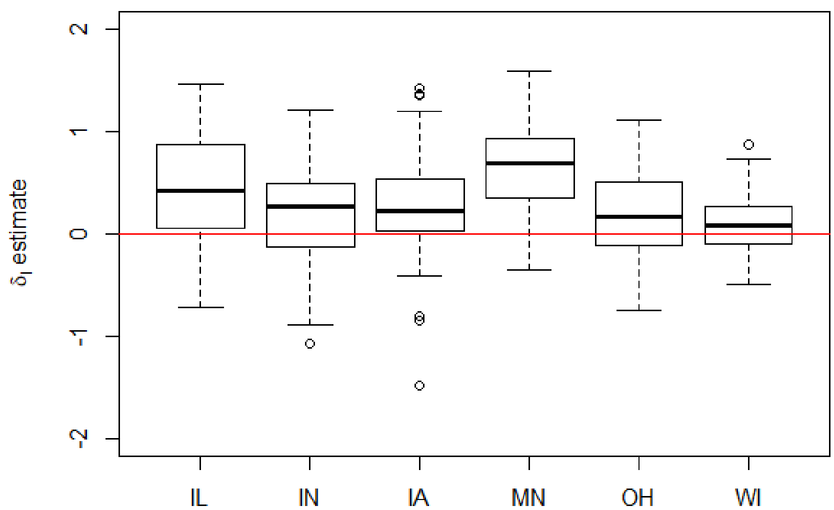


Figure 4.5: Estimates of δ_l for soybean counties by state. Red line at zero is drawn for reference to make it easier to distinguish between negative and positive values.

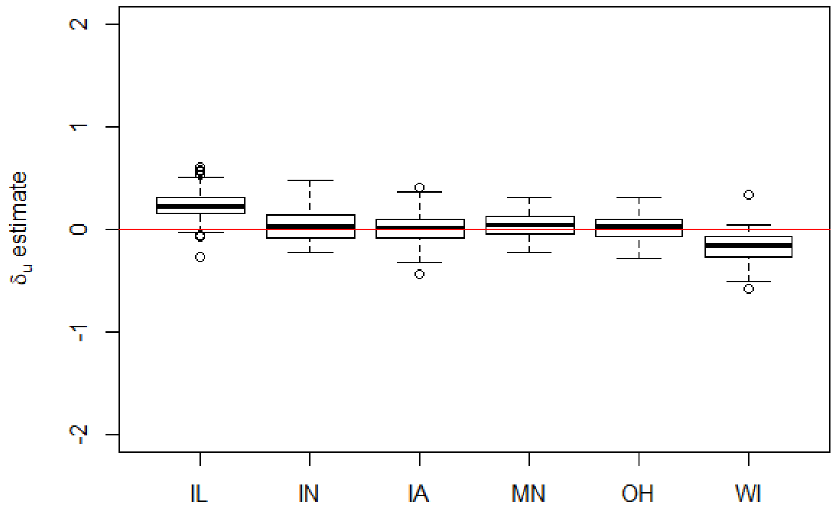
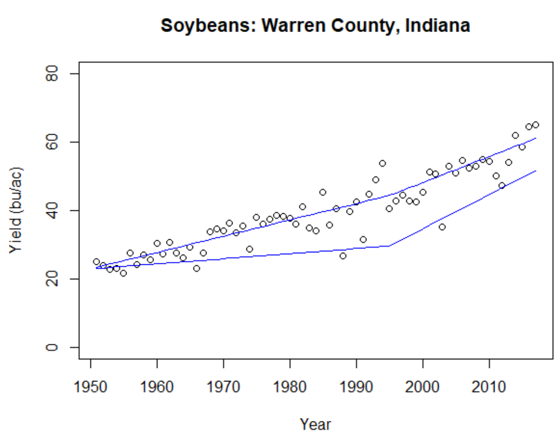
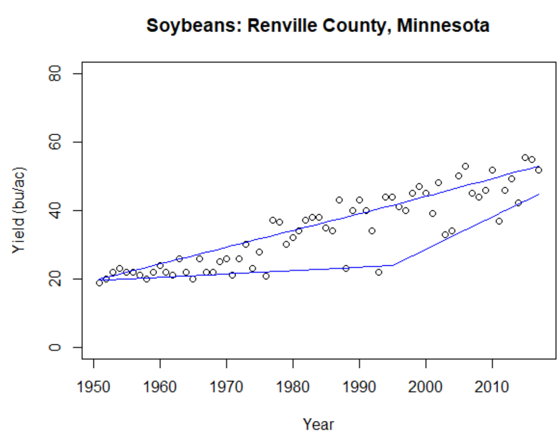


Figure 4.6: Estimates of δ_u for soybean counties by state. Red line at zero is drawn for reference to make it easier to distinguish between negative and positive values.



(a) Warren County, Indiana



(b) Renville County, Minnesota

Figure 4.7: Soybean model estimation results for two representative soybean counties. Note the changes in the slopes of both components after 1995.

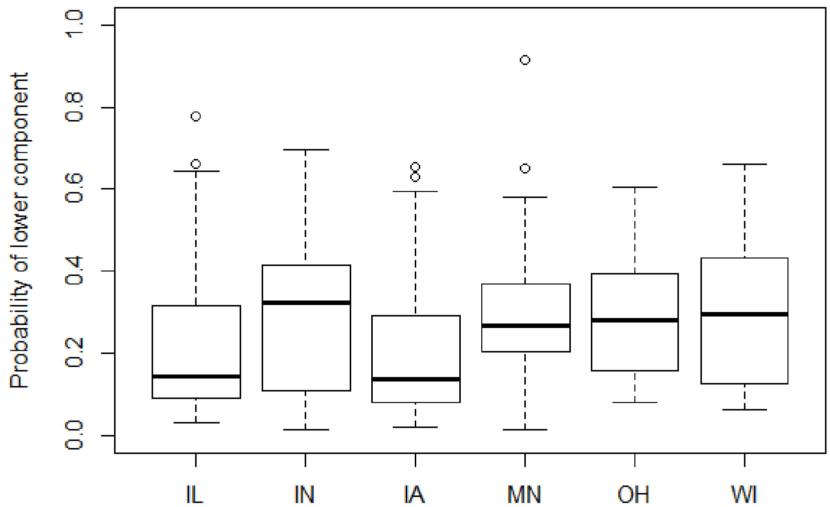


Figure 4.8: Probability of a low yield, $(1 - \lambda_t)$, for soybean counties by state.

from 0.1 to 0.4.

The results of the hypothesis tests are given in Table 4.2. Similar to corn, about one-third of all soybean counties rejected the null hypothesis that either one of the δ_j's or both are zero. Also similar to corn, the change in the rate of technological change in both components was positive on average across the states, and was greater in the lower component (i.e. $\delta_l > \delta_u$). Wisconsin results were different from this overall average: many of the estimated δ_u's were negative and smaller than the δ_l's. None of the estimated δ_λ's from the probability of a low yield model were significantly different from zero.

Table 4.2: Soybeans – number of hypothesis test rejections and direction of estimated effect.

State	N	$\delta_l = 0$	$\delta_u = 0$	$\delta_l = \delta_u$	$\delta_\lambda = 0$
Illinois	71	20 (2); 19	33 (8); 33	19 (3); 6	0 (0); 0
Indiana	55	14 (2); 10	5 (2); 5	13 (2); 6	0 (0); 0
Iowa	84	19 (3); 16	13 (2); 7	17 (3); 5	0 (0); 0
Minnesota	48	23 (8); 22	5 (1); 4	25 (8); 1	0 (0); 0
Ohio	50	11 (1); 9	5 (2); 4	16 (1); 3	0 (0); 0
Wisconsin	33	4 (0); 3	13 (3); 1	9 (1); 0	0 (0); 0
Total	341	91 (16); 79	74 (18); 54	99 (18); 21	0 (0); 0

Notes: Some counties were removed due to convergence issues, so the number of counties used for testing does not add up to the 373 counties included in the soybeans data set. First number is the number of rejections under each hypothesis. Number in parentheses is Holm-Bonferroni significance under multiple testing. Number after semicolon is the number of rejections for (i) $\delta_l \leq 0$; (ii) $\delta_u \leq 0$; (iii) $\delta_l \geq \delta_u$; (iv) $\delta_\lambda \geq 0$. Tests (i), (ii), and (iii) carried out by likelihood ratio test and Test (iv) by t-test. Test (iv) used jackknife standard errors to account for estimated regressor.

4.3 Winter Wheat

Winter wheat estimates of δ_l and δ_u are summarized by state in Figures 4.9 and 4.10. It is interesting to note that the estimates of δ_l are predominantly negative in Kansas and all positive in Michigan. The estimates of δ_u are fairly equally spread between negative and positive in Kansas, but again are predominantly positive in Michigan. Maps in Figures 7.5 and 7.6 in the Appendix show the geographical distribution of these estimates.

Figures 4.11a and 4.11b illustrate these contrasting results for Kansas and Michigan. Figure 4.11a shows winter wheat yields in Phillips County, Kansas, where the rate of technological change in both the lower and the upper components decreased after 1995. In contrast, in Isabella County, Michigan, shown in Figure 4.11b, the rate of technological change after 1995 increased in both components. Thus, Michigan winter wheat estimates of δ_l and δ_u are more similar to corn and soybeans estimation results than Kansas winter

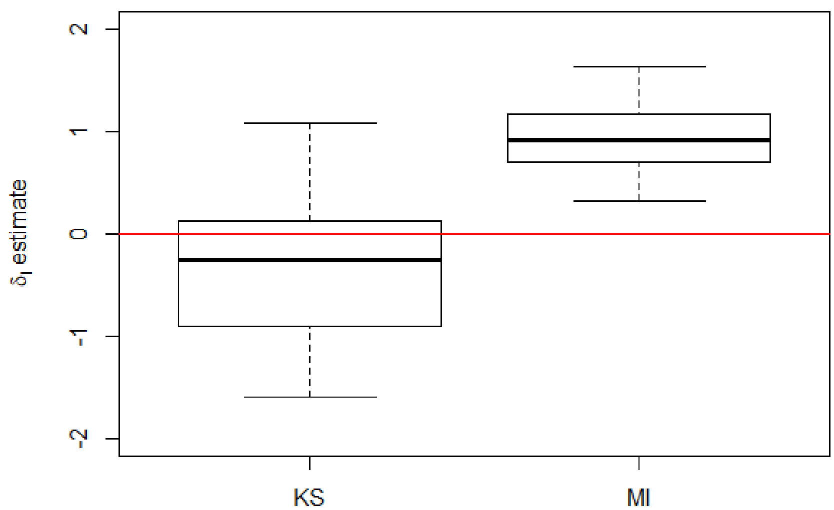


Figure 4.9: Estimates of δ_l for winter wheat counties by state. Red line at zero is drawn for reference to make it easier to distinguish between negative and positive values.

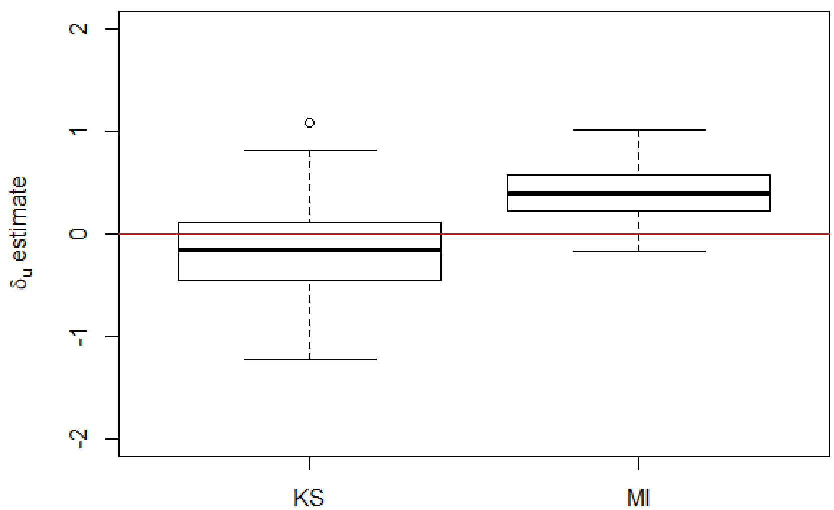
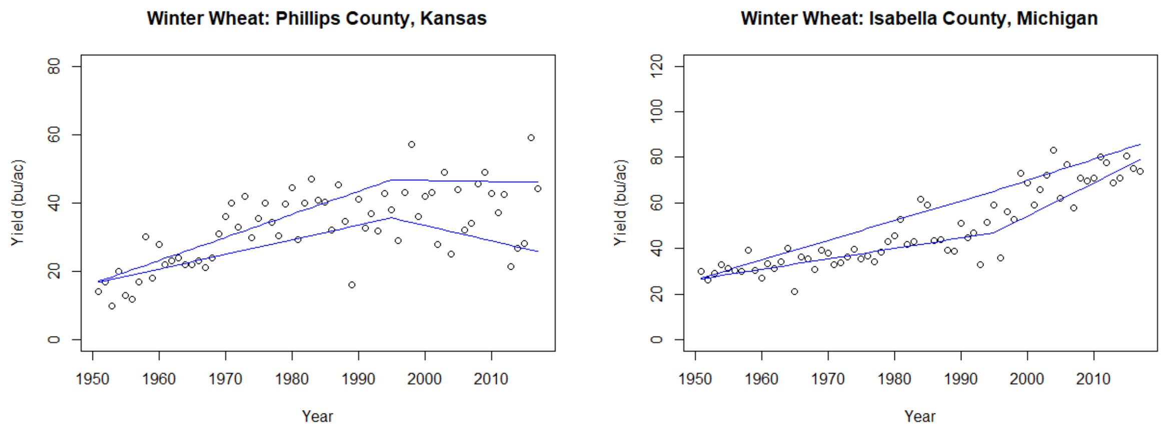


Figure 4.10: Estimates of δ_u for winter wheat counties by state. Red line at zero is drawn for reference to make it easier to distinguish between negative and positive values.



(a) Phillips County, Kansas **(b)** Isabella County, Michigan

Figure 4.11: Winter wheat model estimation results for two representative winter wheat counties. Note the changes in the slopes of both components after 1995.

wheat.

Figure 4.12 shows the probability of the lower component in Kansas and Michigan counties (also see the map in Figure 7.9 in the Appendix). These estimates are fairly similar in both states, with slightly higher variability in Kansas. Similar to corn and soybeans, the majority of the estimates range from 0.1 to 0.4.

The hypothesis tests results are reported in Table 4.3. In Kansas, over one-third of counties had statistically significant non-zero δ_j's. In these counties, δ_l's were predominantly negative; δ_u's were both positive and negative. All δ_l's were smaller than δ_u's. In Michigan, half of counties had δ_l and δ_u significantly different from zero. Both δ_j's were positive in these counties, and δ_l's were larger than δ_u's. None of the δ_λ's were significantly different from zero.

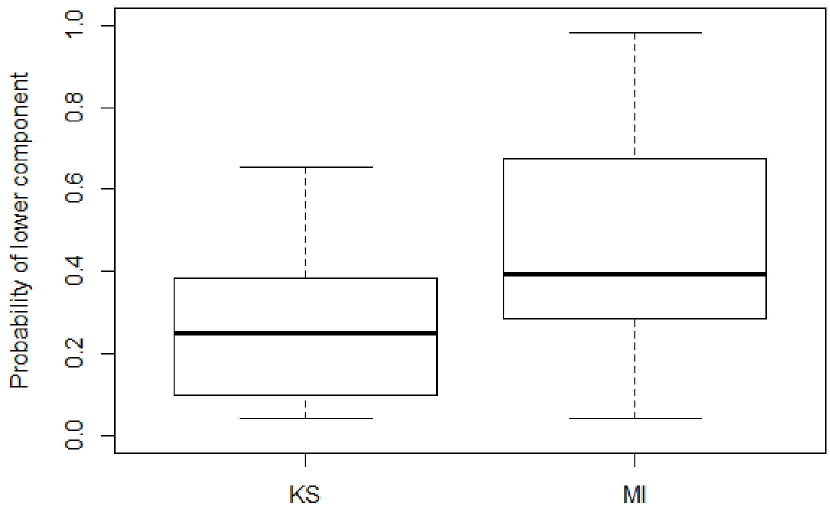


Figure 4.12: Probability of a low yield, $(1 - \lambda_t)$, for winter wheat counties by state.

Table 4.3: Winter wheat – number of hypothesis test rejections and direction of estimated effect.

State	N	$\delta_l = 0$	$\delta_u = 0$	$\delta_l = \delta_u$	$\delta_\lambda = 0$
Kansas	32	12 (2); 2	6 (2); 4	6 (1); 6	0 (0); 0
Michigan	21	9 (5); 9	6 (0); 6	11 (1); 0	0 (0); 0
Total	53	21 (7); 11	12 (2); 10	17 (2); 6	0 (0); 0

Notes: Some counties were removed due to convergence issues, so the number of counties used for testing does not add up to the 64 counties included in the winter wheat data set. First number is the number of rejections under each hypothesis. Number in parentheses is Holm-Bonferroni significance under multiple testing. Number after semicolon is the number of rejections for (i) $\delta_l \leq 0$; (ii) $\delta_u \leq 0$; (iii) $\delta_l \geq \delta_u$; (iv) $\delta_\lambda \geq 0$. Tests (i), (ii), and (iii) carried out by likelihood ratio test and Test (iv) by t-test. Test (iv) used jackknife standard errors to account for estimated regressor.

