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Essays on climate change adaptation and biotechnologies in U.S. agriculture

Jonathan R. McFadden
Iowa State University

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by

Jonathan R. McFadden

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Program of Study Committee:
John A. Miranowski, Co-Major Professor
Wallace E. Huffman, Co-Major Professor
Joseph A. Herriges
Catherine L. Kling
Tanya S. Rosenblat

Iowa State University

Ames, Iowa

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DEDICATION

To my family

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ABSTRACT

This dissertation examines climate change adaptation and biotechnologies in United States (US) agriculture. The first essay seeks a better understanding of the long-term and short-term implications of climate change for corn yields. Bayesian dynamic regressions are estimated for non-irrigated counties during 1960-2011 and used to forecast over 2012-2031. Yields are forecasted to generally increase 10-40% over current averages by 2031, with the Corn Belt and Great Lakes experiencing the greatest growth. The long-run relationship between climate damages and Hicks-neutral technical change is then estimated. Standard damage functions are generalized to include extreme temperatures and precipitation, while controlling for soil productivity. Results indicate significant connections between climate damages and technical change and suggest adaptation possibilities beyond 2031.

The second essay examines consumer demand for genetically modified potatoes. The US potato industry is working to lower acrylamide content, a probable human carcinogen forming naturally in potatoes and processed potato products cooked at high temperatures. Using random n$^{\text{th}}$-price auctions, we test combined effects of food labels and information on willingness-to-pay (WTP) for conventional potatoes and potato products using biotechnology to reduce acrylamide levels. Each subject receives a randomly-assigned information treatment that consists of one or two perspectives, e.g., an industry, scientific, and/or "environmental group" perspective. Results show for the first time that US consumers are willing to pay a premium for food safety obtained using biotechnology for two popular foods in the American diet.

The third essay expands on previous agriculture-climate links by investigating the role of environmental inputs and climate on cropland use and allocation. A discrete-continuous model of crop-tillage combinations and acreage allocation is estimated using field-level data. In the first step, a multinomial logit model is used to estimate farmers'

choices of crops and tillage. In the second step, linear regressions quantify the impacts of climate, economic factors, management, and soil characteristics on crop acreage. There are significant climate impacts on optimal input use. No-till practices may be an effective adaptation strategy to intense heat and precipitation in the short run. In the long run, farmers may adjust crops and acreage, depending on relative output prices and soil characteristics.

CHAPTER 1. INTRODUCTION

The structure of American agriculture has changed extensively over the last several decades. Additional mechanization, increased labor productivity, and increased effectiveness of fertilizers and other chemicals, all the result of targeted research and development, have brought about large increases in partial productivity (e.g., yields) and total factor productivity. In the context of continued productivity gains, climate change and biotechnologies are among the most important features of modern US agriculture. Though both have been researched for decades, they have only recently become a focus of attention because of their potential to considerably impact food security, food safety, domestic energy supply, and global commodity trading. Because such widespread impacts (both positive and negative) may occur swiftly over large regions, with asymmetric effects and limited reversibility, both features merit further study.

Estimating agricultural responses to short-run weather patterns (e.g., yields, total output, plantings, fertilizer use, crop insurance uptake) is not a new research program (Heady, 1952). However, the significance of evolving climate conditions for domestic and international agricultural markets renders it of crucial interest to consumers, producers, and policymakers. Warmer summers with more frequent and persistent heat waves, warmer autumns and winters, increased potential for - and duration of - droughts, and increased intensity of precipitation from storm systems are among the expected consequences of climate change in North America. If mitigation strategies have only limited or little success, adaptation will be necessary to minimize welfare loss.

Unfortunately, there is currently sparse empirical evidence regarding the design and implementation of successful adaptation strategies (Nordhaus, 2013; Wagner and Weitzman, 2015). We can conjecture that agricultural technology firms may respond by improving drought-tolerant seeds or improving access to irrigation. Farmers may schedule plantings earlier in the spring, adjust acreage allocations and fertilizer timing, or switch to less water-intensive crops. Policymakers may codify additional adaptation guidelines or engineer new climate-related risk management tools. Given this limited evidence, major goals of this dissertation are to quantify the impacts of climate change on corn yields and productivity growth (Chapter 2) and identify possible farm-level adaptation strategies through crop-tillage choices and acreage allocations (Chapter 4).

At the same time, recent developments in agricultural biotechnologies present new opportunities for increased productivity and food security, though especially food safety. Since the commercial introduction of Bt corn (using the soil bacterium, *Bacillus thuringiensis*) in 1996, farmers have subsequently adopted more advanced varieties of genetically modified corn, soybeans, and cotton, resulting in current adoption rates of 70-90%. First generations of genetic modification technology were designed to help protect against insect and weed pests. Recent innovations have targeted more specific needs of growers, consumers, and other industry participants. For example, drought-tolerant corn seeds help reduce yield loss under extreme heat and drought conditions; low-oxidation apples stay fresher with less immediate browning after slicing; and new potato varieties reduce browning, bruising, and carcinogen-forming potential.

Despite widespread adoption of biotechnologies from agricultural suppliers, acceptance among US consumers has not been universal. This is clearly seen, for example, in the contention surrounding public debate on mandatory labeling laws and strategies for successful coexistence of conventional and genetically modified crops. Many groups have an interest in the relative success (or failure) of biotechnologies, and information regarding the benefits (or harms) of biotech foods relative to conventional or organic foods reflect these groups' interests. As such, the other major goal of this dissertation is to quantify the combined effect of labeling and dispersed information on consumers' willingness-to-pay for new biotech potatoes and potato products that have been genetically engineered to reduce the potential for forming high concentrations of the probable human carcinogen, acrylamide (Chapter 3).

The general relationship and feedback between climate change and biotechnologies, both at aggregate and disaggregate scales, also remain poorly understood. Only in the past few years have policymakers and researchers begun to consider biotechnologies as useful tools for helping to limit downside climate change risks. Even if the objectives of most genetic modification applications are not concerned with increasing resilience to worsening climate conditions, the indirect benefits associated with increased overall stress resistance have been large (Chapter 2). However, overuse of these technologies are beginning to impose problems on growing conditions, sometimes in ways exacerbated by climate change. As weeds become more resistant to herbicides, such as those used in genetically modified glyphosate- and glufosinate-tolerant seeds, producers may switch to other chemicals with different consequences for local environments. Equally as important, climate change may bring about favorable growing conditions for increased propagation of insects, weeds, and plant diseases.

Thus, there are strong linkages between both features of modern US agriculture and will likely become increasingly interrelated over the next several decades. Apart from these straightforward economic linkages, there are three unifying themes weaving together this dissertation. First, recognition of underlying heterogeneity and small-scale variability is a key aspect of understanding and solving agricultural climate and biotechnology problems. Corn yields in dispersed areas of the US can have significantly different responses to climate change (Chapter 2), as well as farmers responding to climate conditions in their choices of field-level inputs (Chapter 4). Similarly, consumers can have highly variable reactions to information about biotechnologies (Chapter 3), which relates to the second unifying theme: asymmetric effects. In general, very negative information about biotechnologies reduces willingness-to-pay by a dollar amount greater than increases in willingness-to-pay from very positive information. This principle also emerges in county yield-climate relationships and farmers' crop choice. One to two degrees of warming in certain regions may have minimal effects on optimal field choices but could induce crop switching in regions that permit less effective adaptation to increased heat (Chapter 4). Third, climate change economics and information economics present inherently dynamic problems. To ensure greater accuracy, yield forecasts must be updated with the most recent climate and technology conditions (Chapter 2), and cropland must account for past rotations (Chapter 4). Similarly, consumer response to information treatments is tied to learning, a dynamic process that must be recognized in estimation.

This dissertation has the following organization. The first essay, "Climate Change, Technology, and US Corn Yields," uses agriculture and climate data on 770 non-irrigated counties in 1960-2011 to develop Bayesian dynamic corn yield forecasts for 2012-2031. The second essay, "Valuing New (Varieties of) Goods: Evidence from Lab Auctions of Popular Foods Genetically Engineered to Reduce New Food Safety Concerns," estimates the joint impact of labeling and information treatments on consumers' willingness-to-pay for new potatoes and potato products that have been genetically modified to decrease acrylamide that forms during cooking at high temperatures. The third essay, "US Climate Change Adaptation along the Intensive and Extensive Margins: A Field-Level Analysis," uses extensive farm microdata to analyze the association between producers' crop-tillage decisions, acreage allocations, and climate conditions. The final chapter provides concluding remarks and general implications from the separate analyses. Appendices A, B, and C are associated with the respective essays and include robustness checks and supplemental information.

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CHAPTER 2. CLIMATE CHANGE, TECHNOLOGY, AND US CORN YIELDS

2.1 Introduction

Corn has been the most important crop in the United States throughout much of the twentieth century. In recent years, planted corn acreage has averaged 20% of US cropland, with total production value far in excess of other row crops (USDA, 2013). Its importance stems from its many uses as a raw and intermediate input, which links each year's crop to various markets. Substantial yield growth over the past half-century has bolstered domestic food security, increased biofuels feedstock supplies, provided greater quantities of livestock feed, and boosted international food security through larger exports.[1] Growth in yields is directly linked to corn supply increases, input price declines (or stabilization), and other general equilibrium effects. If yield growth slows or reverses, as could happen with severe climate change, there would be substantial impacts in domestic and international food and energy markets.

Unmitigated climate change is expected to adversely impact agricultural production over the next century. The Intergovernmental Panel on Climate Change predicts global temperature increases of 0.3 - 6.4 °C by 2100, with more frequent heat waves and heavy precipitation (Jarvis et al., 2010). Although these projected detriments vary considerably by growing region and crop, the US corn industry is at risk (Schlenker et al., 2006; Schlenker and Roberts, 2009; Roberts et al., 2013; Lobell et al., 2013). Relative to other US cash crops, corn requires substantial water inputs and is vulnerable to temperature extremes. Changes in the intensity, frequency, duration, and timing of precipitation, combined with distributional changes in temperature, could bring about deep changes in US corn production environments and practices.

Our research tests two broad hypotheses with county-level US data: (i). corn yields will decline under climate change in the next two decades, and (ii). climate change

[1] An important factor underlying yield growth in recent years has been genetic modification (GM) of corn. GM technologies have increased yields, lowered costs, and increased profitability since their commercial introduction for corn in 1996 (Nolan and Santos, 2012; Edgerton et al., 2012; Fernandez-Cornejo and Wechsler, 2013).

damages adversely impact yield productivity growth. The former hypothesis is short-run in nature and considers immediate market impacts. The latter hypothesis considers long-run productivity, which is a currently missing prerequisite for longer-term forecasting. Policy recommendations differ crucially based on the validity (or lack thereof) of these hypotheses. For example, if forecasts indicate substantial short-run declines in yield growth (or levels), then this would justify immediate policies designed to thwart food insecurity. If future yield productivity growth is adversely impacted by climate change, or adaptation has been limited, then this may warrant changes to encourage agricultural technology research, development, and adoption. To test (i), time-series data are used to estimate and forecast from a Cobb-Douglas production function. Bayesian methods account for parameter instability, outliers, and obsolescence of older data. To test (ii), we fit damage functions to a cross section of climate change and yield productivity growth.

Our research is novel for several important reasons. We find that yields will increase by 10%-40% over currently observed averages through 2031. Some counties exhibit decreasing yields and decreasing yield growth, but the Corn Belt and Great Lakes areas will remain the top-producing regions. We also find significant relationships between climate change and the direction of yield productivity growth, suggesting opportunities for agricultural adaptation. This is an important aspect missing from the literature and critical for evaluating and designing longer-term public- and private-sector responses to climate change. Our methodological contribution is estimation of a Bayesian dynamic regression model that handles outliers, structural change, and obsolete data in a rigorous and unified fashion. Our production function draws on important concepts in agronomy (e.g., linear genetic gain) and agricultural meteorology (e.g., rainfall intensity). The end result is a set of implications and policy-relevant insights using a novel production specification with a more appropriate estimation framework.

The economics of agricultural production, like those of other natural resources, are characterized by a biological-based production function subject to weather uncertainty and biological risks. These sources of randomness, in combination with evolving technology, are captured in our short-run results. Signals (forecasts) of future yields influence agents' expectations, driving changes in equilibrium behavior within and across markets. To the extent that corn profitability will dwindle in some areas, production will be reallocated to more profitable locations and crops. Hence, our short-run results help inform regional shifts in production, further specialization within an area, and relocation of corn-based industries. Our long-run results provide an analytical context to the forecasts and indicate adaptation possibilities. If yield productivity growth has been influenced by climate change, what are the implications for long-run yields, adaptation, and policies?

The balance of the paper is organized as follows. The next section surveys past research. Section 3 introduces the econometric models. The fourth section presents the regression specifications and climate change data. Results and discussion are offered in the fifth section. The final section concludes. Further discussion, summary statistics, and robustness checks are offered in Appendix A.

2.2 Related research

The current research builds on work in three subdisciplines: applied state space models, agricultural economics, and climate change economics. Our framework proceeds from Miranowski et al. (2011), who fit autoregressive (AR) and linear trend models to annual corn yields during 1960-2009 for US states contributing 1% or more to total 2009 production. Break testing procedures find multiple breaks in some states, and the sample is accordingly partitioned to develop short run and long run forecasts to year 2030. Long run forecasts from linear trends indicate growth of 1-2 bu/ac per year, whereas short run models forecast 3-4 bu/ac growth in recent years. Short run and long run AR forecasts are similar (since AR models are simple cases of linear regressions), though somewhat more optimistic. One major policy implication is that sustained yield growth will free up cropland for alternative uses, assuming the rate of productivity growth outpaces worldwide increases in demand, thus implying reductions in GHG emissions attributable to corn production.

Agronomists have been researching the relationship between corn yields and weather for the past half-century. Thompson (1962) is an early study focusing on yields in Iowa, Indiana, Illinois, Missouri, and Ohio. July rainfall and August temperature are the most important variables across the five-state region. However, there has been more recent emphasis by agricultural economists on corn yields and climate change. Using Illinois field-level data, Dixon et al. (1994) show that models with solar radiation and growth-stage variables can have better performance than conventional specifications.

Since the mid-2000s, the agricultural economics literature has witnessed an increase in empirical studies attempting to pinpoint the prime determinants of crop yields. These studies differ with respect to choice of regressors, breadth of crops, spatial aggregation, and structural change. Schlenker and Roberts (2009) fit eighth-order polynomials to county-level yield data on corn, soybeans, and cotton for 1950-2005 while controlling for weather. The main result for corn yields is threefold: (i). increasing temperatures are beneficial up to 29 °C, (ii). yields are forecasted to decline by 20-30% for 2020-2049, and (iii). there has been limited historical adaptation of agriculture to warmer temperatures. Additional research finds other determinants with nonlinear and asymmetric yield impacts (Roberts et al., 2013).

Tannura et al. (2008) regress annual soybean and corn yields for Iowa, Illinois, and Indiana on monthly temperature and rainfall variables (in the growing season) in a similar time period. Standard tests for heteroskedasticity, autocorrelation in errors, parameter instability, and model misspecification are implemented, all with varying results. June and July precipitation, July and August temperature, and a linear time trend are their most significant predictors.

Xu et al. (2013) examine technological progress for county-level corn and soybean yields by using data on statewide adoption of GM seeds. Among their findings are that early season moisture has significant negative impacts, while GM trait adoption has strong positive impacts. Corn yields will increase at most by 31.8% over 2011-2030. Other corresponding works are Ortiz-Bobea (2013), Ortiz-Bobea and Just (2013), and Lobell et al. (2013), which consider nonlinear influences of temperature and precipitation. The latter considers the impacts of extreme heat and seasonal rainfall within a cropping systems simulation model.

An analysis of climate change adaptation is taken up in Burke and Emerick (2013). The authors use panel data on growing degree day and precipitation bins for counties east of the 100th meridian to explain 31-year long differences (1980-2000) of corn and soybean yields. Based on the percentage change in long difference estimates over panel fixed effects estimates, there is only meager evidence of adaptation. Average yields are forecasted to decline 15% by 2050 under the median climate model. Our long-run analysis implements a similar methodology but uses a 52-year long difference to explain latent yield productivity growth.

A paper with similar methodology and production focus is Jin and Jorgenson (2010). Using data on 35 US industry sectors in 1960-2005, the Kalman filter is fitted to dynamic factor shares from a translog price function. In their *state-space model of producer behavior*, changes in the latent state variables reflect rates and biases of technical change. They find that the rate of autonomous technical change in agriculture over this period has been 0.55, with biases towards capital and energy and biases away from labor and materials. The rate of agriculture's autonomous technical change is forecasted to be 0.3 during 2006-2030.

2.3 Econometric model

We assume that the yield production function takes the Cobb-Douglas form. The Cobb-Douglas production function is less general than other traditional flexible forms but economizes on estimated parameters and has a more straightforward interpretation. For county i in period t, yields (y_{it}) are:

$$y_{it} = A_{it} \prod_j X_{ijt}^{\alpha_{ijt}}, \tag{2.1}$$

where X_{ijt} is the j^{th} production input, α_{ijt} is the associated partial output elasticity, and A_{it} summarizes the level of technology. Log-linearizing (2.1) and appending an econometric disturbance gives the Cobb-Douglas regression equation:

$$\log(y_{it}) = \log(A_{it}) + \sum_{j} \alpha_{ijt} \log(X_{ijt}) + \epsilon_{it}. \tag{2.2}$$

Note that the productivity term, $\log(A_{it})$, is captured in the intercept of the regression. Gradual movement in the regression intercept over time is broadly indicative of technical change, which we term as yield productivity growth.[2] Our dynamic model permits estimation of year-to-year changes in productivity, a key advantage over static approaches. Although the specification in (2.2) does not address induced, biased technical change in US agriculture, it is natural to use a parsimonious model in the context of highly uncertain climate change.[3]

Underlying our model of production is the idea that short-run yield fluctuations in a given area are driven mainly by random weather variation and adopted technologies. The biological connections between corn plant growth and weather (e.g., rainfall, solar radiation, and humidity) are well-documented in agronomy. This biological basis motivates (2.1), and sufficient variability ensures identification of (2.2). Adoption of agricultural technologies in a given year also has a direct effect on yields. To properly analyze climate impacts on production, the role and level of technology must be considered, though this is frequently missing in reduced-form models. Over the latter half of the twentieth-century, yields have risen because of improvements in machinery and management systems, the early diffusion of hybrids and later innovation of genetically-modified varieties, decreases in row spacing accommodated in part by improved pesticides, gains in nitrogen use efficiency, and so on. The joint role of technology and weather in shaping yields is thus explicit in our model.[4]

[2]There is a large empirical literature on total factor productivity (TFP) in agriculture. Capital, labor, land, and other inputs are typically used to calculate regional productivity indices (Ball et al., 2001). As our focus is on weather and climate impacts and their relation to long-run productivity differences, productivity indices do not need to be calculated.

[3]We assume that the composition of farms in each county is not affected by climate change. If climate change influences, for example, farm size or farm labor supply, then this would have indirect effects on county yields. There is little evidence that these indirect effects are large or economically meaningful.

[4]Input endogeneity and the choice of which technologies to include are concerns in the empirical production literature. By restricting our sample to rainfed regions, irrigation and climate-induced reductions in water supply are safely omitted. The other major variable input is nitrogen. Using USGS nitrogen data for 540 Corn Belt counties in 1987-2006, we find that fixed effects panel estimates of

One important aspect missing from (2.2) and short-run studies using time-series variation is biotechnology adaptation. As climate change deepens, technology firms have responded by introducing farm-level adaptation measures, such as drought-tolerant seeds and climate-based management guidelines. This suggests that long run yield productivity growth is endogenous to climate (Dell et al., 2012). One policy-relevant interpretation of this hypothesis is that expected damages from climate change influence yield productivity growth:

$$\log(A_{it}) - \log(A_{it-1}) = D(C_{it}) + \nu_{it}, \tag{2.3}$$

with $D(C_{it})$ a damage function of climate, C_{it}. In integrated assessment models (IAMs), the primary economic models for climate change policy recommendations, $D(C_{it})$ links climate (usually temperatures) to output reductions. Climate damages are poorly understood, and most models calibrate simple nonlinear functions to existing studies (Tol, 2009; Nordhaus, 2013). We propose a more direct approach by using the dynamic results in (2.2) to estimate (2.3) from a cross-sectional long difference. Understanding how yield productivity growth responds to climate is a crucial input into informed policymaking.

Equations (2.2) and (2.3) are the empirical equations of interest and are used to examine the short-run and long-run claims. The Bayesian model used to estimate the dynamics of (2.2) is introduced below, and econometric considerations are given in the following subsection. We then discuss estimation of adaptation equation (2.3).

2.3.1 Dynamic linear model

In linear state space models, data at any time period are a linear, additive function of unobserved states and a random disturbance. Unobserved states evolve according to

weather are unaffected when nitrogen is included, instrumented, or excluded. For example, the weather elasticities for monthly average temperature and precipitation differ by at most 0.07 across the three models. Instrumental variables are soybean acreage in previous years and ammonia exports per mile from New Orleans, the major US import center.

a random walk. Our model is the following:

$$Y_t = \boldsymbol{F_t}^{\top}\boldsymbol{\theta_t} + \nu_t, \qquad \nu_t \sim N(0, k_t\phi_t^{-1}) \tag{2.4}$$

$$\boldsymbol{\theta_t} = \boldsymbol{G_t}\boldsymbol{\theta_{t-1}} + \boldsymbol{\omega_t}, \qquad \boldsymbol{\omega_t} \sim t_{n_{t-1}}(\boldsymbol{0}, \boldsymbol{W_t}) \tag{2.5}$$

At any time t, Y_t is the dependent variable, $\boldsymbol{F_t}^{\top}$ is a $(1 \times n)$ vector of regressors, $\boldsymbol{\theta_t}$ is an $(n \times 1)$ vector of regression coefficients (state parameters), $\boldsymbol{G_t}$ is the system evolution matrix, ν_t is the observation disturbance, and $\boldsymbol{\omega_t}$ is the system disturbance vector. In the above framework, (2.4) is the observation or data equation, and (2.5) denotes the system or state evolution equation. Error terms satisfy temporal and mutual independence, i.e., $Cov(\nu_s, \nu_t) = 0$, $Cov(\boldsymbol{\omega_s}, \boldsymbol{\omega_t}) = \boldsymbol{0_{nxn}}$ for all $t \neq s$ and $Cov(\nu_t, \boldsymbol{\omega_t}) = \boldsymbol{0_n}$ for all t, s. The observation variance is the product of a known variance dispersion parameter, k_t, and ϕ_t, the observation's precision, which is given a gamma prior distribution. The system shock follows a mean-zero, multivariate t-distribution with degrees of freedom that are updated sequentially and a block-diagonal variance (scale matrix), $\boldsymbol{W_t}$. The three submatrices comprising $\boldsymbol{W_t}$ are an intercept block, a regression block, and a time trend block. Since various pieces of explanatory information can decay at different rates, each of the blocks is adjusted by a distinct discount factor: δ_{int}, δ_R, and δ_{tr}.

We assume the following priors on coefficients and the observation variance:

$$\boldsymbol{\theta_t}|I_{t-1} \sim t_{\delta_t n_{t-1}}(\boldsymbol{a_t}, \boldsymbol{R_t}) \tag{2.6}$$

$$\phi_t|I_{t-1} \sim \Gamma\left(\frac{\delta_t n_{t-1}}{2}, \frac{\delta_t d_{t-1}}{2}\right), \tag{2.7}$$

where $\boldsymbol{a_t}$ and $\boldsymbol{R_t}$ are the location and scale parameters of the multivariate t-distribution with $\delta_t n_{t-1}$ degrees of freedom. Correspondingly, $(\delta_t n_{t-1}/2, \delta_t d_{t-1}/2)$ are the shape and scale parameters of the gamma distribution. All knowledge available at time $t-1$ is contained in the information set, I_{t-1}. The discount factor appearing here is an "overall model" discount. This discount should be very close to unity since δ_{int}, δ_R, and δ_{tr} already account for gradual information loss as data become obsolete.

Conjugacy implies that posterior and one-step ahead forecast distributions are:

$$\boldsymbol{\theta_t}|I_t \sim t_{n_t}(\boldsymbol{m_t}, \boldsymbol{C_t}) \tag{2.8}$$

$$\phi_t|I_t \sim \Gamma\left(\frac{n_t}{2}, \frac{d_t}{2}\right) \tag{2.9}$$

$$Y_t|I_{t-1} \sim t_{\delta_t n_{t-1}}\left(f_t, Q_t\right). \tag{2.10}$$

Although the observation depends linearly on the regression coefficients, the set of updating equations shows that several nonlinearities affect posterior distribution shapes.

The k-step ahead forecast distributions are given by:

$$\boldsymbol{\theta_{t+k}}|I_t \sim t_{\delta_t n_t}\left(\boldsymbol{a_t(k)}, \boldsymbol{R_t(k)}\right) \tag{2.11}$$

$$Y_{t+k}|I_t \sim t_{\delta_t n_t}\left(f_t(k), Q_t(k)\right), \tag{2.12}$$

in which the locations and scales are computed from a smaller set of equations. In out-of-sample forecasting, the state prior means are always equal to the state posterior means at the last available date in the sample. Similarly, the state prior variance (scale) is initially equated to the last available state posterior variance but then evolves with changes in $\boldsymbol{W_{t+k}}$. For more details, readers are referred to Pole et al. (1994) and West and Harrison (1997).

2.3.2 Econometric considerations

The dynamic linear regression model exhibits many desirable features. First, structural change is implemented "naturally" via time-varying parameters. Rather than splitting the data into subsamples, the filter uses available information to derive estimates that fluctuate over time. Since there is evidence of multiple breaks over the past 50 years, the potential for future structural change must be taken seriously, i.e., explicit modeling of the break process (Elliott and Timmermann, 2008). Second, DLMs improve on less descriptive ARIMA models by assimilating useful information from regressors. Third, this model accounts for climate-change induced weather variability in out-of-sample forecasts.

A few statistical issues require further clarification. From (2.5), the parameters follow a random walk. Random walks do not satisfy covariance stationarity because their variances depend on time (Enders, 2009). Thus, the model is nonstationary, which is more useful for applied research than restrictive stationary models.[5] One may also be concerned about efficiency losses and forecasting inaccuracy from a dynamic model if the true process is static. If the coefficients are mean-reverting, then a static linear estimator (like OLS) does not produce severely biased results (Elliott and Timmermann, 2008). Simulations from Ciapanna and Taboga (2011) suggest that DLMs fare well under several scenarios, including those in which the data are generated from a constant process, contain a small number of breaks, or contain frequent breaks.[6]

Most dynamic models are not scale invariant, i.e., rescaling regressors without adjusting priors can result in altered posteriors (Ciapanna and Taboga, 2011). This is remedied by standardizing regressors, which ensures commensurability of regressors and gives a correct interpretation of the time-varying intercept (West and Harrison, 1997; Pole et al., 1994). Discount factors also require attention. Discounts lie in $[0, 1]$, with larger values indicating less information decay and downweighting of older data. One automatic practice chooses discounts to maximize the loglikelihood, but this can result in estimation from the most recent three or four observations, such as for $\delta < 0.7$ (Pole et al., 1994). To avoid this problem, we set all discounts in $[0.90, 0.99]$.

2.3.3 Damage function estimation

A fundamental understanding of long-run connections between climate and technology is crucial for assessing short-run forecasts and developing more realistic economic analyses of damages and mitigation opportunities. Investigating the relationship in (2.3) requires a choice of functional form for climate damages. Climate economics theory offers

[5]Durbin and Koopman (2012) argue that "the requirement that the differenced series should be stationary is a weakness of the theory. In the economic and social fields, real series are never stationary however much differencing is done. The investigator has to face the question, how close to stationarity is close enough? This is a hard question to answer" (p. 70).

[6]They find that mean squared error increases by roughly five percent when improperly using a DLM over OLS to estimate coefficients from a static DGP. Additionally, in the presence of numerous breaks, DLMs can reduce mean squared error by up to 60 percent relative to OLS estimation.

several forms, including linear, quadratic, exponential, and others, depending on beliefs about uncertainty, thresholds, and nonlinearities. Among the most widely-accepted is the inverse-quadratic in temperature change used by the Dynamic Integrated Model of Climate and the Economy (Nordhaus, 2013). In the DICE model, percentage changes in gross domestic product depend on the level of temperature change and its square. We modify this intuition and generalize the inverse-quadratic to estimate the following:

$$\widehat{log(A_{i,2011})} - \widehat{log(A_{i,1960})} = \frac{1}{1 + (\boldsymbol{\Delta x_i'})\boldsymbol{\beta}} + \boldsymbol{z_i'}\boldsymbol{\gamma} + \varepsilon_i. \tag{2.13}$$

For the i^{th} county, $\widehat{log(A_{i,2011})} - \widehat{log(A_{i,1960})}$ measures yield productivity growth. It is the difference in 1960 and 2011 estimated intercepts from the Bayesian DLM, i.e., $\hat{\theta}_{i,2011} - \hat{\theta}_{i,1960}$ intercepts in (2.5). The $\boldsymbol{\Delta x_i'}$ are climate variables, $\boldsymbol{z_i'}$ are soil productivity controls, and ε_i is an i.i.d. normal disturbance. Nonlinear least squares (NLS) is used for estimation. The two important features of (2.13) are that: (i). identification comes from cross-sectional variation in exogenous inputs, and (ii). climate change is operationalized as a long difference (half century) of weather variables. These provide a long-run interpretation of the association between yield productivity growth and climate change, inclusive of adaptation. To ensure that our results do not hinge on functional form assumptions, we also estimate the exponential damage function of Weitzman (2009), as well as a direct linear model. See Tables A.4 and A.5 of Appendix A for the coefficients.

2.4 Regression specifications and data

The following subsections detail the econometric specifications needed to examine our two claims. As with any applied econometric study, the true model is unknown. Appendix A contains a number of robustness checks with respect to model specification. See text in this appendix for comparisons involving: a linear trend only (Fig A.3), temperature-precipitation interactions (Fig A.4), union of regressors (Fig A.5), GM trend (Fig A.6-A.7), two-inch intense precipitation (Fig A.8), average and extreme growing degree days

(Fig A.9), sample length (Fig A.10-A.13), climate model (Fig A.14-A.17), and panel fixed effects estimation (Fig A.18-A.19).

2.4.1 Baseline DLM specification

Evidence from agricultural economics, agronomy, and plant biology point to a basic regression model that uses temperature and precipitation variables during important periods of the growing season to explain yields. At a physiological level, water uptake by corn plants occurs via the development of their root structure that absorbs soil moisture. Development of the plant also requires photosynthesis, the biological process by which light is converted into chemical compounds used for energy. To show how temperature and precipitation explain county-level yields, a complete dataset would include plant-level measurements of water uptake, photosynthesis rates, solar radiation, air temperature, technology, and so on. Such detailed records are not available, and few available datasets permit consistent spatial aggregation or application to commercial agriculture.[7]

To proxy physiological effects during peak periods of crop development, we use countywide means of precipitation and temperature for the months of May, June, July, and August. Our sample comprises 770 rainfed counties with a complete data record for 1960-2011 from states producing at least 1% of US production in 2009-2011. Weather data are from two sources. The first is the PRISM AN81m dataset of gridded (4 km x 4 km) monthly temperatures and precipitation (PRISM Climate Group, 2004). The second is the National Oceanic and Atmospheric Administration's (NOAA) CPC Unified Gauge-Based Analysis of Daily Precipitation (NOAA, 2008). These are daily precipitation data interpolated at 0.25° latitude x 0.25° longitude grids. For both sources, we aggregate to the county level based on area-weighted or grid-weighted averages.

[7]Yields also depend on pests and plant diseases. To our knowledge, there are no detailed pest time series data available for the sample counties. To the extent that pest damages correlate with weather (e.g., corn rootworm problems are generally more severe in dry conditions), estimates in the literature are biased. However, there have only been three recent problematic years: the Southern Corn Leaf Blight outbreak in 1970, western corn rootworm in 1995, and the soybean aphid infestation in 2003. States with more serious pest problems, such as those in the South and Southwest, are not in our sample. Thus, the severity of the omitted variable bias is likely minimal. Table A.3 in Appendix A presents long-run results with state fixed effects, which may help reduce this bias if underlying pest susceptibly is invariant and geographically dispersed.

A linear time trend is used to detrend the yield data. This important modeling choice is motivated directly from the agronomy literature. Corn breeders have consistently found linear genetic gain in twentieth-century yields (Duvick, 1984; Crosbie et al., 2006; Smith et al., 2014). Yield models without linear trends (or linearly detrended yields) are in distinct contradiction to the weight of empirical agronomic evidence and are misspecified. The trend is also a suitable proxy for gradually increasing-inputs, such as nitrogen fertilizer use for many years in our sample. We also use the linear trend for near-term forecasting because it reflects improvements in technology from past and current research investments. Modern breeding is a scientifically-advanced, multi-billion dollar industry with research pipelines generally spanning seven years (or longer) from field trials to commercialization (Crosbie et al., 2006; Smith et al., 2014). Omission of the trend for forecasting purposes is equivalent to disregarding useful institutional and economic details and would result in misspecification.[8] Figure A.3 in Appendix A depicts 2031 yield forecasts with an intercept- and trend-only model.

For the i^{th} county in period t, the baseline set of regressors is:

$$\boldsymbol{F}_{\boldsymbol{i,t}}^{\top} = (1 \quad Temp_{i,t} \quad Prec_{i,t} \quad Time_{i,t})\,. \tag{2.14}$$

2.4.2 Alternative DLM specification

One undesirable aspect of the baseline model is its simplistic representation of complex agronomic relationships. The results of Schlenker and Roberts (2009) confirm intuition about temperature nonlinearities: local increases within low-to-moderate temperature intervals are beneficial as they accommodate growth of the plant, but beyond some threshold (or multiple thresholds across growth stages), additional temperatures are harmful. Heat stress is a consequence of isolated or recurring episodes of high temperatures and is among the more harmful physiological stressors, as most major crops are susceptible at every stage of growth. To embody these effects, researchers have proposed Grow-

[8] As Smith et al. (2014) mention, "For the foreseeable future, maize breeders are confident that not only can further genetic gain be achieved for rainfed maize agriculture, but recent increases in breeding efficiencies will further increase the rate of genetic gain" (p. 159).

ing Degree Days (GDD), Heating Degree Days (HDD), Extreme Degree Days (EDD), Killing Degree Days (KDD), and other transformations of temperatures that account for accumulated exposure to either beneficial or extreme sunlight.

Degree day variables have a clear motivation from the plant sciences, but their formulas vary over studies. For transparency, we capture temperature extremes by dummies indicating monthly average maximum temperatures of at least 85 °F in July and August (denoted below as $Jul85$ and $Aug85$).[9] In most regions of US production, the corn plant begins to pollinate and subsequently develop kernels during July and August in growth phases that are sensitive to weather extremes. For 20 counties, there is no variation in the 85 °F indicators. In these counties, we substitute July and August average temperatures.

Besides damage caused by droughts and inundations, durations of high rainfall rates contribute to lower yields by leaching some plant nutrients in soils. Rainfall runoff and erosion carry away nutrients on and bound to the soil surface and limit the effectiveness of fertilizers. Precipitation intensity (or lack thereof) is measured as the proportion of days in a month (May, June, July, or August) not receiving at least one inch of rain per day. To our knowledge, there are few sources in the climate change literature that provide forecasts of extreme rainfall events (Groisman et al., 2012; Daniel, 2015). Therefore, we implement a negative binomial regression on time to generate rainfall intensity forecasts for use in the regressions over the forecasting period.[10] Adding an intercept term and linear time trend, the alternative specification for the i^{th} county in period t is:

$$\boldsymbol{F}_{\boldsymbol{i,t}}^{\top} = (1 \quad Jul85_{i,t} \quad Aug85_{i,t} \quad IntPrec_{i,t} \quad Time_{i,t}) \,, \tag{2.15}$$

where $IntPrec_{i,t}$ indicates separate measures of intense precipitation for the months of May, June, July, and August. Figure A.8 depicts forecasts using two-inch daily intense precipitation regressors.

[9] This cutoff value is designed to be a compromise between the 86 °F used in canonical GDD formulas and Lobell et al. (2013), the 84.2 °F suggested by Schlenker and Roberts (2009), and the 90 °F of Xu et al. (2013).

[10] Poisson regressions for each county are initially attempted, but likelihood ratio tests reject the null hypothesis of equidispersion. Estimates from the Poisson and negative binomial regressions are very similar and do not substantially alter the forecasts.

2.4.3 Climate change scenarios

Given the growing weight of evidence ascribing current weather conditions to global warming (Section 2), it is unlikely that future climate circumstances will be adequately depicted by trends prevailing in 1960-2011. Therefore, it is inappropriate to follow a standard forecasting practice of evaluating the estimated regression model at the sample means of the independent variables. A common practice in applied environmental research is to assimilate output from multiple realizations (runs) of one or more global climate models (GCMs). Although there are drawbacks (e.g., stringent GCM assumptions and conflicting GCM results), this approach is the most plausible for our forecasts (Auffhammer et al., 2013).

Data on precipitation and minimum and maximum daily temperatures for the next two decades (2012-2031) are from NASA's NEX-DCP30 project (Thrasher et al., 2013). These are climate projections from the Coupled Model Intercomparison Project 5 (CMIP5) that NASA has downscaled to the 800m x 800m grid cell with adjustments for mismatches between simulations and the historical record. These data are categorized according to four levels of climate change.[11] Results in the analysis only consider mild climate change, i.e., RCP 2.6. This is because estimates and forecasts under severe climate change, RCP 8.5, are very similar to the RCP 2.6 results in our prior state-level analysis. This is consistent with projections that significant departures from current weather patterns (precipitation, temperature, drought, and flooding, etc.) are not expected over the next two decades.

To ensure that the forecasts are not inordinately influenced by a few GCMs or specific runs within a GCM, future climate regressors are averaged over four models: CCSM4, GFDL-CM3, MIROC5, and HadGEM2-AO. Our choice of models is guided by Pierce et al. (2009), which presents a list of top models according to a "skill score." These models, or similar models from the same climate institutions, have also been used in the climate

[11]These four levels correspond to representative concentration pathways (RCP) 2.6, 4.5, 6.0, and 8.5. The pathways index radiative forcing, the rate of change in the difference between incoming and outgoing solar energy in the atmosphere. Larger radiative forcing generally indicates more severe climate change.

economics literature. Figures A.13-A.16 in Appendix A depict forecasts for each of the models separately.

2.4.4 Damage function specification

Climate change variables in the damage function rely on data from the baseline and alternative models. We fit two specifications of (2.13). The first specification is the conventional inverse-quadratic damage function. Climate change variables in this specification are: $\Delta MayTemp_i$, $(\Delta MayTemp_i)^2$, $\Delta JuneTemp_i$, $(\Delta JuneTemp_i)^2$, $\Delta JulyTemp_i$, $(\Delta JulyTemp_i)^2$, $\Delta AugustTemp_i$, and $(\Delta AugustTemp_i)^2$. Rather than subtracting 1960 from 2011 weather data, we subtract five-year averages at both endpoints (1960-1964 and 2007-2011). This reduces the influence of unusually poor or beneficial weather in 1960 or 2011 in the estimates. The second damage function specification uses: $\Delta July85_i$, $\Delta August85_i$, $\Delta MayIntPrec_i$, $\Delta JuneIntPrec_i$, $\Delta JulyIntPrec_i$, and $\Delta AugustIntPrec_i$. There is less support for quadratic terms in this specification as the variables already consider climate change extremes.

Soil productivity significantly contributes to growth of the corn plant, with important effects on yields. There is general consensus that soil productivity is time-invariant, so its influence on yields would difference out of the long-run econometric model. However, since the long-run analysis uses cross-sectional variation, we follow the convention in the literature and include soil controls. Table A.3 in Appendix A illustrates that our results are robust to excluding soil variables. The Soil Survey Geographic database (SSURGO) contains data collected by the National Cooperative Soil Survey over the past century (USDA-NRCS, 2013). There are several dozen measures of physical and chemical soil properties that affect soil productivity, and more research is needed to identify the most important soil determinants.

We use five soils variables that are well-known and have complete records in all counties: slope gradient, T value, root zone available water storage, National Commodity Crop Productivity Index - Corn and Soybeans (NCCPI-CS), and an erosion indicator. Slope gradient is the elevation difference between two points divided by the distance between the two points. The T value captures maximum sustainable soil erosion. Root zone available water storage is the average volume of available water that can be stored in the plant's root zone. The NCCPI-CS combines several soil properties conducive to growing corn and soybeans. The erosion indicator is the county-level percentage of soils visually identified as eroded. Soil productivity is not a main focus but is an important factor in explaining yields and growth under climate change.

2.5 Results

Descriptive statistics for most of the data used in the analysis are in Table 2.1. Summary statistics for weather data are not decomposed into within- and between- variation ($N = 770$ counties x 52 years). Across the sample, corn yields range from 9 to 207 bu/ac, with a mean of 103 bu/ac. The hottest month is July, averaging 23 °C with roughly 10 cm of precipitation. Intense precipitation events are infrequent: on average, just under one day each month in the growing season experiences at least one inch of precipitation. Weather patterns in 2012-2031 are similar to those in sample. Average temperatures rise 1.5-2.0 °C and August rainfall drops by nearly one cm. Although on the upper end of near-term climate change, these differences are within the range of other major climate model predictions.

The soil controls show that our sample has diverse innate land productivity characteristics. Eroded land within a county ranges from zero to 83 percent, and available water storage at the root zone exhibits substantial variability, despite being restricted to rainfed regions. The average NCCPI of 0.53, with a range of $[0.02, 0.90]$, indicates good overall suitability for growing soybeans and corn. The NCCPI is constructed from many soil properties, including organic matter content, pH, soil depth, and saturated hydraulic conductivity (Dobos et al., 2012). It does not incorporate corn yield data, so spurious correlation in results is not a concern. Using a crop productivity index, such as the NCCPI, is a more parsimonious alternative to including many other soil variables.

Sample counties and their 2011 corn yields are depicted in Figure 2.1. Top-yielding counties are located in Iowa, Illinois, Minnesota, eastern Nebraska, and western Indiana and Ohio.[12] These highly productive areas are predominantly in the Corn Belt, where yields have been the highest over the past half-century. Missouri, Pennsylvania, Kansas, western South Dakota, and eastern North Dakota have lower yields in 2011 and in prior decades. The distribution of yields in Figure 2.1 largely reflect spatial differences in climate, soil productivity, and technology adoption. For instance, central Wisconsin, Michigan, and Minnesota have less productive soils than the Corn Belt, but similar weather patterns, technology adoption, and management practices have kept yields high. The substantial interactions between weather and technology will continue to drive yield growth over the coming decades.

Section A of Appendix A further characterizes the data. Table A.1 provides summary statistics on the averaged long difference data used for the long-run analysis. The direction and magnitude of climate change are consistent with intuition and related studies. Figures A.1-A.2 are illustrative examples of the similarities and differences between average and intense precipitation, particularly in Illinois, Ohio, Wisconsin, and Michigan. Differences in average and intense precipitation in some counties help explain differences between the baseline and alternative forecasts.

To further explore the role of productivity growth, we consider estimates of the dynamic intercept in 1960 and 2011 for the baseline and alternative specifications. For example, Figure 2.2 presents results for the 29 rainfed Nebraska counties. County means of the 1960 and 2011 exponentiated intercepts are plotted, along with 95% credible intervals for the 2011 estimates.[13] These estimates convey information about productivity at different points in time since they capture Hicks-neutral technology.

For the baseline specification, Nebraska counties tend to have high productivity in early years. The 1960 intercepts are consistent with yields of 50-60 bu/ac, which match observed yields in these counties. Assuming average weather conditions, variability among counties reflects differences in soil productivity, management practices, fertilizer applica-

[12] The sample is restricted to dryland agriculture. Schlenker et al. (2005) show that irrigated and non-irrigated counties cannot be pooled in cross-sectional analysis (see Section 5.2). We exclude counties in which the ratio of harvested, irrigated corn acres to total harvested corn acres exceeds 0.5 (averaged over Census of Agriculture data in 1997, 2002, 2007, and 2012).

[13] Credible intervals for the 1960 estimates are wide because of the diffuse prior on the variance terms but narrow as more information becomes available.

tions, and other production dimensions in the county intercept. At the sample endpoint, the intercepts indicate yields in $[90, 125]$ bu/ac, with credible intervals suggesting uncertainty of 10-20 bu/ac. This moderate productivity growth is consistent with the findings of Ball et al. (2014) for state-level agricultural TFP in 1960-2004: states such as Nebraska have had moderate annual growth in output and TFP. Note that the relative rank order among counties has been stable over this time for dryland agriculture, where productivity is not confounded by access to Ogallala Aquifer irrigation water and technology.[14] In sum, the baseline results suggest that small changes in average weather should not reduce yields below $[90, 125]$ bu/ac.

Productivity estimates in the alternative specification are similar but smaller. Figure 2.3 indicates that introducing weather extremes lowers the time path of the intercepts, with initial productivity estimates suggesting 40-60 bu/ac yields. Most county endpoint estimates are reduced in the alternative model to yields of $[90, 115]$ bu/ac. This is consistent with studies documenting the yield-reducing effect of extreme temperatures (Schlenker and Roberts, 2009; Lobell et al., 2013; Burke and Emerick, 2013). Credible intervals increase to roughly 10-15 bu/ac about the mean. For a few outlying counties with very wide intervals, we cannot reject the possibility that yields could revert to historic lows. For a given county in a recent year with very poor weather, yields can drop by 50% or more. Despite higher uncertainty, our finding of moderate productivity growth in all counties is robust to corn production characterized by extreme weather.

The Bayes factor provides guidance on model selection. Bayes factors are ratios that indicate the odds provided by the data for one model over another model (Kass and Raftery, 1995). They are calculated as the ratio of the marginal likelihood of one model to the marginal likelihood of the other model, i.e., $p(y|H_1)/p(y|H_2)$, where $p(\cdot)$ is a continuous density and H_1 and H_2 denote the two models. Although interpretation varies among practitioners, Bayes factors in: $[1, 3]$ are inconclusive, $[3, 10]$ are weak, $[10, 100]$ are strong, and greater than 100 are conclusive for preferring model 1 to model 2. Figure

[14]This contrasts with studies focusing on counties east of the 100$^{\text{th}}$ meridian. Many Kansas and Nebraska counties in this region are irrigated, implying biased and inconsistent estimates: omitted irrigation variables are correlated with included temperature and precipitation regressors.

2.4 depicts the Bayes factor. The figure helps answer the question: should we prefer the baseline to alternative specification? Since the ratio generally lies in $[0.6, 1.2]$, there is little preference for one model over another.

Another practical model selection criterion is the forecast's mean absolute deviation (MAD). Appendix Table A.2 furnishes MAD calculations for the two specifications averaged over the sample counties. The alternative model has somewhat better predictive content for 2012, though the baseline model has more accurate forecasts for 2013 and 2014. As with the Bayes factor, model performance is again mixed. On the basis of these criteria, we continue to use both specifications for the short-run and long-run analyses.

2.5.1 Short-run impacts: yield forecasts

For the 2031 yield forecasts in Figure 2.5, the baseline model generally replicates geographic yield patterns for the last several years in sample. Counties in central and northern Iowa and Illinois and southern Minnesota will experience 25%-35% higher yields over 2011 levels. In these regions, the relatively large intercepts and time trend offset minor short-run weather impacts.[15] Ohio and eastern Nebraska have forecasted yield growth of 16%-20%, with Indiana experiencing slightly lower growth in 14%-16%. Thus, we find that forecasts for traditional Corn Belt counties behave similarly, a result of similar technology, weather, and trend effects. Great Lakes states, such as Michigan and Wisconsin, perform comparably: several regions are forecasted to yield 190-220 bu/ac in 2031. Poorer soil conditions are partially offset by avoiding greater or extreme temperatures.

Yield forecasts for eastern South Dakota and southeastern North Dakota exhibit considerable growth primarily because of large time trends. For example, average yields in both states during 2000-2009 increased by a factor of 2.3 to 3.8 over 1960-1969 averages. In contrast, average Iowa yields during 2000-2009 only increased by a factor of 1.8 to 2.5 over 1960-1969 averages. Because both states experience droughts and extreme summer

[15]The largest (negative) short-run weather coefficients correspond to July and August temperatures and are one-tenth to one-quarter the size of the time trend. These substantial late-season temperature impacts agree with earlier results forecasting state-level yields.

heat, they also fare better in the baseline model that uses average weather. Our results are consistent with those of Deschênes and Greenstone (2007). They find that these states will experience the largest net gains from climate change: an additional $720 mil for South Dakota and $160 mil for North Dakota (not a consequence of short-run price effects).

Lower yield-growth areas are primarily concentrated in Missouri, southern Kentucky, central Pennsylvania, and certain regions of Kansas. Identifying sources of lower growth is more challenging because of heterogeneity in soil productivity, land characteristics, and management and adoption practices. Proximity to the Appalachian Mountains in Pennsylvania and eastern Kentucky and Ohio has key climate effects because of the complex relationship between elevation and precipitation (Daly et al., 2008). These states also have different patterns of crop production and management practices over time. Given these differences, yields are forecasted to increase less than one bu/ac through 2031.[16] For counties in southern Kansas and Missouri, these effects combine with the adverse impacts of increased temperatures to reduce yields by 2031. Slower forecasted yield growth or potentially negative yield growth is a consequence of slow historic yield growth and lower initial productivity.

Trends for the alternative model depicted in Figure 2.6 are similar to those from the baseline model. At an aggregate level, there are two main features. First, yields for most counties drop by roughly 10 bu/ac, with some exceptions. If we hold acreage constant, total production in 2031 increases less under the alternative model than the baseline model, with potential price and welfare consequences for commodity markets.[17] Second, spatial variability between low- and high-yielding locations increases. The main reason for this is clearly seen in comparisons of Figures A.1-A.2.[18] Intense rainfall in early years

[16]Earlier state-level research found evidence of yield decreases in Kansas through 2031 (McFadden and Miranowski, 2014). Decreasing yields are confirmed here in low-producing counties. To the extent that irrigation or other adaptation technologies become available, the rate of declining yields could lessen or reverse to positive growth.

[17]Holding acreage constant under climate change is a strong assumption. We find significant climate effects on field-level crop-tillage choice combinations and acreage in Chapter 4.

[18]Figure 2.1 illustrates large 2011 yield variation for neighboring counties, though there is comparable variation over sample years. One advantage of our county-specific forecasting procedure is that it reproduces some of this spatial variability. We could impose the restriction of matching yields across state boundaries, but this seems artificial.

has a muted effect on yields in recent years because of discounting in the model dynamics, but sample endpoint heavy rainfall has large effects on short-term forecasts. County maximum July and August temperature dummies also contribute to greater variability, but cross-county variation is smoother and mimics the distribution of county mean temperatures. The net effect is yield growth that is less smooth across counties.

Despite increased uncertainty in the alternative forecasts, Corn Belt counties will continue to see the largest yield increases, with levels at roughly 200-210 bu/ac. The composition of the most productive counties in the Corn Belt changes, but central Iowa, northern Illinois, and eastern Indiana and Ohio remain top-producing regions. Yield growth for the Great Lakes areas of Michigan, Wisconsin, and Minnesota is lower relative to the baseline model. However, the northernmost counties in these three states remain high yielding. This again suggests that avoiding late-season extreme temperatures improves yield growth. Although at similar latitudes, South Dakota and North Dakota have lower yield growth relative to the baseline model. One explanation is that a small number of heavy rainfall events in drought-prone areas may be beneficial in alleviating drought stress. In counties that are less drought-prone, extreme rainfall events contribute to lower yield growth forecasts than the baseline model.

Regardless of corn production model specification, climate model considered, and other robustness measures in Appendix A, we find that yields will increase in all but a few low-yielding counties over the next two decades. This finding is an important contribution to a small but significant group of studies finding *increasing* near-term yields or positive trends despite climate change (Westcott and Jewison, 2013; Xu et al., 2013; Smith et al., 2014). Note that our results are not driven by out-of-sample climate assumptions. Figures 2.7 and 2.8 provide 2031 forecasts using median in-sample weather. The results are qualitatively similar to those in Figures 2.5 and 2.6, though there is a small shift of higher yielding counties toward the Corn Belt. Some counties experience relatively lower yield growth, but forecasting from median weather gives 15-20 bu/ac higher forecasts than those from the climate model output. Thus, increasing near-term yields are forecasted under status quo weather and weather from climate models.

2.5.2 Long-run impacts: climate change and yield productivity growth

Given the short-run influence of climate on yields and yield growth through 2031, we next investigate the claim that productivity growth has responded endogenously to climate. Table 2.2 gives nonlinear least squares estimates relating long differences of climate damages to our measure of in-sample yield productivity growth.[19] The regressors are a long difference of five-year averages (1960-1964 and 2007-2011). Smoothing of the long difference avoids potential bias from outlier weather experienced over one or two years at the sample beginning and endpoints.

The first column of Table 2.2 gives coefficient estimates for the linear and quadratic terms of May, June, July, and August temperatures (conventional damage function). The dependent variable is the difference in 2011 and 1960 intercepts from the baseline DLM. Since these estimates are generated from the short-run regressions, standard errors must be adjusted (Dumont et al., 2005). We follow the empirical literature and bootstrap the standard errors with the number of bootstrap replications equal to the sample size. The bootstrapped standard errors are clustered by crop reporting district (CRD) to account for spatial correlations in climate conditions and soil productivity over small areas.[20] Although all regressors vary at the county level, spatial correlations among regressors at higher levels of aggregation (e.g., CRDs) could contribute to underestimation of standard errors (Kloek, 1981; Moulton, 1986). The differenced dependent variable helps alleviate misspecification bias by eliminating time-invariant factors that could confound a given year's intercept.

For the baseline model evaluated at the sample mean, we find that 1 °C increases in May and June temperatures have reduced productivity growth by 2.4 and 1.0 percentage points. A similar 1 °C increase in July temperature has increased productivity growth by roughly 1.0 percentage points. This suggests that, in long-run equilibrium, (Hicks-neutral) technology has adapted to a changing climate. We do not explore specific

[19]The climate change economics literature finds coefficients with small magnitudes. Using a variety of small starting values, the nonlinear least squares routine converges quickly.

[20]Crop reporting districts are USDA-defined groups of contiguous counties within states that have similar agricultural production characteristics. Many states contain nine CRDs, and there is a total of 105 CRDs in our 14-state sample.

adaptation mechanisms, but there may be several reasons why small changes in temperatures improve yield productivity growth. For example, improvements in technology may capture benefits from minor increases in growing degree days and CO_2 fertilization effects. The estimates indicate small but significant climate effects on yield productivity growth, with 46 percent of variation explained by climate and soil controls.

The second column of Table 2.2 reports estimates from the alternative DLM. This is a useful robustness check of the first column results. Since the dependent variable is the result of regressions involving *extreme* climate variables, it is less likely to be correlated with *average* climate variables. This reduces the potential for spurious significance. Evaluated at the sample mean, we find that a 1 °C increase in May temperature reduces productivity growth by 5.5 percentage points, while a 1 °C increase in June temperature increases productivity growth by 5.4 percentage points. The sign switch of the marginal effect of June temperatures from baseline (-1.0 percentage point) to alternative (5.4 percentage points) is driven by the sign switch in the linear June temperature term (-0.007). The reduction in fit, $R^2 = 0.14$, implies that the alternative DLM explains productivity growth less adequately.

The last two columns of Table 2.2 list estimates for the second damage function specification. Coefficient estimates closely approximate marginal effects since there are no quadratic terms. An additional 10 years in which July maximum temperatures exceed 85 °F decrease productivity growth by 10.7 percentage points. Intense precipitation has a similar but smaller influence. A one percentage point increase in the proportion of days in May or August not receiving at least one inch of rain increases productivity growth by about 0.5% and 0.3%. Finally, the R^2 of 0.36 indicates that climate extremes are useful for explaining productivity growth from production functions using average weather.

Turning to the alternative model in the last column, we find that R^2 decreases to 0.15, similar to the R^2 from our other model using the alternative DLM intercepts (second column). Yield productivity growth from a model of production based on weather extremes is more difficult to explain in the long run. Given the increasing variability (or occurrence) of weather extremes, this result is not surprising. Identifying the impacts of infrequent but damaging climate events continues to be a challenge in the empirical literature. The damaging impacts of intense precipitation, though, are robust to the choice of dependent variable. A one percentage point increase in the fraction of days in May and August not experiencing an inch or more of rain increases productivity growth by 0.9% and 0.8%.

The soil productivity variables are generally significant at the 5% and 1% levels and have the expected signs. Counties with steeper slopes and higher percentages of eroded soils have seen smaller productivity gains. Root zone available water storage has a small but positive effect. The links between soils, climate, and productivity growth are less definitive. Landowners may be able to alter some soil characteristics over time in response to changing climate such as organic matter content, drainage, erosion potential, and compaction through improved land management such as cover crops. Other innovative land management practices such as drainage management, bioreactors, and no-till production (see Chapter 4) may help maintain soil health and moisture.

2.5.3 Implications

Why has there been a significant link between yield productivity growth and climate change in the twentieth century? Conventional breeding has not directly targeted phenotypic changes that can better handle climate change. Rather, there have been sequences of new varieties with increased overall stress resistance (Duvick, 1984; Crosbie et al., 2006; Smith et al., 2014). Morphological changes in root and stalk lodging, barrenness, tassel size, leaf angle, and staygreen as a result of breeding have decreased susceptibility to moderate climate change. For example, hardier root systems permit more effective water and nutrient uptake especially during dry conditions; increased staygreen may extend beneficial photosynthesis during periods of greater solar radiation; and insects may be more vulnerable to Bt traits under variable weather conditions. Our results are also consistent with increased drought tolerance for corn and soybeans prior to initiatives to develop drought-tolerant seeds (Yu and Babcock, 2010). This suggests that advances in new varieties, combined with improved crop management practices, will aid agricultural adjustment to less advantageous weather.

Improvements in farm machinery, irrigation, and other capital equipment have brought about labor-saving technical change. The advent of personal computers, the internet, and other information technologies has aided crop management through monitoring, variable application rates, and more precise practices. Extensive genetic modification has boosted yields and created substitution opportunities away from labor, capital, and pesticides (Fernandez-Cornejo et al., 2014; Huffman, 2014).

Representing technical change as augmenting a single factor or small set of factors is therefore too simplistic. Our assumption of disembodied, unbiased technical change is also simplistic but provides tractability in production settings that evolve rapidly over time. Evidence against induced innovation in agriculture supports our decision to omit factor prices in the production function estimation (Liu and Shumway, 2009). The release of drought-tolerant varieties, ongoing development of resistance to salinity and frost, and onset of private firms offering climate-based information technologies and risk management ensure that yield productivity growth in the near future will be multifaceted (McFadden and Miranowski, 2015). Our emphasis on total factor productivity, rather than multifactor productivity or biased technical change, is thus conservative. The short-run forecasts to 2031 will differ from realized yields, but our evidence that yield productivity growth has responded (adapted) to long-run climate is robust and likely to hold in coming years.

Inference from both the short-run and long-run claims show that yields remain sensitive to extreme heat and precipitation rates, but damages can be partially mitigated through targeted research and development (R&D). Improvements in drought-tolerant seeds will play a larger role in helping farmers adapt to persistently hot and dry conditions. Our results are the first to point out that increasingly intense rainfall events will have generally damaging effects on yields. There is also a role for improved management technologies (e.g., cover crops and no-till production) to improve soil health and help reduce climate-induced nutrient and soil losses.

2.6 Conclusion

Climate change poses serious risks to national and global agriculture, food, and feedstock security. Policymakers, consumers, and firms will increasingly consider assessments of climate change impacts to assist decision making. The research tests two general hypotheses, one related to short-run impacts and the other concerning long-run impacts: (i). relative to 2011 yields, corn yields will decline under climate change during 2012-2031, and (ii). climate change damages have had adverse historical effects on yield productivity growth. Using data on 770 non-irrigated counties, the econometric evidence rejects both hypotheses. Under mild (or moderate) climate change, 2031 yields will increase by 10%-40% over 2011 yields, though there are a few outlier counties with greater increases (and possibly decreases) in yields. Assuming 2012 harvested acreage, 2031 corn production under the baseline model in these 770 counties is 12.8 bil bushels, 19% larger than 2012 total US production of 10.8 bil bushels. The evolution of yield productivity growth is addressed by the long-run estimates. Average climate change has had small but significant influences on yield productivity growth. Growth through 2031 is reduced when accounting for weather extremes, particularly early- and late-season intense precipitation.

Our estimates of yield productivity growth compare favorably to related studies. Of particular interest is comparability of our estimates with those of the agriculture sector in Jin and Jorgenson (2010). Using similar techniques, we find that Hicks-neutral yield productivity growth has been 0.48, similar to their rate of autonomous technical change in agriculture of roughly 0.55. Our average forecasted growth of 10%-40% is also consistent with their 0.3 rate of autonomous technical change forecasted for 2006-2030. Dell et al. (2012) find that a 1 °C temperature increase in poor countries reduces economic growth by an average of 1.3 percentage points in a given year. This is a much larger annual effect compared to our findings over the 1960-2011 horizon. However, there is general agreement that climate change can impact growth rates, implying long-run economic consequences in several industries. Thus, our results and forecasts add to (and compare favorably with) a growing literature considering links between climate and technical change.

In the absence of market frictions, crop production should shift to regions of highest comparative advantage. Our baseline results indicate that Corn Belt counties will continue to grow the majority of the nation's corn supply over the next two decades, despite increasing climate risk. Yields in Great Lakes counties will increase somewhat more than those of Plains counties. Over the next 30-50 years, higher-latitude regions will become warmer and experience more variable rainfall and temperatures, but yield productivity growth is expected to partially offset these negative effects.

Even with adverse weather, farmers will continue to maximize expected net returns (see chapter 4). Under moderate climate change, this will entail optimal adjustments along the intensive and extensive margins. For example, farmers will alter planting times and the timing and volume of chemical and nutrient applications. Rainfed farms in frequently drought-stressed regions will adopt drought-tolerant seeds, consistent with the economics of technology adoption (Griliches, 1957; Zilberman et al., 2012). Over the longer term, farmers will begin to plant crops that are more suited to the altered environment (Olmstead and Rhode, 2011; Hornbeck and Keskin, 2014).

The distribution of climate change impacts over the coming decades remains uncertain, especially in determining the impacts of average and extreme weather variables. The payoff to additional research on such impacts and their magnitudes should be high. This research would provide information and knowledge-base for adapting production technologies and management systems to the changing climate. Such information and knowledge can drive adaptation strategies in modern plant breeding and genetic modification, aid the development of climate-based risk management tools, advance precision agriculture, and improve climate forecasts and real-time information. Additional research, combined with effective management practices, may be able to offset adverse climate drag on yields by 2031.

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Table 2.1: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
Yield	40,040	102.93	35.54	9.00	207.00
In-Sample Weather					
May Temp (°C)	40,040	15.89	2.53	7.85	24.33
Jun Temp (°C)	40,040	20.98	2.02	13.28	27.85
Jul Temp (°C)	40,040	23.32	1.94	16.20	31.37
Aug Temp (°C)	40,040	22.29	2.08	15.19	30.23
Jul 85 (0-1)	40,040	0.52	0.50	0	1
Aug 85 (0-1)	40,040	0.34	0.47	0	1
May Prec (cm)	40,040	10.36	5.18	0.10	38.50
Jun Prec (cm)	40,040	10.57	5.21	0.38	45.75
Jul Prec (cm)	40,040	9.99	5.20	0.13	63.79
Aug Prec (cm)	40,040	9.05	4.91	0.01	47.57
May Int Prec (%)	40,040	0.98	0.03	0.77	1.00
Jun Int Prec (%)	40,040	0.97	0.03	0.77	1.00
Jul Int Prec (%)	40,040	0.98	0.03	0.65	1.00
Aug Int Prec (%)	40,040	0.98	0.03	0.77	1.00
Out-of-Sample Weather					
May Temp (°C)	15,400	17.60	1.85	11.56	23.34
Jun Temp (°C)	15,400	22.53	1.84	16.38	27.61
Jul Temp (°C)	15,400	25.43	1.71	20.20	30.82
Aug Temp (°C)	15,400	24.45	1.78	18.94	29.94
Jul 85 (0-1)	15,400	0.92	0.27	0	1
Aug 85 (0-1)	15,400	0.81	0.39	0	1
May Prec (cm)	15,400	10.29	2.48	3.60	19.66
Jun Prec (cm)	15,400	10.71	2.64	3.81	21.11
Jul Prec (cm)	15,400	10.01	2.48	3.70	18.76
Aug Prec (cm)	15,400	8.32	2.22	2.22	17.87
Soils Controls					
Eros Ind (0-1)	770	0.15	0.18	0.00	0.83
Slope Gradient (%)	770	2.64	2.23	0.08	15.24
T Factor (tons/ac/yr)	770	1.80	1.09	0.11	4.86
NCCPI CS (%)	770	0.53	0.17	0.02	0.90
Root Zone AWS (mm)	770	206.75	49.02	12.59	338.20

Yield data for 1960-2011 are from NASS. In-sample weather data are from PRISM AN81m and the CPC Unified Gauge-based Analysis. Out-of-Sample weather data are averages of downscaled climate model data from NEX-DCP30. Soil controls are from SSURGO. See text for details.

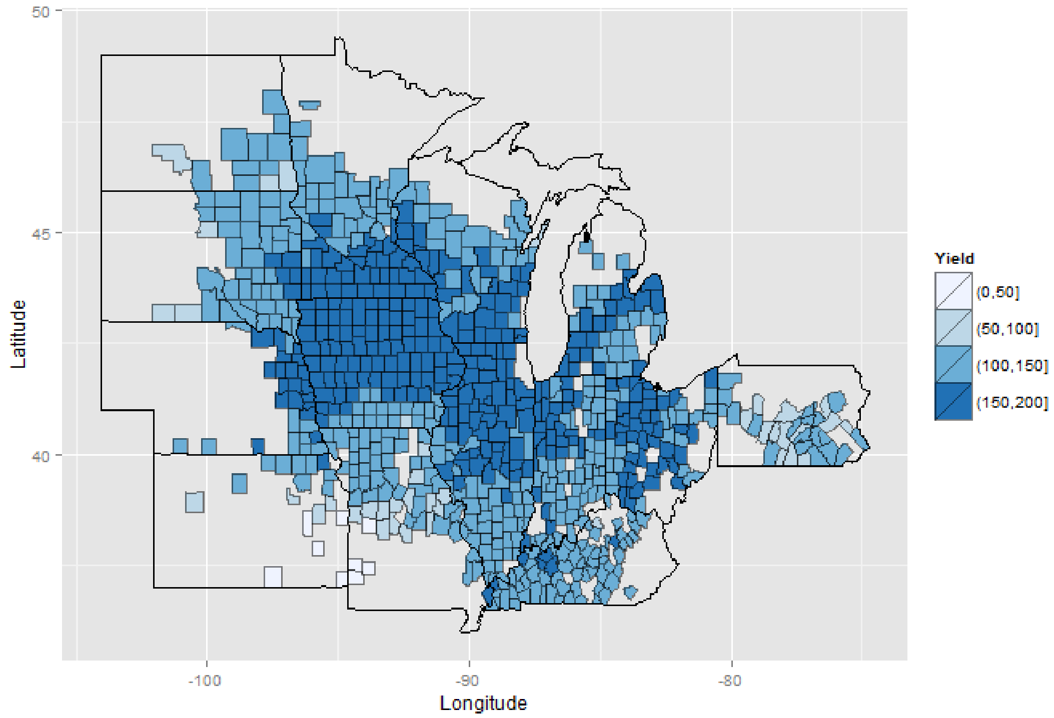

Figure 2.1: Sample Counties and 2011 Corn Yields (bu/ac)

Yield data for 1960-2011 are from NASS. Included counties satisfy three criteria: (i). have complete data record in 1960-2011, (ii). are non-irrigated, and (iii). belong to a state with 1% or more of national production in 2009-2011.

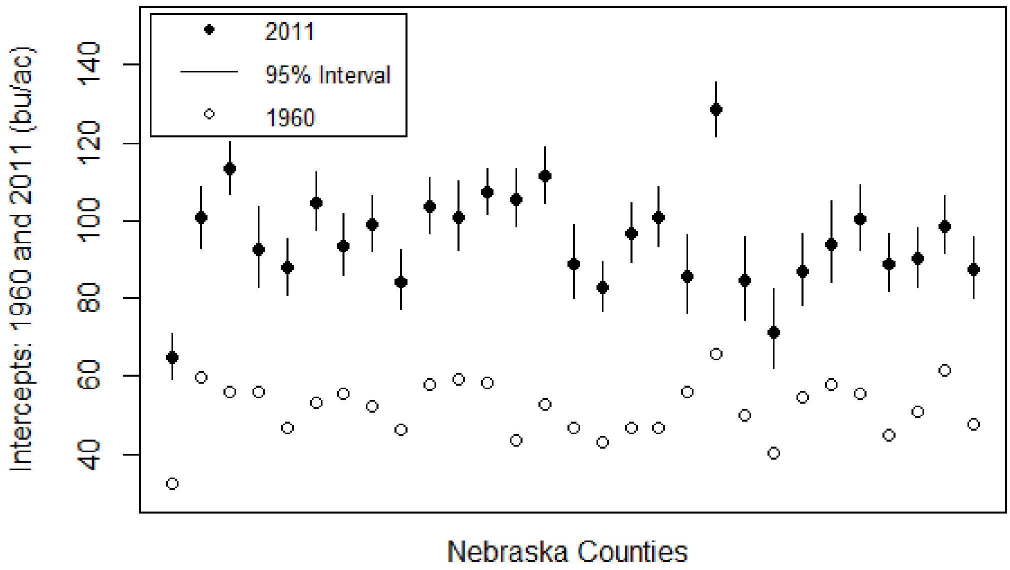

Figure 2.2: Technical Change in Nebraska Yields, Baseline Model, 1960-2011

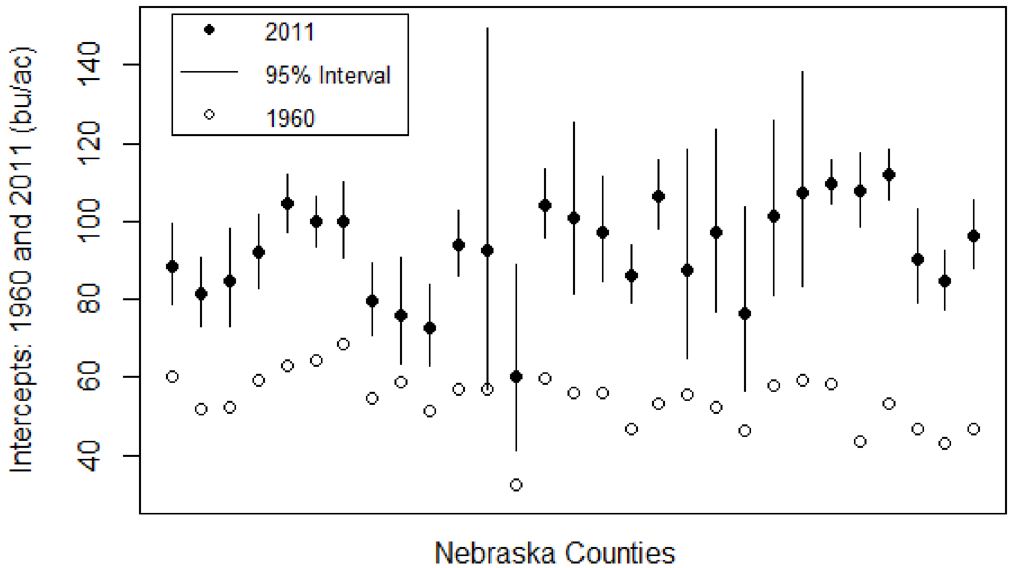

Figure 2.3: Technical Change in Nebraska Yields, Alternative Model, 1960-2011

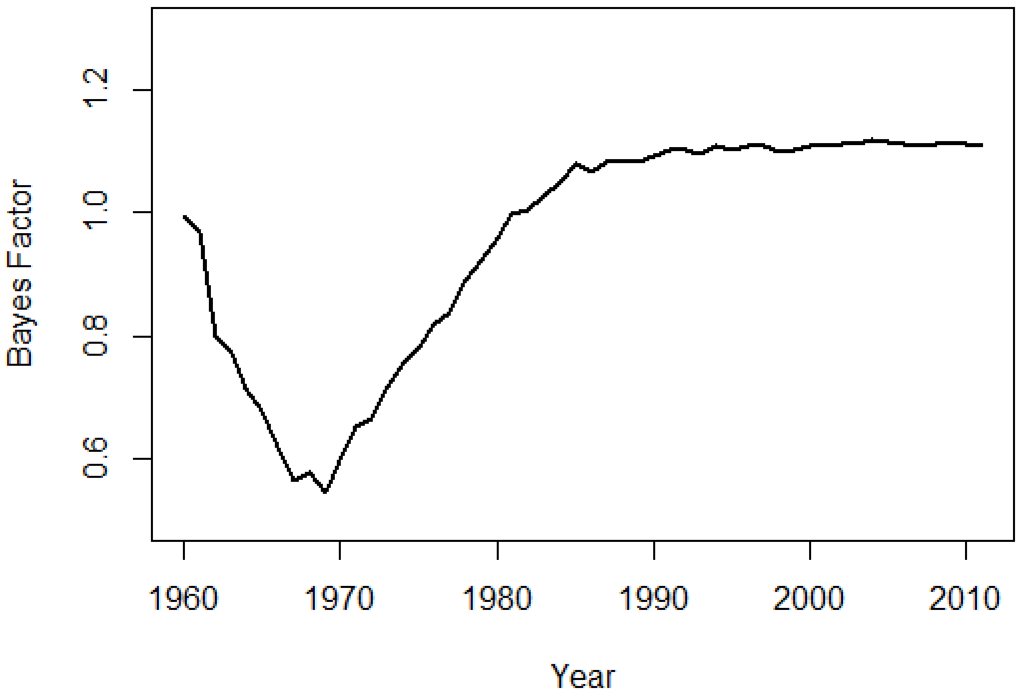

Figure 2.4: Bayes Factor: Baseline vs. Alternative Model

Time plot of the ratio of marginal likelihoods (baseline model/alternative model).

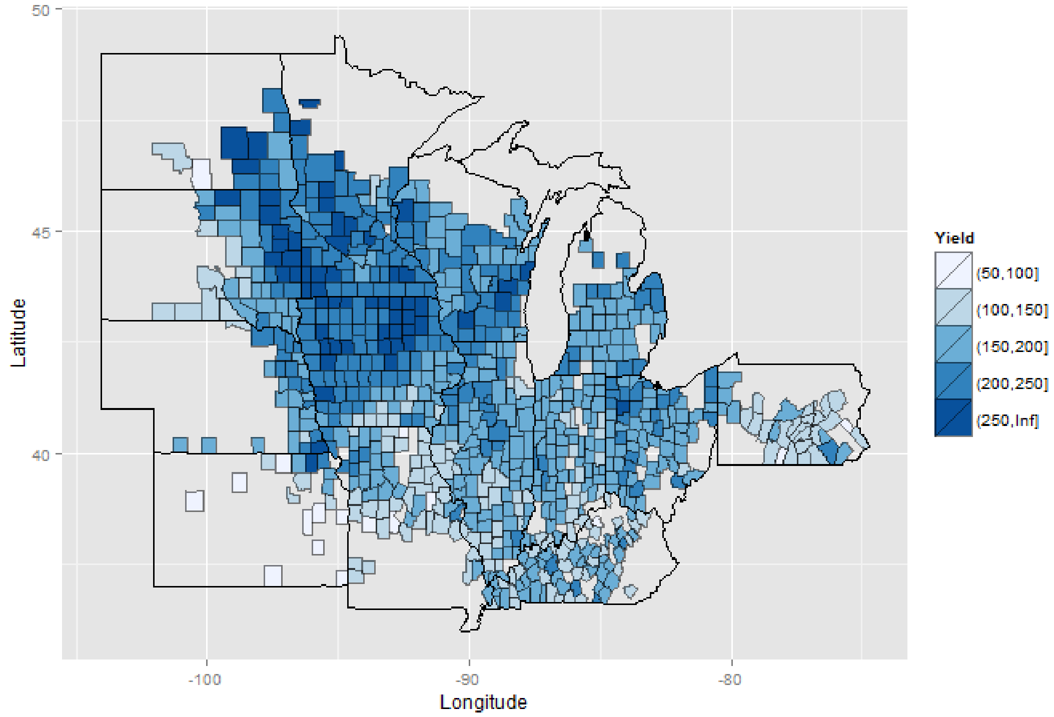

Figure 2.5: 2031 Corn Yields (bu/ac) for Baseline Model

Out-of-sample 2031 forecast means from the baseline model.

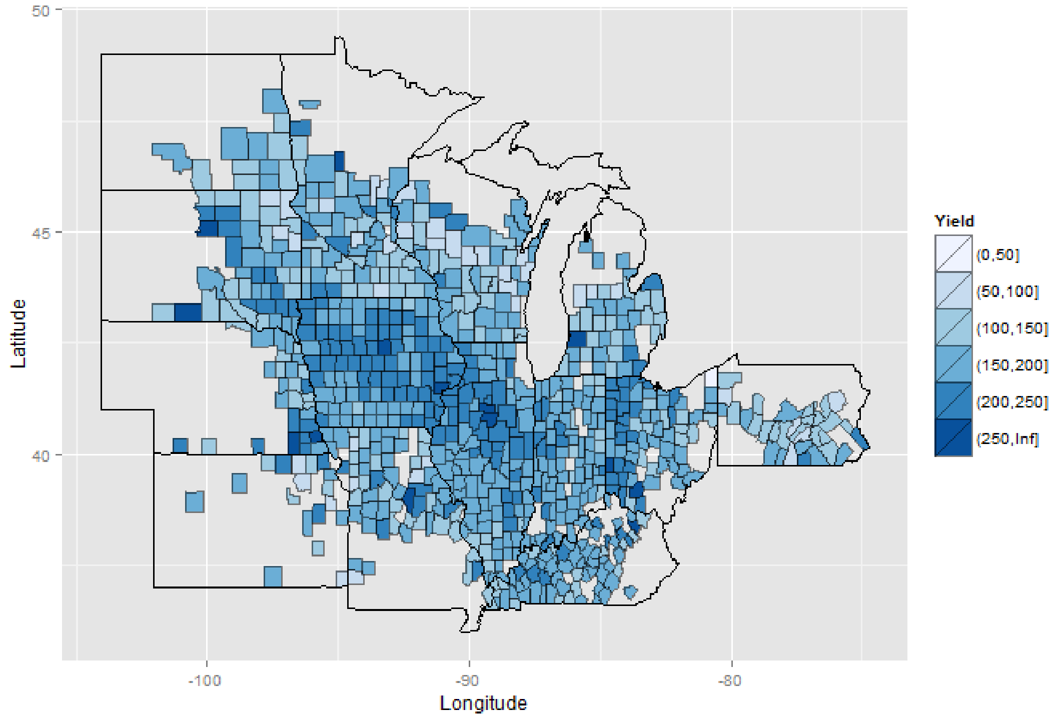

Figure 2.6: 2031 Corn Yields (bu/ac) for Alternative Model

Out-of-sample 2031 forecast means from the alternative model.

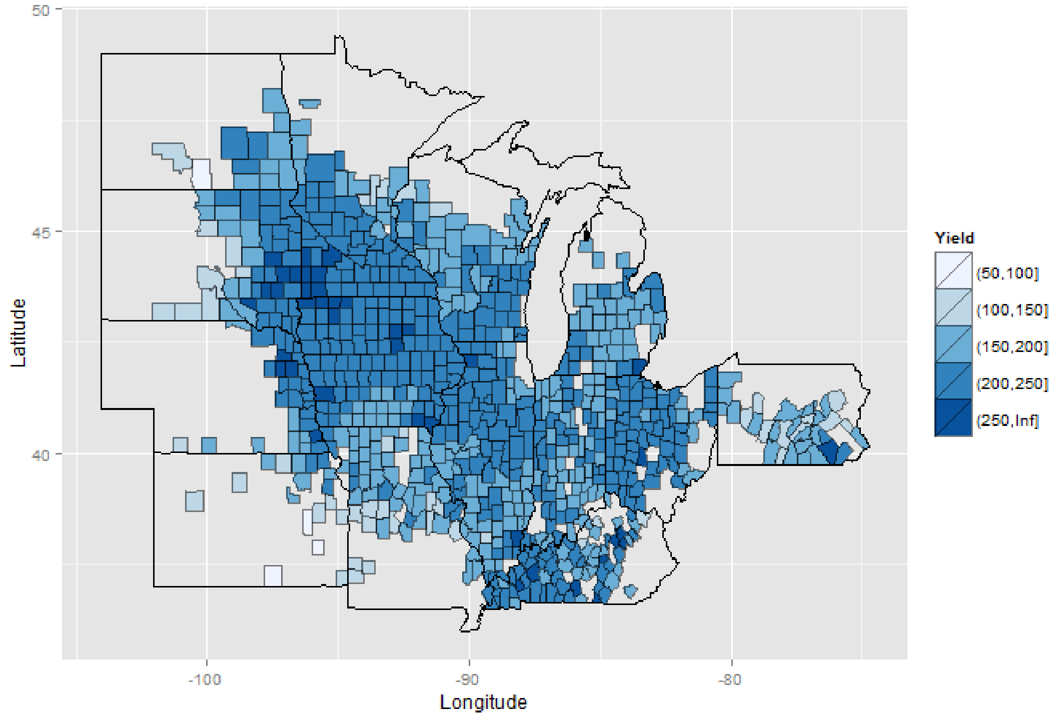

Figure 2.7: 2031 Corn Yields (bu/ac) for Baseline Model at Median Weather

Out-of-sample 2031 baseline forecast means using in-sample median weather.