4.4 Attribution Model Results

Recall that the aim of the attribution model is to use spatial (i.e. non-temporal) variation to identify whether any of the estimated changes in the rates of technological change after the subsidization increase are attributable to climatic variation. The significance of the coefficients on the climate trend variables within the attribution model can be interpreted as follows: with the temporal aspect conditioned out, how much of the spatial variation in the change of rate of technological change is explained by the spatial variation in climate variables? Insignificant coefficients would imply that most of the effect estimated by the crop yield model is attributable to factors other than climate, e.g. policy change. The following subsections summarize the attribution model results for each of the three crops.[9]

4.4.1 Corn

Table 4.4 shows the results of the attribution model for δ_l regressed on climate trend variables. Five of the six estimated trend coefficients are significant: GDD and VPD at one percent, HDD and PCP at five percent, and PCP_{ja} at ten percent. The direction of estimated effects for each trend variable is as expected. When I corrected for estimated regressors using the jackknife standard errors (shown in Table 4.4), the estimated coefficient on GDD remained significant at ten percent. This may possibly suggest that some of the lower tail effect picked up through the crop yield model is attributable to spatial variation in growing degree days, i.e. not only the subsidy increase was driving increased innovation in the lower tail but also an increase in growing degree days. When

[9]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 corn counties, 8 soybean counties, and 23 winter wheat counties (in addition to counties previously removed due to convergence issues).

δ_u – upper tail effect – was regressed on climate trends, four of the estimated coefficients were significant: *GDD*, *HDD* and *VPD* at one percent, and PCP_{ja} at ten percent (Table 4.5). Two of them remained significant when jackknife standard errors were used to correct for the estimated regressors: *GDD* at one percent and *HDD* at five percent. It is surprising that the estimated coefficient on *HDD* is significantly positive; I would expect a greater number of extreme heat days to have a negative effect on the rate of technological change in the upper tail (because extreme heat negatively impacts corn yields).

Table 4.4: Corn – δ_l regressed on climate trends ($R^2 = 0.24$).

Variable	Estimate	SE	SE_{jack}
GDD	1.334	0.257***	0.965*
HDD	-1.402	0.543**	2.021
VPD	-2.290	0.729***	2.063
VPD_{ja}	-0.650	0.942	3.503
PCP	0.077	0.039**	0.149
PCP_{ja}	-0.144	0.073*	0.257

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Table 4.5: Corn – δ_u regressed on climate trends ($R^2 = 0.22$).

Variable	Estimate	SE	SE_{jack}
GDD	0.849	0.095***	0.288***
HDD	0.925	0.201***	0.451**
VPD	-1.786	0.270***	0.758
VPD_{ja}	0.135	0.349	1.103
PCP	-0.008	0.014	0.032
PCP_{ja}	0.051	0.027*	0.083

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Note how the jackknife standard errors are several orders of magnitude greater than the conventional standard errors. Also note that the increase in the jackknife standard errors relative to the conventional ones is larger for the lower component. This is expected since the crop yield model has identified a greater increase in the rate of technological change in the lower component relative to the upper component. Thus, I would expect that more of this change in the lower component was driven by the policy change (increased subsidies) and not so much by climatic changes, relative to the upper component. In the upper tail where the policy effect was not as great, it is expected that a larger proportion (relative to the lower tail) of the change would be explained by climatic variation.

It is somewhat surprising that regressing the estimated rates of technological change in the lower and upper tails (β_l and β_u, respectively) on climate trend variables does not show stronger climatic effects than in the previous two regressions (Tables 4.6 and 4.7). I would expect at least a part of the spatial differences in the rates of technological change to be explained by spatial variation in climatic factors. However, when β_l was regressed on climatic trends, only *GDD* was significant at five percent, without correcting for estimated regressors (Table 4.6). When β_u was regressed on climatic variables, five of the estimated coefficients were significant but only *PCP* remained significant with the corrected standard errors (Table 4.7).

Table 4.6: Corn – β_l regressed on climate trends ($R^2 = 0.07$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.170	0.066**	0.457
HDD	-0.052	0.140	0.700
VPD	0.269	0.188	0.934
VPD_{ja}	-0.060	0.243	0.984
PCP	0.006	0.010	0.039
PCP_{ja}	0.009	0.019	0.066

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

When the probability of a low yield trend (β_λ) was regressed on the climate trends, all of the estimated coefficients except for the coefficient on precipitation in July and August

Table 4.7: Corn – β_u regressed on climate trends ($R^2 = 0.08$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.086	0.035**	0.120
HDD	-0.058	0.074	0.194
VPD	0.225	0.099**	0.290
VPD_{ja}	-0.211	0.128*	0.390
PCP	0.022	0.005***	0.012**
PCP_{ja}	-0.026	0.010**	0.027

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

were highly significant (Table 4.8). However, none remained significant after correcting for estimated regressors. The same was also true for the change in the probability of a low yield after 1995 (δ_λ) regressed on climate trends: four of the variables were significant without the corrected standard errors but failed to remain significant under jackknife standard errors (Table 4.9). This is not surprising because the crop yield model did not show a significant change in the probability of a low yield after 1995.

Table 4.8: Corn – β_λ regressed on climate trends ($R^2 = 0.14$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.00241	0.00041***	0.00355
HDD	-0.00298	0.00086***	0.00398
VPD	0.00687	0.00115***	0.00747
VPD_{ja}	-0.00376	0.00149**	0.00708
PCP	0.00020	0.00006***	0.00022
PCP_{ja}	-0.00019	0.00012	0.00041

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

4.4.2 Soybeans

In the soybean attribution model where δ_l was regressed on climate trend variables, four of the six estimated coefficients were significant: VDP_{ja}, PCP and PCP_{ja} at one percent,

Table 4.9: Corn – δ_λ regressed on climate trends ($R^2 = 0.12$).

Variable	Estimate	SE	SE_{jack}
GDD	0.00541	0.00127***	0.01487
HDD	0.00402	0.00248	0.02070
VPD	-0.01525	0.00333***	0.03197
VPD_{ja}	0.00742	0.00430*	0.02394
PCP	-0.00037	0.00017**	0.00066
PCP_{ja}	0.00006	0.00033	0.00206

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

and GDD at five percent (Table 4.10). Only one, PCP, remained significant at five percent when corrected for estimated regressors with jackknife standard errors. When δ_u was regressed on climate trends, four of the estimated coefficients were significant: HDD, VPD_{ja}, PCP and PCP_{ja}, all at one percent (Table 4.11). With jackknife standard errors, two of them remained significant: HDD at five percent and PCP at one percent. As with the corn results, it is somewhat surprising to find that the estimated HDD effect is significantly positive in the upper tail.

Table 4.10: Soybeans – δ_l regressed on climate trends ($R^2 = 0.09$).

Variable	Estimate	SE	SE_{jack}
GDD	0.229	0.098**	0.244
HDD	0.086	0.210	0.654
VPD	-0.164	0.239	0.617
VPD_{ja}	-0.709	0.263***	0.747
PCP	0.039	0.010***	0.022**
PCP_{ja}	-0.073	0.019***	0.055

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Again, note that the jackknife standard errors are several orders of magnitude greater than the conventional standard errors, and that the increase in the jackknife standard errors relative to the conventional ones is larger for the lower component. As with the corn model, I would expect to see this since the soybean yield model has also identified

Table 4.11: Soybeans – δ_u regressed on climate trends ($R^2 = 0.33$).

Variable	Estimate	SE	SE_{jack}
GDD	0.038	0.032	0.069
HDD	0.328	0.069***	0.175**
VPD	0.036	0.078	0.207
VPD_{ja}	-0.434	0.086***	0.276
PCP	0.023	0.003***	0.009***
PCP_{ja}	-0.021	0.006***	0.019

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

a greater increase in the rate of technological change in the lower component relative to the upper component. The differences in the standard errors thus show that changes in the lower component were more driven by increased subsidies relative to the upper component and not as much by climatic changes. In the upper tail where the policy effect was not as great, a larger proportion of the change is explained by climatic variation.

Also similar to corn, regressing the estimated β_l and β_u on climate trend variables did not show stronger climatic effects than with the δ_j regressions, even though I would expect at least a part of the spatial differences in the rates of technological change to be explained by spatial variation in climatic factors. When β_l was regressed on climatic trends, VPD_{ja} was significant at one percent and PCP at five percent without correcting for estimated regressors (Table 4.12), but neither remained significant with the jackknife standard errors. The results were somewhat stronger when β_u was regressed on climatic variables, with four significant estimated coefficients: HDD, VPD_{ja}, and PCP at one percent and VPD at five percent (Table 4.13). The PCP effect remained strongly significant even with the correction for estimated regressors.

When the probability of a low yield trend (β_λ) was regressed on the climate trends, four of the variables were highly significant without the corrected standard errors (Table 4.14). However, none remained significant after correcting for estimated regressors.

Table 4.12: Soybeans – β_l regressed on climate trends ($R^2 = 0.05$).

Variable	Estimate	SE	SE_{jack}
GDD	0.001	0.029	0.080
HDD	0.069	0.061	0.184
VPD	-0.093	0.070	0.199
VPD_{ja}	0.231	0.077***	0.205
PCP	-0.008	0.003**	0.008
PCP_{ja}	0.006	0.006	0.019

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Table 4.13: Soybeans – β_u regressed on climate trends ($R^2 = 0.40$).

Variable	Estimate	SE	SE_{jack}
GDD	0.005	0.015	0.022
HDD	-0.098	0.032***	0.052
VPD	-0.085	0.036**	0.064
VPD_{ja}	0.291	0.040***	0.081
PCP	-0.009	0.002***	0.003***
PCP_{ja}	0.005	0.003	0.005

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

The same was also true for the change in the probability of a low yield after 1995 (δ_λ) regressed on climate trends: all of the estimated coefficients except for *HDD* were significant without the corrected standard errors but failed to remain significant under jackknife standard errors (Table 4.15). As with corn, this is not surprising because the crop yield model did not show a significant change in the probability of a low yield after 1995.

Table 4.14: Soybeans – β_λ regressed on climate trends ($R^2 = 0.17$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.00146	0.00060**	0.00342
HDD	-0.00166	0.00128	0.00806
VPD	0.00508	0.00146***	0.00804
VPD_{ja}	-0.00439	0.00160***	0.00435
PCP	-0.00005	0.00006	0.00024
PCP_{ja}	0.00026	0.00012**	0.00032

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Table 4.15: Soybeans – δ_λ regressed on climate trends ($R^2 = 0.17$).

Variable	Estimate	SE	SE_{jack}
GDD	0.00457	0.00204**	0.00924
HDD	0.00595	0.00436	0.02191
VPD	-0.01747	0.00496***	0.02143
VPD_{ja}	0.02048	0.00546***	0.01742
PCP	0.00037	0.00022*	0.00063
PCP_{ja}	-0.00066	0.00040*	0.00107

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

4.4.3 Winter Wheat

My winter wheat data set consisted of two states, Kansas and Michigan, which are in quite different geographic (and thus climatic) locations – Kansas is in the south and

Michigan is in the north. Also, their crop yield model estimation results were very different. Thus, it is interesting to use the attribution model to see how much of the spatial variation is attributable to climatic changes.

When δ_l was regressed on climate trend variables, four variables were significant: *HDD* and *PCP* at one percent, and *GDD* and PCP_{ja} at ten percent. Only one, *PCP*, remained significant when jackknife standard errors were used to correct for estimated regressors (Table 4.16). When δ_u was regressed on climate variables, *VPD* and VPD_{ja} were significant at five percent without the correction for estimated regressors, and VPD_{ja} remained significant at ten percent after the correction (Table 4.17). Just as with corn and soybeans, notice how the jackknife standard errors are several orders of magnitude greater than the conventional standard errors, and that the increase in the jackknife standard errors relative to the conventional ones is larger for the lower component. Again, these differences demonstrate that changes in the lower component were more driven by increased subsidies and not as much by climate relative to the upper component.

Table 4.16: Winter wheat – δ_l regressed on climate trends ($R^2 = 0.73$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.050	0.027*	0.081
HDD	0.223	0.059***	0.210
VPD	0.073	0.286	0.735
VPD_{ja}	-0.498	0.781	1.778
PCP	0.130	0.044***	0.097*
PCP_{ja}	-0.182	0.105*	0.262

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Similar to corn and soybeans, regressing the estimated β_l and β_u parameters on climate trend variables did not show stronger climatic effects than with the δ_j regressions (Tables 4.18 and 4.19). When the probability of a low yield trend, β_λ, was regressed

Table 4.17: Winter wheat – δ_u regressed on climate trends ($R^2 = 0.47$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.031	0.023	0.041
HDD	0.039	0.050	0.100
VPD	-0.571	0.240**	0.377
VPD_{ja}	1.475	0.655**	0.978*
PCP	0.061	0.037	0.053
PCP_{ja}	-0.109	0.088	0.142

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

on the climate trends, only one variable was significant: GDD at five percent (Table 4.20). It did not remain significant after correcting for estimated regressors. When the change in the probability of a low yield, δ_λ, was regressed on climate trends, none of the estimated coefficients were significant (Table 4.21).

Table 4.18: Winter wheat – β_l regressed on climate trends ($R^2 = 0.35$).

Variable	Estimate	SE	SE_{jack}
GDD	0.016	0.009	0.018
HDD	-0.042	0.020**	0.041
VPD	0.116	0.098	0.219
VPD_{ja}	-0.369	0.268	0.474
PCP	0.013	0.015	0.029
PCP_{ja}	0.0004	0.036	0.067

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Table 4.19: Winter wheat – β_u regressed on climate trends ($R^2 = 0.71$).

Variable	Estimate	SE	SE_{jack}
GDD	0.006	0.006	0.040
HDD	0.011	0.014	0.090
VPD	0.247	0.066***	0.366
VPD_{ja}	-0.749	0.181***	0.977
PCP	0.035	0.010***	0.039
PCP_{ja}	-0.048	0.024	0.094

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Table 4.20: Winter wheat – β_λ regressed on climate trends ($R^2 = 0.45$).

Variable	Estimate	SE	SE_{jack}
GDD	-0.00034	0.00013**	0.00038
HDD	0.00038	0.00029	0.00062
VPD	-0.00123	0.00139	0.00421
VPD_{ja}	0.00563	0.00378	0.01025
PCP	-0.00014	0.00021	0.00061
PCP_{ja}	0.00064	0.00051	0.00128

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Table 4.21: Winter wheat – δ_λ regressed on climate trends ($R^2 = 0.26$).

Variable	Estimate	SE	SE_{jack}
GDD	0.00072	0.00052	0.00161
HDD	-0.00047	0.00114	0.00384
VPD	0.00518	0.00550	0.01186
VPD_{ja}	-0.01777	0.01502	0.03081
PCP	0.00108	0.00085	0.00251
PCP_{ja}	-0.00328	0.00202	0.00496

Note: * indicates significance at 10 percent, ** at five percent, and *** at one percent.

Chapter 5 Economic Implications

5.1 Income and Risk Effects

Recall that higher crop insurance premium subsidies may have two effects on the rate of technological change in crop production: an income effect and a risk effect. The income effect is an overall increased rate of technological change resulting from a greater willingness to adopt technologies and a greater supply of technologies. The risk effect is an increased adoption of high-risk high-reward technologies at the expense of competing risk-reducing technologies. I used the substantial increase of U.S. crop insurance premium subsidies in the late 1990s as a natural experiment setting to empirically test whether this policy change had an income effect or a risk effect, or both, on the rates of technological change in the lower and upper tails of crop yield distributions.

My empirical analysis results indicate that an income effect from the increased subsidies has possibly occurred in the United States crop production. The rates of technological change in both the lower and the upper components have increased with the higher subsidies in many counties across all three crops. Although statistical significance was found for only a third of counties on average, these results nevertheless constitute strong evidence of an income effect.[10] The probability of a low yield over time, as measured by the model, has not changed and was not affected by the increased subsidies.

The results of the climate attribution model suggest that the increases in the rates

[10] In fact, it was surprising to find significance in an entire third of the counties, considering that the two-component mixture models were estimated from only 67 data points.

of technological change post 1995 were not driven solely by changes in climate. It is true that some of the estimated coefficients on the climate trend variables were statistically significant even after correcting for estimated regressors. However, with a probability of type one error of five percent, I would expect to see a true null hypothesis rejected in five percent of tests – so about five or six tests of the total 108 tests that I performed for corn, soybeans, and winter wheat. After correcting for estimated regressors, I found significance at the five percent level in seven out of the 108 tests (6.5 percent) – just slightly higher than the probability of type one error. Therefore, the results of the attribution model are not strong enough to suggest that spatial variation in the estimated income effect is attributable to climatic changes. With the climate effect ruled out in this way, it is even more likely that the estimated changes in the rates of technological change are evidence of an income effect driven by increased insurance premium subsidies.

Under the risk effect, one would expect to see a lower rate of technological change in the lower tail of the yield distribution compared to the upper tail. My empirical analysis does not find evidence of this in the United States crop production. In fact, I tend to find the opposite: after the subsidy increase, technological change in the lower component appears to have been increasing at a higher rate than in the upper component. The likely reason for this is that the main available technologies are non-competing. An example is genetically modified seeds with stacked traits. As was shown in Figure 2.5, the adoption of drought-tolerant corn has been rapidly increasing since its introduction. This is an example of a risk-reducing technology that is non-competing because the drought-tolerant trait can be "stacked" on top of other desired traits in genetically modified varieties. The rapid adoption of drought-tolerant corn supports my empirical findings that there has not been a decrease in the adoption of risk-reducing technologies because they do not compete with riskier high-reward technologies.