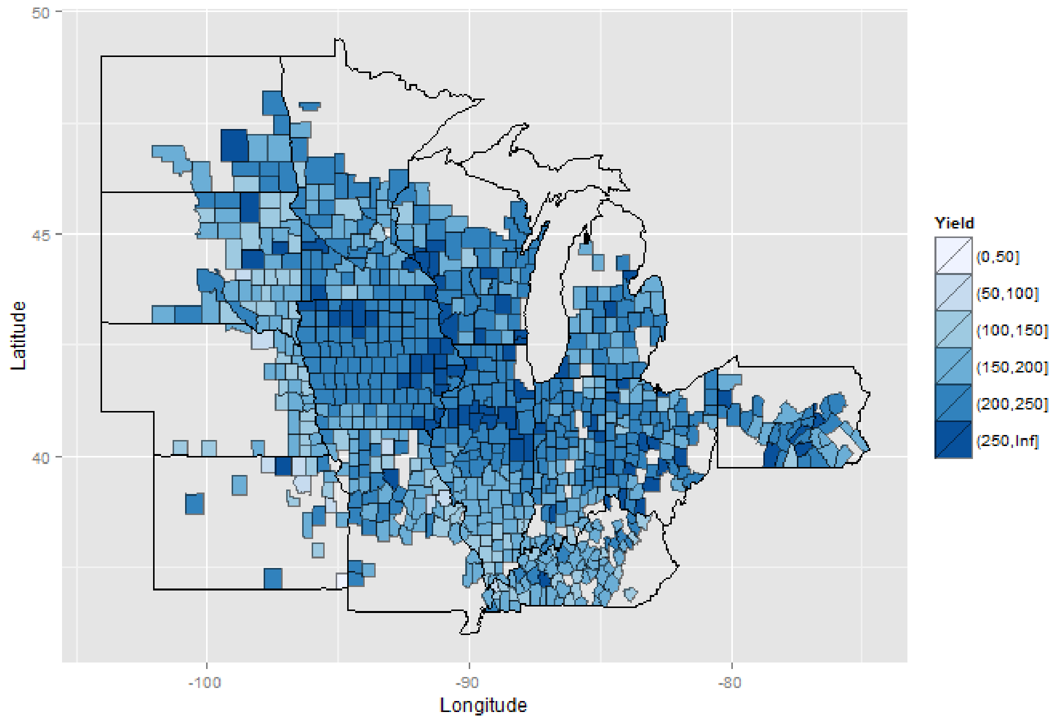

Figure 2.8: 2031 Corn Yields (bu/ac) for Alternative Model at Median Weather

Out-of-sample 2031 alternative forecast means using in-sample median weather.

Table 2.2: Long-Run Technical Change in Yields and Climate

Regressors	Baseline	Alternative	Baseline	Alternative
Constant	-0.48^{***}	-0.52^{***}	-0.46^{***}	-0.52^{***}
	(0.04)	(0.04)	(0.04)	(0.03)
Δ May Temp	0.02	0.06^{***}	–	–
	(0.02)	(0.02)	–	–
Δ May Temp^2	-0.004	0.02	–	–
	(0.02)	(0.02)	–	–
Δ Jun Temp	0.09^{***}	-0.007	–	–
	(0.03)	(0.03)	–	–
Δ Jun Temp^2	-0.07^{***}	-0.04^{**}	–	–
	(0.02)	(0.02)	–	–
Δ Jul Temp	-0.04	-0.02	–	–
	(0.06)	(0.04)	–	–
Δ Jul Temp^2	0.08	0.06	–	–
	(0.06)	(0.05)	–	–
Δ Aug Temp	0.04	0.04	–	–
	(0.04)	(0.03)	–	–
Δ Aug Temp^2	-0.02	-0.01	–	–
	(0.03)	(0.02)	–	–
Δ Jul 85	–	–	0.11^{***}	0.01
	–	–	(0.02)	(0.03)
Δ Aug 85	–	–	0.03	0.13^{***}
	–	–	(0.03)	(0.03)
Δ May Int Prec	–	–	-0.53	-0.89^{***}
	–	–	(0.40)	(0.33)
Δ Jun Int Prec	–	–	-0.08	-0.04
	–	–	(0.32)	(0.30)
Δ Jul Int Prec	–	–	-0.16	0.04
	–	–	(0.39)	(0.36)
Δ Aug Int Prec	–	–	-0.31	-0.85^{***}
	–	–	(0.37)	(0.31)
Obs.	770	770	770	770
Soil Controls	Yes	Yes	Yes	Yes
R^2	0.46	0.14	0.36	0.15

The first two columns give results for the conventional damage function, while the last two columns are results for the second damage function. "Baseline" refers to technical change for the baseline model's coefficients. "Alternative" refers to technical change for the alternative model's coefficients. Bootstrap standard errors are clustered by CRD (in parentheses). $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

APPENDIX A. FORECAST EVALUATION AND ROBUSTNESS

A.1 Summary data and forecast evaluation

Table A.1 reports descriptive statistics for the climate variables used as regressors in the long run analysis (except intense rainfall events, reported here as the difference of averaged integer events). For each row, the variable is constructed to be the 2007-2011 average minus the 1960-1964 average, where smoothing reduces bias from outlier years. Average May temperature has declined by one-quarter of one degree Celsius, though June and August temperatures have risen by a little over one-half degree. There is also variation in July and August months with average maximum temperatures above 85 °F but has small average impacts.

Accompanying a moderate change in early-season temperatures has been a relatively large increase in early-season precipitation. May and June precipitation have risen by 1.80 and 4.17 cm, while late-season increases have been modest. This is further reflected in intense rainfall trends. The increase in extreme rainfall is concentrated in June, which has experienced almost one additional day of intense rainfall over the 52-year period. However, intensification of average precipitation has occurred in all growing season months but with important regional variability. Spatial variation in late-season precipitation, for example July 2011, is depicted in Figures A.1 and A.2. Average July rainfall is spatially smoother than intense rainfall, especially in the Dakotas, Pennsylvania, and Kentucky. Eastern regions of North and South Dakota have spatially uniform average rainfall but not intense events. This discrepancy in intense rainfall among neighboring counties, combined with the late-season intense heat dummies, contributes to less smooth forecasts from the alternative specification. However, there is some overlap between average and intense precipitation within counties. Correlations among May, June, July,

Table A.1: Differences of Averaged Weather (N = 770)

Variable	Mean	St. Dev.	Min	Max
May Temp (°C)	−0.23	0.62	−1.92	1.13
Jun Temp (°C)	0.59	0.75	−1.57	2.25
Jul Temp (°C)	0.22	0.36	−0.81	1.23
Aug Temp (°C)	0.51	0.54	−1.18	1.85
Jul 85 (0-1)	−0.07	0.21	−0.60	0.60
Aug 85 (0-1)	−0.06	0.20	−0.60	0.60
May Prec (cm)	1.80	2.91	−7.53	10.31
Jun Prec (cm)	4.17	3.47	−5.89	15.10
Jul Prec (cm)	0.53	2.60	−7.71	7.90
Aug Prec (cm)	1.17	2.89	−5.86	10.37
May Int Event (integer)	0.22	0.53	−1.40	1.80
Jun Int Event (integer)	0.59	0.63	−1.00	2.80
Jul Int Event (integer)	0.23	0.59	−1.60	2.00
Aug Int Event (integer)	0.21	0.53	−1.20	2.40

Table A.2: Mean Absolute Deviations, 2012-2014

Model	2012	2013	2014	Grand Mean
Baseline (bu/ac)	49	20	26	32
Alternative (bu/ac)	46	26	33	35
Sample size (N)	745	708	708	–

and August 2011 average and intense precipitation are 0.69, 0.82, 0.75, and 0.72. These correlations are similar in magnitude across sample years. Average weather is a poor substitute for extreme weather, but strong correlations imply that there could be imprecise estimates from models with both sets of precipitation variables due to multicollinearity (e.g., Figure A.5 below).

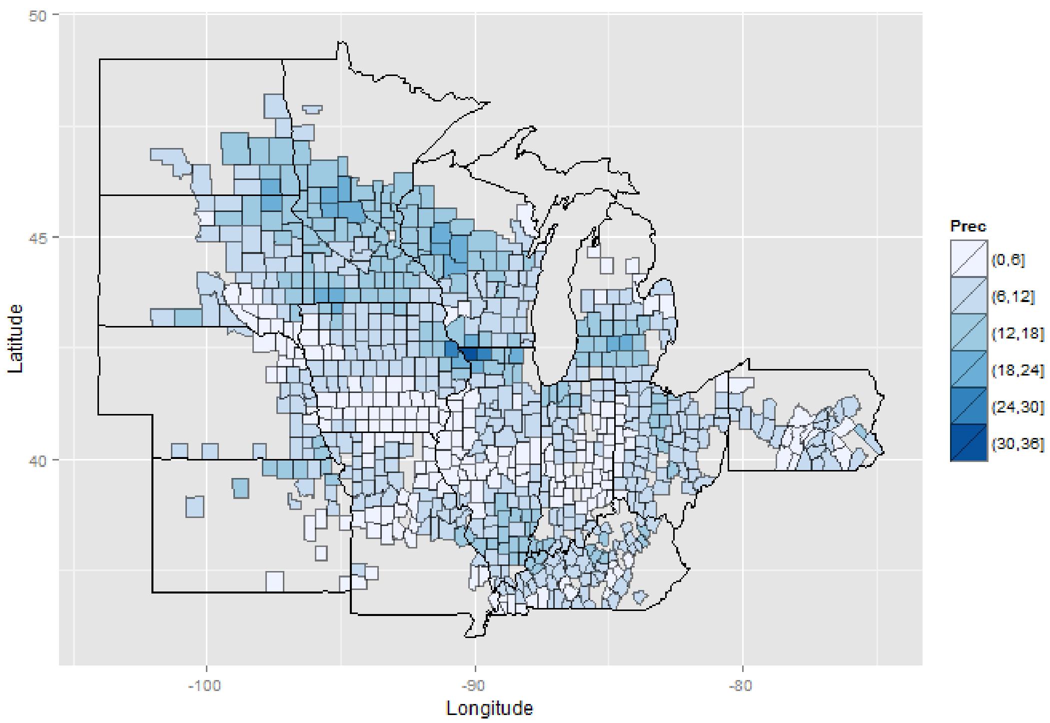

Figure A.1: July 2011 Average Precipitation

As a final check, we perform out-of-sample forecast assessment in Table A.2 using a mean absolute deviation (MAD) criterion. The absolute value of the difference in forecasts and realized yields across both model specifications for years 2012-14 is averaged over sample counties. Yield data are not available for 25, 62, and 62 separate counties in the three years. The models have similar results, but the baseline specification gives somewhat more accurate predictions with an average MAD of 32 bu/ac. The alternative model, which accounts for extreme weather, performed slightly better in a drought year with extreme heat and little rainfall (2012). With improved growing conditions (more optimal weather) in 2013, there is an improvement in forecast accuracy and a preference for the baseline model. The baseline preference continues into 2014.

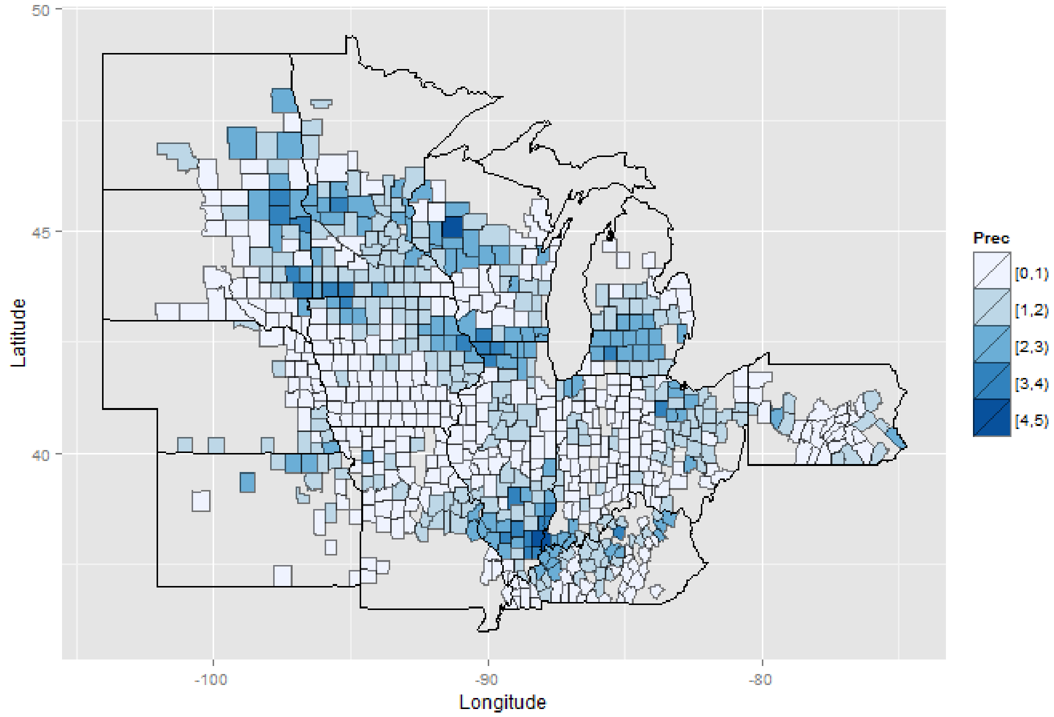

Figure A.2: July 2011 Intense Precipitation Events

A.2 Forecast robustness

Figures A.3-A.9 present variations of the regression specification for the baseline and alternative models. We consider the possibility that yields are influenced by: (i). a linear time trend, (ii). the baseline model with temperature-precipitation interactions, (iii). both sets of baseline and alternative weather variables, (iv). an additional linear trend beginning in 1996 (the commercialization of glyphosate-tolerant corn), (v). two-inch daily precipitation instead of one-inch daily precipitation, and (vi). average and extreme GDD and precipitation. These are useful robustness checks and lend comparability with other studies.

A.2.1 Regression specification

Figure A.3 answers the question of how yields would evolve by 2031 without weather shocks. This reflects some breeders' viewpoint that short-run weather fluctuations do not alter long-run genetic gain. Although this is a simplistic representation of yield-weather dynamics, the linear trend extrapolation provides a useful benchmark for forecast comparison. We find that the majority of counties will realize yields of 200-250 bu/ac in 2031, with the highest-yielding counties in the traditional Corn Belt. This agrees with the linear trend forecasts in Miranowski et al. (2011). In the absence of weather inputs, there are uniformly high yields (150-250 bu/ac) with very few outlying counties. This suggests that technologies designed to offset adverse climate impacts would be valuable measured in real terms.

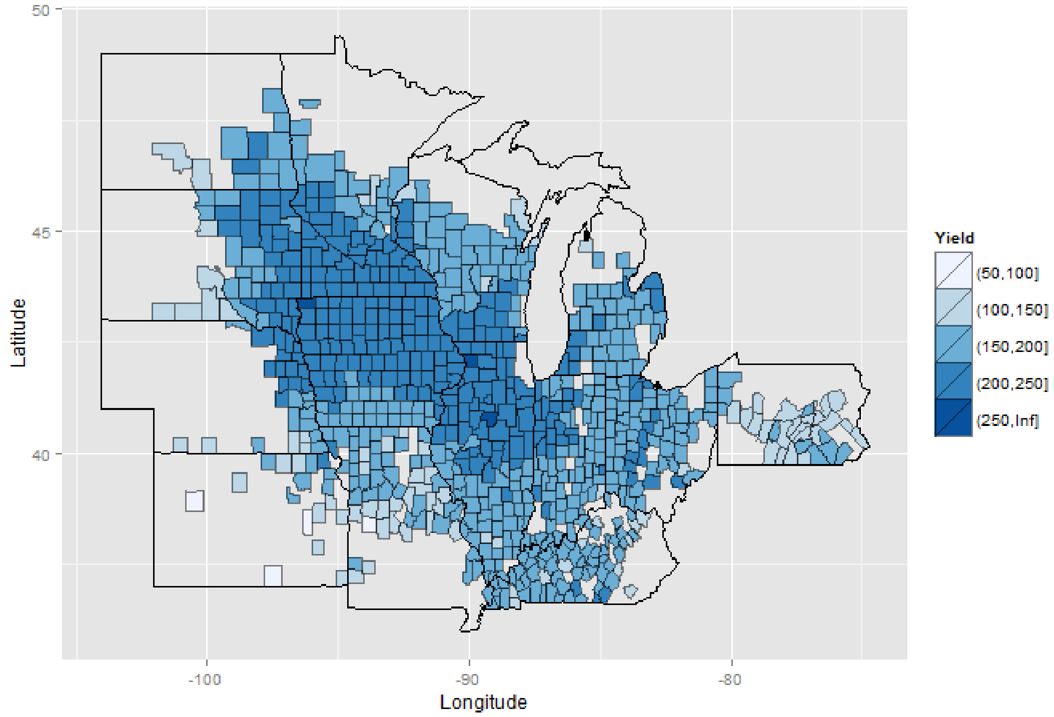

Figure A.3: 2031 Corn Yields (bu/ac) with Only Linear Trend

There are several other specifications designed to examine the impacts of weather on yields. Among them is a model imposing that the marginal productivities of temperature are affected by precipitation, and conversely. This is consistent with the agronomy literature's emphasis of limiting factors in corn production, e.g., the marginal productivity of water differs according to the presence and magnitude of heat stress. Though there are small within-month correlations of temperature and precipitation, Figure A.4 illustrates forecasts that are similar to our preferred baseline results.[1] The Corn Belt remains highly productive, with several northern counties experiencing the highest yields. These are plausible forecasts assuming that relatively cool temperatures continue to complement abundant rainfall.

One interpretation of our two specifications is that they arise as special cases of a more general model that includes both sets of weather inputs. By using the union of regressors, our Bayesian dynamic model updates (estimates) 16 regression coefficients for each county in each year. This is disadvantageous because of multicollinearity among average and extreme weather measures and fewer degrees of freedom. Figure A.5 shows the poor forecasting results. There is much local variability, and spatial patterns are inconsistent with historical data. Although it is useful to fit nested models that facilitate use of standard testing procedures (e.g., through calculation of usual F statistics), the inadequate model performance validates our preference for the two nonnested specifications.

Another common viewpoint holds that biotechnologies have brought about fundamental changes to the nature of corn production. Higher yields are more likely in the

[1]Using the cross-section variation, there are only 12, 3, 6, and 3 years out of the 52-year sample in which the May, June, July, and August average temperature-precipitation correlations exceed 0.5 in absolute value. These correlations are generally much smaller using time-series variation. For example, correlations for Story County, Iowa are -0.13, -0.21, -0.23, and 0.03 across the four growing season months.

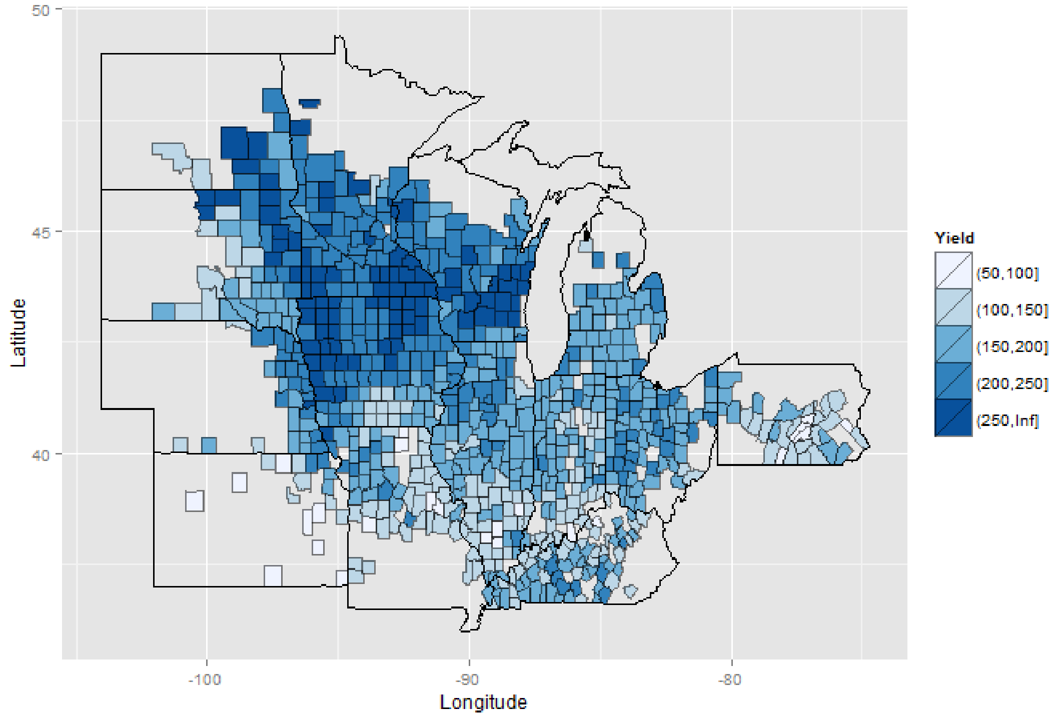

Figure A.4: 2031 Baseline Corn Yields (bu/ac) with Temp/Prec Interaction

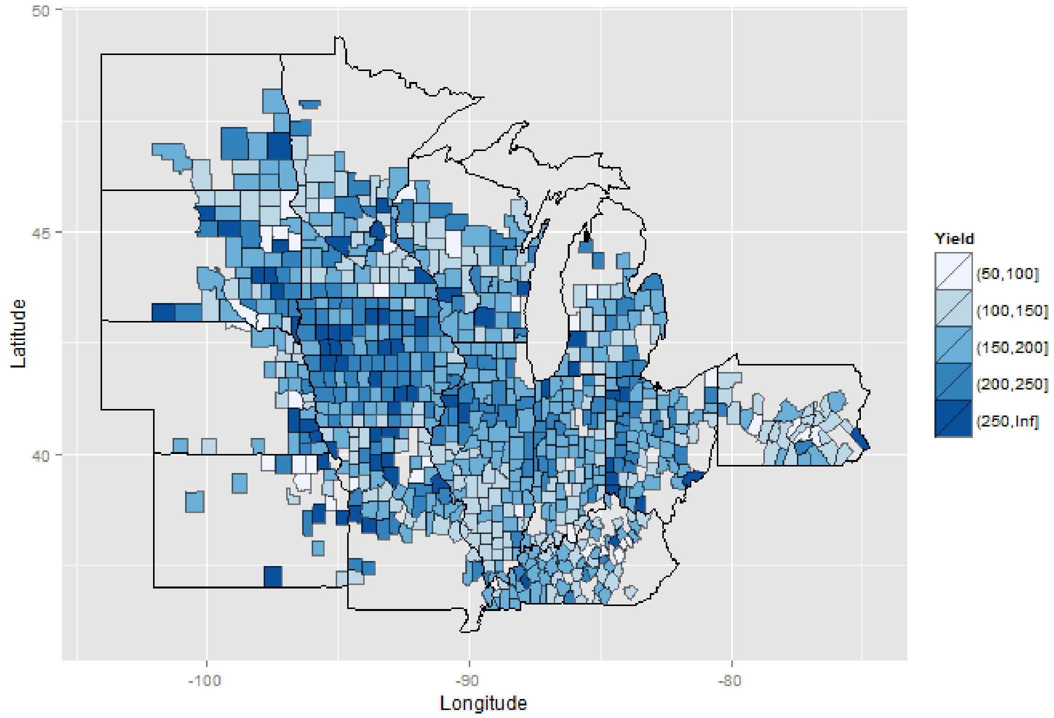

Figure A.5: 2031 Corn Yields (bu/ac), Union of Baseline and Alternative

near term because of reduced susceptibility to several stresses (Nolan and Santos, 2012; McFadden and Miranowski, 2015). A strong version of this hypothesis is that biotechnologies have caused a transformation of the yield distribution from one that is symmetric and thick-tailed to another that has more negative skew and smaller variance. Although we do not attempt to test a distributional change, our dynamic model is more suited to addressing the issue of mean and variance shifts over time than past studies.

Figures A.6 and A.7 present the baseline and alternative 2031 forecasts that include an additional indicator variable that equals one in all years past 1995. This proxies for a linear yield bump due to biotechnologies sustained beyond the commercial introduction of Bt (*Bacillus thuringiensis*) corn in 1996. We find that our main results are robust: forecasts differ somewhat quantitatively, but the most and least productive counties and associated yields are similar. Interestingly, our forecasts replicate a biotechnology yield gain. The average baseline 2031 yield forecast is 2.8 bu/ac higher with the 1996 trend, while the average alternative 2031 yield forecast is 5.2 bu/ac higher with the same trend. These are within the [0.9, 13.8] bu/ac range estimated by Nolan and Santos (2012) using 1997-2009 data.

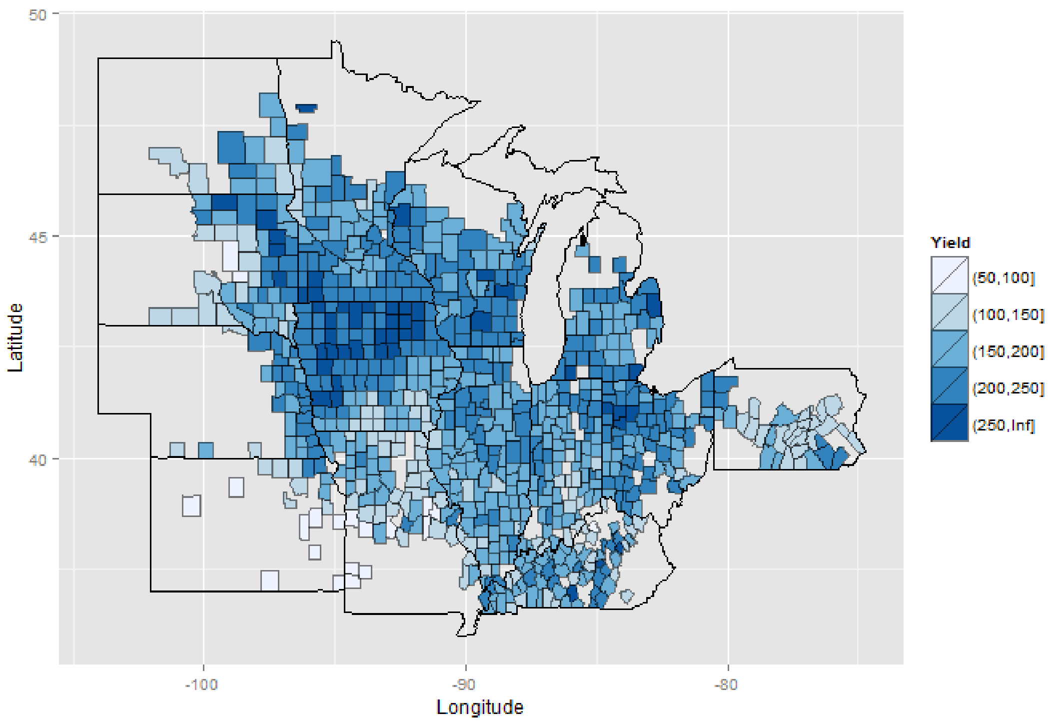

Figure A.6: 2031 Baseline Corn Yields (bu/ac) with 1996 Trend

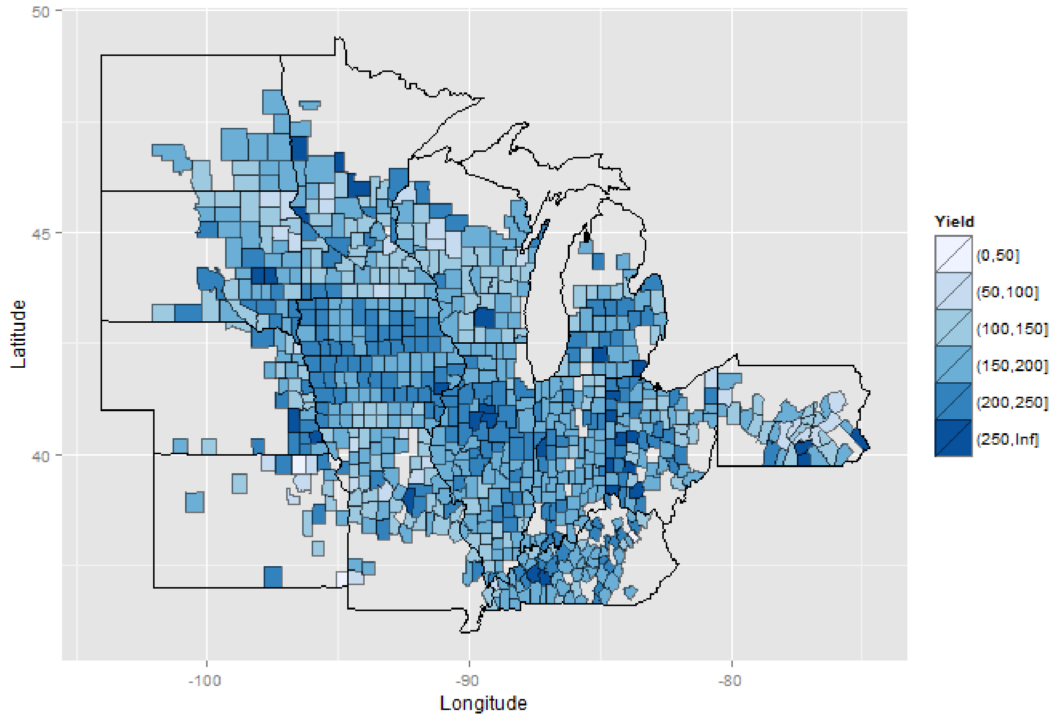

Figure A.7: 2031 Alternative Corn Yields (bu/ac) with 1996 Trend

The precise definition of intense rainfall in climatology and agricultural meteorology is still subject to debate. Certain studies use the 99th (or higher) percentiles of empirical rainfall distributions, while others use hourly thresholds or one- to four-inch daily thresholds (Groisman et al., 2012; Daniel, 2015). As a check of sensitivity to the one-inch daily rainfall regressors, we re-estimate the alternative model using two-inch daily rainfall events. Since there are 140 counties (18% of sample counties) that do not receive two inches of 24-hour rainfall during the growing season in 1960-2011, we use two-way fixed effects panel estimation to account for multiple zeroes (see Section A.2.4).

Figure A.8 illustrates that the alternative model forecasts are robust to using two-inch daily rainfall events. As expected, there are few differences between these forecasts and those in Figure A.19, partially resulting from the fixed effects estimation. The negative impacts of intense precipitation are small relative to the positive (and increasing) time effects. Even though two-inch daily precipitation is rarer than one-inch daily precipitation, the forecasts remain relatively unchanged from Figure A.19 because of similar regression effects.

A final check on specification concerns the use of growing degree days (GDD) and extreme degree days (EDD). Despite their relatively ad hoc formulation and weak relationship to climate model output, agronomists and agricultural economists have consistently found significant contributions to yield (Schlenker et al., 2006; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Roberts et al., 2013; Ortiz-Bobea and Just, 2013). We use county data on monthly GDD in the 8-32 °C interval and monthly GDD over 34 °C as proxies for extreme heat (Schlenker et al., 2006; Schlenker and Roberts, 2009). In addition to the intercept, time trend, and these eight weather regressors, we add the four monthly average precipitation variables. For more similarity to past studies, the model

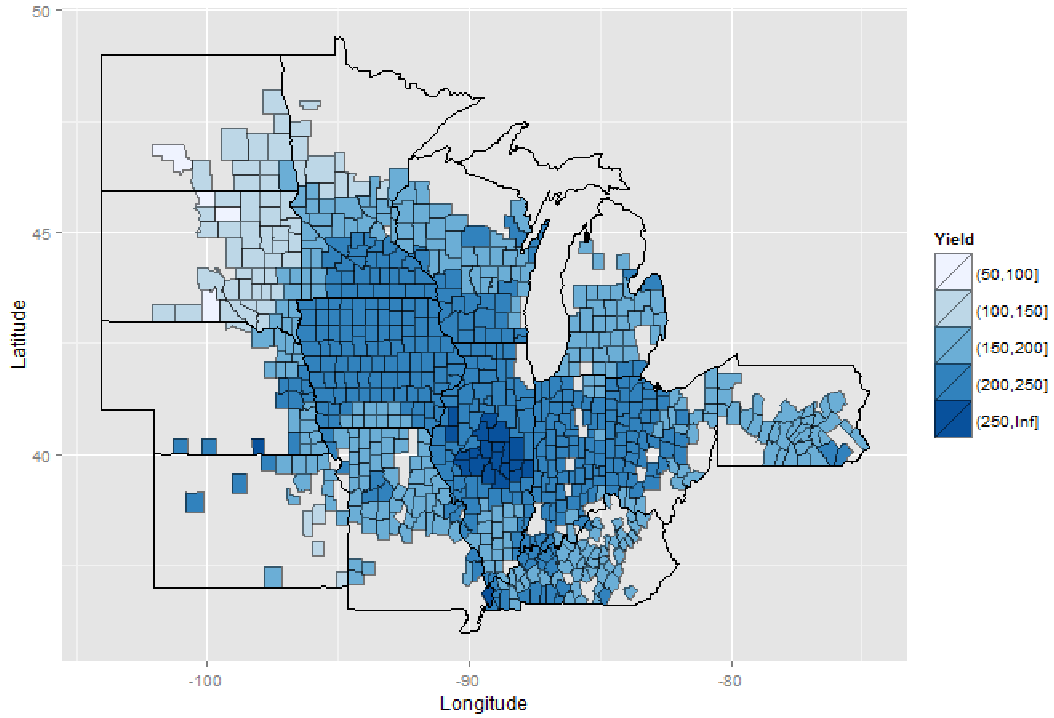

Figure A.8: 2031 Alternative Corn Yields (bu/ac) with Two-Inch Intense Precipitation

is fitted to counties with available data in 1950-2005 ($N = 711$) and uses median weather values for out-of-sample forecasting.

Figure A.9 shows no major departures from our preferred baseline forecasts. The highest-yielding areas continue to be Iowa, Illinois, southern Minnesota, other Corn Belt areas, and eastern South Dakota. Although there are differences in forecast levels, the models have generally similar qualitative features, e.g., yield forecasts are in similar 50 bu/ac bins. The average 2031 forecast in this specification is 8.6 bu/ac higher than the baseline average for the same 711 counties (Figure 5).

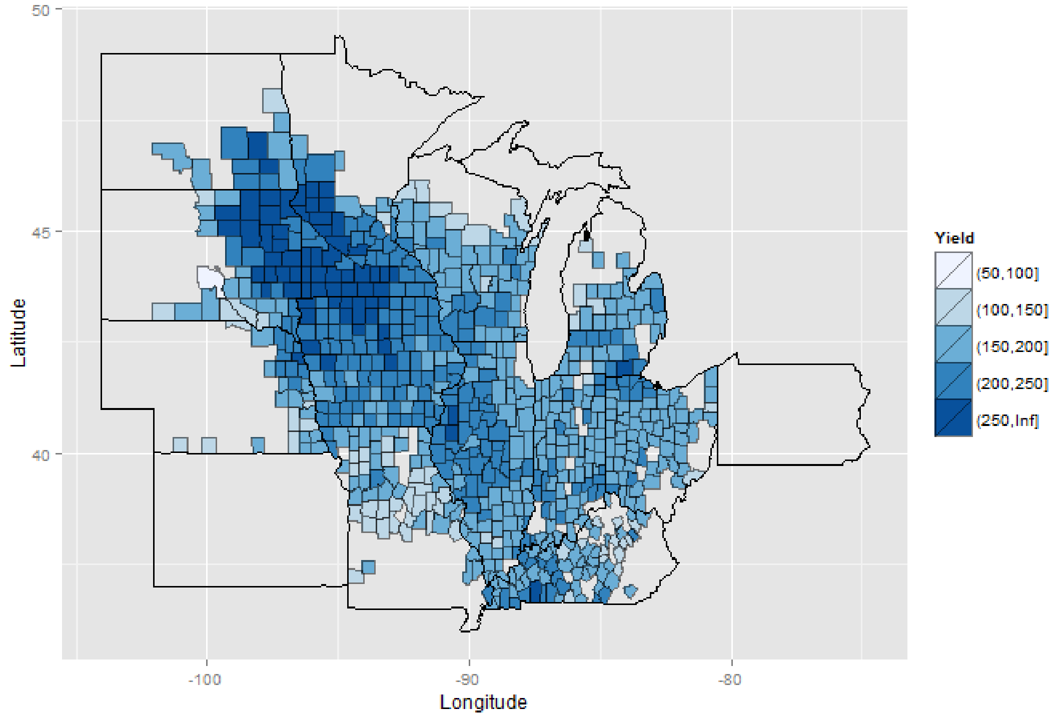

Figure A.9: 2031 Corn Yields (bu/ac) with Avg GDD, Extreme GDD, and Prec

A.2.2 Sensitivity to ending year

Dynamic forecasting results generally depend on coefficient estimates from the last in-sample year since they are extended into the forecasting time period. Figures A.10-A.13 illustrate the 2031 baseline and alternative forecasts from a model with a 51-year sample (ending in 2010) and a 53-year sample (ending in 2012). Relative to the baseline estimates, Figure A.10 shows a minor shift of higher yields towards counties north of the 45^{th} parallel, though the difference in average 2031 yields is 3.2 bu/ac. There is also little difference among the alternative forecasts for the 2010 versus 2011 ending year, with a 3.5 bu/ac difference between the average 2031 yield. Regional yield patterns in the results for the 2012 ending year are comparable, though the set of highest-yielding counties is smaller. This is because the extremely dry and hot conditions of 2012 produce larger negative (or smaller positive) weather elasticities. Average 2031 forecasts decline by 20 bu/ac and 26 bu/ac for the baseline and alternative models when the sample ends in 2012.

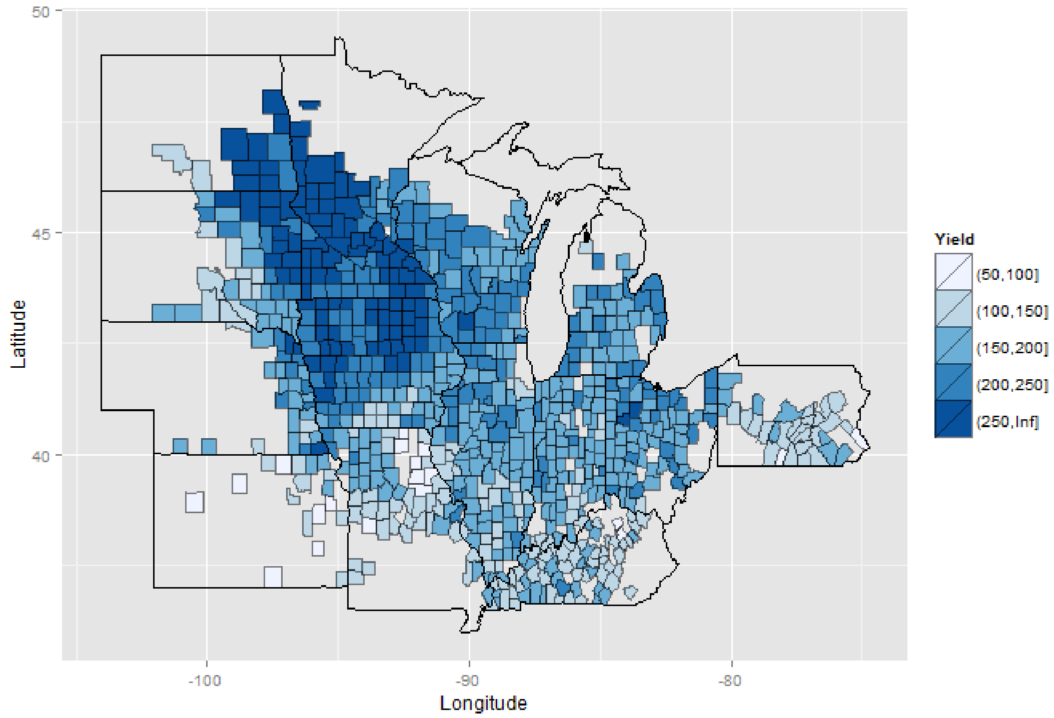

Figure A.10: 2031 Baseline Corn Yields (bu/ac) with 2010 Ending Year

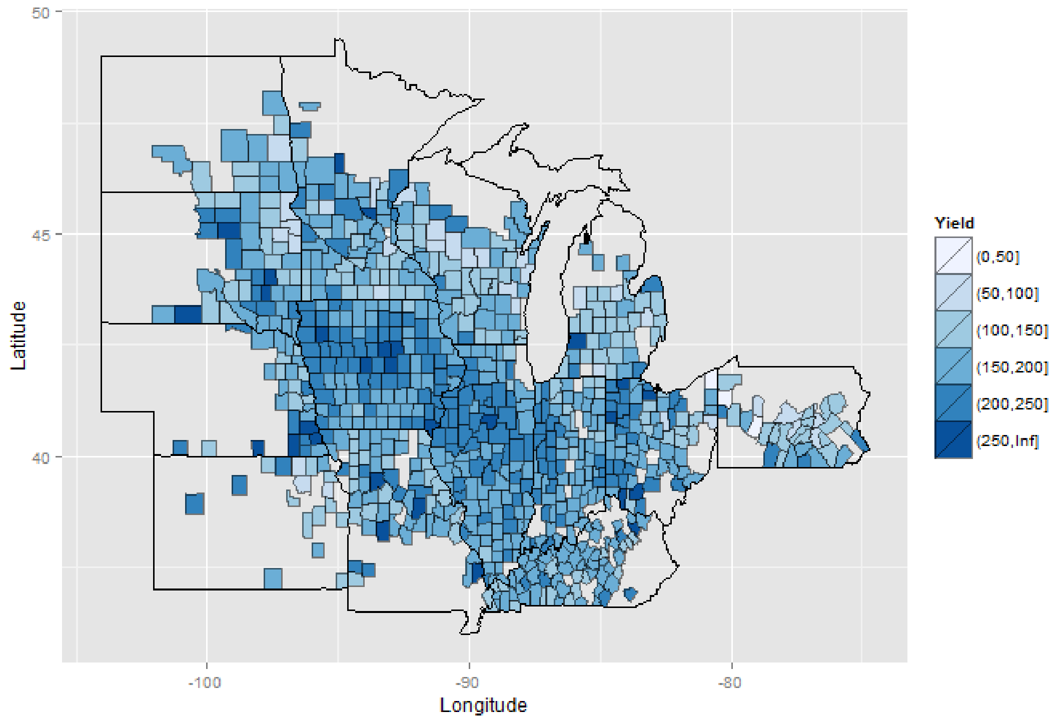

Figure A.11: 2031 Alternative Corn Yields (bu/ac) with 2010 Ending Year

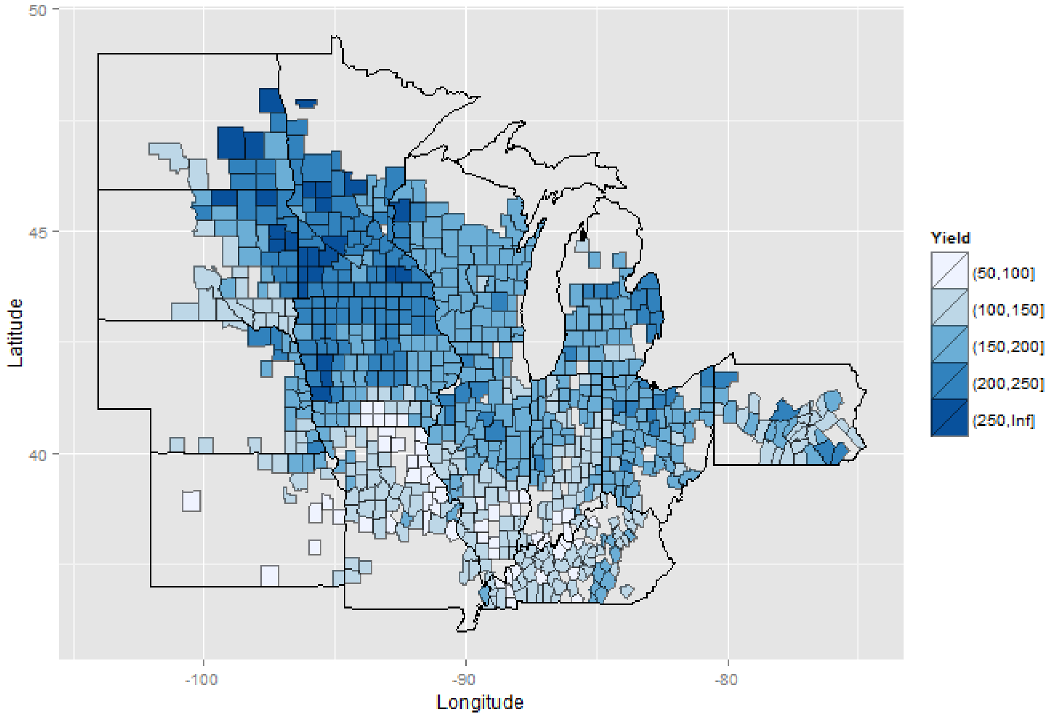

Figure A.12: 2031 Baseline Corn Yields (bu/ac) with 2012 Ending Year

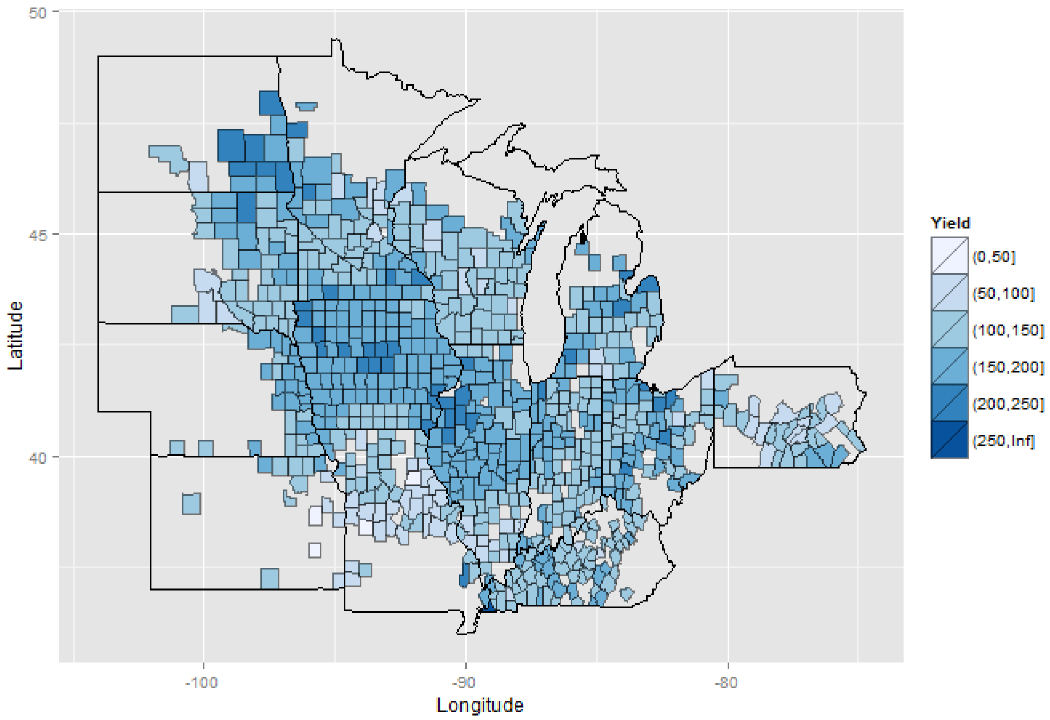

Figure A.13: 2031 Alternative Corn Yields (bu/ac) with 2012 Ending Year

A.2.3 Sensitivity to climate model

One potential concern when averaging climate model output is that extremes will tend to be smoothed, which could bias the results if measurement error is introduced. Several climatology studies find that multi-model ensembles give more accurate predictions, but it is useful to examine how forecasts change with model disaggregation. GCM output can differ for the same region and climate scenario because of differences in parameters, boundary settings, and other aspects of the physical modeling process. For example, the largest difference in May aggregate temperatures averaged over 2012-2031 for the four models is 0.7 °C. Average monthly precipitation aggregated across counties is more variable and differs by as much as 2.6 cm. In general, the GFDL model produces the most precipitation, while MIROC and HadGEM predict drier weather. The CCSM and GFDL models generate relatively warmer weather.

Heterogeneity among GCMs is evidenced in the 2031 baseline forecasts of Figures A.14-A.17. The sole difference between Figure 5 and the baseline forecasts using only the CCSM output (Figure A.14) is that eastern Wisconsin becomes more productive. Average 2031 yield under CCSM alone is 4.7 bu/ac lower than the baseline results that average the four models. Although GFDL generates relatively warmer weather, the additional average rainfall is beneficial. Yields increase in nearly all counties, with 2031 average yield increasing by 19.7 bu/ac relative to the main baseline specification. The HadGEM and MIROC-alone models forecast similar and similarly-low 2031 yields, consistent with their lower moisture. The relative yield decline is much more uniform in the HadGEM model. In contrast, counties in Iowa, Minnesota, Wisconsin, and the eastern Dakotas have the highest yields under the MIROC model. The average 2031 yield for these two latter models differ by 1.9 bu/ac and decrease from the main baseline results by 6.2 and 8.0 bu/ac.

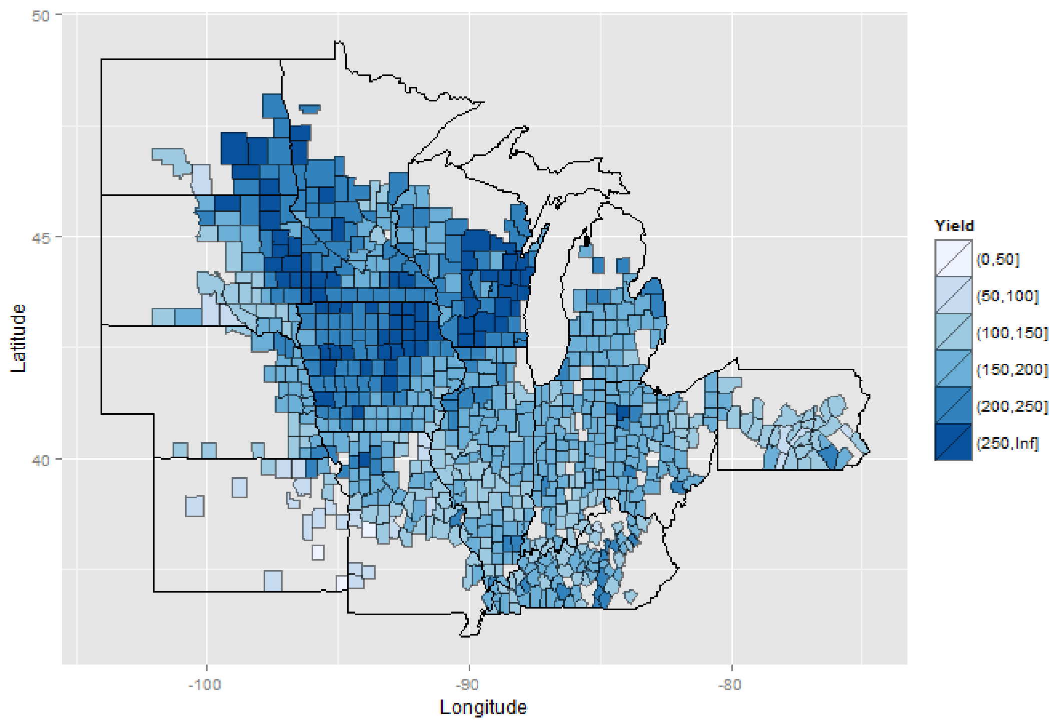

Figure A.14: 2031 Baseline Corn Yields (bu/ac), Only CCSM Climate

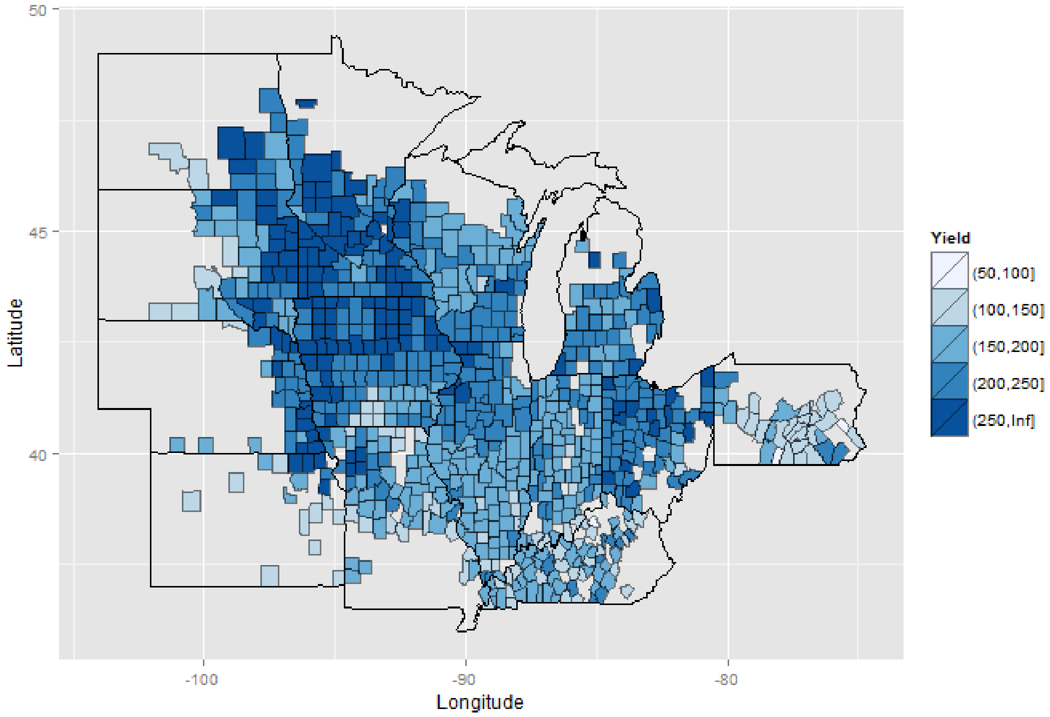

Figure A.15: 2031 Baseline Corn Yields (bu/ac), Only GFDL Climate

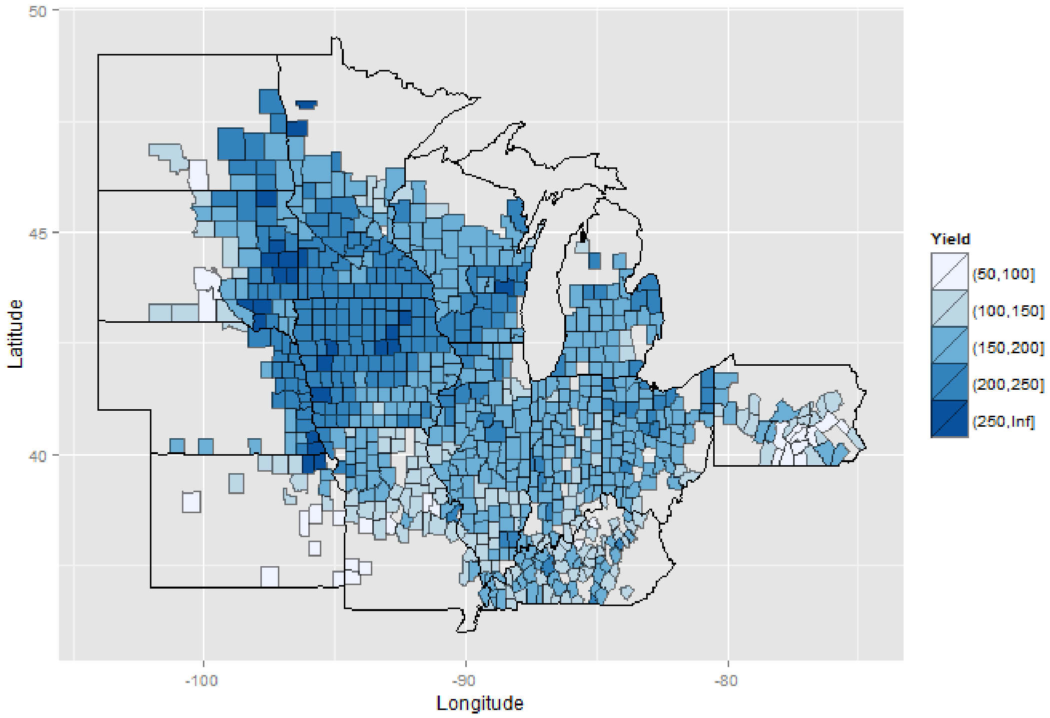

Figure A.16: 2031 Baseline Corn Yields (bu/ac), Only HadGEM Climate

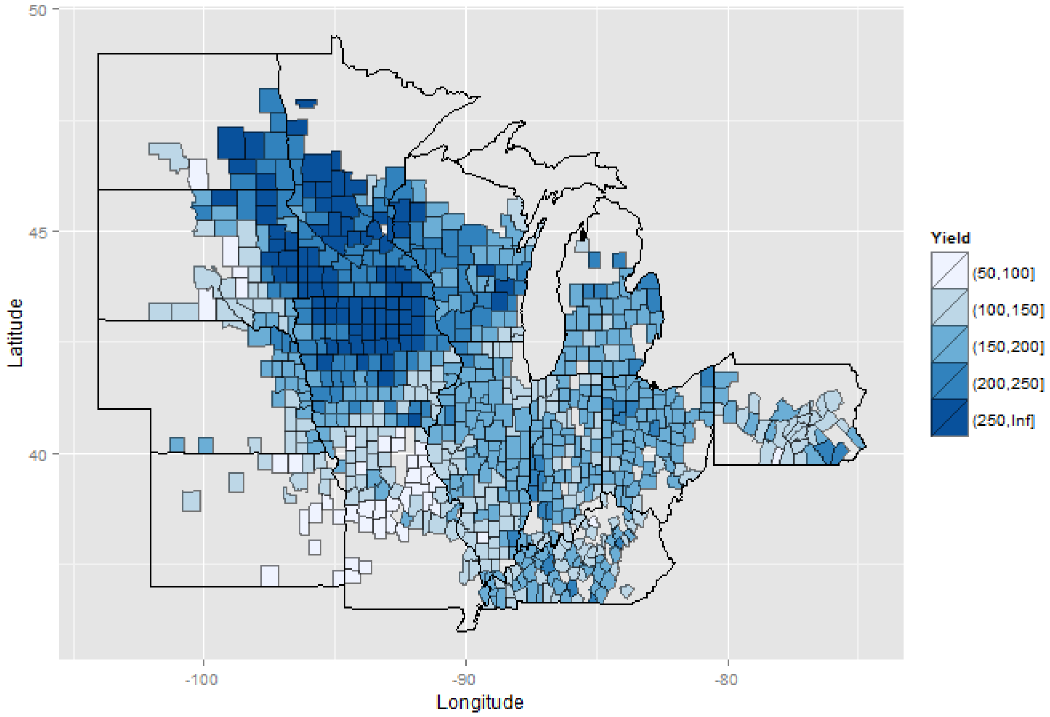

Figure A.17: 2031 Baseline Corn Yields (bu/ac), Only MIROC Climate

A.2.4 Sensitivity to estimation: fixed effects panel analysis

The conventional econometric approach in climate economics is fixed effects panel methods. However, our Bayesian filtering model addresses parameter instability, outliers, and information decay in a unified and rigorous way. This improves upon econometric methods that ignore these important issues identified in the agricultural economics literature. Key advantages of panel approaches are their greater degrees of freedom and ability to control for unobserved heterogeneity (e.g., county-level management practices and human capital).

Figures A.18 and A.19 provide forecasts for the baseline and alternative specifications from a two-way fixed effects analysis. County fixed effects absorb the impacts of time-invariant production factors (e.g., soil productivity and local infrastructure), while time fixed effects capture discrete temporal impacts common to all counties (e.g., the 1970 Southern Corn Leaf Blight outbreak and, less importantly, the 2003 soybean aphid infestation). Although the full set of fixed effects absorbs a large amount of independent variation, the approach is plausible because of the relatively large sample (N= 40,040). For each specification, the forecasts are produced from a single estimated model and are thus spatially smooth. Standard errors are clustered by county. The most productive regions in both models continue to be the traditional Corn Belt and the Great Lakes, with a set of high-yielding counties in central Illinois. The baseline average 2031 yield is 6.4 bu/ac lower, whereas the average 2031 yield from the alternative panel model is 28 bu/ac higher.

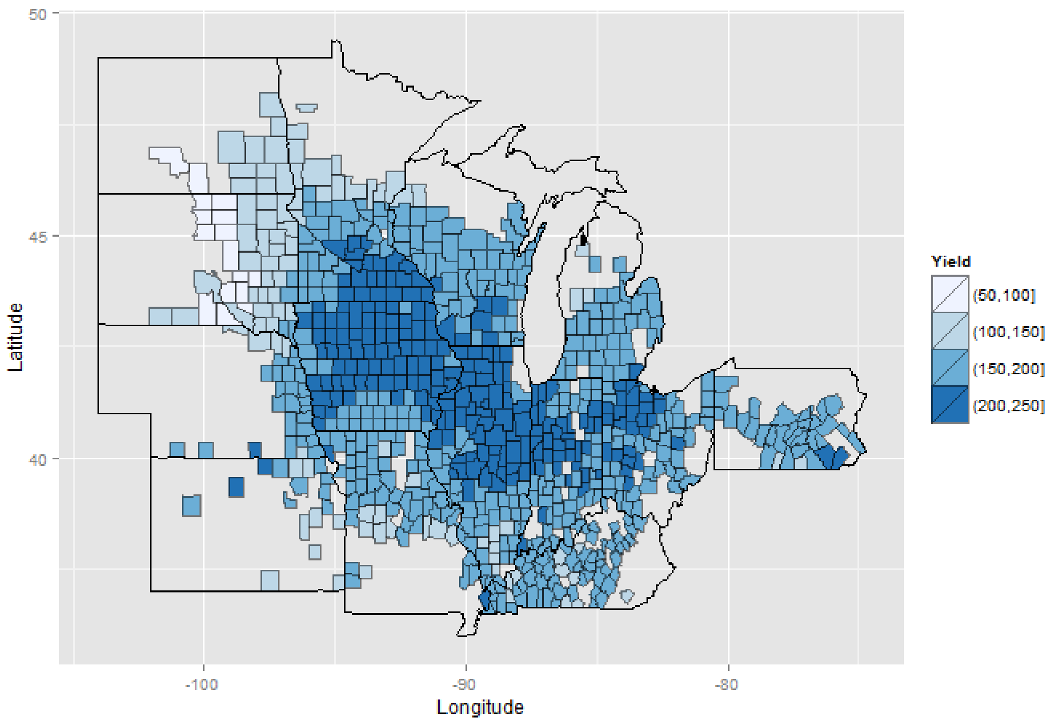

Figure A.18: 2031 Baseline Corn Yields (bu/ac), Two-Way FE Panel

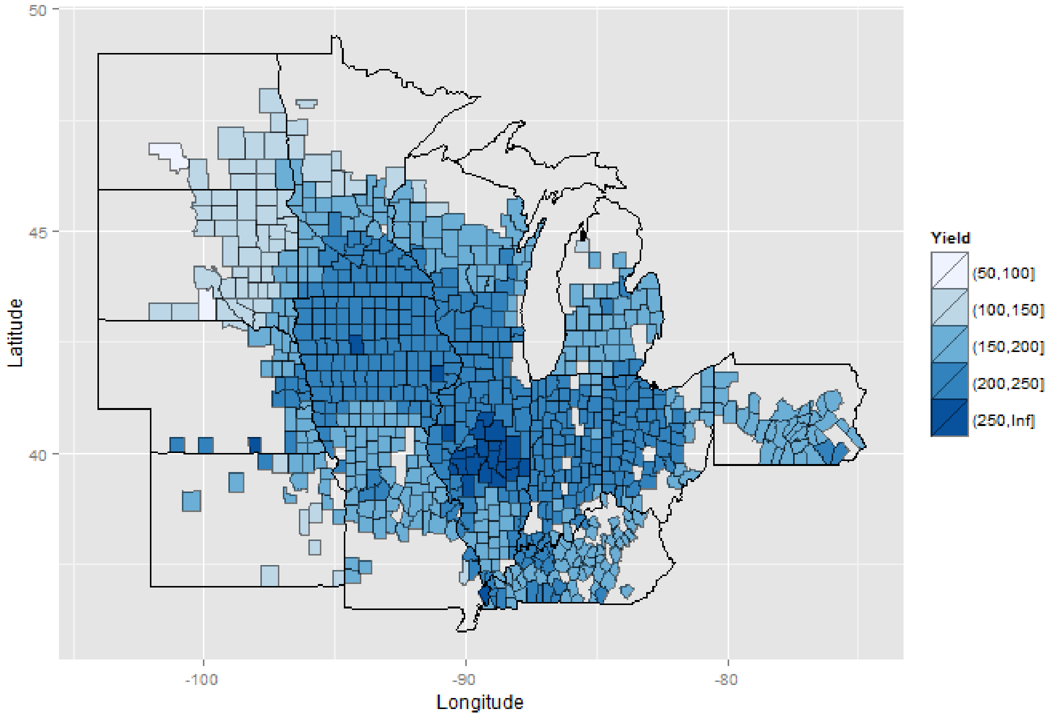

Figure A.19: 2031 Alternative Corn Yields (bu/ac), Two-Way FE Panel

A.3 Productivity growth robustness

Table A.3 addresses robustness of our long-run results to inclusion and exclusion of soil controls and state fixed effects. Since the long-run analysis uses cross-sectional variation, it is natural to control for regional variation in agricultural suitability for growing corn (e.g., soil productivity). Yet if soil productivity is additively separable from climate damages and time-invariant, then it differences out of the econometric model. Columns (1)-(4) of Table A.3 replicate those of Table 2.2 in the paper, except soil controls have been removed. Goodness-of-fit is similar across the tables, though with a 19-percentage point drop in column (3), suggesting that soils are not a primary determinant of rising corn productivity.

The signs and magnitudes of the climate coefficients are robust to the omission of soil productivity. Similar to results in Table 2.2, July and August temperature variable are unimportant. August temperatures are less important. A 1 °C increase in May temperature reduces productivity growth by 4-7 percentage points at the sample mean. A similar increase in June temperature has a -3 percentage point impact. However, yield productivity growth is increasing (at a diminishing rate) in July temperature, with an average 5 percentage point influence per 1 °C.

The only substantive change in the alternative damage function estimates (the third and fourth columns) is more detrimental intense precipitation throughout the growing season. Soils play a small but significant role in agricultural adaptation (e.g., through water infiltration or absorption), and movement of coefficients in this direction is anticipated (McFadden and Miranowski, 2014). An additional percentage point in the fraction of days without intense rainfall in the four separate months increases productivity growth by 2%, 1%, 0.8%, and 0.6% (column 3).

The fifth through eighth columns of Table A.3 show that many of the results are unchanged after adding state fixed effects (FE). State FE soak up geographic variation in the production environment not directly associated with soils (e.g., pest susceptibility, human capital, and quality of public extension services). Inference for the baseline damage function in columns (5) and (6) is similar to that of columns (1) and (2). May and June temperature have small negative, nonlinear effects on yield productivity growth, and July temperature has a small positive linear impact.

Of more interest and potential policy relevance is inference from extreme climate damages. Harmful climate impacts on yield productivity growth decrease after including this richer set of controls. The marginal effect of a decade increase in which monthly maximum July and August temperatures exceed 85 °F is half the size of the main estimates in Table 2.2. Intense precipitation retains its negative impacts. An interesting commonality is the importance of August intense rainfall. An additional percentage point in the fraction of days in August without intense precipitation increases yield productivity growth by 0.8%.

Table A.3: Omitting Soil Controls vs. Adding State FE

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.53^{***}	-0.55^{***}	-0.49^{***}	-0.51^{***}	-0.43^{***}	-0.65^{***}	-0.40^{***}	-0.59^{***}
	(0.02)	(0.02)	(0.02)	(0.01)	(0.06)	(0.07)	(0.06)	(0.05)
Δ May Temp	0.04^{**}	0.07^{***}	–	–	0.02	0.05	–	–
	(0.02)	(0.02)	–	–	(0.03)	(0.04)	–	–
Δ May Temp^2	0.0002	0.01	–	–	0.01	0.03	–	–
	(0.02)	(0.02)	–	–	(0.02)	(0.03)	–	–
Δ Jun Temp	0.12^{***}	0.02	–	–	0.07^{*}	-0.04	–	–
	(0.03)	(0.04)	–	–	(0.04)	(0.04)	–	–
Δ Jun Temp^2	-0.07^{***}	-0.05^{**}	–	–	-0.07^{***}	-0.03^{*}	–	–
	(0.02)	(0.02)	–	–	(0.02)	(0.02)	–	–
Δ Jul Temp	-0.08	-0.06	–	–	-0.10^{*}	-0.04	–	–
	(0.07)	(0.04)	–	–	(0.06)	(0.05)	–	–
Δ Jul Temp^2	0.06	0.04	–	–	0.06	0.02	–	–
	(0.07)	(0.05)	–	–	(0.05)	(0.04)	–	–
Δ Aug Temp	0.05	0.05	–	–	0.06	0.06	–	–
	(0.04)	(0.03)	–	–	(0.04)	(0.05)	–	–
Δ Aug Temp^2	-0.02	-0.02	–	–	0.005	-0.005	–	–
	(0.03)	(0.02)	–	–	(0.03)	(0.03)	–	–
Δ Jul 85	–	–	0.11^{**}	-0.004	–	–	0.05^{*}	-0.006
	–	–	(0.04)	(0.04)	–	–	(0.02)	(0.03)
Δ Aug 85	–	–	0.12^{***}	0.15^{***}	–	–	0.007	0.08^{**}
	–	–	(0.04)	(0.03)	–	–	(0.04)	(0.04)
Δ May Int Prec	–	–	-2.16^{***}	-1.51^{***}	–	–	0.03	-0.40
	–	–	(0.49)	(0.36)	–	–	(0.32)	(0.39)
Δ Jun Int Prec	–	–	-1.11^{**}	-0.32	–	–	-0.18	-0.19
	–	–	(0.47)	(0.31)	–	–	(0.30)	(0.32)
Δ Jul Int Prec	–	–	-0.85^{**}	-0.22	–	–	0.59^{**}	0.17
	–	–	(0.46)	(0.38)	–	–	(0.30)	(0.36)
Δ Aug Int Prec	–	–	-0.61	-0.98^{***}	–	–	-0.31	-0.83^{***}
	–	–	(0.48)	(0.33)	–	–	(0.30)	(0.32)
Obs.	770	770	770	770	770	770	770	770
Soil Controls	No	No	No	No	Yes	Yes	Yes	Yes
State FE	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.40	0.11	0.17	0.11	0.57	0.23	0.54	0.22

The dependent variable in columns (1), (3), (5), and (7) is the difference in productivity estimated from the baseline model. The dependent variable in columns (2), (4), (6), and (8) is the difference in productivity estimated from the alternative model. Columns (1), (2), (5), and (6) use regressors similar to the baseline specification. Columns (3), (4), (7), and (8) use regressors from the alternative specification. Bootstrap standard errors are clustered by CRD (in parentheses). $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Another critique of our results concerns estimation of the Nordhaus (2013) damage function. There is uncertainty about the nature of climate change damages, and there is no consensus on the most appropriate functional form. A plausible alternative to the inverse quadratic function is Weitzman (2009) exponential damages:

$$D(C_{it}) = \exp[-\beta(\Delta T_{it})^2] + \varepsilon_{it}, \tag{A.1}$$

where (ΔT_{it}) is temperature change for county i in year t, and ε_{it} is an econometric error. This function may be preferred because of the relatively larger weight given to larger temperature changes.

Table A.4 provides nonlinear least squares estimates for the alternative model and an analogous baseline specification. Coefficients on the quadratic temperature changes are very similar to those in Table 2.2, as well as those for the alternative model in the last two columns. There are also comparable marginal effects, after reflecting $\exp[\Delta T_{it}]$ across they y axis, in line with Weitzman's emphasis of relatively larger damages at higher temperatures. Our inference is largely robust to damage functional form assumption.

Lastly, one might ask how a relatively simple model defined over climate change – not climate change damages – performs. Given unknown damages, it could be argued that a more conservative approach is to drop the damage function and (linearly) estimate the linear and quadratic climate effects. Estimates from linear regressions of productivity growth on climate change are presented in Table A.5. These estimates coincide with marginal effects. There are minor changes in magnitudes relative to the parameters in Table 2.2, and estimates retain the same sign (recall that coefficients of Table 2.2 are in the damage function's denominator). As in the previous sections, we again confirm the robustness of our long-run analysis.

Table A.4: Weitzman (2009) Exponential Damage Function

Regressors	(1)	(2)	(3)	(4)
Constant	-0.47^{***}	-0.52^{***}	-0.45^{***}	-0.52^{***}
	(0.05)	(0.04)	(0.04)	(0.03)
Δ May Temp^2	-0.009	-0.01	–	–
	(0.02)	(0.01)	–	–
Δ Jun Temp^2	-0.03^{**}	-0.04^{***}	–	–
	(0.01)	(0.01)	–	–
Δ Jul Temp^2	0.09^{**}	0.10^{**}	–	–
	(0.05)	(0.04)	–	–
Δ Aug Temp^2	0.01	0.03	–	–
	(0.02)	(0.02)	–	–
Δ Jul 85	–	–	0.11^{***}	0.01
	–	–	(0.03)	(0.03)
Δ Aug 85	–	–	0.03	0.13^{***}
	–	–	(0.03)	(0.03)
Δ May Int Prec	–	–	-0.51	-0.89^{***}
	–	–	(0.40)	(0.34)
Δ Jun Int Prec	–	–	-0.05	-0.03
	–	–	(0.32)	(0.30)
Δ Jul Int Prec	–	–	-0.15	0.02
	–	–	(0.38)	(0.36)
Δ Aug Int Prec	–	–	-0.32	-0.87^{***}
	–	–	(0.37)	(0.31)
Obs.	770	770	770	770
Soil Controls	Yes	Yes	Yes	Yes
State FE	No	No	No	No
R^2	0.34	0.12	0.36	0.15

The dependent variable in columns (1) and (3) is the difference in productivity estimated from the baseline model. The dependent variable in columns (2) and (4) is the difference in productivity estimated from the alternative model. Columns (1) and (2) use regressors similar to the baseline specification. Columns (3) and (4) use regressors from the alternative specification. Bootstrap standard errors are clustered by CRD (in parentheses).

Table A.5: OLS without Damages

Regressors	(1)	(2)	(3)	(4)
Constant	0.54***	0.49***	0.55***	0.49***
	(0.04)	(0.04)	(0.04)	(0.03)
Δ May Temp	−0.02	−0.06***	–	–
	(0.02)	(0.02)	–	–
Δ May Temp^2	0.002	−0.02	–	–
	(0.02)	(0.02)	–	–
Δ Jun Temp	−0.10**	0.0004	–	–
	(0.04)	(0.04)	–	–
Δ Jun Temp^2	0.08***	0.04**	–	–
	(0.02)	(0.02)	–	–
Δ Jul Temp	0.02	0.02	–	–
	(0.06)	(0.04)	–	–
Δ Jul Temp^2	−0.08	−0.07	–	–
	(0.06)	(0.05)	–	–
Δ Aug Temp	−0.06	−0.04	–	–
	(0.05)	(0.04)	–	–
Δ Aug Temp^2	0.04	0.01	–	–
	(0.03)	(0.03)	–	–
Δ Jul 85	–	–	−0.11***	−0.01
	–	–	(0.03)	(0.03)
Δ Aug 85	–	–	−0.03	−0.13***
	–	–	(0.03)	(0.03)
Δ May Int Prec	–	–	0.49	0.90***
	–	–	(0.39)	(0.34)
Δ Jun Int Prec	–	–	0.02	0.02
	–	–	(0.32)	(0.30)
Δ Jul Int Prec	–	–	0.15	0.002
	–	–	(0.38)	(0.36)
Δ Aug Int Prec	–	–	0.32	0.89***
	–	–	(0.38)	(0.31)
Obs.	770	770	770	770
Soil Controls	Yes	Yes	Yes	Yes
State FE	No	No	No	No
R^2	0.46	0.14	0.36	0.15

The dependent variable in columns (1) and (3) is the difference in productivity estimated from the baseline model. The dependent variable in columns (2) and (4) is the difference in productivity estimated from the alternative model. Columns (1) and (2) use regressors similar to the baseline specification. Columns (3) and (4) use regressors from the alternative specification. Bootstrap standard errors are clustered by CRD (in parentheses).

CHAPTER 3. VALUING NEW (VARIETIES OF) GOODS: EVIDENCE FROM LAB AUCTIONS OF POPULAR FOODS GENETICALLY ENGINEERED TO REDUCE NEW FOOD SAFETY CONCERNS

3.1 Introduction

New goods and new varieties of existing goods are central to improving consumer welfare (Bresnahan and Gordon, 1997). Some of these goods reduce the probability of humans getting sick, which can result in temporary illnesses — causing loss of utility — or even terminal illnesses that shorten one's expected length of life. One strand of the literature on valuing new goods is a virtual price model of household demand (Hausman, 1997). A second strand of the literature is experimental lab auctions of new goods (Hoffman et al., 1992; Lusk and Shogren, 2007). In particular, Colson and Huffman (2011) use experimental lab auctions to assess consumers' valuation of fresh vegetables that have enhanced nutrient value related to good health, and Hayes et al. (1995) use experimental auction markets to value a new variety of a common food product that lowers the probability of consumers contracting a serious foodborne illness that is fatal in some cases.

A new foodborne risk was only recently discovered in starchy foods cooked at high temperatures. In 2002, trace amounts of acrylamide, a small organic compound, were found in several carbohydrate-rich foods cooked at high temperatures (Tareke et al., 2002). French fries, hash browns, potato chips, and other potato products cooked at high temperatures form relatively high concentrations of acrylamide.[1] Roasted coffee beans, baked breads and cookies, and other foods with high levels of asparagine (an amino acid) and certain sugars also contain acrylamide (Bethke and Bussan, 2013). It has been classified as a toxin and potential carcinogen based on various medical studies (Garland and Patterson, 1967; Shiraishi, 1978; Naruszewicz et al., 2009; JECFA, 2011; Nixon et al., 2012). Medical research uses clinical, epidemiological, and laboratory data, but most are

[1]Raw, boiled, and steamed potatoes do not contain acrylamide.

laboratory studies of rats and mice that have been exposed to acrylamide (similar to much other medical research). These studies have consistently found significant links between acrylamide exposure and the formation of cancers, benign tumors, and developmental defects. Other studies analyze the short-term effects of dietary acrylamide on human cancer risk. Moreover, the International Agency for Research on Cancer (IARC) classifies acrylamide as “probably carcinogenic to humans (Group 2A)” (Lineback et al., 2012).

Acrylamide is a by-product of the Maillard chemical reaction and is a stable compound after formation. After controlling for water content, there is a positive relationship between chip and fry color and acrylamide content. Processing conditions, environmental factors during plant growth, storage, and field management practices influence acrylamide-forming potential.[2] The potato industry is targeting many of these aspects to mitigate health concerns. Recent biotechnology (biotech) solutions include gene silencing to reduce asparagine and sugar content (Bethke and Bussan, 2013). The industry, and J.R. Simplot Company, have currently achieved lower levels of acrylamide-forming potential using genetic engineering than with changes in field and storage management and processing methods. Moreover, the FDA has indicated that biotech varieties may be the most effective solution for acrylamide reduction (Food and Drug Administration, 2013).

Mucci and Adami (2009) estimate that up to one-third of daily food calories contains detectable levels of acrylamide, which apart from clear health concerns, also have impacts on food safety, labor productivity, and the economic viability of the potato industry. Under the Safe Drinking Water and Toxic Enforcement Act of 1986 (Proposition 65), the California Office of Environmental Health Hazard Assessment added acrylamide as a carcinogen in 1990 and again as a male developmental toxin in 2011 (OEHHA, 2014). As part of a broad 2005 lawsuit under Proposition 65 initiated by California’s Office of the Attorney General, many restaurant chains are now posting acrylamide warnings on their premises (OAG, 2008). These warnings, designed to promote public health, may reduce

[2]Acrylamide concentrations in potatoes vary widely as a function of reducing sugar content and cooking temperatures, though concentrations in chips and fries are 100-1000 $\mu g\, kg^{-1}$ and 100-700 $\mu g\, kg^{-1}$, respectively. US per capita use of white potatoes in 2013 is approximately the same as in 1980, about 115 lbs., but the share going to processed foods increased from 53% to 69%. Since some of the potato is lost in processing waste, per capita consumption of potatoes has declined over this period (Institute of Medicine, 2015).

potato consumption or lower utility from fixed consumption, depending on specification of preferences (Becker and Murphy, 1993). Thus, it is economically interesting to determine consumers' valuations for conventional potatoes (perceived by some consumers to have risk from potential carcinogens but no risk from genetic engineering) and biotech potatoes (perceived by some to have risk from genetic engineering but no risk from potential carcinogens), and the effects of information and labeling on these valuations. However, not a single human health problem has resulted from 20 years of human consumption of GM foods.

The objective of this paper is to assess consumers' valuation for a new food product that has greatly reduced food safety concerns achieved using genetic engineering. To do this, we design and conduct lab auctions of three popular food items in the American diet: fresh whole potatoes, frozen French fries, and chips. Although economists sometimes use Vickrey (1961) second-price auctions to identify a single winner in auctions of a single commodity, we choose a random n^{th}-price auction (Shogren et al., 2001). When subjects have heterogeneous preferences, as reflected in willingness-to-pay (WTP) for a food product, the random n^{th}-price auction has been shown to be superior for revealing private valuations than the second-price auction. This occurs because every subject in a lab session has a positive probability of winning the random n^{th}-price auction (there can be multiple winners), whereas the Vickrey auction chooses a single winner, irrespective of the number of bidders. The second-price auction is marginally superior to a random n^{th}-price auction when a single winner is to be identified, but it does not suit our needs for assessing the distribution of WTP for a product. The subjects in these auctions are 304 randomly-chosen adults (18-65 years of age) from diversion regions of the United States — Boston, Des Moines, and Los Angeles, who are paid to come to nearby locations and participate in our lab auctions.