It is interesting to note that the income and risk effects vary substantially across states, suggesting that the policy change had differing effects based on geographic location. This difference is particularly prominent in the winter wheat results. Although my winter wheat data set consisted of only two states, these states are very different because of their location: Kansas is in the south and Michigan is in the north. Southern production regions are predicted be more severely impacted by a changing climate than northern regions mainly because of the increased frequency of extreme heat in the south. Thus, adaptation and technological change in the southern regions is particularly important for sustaining production and building yield resiliency. The results of my analysis indicate that higher subsidies possibly created a moral hazard problem in Kansas winter wheat production, as producers may have reduced the use of technologies that can help them mitigate the negative impacts of climate change and instead increased the use of riskier technologies. As genetically modified varieties of winter wheat are not currently commercially available, it is likely that no other non-competing risk-reducing technologies for winter wheat production in Kansas are available. Thus, higher subsidies may have potentially incentivized producers to substitute high-risk technologies for the existing risk-reducing ones, and this may have resulted in the decreased rates of technological change that my empirical analysis has been finding.

5.2 Implications for Crop Insurance Premiums

The differing rate of technological change resulting from the subsidization increase has important implications for crop insurance premium rates. To illustrate this, I calculated hypothetical premium rates for the year 2019 for each county using parameter estimates from my model. I also calculated premium rates using the same parameter estimates but assuming that the rates of technological change have not changed – δ_l and δ_u are zero – i.e. that there was no policy change (or no effect of the policy change). I then compared the two premium rates to identify the effect of the changed rates of technological change on premiums.

To calculate the premium rates, I looked at three levels of coverage – 70, 80, and 90 percent. The yield guarantee is equal to

$$y_{guar} = ((1 - \lambda)\mu_l + \lambda\mu_u) * pct \tag{5.1}$$

where λ is the probability of the upper component, μ_l and μ_u are the lower and upper component mean yields, respectively, in 2019 ($\mu_j = \alpha_j + \beta_j t + \delta_j t I_{[1995,T]}(t)$), and pct is the chosen percentage coverage level (0.7, 0.8 or 0.9). The expected yield for each component under yield loss is then

$$EY_j = E[y_j | y_j < y_{guar}] = \mu_j - \sigma_j \frac{\phi(\frac{y_{guar} - \mu_j}{\sigma_j})}{\Phi(\frac{y_{guar} - \mu_j}{\sigma_j})} \tag{5.2}$$

where σ_j is the variance of component j, $\phi(.)$ is the standard normal probability density function, and $\Phi(.)$ is the standard normal cumulative density function. Given the expected yield for each component, the expected loss is

$$Expected\ Loss = y_{guar} - E[y | y < y_{guar}] \tag{5.3}$$

where $E[y|y < y_{guar}] = (1 - \lambda)EY_l + \lambda EY_u$ (i.e. weighted mean of the expected yields), and the probability of a loss is

$$P_{loss} = (1-\lambda)P(y_l < y_{guar}) + \lambda P(y_u < y_{guar}) \tag{5.4}$$

Therefore, the actuarially fair premium rate is equal to the probability of a yield loss times the expected yield loss, all divided by the yield guarantee:

$$Premium\ Rate = \frac{P_{loss} * Expected\ Loss}{y_{guar}} \tag{5.5}$$

Figure 5.1 compares the insurance premium rates for 70 percent coverage level for corn counties when the subsidy effect is taken into account and when it is assumed away. Note that the figure has been truncated for better visual representation; the actual values range from 0.0 to 7.4 percent in the boxplot on the left and from 0.0 to 14.0 percent in the boxplot on the right. Figures 5.2a and 5.2b show the calculated premium rates for 80 and 90 percent coverage levels, respectively. Similar to Figure 5.1, the figures have been truncated for a clearer comparison. The premium rates in Figure 5.2a range from 0.0 to 7.9 percent in the left boxplot and from 0.0 to 26.4 percent in the right boxplot, and in Figure 5.2b from 0.0 to 9.0 percent in the left boxplot and from 0.2 to 34.9 percent in the right boxplot. Notice how the insurance premium rates under the subsidy effect are smaller on average than those that assume no effect, especially at the 90 percent coverage level.

Figure 5.3 shows the calculated insurance premium rates for soybean counties. Again, for a better visual comparison, the boxplots have been truncated. The actual calculated values range from 0.0 to 1.4 percent in the left boxplot and from 0.0 to 3.4 percent in the right boxplot. The premium rates for 80 and 90 percent coverage levels for

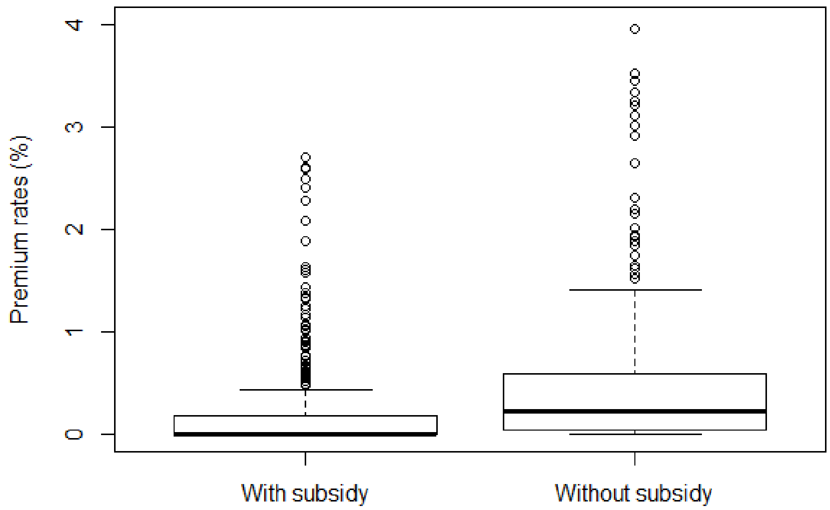
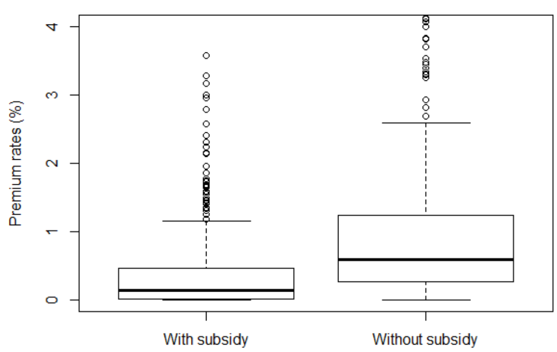
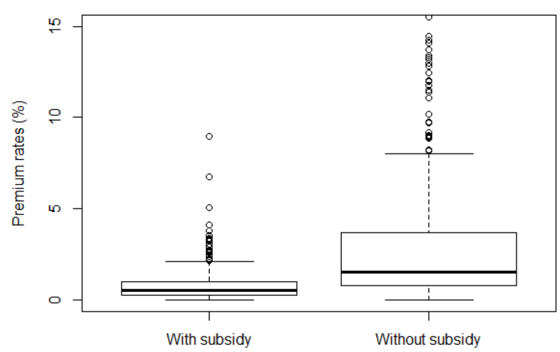


Figure 5.1: Insurance premium rates for 70 percent coverage level for corn counties in 2019, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.



(a) 80 percent coverage



(b) 90 percent coverage

Figure 5.2: Insurance premium rates for (a) 80 and (b) 90 percent coverage levels for corn counties in 2019, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.

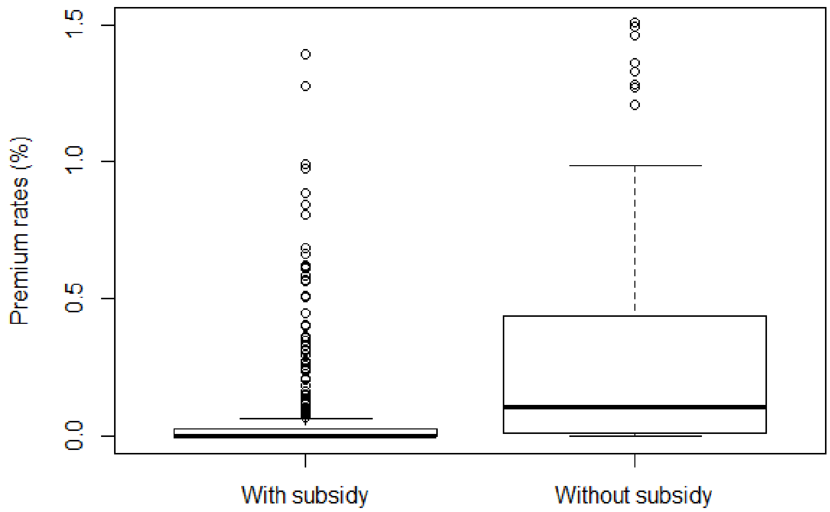
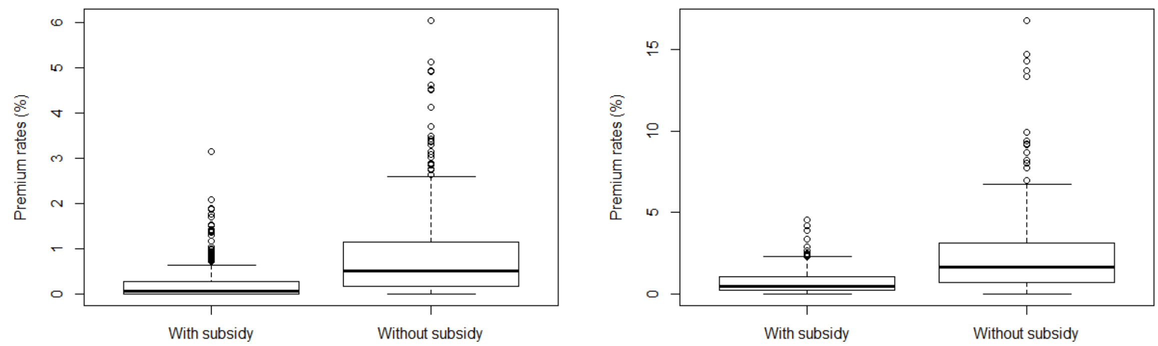


Figure 5.3: Insurance premium rates for 70 percent coverage level for soybean counties in 2019, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.

soybean counties are shown in Figures 5.4a and 5.4b, respectively. There was no need to truncate either figure, as the boxplots in each figure were clearly comparable, and thus the boxplots illustrate the full range of the calculated premium rates. Again, note how the insurance premium rates that account for the subsidy effect are much smaller on average than those that do not, at all coverage levels.

Figures 5.5, 5.6a, and 5.6b summarize the calculated premium rates for winter wheat counties at 70, 80, and 90 percent coverage levels, respectively. The boxplots did not need to be truncated as the calculated values did not range as much as the corn or soybean rates. Just like with corn and soybeans, notice how the insurance premium rates that account for the subsidy effect are smaller on average than those that assume no effect, less so at the 70 percent coverage level and more so at the 80 and 90 percent



(a) 80 percent coverage **(b)** 90 percent coverage

Figure 5.4: Insurance premium rates for (a) 80 and (b) 90 percent coverage levels for soybean counties in 2019, with and without subsidy effect.

coverage levels.

Hypothetical premium rates for all three crops and three coverage levels were also calculated ten years into the future for the year 2029. The results are shown in Figures 7.10 to 7.15b in the Appendix. Here, the differences between the premium rates calculated with and without the subsidy effect are even more prominent, with the rates accounting for the subsidy effect being much smaller on average than those that assume the effect away. These differences highlight the implications that the subsidy effect has for future insurance premium rates.

It is quite remarkable that for all three crops and three different coverage levels the insurance premium rates calculated under the subsidy effect are smaller than the premium rates without the subsidy effect. These results suggest that the subsidy increase has been beneficial because it has resulted in lower premium rates, which are desirable in several aspects: lower cost for producers, lower cost for government, and lower spending of taxpayer money. This favourable effect of the policy change is occurring because the

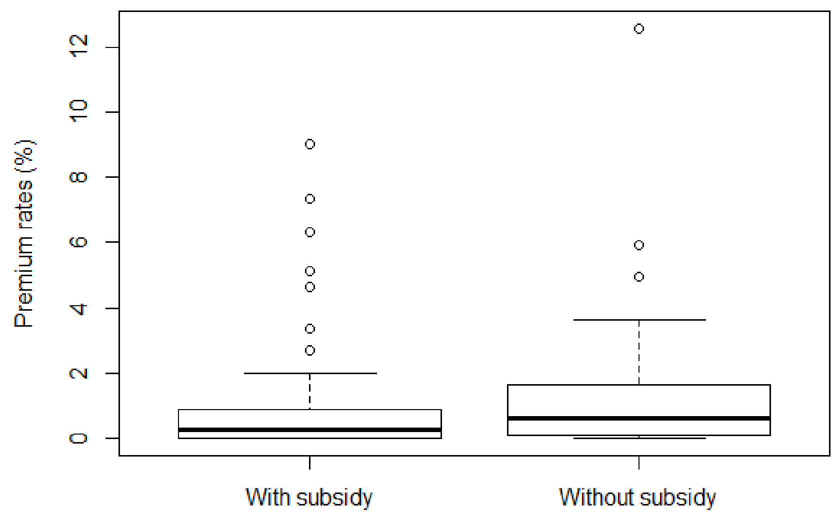
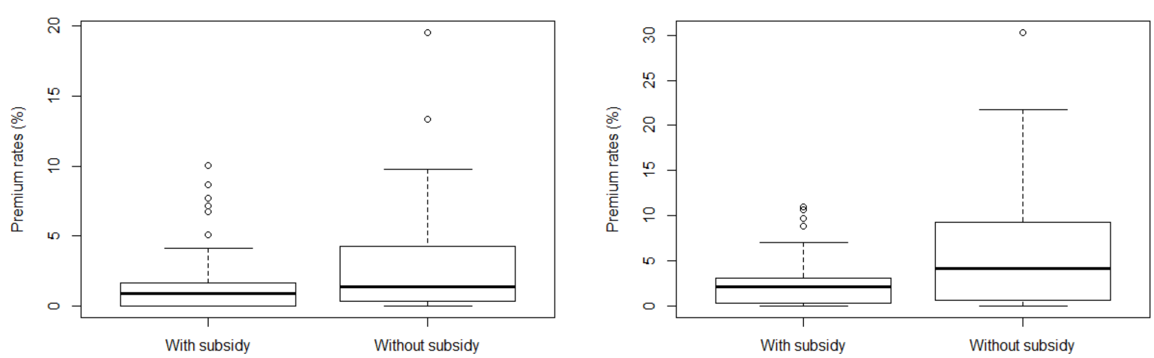


Figure 5.5: Insurance premium rates for 70 percent coverage level for winter wheat counties in 2019, with and without subsidy effect.



(a) 80 percent coverage **(b)** 90 percent coverage

Figure 5.6: Insurance premium rates for (a) 80 and (b) 90 percent coverage levels for winter wheat counties in 2019, with and without subsidy effect.

income effect is dominating the risk effect. If instead the risk effect were significant and dominating, the premium rates under the policy change would be greater than those without the policy change, and thus the increased subsidies would have undesirable implications for crop insurance premium rates.

Chapter 6 Conclusions

Agricultural producers face an increasingly volatile and complex production environment, most notably because of changing climate, changing innovation, changing technology, and their complex interactions. The ability of growers to adapt to the changing production environment and produce yields that are resilient to adverse weather events and growing conditions is extremely important for meeting the world's growing food demand and addressing food security issues. While there are numerous ways to address these challenges, agricultural innovation has been particularly successful especially over the past century in enabling farmers to adapt to changing conditions and substantially increase crop yields.

Most of the world's agricultural crops, particularly in developed countries, are produced under heavily government-subsidized crop insurance programs. The United States is no exception, as the Federal Crop Insurance Program is the cornerstone of domestic farm policy and is heavily subsidized. In this context, understanding if and how subsidized insurance affects producers' decisions to adopt innovations is paramount to meeting global food demand, mitigating the effects of climate change, and remaining competitive. Currently, there is very little empirical literature looking at the effect of crop insurance premium subsidies on innovation in crop production. Economic theory would suggest that premium subsidies can have two effects on technological change: an income effect and a risk effect. The income effect would have a positive impact on technological change, while the risk effect would have a negative impact. The magnitude of the effects relative to each other would determine the overall dominating effect.

In this thesis, I tested for the presence of these two effects in the United States corn, soybean, and winter wheat production using the substantial increase in insurance subsidization that occurred under the 1994 Federal Crop Insurance Reform and Department of Agriculture Reorganization Act and the 2000 Agricultural Risk Protection Act. Under these two Acts, subsidies on crop insurance premiums were increased from only 30 percent to 60 percent on average. My results find evidence of the income effect but not the risk effect in corn and soybean yields. This is reassuring because it suggests that the high subsidies are not impeding technological change and are not creating a moral hazard issue. In fact, the results suggest that the higher subsidies have actually increased the rate of technological change, particularly in the lower tail. The main reason for the absence of the risk effect is that the main existing risk-reducing technologies are not competing with high-risk high-reward technologies, i.e. the adoption of one technology does not preclude the adoption of another. An example of this is stacked traits in genetically modified seeds. The risk effect may have been present and more prominent if the technologies were competing. Since this is not the case, the income effect has been dominating and driving the rate of technological change up.

Statistically significant increases in the rates of technological change in both tails of the yield distribution have been found across one-third of corn and soybean counties on average. These are fairly strong results, especially when considering that the two-component crop yield model was estimated with only 67 data points per county. The attribution model results demonstrated that while spatial variation in climatic factors may explain part of the increases in the rates of technological change, particularly in the upper tail, most of the increases were likely driven by the policy change. This result serves as a confirmation for the presence of a strong beneficial income effect induced by higher subsidies. Although one may argue that the income effect was not induced solely by higher subsidies and that there could have been other contributing factors, the natural experiment type of setting that I am looking at supports my conclusions. There has been a substantial increase in premium subsidies at a particular point in time, and, with the climate effects ruled out through the attribution model, it is appropriate to attribute the identified changes in the rates of technological change to this policy change. In fact, it would be surprising to find no income effect from increased subsidies, considering how important the crop insurance program is and how much of the subsidy actually stays with the producers.