Our empirical results show strong combined labeling and information treatments effects. Consumers are willing to pay more for low-acrylamide fresh potatoes, potato chips, and frozen French fries when they receive a scientific perspective on acrylamide, an industry perspective on reducing acrylamide using biotech methods, or a combination of the two. We find that the scientific and industry perspectives have additive effects on WTP, and subjects do not anchor on a particular information perspective. WTP is not significantly affected by several socio-demographic attributes of subjects. Hence, the empirical evidence is that consumers will pay for improved food safety (reduced acrylamide formation in cooked potato products) achieved using biotech methods.

The remainder of this paper has the following organization. The next section briefly surveys the related literature. Section 3 outlines the experimental design and research hypotheses, while the subsequent section presents the econometric model and data. Section 5 discusses the empirical results, and section 6 concludes. Tables and figures of results are at the end. Appendix B contains the protocol used in the experiments, including all information perspectives, as well as empirical robustness checks.

3.2 Past research

The current study stems from past applied work on incentive-compatible elicitation mechanisms, food experiments, and experiments involving information and labeling treatments. For the past half-century, economists have used the the Vickrey (1961) second-price auction to learn about consumer WTP. Subjects submit private bids, and the highest bidder wins but pays the second-highest price. Since the weakly dominant strategy is sincere bidding, the auction is said to be incentive compatible (Hurwicz, 1972). Second-price auctions remain widely used because of their incentive-compatible properties and ease of implementation.

Another common method of eliciting consumer valuations is the Becker et al. (1964) mechanism (hereafter denoted as BDM). In this value elicitation procedure, subjects are asked to report their WTP for a good (or group of goods) and then a random price is drawn, typically from a uniform distribution. Those whose valuations are higher than the random price receive the good and pay the random price, whereas subjects with a WTP less than the random price do not receive the good and pay nothing. The BDM device is therefore incentive compatible.

Shogren et al. (2001) builds on the BDM mechanism and Vickrey auction with a mechanism known as random n^{th}-price auctions. In this method, after participants bid on the experimental product, a random number, n, is drawn uniformly on $[2, k]$, where k is the number of session participants. The bids are then ranked from highest to lowest. Those who bid higher than the n^{th} bid are winners but pay the n^{th} bid, not their submitted bid. As in the BDM, the bidders' dominant strategy is to truthfully reveal their valuations.[3] Shogren et al. (2001) argues that random n^{th}-price auctions are desirable because of engaging "off-margin" bidders, i.e., low-value subjects still have a positive probability of winning. Using an experiment with induced values, the authors find more sincere bidding from low-value individuals in the random n^{th}-price auction than the Vickrey auction.[4]

Early studies on information treatments in experimental auctions for food products are Menkhaus et al. (1992), Hoffman et al. (1992), and Schmitz et al. (1993). Fifth-price auctions with repeated trials were conducted in the Denver and Los Angeles areas to assess WTP for beef steaks. The experimenters were interested in the marketing viability of a new beef steak packaging - vacuum-sealed packaging - relative to conventional packaging in an overwrapped styrofoam tray. Regarding information treatments, there is a no-information baseline; verbal information about vacuum-sealing benefits, beef coloration, and meat juices; and verbal information plus a demonstration of beef coloration upon vacuum package removal. They find that information treatments, income, household size, employment, beef shape, and "all natural" labels significantly influence the WTP difference between vacuum-sealed and plastic overwrapped steaks. There are also significant health effects: cholesterol concerns substantially reduced WTP, regardless of packaging.

[3]Following Karni and Safra (1987), Horowitz (2006) shows that BDM, n^{th}-price auctions, and Vickrey auctions are incentive compatible if and only if the independence axiom is satisfied, i.e., bidders are expected utility maximizers. The underlying intuition is that after submitting a bid, the subject still faces uncertainties about "winning" the auction and realization of the random price. As such, the bid may depend on the distribution of prices since uncertainty (about winning) is partially resolved by the subject's bid. Starting with Allais (1953), there have been persistent challenges to expected utility maximization. To our knowledge, there are few incentive-compatible mechanisms that are generally robust to expected utility maximization.

[4]There is a growing literature examining potential divergence between incentive compatibility in theory and in practice (Lusk and Shogren, 2007). In recent work, Malmendier and Lee (2011) document irrational bidding behavior in eBay auctions. We use random n^{th}-price auctions because of their frequent use in food auction research and their desirable properties in practice.

The artefactual field experiment performed here also draws from, and parallels, studies on food safety valuation. One well-known work in the agricultural economics literature is Hayes et al. (1995). Using Vickrey auctions, the authors obtained two types of valuations from 230 Iowa State University (ISU) undergraduates: (i). bids to "upgrade" an endowed meat sandwich with "typical" risk of a foodborne pathogen to a meat sandwich with very low risk, and (ii). compensation bids to "downgrade" from an endowed very low-risk sandwich to the "typical" sandwich. After 10 rounds of bidding, subjects were given information on one of five pathogens (related to probabilities of becoming ill and health severity), and then bid an additional 10 times. Among their main findings are that subjects place a $0.70 per-meal premium on food safety and tend to weight their own prior beliefs about the odds of illness more heavily than new information.

Our methodology improves on this early study by: (i). eliminating endowment effects and framing, e.g., we do not mention "upgrade" between products; (ii). removing the possibility of correlated bidding by not posting winning bids after each bidding round; and (iii). implementing an auction format that performs better in practice, e.g., engages low-value subjects. Another closely related food safety study is Fox et al. (2002). Again using Vickrey auctions, the researchers find that positive information about food irradiation increases WTP for pork sandwiches that have been irradiated to kill the *Trichinella* parasite. They also find that negative information exerts downward pressure on bids, with similarly lower valuations from subjects receiving positive and negative information.

Since the wider adoption of laboratory experimental methods in agricultural economics, there has been a sharp rise in publications examining information and labeling effects on food values (Noussair et al., 2002; Huffman et al., 2003; Huffman et al., 2007; Rousu et al., 2007; Lusk and Briggeman, 2009; Kanter et al., 2009; Colson et al., 2011; Gracia et al., 2011; Liaukonyte et al., 2013). Although these studies use different experimental methods, one commonality is that prior beliefs, information treatments, labels and seals, and framing have substantial effects on consumer values (Colson and Rousu, 2013). In certain studies, information and labeling effects can be isolated to look at very specific influences on WTP. However, disentangling the effects of food labels, new information, and prior beliefs can be difficult. This is a major reason for using laboratory auctions to identify consumer WTP.

3.3 Experimental design

3.3.1 Overview

To create significant regional diversity in our subjects, we choose to conduct experiments in three areas: Boston, Los Angeles, and Des Moines. The dates of the experiments are April 12, April 26, and May 17, 2014 (Saturdays), respectively. The sessions begin at 9:00 a.m., 11:00 a.m., and 1:30 p.m. on these dates. There are two concurrent sessions at each starting time, so there are a total of six sessions (3x2) at each site. Our sample comprises 304 subjects.

Survey and Behavioral Research Services (SBRS) at Iowa State University developed the protocol for recruiting participants. A random sample of households was contacted to determine if there was an eligible individual to participate in group sessions in a project by Iowa State University on how people select food and household products. Recruiters were seeking adults who were 18-65 years of age who could follow directions and write in English, and could come on a target date to a laboratory site. In particular, they were told that the sessions involve a food preference experiment set up like an auction or bidding activity, and they would be paid $65 for about an hour of their time. Willing subjects were asked to pick among the three available starting times. They were told that there would be follow-up communication confirming time and location and directions to the lab site.

SBRS undertook recruitment for the Des Moines area. They started with a set of random telephone numbers. When a willing participant was obtained, the individual was also permitted to suggest the name of other family members and friends that might be willing to participate in the experiments, sometimes referenced as “snowball” recruiting. To obtain subjects in Los Angeles and Boston, we worked with two marketing research companies - Focus and Testing and Answer Quest. Focus and Testing randomly sampled from its subject pool of 100,000 adults in the Los Angeles area, and Answer Quest randomly sampled from its subject pool of 60,000 adults in the Boston area. These recruits had participated in one or more prior marketing research projects undertaken by these companies but not experimental auctions. Recruitment at the latter two sites was similar to the Des Moines area, except that subjects were not permitted to suggest names of other possible recruits, and there was a 60-40 female-male division of recruits. This was to insure that subjects matched the gender ratio of the population of US grocery store shoppers.[5]

We measure WTP for the following products: potatoes (Russet, 5 lbs.), potato chips (classic-cut, 12 oz.), and frozen French fries (crinkle-cut, 2 lbs.). We offer a diverse set of commodities because of the experiment's high fixed costs and subjects' heterogeneous preferences. These potato products are good sources of potassium and fiber but differ according to preparation and eating time, convenience, and storability (Institute of Medicine, 2015).[6] Each product has two types, conventional (available in grocery store) and low-acrylamide using biotechnology (truly experimental products). Low-acrylamide products using biotechnology had not been deregulated by the USDA for commercial sale at the time of the experiment.[7] However, the J.R. Simplot Company had low-acrylamide, biotech potato products under development that would meet our display needs, which they provided as display products for the bidding rounds. At the end of each session, all subjects were told that only conventional potato products were available to take home on the day of the experiment.

Our experiments provide two types of information to subjects: food labels and prepackaged information. All commodities are packaged in transparent plastic (not commercial packaging) to focus attention on the food labels. Conventional products carry a

[5]Approximately 71% of Des Moines subjects are female, which is somewhat larger than the proportion of women in the US grocery shopper population. However, 62% of our total sample are women.

[6]These diverse attributes suggest that fresh potatoes, potato chips, and frozen French fries are not strong substitutes or complements. Given that the commodities serve different needs, understatements or overstatments of WTP arising from complementary or substitutable commodities is very unlikely (Rousu et al., 2008).

[7]The USDA deregulated biotech potatoes used in these experiments on November 7, 2014. The Innate^{TM} 1.0 biotech potato is resistant to black-spot bruising, will not brown when cut and exposed to air, and has low sugar content and acrylamide-forming potential (O'Connell, 2014).

plain label briefly describing the product and net weight. The low-acrylamide, biotech products have labels that briefly describe the product, including "low acrylamide," and net weight but also include the added information: "Product Made Using Biotechnology." These labels are affixed to the front of each product's packaging. Figure 1 depicts the labels for the conventional and low-acrylamide products.

Information treatments are constructed from three perspectives, each limited to one 8.5" x 11" sheet of paper. These perspectives are (i). an industry perspective on using biotechnology to reduce acrylamide levels in food products, (ii). a scientific perspective on health risks of acrylamide exposure, and (iii). an environmental group's (negative) perspective on biotechnology.[8] Each of these perspectives is organized under the same three headings (General Statement, Nutrition and Health, and Environmental Impacts and Food Security; see Appendix) to aid subjects in reading and processing information contained in them.

The information perspectives are adapted from websites, medical research, government reports, non-governmental organization (NGO) reports, and statements from anti-biotechnology advocacy groups.[9] Some statements in the industry perspective are adapted from Rasmussen et al. (2013) and the J.R. Simplot Company's website, `www.simplot.com`. Information about the harmful impacts of acrylamides exposure used in the scientific perspective are from various medical journal articles and government reports (Garland and Patterson, 1967; Shiraishi, 1978; Naruszewicz et al., 2009; JECFA, 2011; Nixon et al., 2012). For the environmental group perspective, many statements are based on claims from Antoniou et al. (2012) and the Non-GMO Project's website, `www.nongmoproject.org`. As with other design features, the information perspectives were pretested and subsequently revised on several occasions prior to implementation in the experiment.

With order effects, there are a total of nine distinct information treatments: (1). industry perspective only, (2). scientific perspective only, (3). environmental group

[8]We do not suggest that all environmental groups view GM products negatively. Environmental non-profit organizations have very diverse objectives, such as conservation of wetlands, freshwater rivers, and bird habitats. This perspective only refers to groups that are opposed to biotechnology. Our choice of the term "environmental group" was guided by similar studies in the food auctions literature.

[9]Our design does not test "authority" effects. A potentially interesting design alternative would assign information perspectives that have identical content but attributions to differing groups.

perspective only, (4). industry then scientific perspective, (5). scientific then industry perspective, (6). industry then environmental perspective, (7). environmental then industry perspective, (8). scientific then environmental perspective, and (9). environmental then scientific perspective. Each subject is randomly assigned one of the information treatments in their packet with the protocol for the experiment.[10]

The design of the experiments introduces randomness at several levels. First, subjects are recruited randomly. Second, subjects are randomly assigned to a packet containing the protocol and information treatment. Third, they are alternately assigned to one of two concurrent sessions. Fourth, the order of bidding on products across four rounds of bidding is randomized (e.g., we randomly select the order of conventional versus biotech products). Fifth, we randomly select one of the two rounds of bidding on conventional products as the binding round. This multilevel randomized design permits simpler identification and obviates controlling for selection effects (Lusk and Shogren, 2007; Glennerster and Takavarasha, 2013).

3.3.2 Timeline of subject activities

We now briefly review the steps of a typical auction session to provide a more detailed description. Figure 2 is a flowchart of these steps. Upon arriving at the experimental site, participants read and sign an informed consent sheet, required for human subjects research. After agreeing to participate, subjects are given an ID number and are randomly assigned to one of two concurrent sessions and a packet (random assignment to treatment).[11] They are then instructed to begin completing the pre-auction questionnaire. The 19 questions in the pre-auction questionnaire mainly relate to demographics, prior knowledge about acrylamide, biotech foods, and non-biotech foods, and health (subjective risk for developing cancer and current level of hunger). We distribute a $65

[10] No participant received a treatment consisting of all three information perspectives. This reduces subject burden and session lengths.

[11] Individuals who arrive together (e.g., friends and family members) are placed in separate sessions, unless special circumstances require assignment to the same session. In this case, we ask that they do not sit next to each other, unless this is also necessary for extenuating reasons. There were very few such instances.

participation fee and have participants sign a receipt while they begin completing the pre-auction questionnaire.

Subjects are told to turn off electronic devices and not talk with other participants. After all subjects have completed the pre-auction questionnaire, session monitors tell subjects that they will be participating in an experimental auction and explain how the auction works. Subjects are also notified that they can win at most one unit of each commodity. At this stage of the experiment, subjects are allowed and encouraged to ask clarifying questions. We proceed to one of two practice rounds once any questions have been addressed.[12] The commodity in the first practice round is a ceramic mug. Subjects are asked to come to the front of the room, view the mug, return to their seats, and write down bids. The session monitor and assistant then collect and rank the bids (in a spreadsheet), randomly draw the binding round, and determine the winner(s) via the auction rules.[13] After the first practice round, a brief quiz is administered to check understanding of the auction rules. We allow subjects four to five minutes to finish the quiz and then review the answers with additional explanation. In the second practice round, subjects gain experience placing three bids at one time on a notepad, binder, and a package of pens. Bids for the three products are sorted separately and displayed, and "winner" IDs are revealed.

There are two distinct rounds of bidding on the three potato products after completion of the practice rounds. As in the practice rounds, subjects are asked to come to the front of the room, view the products, return to their seats, and write their bids on a bid sheet. Subjects are not allowed to pick up the products.[14] After bid sheets have

[12]The use of practice rounds in economics experiments is not universally accepted. Some studies indicate training could influence bids via incidental prices or coherent arbitrariness (Ariely et al., 2003; Nunes and Boatwright, 2004). However, we agree with Plott and Zeiler (2005) and Lusk and Shogren (2007) that practice rounds boost understanding, lower the possibility of subject misconceptions, and do not alter subjects' underlying values for products. Further, our non-food practice round items are neutral relative to the experimental commodities.

[13]Since there is only one round of bidding in each practice round, and the practice round is not binding, there is no need to randomly select the binding round. At this stage, we show an example so that subjects will understand the procedure in the later, actual rounds of bidding.

[14]Subjects are permitted to touch the commodities' packaging. Peck and Shu (2009) find that, across a wide array of household objects, simply touching an item can increase perceived ownership, which raises valuations if the object does not provide negative sensory feedback. We expect that prohibiting subjects from picking up the products will not influence our results, given consumers' widespread experience with conventional potato products.

been collected, subjects are given approximately ten minutes to read their assigned information treatment.[15] Subjects then bid again on both sets of products, and bid sheets are collected. The only posted bids are those for the binding type (conventional) in the binding round at the end of the auctions. Note that subjects are bidding on a separate set of products for each of the four rounds. However, both sets of conventional products have identical packaging and labeling and look very similar, as do the biotech products.

Subjects are then asked to complete a post-auction questionnaire with 21 questions. We ask participants about monthly purchases, weekly consumption, and household inventories of potato products and their complements and substitutes. Additional questions concern health-related indicators and subjects' level of understanding and agreement with the information perspectives.

In the final stage of a session, the binding round, random n, winning prices, and winning IDs are revealed. Subjects are told that only the conventional products are available to the winners. For purposes of product control, we randomly choose the binding conventional round and random n prior to all sessions. After inputting bids for the binding round into a spreadsheet, the bids for all products are projected at the front of each session's room, and subjects watch as the session monitor ranks the bids and reveals the winning IDs. Winners are then directed to a "stockroom" to purchase the won item(s).[16] Questionnaires are quickly checked to ensure completion prior to each subject's departure.

3.3.3 Research hypotheses

The experimental design and corresponding questionnaire data permit the following testable hypotheses, among others:

[15]To ensure that outside information does not contaminate any specific treatment, session monitors and assistants do not answer questions related to informational content. To avoid confusion, we state that subjects will have either one or two pages of information. This added piece of information about the design is not expected to substantially influence the treatments' efficacy or bidding behavior.

[16]Demand reduction is an unlikely problem in our setting. This is because subjects are not bidding on multiple units of the same commodity. Rather, they are bidding on commodities that are not strong complements or substitutes. Although demand reduction can occur when auctioning many units of the same good (Corrigan and Rousu, 2006), this is not problematic when the goods are unrelated in consumption (Lusk and Shogren, 2007).

1. Scientific information about presence of acrylamide in potato products increases WTP for GM potato products.
2. An industry perspective on reducing acrylamide content in potato products using GM technologies increases WTP for GM potato products.
3. Combinations of two information perspectives may have larger or smaller effects on WTP than single information perspectives.
4. Subjects' demographics, prior knowledge, beliefs, and health affect WTP.
5. The order in which subjects receive information affects WTP.

However, this list of hypotheses is incomplete. The questionnaires elicit many kinds of information, motivated by previous economics or marketing studies. Additional research will consider the impacts of self-assessed cancer risk on WTP differences, in addition to stock or "household inventory" effects.

3.4 Econometric model and data

3.4.1 Econometric model

The nature of the experiment (repeated measurement of valuations), breadth and depth of questionnaires, and sample of 304 subjects provides latitude for empirical methods. Regression analysis of WTP levels, however, is problematic for two reasons. First, some zero bids are truncated at zero, i.e., subjects would have preferred to bid a negative value but felt constrained to bid zero instead. Other zero bids are legitimate bids with no truncation, i.e., zero was the preferred bid (Maddala, 1983). Second, valuation levels, although sincere, may be arbitrary (Ariely et al., 2003).[17] Our approach uses WTP differences across subjects for parameter estimation. Another benefit of this method is that unobserved heterogeneity (e.g., subject fixed effects) are differenced out in the estimation.

[17]Maniadis et al. (2014) find limited evidence of anchoring in a replication of Ariely et al. (2003). As such, the economic consequences of arbitrariness may be small in practice.

We propose the following model of WTP differences:

$$Bid^{GMPot}_{i,post} - Bid^{GMPot}_{i,pre} = \boldsymbol{x_i'\beta_1} + \boldsymbol{T_i'\gamma_1} + \varepsilon_{1,i} \tag{3.1}$$

$$Bid^{GMPot}_{i,post} - Bid^{ConvPot}_{i,pre} = \boldsymbol{x_i'\beta_2} + \boldsymbol{T_i'\gamma_2} + \varepsilon_{2,i} \tag{3.2}$$

$$Bid^{GMFry}_{i,post} - Bid^{GMFry}_{i,pre} = \boldsymbol{x_i'\beta_3} + \boldsymbol{T_i'\gamma_3} + \varepsilon_{3,i} \tag{3.3}$$

$$Bid^{GMFry}_{i,post} - Bid^{ConvFry}_{i,pre} = \boldsymbol{x_i'\beta_4} + \boldsymbol{T_i'\gamma_4} + \varepsilon_{4,i} \tag{3.4}$$

$$Bid^{GMChip}_{i,post} - Bid^{GMChip}_{i,pre} = \boldsymbol{x_i'\beta_5} + \boldsymbol{T_i'\gamma_5} + \varepsilon_{5,i} \tag{3.5}$$

$$Bid^{GMChip}_{i,post} - Bid^{ConvChip}_{i,pre} = \boldsymbol{x_i'\beta_6} + \boldsymbol{T_i'\gamma_6} + \varepsilon_{6,i}. \tag{3.6}$$

In the above equations, $\boldsymbol{x_i'}$ is a vector of demographics and other controls for person i, $\boldsymbol{T_i'}$ are indicator variables for information treatments, and $\varepsilon_{.,i}$ is a random error. Further, $Bid^{GMPot}_{i,post} - Bid^{GMPot}_{i,pre}$ is the difference in WTP for biotech potatoes before and after the information treatments, while $Bid^{GMPot}_{i,post} - Bid^{ConvPot}_{i,pre}$ is the difference in WTP for biotech potatoes and conventional potatoes before and after the information treatments. The latter is designed to examine information impacts in transitioning from conventional potatoes to low-acrylamide biotech potatoes.[18] This is of practical significance given recent USDA deregulation. Note that estimates of the $\gamma_.$ parameters indicate treatment effects.

When there is truncation at zero for a WTP value, the WTP difference in equation (1)-(6) is sometimes censored. To accommodate censoring, a general version of a differenced Tobit model is developed. The general nature of this model arises from multiple sources of truncation of WTP at zero. Coefficients are obtained by maximizing each equation's log-likelihood, which is the sum of continuous and discrete distributions. Estimated coefficients of this new model can be compared to those of OLS estimates of equation (1)-(6) ignoring possible censoring of some WTP differences.

There are four censoring cases to consider, depending on the location of zeros in the dependent variables of equations (1)-(6). *Case 1*: both bids are positive. The dependent

[18]Interpreting this dependent variable is more challenging. It does not represent a premium for food safety because it confounds sources of perceived risk: the biotech products reduce acrylamide potential but use biotechnologies that are not universally accepted by consumers.

variable is uncensored and the likelihood is continuous. *Case 2*: the post-information bid is zero because the subject preferred to bid a negative value but felt constrained to bid zero, and the pre-information bid is positive. In this case, the true WTP difference is left-censored at the value of subject i's pre-information bid. *Case 3*: the post-information bid is positive and the pre-information bid is zero because the subject preferred to bid a negative value but bid zero instead. In this case, the true WTP difference is right-censored at the value of subject i's post-information bid. *Case 4*: both bids are truncated at zero because a subject preferred a negative value but bid zero instead. Unfortunately, when we observe a zero value for WTP, we do not know whether it is a legitimate zero or a "constrained" zero.

This estimation procedure is inefficient if WTP among potato products is jointly determined. Since subjects are informed at the beginning of the experiments that they will be bidding on potatoes, French fries, and potato chips, this could condition subjects to think about their WTP simultaneously. We could impose cross-equation correlation of disturbances and fit a Seemingly Unrelated Regression (SUR) model (Zellner, 1962). However, the auction commodities differ greatly with respect to preparation times, convenience, and storage, so it is likely that valuations are formed independently.

3.4.2 Data

Our questionnaires provide a much richer dataset than most experimental studies and some marketing research. The extensive data collection arises, in part, because of limited understanding of general trends across marketing research. We draw on past food experiment research, economic theory, and practical considerations to guide question choice in the questionnaires.[19]

The resulting questionnaire data can be classified into four groups: (i). demographics, (ii). subject attributes, (iii). health and diet, and (iv). food product flows and stocks. Demographic variables include: marital status, gender, age, household size and income, religion, years of education, race, residential location, and occupation. We expect per-

[19] A consultation with the ISU Department of Statistics also provided assistance on sampling, question arrangement, and question wording in the questionnaires.

capita income and years of schooling to have positive, potentially nonlinear, effects on WTP differences. The expected influence of other demographic variables on valuations is less certain. Variables in the second category include subjective level of hunger, previous participation in an economics experiment, distance traveled to the site and whether or not accompanied by another participant, allergies and food intolerances, and indicators of blemishes and discolorations in the displayed products.[20] Of additional interest to the analysis are measures of stocks (i.e., household inventories of related goods) and flows (i.e., purchases and consumptions of related goods). We also inquire about perceived overall health status, cigarette smoking, diet, and frequency of exercise.

Of the 304 subjects, 101 subjects are from Des Moines, 106 subjects are from Los Angeles, and 97 are from Boston. The average number of subjects per session is 16.9. Four subjects had missing data and were excluded from the analysis, leaving a sample of 300. Of these 300 observations, there are 3-5 double-zero bids for potatoes, 9-13 double-zero bids for French fries, and 6-10 double-zero bids for potato chips. Roughly 4.7% of the potatoes bids are single-zero bids, 4.9-5.8% of the French fry bids are single-zero bids, and 4.8-5.8% of the potato chips bids are single-zero bid (not including double-zero bids). The number of reported zero bids represents the maximum number of possible censored bid differences. Summary statistics for the sample are reported in Table 3.1 for all 300 subjects for all of their bids on all products.

Table 3.1 gives summary statistics on bid levels for the three commodities across types and before and after subjects receive information. Mean bids within a commodity across the conventional and biotech type tend to be very similar. Prior to receiving diverse information, subjects discount biotech potatoes by two cents, relative to the $2.57 for the conventional potatoes. Conventional and biotech chips have an average valuation of $2.03, while biotech French fries are six cents higher than their conventional counterpart at $2.33. The premium for biotech French fries declines to three cents after subjects

[20]Capra et al. (2010) show that induced positive moods are associated with roughly 11% overbidding on products with induced values. However, mood has weak or no effects on WTP for movie tickets (a good with “homegrown” value). Our experiment does not control for mood or a host of other psychological or mental states that could potentially affect values or results in a between-subjects analysis.

receive information. This is part of a broader downward trend in post-information bids for all commodities.

Summary statistics of variables in this analysis are contained in Table 3.2. The descriptive statistics for WTP differences confirm that valuations for the biotech products decline after receiving information treatments. For example, average WTP for the biotech potatoes is \$0.11 lower after reading information treatments, while WTP for conventional potatoes before information is roughly \$0.13 higher than WTP for low-acrylamide potatoes after information. This trend is similar for French fries and potato chips, though potato chips have the smallest WTP differences at roughly \$0.07-\$0.08.

There is substantial variability in WTP differences across commodities, with standard deviations ranging from \$1.17 to \$1.67. A sizeable asymmetry exists between maximum and minimum WTP differences. Some individuals value the biotech products \$7-\$10 less after receiving information. However, upward influences on WTP are roughly half this size at \$4-\$7. This suggests that marketers should carefully consider the potential consequences of advertising on information-sensitive consumers. Note that the data are not being skewed by extreme underrepresentation or overrepresentation of potato product consumers, and we did not randomly select our sample on this criterion. On average, 64% of subjects are from households that consume potatoes once or twice per week, 53% consume French fries once or twice per week, and 49% consume potato chips with this regularity.

The "average household" has a respondent who is 43 years old with 14.4 years of schooling, living with one other adult in the household, and maintaining a per-person annual pre-tax income of \$28,550.[21] Roughly 42% and 49% of the sample were at least somewhat informed about biotech and non-biotech food products prior to the experiment ("Previously informed about biotech" and "Previously informed about non-biotech"), and 88% read labels at least some of the time when buying new food products ("Looks at labels"). On average, 22% of the subjects came with another experiment participant ("Arrived with someone else") and traveled just over nine miles to reach the site ("Dis-

[21] Annual incomes are coded as the midpoint of the income bracket chosen by the respondent in the pre-auction questionnaire.

tance traveled").[22] In general, there is considerable variation in subject demographics, particularly in per-person incomes and previous knowledge of biotech and non-biotech food products.[23]

Regarding health, diet, and exercise, 83% are in at least good health ("Healthy"), with 75% of the sample exercising at least twice per week ("Exercises regularly"). These health measures are, on average, consistent with the fact that only 15% of the sample are smokers, and 38% are in households with at least one person dieting. Interestingly, 65% of subjects are at least moderately hungry at the beginning of the experiment ("Hungry"). Many previous food experiments do not control for degree of hunger or diet, although these would be expected to have straightforward effects on WTP and possibly WTP differences. As with other studies, we cannot verify subjective assessments of participants' own health and exercise status.

Other controls include the number of children in the household less than or equal to 12 years of age ("Number of preteen children") and number of children in the household aged thirteen years or older ("Number of teen children"). Aspects of the experimental design are also included in the analysis. There is a roughly equal distribution of sessions across the three sites, though Los Angeles contains 35% of all sessions ("LA site"). Exactly half of the subjects are assigned to one of two monitor's ("Monitor") concurrent sessions, and they are equally distributed across the 9:00 a.m., 11:00 a.m., and 1:30 p.m. starting times ("11:00 a.m. session" and "1:30 p.m. session").[24] Lastly, the distribution of information treatments is given at the bottom of Table 3.2. Our target was an equal

[22]Subjects in the Des Moines area consisted of randomly-dialed participants, returning participants from a previous food experiment, and contacts of randomly-dialed participants. This substantially reduced recruitment expense. However, we are not concerned about correlated bids, dependent data, or an unrepresentative sample for the following reasons: (i). subjects who arrive with other subjects are assigned to different concurrent sessions, (ii). the auctions are incentive compatible, regardless of subjects' familiarity with other subjects, (iii). the sample matches several key dimensions of the population of US grocery shoppers, and (iv). these types of recruits comprise less than 25% of our sample.

[23]Roughly 76% of the sample is white, a consequence of the eligibility requirement that subjects can read and write English. This has some bearing on average demographics, but Table 3.2 confirms there is ample variation in our data. Although our sample is quite diverse, our results generalize mainly to the population of English-speaking US grocery shoppers.

[24]Rather than include design controls in the regression analysis, we could perform Chow, Kruskal-Wallis, or other tests of the appropriateness of pooling across experimental sites and starting times. Direct inclusion in the regression is straightforward and does not rely on small subsamples for estimation of other parameters.

distribution of treatments across subjects: 16.67%. Approximately 19% of the sample received the industry-only statement, 18% received the scientific-only statement, 17% received a combination of the industry and scientific statements, and similarly for the other treatments. The environmental-only treatment is the reference category.[25]

3.5 Empirical results

3.5.1 Information ordering effects

First, we explore the significance of information-perspective ordering effects. Subjects who are randomly assigned to one of the six treatments with two perspectives may place more emphasis on the first (or second) perspective. That is, subjects may anchor on either of the perspectives. If this occurs, coefficient estimates across these treatments would differ depending on information perspective ordering. To test this joint hypothesis, equations (1)-(6) are estimated with indicators for fine information treatments, i.e., we include indicators for subjects whose packets include the industry perspective first and scientific perspective second, industry perspective second and scientific perspective first, and so on. Regression coefficients are not displayed but are similar to coefficients in Tables 3.4, 3.5, and 3.6 below. The environmental-only perspective is the reference category.

Table 3.3 presents the results of the joint F-test. For each of the six regressions, the joint null hypothesis is $\beta_{SI} = \beta_{IS}$, $\beta_{IE} = \beta_{EI}$, $\beta_{SE} = \beta_{ES}$. Note that β_{SI} is the coefficient on the indicator for the treatment in which the scientific perspective is first and the industry perspective is second, β_{IS} is the coefficient on the indicator for the treatment in which the industry perspective is first and the scientific perspective is second, β_{IE} is the coefficient on the indicator for the treatment in which the industry perspective is first and the environmental perspective is second, etc. We cannot reject the null hypothesis (at the 5% significance level) that the order in which subjects read the information has no effect. This lack of asymmetry indicates that subjects with two perspectives actively

[25] This is a modeling choice. One information treatment must be excluded for identification. Interpretation of regression coefficients is straightforward when the intercept absorbs the negative environmental information. Our findings are robust to using another information treatment as the base category, though the impact of the environmental group perspective is large, negative, and significant at the 1% level (as expected).

consider both when forming their WTP, i.e., there is no anchoring effect. One practical implication is that in advertising projects, marketers may not need to be concerned about the order in which information is displayed to consumers.

3.5.2 WTP and the value of information

Table 3.4 contains regression results on WTP differences for potatoes. The dependent variable for columns (1a) and (1b) is $Bid_{post}^{GMPot} - Bid_{pre}^{GMPot}$, the WTP difference for biotech potatoes pre- and post-information. The dependent variable for columns (2a) and (2b) is $Bid_{post}^{GMPot} - Bid_{pre}^{ConvPot}$, the WTP difference for biotech potatoes post-information and conventional potatoes pre-information. Note that (1b) and (2b) are reduced versions of (1a) and (2a).[26] The first two columns point to large information effects significant at the 1% level. Relative to those receiving the environmental group-only treatment, the industry-only treatment increases WTP for biotech potatoes by \$1.17 and the scientific-only treatment increases WTP by \$1.91. The relative impact of receiving either combination of both industry and scientific perspectives is \$1.78, which appears to be a weighted average of the industry-only and scientific-only perspectives. The relative effects on WTP for the industry and environmental treatments and the scientific and environmental treatments are similar at \$1.04 and \$1.01. The reduction in magnitude suggests that the "environmental group" perspective (negative on biotechnologies) decreases the positive WTP effects of the industry-only and scientific-only perspectives. Estimated information effects in the reduced model (1b) are largely robust to dropping insignificant demographic variables. Insignificant health and child controls and design controls (see Table 3.2) are also dropped in model (1b).[27] We reject the null hypothesis that all coefficients equal zero (the likelihood ratio test statistics of 70.9-74.6 exceed the relevant 5% critical values of the χ^2 distributions).

The informational impacts in models (2a) and (2b) are similar but differ in exact size across treatments. Those receiving the industry-only perspective have increased

[26] Using standard F-tests, we fail to reject the null hypotheses that coefficients on the dropped regressors are jointly equal to zero at the 1% significance level.

[27] Since the coefficients on the Los Angeles, Boston, monitor, 11:00 a.m. start time, and 1:30 p.m. start time are insignificant, pooling experimental data from all sessions is appropriate.

WTP by \$0.98, while those reading the scientific-only perspective have increased WTP by \$1.37, relative to those getting the environmental-only statement. However, the effect of getting either combination of both perspectives is \$1.63, which exceeds each of the individual information effects. This suggests that a pairing of negative information on acrylamides and positive information on low-acrylamide levels and biotechnologies raises WTP across the mixed commodity type. In particular, marketers may want to emphasize both kinds of information in a transition from conventional potatoes to low-acrylamide biotech potatoes. As with the other regressions, the combinations of industry and environmental perspectives and the combinations of scientific and environmental perspectives have smaller WTP effects than their individual perspectives. Results are generally unchanged in reduced model (2b). The somewhat differing information effects in the mixed commodity type suggest there could be other factors influencing the demand for low-acrylamide biotech potatoes over conventional potatoes.

Some demographics variables across the potato WTP results are significant. Prior knowledge of biotech products increases WTP differences by \$0.49-\$0.52 (Models 1a and 1b), whereas prior knowledge of non-biotech products reduces the WTP difference by \$0.44-\$0.49 (Models 2a and 2b). Distance traveled to the experimental site has small but significant effects. Those who exercise at least twice per week experience relative reductions of \$0.46-\$0.56 in WTP for potatoes after the information treatments. It is difficult to determine the sources of these demographic effects on WTP differences.[28] Demographics play a mediating role, but information treatments are the most substantial determinants of WTP differences.

Regression results for WTP differences in French fries, displayed in Table 3.5, are comparable to those of potatoes. Information impacts are large, relative to the \$2.25-\$2.30 average WTP levels for conventional and biotech French fries. Most treatment effects are significant at the 1% level. Effects from the combined industry and environmental information treatments are now significant at the 5% level, though. Again relative to the environmental group treatment, subjects receiving the industry perspective have WTP

[28] We leave for future research the possibility of demographics-information treatment interactions, though interpretability and reduction in degrees of freedom are important drawbacks.

$0.81 higher in the second round of bidding, while WTP is $1.46 higher after receiving the scientific perspective. For those receiving both perspectives, the relative impact is $1.63, again higher than the treatment effect from a single statement. This suggests that receiving both information perspectives may have an additive effect relative to the single perspectives. Table 3.7 explores the extent to which the sum of the industry-only and scientific-only information coefficients approximates the impact of receiving both statements (discussed below). WTP for French fries is pulled in the direction of the scientific perspective when subjects receive both industry and scientific perspectives. As in the potato results, when subjects receive the environmental perspective and another perspective, the information impacts are lower than if the subject had received a single non-environmental-group perspective. For example, there is a relative WTP effect of $0.64 for those getting the industry and environmental perspective, a drop of $0.17 from the industry-only impact of $0.81. Estimated treatment effects are similar after dropping insignificant regressors.

Regressions (4a) and (4b), which explain the difference in WTP for biotech French fries post-information and conventional French fries pre-information, give similar results. One major difference is that the industry-only perspective effects increase by $0.18-$0.20 relative to their impacts on WTP differences for biotech French fries (columns 3a and 3b). The implication is that consumers may be more sensitive to industry information, such as standard advertising campaigns, when switching from conventional fries to the low-acrylamide fries. The other treatment effects resemble those of the previous model. Specifically, pairings of industry and scientific information have larger impacts ($1.49-$1.54) than the individual statements, and pairings of information involving the environmental statement have smaller impacts than the single statement. Given that potatoes are a staple vegetable of the American diet, whereas French fries are perceived to be a less healthy food, the complementary findings are surprising. Analogous information impacts are useful for industry and public health agencies and suggest that, with respect to treatment effects, consumers view fresh potatoes and frozen French fries somewhat similarly.

Other distinguishing features of Table 3.5 are the significant health and demographics variables. WTP differences in biotech French fries are increasing in annual per-person income up to \$90,000-\$130,000, depending on model (3a) or (3b). The impact of per-person income is small, at roughly 1.2-2.0 cents per thousand dollars of income (evaluated at the sample mean). Further, those with prior knowledge of non-biotech products have reduced WTP of \$0.37-\$0.43 for biotech fries relative to conventional fries after receiving information. One explanation is that those with superior prior knowledge of non-biotech products may prefer “natural” products or have a strong aversion to biotech foods, thus driving down their WTP for biotech foods. Lastly, the number of adults in the household has positive significant effects (models 3a and 3b), and there are substantial downward effects on WTP for those who regularly exercise.

The analysis of potato chips WTP differences is given in Table 3.6. Compared to average WTP of \$1.99 for both the conventional and biotech potato chips, the information effects are relatively small. Treatment effects for combinations of the industry and environmental perspective and scientific and environmental perspective are significant at the 5% and 10% levels. Across the four specifications, the relative effect of the industry-only perspective is to increase WTP by \$0.55-\$0.70. These are one-half the size of the scientific-only perspective effects, \$1.14-\$1.30. The combined effect of both perspectives is an increase in WTP by \$1.22-\$1.30, although for model (5b), the combined-perspective effect seems to be an average of the two single-perspective effects. We again confirm the finding that joining the environmental group perspective with either of the other two perspectives produces smaller relative WTP impacts. As with the other regressions, our specifications outperform empty models (as indicated by the likelihood ratio test statistics).

Subject characteristics have much more influence on WTP differences for potato chips than the other two commodities. WTP differences in potato chips increase with age up to 35-42 years and then decline. At the mean sample age, an additional year reduces the WTP difference by 0.2-1.6 cents. There is a similar concave relationship in per-person income. Beyond \$70,000-\$90,000, an additional thousand dollars of per-person income has small negative WTP effects. An additional adult in the household has a \$0.25-\$0.35 impact. In the context of switching from conventional to low-acrylamide potato chips, an increase in the number of adult consumers could be interpreted as a demand increase, thus driving up WTP. Surprisingly, there is little WTP effect among those who read labels or have prior knowledge of biotech and non-biotech foods. However, those who exercise regularly have decreased WTP by \$0.32-\$0.33 after receiving random information treatments.

Why is the WTP difference for biotech potato chips and the low-acrylamide premium relatively less responsive to information effects? A definitive answer requires further analysis, but several explanations are possible. Compared to potatoes and some frozen French fries, potato chips are usually highly processed food items with little nutritional value. Yet they are a common part of the US diet for which some consumers may have strong preferences. Many consumers may want to maintain consumption despite learning about possible negative health consequences. Thus, a persistent consumption "habit" could lead subjects to discount the information treatments. Another explanation is that subjects form various beliefs about acrylamide content of food after reading the information treatments. If subjects believe potato chips have very low concentrations of acrylamide relative to potatoes and frozen French fries, it could be rational for them to discount the information treatments, with little influence on valuations. Subsequent analysis could use data on household stocks, purchases, and consumption of potato chips to test the first claim.

Our preferred set of information treatment effects are from the reduced models for the biotech commodity WTP differences, i.e., the second columns of Tables 3.4-3.6. Figure **??** summarizes these effects. Comparisons across commodities are complicated by differences in product sizes and potato content. However, the same relative patterns emerge in all commodities. First, industry perspective effects are roughly half the size of those for the scientific perspective, the perspective with the largest impact. Second, the scientific perspective outweighs the industry perspective in the paired scientific and industry information treatment. Third, the environmental group perspective decreases the effects of the industry-only and scientific-only perspectives.