In Kansas winter wheat production, however, I found decreased rates of technological change after the subsidization increase, which is alarming because Kansas, being a southern state, will be most impacted by the increased frequency of extreme heat and drought. Considering how contrasting the winter wheat results were due to the inclusion of only two states, a potential next step for extending this research is to expand the number of winter wheat states, as well as to include other types of wheat in the analysis. Because wheat production has seen less innovation than corn or soybeans over the past few decades (e.g. there is currently no commercially available genetically modified wheat), it would provide an interesting, and potentially contrasting, comparison to other crops in terms of the subsidy effect.

In summary, this thesis is among the first to address the question of how high crop insurance premium subsidies influence technological change in crop production. The empirical analysis provides strong evidence that higher subsidies have increased the rates of technological change in the United States corn and soybean production. There appears to be no evidence of a moral hazard effect, primarily because most of the available technologies are non-competing. Because crop insurance in Canada is also heavily subsidized, an interesting extension to this thesis would be to perform a similar analysis using Canadian crop yield data and to compare the results to the United States. This may provide insights on whether similar policies and policy changes have similar effects in the two countries.

Bibliography

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.

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.

Atwood, J., S. Shaik, and M.J. Watts. 2003. "Are Crop Yields Normally Distributed? A Reexamination." *American Journal of Agricultural Economics* 85:888–901.

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.

Bryant, C.R., B. Smit, M. Brklacich, T.R. Johnston, J. Smithers, Q. Chiotti, and

B. Singh. 2000. "Adaptation in Canadian Agriculture to Climatic Variability and Change." *Climatic Change* 45:181–201.

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.

Claassen, R., C. Langpap, and J. Wu. 2017. "Impacts of Federal Crop Insurance on Land Use and Environmental Quality." *American Journal of Agricultural Economics* 99:592–613.

Congressional Budget Office. 2017. "Options to Reduce the Budgetary Costs of the Federal Crop Insurance Program."

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.

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.

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., T.N. Tolhurst, A.P. Ker, K. Janovicek, C. Tortora, R.C. Martin, and W. Deen. 2015. "Increasing Crop Diversity Mitigates Weather Variations and Improves Yield Stability." *PLoS ONE* 10:e0113261.

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., and A.P. Ker. 1998. "Nonparametric Estimation of Crop Yield Distributions: Implications for Rating Group-Risk Crop Insurance Contracts." *American Journal of Agricultural Economics* 80:139–153.

Goodwin, B.K., and V.H. Smith. 2003. "An Ex Post Evaluation of the Conservation Reserve, Federal Crop Insurance, and Other Government Programs: Program Participation and Soil Erosion." *Journal of Agricultural and Resource Economics* 28:201–216.

Goodwin, B.K., M.L. Vandeveer, and J.L. Deal. 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86:1058–1077.

Green, T.R., H. Kipka, O. David, and G.S. McMaster. 2018. "Where is the USA Corn Belt, and How is it Changing?" *Science of the Total Environment* 618:1613–1618.

Holm, S. 1979. "A Simple Sequentially Rejective Multiple Test Procedure." *Scandinavian Journal of Statistics* 6:65–70.

Horowitz, J.K., and E. Lichtenberg. 1993. "Chemical Use in Agriculture." *American Journal of Agricultural Economics* 75:926–935.

Jiang, Y. 2017. "The Effect of Climate and Innovation on Year-to-Year Crop Yield Volatility in Ontario." Master of science, University of Guelph.

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 K. Coble. 2003. "Modeling Conditional Yield Densities." *American Journal of Agricultural Economics* 85:291–304.

Ker, A.P., and A.T. Ergun. 2007. "On the Revelation of Private Information in the U.S. Crop Insurance Program." *Journal of Risk and Insurance* 74:761–776.

Ker, A.P., and B.K. Goodwin. 2000. "Nonparametric Estimation of Crop Insurance Rates Revisited." *American Journal of Agricultural Economics* 82:463–478.

Ker, A.P., and P. McGowan. 2000. "Weather-Based Adverse Selection and the U. S. Crop Insurance Program: The Private Insurance Company Perspective." *Journal of Agricultural and Resource Economics* 25:386–410.

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.

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.

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.

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.

Miao, R., D.A. Hennessy, and H. Feng. 2016. “The Effects of Crop Insurance Subsidies and Sodsaver on Land-use Change.” *Journal of Agricultural and Resource Economics* 41:247–265.

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

Mueller, N.D., J.S. Gerber, M. Johnston, D.K. Ray, N. Ramankutty, and J.A. Foley. 2012. “Closing Yield Gaps Through Nutrient and Water Management.” *Nature* 490:254–257.

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

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

Ort, D.R., and S.P. Long. 2014. "Limits on Yields in the Corn Belt." *Science* 344:484–485.

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.

Racine, J., and A.P. Ker. 2006. "Rating Crop Insurance Policies with Efficient Nonparametric Estimators that Admit Mixed Data Types." *Journal of Agricultural and Resource Economics* 31:27–39.

Ramirez, O.A., S. Misra, and J. Field. 2003. "Crop-Yield Distributions Revisited." *American Journal of Agricultural Economics* 85:108–120.

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.

Roll, K.H. 2019. "Moral Hazard: The Effect of Insurance on Risk and Efficiency." *Agricultural Economics* 50:367–375.

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.

Schoengold, K., Y. Ding, and R. Headlee. 2014. "The Impact of Ad Hoc Disaster and Crop Insurance Programs on the Use of Risk-Reducing Conservation Tillage Practices." *American Journal of Agricultural Economics* 97:897–919.

Sherrick, B.J., F.C. Zanin, G.D. Schnitkey, and S.H. Irwin. 2004. "Crop Insurance Validation under Alternative Yield Distributions." *American Journal of Agricultural Economics* 86:406–419.

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 L.L. Nalley. 2015. "Effect of Warming Temperatures on US Wheat Yields." *Proceedings of the National Academy of Sciences* 112:6931–6936.

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.

Tilman, D. 1998. "The Greening of the Green Revolution." *Nature* 396:211–212.

Tolhurst, T.N., and A.P. Ker. 2016. "Adapting Agronomic Metrics to Crop Yield Models in Ontario: The Importance of Cold Temperature Stress." Working paper, Department of Food, Agricultural and Resource Economics, University of Guelph.

—. 2015. "On Technological Change in Crop Yields." *American Journal of Agricultural Economics* 97:137–158.

United States Department of Agriculture. 2018. "USDA Agricultural Projections to 2027."

Walters, C.G., C.R. Shumway, H.H. Chouinard, and P.R. Wandschneider. 2012. "Crop Insurance, Land Allocation, and the Environment." *Journal of Agricultural and Resource Economics* 37:301–320.

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.

Weber, M., and G. Hauer. 2003. "A Regional Analysis of Climate Change Impacts on Canadian Agriculture." *Canadian Public Policy* 29:163–180.

Woodard, J.D., A.D. Pavlista, G.D. Schnitkey, P.A. Burgener, and K.A. Ward. 2012. "Government Insurance Program Design, Incentive Effects, and Technology Adoption: The Case of Skip-Row Crop Insurance." *American Journal of Agricultural Economics* 94:823–837.

Woodard, J.D., and B.J. Sherrick. 2011. "Estimation of Mixture Models Using Cross-Validation Optimization: Implications for Crop Yield Distribution Modeling." *American Journal of Agricultural Economics* 93:968–982.

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

Wu, J. 1999. "Crop Insurance, Acreage Decisions, and Nonpoint-Source Pollution." *American Journal of Agricultural Economics* 81:305–320.

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.

Zhu, Y., B.K. Goodwin, and S.K. Ghosh. 2011. "Modeling Yield Risk Under Technological Change: Dynamic Yield Distributions and the U.S. Crop Insurance Program." *Journal of Agricultural and Resource Economics* 36:192–210.

Chapter 7 Appendix

7.1 Corn Model Parameter Estimates

Table 7.1: Illinois corn county model parameter estimates (71 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.276	0.735	0.880	0.812	0.926	0.971
α_u	23.281	46.276	57.749	53.614	61.997	74.627
α_l	1.241	38.375	56.966	48.602	61.559	74.627
β_u	1.367	1.755	1.917	1.935	2.029	2.597
β_l	−0.426	0.358	1.013	0.963	1.527	2.074
δ_u	−1.072	−0.193	0.219	0.291	0.673	1.897
δ_l	−5.414	−1.224	0.044	0.056	1.493	5.883
σ_u	2.310	10.242	13.272	12.034	14.647	17.211
σ_l	0.0004	3.780	10.101	10.902	17.220	24.217

Table 7.2: Indiana corn county model parameter estimates (60 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.588	0.746	0.829	0.804	0.878	0.959
α_u	37.563	46.003	51.566	50.548	55.024	62.265
α_l	8.338	44.948	50.627	49.081	55.024	62.265
β_u	1.450	1.859	2.013	1.966	2.078	2.261
β_l	0.002	0.822	1.193	1.099	1.373	2.119
δ_u	−1.484	−0.594	−0.293	−0.280	0.057	0.653
δ_l	−4.134	−1.512	−0.399	−0.526	0.814	4.231
σ_u	5.281	8.053	10.548	10.124	11.933	14.591
σ_l	1.760	7.322	12.494	11.730	15.801	25.278

Table 7.3: Iowa corn county model parameter estimates (86 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.342	0.788	0.889	0.822	0.926	0.979
α_u	36.408	47.614	51.593	51.298	54.817	66.798
α_l	5.791	40.757	50.528	46.800	54.784	66.798
β_u	1.604	1.927	2.035	2.035	2.136	2.770
β_l	−0.160	0.614	0.908	0.964	1.356	2.229
δ_u	−1.483	−0.096	0.390	0.351	0.745	1.914
δ_l	−0.631	1.148	2.041	2.148	3.217	6.071
σ_u	3.001	8.880	10.616	10.533	12.335	17.801
σ_l	0.0002	4.531	11.439	11.505	17.249	30.103

Table 7.4: Minnesota corn county model parameter estimates (51 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.406	0.702	0.805	0.770	0.867	0.943
α_u	19.194	31.900	42.901	40.342	48.493	57.109
α_l	18.376	31.900	38.739	38.775	46.814	57.109
β_u	1.295	1.909	2.008	1.997	2.164	2.441
β_l	−0.058	0.623	0.819	0.925	1.089	1.997
δ_u	−0.262	0.283	0.843	0.786	1.201	2.562
δ_l	−0.455	2.172	3.225	3.198	4.266	6.599
σ_u	3.454	7.050	9.041	8.719	10.376	12.765
σ_l	0.498	6.881	11.589	11.086	14.415	28.728

Table 7.5: Ohio corn county model parameter estimates (57 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.389	0.652	0.738	0.730	0.857	0.941
α_u	36.183	46.022	49.636	48.977	51.626	56.543
α_l	22.929	45.234	49.444	48.245	51.545	56.142
β_u	1.217	1.800	1.957	1.926	2.100	2.276
β_l	0.106	0.894	1.177	1.108	1.345	1.814
δ_u	−1.185	−0.604	−0.271	−0.209	0.026	1.728
δ_l	−2.677	−0.065	0.462	0.433	0.904	4.035
σ_u	2.912	7.096	8.286	8.381	9.689	13.598
σ_l	0.981	6.887	11.803	11.293	15.926	22.614

Table 7.6: Wisconsin corn county model parameter estimates (48 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.252	0.644	0.808	0.760	0.909	0.977
α_u	33.666	45.026	52.283	51.464	58.160	64.601
α_l	25.489	41.403	49.674	48.584	57.362	64.601
β_u	1.215	1.514	1.626	1.627	1.779	2.036
β_l	−0.072	0.518	0.872	0.833	1.184	1.642
δ_u	−0.836	−0.116	0.345	0.358	0.773	1.600
δ_l	−1.623	0.495	1.090	1.102	1.884	3.529
σ_u	1.802	6.549	8.499	8.225	10.383	12.424
σ_l	0.033	4.156	9.019	8.372	12.776	19.267

Table 7.7: South Dakota corn county model parameter estimates (23 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.595	0.747	0.868	0.829	0.915	0.956
α_u	9.181	12.848	16.415	18.939	25.231	35.881
α_l	0.843	11.928	16.415	18.124	23.442	35.881
β_u	1.050	1.314	1.596	1.540	1.727	1.998
β_l	−0.404	0.538	0.655	0.669	0.877	1.142
δ_u	1.128	1.603	1.857	1.904	2.228	2.669
δ_l	−3.418	−0.409	1.528	1.445	3.557	5.214
σ_u	8.852	10.490	11.957	12.129	13.876	16.273
σ_l	1.434	2.517	5.550	6.208	10.424	13.445

7.2 Soybean Model Parameter Estimates

Table 7.8: Illinois soybean county model parameter estimates (71 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.222	0.684	0.855	0.769	0.908	0.969
α_u	14.951	19.483	24.568	23.242	26.389	28.738
α_l	3.556	15.711	21.170	20.085	24.806	28.738
β_u	0.265	0.376	0.406	0.414	0.446	0.693
β_l	-0.095	0.110	0.271	0.227	0.331	0.617
δ_u	-0.263	0.159	0.229	0.235	0.302	0.601
δ_l	-0.721	0.060	0.426	0.461	0.865	1.463
σ_u	0.399	2.421	2.860	2.775	3.168	4.666
σ_l	0.242	1.555	2.611	2.823	4.116	6.614

Table 7.9: Indiana soybean county model parameter estimates (55 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.303	0.584	0.675	0.711	0.890	0.985
α_u	14.960	19.609	21.224	21.451	23.490	27.878
α_l	3.156	17.824	20.088	19.605	22.287	26.291
β_u	0.346	0.454	0.494	0.491	0.531	0.598
β_l	-0.006	0.228	0.312	0.312	0.398	0.664
δ_u	-0.231	-0.091	0.026	0.039	0.145	0.475
δ_l	-1.075	-0.130	0.267	0.174	0.488	1.209
σ_u	1.105	2.287	2.826	2.804	3.272	4.177
σ_l	0.00000	1.821	3.144	2.729	3.536	5.285

Table 7.10: Iowa soybean county model parameter estimates (84 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.344	0.708	0.861	0.793	0.917	0.977
α_u	13.249	20.076	22.632	21.942	24.209	27.943
α_l	10.285	17.797	20.560	20.196	22.765	26.448
β_u	0.296	0.437	0.493	0.503	0.533	0.757
β_l	-0.062	0.162	0.265	0.264	0.370	0.663
δ_u	-0.440	-0.086	0.015	0.009	0.095	0.401
δ_l	-1.480	0.031	0.228	0.258	0.527	1.415
σ_u	0.963	2.588	3.018	2.913	3.354	4.158
σ_l	0.0005	1.612	3.517	3.090	4.203	6.815

Table 7.11: Minnesota soybean county model parameter estimates (48 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.086	0.633	0.734	0.706	0.790	0.985
α_u	9.154	12.412	15.721	15.797	19.160	21.532
α_l	2.535	11.260	15.433	14.513	17.887	21.532
β_u	0.392	0.474	0.506	0.509	0.530	0.746
β_l	−0.216	0.146	0.226	0.228	0.312	0.546
δ_u	−0.230	−0.044	0.042	0.051	0.124	0.309
δ_l	−0.356	0.347	0.682	0.625	0.925	1.586
σ_u	1.105	2.586	3.039	3.054	3.428	5.103
σ_l	0.00000	1.762	2.566	2.377	3.187	4.978

Table 7.12: Ohio soybean county model parameter estimates (50 counties).

Parameters	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.395	0.608	0.718	0.714	0.841	0.919
α_u	14.415	18.692	20.432	20.225	21.590	26.650
α_l	10.210	17.808	19.911	19.379	21.153	25.036
β_u	0.352	0.436	0.488	0.474	0.513	0.581
β_l	−0.040	0.213	0.290	0.254	0.329	0.465
δ_u	−0.278	−0.069	0.032	0.027	0.098	0.306
δ_l	−0.747	−0.111	0.170	0.202	0.486	1.102
σ_u	1.464	2.234	2.622	2.719	3.225	4.465
σ_l	0.370	1.470	2.414	2.398	3.395	4.602

Table 7.13: Wisconsin soybean county model parameter estimates (33 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.338	0.566	0.704	0.707	0.871	0.935
α_u	8.587	10.808	11.500	11.983	13.231	16.766
α_l	1.384	10.808	11.500	11.711	13.231	16.766
β_u	0.442	0.594	0.631	0.633	0.666	0.813
β_l	0.031	0.295	0.363	0.345	0.422	0.492
δ_u	−0.581	−0.268	−0.161	−0.180	−0.073	0.330
δ_l	−0.488	−0.094	0.084	0.115	0.269	0.871
σ_u	1.857	3.076	3.352	3.369	3.729	5.019
σ_l	0.385	1.433	3.251	2.863	3.795	5.154

7.3 Winter Wheat Model Parameter Estimates

Table 7.14: Kansas winter wheat county model parameter estimates (32 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.346	0.617	0.752	0.734	0.899	0.956
α_u	12.155	16.456	19.817	19.474	21.687	26.993
α_l	4.853	12.677	17.690	16.754	21.343	26.993
β_u	0.230	0.377	0.482	0.485	0.587	0.906
β_l	-0.150	0.061	0.355	0.252	0.399	0.507
δ_u	-1.223	-0.430	-0.159	-0.150	0.107	1.085
δ_l	-1.594	-0.885	-0.257	-0.371	0.119	1.078
σ_u	3.634	5.290	5.931	6.055	6.546	8.537
σ_l	0.00003	1.661	3.900	4.466	6.395	13.247

Table 7.15: Michigan winter wheat county model parameter estimates (21 counties).

Parameter	Min	1st Qu	Median	Mean	3rd Qu	Max
λ_t	0.020	0.325	0.605	0.548	0.716	0.956
α_u	22.687	25.499	26.978	26.937	28.436	29.738
α_l	22.687	25.271	26.978	26.900	28.436	29.738
β_u	0.504	0.615	0.691	0.687	0.759	0.875
β_l	0.031	0.267	0.383	0.350	0.418	0.530
δ_u	-0.169	0.224	0.386	0.383	0.576	1.009
δ_l	0.318	0.705	0.917	0.940	1.160	1.630
σ_u	0.407	4.356	4.731	4.664	5.168	9.819
σ_l	0.459	2.899	4.075	3.446	4.607	5.531

7.4 Maps

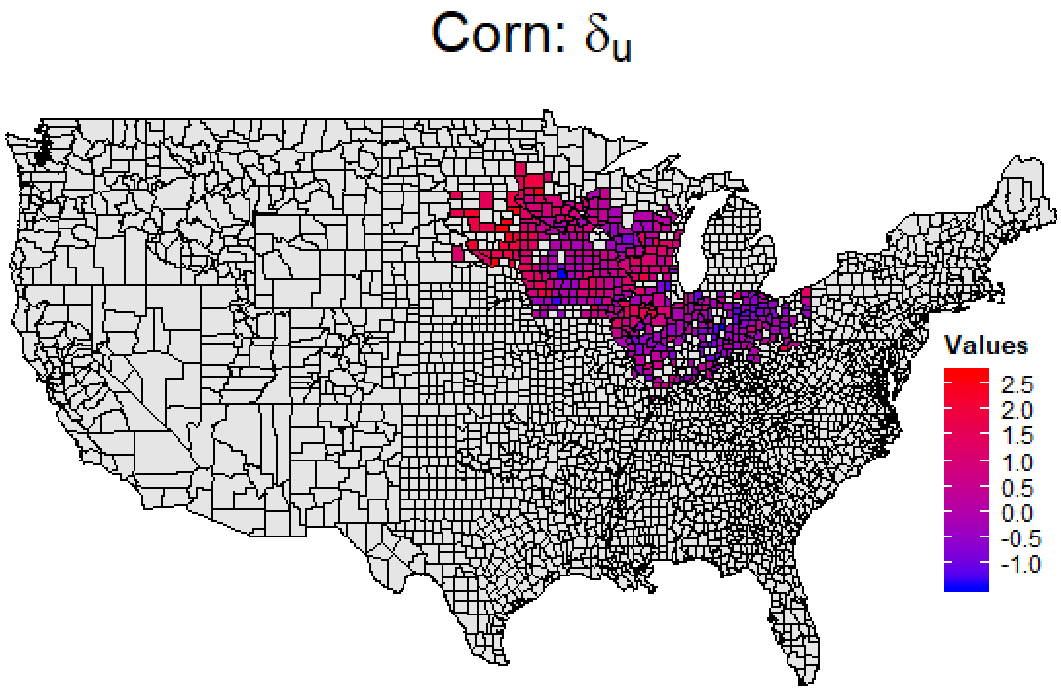


Figure 7.1: Corn: change in the rate of technological change in the upper component after 1995 (δ_u).

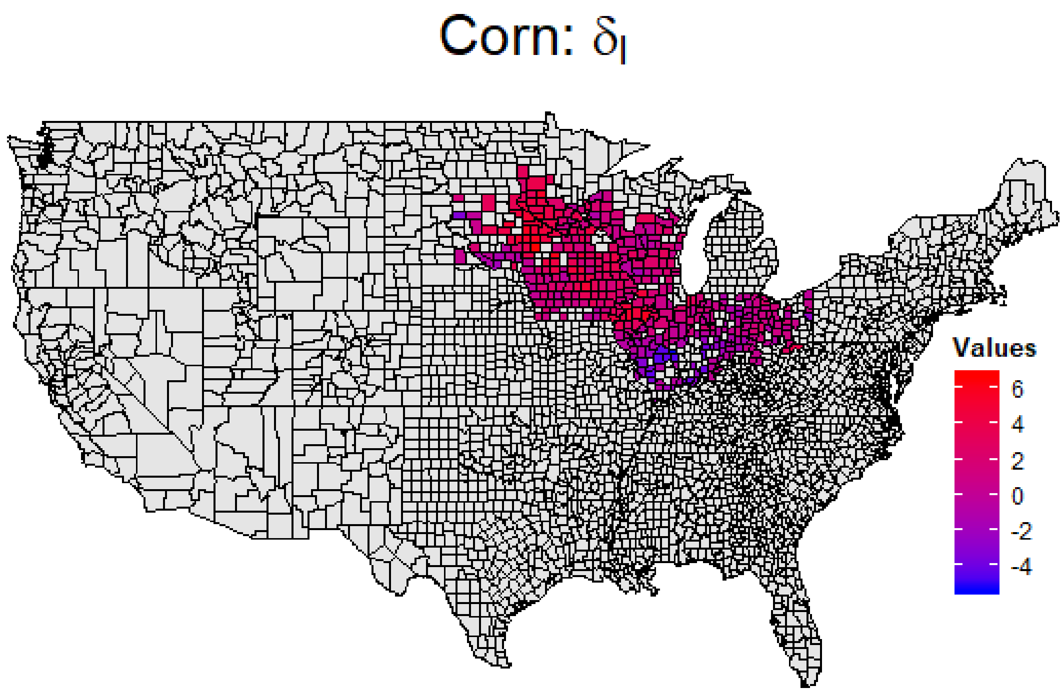


Figure 7.2: Corn: change in the rate of technological change in the lower component after 1995 (δ_l).

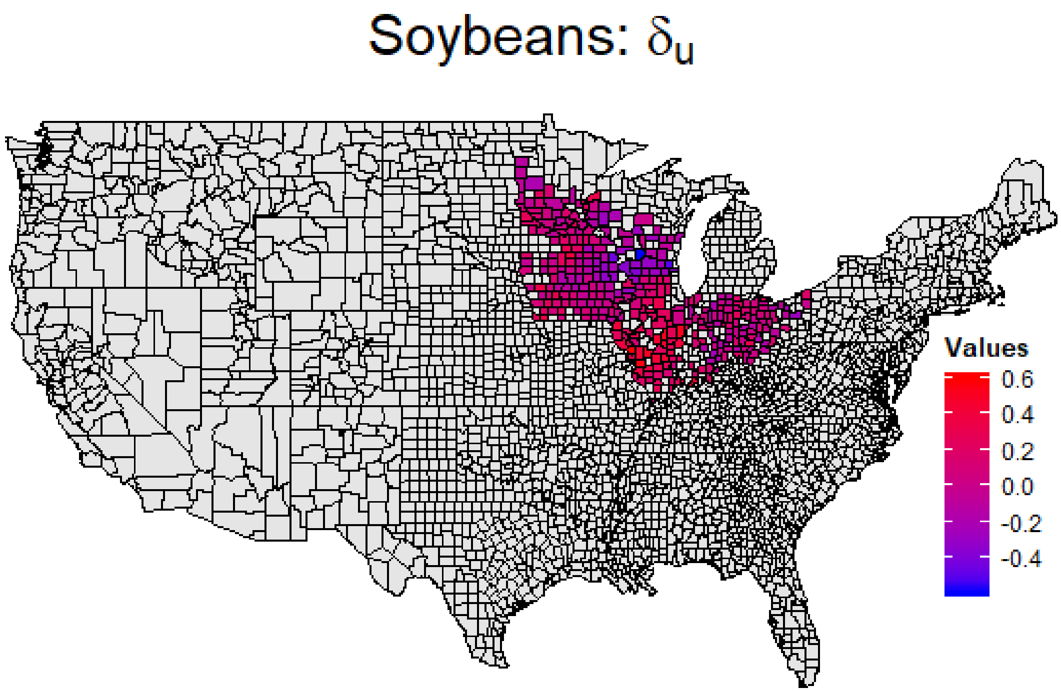


Figure 7.3: Soybeans: change in the rate of technological change in the upper component after 1995 (δ_u).

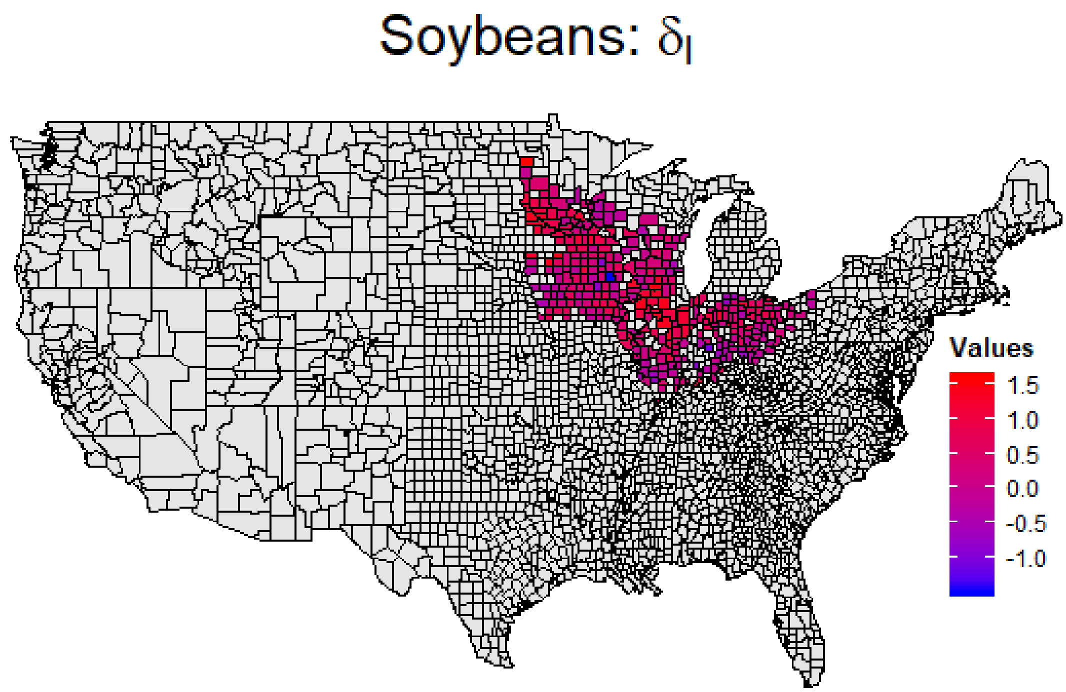


Figure 7.4: Soybeans: change in the rate of technological change in the lower component after 1995 (δ_l).

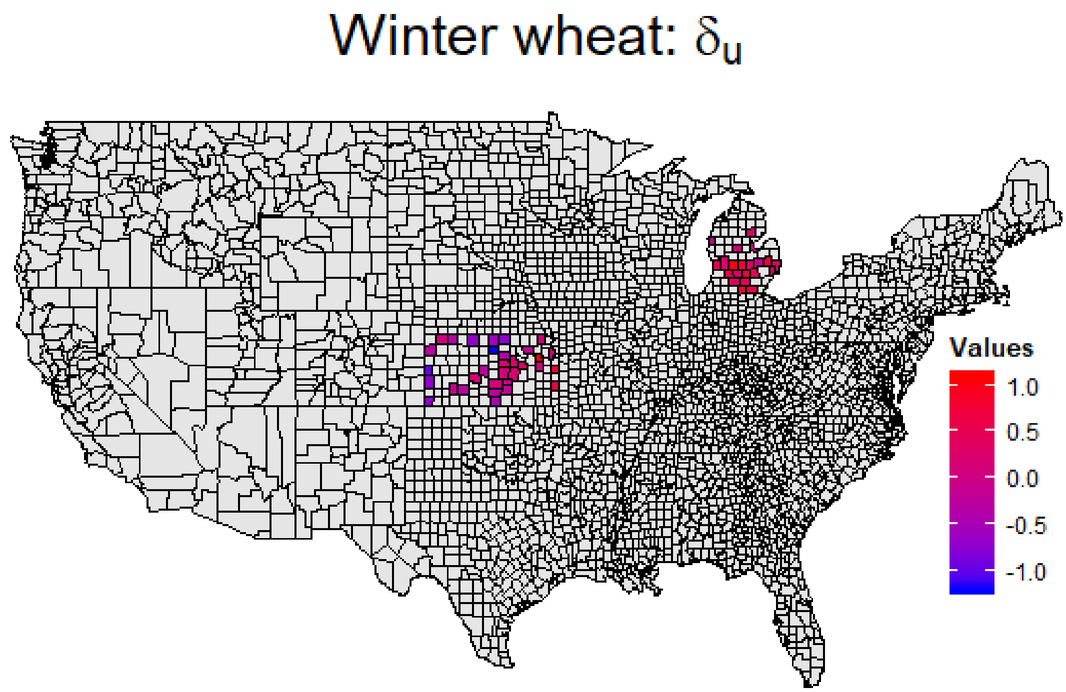


Figure 7.5: Winter wheat: change in the rate of technological change in the upper component after 1995 (δ_u).

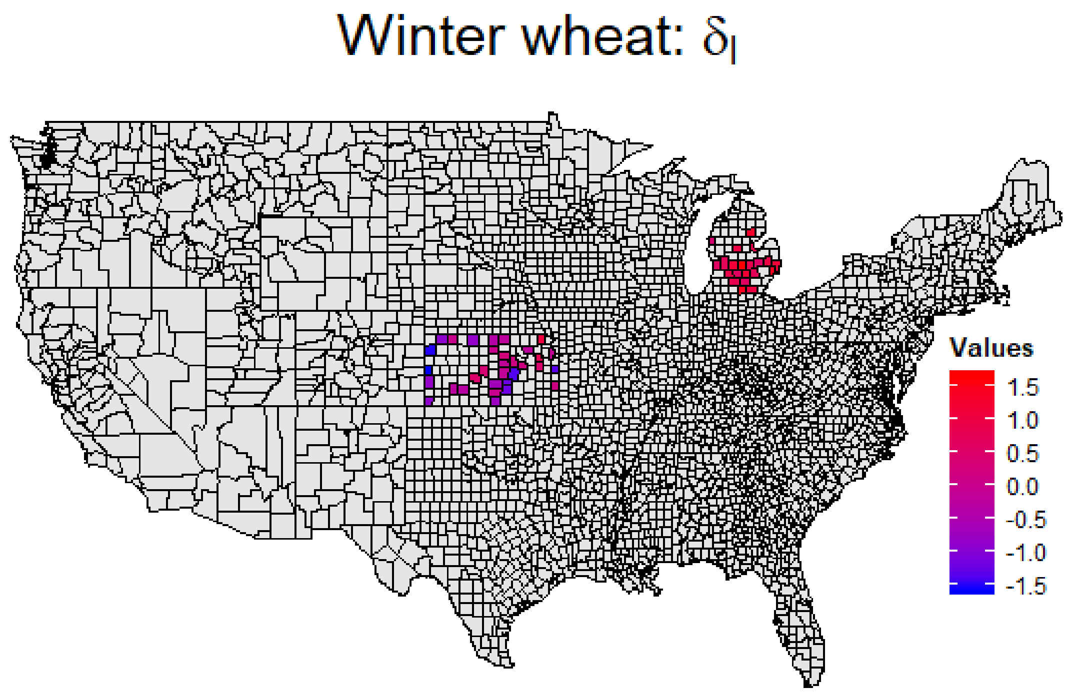


Figure 7.6: Winter wheat: change in the rate of technological change in the lower component after 1995 (δ_l).

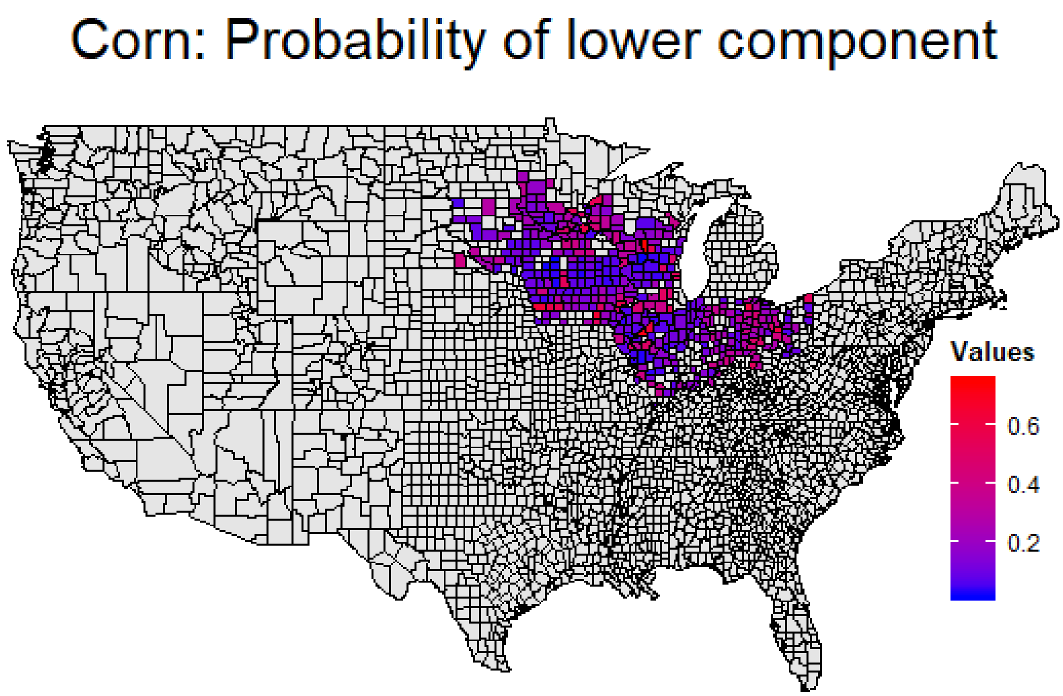


Figure 7.7: Corn: probability of a low yield $(1 - \lambda_t)$.