3.5.3 Information additivity effects

Table 3.7 provides evidence of additive information effects. Using the reduced models corresponding to (1b)-(6b), we test the claim that $\beta_I+\beta_S=\beta_{SI}$, where β_I is the slope on the indicator for the scientific-only treatment, β_S is the slope on the indicator for the industry-only treatment, and β_{SI} is the slope on the indicator for the scientific and industry treatment. Note that, as in Tables 3.4, 3.5, and 3.6, this latter indicator does not account for sequencing effects. Except for equation (1b) explaining WTP differences for biotech potatoes, we cannot reject the null hypothesis at the 1% level that the sum of the industry and scientific effects equals the effect from receiving both perspectives.

This additivity feature is well within the range of outcomes implied by the standard errors of the treatments effects. Additivity is not observed for the biotech potatoes (equation 1b) primarily because of the scientific-only perspective's considerable impact. In this instance, the sum of the two single perspective impacts, \$3.08, is nearly double the size of the combined-perspective impact, \$1.78. If this joint impact represents a weighted average of the two single-perspective impacts, then the potato industry might consider a segmentation approach to marketing. Information that portrays low-acrylamide and biotech food products positively may have more impact for some market segments, while others may be more responsive to the negative health ramifications of acrylamides. The results for the French fries and potato chips, however, recommend a different information strategy. For these commodities, an effective approach would be to combine information perspectives, particularly if marketing costs are subadditive.

3.5.4 OLS results ignoring censoring

As there are fewer than 10% zero bids for any commodity, the OLS results should be comparable. Tables B.1, B.2, and B.3 confirm our expectation. Estimates are very similar to the censored results, though certain OLS slopes are smaller in magnitude.

It is well known that OLS results are downward biased when the dependent variable is censored (Amemiya, 1973). This is clearly seen in the information treatment effects. Information effects in the censored regressions for potatoes are \$0.05-\$0.16 larger than OLS effects. Censored information effects for French fries are \$0.01-\$0.14 larger. Information effects for chips tend to be \$0.01-\$0.09 larger than the OLS results, though there are a few instances in which the OLS estimates are marginally larger. Estimates for the demographics, health, children, and experimental design variables are also similar, with the main conclusions remaining unchanged.

3.6 Conclusion

Acrylamide is a probable carcinogen in humans and forms naturally in potatoes and potato products that have been cooked at high temperatures. This has been a concern of the US potato industry in recent years. Proposition 65 in the State of California requires a public notice to be displayed at businesses selling foods with acrylamide. Thus, US potato consumers and producers have a joint interest in the introduction of potato products with decreased acrylamide concentrations. Using experimental methods, we test the combined effects of labeling and information on WTP differences for conventional potato products and potato products using biotechnology to reduce acrylamide. Experiments took place in the Des Moines, Los Angeles, and Boston areas, with a combined sample of 304 subjects and 300 useable observations. Random n^{th}-price auctions elicit WTP before and after each subject receives (reads) a randomly assigned information treatment. Each information treatment contains one or two perspectives: (i). industry perspective, (ii). scientific perspective, and (iii). "environmental group" perspective.

We find that the various information treatments have differing, but sizeable, effects on WTP differences. These differences increase by \$0.43-\$1.95 for positive information perspectives relative to the "environmental group" perspective. The scientific perspective is the most influential single perspective, but treatments that combine the scientific perspective and industry perspective have the largest effect on WTP differences. Generally, information effects are additive, e.g., the effect of combining industry and scientific information equals the sum of the separate effects. Treatments that combine the "environmental group" perspective with either the industry perspective or scientific perspective have lower effects on WTP differences than treatments containing the industry-only or scientific-only perspective. However, there are insignificant sequencing effects of information perspectives within a treatment. Prior knowledge of biotech and non-biotech food products, health and exercise, and a few demographic variables have substantial impacts.

Comparing our results with those of other food valuation studies using experimental auctions is less straightforward. Our experiment elicits WTP before and after subjects receive information treatments for conventional food products and those that have been genetically modified to reduce a plausible cancer concern. As such, our study incorporates a unique combination of information treatments, labels, and repeated measurement of WTP within a GM food safety context. However, we confirm several of the results in Huffman et al. (2003) and Huffman et al. (2007). Subject demographics have little influence on valuation differences, although GM potato products are not discounted relative to conventional products, nor are there significant anchoring effects. Related results appear in Colson et al. (2011), but we cannot separate the impacts on transgenic versus intragenic technologies since our biotech products only rely on genes from other potato varieties. We add to the recent literature on labeling, such as Liaukonyte et al. (2013), Gracia et al. (2011), and Dannenberg et al. (2011). Relative to mean WTP for conventional products (Table 3.2) or mean WTP differences (Table 3.1), the size of information effects are quite large. This may be of further interest to industry and government stakeholders.

Our estimates of information effects contribute to a growing literature analyzing the role of information in behavioral economics (Chetty, 2015). Several field experiments show that providing basic information to consumers can substantially improve decision making and economic outcomes. For example, Bhargava and Manoli (2014) find that simplified information and benefit displays in experimental mailings to US taxpayers eligible for the Earned Income Tax Credit significantly increase take-up rates. In a school choice setting, the fraction of low-income parents choosing high-performing schools significantly increases after receiving information on school test scores (Hastings and Weinstein, 2008).

Our study suggests basic scientific and industry information on biotechnologies and acrylamide increases consumers' valuations for popular biotech foods and could aid the expansion of markets for foods using genetic modification to reduce food safety concerns. Importantly, scientific information and industry information can be used to "nudge" consumers in a direction to improve the quality of decision making.

Disentangling the potential interactions between consumers' prior knowledge of biotechnology and experience with biotech foods, food labels, and information required for updating beliefs is a challenging economic problem. Our results, aided by experimental control, shed light on how various groups (often with conflicting economic objectives) can influence consumer WTP. Low-acrylamide biotech potatoes have been recently approved in the US for commercial sale. This brings an opportunity to considerably reduce a principal source of carcinogens in the US diet. Consumer and producer acceptance of these biotech foods will, in large part, be determined by the relative success of these groups in influencing public opinion. Toward a goal of improving US health outcomes, our results demonstrate the importance of information disseminated by scientific and biotech food groups in increasing acceptance and demand for low-acrylamide products made using biotechnology.

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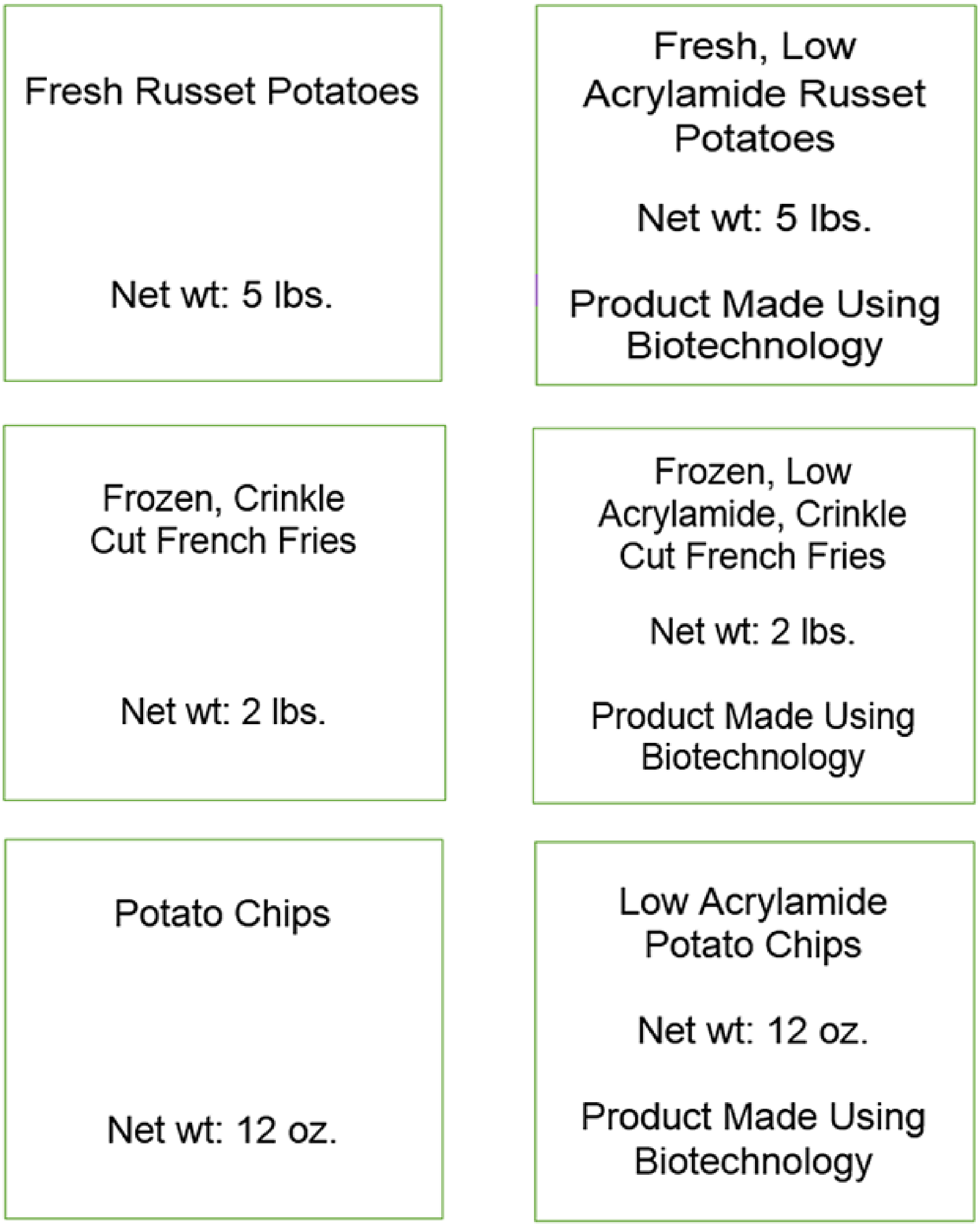


Figure 3.1: Commodity Labels: Conventional (left) and Low-Acrylamide (right)

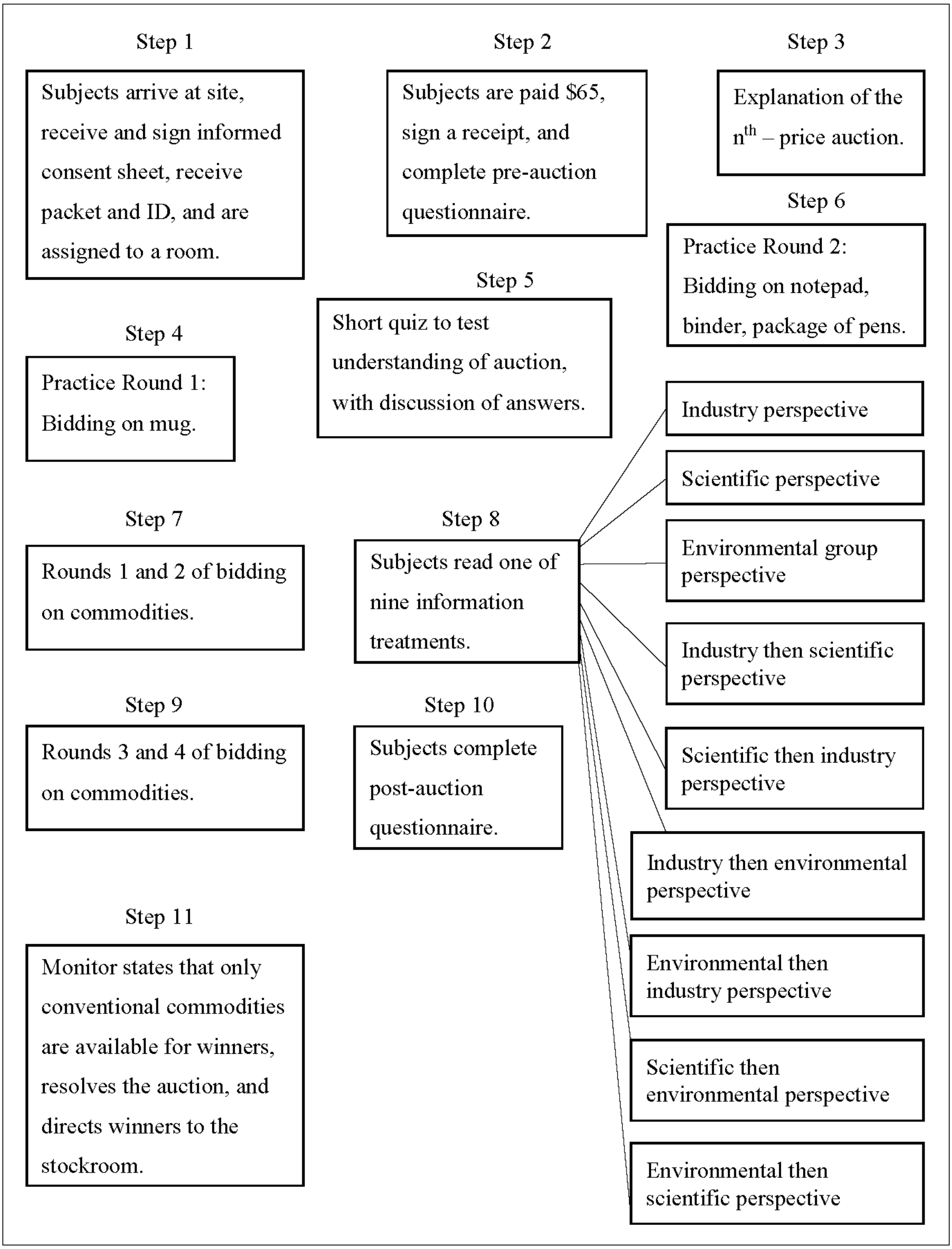


Figure 3.2: Session Timeline of Subject Activities

Table 3.1: Summary Statistics: Commodity Bids (N = 300)

Bid	Mean	St. Dev.	Min	Max
Pre-Information				
Conv. Potatoes ($)	2.57	1.66	0.00	15.00
GM Potatoes ($)	2.55	1.79	0.00	11.00
Conv. Fries ($)	2.33	1.50	0.00	12.00
GM Fries ($)	2.39	1.72	0.00	12.00
Conv. Chips ($)	2.03	1.25	0.00	9.00
GM Chips ($)	2.03	1.41	0.00	8.00
Post-Information				
Conv. Potatoes ($)	2.49	1.71	0.00	10.99
GM Potatoes ($)	2.44	1.92	0.00	13.99
Conv. Fries ($)	2.17	1.55	0.00	9.00
GM Fries ($)	2.20	1.74	0.00	11.99
Conv. Chips ($)	1.94	1.40	0.00	9.00
GM Chips ($)	1.95	1.52	0.00	8.99

Table 3.2: Summary Statistics: Bid Differences and Regressors (N=300)

Variable	Mean	St. Dev.	Min	Max
Dependent Variable				
GM Pot Bid Post - GM Pot Bid Pre ($)	-0.11	1.56	-8.95	7.00
GM Pot Bid Post - Conv Pot Bid Pre ($)	-0.13	1.67	-13.95	6.00
GM Fry Bid Post - GM Fry Bid Pre ($)	-0.20	1.37	-9.55	4.65
GM Fry Bid Post - Conv Fry Bid Pre ($)	-0.13	1.39	-11.55	4.50
GM Chip Bid Post - GM Chip Bid Pre ($)	-0.07	1.19	-7.32	4.90
GM Chip Bid Post - Conv Chip Bid Pre ($)	-0.08	1.17	-8.32	4.70
General Demographics				
Age (years)	42.82	14.08	18	65
Age^2 (years)	2,031.04	1,191.22	324	4,225
Years of Schooling (years)	14.41	2.17	10.00	19.50
Adults in household (integer)	2.08	0.85	1	6
Hungry (0-1)	0.65	0.48	0	1
Per capita income ($ thousand)	28.55	19.53	1.50	112.50
Per capita income^2 ($ thousand)	2,792.60	3,322.49	9.00	24,200.00
Looks at labels (0-1)	0.88	0.33	0	1
Previously informed about biotech (0-1)	0.42	0.49	0	1
Previously informed about non-biotech (0-1)	0.49	0.50	0	1
Arrived with someone else (0-1)	0.22	0.42	0	1
Distance traveled (miles)	9.32	7.99	1.00	100.00
Exercises regularly (0-1)	0.75	0.43	0	1
Health Controls				
Healthy (0-1)	0.83	0.38	0	1
Smoker (0-1)	0.15	0.36	0	1
At least one dieting person in household (0-1)	0.38	0.49	0	1
Child Controls				
Number of preteen children (integer)	0.37	0.74	0	4
Number of teen children (integer)	0.56	0.86	0	4
Design Controls				
LA site (0-1)	0.35	0.48	0	1
Boston site (0-1)	0.32	0.47	0	1
Monitor (0-1)	0.50	0.50	0	1
11:00 a.m. session (0-1)	0.33	0.47	0	1
1:30 p.m. session (0-1)	0.33	0.47	0	1
Information Treatments				
Industry Info	0.19	0.39	0	1
Scientific Info	0.18	0.38	0	1
Industry and Scientific Info	0.17	0.38	0	1
Industry and Environmental Info	0.15	0.36	0	1
Scientific and Environmental Info	0.13	0.34	0	1

Table 3.3: Joint Likelihood Ratio Tests: Information Ordering Effects

Regression Equation	LR statistic
GM Potatoes WTP Differences	1.75
GM Potatoes WTP Post Information - Conv. Potatoes WTP Pre Information	0.18
GM Fries WTP Differences	0.44
GM Fries WTP Post Information - Conv. Fries WTP Pre Information	0.16
GM Chips WTP Differences	0.38
GM Chips WTP Post Information - Conv. Chips WTP Pre Information	0.56

Each row corresponds to the censored models in Tables 3.4, 3.5, and 3.6. For each regression, the joint null hypothesis is that $\beta_{SI} = \beta_{IS}$, $\beta_{IE} = \beta_{EI}$, $\beta_{SE} = \beta_{ES}$. Note that β_{SI} is the coefficient on the indicator for scientific and then industry information, β_{IE} is the coefficient on the indicator for industry and then environmental information, and β_{SE} is the coefficient on the indicator for scientific and then environmental information. The 5% critical value of the $\chi^2(3)$ distribution is 7.81.

Table 3.4: Estimates of Model of WTP Differences with Possible Censoring: Biotech and Conventional Potatoes

	(1a)	(1b)	(2a)	(2b)
Age	0.027	0.034	0.019	0.025
	(0.048)	(0.045)	(0.053)	(0.050)
Age^2	−0.0004	−0.0004	−0.0001	−0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Years of schooling	−0.040		−0.037	
	(0.045)		(0.050)	
Adults in household	0.222	0.195	0.265*	0.263*
	(0.141)	(0.128)	(0.157)	(0.143)
Hungry	−0.321*	−0.258	−0.052	−0.002
	(0.186)	(0.182)	(0.208)	(0.204)
Per capita income	0.014	0.009	0.015	0.010
	(0.013)	(0.011)	(0.014)	(0.012)
Per capita income^2	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Looks at labels	−0.177	−0.224	−0.273	−0.256
	(0.287)	(0.277)	(0.318)	(0.308)
Previously informed about biotech	0.489**	0.516**	0.318	0.369
	(0.220)	(0.218)	(0.246)	(0.244)
Previously informed about non-biotech	−0.342	−0.369*	−0.441*	−0.491*
	(0.220)	(0.217)	(0.245)	(0.242)
Arrived with someone else	−0.447	−0.369*	−0.147	−0.233
	(0.304)	(0.215)	(0.338)	(0.239)
Distance traveled	0.024**	0.022**	0.023*	0.022*
	(0.012)	(0.011)	(0.013)	(0.013)
Exercises regularly	−0.555**	−0.554***	−0.507**	−0.459**
	(0.215)	(0.206)	(0.239)	(0.229)
Industry Info	1.166***	1.172***	0.982***	0.974***
	(0.291)	(0.287)	(0.324)	(0.320)
Scientific Info	1.910***	1.954***	1.372***	1.428***
	(0.290)	(0.288)	(0.322)	(0.321)
Industry and Scientific Info	1.782***	1.727***	1.628***	1.589***
	(0.296)	(0.289)	(0.330)	(0.323)
Industry and Environmental Info	1.037***	1.056***	0.948**	0.972***
	(0.305)	(0.302)	(0.340)	(0.338)
Scientific and Environmental Info	1.014***	1.023***	0.682*	0.747**
	(0.322)	(0.320)	(0.357)	(0.356)
Constant	−1.135	−1.758	−1.515	−2.033
	(1.233)	(1.103)	(1.375)	(1.233)
Health and Child Controls	Yes	No	Yes	No
Design Controls	Yes	No	Yes	No
Observations	295	295	297	297
LR χ^2 Statistic	74.6***	70.9***	48.3**	43.1***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Dependent variable in columns (1a) and (1b) is the WTP difference for biotech potatoes pre- and post-information. Dependent variable in columns (2a) and (2b) is the WTP difference for biotech potatoes post-information and conventional potatoes pre-information. See equations (1) and (2) in text for more information about the dependent variable. The 5% critical values of $\chi^2(28)$ and $\chi^2(17)$ are 41.3 and 27.6.

Table 3.5: Estimates of Model of WTP Differences with Possible Censoring: Biotech and Conventional French Fries

	(3a)	(3b)	(4a)	(4b)
Age	0.038	0.052	0.049	0.061
	(0.044)	(0.042)	(0.045)	(0.043)
Age^2	−0.0005	−0.001	−0.0004	−0.001
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Years of schooling	−0.054	−0.046		
	(0.042)		(0.042)	
Adults in household	0.281**	0.214*	0.202	0.173
	(0.131)	(0.120)	(0.133)	(0.121)
Hungry	−0.093	−0.023	0.070	0.128
	(0.171)	(0.170)	(0.175)	(0.173)
Per capita income	0.026**	0.018*	0.017	0.013
	(0.011)	(0.010)	(0.012)	(0.010)
Per capita income^2	−0.0001**	−0.0001*	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Looks at labels	−0.118	−0.191	−0.264	−0.244
	(0.262)	(0.255)	(0.268)	(0.260)
Previously informed about biotech	0.112	0.170	0.050	0.095
	(0.201)	(0.203)	(0.207)	(0.207)
Previously informed about non-biotech	−0.078	−0.182	−0.373*	−0.428**
	(0.202)	(0.201)	(0.207)	(0.205)
Arrived with someone else	−0.255	−0.154	−0.114	−0.148
	(0.281)	(0.201)	(0.288)	(0.204)
Distance traveled	0.012	0.012	0.014	0.012
	(0.011)	(0.010)	(0.011)	(0.011)
Exercises regularly	−0.490**	−0.461**	−0.342*	−0.278
	(0.196)	(0.190)	(0.202)	(0.194)
Industry Info	0.810***	0.824***	1.004***	1.000***
	(0.267)	(0.266)	(0.275)	(0.272)
Scientific Info	1.457***	1.549***	1.343***	1.398***
	(0.265)	(0.265)	(0.271)	(0.270)
Industry and Scientific Info	1.629***	1.540***	1.540***	1.485***
	(0.268)	(0.266)	(0.276)	(0.272)
Industry and Environmental Info	0.640**	0.692**	0.589**	0.604**
	(0.278)	(0.278)	(0.285)	(0.283)
Scientific and Environmental Info	0.746**	0.790***	0.638**	0.693**
	(0.293)	(0.295)	(0.300)	(0.300)
Constant	−1.468	−2.340**	−2.014*	−2.621**
	(1.160)	(1.033)	(1.167)	(1.048)
Health and Child Controls	Yes	No	Yes	No
Design Controls	Yes	No	Yes	No
Observations	287	287	291	291
LR χ^2 Statistic	66.1***	55.4***	59.4**	52.4***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Dependent variable in columns (3a) and (3b) is the WTP difference for biotech fries pre- and post-information. Dependent variable in columns (4a) and (4b) is the WTP difference for biotech fries post-information and conventional fries pre-information. See equations (3) and (4) in text for more information about the dependent variable. The 5% critical values of $\chi^2(28)$ and $\chi^2(17)$ are 41.3 and 27.6.

Table 3.6: Estimates of Model of WTP Differences with Possible Censoring: Biotech and Conventional Potato Chips

	(5a)	(5b)	(6a)	(6b)
Age	0.075**	0.084**	0.070*	0.072**
	(0.037)	(0.036)	(0.038)	(0.036)
Age^2	−0.001**	−0.001**	−0.001*	−0.001*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Years of schooling	−0.001		−0.045	
	(0.035)		(0.035)	
Adults in household	0.351***	0.342***	0.261**	0.249**
	(0.110)	(0.099)	(0.109)	(0.099)
Hungry	−0.057	−0.019	0.071	0.120
	(0.146)	(0.144)	(0.146)	(0.144)
Per capita income	0.018*	0.014*	0.011	0.009
	(0.010)	(0.008)	(0.010)	(0.008)
Per capita income^2	−0.0001**	−0.0001*	−0.0001	−0.00005
	(0.0001)	(0.00005)	(0.0001)	(0.00005)
Looks at labels	0.063	−0.006	−0.097	−0.055
	(0.223)	(0.217)	(0.222)	(0.216)
Previously informed about biotech	0.155	0.201	−0.010	0.004
	(0.174)	(0.173)	(0.173)	(0.172)
Previously informed about non-biotech	−0.181	−0.199	−0.244	−0.278
	(0.172)	(0.170)	(0.171)	(0.170)
Arrived with someone else	−0.254	−0.190	−0.196	−0.199
	(0.241)	(0.171)	(0.241)	(0.171)
Distance traveled	0.018**	0.017*	0.014	0.013
	(0.009)	(0.009)	(0.009)	(0.009)
Exercises regularly	−0.315*	−0.328**	−0.333**	−0.317*
	(0.168)	(0.162)	(0.169)	(0.162)
Industry Info	0.553**	0.602***	0.703***	0.697***
	(0.227)	(0.225)	(0.227)	(0.225)
Scientific Info	1.223***	1.300***	1.135***	1.167***
	(0.226)	(0.225)	(0.226)	(0.225)
Industry and Scientific Info	1.293***	1.272***	1.296***	1.215***
	(0.228)	(0.224)	(0.228)	(0.225)
Industry and Environmental Info	0.496**	0.560**	0.443*	0.450*
	(0.236)	(0.236)	(0.236)	(0.236)
Scientific and Environmental Info	0.377	0.404	0.431*	0.450*
	(0.250)	(0.250)	(0.249)	(0.250)
Constant	−2.955***	−3.176***	−2.219**	−2.741***
	(0.961)	(0.865)	(0.962)	(0.869)
Health and Child Controls	Yes	No	Yes	No
Design Controls	Yes	No	Yes	No
Observations	290	290	294	294
LR χ^2 Statistic	70.1***	62.9***	61.5**	53.8***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Dependent variable in columns (5a) and (5b) is the WTP difference for biotech chips pre- and post-information. Dependent variable in columns (6a) and (6b) is the WTP difference for biotech chips post-information and conventional chips pre-information. See equations (5) and (6) in text for more information about the dependent variable. The 5% critical values of $\chi^2(28)$ and $\chi^2(17)$ are 41.3 and 27.6.

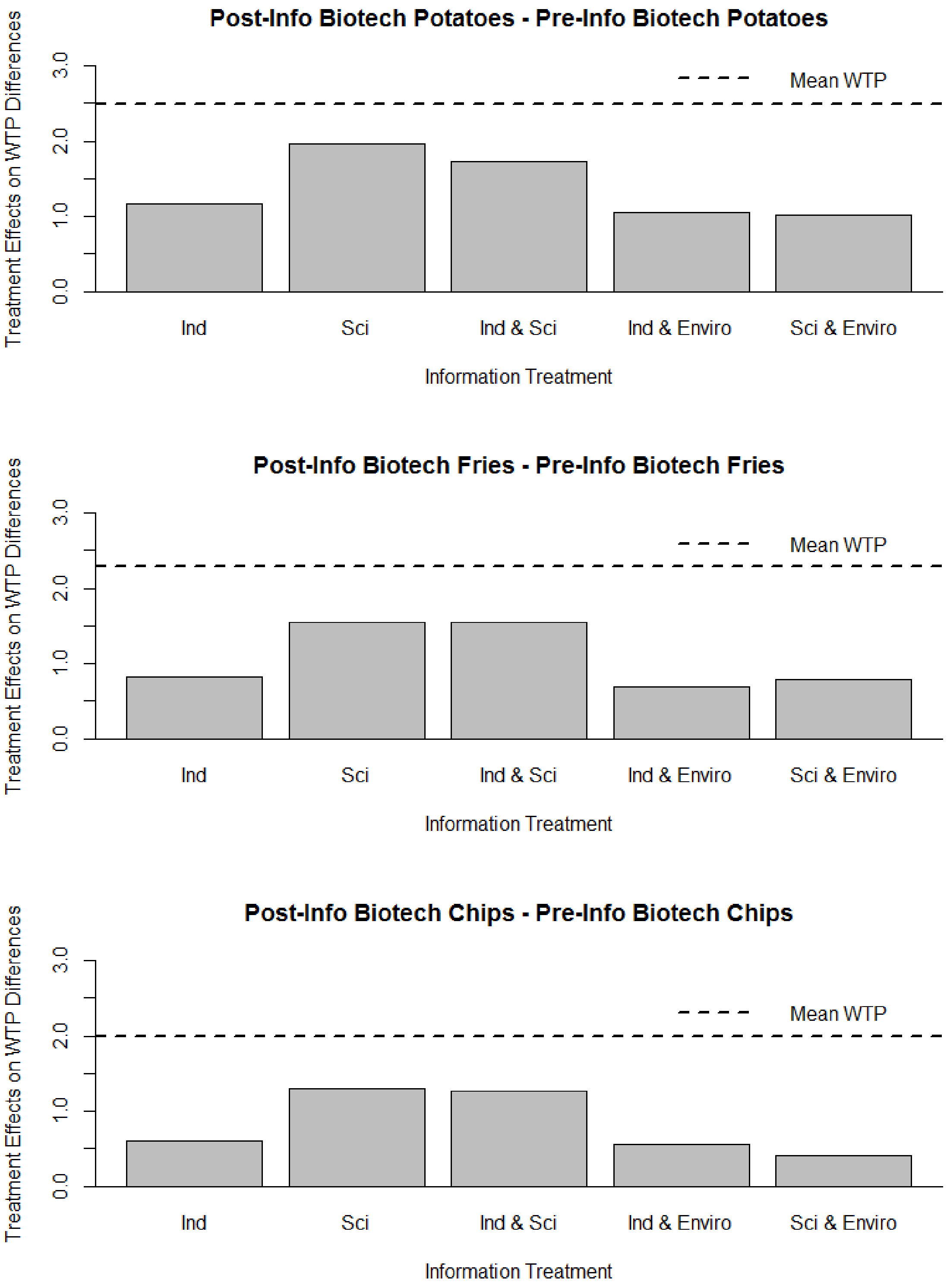


Figure 3.3: Information Treatment Effects on Biotech Commodity WTP Differences

Table 3.7: Likelihood Ratio Tests: Additive Industry and Scientific Information

Regression Equation	F statistic
GM Potatoes WTP Differences (1b)	11.77***
GM Potatoes WTP Post Information - Conv. Potatoes WTP Pre Information (2b)	3.23
GM Fries WTP Differences (3b)	4.89
GM Fries WTP Post Information - Conv. Fries WTP Pre Information (4b)	5.64
GM Chips WTP Differences (5b)	3.90
GM Chips WTP Post Information - Conv. Chips WTP Pre Information (6b)	4.14

Significance is denoted as ***p<0.01. Each row corresponds to the reduced models in Tables 3.4, 3.5, and 3.6. For each row, the null hypothesis is that $\beta_I + \beta_S = \beta_{SI}$. Note that β_I is the coefficient on the indicator for the industry-only treatment, β_S is the coefficient on the indicator for the scientific-only treatment, and β_{SI} is the coefficient on the indicator for scientific and industry information (regardless of sequencing). The 1% critical value of the $\chi^2(1)$ distribution is 6.63.

APPENDIX B. EXPERIMENT PROTOCOL, INFORMATION PERSPECTIVES, AND ROBUSTNESS

Appendix B is comprised of two parts. The first part consists of Tables B.1-B.3 presenting OLS estimates that do not account for censoring. These tables correspond to Tables 3.4-3.6 from the main paper. As discussed in Section 3.5.4, there are very few differences between maximum likelihood estimates that permit censoring and OLS estimates without censoring.

The second part contains a general version of the protocol used in the experimental auctions. The protocol is the randomly-assigned packet containing instructions, questionnaires, bid sheets, and one information treatment. For transparency, all three information perspectives are included in the protocol below. Experiment subjects (randomly) received up to two information perspectives in their packets for use during the experiments (see Section 3.3.1).

Table B.1: Estimates of Model of WTP Differences without Censoring: Biotech and Conventional Potatoes

	(1a)	(1b)	(2a)	(2b)
Age	0.027	0.037	0.016	0.026
	(0.048)	(0.044)	(0.053)	(0.050)
Age^2	−0.0004	−0.0005	−0.0001	−0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Years of schooling	−0.031		−0.021	
	(0.044)		(0.050)	
Adults in household	0.212	0.178	0.248	0.241*
	(0.139)	(0.123)	(0.156)	(0.138)
Hungry	−0.316*	−0.272	−0.070	−0.041
	(0.185)	(0.178)	(0.208)	(0.200)
Per capita income	0.013	0.008	0.014	0.010
	(0.013)	(0.010)	(0.014)	(0.012)
Per capita income^2	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Looks at labels	−0.242	−0.290	−0.328	−0.328
	(0.283)	(0.269)	(0.318)	(0.302)
Previously informed about biotech	0.504**	0.531**	0.326	0.378
	(0.221)	(0.214)	(0.248)	(0.241)
Previously informed about non-biotech	−0.359	−0.378*	−0.434*	−0.470*
	(0.220)	(0.212)	(0.247)	(0.239)
Arrived with someone else	−0.496*	−0.375*	−0.195	−0.215
	(0.300)	(0.207)	(0.337)	(0.233)
Distance traveled	0.025**	0.023**	0.025*	0.023*
	(0.012)	(0.011)	(0.013)	(0.012)
Exercises regularly	−0.487**	−0.478**	−0.437*	−0.387*
	(0.215)	(0.202)	(0.241)	(0.227)
Industry Info	1.079***	1.101***	0.889***	0.906***
	(0.288)	(0.279)	(0.324)	(0.314)
Scientific Info	1.771***	1.818***	1.268***	1.329***
	(0.287)	(0.279)	(0.322)	(0.314)
Industry and Scientific Info	1.654***	1.604***	1.466***	1.438***
	(0.294)	(0.282)	(0.330)	(0.318)
Industry and Environmental Info	0.932***	0.954***	0.823**	0.857***
	(0.302)	(0.294)	(0.339)	(0.330)
Scientific and Environmental Info	0.930***	0.937***	0.636*	0.698**
	(0.316)	(0.308)	(0.354)	(0.346)
Constant	−1.054	−1.620	−1.398	−1.831
	(1.219)	(1.075)	(1.369)	(1.209)
Health and Child Controls	Yes	No	Yes	No
Design Controls	Yes	No	Yes	No
R^2	0.224	0.213	0.149	0.132
F Statistic	2.802***	4.486***	1.694**	2.521***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Dependent variable in columns (1a) and (1b) is the WTP difference for biotech potatoes pre- and post-information. Dependent variable in columns (2a) and (2b) is the WTP difference for biotech potatoes post-information and conventional potatoes pre-information.

Table B.2: Estimates of Model of WTP Differences without Censoring: Biotech and Conventional French Fries

	(3a)	(3b)	(4a)	(4b)
Age	0.038	0.045	0.041	0.053
	(0.042)	(0.040)	(0.044)	(0.041)
Age^2	−0.001	−0.001	−0.0004	−0.001
	(0.0005)	(0.0005)	(0.001)	(0.0005)
Years of schooling	−0.037		−0.031	
	(0.040)		(0.041)	
Adults in household	0.236*	0.182	0.195	0.164
	(0.124)	(0.111)	(0.127)	(0.113)
Hungry	−0.088	−0.039	0.059	0.094
	(0.165)	(0.161)	(0.170)	(0.164)
Per capita income	0.024**	0.017*	0.016	0.012
	(0.011)	(0.009)	(0.012)	(0.010)
Per capita income^2	−0.0001**	−0.0001*	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Looks at labels	−0.172	−0.233	−0.248	−0.266
	(0.253)	(0.242)	(0.260)	(0.248)
Previously informed about biotech	0.151	0.203	0.084	0.128
	(0.197)	(0.193)	(0.202)	(0.198)
Previously informed about non-biotech	−0.097	−0.176	−0.345*	−0.390**
	(0.197)	(0.192)	(0.202)	(0.196)
Arrived with someone else	−0.286	−0.143	−0.150	−0.110
	(0.268)	(0.187)	(0.275)	(0.191)
Distance traveled	0.013	0.012	0.014	0.012
	(0.010)	(0.010)	(0.011)	(0.010)
Exercises regularly	−0.421**	−0.388**	−0.268	−0.208
	(0.192)	(0.182)	(0.197)	(0.186)
Industry Info	0.748***	0.791***	0.974***	0.987***
	(0.258)	(0.252)	(0.265)	(0.257)
Scientific Info	1.328***	1.418***	1.267***	1.318***
	(0.256)	(0.252)	(0.263)	(0.258)
Industry and Scientific Info	1.490***	1.426***	1.418***	1.366***
	(0.263)	(0.255)	(0.270)	(0.261)
Industry and Environmental Info	0.556**	0.627**	0.534*	0.558**
	(0.270)	(0.265)	(0.277)	(0.271)
Scientific and Environmental Info	0.711**	0.759***	0.655**	0.697**
	(0.282)	(0.278)	(0.290)	(0.284)
Constant	−1.375	−1.978**	−1.786	−2.301**
	(1.089)	(0.970)	(1.119)	(0.992)
Health and Child Controls	Yes	No	Yes	No
Design Controls	Yes	No	Yes	No
R^2	0.200	0.170	0.181	0.159
F Statistic	2.420***	3.400***	2.142***	3.131***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Dependent variable in columns (3a) and (3b) is the WTP difference for biotech fries pre- and post-information. Dependent variable in columns (4a) and (4b) is the WTP difference for biotech fries post-information and conventional fries pre-information.

Table B.3: Estimates of Model of WTP Differences without Censoring: Biotech and Conventional Potato Chips

	(5a)	(5b)	(6a)	(6b)
Age	0.064*	0.073**	0.062*	0.064*
	(0.036)	(0.034)	(0.037)	(0.034)
Age^2	−0.001*	−0.001**	−0.001	−0.001*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Years of schooling	0.004		−0.033	
	(0.034)		(0.034)	
Adults in household	0.313***	0.303***	0.231**	0.228**
	(0.106)	(0.095)	(0.107)	(0.095)
Hungry	−0.071	−0.042	0.050	0.083
	(0.142)	(0.138)	(0.143)	(0.138)
Per capita income	0.017*	0.014*	0.009	0.008
	(0.010)	(0.008)	(0.010)	(0.008)
Per capita income^2	−0.0001**	−0.0001*	−0.00005	−0.00005
	(0.0001)	(0.00005)	(0.0001)	(0.00005)
Looks at labels	0.034	−0.053	−0.098	−0.092
	(0.217)	(0.208)	(0.219)	(0.209)
Previously informed about biotech	0.166	0.209	0.032	0.040
	(0.169)	(0.166)	(0.170)	(0.167)
Previously informed about non-biotech	−0.173	−0.181	−0.234	−0.258
	(0.169)	(0.164)	(0.170)	(0.165)
Arrived with someone else	−0.306	−0.184	−0.234	−0.163
	(0.230)	(0.160)	(0.232)	(0.161)
Distance traveled	0.019**	0.017**	0.014	0.013
	(0.009)	(0.009)	(0.009)	(0.009)
Exercises regularly	−0.263	−0.278*	−0.270	−0.255
	(0.165)	(0.156)	(0.166)	(0.157)
Industry Info	0.548**	0.608***	0.706***	0.711***
	(0.221)	(0.216)	(0.222)	(0.217)
Scientific Info	1.144***	1.213***	1.080***	1.106***
	(0.220)	(0.216)	(0.221)	(0.217)
Industry and Scientific Info	1.229***	1.205***	1.207***	1.128***
	(0.226)	(0.218)	(0.227)	(0.219)
Industry and Environmental Info	0.443*	0.516**	0.408*	0.420*
	(0.232)	(0.227)	(0.233)	(0.228)
Scientific and Environmental Info	0.388	0.415*	0.457*	0.466*
	(0.242)	(0.238)	(0.243)	(0.239)
Constant	−2.528***	−2.742***	−1.942**	−2.417***
	(0.935)	(0.832)	(0.940)	(0.835)
Health and Child Controls	Yes	No	Yes	No
Design Controls	Yes	No	Yes	No
R^2	0.218	0.191	0.189	0.163
F Statistic	2.691***	3.926***	2.251***	3.232***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Dependent variable in columns (5a) and (5b) is the WTP difference for biotech chips pre- and post-information. Dependent variable in columns (6a) and (6b) is the WTP difference for biotech chips post-information and conventional chips pre-information.