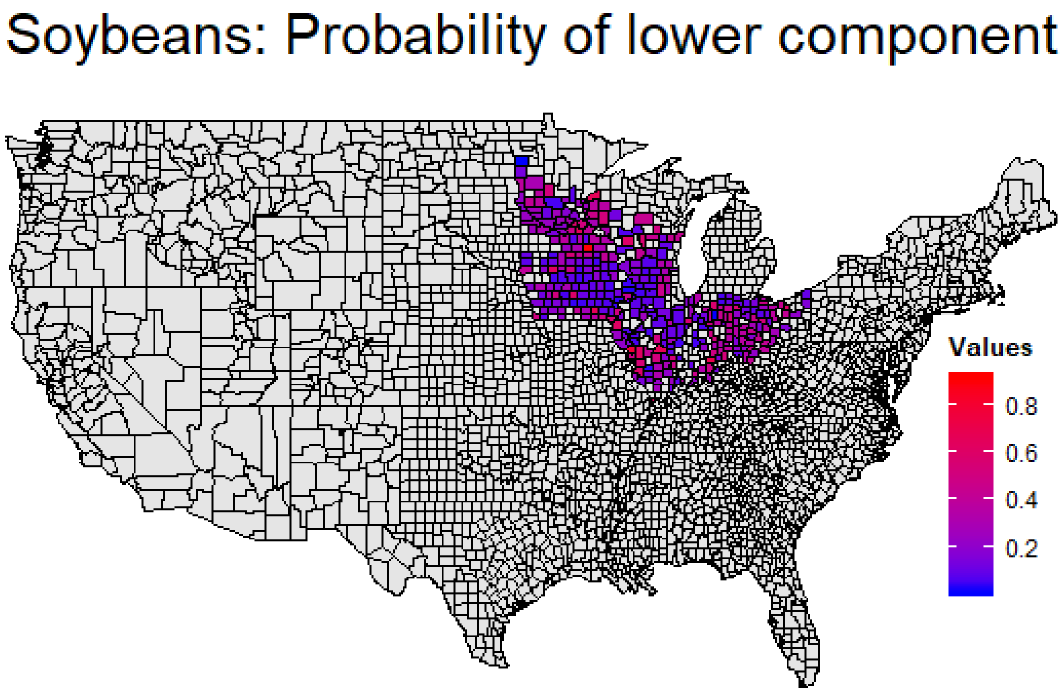


Figure 7.8: Soybeans: probability of a low yield $(1 - \lambda_t)$.

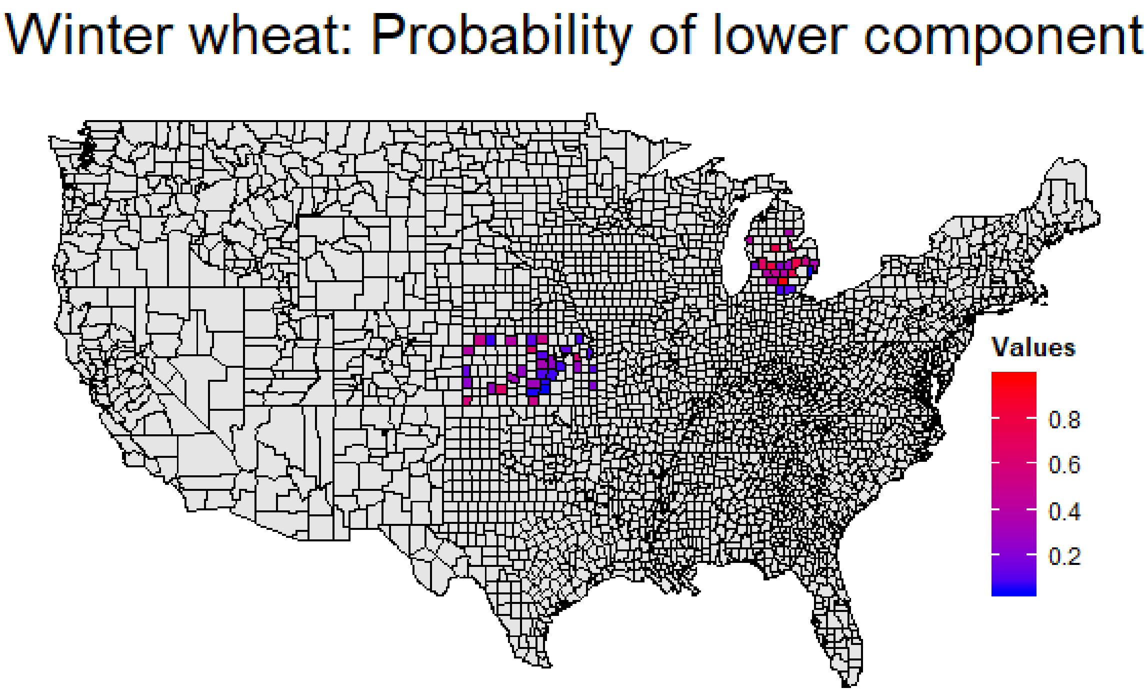


Figure 7.9: Winter wheat: probability of a low yield $(1 - \lambda_t)$.

7.5 Insurance Premium Rates for 2029

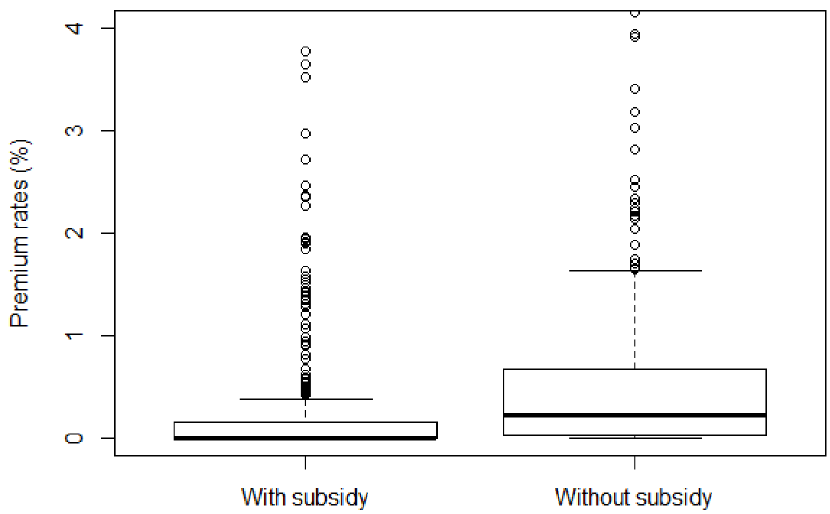
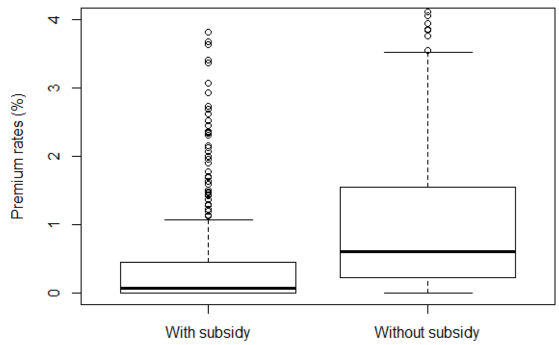
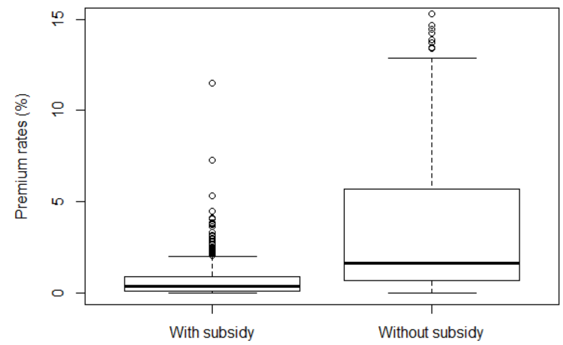


Figure 7.10: Insurance premium rates for 70 percent coverage level for corn counties in 2029, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.



(a) 80 percent coverage



(b) 90 percent coverage

Figure 7.11: Insurance premium rates for (a) 80 and (b) 90 percent coverage levels for corn counties in 2029, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.

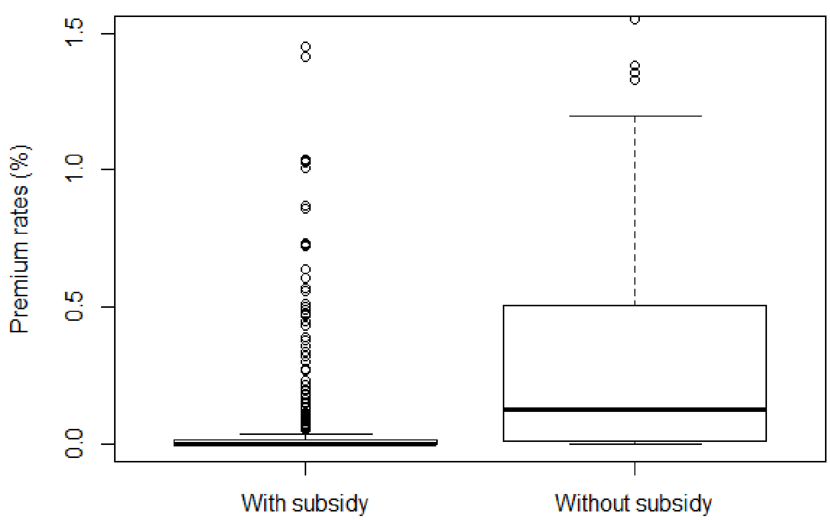
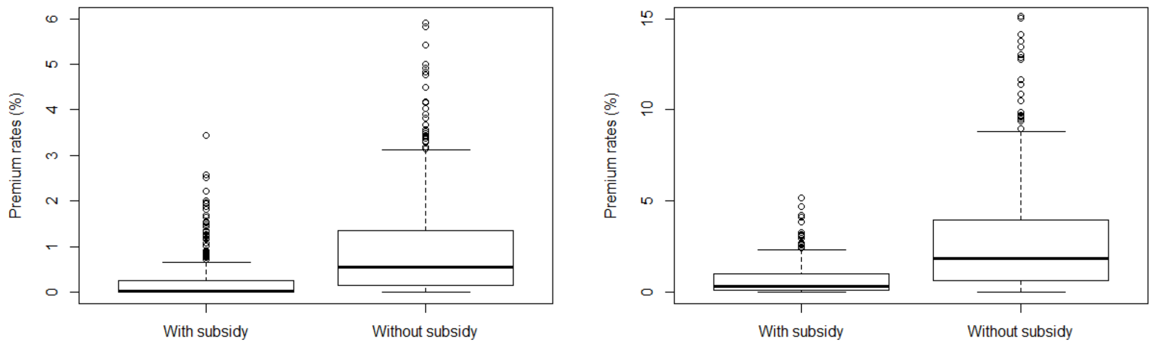


Figure 7.12: Insurance premium rates for 70 percent coverage level for soybean counties in 2029, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.



(a) 80 percent coverage **(b)** 90 percent coverage

Figure 7.13: Insurance premium rates for (a) 80 and (b) 90 percent coverage levels for soybean counties in 2029, with and without subsidy effect. Note that the boxplots have been truncated for better visual comparison.

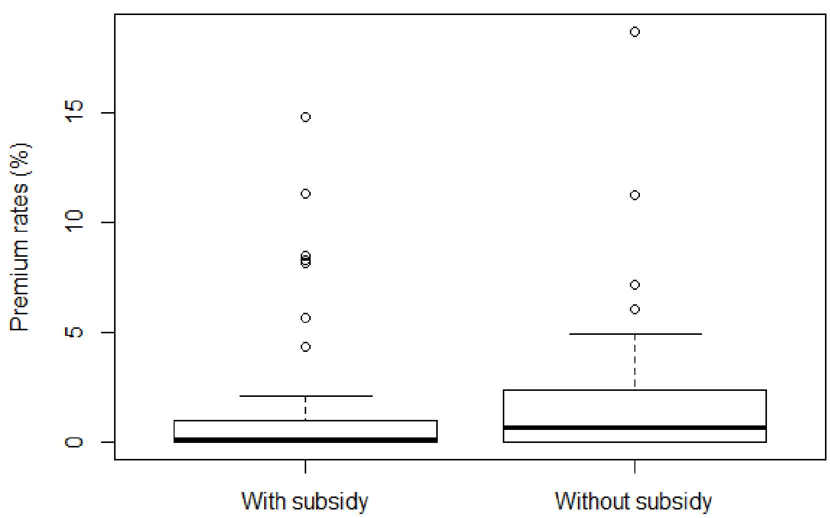
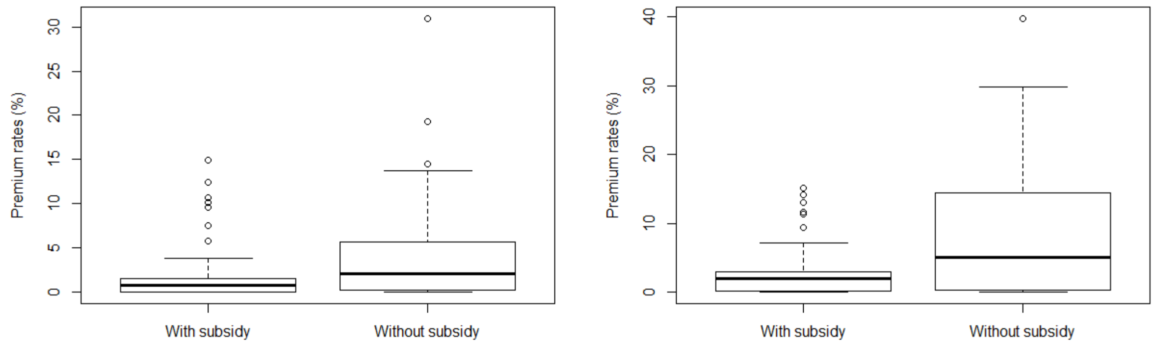


Figure 7.14: Insurance premium rates for 70 percent coverage level for winter wheat counties in 2029, with and without subsidy effect.



(a) 80 percent coverage **(b)** 90 percent coverage

Figure 7.15: Insurance premium rates for (a) 80 and (b) 90 percent coverage levels for winter wheat counties in 2029, with and without subsidy effect.