ID ___________

IOWA STATE UNIVERSITY

Welcome! Thank you for choosing to participate in an experiment about decision making. This is a packet of information that you will need during the experiment. Once you have looked at a page during the experiment, feel free to go back and examine that page again if needed. However, when you reach a stop sign in the packet, please do not go past the stop sign until instructed by your monitor.

Please follow the instructions carefully. To ensure accuracy of the results, please do not talk to any other participants during the experiment.

All information obtained today will be used only for group comparisons. No information on any individual will be divulged for any reason.

Please turn to the next page and fill out a short questionnaire.

ID ___________

Please answer these demographic questions as accurately as possible. For each question, please circle the appropriate number or fill in the blank, unless instructed otherwise.

1. In what area do you currently live?
   1 = Rural
   2 = Suburban
   3 = Urban

2. What best describes your marital status?
   1 = Married
   2 = Single with live-in partner
   3 = Single – never married
   4 = Divorced
   5 = Widowed
   6 = Other

3. What is your gender?
   1 = Male
   2 = Female

4. What is your age? ________

5. How many people live in your current household? _________

6. What is your current religious affiliation?
   1 = Assembly of God
   2 = Baptist
   3 = Catholic
   4 = Church of Jesus Christ of Latter-day Saints
   5 = Episcopalian
   6 = Hindu
   7 = Jewish
   8 = Lutheran
   9 = Methodist
   10 = Muslim
   11 = Nondenominational Christian
   12 = Presbyterian
   13 = Other (please write in) ______________________
   14 = No religion

7. What is your current level of hunger (for food)?
   1 = Very low
   2 = Low
   3 = Moderate
   4 = High
   5 = Very high

8. How many children in each age group are living in your current household? (If you have no children, enter zero for all age groups.)
    a. 0-3 years old ________
    b. 4-7 years old ________
    c. 8-12 years old ________
    d. 13-18 years old ________
    e. Older than 18 ________

9. What is the highest level of schooling that you have completed?
    1 = Less than high school (8 years or less)
    2 = Some high school (between 9 and 12 years)
    3 = Graduated from high school (12 years)
    4 = Some college (between 12 and 14 years)
    5 = 2 year college degree (14 years)
    6 = 4 year college degree (16 years)
    7 = Some education beyond 4 year college degree (between 16 and 18 years)
    8 = Master's degree (18 years)
    9 = Doctorate or professional degree (greater than 18 years)

10. What best describes your ethnic background?
    1 = Asian
    2 = Black
    3 = Hispanic
    4 = Native American
    5 = White (non Hispanic)
    6 = Other (please write in) ________________

11. What was your total household income before taxes in 2013?
    1 = Under 10,000
    2 = $10,000-$14,999
    3 = $15,000-$19,999
    4 = $20,000-$24,999
    5 = $25,000-$29,999
    6 = $30,000-$34,999
    7 = $35,000-$39,999
    8 = $40,000-$49,999
    9 = $50,000-$59,999
    10 = $60,000-$74,999
    11 = $75,000-$99,999
    12 = $100,000-$124,999
    13 = $125,000-$149,999
    14 = $150,000-$174,999
    15 = $175,000-$199,999
    16 = $200,000 or more

12. Are you a member of an environmental group?
    1 = Yes
    2 = No

13. What best describes your primary current occupation?
    - 1 = Architecture/Engineering
    - 2 = Art and Design or Entertaining/Performing (e.g., artist, athlete, musician, coach)
    - 3 = Building and Grounds Cleaning and Maintenance
    - 4 = Business Operations or Sales (e.g., budget analyst, accountant, sales representative)
    - 5 = Community and Social Service (e.g., social worker, guidance counselor, clergy)
    - 6 = Computers/Mathematical (e.g. computer programmer, web developer, statistician)
    - 7 = Construction/Installation/Repair
    - 8 = Education/Training
    - 9 = Farming/Fishing/Forestry
    - 10 = Healthcare (e.g., physician, nurse, therapist, veterinarian, home health aide)
    - 11 = Housework or Retired
    - 12 = Legal (e.g. attorney, paralegal, title examiner)
    - 13 = Life, Physical, or Social Sciences (e.g., biologist, chemist, psychologist)
    - 14 = Management
    - 15 = Media and Communications (e.g., reporter, photographer, public relations)
    - 16 = Military or Protective Services (e.g., member of military, police officer, firefighter)
    - 17 = Office/Administrative Support (e.g., bookkeeper, teller, administrative assistant)
    - 18 = Personal Care or Food Service (e.g., hairstylist, fitness trainer, waitstaff, chef)
    - 19 = Production/Manufacturing
    - 20 = Student
    - 21 = Transportation (e.g., professional driver, flight attendant, railway worker)
    - 22 = Unemployed
    - 23 = Other (please write in) ____

Please answer these non-demographic questions as accurately as possible. For each question, please circle the appropriate number or fill in the blank, unless instructed otherwise.

14. Regarding acrylamide (a chemical compound), how informed do you consider yourself?
    - 1 = Extremely well informed
    - 2 = Well informed
    - 3 = Somewhat informed
    - 4 = Not very informed
    - 5 = Not informed at all
    - 6 = I don’t know

15. Regarding biotechnology (biotech) food products, how informed do you consider yourself?
    - 1 = Extremely well informed
    - 2 = Well informed
    - 3 = Somewhat informed
    - 4 = Not very informed
    - 5 = Not informed at all
    - 6 = I don’t know

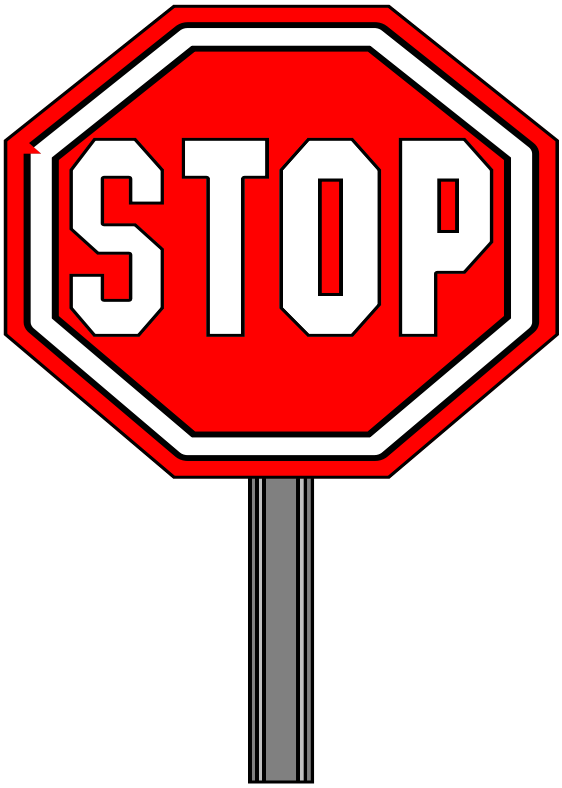
16. When you buy a food product for the first time, do you read the food label (nutrition facts, ingredients list, and logo)?
   1 = Never
   2 = Rarely
   3 = Some of the time
   4 = Often
   5 = Always

17. Regarding <u>non-biotech</u> food products, how informed do you consider yourself?
   1 = Extremely well informed
   2 = Well informed
   3 = Somewhat informed
   4 = Not very informed
   5 = Not informed at all
   6 = I don't know

18. What do you think your risk level is for developing any form of cancer sometime during your lifetime?
   1 = Very low
   2 = Low
   3 = Moderate
   4 = High
   5 = Very high
   6 = I don't know

19. Do you think there is a difference between biotech foods and genetically modified foods?
   1 = Yes
   2 = No
   3 = I don't know

Thank you.



Please do not turn the page until instructed by your monitor.

Once again, I would like to thank you for participating in this experiment.

Today we will be holding auctions of some common products. These products will be potatoes (5 pounds), frozen French fries (2 pounds), and potato chips (12 ounces). One round out of four rounds of bidding will be chosen as the binding round in which bids are executed, i.e. winning bidder(s) will be asked to buy the won item(s). Though you could end up winning all three products, we assure you that you will purchase at most one unit of each product. In addition, there will be two practice rounds, but these rounds are not binding, i.e. the winning bidder(s) will not be asked to buy the item. Detailed instructions of how the auction works will be provided shortly.

Because we are trying to determine individual responses, we ask that you please do not communicate with the other participants. If you have any questions, the monitor can assist you.

How the Auction Works

The random price auction

We are going to be holding an auction of food products today. It is a random price auction. In this auction, everyone places a bid on the product(s). It is always in your best interest to bid how much you value the product(s).

How this auction works can be shown in five easy steps. We will also go through examples of the steps in two practice rounds. If there are questions about how the auction works, we will answer them after reading these instructions.

1. Examine the product(s)
   Before we ask you to bid on the product(s), we will ask you to come to the front of the room and view the product(s).

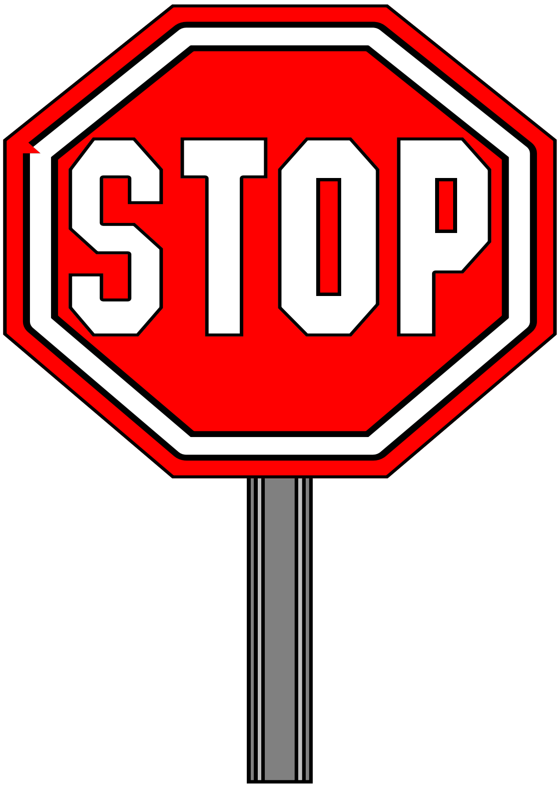
2. Write down your bid for the product(s)
   After returning to your seat, we ask you to write down your bid for the product(s) on your "bid sheet(s)." Completed bid sheets will be collected by the session monitor or an assistant.

3. Choosing the binding round
   Once bids have been submitted for all rounds, we will randomly select one round to be the binding round, i.e., the round of bidding from which the winner(s) will be selected.

4. Choosing the random price
   For the binding round, we will rank the bids for each product from highest to lowest. Next, we will choose a random number larger than 1 but not larger than the total number of participants. This random number determines the rank of the bid that becomes the "random price."

5. Determining who wins the auction for each good
   Everybody who bids strictly higher than the random price will be a winner of the product(s) but will pay the random price, and not the price that she or he bids. No winner(s) will buy more than one unit of each product, though the winner(s) could win different product(s).

Again, in this auction, it is always in your best interest to bid how much you truly value the product. The goal in this auction is not to place the highest bid; that could lead you to bid more than how much you truly value the product. Also, unlike in some auctions where you bid less to try to "get a deal," this auction does not reward that behavior. If you are a winner, you do not pay your bid, but pay the random price, which will be less than what you bid. We use a random process to choose the rank of the bid that is the random price.



Please do not turn the page until instructed by your monitor.

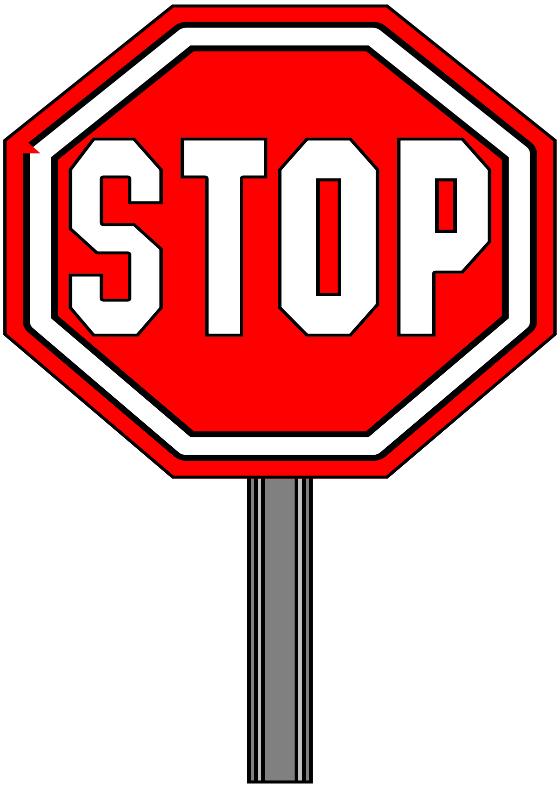
Practice Round One – Mug

Explanation of Practice Round One

There will be separate rounds of bidding in the practice session to make sure all participants understand the process. This is similar to upcoming rounds, but participants are encouraged to ask questions before we begin the actual rounds.

Step 1: Please come to the front of the room. Please view the product in this practice round.

Step 2: Please return to your seat. There is a bid sheet at the bottom of this page. **Please enter your I.D. #**, bid on the product, and remove the bid sheet. When you are finished, a monitor will collect your bid sheet (please turn it face down and place in front of you).



Please do not turn the page until instructed by your monitor.

Practice Round One (continued)

Step 3: Determination of the binding round (computer generated).

Step 4: Selection of the random number (computer generated) and the random price.

Step 5: Announcement of the auction winners for the product. This practice round was not binding. If it were, goods and money would be exchanged at the end of the auction.

Short Quiz on Auction Format

This quiz is just to check understanding of the auction format.

True or False

1. The people who win will always pay the amount they bid for a product.

   1 = True
   2 = False

2. If you have the fourth-highest bid, and the random price is the second-highest bid, you will be a winner.

   1 = True
   2 = False

3. I might get to pay less than my bid for a product, but I will never have to pay more than my bid for a product.

   1 = True
   2 = False

Multiple choice

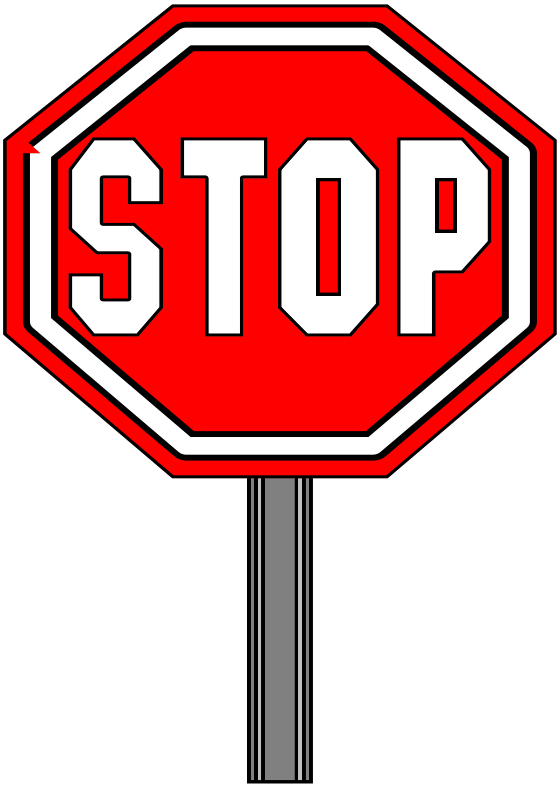
4. If each person has a different bid, and the random price is the fifth-highest bid, then how many people win the good?

   a = 2

   b = 3

   c = 4

   d = 5



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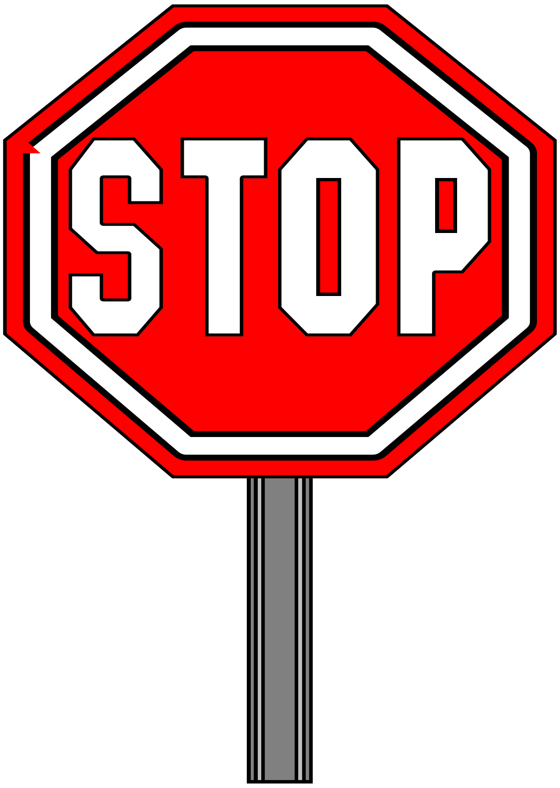
Practice Round Two – Notepad, binder, package of pens

Explanation of Practice Round Two

This is the second round of bidding in the practice rounds. This is similar to upcoming rounds, but participants are encouraged to ask questions before we begin the actual rounds.

Step 1: Please come to the front of the room. Please view the three products in this practice round.

Step 2: Please return to your seat. There is a bid sheet at the bottom of this page. **Please enter your I.D. #**, bid on the products, and remove the bid sheet. When you are finished, a monitor will collect your bid sheet (please turn it face down and place in front of you).



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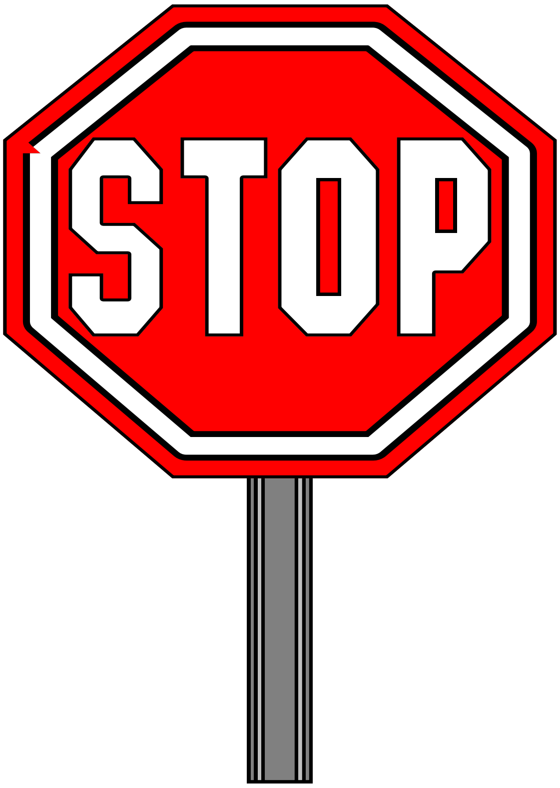
Practice Round Two (continued)

Step 3: Determination of the binding round (computer generated).

Step 4: Selection of the random number (computer generated) and the random price.

Step 5: Announcement of the auction winners for the products. This practice round was not binding. If it were, goods and money would be exchanged at the end of the auction.

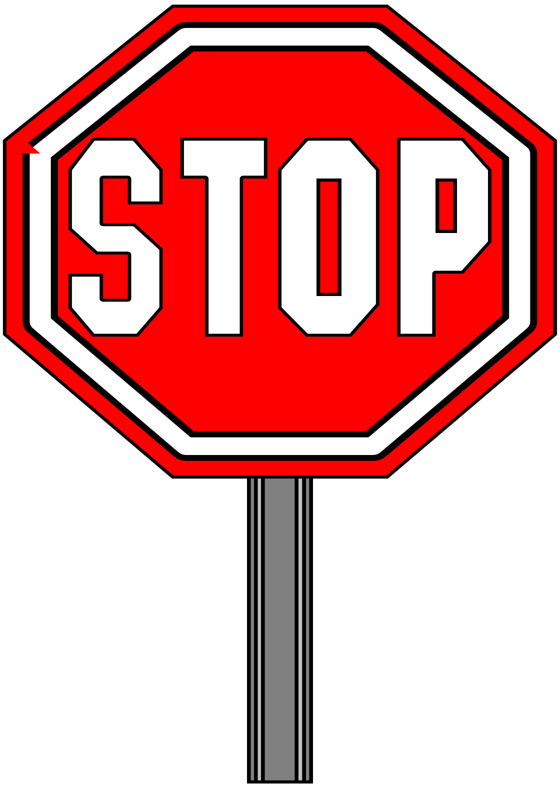


Please do not turn the page until instructed by your monitor.

Round 1 of 4

Step 1: Please come to the front of the room. Please view the products that are in the auction.

Step 2: Please return to your seat. There is a bid sheet at the bottom of this page. **Please enter your I.D. #**, bid on the products, and remove the bid sheet. When you are finished, a monitor will collect your bid sheet (please turn it face down and place in front of you).

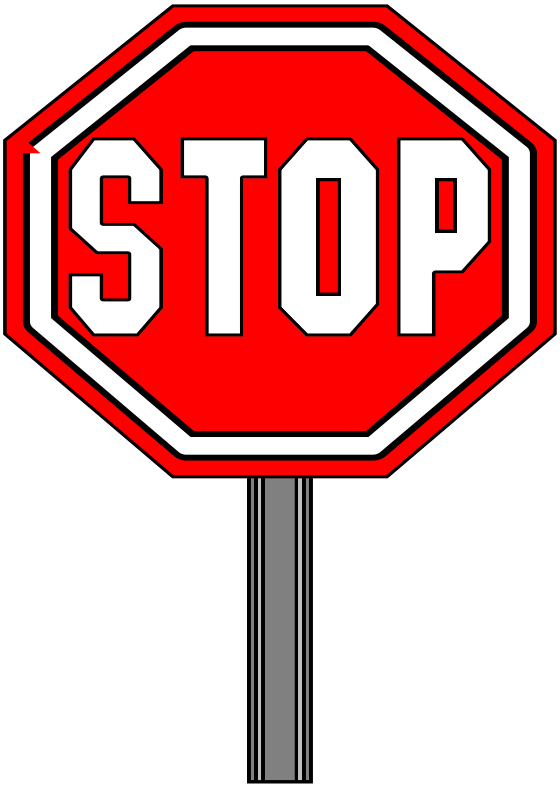


Please do not turn the page until instructed by your monitor.

Round 2 of 4

Step 1: Please come to the front of the room. Please view the products that are in the auction.

Step 2: Please return to your seat. There is a bid sheet at the bottom of this page. **Please enter your I.D. #**, bid on the products, and remove the bid sheet. When you are finished, a monitor will collect your bid sheet (please turn it face down and place in front of you).



Please do not turn the page until instructed by your monitor.

Please take a few minutes to read the following.

A scientific perspective on acrylamide exposure

General Statement:

- In 2002, acrylamide was discovered in foods containing certain natural sugars when cooked at high temperatures (above roughly 250° F), such as French fries, hash browns and potato chips. Acrylamide is also formed in the baking of bread (crust) and cookies and roasting of coffee beans.
- Acrylamide, a chemical compound, is formed in these foods from naturally occurring sugars and asparagine (a building block of a protein).
- Compared to other foods in the American diet, French fries and potato chips are a major source of acrylamide.
- The amount of acrylamide increases with longer frying or baking times and higher cooking temperatures. However, boiling, steaming, and microwaving potatoes produces negligible acrylamide.
- Under Proposition 65, California requires certain restaurants, including Applebee's, Chili's, McDonald's, Burger King, Wendy's, and KFC, to post a warning stating that "cooked potatoes that have been browned, such as French fries, hash browns and baked potatoes, contain acrylamide, a chemical known to the State of California to cause cancer."
- However, the FDA has not advised people to stop eating these potato products.

Nutrition and Health:

- The International Agency for Research on Cancer (IARC) designates acrylamide as a "probable human carcinogen," and the US National Toxicology Program classifies acrylamide as "reasonably anticipated" to be capable of causing cancer in humans.
- The first health studies of acrylamide occurred in the 1960s and explored health hazards with on-the-job contact. Chronic exposure produces toxicity that weakens muscles and reflexes and leads to sensory loss.
- Evidence from studies in the 1970s and 1980s advanced the linkages between cancer and acrylamide.
- In a recent study, lab animals that consumed low doses of acrylamide placed in drinking water over a long period of time (roughly equal to annual acrylamide consumption of an adult) experienced gene damage.
- Another study found that humans who consumed conventional potato chips daily for four weeks had higher incidence of early development of cardio-vascular diseases.
- Additional studies suggest linkages between high acrylamide diets and development of breast cancer. High levels of acrylamide consumption by pregnant women have been associated with increased frequency of low birth weight babies.

Environmental Impacts and Food Security:

- Acrylamide is used in industrial processes to make paper, dyes, and plastics, but food and cigarette smoke are the two main sources of human exposure to acrylamide.
- If the occupational and health risks associated with acrylamide were to be substantially reduced or eliminated, food security would improve, especially in the United States and some other developed countries where a majority of the population regularly consumes foods that contain acrylamide.

Please take a few minutes to read the following.

An industry perspective on low acrylamide potatoes using biotechnology

General Statement:

- In 2002, acrylamide was discovered in foods containing certain natural sugars when cooked at high temperatures (above roughly 250° F), such as French fries, hash browns and potato chips. They are also formed in the baking of bread (crust) and cookies and roasting of coffee beans.
- Acrylamide, a chemical compound, is formed in foods from naturally occurring sugars and asparagine (a building block of a protein). It is a toxin and possible carcinogen in humans.
- Conventional plant breeding efforts have resulted in only small reductions of acrylamide in processed potato products.
- In contrast, biotech methods have significantly reduced the acrylamide level in processed potato products, thereby improving food safety.
- Biotech plant breeding methods take genes from one organism and transfer them to another. In new biotech potatoes, all genes come from wild and domesticated potato varieties. Hence, this biotech method has much in common with conventional plant breeding.

Nutrition and Health:

- Long-term, low-level intake of acrylamide by lab animals has been shown to create serious health problems. One study found that consuming conventional potato chips regularly for a month caused some health changes in humans.
- Under Proposition 65, California requires certain restaurants, including Applebee's, Chili's, McDonald's, Burger King, Wendy's, and KFC, to post a warning stating that "cooked potatoes that have been browned, such as French fries, hash browns and baked potatoes, contain acrylamide, a chemical known to the State of California to cause cancer."
- A major biotech accomplishment has been the development of new potato varieties that have approximately a 70% reduction in acrylamide levels in processed potato products relative to conventional.
- Biotech methods were also used to develop golden rice, which enhanced vitamin A content. Other opportunities exist for enhancing consumer attributes, such as, antioxidants and vitamins in food.
- All Food and Drug Administration (FDA)-approved biotech-foods have been assessed to be substantially equivalent in nutrient content to conventional foods. As such, labeling in the U.S. is voluntary.
- Biotech foods, relative to conventional foods, have similar low allergy potential.

Environmental Impacts and Food Security:

- Acrylamide is used in industrial processes to make paper, dyes, and plastics, but food and cigarette smoke are the two main sources of human exposure to acrylamide.
- Commercial potatoes are grown from pieces of whole potato and not seed. In addition, many commercial potatoes are either sterile or not sexually compatible with wild potatoes. Hence, there is very low risk of biotech potatoes crossing with other potato varieties or other plants.
- There are no adverse impacts on the environment of the new biotech potatoes.
- In general, biotech crops have reduced the use of toxic insecticides and increased the use of other environmentally friendly farming practices.
- Food security can be greatly improved with continued advancement and adoption of genetically modified crops.
- Approval is being sought for biotech potato exports to Canada, Mexico, South Korea and Japan.

Please take a few minutes to read the following.

An environmental group perspective on biotechnology

General Statement:

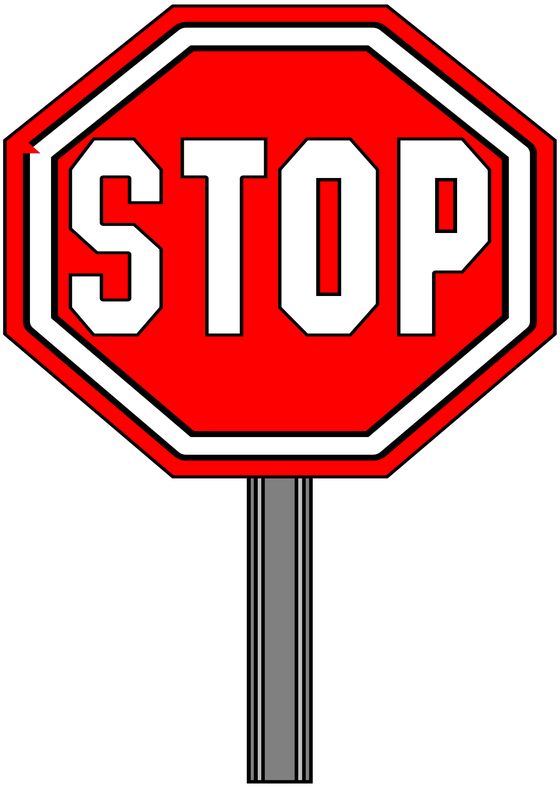
- Biotech plant breeding takes genes from one organism and places them into another. This process manipulates genes and alters genetic makeup and properties. The cutting of genetic material from one organism and inserting it into another is quite imprecise and can cause mutations. There has been inadequate testing of these products.
- Biotech methods frequently use antibiotic-resistant gene segments in soil bacteria or viruses and transfer them into plants. This process is risky, leading to unanticipated outcomes.
- Biotech plants are regulated by the federal government, but federal regulation relies heavily on data collected from field trials and other testing by the biotech industry.
- Biotech seeds were first marketed to U.S. farmers in the mid-1990s, and rapid farmer adoption occurred in field crops (corn, soybean, cotton and canola). Later developments have been in papaya and vegetables (sugar beet, squash and potato).
- In the United States, the sales of biotech foods have grown very rapidly. This growth is driven by self-interested producers and marketers seeking to maximize crop yields and minimize production costs.

Nutrition and Health:

- Of the laboratory plants that are successfully modified to express the "right" traits, genetic engineers select among those that look strong, healthy, and capable of further breeding. There is poor screening to eliminate varieties that produce harmful substances or low nutrient quality.
- New allergens are likely to be introduced into the food supply.
- Early research reported some health problems in laboratory animals consuming first-generation insect- resistant potatoes.
- Several scientific studies show that laboratory animals that have been fed biotech food developed one or more toxic effects on vital and/or reproductive organ functioning, relative to a control group.
- A recent Canadian study found a common protein from insect-resistant corn in the bloodstream of pregnant women and their fetuses. Another recent study found that high concentrations of this protein resulted in severe damage to human embryonic kidney cells.
- The nutritional content of biotech foods, relative to conventional foods, is variable.

Environmental Impacts and Food Security:

- Private companies are not capable of screening new biotech materials for every possible pathogen or environmental stress. Unnoticed and unsafe mutations could strike after the occurrence of extreme stress, such as plant disease outbreaks, droughts, floods, and heat waves.
- New biotech crops may cross-pollinate with other plants and are likely to cause super weeds.
- Some herbicides used on biotech crops diffuse into the air and leach into streams and waterways in some areas. These herbicides are toxic to amphibians (e.g., frogs, salamanders) and earthworms, which impacts bird populations.
- Biotech crops are doing little to help international food security or relieve hunger in poor countries. The major biotech crops, corn and soybeans, are mainly used for animal feed, biofuels, and processed human food in developed countries.

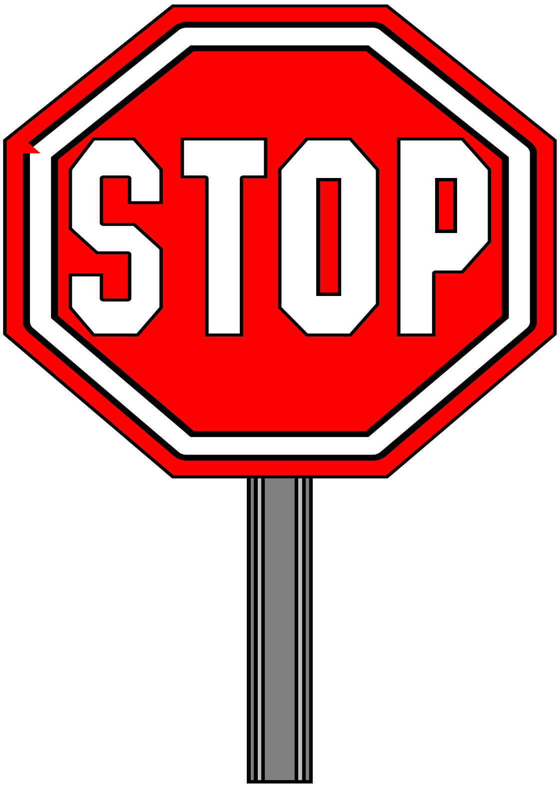


Please do not turn the page until instructed by your monitor.

Round 3 of 4

Step 1: Please come to the front of the room. Please view the products that are in the auction.

Step 2: Please return to your seat. There is a bid sheet at the bottom of this page. **Please enter your I.D. #**, bid on the products, and remove the bid sheet. When you are finished, a monitor will collect your bid sheet (please turn it face down and place in front of you).

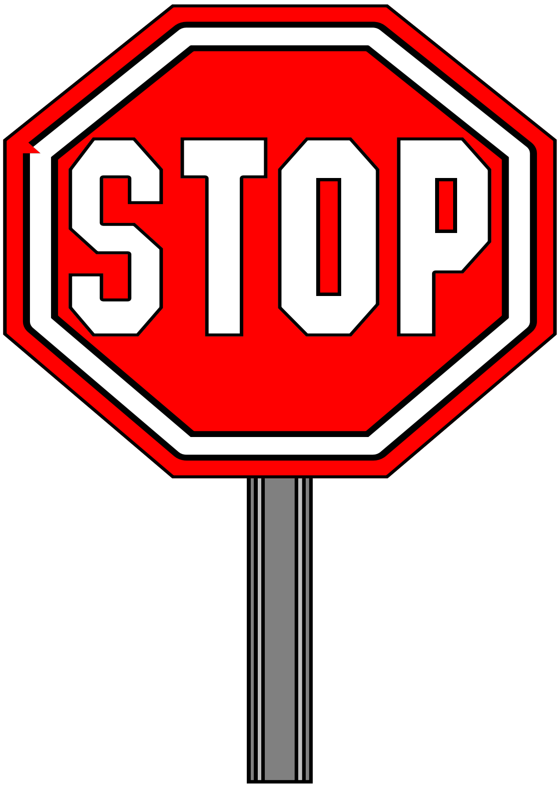


Please do not turn the page until instructed by your monitor.

Round 4 of 4

Step 1: Please come to the front of the room. Please view the products that are in the auction.

Step 2: Please return to your seat. There is a bid sheet at the bottom of this page. **Please enter your I.D. #**, bid on the products, and remove the bid sheet. When you are finished, a monitor will collect your bid sheet (please turn it face down and place in front of you).



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ID ________

Please complete the short post – auction questionnaire.

1. How often does your household purchase the following foods each month?

		Don't purchase	1 – 2 times	3 – 5 times	More than 5 times	Don't know
a.	Potatoes (at least 1 potato)	1	2	3	4	5
b.	Frozen French fries (1 bag)	1	2	3	4	5
c.	Potato chips (1 bag)	1	2	3	4	5
d.	Pasta, rice or bean (1 package)	1	2	3	4	5
e.	Nuts/mixed nuts (1 package)	1	2	3	4	5
f.	Frozen hash browns (1 bag)	1	2	3	4	5
g.	Sour cream (1 container)	1	2	3	4	5
h.	Spreads/dips (1 container)	1	2	3	4	5
i.	Ketchup (1 bottle)	1	2	3	4	5

2. How often does your household consume the following foods each week?

		Don't consume	1 – 2 times	3 – 5 times	More than 5 times	Don't know
a.	Potatoes	1	2	3	4	5
b.	French fries	1	2	3	4	5
c.	Potato chips	1	2	3	4	5
d.	Pasta, rice or beans	1	2	3	4	5
e.	Nuts/mixed nuts	1	2	3	4	5
f.	Hash browns	1	2	3	4	5
g.	Sour cream	1	2	3	4	5
h.	Spreads/dips	1	2	3	4	5
i.	Ketchup	1	2	3	4	5

3. Do you currently have the following foods at home?

		Yes	No	Don't know
a.	Potatoes	1	2	3
b.	French fries	1	2	3
c.	Potato chips	1	2	3
d.	Pasta, rice or beans	1	2	3
e.	Nuts/mixed nuts	1	2	3
f.	Hash browns	1	2	3
g.	Sour cream	1	2	3
h.	Spreads or dips	1	2	3
i.	Ketchup	1	2	3

4. Are you the main grocery buyer for your household?
   1 = Yes
   2 = No

5. How often does your household consume organic potato products each month?
   1 = Do not consume
   2 = 1 – 2 times
   3 = 3 – 5 times
   4 = More than 5 times
   5 = I don't know

6. Does anyone in your household have allergies, intolerances, or sensitivities to any of the following foods?

		Yes	No	Don't know
a.	Potatoes	1	2	3
b.	French fries	1	2	3
c.	Potato chips	1	2	3

7. Did any of today's food products appear to be discolored, blemished, or otherwise unusual to you?

		Yes	No	Don't know
a.	Potatoes (conventional)	1	2	3
b.	Potatoes (biotech)	1	2	3
c.	French fries (conventional)	1	2	3
d.	French fries (biotech)	1	2	3
e.	Potato chips (conventional)	1	2	3
f.	Potato chips (biotech)	1	2	3

8. After completing today's experiment, how informed about biotech food products do you consider yourself?
   1 = Extremely well informed
   2 = Well informed
   3 = Somewhat informed
   4 = Not very informed
   5 = Not informed at all
   6 = I don't know

9. After completing today's experiment, how informed about non-biotech foods do you consider yourself?
   1 = Extremely well informed
   2 = Well informed
   3 = Somewhat informed
   4 = Not very informed
   5 = Not informed at all
   6 = I don't know

10. After completing today's experiment, how informed about acrylamide do you consider yourself?
   1 = Extremely well informed
   2 = Well informed
   3 = Somewhat informed
   4 = Not very informed
   5 = Not informed at all
   6 = I don't know

11. After completing today's experiment, what do you think your risk level is for developing any form of cancer sometime during your lifetime?

1 = Very low
2 = Low
3 = Moderate
4 = High
5 = Very high
6 = I don't know

12. How well did you understand the first information statement (scientific perspective) earlier in this packet?

1 = Very well
2 = Well
3 = Somewhat well
4 = Not well
5 = Did not understand at all
6 = I don't know

13. How strongly did you agree with the first information statement (scientific perspective) earlier in this packet?

1 = Very strongly agree
2 = Strongly agree
3 = Did not agree or disagree
4 = Strongly disagree
5 = Very strongly disagree
6 = I don't know

14. How well did you understand the second information statement (industry perspective) earlier in this packet?

1 = Very well
2 = Well
3 = Somewhat well
4 = Not well
5 = Did not understand at all
6 = I don't know

15. How strongly did you agree with the second information statement (industry perspective) earlier in this packet?

1 = Very strongly agree
2 = Strongly agree
3 = Did not agree or disagree
4 = Strongly disagree
5 = Very strongly disagree
6 = I don't know

16. Did you come with someone else who is also participating in today's experiment?

1 = Yes
2 = No

17. After completing today's experiment, would you be more or less likely to purchase these in the future?

		More likely	Less likely	Unchanged	Don't know
a.	Potatoes	1	2	3	4
b.	French fries	1	2	3	4
c.	Potato chips	1	2	3	4

18. Have you participated in one or more economics experiments in the past?
    1 = Yes – Once
    2 = Yes – More than once
    3 = No

19. Approximatey how far did you travel to reach the site of today's experiment?

    __________ miles (please write in)

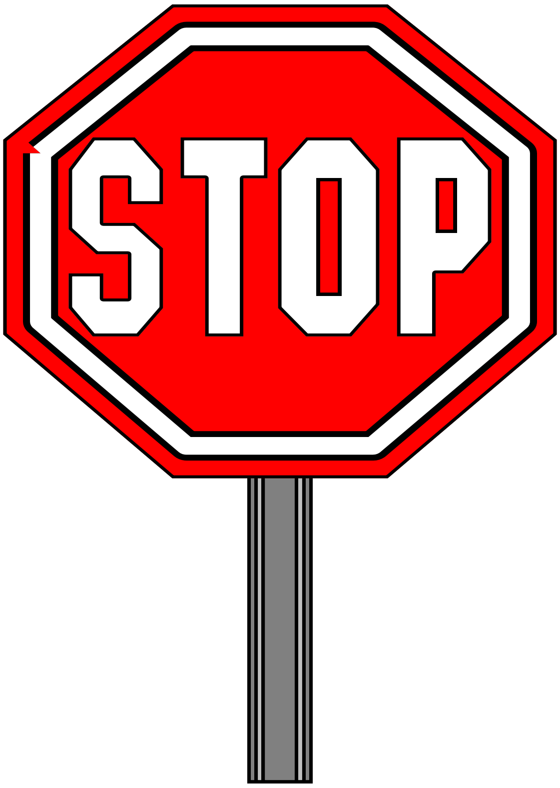
20. What is your physical health status?
    1 = Excellent
    2 = Good
    3 = Moderate
    4 = Poor
    5 = Very poor

21. Do you smoke cigarettes?
    1 = Yes – at least once per day
    2 = Yes – less than once per day
    3 = No

22. Are one or more people in your household currently on a diet?
    1 = Yes
    2 = No

23. How often do you usually exercise (any type of exercise)?
    1 = Once per week
    2 = Twice per week
    3 = Three times per week
    4 = Four or more times per week
    5 = Do not exercise regularly
    6 = I don't know

Thank you.