7.6 R code

```
##### Penalized maximum likelihood functions #####
#County unrestricted model
ll.func.pn <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[3]+parm[5]*time+parm[7]*indic, parm[8])
    +parm[1]*dnorm(yield, parm[2]+parm[4]*time+parm[6]*indic, parm[9])))-penalty
    *((1-parm[1])-0)^2)
}
ll.func <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[3]+parm[5]*time+parm[7]*indic, parm[8])
    +parm[1]*dnorm(yield, parm[2]+parm[4]*time+parm[6]*indic, parm[9]))))
}
ll.func.pn.r <- function(parm){
```

```
-(sum(log((1-parm[1])*dnorm(yield, parm[2]+parm[4]*time+parm[6]*indic, parm[7])
    +parm[1]*dnorm(yield, parm[2]+parm[3]*time+parm[5]*indic, parm[8])))-penalty
    *((1-parm[1])-0)^2)
}
ll.func.r <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[2]+parm[4]*time+parm[6]*indic, parm[7])
    +parm[1]*dnorm(yield, parm[2]+parm[3]*time+parm[5]*indic, parm[8]))))
}
#County restricted model
#Both deltas zero
ll.func.pnR <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[3]+parm[5]*time, parm[6])+parm[1]*
    dnorm(yield, parm[2]+parm[4]*time, parm[7])))-penalty*((1-parm[1])-0)^2)
}
ll.funcR <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[3]+parm[5]*time, parm[6])+parm[1]*
    dnorm(yield, parm[2]+parm[4]*time, parm[7]))))
}
ll.func.pnR.r <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[2]+parm[4]*time, parm[5])+parm[1]*
    dnorm(yield, parm[2]+parm[3]*time, parm[6])))-penalty*((1-parm[1])-0)^2)
}
ll.funcR.r <- function(parm){
```

```
-(sum(log((1-parm[1])*dnorm(yield, parm[2]+parm[4]*time, parm[5])+parm[1]*
    dnorm(yield, parm[2]+parm[3]*time, parm[6]))))
}
#Equal deltas
ll.func.pnR <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[3]+parm[5]*time+parm[6]*indic, parm[7])
    +parm[1]*dnorm(yield, parm[2]+parm[4]*time+parm[6]*indic, parm[8]))))-penalty
    *((1-parm[1])-0)^2)
}
ll.funcR <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[3]+parm[5]*time+parm[6]*indic, parm[7])
    +parm[1]*dnorm(yield, parm[2]+parm[4]*time+parm[6]*indic, parm[8]))))
}
ll.func.pnR.r <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[2]+parm[4]*time+parm[5]*indic, parm[6])
    +parm[1]*dnorm(yield, parm[2]+parm[3]*time+parm[5]*indic, parm[7]))))-penalty
    *((1-parm[1])-0)^2)
}
ll.funcR.r <- function(parm){
-(sum(log((1-parm[1])*dnorm(yield, parm[2]+parm[4]*time+parm[5]*indic, parm[6])
    +parm[1]*dnorm(yield, parm[2]+parm[3]*time+parm[5]*indic, parm[7]))))
}
#Lower delta zero
ll.func.pnR <- function(parm){
```

```
−(sum(log((1−parm[1])∗dnorm(yield, parm[3]+parm[5]∗time, parm[7])+parm[1]∗
    dnorm(yield, parm[2]+parm[4]∗time+parm[6]∗indic, parm[8])))−penalty∗((1−
    parm[1])−0)ˆ2)
}
ll .funcR <− function(parm){
−(sum(log((1−parm[1])∗dnorm(yield, parm[3]+parm[5]∗time, parm[7])+parm[1]∗
    dnorm(yield, parm[2]+parm[4]∗time+parm[6]∗indic, parm[8]))))
}
ll .func.pnR.r <− function(parm){
−(sum(log((1−parm[1])∗dnorm(yield, parm[2]+parm[4]∗time, parm[6])+parm[1]∗
    dnorm(yield, parm[2]+parm[3]∗time+parm[5]∗indic, parm[7])))−penalty∗((1−
    parm[1])−0)ˆ2)
}
ll .funcR.r <− function(parm){
−(sum(log((1−parm[1])∗dnorm(yield, parm[2]+parm[4]∗time, parm[6])+parm[1]∗
    dnorm(yield, parm[2]+parm[3]∗time+parm[5]∗indic, parm[7]))))
}
#Upper delta zero
ll .func.pnR <− function(parm){
−(sum(log((1−parm[1])∗dnorm(yield, parm[3]+parm[5]∗time+parm[6]∗indic, parm[7])
    +parm[1]∗dnorm(yield, parm[2]+parm[4]∗time, parm[8])))−penalty∗((1−parm[1])
    −0)ˆ2)
}
ll .funcR <− function(parm){
```

```
−(sum(log((1−parm[1])∗dnorm(yield, parm[3]+parm[5]∗time+parm[6]∗indic, parm[7])
    +parm[1]∗dnorm(yield, parm[2]+parm[4]∗time, parm[8]))))
}
ll.func.pnR.r <− function(parm){
−(sum(log((1−parm[1])∗dnorm(yield, parm[2]+parm[4]∗time+parm[5]∗indic, parm[6])
    +parm[1]∗dnorm(yield, parm[2]+parm[3]∗time, parm[7]))))−penalty∗((1−parm[1])
    −0)^2)
}
ll.funcR.r <− function(parm){
−(sum(log((1−parm[1])∗dnorm(yield, parm[2]+parm[4]∗time+parm[5]∗indic, parm[6])
    +parm[1]∗dnorm(yield, parm[2]+parm[3]∗time, parm[7]))))
}
##### Jackknife standard errors function #####
SE.jack <− function(d){
((length(d)−1)∗var(d))^0.5
}
##### Crop yield model #####
crop <− corn
#crop <− soy
#crop <− wheat
statel <− length(crop[,2])
ustate <− unique(crop[,2])
ustatel <− length(ustate)
time <− seq(1:67)
```

```
statesdata <- subset(crop, crop[,2]==ustate[1])
ctyl <- length(statesdata[,4])
ucty <- unique(statesdata[,4])
uctyl <- length(ucty)
all.coef.unrest <- matrix(NA, uctyl, 9)
w2_coef <- matrix(NA, uctyl, 6) #omega regression coefficients for each county
for (k in 1:uctyl){
ctydata <- subset(statesdata, statesdata[,4]==ucty[k])
#ctydata <- subset(statesdata, statesdata[,4]==ucty[29])
year <- ctydata[,1]
yield <- ctydata[,5]
n <- length(yield)
indic <- year-1995
indic[indic<0] <- 0
#Creating the indicator matrix, 1st set of rows for upper, 2nd for lower:
indicmat <- rbind(cbind(indic, rep(0,n)), cbind(rep(0,n), indic))
st.yields <- c(yield, yield) #yields
#Creating the X matrix, 1st set of rows for upper, 2nd for lower:
Xmat <- rbind(cbind(rep(1,n), rep(0,n), seq(1:n), rep(0,n)), cbind(rep(0,n), rep(1,n
    ), rep(0,n), seq(1:n)))
#Unrestricted model
T <- length(st.yields) #length of county yields doubled
m <- 500
tol <- 0.001
```

```r
conv <- 0
it.conv <- 0
like <- it.conv.fin <- rep(0,10)
coef.fin <- matrix(0,10,9) #Saving mw, two alphas, two betas, two deltas, s1, s2
like[1] <- -99999999
for (z in 2:10){
coef <- matrix(0,m,9) #this will save all coefficients from all iterations
all.ll <- matrix(NA,m,2) #saving all the likelihoods
all.w2 <- matrix(NA, m, n) #saving the lower omegas
result <- rq(st.yields~Xmat+indicmat-1, z/20)
w <- rep(1,T)
w[result$residuals<0] <- 0
w1 <- w[1:(T/2)]
w2 <- 1-w1
w <- c(w1,w2)
temp.a <- 10 #temporary difference between iterations until j>10
conv <- 0
j <- 1
while (conv<1){
result.both <- lm(st.yields~Xmat+indicmat-1, weights=w)
au <- result.both$coefficients[1]
al <- result.both$coefficients[2]
bu <- result.both$coefficients[3]
bl <- result.both$coefficients[4]
```

```
du <- result.both$coefficients [5]
dl <- result.both$coefficients [6]
if (al>au){
Xmat_R <- rbind(cbind(rep(1,n),seq(1:n),rep(0,n)),cbind(rep(1,n),rep(0,n),seq(1:n)))
result.both <- lm(st.yields~Xmat_R+indicmat-1,weights=w)
au <- al <- result.both$coefficients[1]
bu <- result.both$coefficients [2]
bl <- result.both$coefficients [3]
du <- result.both$coefficients [4]
dl <- result.both$coefficients [5]
}
reg.coef <- c(au,al,bu,bl,du,dl)
mul <- result.both$fitted.values[((T/2)+1):T] #lower fitted values
muu <- result.both$fitted.values[1:(T/2)] #upper fitted values
s1 <- (sum(w[((T/2)+1):T]*((st.yields[((T/2)+1):T]-mul)^2))/(sum(w[((T/2)+1):T
    ])))^0.5 #lower standard deviation
s2 <- (sum(w[1:(T/2)]*((st.yields[1:(T/2)]-muu)^2))/(sum(w[1:(T/2)])))^0.5 #
    upper standard deviation
mw <- mean(w[1:(T/2)]) #mean weight (for upper)
p1 <- dnorm(st.yields[((T/2)+1):T], mul, s1) #probability of lower mixture
p2 <- dnorm(st.yields[1:(T/2)], muu, s2) #probability of upper mixture
w <- p2/(p1+p2) #updated weights
w1 <- w
w2 <- 1-w1
```

```
w <- c(w1,w2)
all.w2[j,] <- w2 #saving the lower omegas from this iteration
coef[j,] <- c(mw,reg.coef,s1,s2) #saving coefficients from this iteration
if (j>10) temp.a <- sum(abs(coef[j,]-coef[j-1,]))
all.ll[j,1] <- sum(log((1-mw)*dnorm(st.yields[((T/2)+1):T],mul,s1)+mw*dnorm(
    st.yields[1:(T/2)],muu,s2)))
#Detecting crossovers:
Xover <- (muu[1]-mul[1])*(muu[67]-mul[67])
if (Xover<0) temp.a <- 10
#all.ll[j,2] <- ifelse(Xover<0,0,1)
if (al<0) temp.a <- 10
if (s1<(0.10*s2)) temp.a <- 10
all.ll[j,2] <- ifelse(temp.a==0,0,1)
#If difference is less than tolerance level, stop loop, save iteration:
conv <- ifelse(temp.a<tol,1,0)
it.conv <- ifelse(temp.a<tol,j,0)
j <- j+1
if (j>m) conv <- 1 #stop after 500 iterations
}
mw <- mean(w[1:(T/2)]) #mean weight for upper
#like[z] <- sum(log((1-mw)*dnorm(st.yields[((T/2)+1):T],mul,s1)+mw*dnorm(st.
    yields[1:(T/2)],muu,s2))) #loglikelihood for this quantile
xover.ll <- all.ll[,1]
xover.ll <- xover.ll[all.ll[,2]>0]
```

```
xx <- which.max(xover.ll)
like[z] <- xover.ll[xx]
#coef.fin[z,] <- c(mw, reg.coef, s1, s2)
coef.fin[z,] <- coef[xx,]
it.conv.fin[z] <- it.conv #iteration on which convergence occurred
}
ii <- which.max(like) #maximum loglikelihood
coef.new <- coef.fin[ii,] #ll.func.pn input parameters
omegas <- all.w2[ii,] #lower omegas for each county
omega.reg <- lm(omegas~time+indic)
save <- summary(omega.reg)
w2_coef[k,1] <- save$coefficients[2,1]
w2_coef[k,2] <- save$coefficients[2,2]
w2_coef[k,3] <- save$coefficients[2,4]
w2_coef[k,4] <- save$coefficients[3,1]
w2_coef[k,5] <- save$coefficients[3,2]
w2_coef[k,6] <- save$coefficients[3,4]
#This code determines the "optimal" penalty on mle:
if (au==al) coef.new <- coef.new[-3]
if (length(coef.new)==9){
parm <- coef.new
parm[1] <- pmin(1,coef.new[1]) #make the lambda the min of mw and 1 (so that it
    is not greater than one)
ll <- rep(99999999, 50)
```

```
trial <- matrix(0, 50, length(coef.new))
for (f in 1:50){
penalty <- f
result.opt <- optim(parm,ll.func.pn)
coef.opt <- result.opt$par
ll[f] <- ll.func(coef.opt)
if (abs(coef.opt[1])>1) ll[f] <- 99999999
if (coef.opt[2]<0) ll[f] <- 99999999
if (coef.opt[3]<0) ll[f] <- 99999999
if (coef.opt[8]<(0.10*coef.opt[9])) ll[f] <- 999999999
fit.up <- coef.opt[2]+coef.opt[4]*time+coef.opt[6]*indic
fit.lw <- coef.opt[3]+coef.opt[5]*time+coef.opt[7]*indic
Xover <- (fit.up[1]-fit.lw[1])*(fit.up[67]-fit.lw[67])
if (Xover<0) ll[f] <- 99999999
trial[f,] <- result.opt$par #can also do trial[f,] <- coef.opt
}
penalty <- which.min(ll) #"optimal" penalty
result.opt <- optim(parm,ll.func.pn) #re-estimating with the optimal penalty
coef.opt <- result.opt$par #coefficient estimates from this re-estimation
llnew <- ll.func(coef.new)
llopt <- ll.func(coef.opt)
llboth <- c(llnew,llopt)
ee <- which.min(llboth)
LRunrest <- llboth[ee]
```

```
if (ee==1){
all.coef.unrest[k,] <- coef.new
}
if (ee==2){
all.coef.unrest[k,] <- coef.opt
}
if (coef.opt[3]>coef.opt[2]){
for (z in 2:10){
coef <- matrix(0,m,9) #this will save all coefficients from all iterations
all.ll <- matrix(NA,m,2) #saving all the likelihoods
result <- rq(st.yields~Xmat+indicmat-1, z/20)
w <- rep(1,T)
w[result$residuals<0] <- 0
w1 <- w[1:(T/2)]
w2 <- 1-w1
w <- c(w1,w2)
temp.a <- 10 #temporary difference between iterations until j>10
conv <- 0
j <- 1
while (conv<1){
result.both <- lm(st.yields~Xmat_R+indicmat-1,weights=w)
au <- al <- result.both$coefficients[1]
bu <- result.both$coefficients[2]
bl <- result.both$coefficients[3]
```

```
du <- result.both$coefficients [4]
dl <- result.both$coefficients [5]
reg.coef <- c(au,al,bu,bl,du,dl)
mul <- result.both$fitted.values[((T/2)+1):T] #lower fitted values
muu <- result.both$fitted.values[1:(T/2)] #upper fitted values
s1 <- (sum(w[((T/2)+1):T]*((st.yields[((T/2)+1):T]-mul)^2))/(sum(w[((T/2)+1):T
    ])))^0.5 #lower standard deviation
s2 <- (sum(w[1:(T/2)]*((st.yields[1:(T/2)]-muu)^2))/(sum(w[1:(T/2)])))^0.5 #
    upper standard deviation
mw <- mean(w[1:(T/2)]) #mean weight (for upper)
p1 <- dnorm(st.yields[((T/2)+1):T], mul, s1) #probability of lower mixture
p2 <- dnorm(st.yields[1:(T/2)], muu, s2) #probability of upper mixture
w <- p2/(p1+p2) #updated weights
w1 <- w
w2 <- 1-w1
w <- c(w1,w2)
coef[j,] <- c(mw,reg.coef,s1,s2) #saving coefficients from this iteration
if (j>10) temp.a <- sum(abs(coef[j,]-coef[j-1,]))
all.ll[j,1] <- sum(log((1-mw)*dnorm(st.yields[((T/2)+1):T],mul,s1)+mw*dnorm(
    st.yields[1:(T/2)],muu,s2)))
#Detecting crossovers:
Xover <- (muu[1]-mul[1])*(muu[67]-mul[67])
if (Xover<0) temp.a <- 10
#all.ll[j,2] <- ifelse(Xover<0,0,1)
```

```
if (al<0) temp.a <- 10
if (s1<(0.10*s2)) temp.a <- 10
all.ll[j,2] <- ifelse(temp.a==0,0,1)
#If difference is less than tolerance level, stop loop, save iteration:
conv <- ifelse(temp.a<tol,1,0)
it.conv <- ifelse(temp.a<tol,j,0)
j <- j+1
if (j>m) conv <- 1 #stop after 500 iterations
}
mw <- mean(w[1:(T/2)]) #mean weight for upper
#like[z] <- sum(log((1-mw)*dnorm(st.yields[((T/2)+1):T],mul,s1)+mw*dnorm(st.
    yields[1:(T/2)],muu,s2))) #loglikelihood for this quantile
xover.ll <- all.ll[,1]
xover.ll <- xover.ll[all.ll[,2]>0]
xx <- which.max(xover.ll)
like[z] <- xover.ll[xx]
#coef.fin[z,] <- c(mw, reg.coef, s1, s2)
coef.fin[z,] <- coef[xx,]
it.conv.fin[z] <- it.conv #iteration on which convergence occurred
}
ii <- which.max(like) #maximum loglikelihood
coef.new <- coef.fin[ii,] #ll.func.pn input parameters
coef.new <- coef.new[-3] #because au=al
parm <- coef.new
```

```
parm[1] <- pmin(1,coef.new[1]) #make the lambda the min of mw and 1 (so that it
    is not greater than one)
ll <- rep(99999999, 50)
trial <- matrix(0, 50, length(coef.new))
for (f in 1:50){
penalty <- f
result.opt <- optim(parm,ll.func.pn.r)
coef.opt <- result.opt$par
ll[f] <- ll.func.r(coef.opt)
if (abs(coef.opt[1])>1) ll[f] <- 99999999
if (coef.opt[2]<0) ll[f] <- 99999999
if (coef.opt[7]<(0.10*coef.opt[8])) ll[f] <- 99999999
fit.up <- coef.opt[2]+coef.opt[3]*time+coef.opt[5]*indic
fit.lw <- coef.opt[2]+coef.opt[4]*time+coef.opt[6]*indic
Xover <- (fit.up[1]-fit.lw[1])*(fit.up[67]-fit.lw[67])
if (Xover<0) ll[f] <- 99999999
trial[f,] <- result.opt$par #can also do trial[f,] <- coef.opt
}
penalty <- which.min(ll) #"optimal" penalty
result.opt <- optim(parm,ll.func.pn.r) #re-estimating with the optimal penalty
coef.opt <- result.opt$par #coefficient estimates from this re-estimation
if (coef.opt[4]>coef.opt[3]){
coef.opt2 <- rep(0,8)
coef.opt2[1] <- 1-coef.opt[1]
```

```
coef.opt2[2] <- coef.opt[2]
coef.opt2[3] <- coef.opt[4]
coef.opt2[4] <- coef.opt[3]
coef.opt2[5] <- coef.opt[6]
coef.opt2[6] <- coef.opt[5]
coef.opt2[7] <- coef.opt[8]
coef.opt2[8] <- coef.opt[7]
coef.opt <- coef.opt2
}
llnew <- ll.func.r(coef.new)
llopt <- ll.func.r(coef.opt)
llboth <- c(llnew,llopt)
ee <- which.min(llboth)
LRunrest <- llboth[ee]
coef.new2 <- c(coef.new[1:2],coef.new[2],coef.new[3:8])
coef.opt2 <- c(coef.opt[1:2], coef.opt [2], coef.opt [3:8])
if (ee==1){
all.coef.unrest[k,] <- coef.new2
}
if (ee==2){
all.coef.unrest[k,] <- coef.opt2
}
}
}
```

```
if (length(coef.new)==8){
parm <- coef.new
parm[1] <- pmin(1,coef.new[1]) #make the lambda the min of mw and 1 (so that it
    is not greater than one)
ll <- rep(99999999, 50)
trial <- matrix(0, 50, length(coef.new))
for (f in 1:50){
penalty <- f
result.opt <- optim(parm,ll.func.pn.r)
coef.opt <- result.opt$par
ll[f] <- ll.func.r(coef.opt)
if (abs(coef.opt[1])>1) ll[f] <- 99999999
if (coef.opt[2]<0) ll[f] <- 99999999
if (coef.opt[7]<(0.10*coef.opt[8])) ll[f] <- 99999999
fit.up <- coef.opt[2]+coef.opt[3]*time+coef.opt[5]*indic
fit.lw <- coef.opt[2]+coef.opt[4]*time+coef.opt[6]*indic
Xover <- (fit.up[1]-fit.lw[1])*(fit.up[67]-fit.lw[67])
if (Xover<0) ll[f] <- 99999999
trial[f,] <- result.opt$par #can also do trial[f,] <- coef.opt
}
penalty <- which.min(ll) #"optimal" penalty
result.opt <- optim(parm,ll.func.pn.r) #re-estimating with the optimal penalty
coef.opt <- result.opt$par #coefficient estimates from this re-estimation
if (coef.opt[4]>coef.opt[3]){
```

```
coef.opt2 <- rep(0,8)
coef.opt2[1] <- 1-coef.opt[1]
coef.opt2[2] <- coef.opt[2]
coef.opt2[3] <- coef.opt[4]
coef.opt2[4] <- coef.opt[3]
coef.opt2[5] <- coef.opt[6]
coef.opt2[6] <- coef.opt[5]
coef.opt2[7] <- coef.opt[8]
coef.opt2[8] <- coef.opt[7]
coef.opt <- coef.opt2
}
llnew <- ll.func.r(coef.new)
llopt <- ll.func.r(coef.opt)
llboth <- c(llnew,llopt)
ee <- which.min(llboth)
LRunrest <- llboth[ee]
coef.new2 <- c(coef.new[1:2],coef.new[2],coef.new[3:8])
coef.opt2 <- c(coef.opt[1:2], coef.opt [2], coef.opt [3:8])
if (ee==1){
all.coef.unrest[k,] <- coef.new2
}
if (ee==2){
all.coef.unrest[k,] <- coef.opt2
}
```

```
}
# if (k==32){
# all.coef.unrest[k,] <- coef.new2 #for KS wheat only
# }
}
Xover_remove <- c(29, 16, 6) #counties with crossovers to be removed
 all_crop_coef  <- all.coef.unrest[-(Xover_remove),]
##### Hypothesis tests #####
LRall <- (2)*(LRrestAll-LRunrestAll) #LR from restricted and unrestricted models
#Two restrictions
qchi5 <- qchisq(0.95,2) #5.991465
#One restriction
qchi5 <- qchisq(0.95,1) #3.841459
 liketest5  <- rep(0,uctyl)
 liketest5 [LRall>qchi5] <- 1
sum(liketest5)
#remove crossovers here
Xover_remove <- c(29, 16, 6)
crop_hyp_nx <- crop_hyp[-(Xover_remove),]
#Holm-Bonferroni method
 ff  <- dim(crop_hyp_nx)[1] #number of counties in the state
hh <- seq(0,ff)
HMqchi <- rep(NA, ff)
for (h in 1:ff){
```

```
HMqchi[h] <- qchisq((1-(0.05/(ff-hh[h]))), 1) #remember to change the df!
}
orderedLR <- sort(crop_hyp_nx[,10], decreasing = TRUE)
HMdif <- orderedLR-HMqchi
HMsig <- rep(0,ff)
HMsig <- ifelse(HMdif>0, 1, 0)
sum(HMsig)
##### Climate data #####
climate_corn <- readRDS(file = file.choose())
ustate <- unique(climate_corn[,1])
ustatel <- length(ustate)
clim_part <- subset(climate_corn, climate_corn[,1]==ustate[1])
ucty <- unique(clim_part[,2])
uctyl <- length(ucty)
t <- seq(45,65)
corn_clim_trends <- matrix(NA, uctyl, 12)
for (i in 1:uctyl){
clim_cty <- subset(clim_part, clim_part[,2]==ucty[i])
for (j in 7:12){
clim_reg <- lm(clim_cty[45:65,j]~t)
#summary(clim_reg)
corn_clim_trends[i,j] <- clim_reg$coefficients[2]
}
}
```

```
corn_clim_trends <- corn_clim_trends[,-(1:6)]
cty <- as.character(ucty)
clim_trends <- cbind(corn_clim_trends, cty, ucty)
colnames(clim_trends) <- c("pcp", "pcpja", "vpd", "vpdja", "gdd", "hdd","X","cty")
clim_trends <- clim_trends[order(ucty),]
#The following code pairs up the regression data with climate data
crop <- corn
statel <- length(crop[,2])
ustate <- unique(crop[,2])
ustatel <- length(ustate)
statesdata <- subset(crop, crop[,2]==ustate[3]) #make sure you're grabbing the right number!
ctyl <- length(statesdata[,4])
ucty <- unique(statesdata[,4])
#remove crossovers here
Xover_remove <- c(52, 48, 29) #change depending on crop and state
ucty <- ucty[-(Xover_remove)]
#ucty <- ucty
temp_crop <- IAcorn #change state and crop!
uctyl <- length(ucty)
cty <- as.character(ucty)
crop_mat <- cbind(temp_crop[,6:7], cty, ucty)
colnames(crop_mat) <- c("du","dl","X","cty")
```

```
crop_mat <- crop_mat[order(ucty),]
diff <- dim(clim_trends)[1]-dim(crop_mat)[1]
both_cty <- cbind(as.character(clim_trends[,7]), c(crop_mat[,3],rep(NA,diff))) #Go
    through and check which counties need to be removed!!!
temp_cty_rm <- c(20, 27, 30, 55, 59, 65, 68, 72, 87, 88, 93)
clim_trends <- clim_trends[-temp_cty_rm,]
both_cty <- cbind(as.character(clim_trends[,7]), c(crop_mat[,3]))
crop_mat <- temp_crop[,6:7]
crop_mat <- crop_mat[order(ucty),]
clim_xy_mat <- cbind(clim_trends[,1:7], crop_mat)
IA_corn_clim <- clim_xy_mat #change state and crop!
full_corn_clim <- rbind(IL_corn_clim, IN_corn_clim, IA_corn_clim, MN_corn_clim,
    OH_corn_clim, WI_corn_clim, SD_corn_clim)
test_clim <- cbind(as.numeric(full_corn_clim[,1]),as.numeric(full_corn_clim[,2]),as.
    numeric(full_corn_clim[,3]),as.numeric(full_corn_clim[,4]),as.numeric(
    full_corn_clim[,5]),as.numeric(full_corn_clim[,6]),as.numeric(full_corn_clim[,8])
    ,as.numeric(full_corn_clim[,9]))
colnames(test_clim) <- c("pcp","pcpja","vpd","vpdja","gdd","hdd","du","dl")
full_corn_clim <- test_clim
#Regressions
clim_corn_up <- lm(full_corn_clim[,7]~ full_corn_clim[,1]+ full_corn_clim[,2]+
    full_corn_clim[,3]+ full_corn_clim[,4]+ full_corn_clim[,5]+ full_corn_clim[,6])
summary(clim_corn_up)
##### Jackknifing #####
```

```
n <- 66
all.delta.lw <- matrix(NA, uctyl, 67)
all.delta.up <- matrix(NA, uctyl, 67)
omegas.coef.matrix <- rep(NA,6)
for (k in 1:uctyl){
for (t in 1:67){
ctydata <- subset(statesdata, statesdata[,4]==ucty[k])
year <- ctydata[,1]
year <- year[-t]
yield <- ctydata[,5]
yield <- yield[-t]
n <- length(yield)
indic <- year-1995
indic[indic<0] <- 0
#Creating the indicator matrix, 1st set of rows for upper, 2nd for lower:
indicmat <- rbind(cbind(indic, rep(0,n)), cbind(rep(0,n), indic))
st.yields <- c(yield, yield) #yields
#Creating the X matrix, 1st set of rows for upper, 2nd for lower:
Xmat <- rbind(cbind(rep(1,n), rep(0,n), seq(1:n), rep(0,n)), cbind(rep(0,n), rep(1,n
    ), rep(0,n), seq(1:n)))
#Unrestricted model (with splines)
T <- length(st.yields) #length of county yields doubled
m <- 500
tol <- 0.001
```

```
conv <- 0
it.conv <- 0
like <- it.conv.fin <- rep(0,10)
coef.fin <- matrix(0,10,9) #Saving mw, two alphas, two betas, two deltas, s1, s2
like[1] <- -99999999
for (z in 2:10){
coef <- matrix(0,m,9) #this will save all coefficients from all iterations
all.ll <- matrix(NA,m,2) #saving all the likelihoods
all.w2 <- matrix(NA, m, n) #saving the lower omegas
result <- rq(st.yields~Xmat+indicmat-1, z/20)
w <- rep(1,T)
w[result$residuals<0] <- 0
w1 <- w[1:(T/2)]
w2 <- 1-w1
w <- c(w1,w2)
temp.a <- 10 #temporary difference between iterations until j>10
conv <- 0
j <- 1
while (conv<1){
result.both <- lm(st.yields~Xmat+indicmat-1, weights=w)
au <- result.both$coefficients[1]
al <- result.both$coefficients[2]
bu <- result.both$coefficients[3]
bl <- result.both$coefficients[4]
```

```
du <- result.both$coefficients[5]
dl <- result.both$coefficients[6]
if (al>au){
Xmat_R <- rbind(cbind(rep(1,n),seq(1:n),rep(0,n)),cbind(rep(1,n),rep(0,n),seq(1:n)))
result.both <- lm(st.yields~Xmat_R+indicmat-1,weights=w)
au <- al <- result.both$coefficients[1]
bu <- result.both$coefficients[2]
bl <- result.both$coefficients[3]
du <- result.both$coefficients[4]
dl <- result.both$coefficients[5]
}
reg.coef <- c(au,al,bu,bl,du,dl)
mul <- result.both$fitted.values[((T/2)+1):T] #lower fitted values
muu <- result.both$fitted.values[1:(T/2)] #upper fitted values
s1 <- (sum(w[((T/2)+1):T]*((st.yields[((T/2)+1):T]-mul)^2))/(sum(w[((T/2)+1):T
   ])))^0.5 #lower standard deviation
s2 <- (sum(w[1:(T/2)]*((st.yields[1:(T/2)]-muu)^2))/(sum(w[1:(T/2)])))^0.5 #
   upper standard deviation
mw <- mean(w[1:(T/2)]) #mean weight (for upper)
p1 <- dnorm(st.yields[((T/2)+1):T], mul, s1) #probability of lower mixture
p2 <- dnorm(st.yields[1:(T/2)], muu, s2) #probability of upper mixture
w <- p2/(p1+p2) #updated weights
w1 <- w
w2 <- 1-w1
```

```
w <- c(w1,w2)
all.w2[j,] <- w2 #saving the lower omegas from this iteration
coef[j,] <- c(mw,reg.coef,s1,s2) #saving coefficients from this iteration
if (j>10) temp.a <- sum(abs(coef[j,]-coef[j-1,]))
all.ll[j,1] <- sum(log((1-mw)*dnorm(st.yields[((T/2)+1):T],mul,s1)+mw*dnorm(
    st.yields[1:(T/2)],muu,s2)))
#Detecting crossovers:
Xover <- (muu[1]-mul[1])*(muu[66]-mul[66])
if (Xover<0) temp.a <- 10
#all.ll[j,2] <- ifelse(Xover<0,0,1)
if (al<0) temp.a <- 10
if (s1<(0.1*s2)) temp.a <- 10
all.ll[j,2] <- ifelse(temp.a==0,0,1)
#If difference is less than tolerance level, stop loop, save iteration:
conv <- ifelse(temp.a<tol,1,0)
it.conv <- ifelse(temp.a<tol,j,0)
j <- j+1
if (j>m) conv <- 1 #stop after 500 iterations
}
mw <- mean(w[1:(T/2)]) #mean weight for upper
#like[z] <- sum(log((1-mw)*dnorm(st.yields[((T/2)+1):T],mul,s1)+mw*dnorm(st.
    yields[1:(T/2)],muu,s2))) #loglikelihood for this quantile
xover.ll <- all.ll[,1]
xover.ll <- xover.ll[all.ll[,2]>0]
```

```
xx <- which.max(xover.ll)
like[z] <- xover.ll[xx]
#coef.fin[z,] <- c(mw, reg.coef, s1, s2)
coef.fin[z,] <- coef[xx,]
it.conv.fin[z] <- it.conv #iteration on which convergence occurred
}
ii <- which.max(like) #maximum loglikelihood
all.delta.lw[k,t] <- coef.fin[ii,7]
all.delta.up[k,t] <- coef.fin[ii,6]
omegas <- all.w2[ii,] #lower omegas for each county
time.jack <- seq(1:67)
time.jack <- time.jack[-t]
omega.reg <- lm(omegas~time.jack+indic)
save <- summary(omega.reg)
w2.coef <- rep(NA,6)
w2.coef[1] <- save$coefficients[2,1]
w2.coef[2] <- save$coefficients[2,2]
w2.coef[3] <- save$coefficients[2,4]
w2.coef[4] <- save$coefficients[3,1]
w2.coef[5] <- save$coefficients[3,2]
w2.coef[6] <- save$coefficients[3,4]
omegas.coef.matrix <- rbind(omegas.coef.matrix,w2.coef)
}
}
```

```
##### Calculating jackknife standard errors #####
crop_delta_lw_state <- corn_delta_lw_all #corn, soy, wheat
crop_delta_up_state <- corn_delta_up_all #corn, soy, wheat
full_crop_clim <- full_corn_clim #corn, soy wheat
#Jackknife standard errors
clim_coef <- matrix(NA, 67, 7)
for (b in 1:67){
clim.reg <- lm((crop_delta_up_state[,b])~ full_crop_clim [,1]+ full_crop_clim [,2]+
    full_crop_clim [,3]+ full_crop_clim [,4]+ full_crop_clim [,5]+ full_crop_clim [,6])
save <- summary(clim.reg)
clim_coef[b,1] <- save$coefficients [1,1]
clim_coef[b,2] <- save$coefficients [2,1]
clim_coef[b,3] <- save$coefficients [3,1]
clim_coef[b,4] <- save$coefficients [4,1]
clim_coef[b,5] <- save$coefficients [5,1]
clim_coef[b,6] <- save$coefficients [6,1]
clim_coef[b,7] <- save$coefficients [7,1]
}
sejack <- rep(NA, 7)
for (d in 1:7){
sejack[d] <- SE.jack(clim_coef[,d])
}
orig_reg <- clim_corn_up
t_clim <- rep(NA, 7)
```

```
t_clim [1]  <- ( orig_reg$coefficients [1]) /(sejack [1])
t_clim [2]  <- ( orig_reg$coefficients [2]) /(sejack [2])
t_clim [3]  <- ( orig_reg$coefficients [3]) /(sejack [3])
t_clim [4]  <- ( orig_reg$coefficients [4]) /(sejack [4])
t_clim [5]  <- ( orig_reg$coefficients [5]) /(sejack [5])
t_clim [6]  <- ( orig_reg$coefficients [6]) /(sejack [6])
t_clim [7]  <- ( orig_reg$coefficients [7]) /(sejack [7])
#Printing what you want: original regression,  jackknife  se,  t-stats
summary(orig_reg)
sejack
t_clim
pt(t_clim,  30,  lower. tail  = FALSE) #change df!
##### Crop insurance premium rates #####
crop_prm <- rbind(ILcorn, INcorn, IAcorn, MNcorn, OHcorn, WIcorn, SDcorn)
tt  <- 69 #time=2019
ind <- 24 #indic for t=2019
#tt <- 79 #time=2029
#ind <- 34 #indic for t=2029
PCT <- 0.7 #guarantee percentage/coverage level
rates  <- matrix(NA, dim(crop_prm)[1], 4)
colnames(rates) <- c("Premium_delta", "%", "Premium_without", "%")
for  (i  in  1:(dim(crop_prm)[1])){
#With deltas:
yml <- crop_prm[i,3]+crop_prm[i,5]*tt+crop_prm[i,7]*ind
```

```
ymu <- crop_prm[i,2]+crop_prm[i,4]*tt+crop_prm[i,6]*ind
guar <- (((1-crop_prm[i,1])*yml)+(crop_prm[i,1]*ymu))*PCT
EYl <- yml-crop_prm[i,8]*(dnorm((guar-yml)/crop_prm[i,8]))/pmax(0.000001,
    pnorm((guar-yml)/crop_prm[i,8]))
EYl <- pmin(EYl, guar)
EYu <- ymu-crop_prm[i,9]*(dnorm((guar-ymu)/crop_prm[i,9]))/pmax(0.000001,
    pnorm((guar-ymu)/crop_prm[i,9]))
EYu <- pmin(EYu, guar)
rates[i,1] <- ((1-crop_prm[i,1])*pnorm(guar, yml, crop_prm[i,8])+crop_prm[i,1]*
    pnorm(guar, ymu, crop_prm[i,9]))*(guar-((1-crop_prm[i,1])*EYl+crop_prm[i,1]*
    EYu))
rates[i,2] <- (rates[i,1]/guar)*100
#without deltas:
yml <- crop_prm[i,3]+crop_prm[i,5]*tt
ymu <- crop_prm[i,2]+crop_prm[i,4]*tt
EYl <- yml-crop_prm[i,8]*(dnorm((guar-yml)/crop_prm[i,8]))/pmax(0.000001,
    pnorm((guar-yml)/crop_prm[i,8]))
EYl <- pmin(EYl, guar)
EYu <- ymu-crop_prm[i,9]*(dnorm((guar-ymu)/crop_prm[i,9]))/pmax(0.000001,
    pnorm((guar-ymu)/crop_prm[i,9]))
EYu <- pmin(EYu, guar)
rates[i,3] <- ((1-crop_prm[i,1])*pnorm(guar, yml, crop_prm[i,8])+crop_prm[i,1]*
    pnorm(guar, ymu, crop_prm[i,9]))*(guar-((1-crop_prm[i,1])*EYl+crop_prm[i,1]*
    EYu))
```

```
rates[i,4] <- (rates[i,3]/guar)*100
}
```