After everyone has completed the post – auction questionnaire, we will reveal the binding round and the random number, state the random price of each product, and notify the winning participant(s) by I.D. number. Once this is done, the winner(s) will be directed to the stock room to purchase the won product(s). All others may leave. Thanks again for your participation today.

CHAPTER 4. US CLIMATE CHANGE ADAPTATION ALONG THE INTENSIVE AND EXTENSIVE MARGINS: A FIELD-LEVEL ANALYSIS

4.1 Introduction

In the United States, the share of land among cropland, pasture and rangeland, and forests has changed little over the past fifty years. In 2007, cropland use was 408 million acres, grassland pasture and range was 614 million acres, and forests accounted for 671 million acres. However, these aggregate data veil interesting and economically-motivated transitions among and between uses. During 1997-2007, five million acres of pasture, six million acres of Conservation Reserve Program (CRP) land, and 11 million acres of hay became cropland. Roughly 11 million, 12 million, and 16 million acres converted from cropland to pasture, CRP land, and hay, respectively (Claasen et al., 2011). In well-functioning land markets, these transitions reflect an array of local economic factors, including changes in production environments and climatic conditions.

Changes in production environments (e.g., resource endowments, improvements in bio- and information technologies, and management practices) can substantially alter firm productivity and profitability. Weather is a classic example of a stochastic input with interactive and nonlinear impacts on agricultural and resource-based production. As Earth heads toward temperature increases of 1.5 °C by 2100 (relative to 1850-1900), climate models predict warmer and more frequent hot days, warmer and fewer cold days, expansions in drought-prone areas, and increases in heavy precipitation (IPCC, 2013; Jarvis et al., 2010; Groisman et al., 2012). It is poorly understood how US farms and other agricultural firms will mitigate or adapt to climate change by 2100, as perhaps important future policies and technologies have not yet been engineered. However, near-term adaptation can be more reliably estimated from current behavior.

Many climate adaptation strategies exist for US farms (Ortiz-Bobea and Just, 2013). In the short run, firms can adjust quantities and timing of irrigation water, fertilizer, and pesticides, plant earlier in the season or adjust acreage allocations, and adopt drought-tolerant seeds or no-till production practices. In the long run, land can be substituted towards less water-intensive crops, retired from production, or relocated to less impacted or favorably impacted regions. Future adaptation options could include "prescription agriculture" (e.g., seeds designed to meet individual operation requirements). Farmers are likely to adjust cropland allocation or crop choice, especially in regions where other adaptation strategies are unavailable or too costly. For example, in response to reduced access to irrigation water, farmers engaged in irrigated agriculture may need to alter planted acreage, whereas others may switch crops (Hornbeck and Keskin, 2014; Hendricks and Peterson, 2012).

This chapter addresses the following question: how do climate conditions influence farm behavior? To answer this question, we examine the impacts of climate on the choice and acreage allocations of corn, soybeans, winter wheat, and other major crops in the central US. We implement well-known two-step estimation routines on pooled cross-sectional field data from seventeen states. In the first step, farmers choose a combination of crop and tillage practices. Our focus on no-till methods is motivated by findings that no-till practices help reduce nitrogen leaching and runoff during heavy rainfall (Rice and Smith, 1984; Dinnes et al., 2002; Shipitalo et al., 2013). In the second step, farmers choose acreage allocations conditional on crop choice. The estimation controls for management practices, regional output and input prices, and county variation in soil characteristics. We find that climate conditions significantly affect choice of crop, tillage, and acreage, and all may be appropriate adaptation strategies depending on economic and soil conditions.

The balance of the paper is arranged as follows. The next section briefly surveys recent studies on cropland use and climate, with an emphasis on selection models using farm data. Section 3 describes the basic empirical model. Section 4 explains data sources and construction of variables and presents summary statistics. Section 5 discusses the empirical results and provides implications about near-term climate change. Section 6 concludes. Tables of econometric results are contained at the end. Appendix C contains checks on robustness to two econometric issues discussed in the analysis.

4.2 Related research

The chief economic sources of land-use change in developed countries are government policies, technical change, energy feedstock demands, increasing export demands, and climate change. To evaluate the impacts of each of these factors on land use and allocation requires careful econometric work. For example, Mendelsohn and Dinar (2009) review the following well-known feedback loop: land use influences climate change through greenhouse gas (GHG) emissions, while climate change and frequency of extreme climate events alters land use. In the first part of the feedback loop, cropland use emits carbon and nitrogen dioxide, timber harvests and forest conversion emit carbon, and livestock emit methane. These emissions contribute to adverse climate change and have welfare effects, sometimes with negative or positive implications for local agriculture. The second part of the climate-land use feedback loop draws on econometric analyses of yields or land values, crop or farm simulation models, and general equilibrium models. The results vary widely, but they all underscore the continued importance of an evolving climate for agriculture.

A recent strand of land-use economics research emphasizes structural econometric techniques. Fezzi and Bateman (2011), Lacroix and Thomas (2011), and Kaminski et al. (2013) are a group of closely-linked studies starting from underlying models of farm profit maximization to examine the relationships between climate and land use in England, France, and Israel, respectively. The first paper implements quasi-maximum likelihood techniques for two systems of Tobit equations characterizing livestock supplies and land use shares. Among their findings are that shares of cereals land, root crops, and permanent grasslands are highly nonlinear in soil suitability indices. Lacroix and Thomas (2011) estimate elasticities of output, land, and fertilizer using a model that accounts for multivariate selection, i.e., weather shocks influence a certain crop's yields while also influencing probabilities of planting other crops. The last paper in this group starts from an expected-profit maximizing farmer with a Pope and Just (2003) yield function to derive climate impacts on technology and land allocations. They consider four technological attributes (yield potential, input requirements, yield tolerance to suboptimal input use, and managerial costs). One conclusion is that climate adaptation research should target input requirement sensitivity to precipitation.

Empirical energy economics use similar selection models, usually two-step methods, to analyze fuel switching and energy demand (Mansur et al., 2008; Newell and Pizer, 2008; Hanemann et al., 2013). This line of research adapts earlier work on selection and models that relate first- and second-step choices via correlations in disturbances (Heckman, 1979; Lee, 1983; Dubin and McFadden, 1984). For example, Mansur et al. (2008) explain fuel choice for residential and commercial buildings using firm information, building characteristics, demographics, and climate data. They find that climate change will likely boost electricity use for cooling and reduce other fuels for heating. In a similar study, Seo and Mendelsohn (2008) use data on 949 farmers in South America (Brazil, Chile, Uruguay, Argentina, Ecuador, Venezuela, and Columbia) to estimate a multinomial logit model of crop choice. Although the intensive margin (land allocation) is not estimated, they find that farmers will switch from wheat, potatoes, and corn to squash, vegetables, and fruit through year 2100. In a related discrete-continuous study, Seo (2010) finds that South American farms choose joint livestock and crop systems in hotter climates. These farms can reduce losses in land values from climate change up to 10 percentage points by adaptation through crop and livestock systems.

Anderson et al. (2012) use an underlying multinomial logit model to motivate log-linear regressions of crop shares on interactions of county soil and climate characteristics. The authors consider interactions between degree days, minimum temperatures, precipitation, sunshine, soil variables, and plant characteristics. Tentative findings point out significant effects of these interactions on crop shares.

Finally, our research extends the literature on the use of the Agricultural Resource Management Survey (ARMS) data. This is a complex stratified dataset that has been little employed in environmental economics. ARMS data have been much more widely used in applied agricultural economic analyses. Such studies can provide insight into methodologies, model selection, and data differences over survey years (Goodwin and Mishra, 2005; Kirwan, 2009; Mayen et al., 2010; Gillespie et al., 2010). There are known limitations with the data, most notably that it does not contain farm-level panels. Analysts must be careful to take these limitations into consideration (National Research Council, 2008).

4.3 Empirical model

The two-step estimation procedure used to correct for selection in the acreage equations is the discrete-continuous framework of Dubin and McFadden (1984). This is a well-known selection correction technique and is more robust and general than the Lee (1983) approach. Despite potential problems arising from multicollinearity between regressors and selection terms, the Dubin and McFadden (1984) method requires fewer assumptions and can provide adequate correction when the Independence of Irrelevant Alternatives (IIA) assumption does not hold (Bourguignon et al., 2007; Schmertmann, 1994).

4.3.1 Discrete-continuous model

Following the notation of Bourguignon et al. (2007), assume that agricultural producer i maximizes latent economic net returns per field by choosing crop-tillage combination c and then planted acreage, A_c. Farm accounting profits are observable but economic net returns per field are latent. For example, we do not observer farmers' opportunity costs or complete measures of human capital. These partially motivate the econometric error, which is assumed to be uncorrelated with explanatory variables of crop-tillage choice. However, unobservables influencing crop choice are assumed to influence planted acreage. Significance of the selection correction terms in the acreage equations is discussed in the fifth section.

For choice c $\in$ C crop-tillage combinations, producer i receives latent economic net returns:

$$\Pi^*_{ic} = \gamma' z_{ic} + \eta_{ic}. \tag{4.1}$$

In the above equation, z_{ic} is a vector of observable variables, η_{ic} is an unobserved disturbance, and the analyst observes $\Pi_{ic} = 1$ if c is chosen (and zero otherwise). After selection, the producer's crop acreage decision (conditional input demand) is:

$$A_c = x_c\beta_c + u_c, \tag{4.2}$$

where x_c is a vector of exogenous factors that influence allocations, and u_c is a random error. Note that $E(u_c|x, z) = 0$ and $Var(u_c|x, z) = \sigma_c^2$. Selection occurs as a result of $Corr(u_c, \eta_c) \neq 0$, which renders ordinary least squares (OLS) estimates of β_c in (4.2) inconsistent.

Crop-tillage combination c is chosen if it yields the highest latent economic net returns on the field:

$$\Pi_{ic}^* > \max_{j \neq c} \Pi_{ij}^*. \tag{4.3}$$

Assuming that η_{ic} is distributed type I extreme value, the discrete choice problem implies a multinomial logit model (McFadden, 1973). The probability that the condition in (4.3) holds is:

$$P_{ic} \equiv Prob\left(\gamma' z_{ic} > \max_{j \neq c}(\Pi_{ij}^* - \eta_{ic})\right) = \frac{\exp(\gamma' z_{ic})}{\sum_{j=1}^{C} \exp(\gamma' z_{ij})}. \tag{4.4}$$

Dubin and McFadden (1984) impose the assumption that the conditional expectation $E(u_c|\eta_c, \ldots, \eta_C)$ is linear in $(\eta_{ij} - E(\eta_{ij}))$, which further restricts distributional forms for u_c. Correcting for selection, equation (4.2) for the i^{th} observation becomes:

$$A_{ic} = x_{ic}\beta_c + \sigma_c \frac{\sqrt{6}}{\pi} \sum_{j \neq c} r_{ij} \left(\frac{P_{ij}\ln(P_{ij})}{1 - P_{ij}} + \ln(P_{ic})\right) + w_{ic}, \tag{4.5}$$

where $r_{ic} = corr(u_{ic}, \eta_{ij})$ and w_{ic} is an independent error. See Bourguignon et al. (2007) for more details. As pointed out by Mansur et al. (2008), the correction terms in the above equation provide some economic insight. Particularly, the correction term for crop-tillage combination j in equation c measures the impact on acreage of crop c for those farmers predicted to have selected j on a particular field. For example, if there is a statistically significant and positive correction term for no-till soybeans in the OLS regression of no-till corn acreage, then fields planted to no-till soybeans are predicted to be positively associated with no-till corn acreage.

4.3.2 Identification

For identification of Equations 4.1 and 4.5, we impose the following two assumptions. First, we assume that crop rotation history affects the discrete crop-tillage choice but not planted acreage. Although the model is identified without such restrictions, we follow the literature and include a larger set of regressors in the first step than in the second step.

Second, we only observe field planted acreage in survey years and not for the full crop-tillage choice history. Thus, we assume that the acreage of the (randomly-surveyed) field in a particular years equals its acreage planted to other crops in past years. For example, if a randomly-selected field has a rotation history of corn-soybeans-corn in 2008, 2009, and 2010 with a 2010 planted corn allocation of 50 acres, then we assume this field had 50 acres planted to soybeans in 2009 and 50 acres planted to corn in 2008.

To obtain consistent estimates, any change in a farmer's field size over time in the sample should be random and absorbed by the econometric error in a way that does not induce correlation with the regressors. This is likely an innocuous assumption for two reasons. First, field sizes are generally predetermined and often have one or more natural or physical boundaries, e.g., creeks, streams, or county roads. Many fields on Midwest farms were originally fenced to accommodate livestock in an era in which combined livestock and crop operations were much more common. Second, the mean number of repeat years per field is 3 in the spring dataset and 1.5 in the fall dataset. Any change in the size of the randomly-selected field would have had to be made over a very short period and would likely not vary with changes in climate conditions, soil characteristics, or prices.

As with nearly all other studies in this literature, we abstract from field-level economies of density. Spatial contiguity of fields can produce economies of density because of reduced drive time and reduced capital configuration costs across non-adjacent fields (Holmes and Lee, 2012). Our data contain information only on a single randomly-selected field per farm. Randomization of fields is beneficial because farmers' selection into groups of fields can be safely omitted, unlike studies with data on all fields in each farm. Moreover, modern farmers are much more likely to operate one or more non-adjacent fields located several miles apart. Field studies that estimate spatial correlations and economies of density must control for farm/operation switches in the cross section. Otherwise, spatial economies may be confounded by a specific farm's management practices varying over both adjacent and non-adjacent fields. Given the lack of clean evidence, interactions among fields seem second order in nature for our estimates of the relationship between climate, crop-tillage selection, and land allocation.

In the following econometric analysis, Equations (4.1) and (4.5) are of primary interest. A maximimum likelihood routine is used to estimate the multinomial logit model in (4.1) for two different datasets, divided according to spring crops and fall crops. The spring crop choice set is {tilled corn, no-till corn, tilled soybeans, no-till soybeans, all other spring crops}. The fall crop choice set is {tilled winter wheat, no-till winter wheat, all other fall crops}. The standard errors for the average marginal effects are computed by the delta method. Having corrected for selection, OLS is applied separately to (4.5) corresponding to the acreages of the eight crop-tillage combinations. As is common with multi-stage estimation, bootstrapping is used for computing standard errors. For each of the eight acreage equations, the standard errors are computed as the standard deviation of the coefficients estimated from 1,000 bootstrap samples with replacement.

4.4 Data

4.4.1 Compilation and construction

ARMS is a key source of information about agricultural production, management practices, financial conditions, and household attributes of US farms. In its current format since 1996, it dates back to earlier surveys starting in 1975 regarding farm costs and returns, chemical use, and cropping practices. The survey occurs over three phases in a crop year, with stratified sampling over two mutually exclusive frames: a list frame of farms with certain production aspects and an area frame that randomly samples land segments. Sets of thirty replicate weights are constructed in each survey year so that analyses can "extend" the observations to the population. Field weights are designed so that field data represent the population of all fields of a certain crop in a certain year. Farm weights are designed so that farm data represent the population of all farms growing the crop(s) of interest in the survey year (ERS, 2013). We do not perform a weighted analysis because we pool data over multiple years and crops.

Field data for seventeen states are taken from the 2009, 2010, and 2012 ARMS Phase II Production Practices and Costs surveys.[1] We consider cross-sectional data in these three surveys because they are the most recent years available with extensive information on crop rotation and tillage practices. Importantly, the ARMS enumerators randomly select a field from the farmer's set of fields, which alleviates concerns about systematically productive or unproductive fields entering the sample.

We use the following field information from the ARMS surveys: crop choice, planted acreage, use of no-till practices, years of experience operating the field, and whether or not any portion of the field is "highly erodible" or contains a wetland (according to criteria from the Natural Resource Conservation Service). Additional indicators of rotation histories and double-cropping are constructed from these data. Specifically, separate dummy variables indicate if the field was planted to corn, soybeans, or winter wheat in the previous season. Rotations help maintain soil health, help reduce soil erosion and pest infestation, and can contribute to yield gains in the next season. These are important predictors of crop choice and are used as controls.[2] For this analysis, a field is considered "double-cropped" if it is planted to crops in the spring and fall of the same calendar year, i.e., the field is not fallow or enrolled in the Conservation Reserve Program.

Monthly weather information is from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). The PRISM model outputs daily interpolated weather

[1] States included in the sample are Colorado, Iowa, Illinois, Indiana, Kansas, Kentucky, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, Oklahoma, Pennsylvania, South Dakota, Texas, and Wisconsin. These states are generally the most productive regions in the US for corn, soybeans, and winter wheat.

[2] Rotation controls do not cause endogeneity bias in logit models because the errors are assumed to be serially independent (Train, 2009).

data for grids of size 4km x 4km (Daly et al., 2008). We construct county weather data as the mean of weather variables in all grid points in the county. Weather data are then averaged over the previous 25 years to construct the climate variables in our analysis. Growing Degree Days (GDD) are a measure of beneficial exposure to sunlight. We use the Snyder (1985) approach with an upper bound of 34 °C and lower bound of 8 °C provided by Ritchie and NeSmith (1991). Heating Degree Days (HDD) are a measure of harmful exposure to high temperatures. These are calculated similarly to GDD but are only positive if the daily maximum temperature exceeds the 34 °C bound.

Mean precipitation and intense precipitation are also important for agricultural outcomes. Many climate models predict increases in intense precipitation in the United States. One reason is that increased atmospheric temperatures are associated with increased moisture-holding capacity of the surrounding air, an effect known as the Clausius-Clapeyron relation. Climatologists are beginning to recognize the importance of potential feedback between intense precipitation and agriculture (Groisman et al., 2012; Daniel, 2015). To control for these important effects, we define intense precipitation as an instance in which a grid receives an inch or more of precipitation per day. Monthly intense precipitation is the count of such events throughout the month, again averaged over the previous 25 years.

Following much of the land-use change literature, we control for time-invariant geologic and hydrologic factors in soils that contribute to soil productivity. Soil structure and land characteristics have significant bearing on land use and allocation. Significance of these factors for agricultural decision making may increase with an evolving climate. Soils data are from the most recent version of the Soil Survey Geographic database (SSURGO), which comprises data collected by the National Cooperative Soil Survey over the century (USDA-NRCS, 2013). Spatial areas of analysis are in "map unit polygons," with states being comprised of hundreds of thousands or millions of soil polygons. To get county-level measures of soil attributes, we include all polygons within a county and weight according to each polygon's area. For certain soil features, data are reported at multiple soil layers (depths) within a polygon, and we compute a simple average over these layers.[3]

We use a variety of soil controls as there are no definitive guidelines on the economic importance of specific soil characteristics (National Soil Survey Center, 2014; Earth Systems Modeling Group, 2014). Slope measures the difference in elevation between two points relative to the distance between these points. Regarding soil texture, the percentage of silt and clay are included to capture substantial qualitative aspects of soils. Closely related to these innate soil characteristics are saturated hydraulic conductivity (Ksat), root zone available water storage (AWS), and the K Factor and T Factor. The first variable relates to permeability and measures the soil's ability to transfer water. Root zone AWS is the volume of water that a soil can store in the root zone for plant use. The K Factor is one of several factors used in the Revised Universal Soil Loss Equation (RUSLE) and indicates vulnerability of soils to water erosion. The T Factor, soil loss tolerance, measures the maximum amount of soil erosion that maintains viability of plant growth. Root zone depth is the depth of the soil used by plants to obtain water and nutrients. Organic matter is residue from decomposed plants and animals and is a source of nitrogen and other nutrients (Soil Survey Division Staff, 1993). We also include total county cropland so that regression estimates may be interpreted as holding county cropland fixed.[4]

State-level expected prices for corn, soybeans, and winter wheat are calculated according to the methods of (Barr et al., 2011). For corn and soybeans, we first average the daily February close prices of the December corn futures contract and November soybean futures contract traded on the Chicago Board of Trade (CBOT). Next, basis (the difference between the cash and futures price) is subtracted from these February averages. To calculate basis, we first average the daily November and December close prices for the harvest time soybean and corn contracts. From this, we subtract state-level corn and soybean prices received by farmers in the marketing year (cash prices), pub-

[3]By averaging across soil horizons, the data reflect agronomic considerations at two critical areas: surface effects near the uppermost layers of topsoil and root zone effects in lower layers.

[4]County cropland is the sum of barley, canola, corn, cotton (upland), flaxseed, oats, rye, sorghum, soybeans, sugarbeets, sunflower, and wheat (winter, Durum, and other spring).

lished by the National Agricultural Statistics Service (NASS). By accounting for basis, we eliminate possible bias from systematic differences between spot and futures prices. To derive expected prices for winter wheat, we start with the average of February daily closing prices for the July Kansas City Board of Trade (KCBT) wheat contract. Basis is calculated similarly, except the harvest-time contract is July. Expected prices are used in the analysis of the spring data. However, we use prices received by farmers in the previous marketing year in the fall data. These prices may more closely match the timing of fall planting decisions.

State-level nitrogen prices are calculated from multi-state NASS nitrogen data. Each state is assigned to a multi-state region. We then take a simple average of all reported prices of nitrogen fertilizers and solutions, including anhydrous ammonia. All output and input prices are calculated in 2009 dollars. Prices are deflated to the state level using a price index constructed from gross state product data obtained from the Bureau of Economic Analysis.

4.4.2 Summary statistics

Table 4.1 contains summary statistics on the number of observations in each crop-tillage combination, decomposed by the spring and fall data. The 16,415 spring field-year observations are obtained from 5,422 unique farms across the seventeen-state sample during years 2006-2012. Tilled corn is the most frequently chosen crop, representing 31% of the spring sample. The next largest category, tilled soybeans, comprises 22% of the sample. The shares of no-till corn and soybeans are 13% and 18%, respectively. The smaller proportion of no-till crops is expected since its adoption has only become more widespread in recent decades. The remaining 16% of crops are categorized as "other spring crops" and are not broken down by tillage practice.[5] The 2,137 field-year observations

[5]For the spring and fall datasets, the "other crop" category contains fields planted to the following: barley, canola, clover, cotton (upland and Pima), dry beans and peas, grasses (other than clover), hay (alfalfa and other), mustard seed, oats, peanuts, potatoes (including sweet potatoes), rice, rye, tobacco (burley and flue cured), safflower, sorghum (for grain and silage), sugarbeets, sunflowers, vegetables, and wheat (Durum and other spring wheat). Cotton, hay, and spring wheat have among the most observations in the "other" category. We drop fields that are fallow or are placed in the Conservation Reserve Program. See Appendix C for robustness to the inclusion of fields that are not planted.

in the fall during years 2006-2011 are from 1,143 farms. Of these farms, 82% are also represented in the spring data. Fall fields are somewhat more equitably partitioned across categories. The share of tilled winter wheat is 39%, while the share of no-till winter wheat is 25%. The remaining 36% are "other fall crops."

Table 4.2 contains summary statistics (means) of acreage dependent variables used in the acreage (second-step) regressions. No-till corn fields average six acres larger than tilled corn fields, but no-till soybean fields are three acres smaller than their tilled counterpart. Average tilled winter wheat fields are 10 acres larger than no-till winter wheat fields. Tilled winter fields may be larger because of lower adoption rates of no-till among relatively large wheat farms in the southern Great Plains. Though there is no difference in size between tilled and no-till other fall crop fields, no-till other spring crop fields are 52 acres larger on average than tilled other spring crop fields. This is a result of few observations (e.g., 838 observations) of no-tilled other crops. This partially motives our choice of aggregation across all other crops without regard to tillage practices.

Summary statistics of regressors used in the spring analysis are given in Table 4.3. Average climate conditions and variability are similar to climate regressors used in related agriculture-climate studies. For example, monthly GDD range from 249 to 467 across the growing season, with a standard deviation of roughly 60 GDD. Extreme heat, as captured by monthly HDD variables, is less widespread and less frequently-occurring. Monthly HDD range from 0.03 in May to 1.20 in July. Precipitation averages approximately three inches each month in the growing season, though there is substantial variability across counties and time periods. Intense precipitation occurs more often in the early season, with 0.63-0.73 days in the month experiencing at least one inch of 24-hour rainfall.

The economic and management variables also convey adequate sample variation. Expected corn and soybeans prices are \$4.66/bu and \$10.56/bu, with standard deviations of \$1.07 and \$2.76. Nitrogen prices average \$0.22/lb and have somewhat lower variability over years in the sample. Nearly half of the field-year observations have corn planted the previous spring, while roughly one-third have soybeans planted the previous spring. Double-cropping occurs in 14% of the sample.

The soil controls suggest that soil and land characteristics are beneficial for corn and soybean farming. Fields that are highly erodible comprise less than 12% of the sample, and 4% of field-years are located on wetlands. This is consistent with a relatively low county average T factor of 1.73. Average root zone depth is roughly four feet (123 cm), with roots capable of accessing water available to 8.5 inches (214 mm). Saturated hydraulic conductivity (a measure of water flow and infiltration) and the K Factor (a measure of soil erosion and runoff rates) are relatively low. County-level organic matter content averages 1.3% by weight, and total county cropland averages 229,000 acres.

Summary statistics for the fall data are similar to those of the spring data (Table 4.4). Fall GDD and HDD are relatively low because of cool temperatures in September and October. Mean precipitation in the fall is 0.9-1.2 inches lower than in the spring, but intense precipitation has a similarly narrow range of 0.55-0.85 days per month across the winter wheat growing season. Average previous year output prices are roughly one dollar less than expected prices because they include relatively low prices for year 2005 and omit relatively high 2012 prices. Double-cropping is done on 67% of fall field-years, a consequence of a reduced sample size with emphasis on winter wheat. There are no major differences in soil and land characteristics between the spring and fall data.

4.5 Empirical results

The empirical findings are presented and discussed in the following order: spring crop choice, conditional spring crop acreage, fall crop choice, and conditional fall crop acreage. For each regressor in the crop choice models, we present the average of the marginal effect over the sample. Marginal effects need not have the same sign as coefficient estimates in multinomial logit models (Greene, 2011). Many of the soil characteristics are significant at the 10% level or better, but these are not reported to keep the set of results manageable. Appendix C contains first-step estimates in which: (i). fields that have nothing planted are added back to the analysis, and (ii). standard errors are clustered by county.

4.5.1 Spring crop choice

Table 4.5 reports the climate, economic, and management marginal effects on crop choice for spring observations. In general, many of the coefficients (not reported) are statistically significant at the 5% and 1% significance levels, with adequate goodness of fit.[6] Monthly GDD are among the most important climate variables impacting crop choice. An additional 10 GDD in May increases the choice of corn by two to six percentage points and decreases the choice of soybeans by four to seven percentage points. June GDD have similarly small but opposite effects on the choice of corn and soybeans. Fewer late-season GDD are significant and have diverse effects. Greater August GDD are associated with increases in the probability of choosing no-till corn and soybeans, while increased July GDD favor choice of tilled corn relative to no-till soybeans.

Late-season extreme heat has similarly counteracting effects across crops and months. One additional HDD induces a five-percentage-point shift in probability from tilled soybeans to no-till corn. However, areas with greater August HDD have increased probabilities of choosing tilled corn and soybeans and generally decreased probabilities of the other spring crops. These results suggest an interesting finding. On-field crop residue may influence effective plant cooling, so that beneficial and harmful sunlight have differing impacts on crops.

Average precipitation is also significant across nearly all months. An additional inch of May precipitation increases the probability of choosing corn and no-till soybeans by two to six percentage points. June has similar negative effects on no-till corn and soybeans. The large negative coefficient on July precipitation for tilled corn is not surprising given our sample includes farms in areas suffering drought in recent years. However, this is offset by a positive 11-percentage-point August precipitation effect on tilled corn. August precipitation tends to increase corn selection and decrease soybeans selection, perhaps a reflection that farmers prefer soybean crops to be dry by a relatively earlier harvest time.

[6] The value of the converged log-likelihood is -18,690. The pseudo-R^2 is 0.27, and a likelihood ratio test rejects the null hypothesis that all coefficients are jointly zero at the 1% significance level. The χ^2_{140} test statistic is 13,954 with an associated critical value of 181.8.

Though several monthly intense precipitation variables are insignificant, the sign pattern of significant variables suggests interesting potential adaptation behavior. An increase by one day in May in which daily precipitation exceeds one inch decreases the probability of choosing tilled corn and tilled soybeans by three to seven percentage points.[7] This is accompanied by an eight-percentage-point increase in the probability of choosing no-till corn. Switching from tilled corn to no-till corn as a result of increasingly intense early-season rainfall could be an important adaptation tool. No-till practices reduce soil erosion, restrict movement of soil particles during heavy rain, and help to limit nitrogen runoff and leaching under certain conditions. Thus, continued or increased substitution towards no-till agriculture could be a valuable tool for limiting downside risk from substantial climate change. This may already be occurring in Nebraska and North Dakota, states with the greatest number of no-till fields in our sample. Increases in August intense precipitation are also associated with decreased choice of tilled corn and increased (but insignificant) no-till corn. Increases in intense July precipitation are consistent with switching from no-till corn to tilled soybeans.

Table 4.9 confirms that these intense precipitation effects are significant. The statistic from a Wald test of the null hypothesis that the difference in coefficients on May intense precipitation for no-till and tilled corn crop choice equals zero is 12.43, significant at the 1% level. A similar test of equality of the July intense precipitation coefficients between tilled and no-till corn is also rejected. However, these tests are not rejected for any of the monthly intense precipitation variables in the choice of tilled and no-till soybeans. The combined evidence from Tables 4.5 and 4.9 suggest that switching from tilled to no-till corn or corn to soybeans may be important factors to consider when evaluating farm-level climate adaptation.

The signs and magnitudes of the economic and management marginal effects in Table 4.5 generally agree with intuition. Corn and soybeans have own- expected price effects of two and four-to-seven percentage points, respectively. The cross-price effect of soybeans

[7]The marginal effect of May intense precipitation on the probability of choosing tilled corn becomes significant if total county cropland is dropped. Dropping this variable gives the interpretation that crop choice may freely adjust without holding total county cropland fixed.

on corn, -0.04, is smaller than the cross-price effect of corn on soybeans, [-0.07, -0.09]. This asymmetry in cross-price effects is expected because of the relatively greater value of corn, especially reflected in the 2006-2012 era of increasing relative corn prices. No-till corn and soybean choices are somewhat less price sensitive than their tilled counterparts. This could arise because no-till farmers are relatively more concerned with production cost savings. Another potential explanation is that farmers who use no-till practices have strong preferences for conservation. Nitrogen price effects on soybeans are either insignificant or positive for choice of soybeans. Given that soybeans fix nitrogen and so have low nitrogen applications, farms are either insensitive to nitrogen prices or may switch to soybeans with increases in nitrogen prices.

Rotation considerations and double-cropping are also significant and intuitive. If the field is planted to corn or soybeans last season, then the choice of soybeans or corn this season (respectively) is much more likely. The own-choice crop effects are negative, reflecting limited occurrence of continuous cropping. Subtle asymmetries in rotational effects across tillage practices also exist. The magnitudes of the own-choice effects are smaller for no-till corn (-0.04 compared to -0.13) and no-till soybeans (-0.004 compared to -0.11). Double-cropping has negative effects on the choice of corn but positive effects on the choice of soybeans, i.e., double-cropping is relatively more likely among primarily soybean fields than among primarily corn fields. Lastly, years of experience have small or insignificant effects on crop-tillage combinations. This is similar to the Rahm and Huffman (1984) finding of insignificant effects of years of experience on the efficiency of reduced tillage adoption.

4.5.2 Conditional spring crop acreage

Table 4.6 contains estimates of the impacts of primarily cross-sectional variation in climate, economic, and management conditions on planted acreage after controlling for soil characteristics, total county cropland, and selection into a crop. There is general overlap in significant climate variables between spring crop choice and acreage. An additional 10 May GDD are associated with 3-7 acre increases in all crops except no-till corn. June GDD have small negative impacts on no-till soybeans and the other crop category, while increases in July GDD have roughly one-acre impacts on no-till corn and soybeans. August GDD are generally insignificant, suggesting that July GDD is relatively more important for spring crop acreage. Monthly HDD are similarly insignificant, apart from negative and positive effects on tilled corn acreage from May and June HDD. Extreme heat may be less important for field acreage if there is adequate soil moisture and productivity.

Many precipitation variables are significant and exhibit an interesting pattern between average and intense measures. May mean precipitation is associated with 18-23 fewer acres across crops. Acreage for corn and soybeans are positively associated with June GDD, especially among no-till crops for which there is less concern about soil erosion. Late-season mean precipitation has negative effects with the exception of generally insignificant August effects. August climate conditions are unimportant determinants of acreage allocation. One reason is that farmers may have limited ability to respond to weather-climate conditions in the growing season (e.g., planting time rescheduling, field re-plantings, and re-applied or sidedressed nitrogen are infeasible during most of July and August). In contrast, areas with more intense May and July precipitation have greater acreage planted to soybeans and corn, respectively.

Economic and management variables are also important but less so for acreage than crop choice. A one dollar increase in the expected corn price increases tilled corn by 15 acres and decreases soybeans by 11-13 acres. As with the spring crop choice results, nitrogen prices are insignificant for all crop acreage besides tilled corn. Double-cropping has no influence on corn, but double-cropped fields have decreased soybean acreage particularly for tilled soybeans. Lastly, fields with operators who have an additional year of experience with the field have 0.2-1.1 smaller acreage. This may reflect retirement considerations, which we do not include because of sizeable nonresponse to this survey question.

Selection correction terms for crop choice appear at the bottom of Table 4.6 and are denoted as S_{-j_1}, S_{-j_2}, S_{-j_3}, and S_{-j_4}. Application of the discrete-continuous model is supported by nine out of 20 selection terms being significant.[8] The sign pattern of the significant terms is expected. For example, fields that would have been planted to no-till corn but are instead planted to tilled corn have increased acreage (S_{-j_1} in column 1).[9] Similarly, fields that are "selected" for no-till soybeans are positively associated with tilled soybean acreage. This is intuitive given that the choice of no-till or conventional tillage practices for a particular crop in our choice set can be adjusted prior to planting. Further, there is a negative correlation between selection into tilled soybeans and tilled corn acreage (S_{-j_2} in column 1) and selection into tilled corn and tilled soybean acres (S_{-j_1} in column 3). The results suggest that choice of crop, tillage, and acreage are highly interrelated and should be carefully considered in future analyses of farm adaptation to climate change.

4.5.3 Fall crop choice

Crop choice of tilled and no-till winter wheat and other fall crops are less influenced by climate conditions (Table 4.7). This is likely a consequence of environmental and economic factors associated with winter wheat farming, rather than inadequate model performance.[10] Similar to spring crop choice, many of the monthly GDD variables are significant. April GDD have a small positive effect on the choice of no-till wheat, but May GDD have negative effects for both wheat categories. Favorable May GDD pull crop choice away from winter wheat towards higher-value crops, consistent with the nearly one-percentage-point effect on "other" crops. To the extent that no-till practices somewhat decrease soil temperature, tilled winter wheat may benefit relatively more from GDD in cooler months.

[8]In a discrete-continuous study of fuel choice, Mansur et al. (2008) find that 40% of selection terms are significant in regression equations explaining residential fuel use.

[9]Selection terms for each crop except the acreage of the crop under consideration enter each regression equation. For example, in the first column of Table 4.6, S_{-j_1} is the selection term for no-till corn, S_{-j_2} is the selection term for tilled soybeans, S_{-j_3} is the selection term for no-till soybeans, and S_{-j_4} is the selection term for other crops. In the second column, S_{-j_1} is the selection term for tilled corn, S_{-j_2} is the selection term for tilled soybeans, S_{-j_3} is the selection term for no-till soybeans, and S_{-j_4} is the selection term for other crops. This notational convention also applies to the third and fourth columns.

[10]The value of the converged log-likelihood is -1,768, with an associated pseudo-R^2 of 0.23. A likelihood ratio test of the null hypothesis that the coefficients are jointly zero is rejected at the 1% significance level. The χ^2_{70} test statistic is 1,085 compared to the critical value of 100.43.

Extreme heat and mean and intense precipitation have little influence on fall crop-tillage choices. The implausible coefficient on April HDD for no-till winter wheat reflects very little variation in April HDD (see Table 4.4). Mean September precipitation decreases the no-till winter wheat choice by eight percentage points. The negative marginal effect of October intense precipitation is twice the size of the mean September precipitation effect. From Table 4.9, we find that Wald tests of the equality of monthly intense precipitation coefficients between tilled and no-till wheat cannot be rejected at the 10% significance level.[11] The results confirm that winter wheat crop choice is largely unresponsive to climate, perhaps a partial consequence of breeding for suitability in North American production environments (Olmstead and Rhode, 2011). Given winter wheat's relatively better performance in hotter and drier conditions, it may become more widely-grown in the long run under severe climate change (Hornbeck and Keskin, 2014).

Fall crop choice tends to be more responsive to management practices and soil characteristics than output and input prices. Corn prices in the previous year have a negative five-percentage-point effect on tilled wheat, but there is a positive own-price effect of similar magnitude on no-till wheat. In general, analysis of output prices must consider dynamic effects (Orazem and Miranowski, 1994). For example, if current nitrogen prices are high and next season's corn prices are expected to be high, then the farmer is more likely to plant soybeans (all other things equal). These factors could further influence rotations of wheat, corn, and soybeans or corn and multi-year hay.

Unlike corn and soybean fields, winter wheat fields are more likely to be double-cropped by operators with more years of field experience. The latter effect could be associated with increasing winter wheat farm sizes accommodated by somewhat greater availability of cropland in regions where winter wheat is concentrated. Lastly, the choice of winter wheat is decreasing in land slope and root zone available water storage (not reported in Table 4.7). The fact that winter wheat fields are negatively associated with water storage at the root zone affirms its relevance to climate change adaptation. Holding

[11] An earlier farm-level analysis using 2010 Phase III ARMS data in which winter wheat is subsumed into the "other" crop category finds unresponsiveness to weather conditions (McFadden and Miranowski, 2014).

fixed prices and management practices, winter wheat could be selected on fields increasingly exposed to drought under severe climate change.

4.5.4 Conditional fall crop acreage

These trends are reiterated in the winter wheat acreage results contained in Table 4.8. Among the significant climate variables, April GDD and September HDD have positive effects on no-till wheat acreage, whereas September and October mean precipitation have negative effects on no-till and tilled winter wheat, respectively. The implausible effects of April and October HDD arise from very low occurrences (and variability) of extreme heat in these relatively cool months. Lack of responsiveness to intense precipitation is also evident. Nearly half of the fall data are comprised of fields in Kansas, Oklahoma, Missouri, and Texas, where intense precipitation is relatively homogenous and mainly results from strong storm cells. The results suggest that acreage of large-scale wheat operations (with larger field sizes) are not associated with intense precipitation.

Prices are insignificant predictors of planted acreage, similar to the relatively few significant price effects in the crop choice model. Fields with double-cropped winter wheat tend to be 40 acres smaller, while double-cropped fields planted to other crops tend to be 32 acres larger. Years of field experience exhibit a negative effect of 0.5-1.2 ac/yr and is similar to experience effects on spring crop acres. Selection correction terms are also generally insignificant. However, selection into "other crops" is negatively correlated with tilled winter wheat acreage. Intuition for this effect is unclear because of the aggregate nature of the "other crops" category. In sum, it is interesting that explanatory measures of winter wheat acreage differ substantially from those for corn and soybeans. Further research on wheat crops and tillage is required for a better understanding of climate change adaptation.

4.5.5 Economic implications of farm adaptation to climate change

The economics of farm and field adaptation to changing climate conditions are poorly understood. Much of the past research has simulated the effects of adverse weather on yields, supply, and prices of major crops. These studies suggest that certain adaptation options could partly alleviate adverse outcomes (e.g., yield losses or decreases in agricultural profitability). In contrast, our results suggest novel econometric relationships between field practices and climate that are consistent with maximizing latent economic net returns.

We find that average and intense degree days and precipitation significantly influence field choices of crop, tillage, and acreage. However, adjustment of these optimal choices must account for input and output prices and soil characteristics. Major crops will continue to be corn and soybeans in regions with high net returns to corn (e.g., Iowa, Illinois, southern Minnesota, and north-central Indiana). As occurrences of drought and intense precipitation become more likely over the next decades, our results suggest that farmers may increasingly use alternative field practices, such as no-till or possibly cover crops. Farms may switch from primarily corn and soybeans to winter wheat in drought-prone regions with reduced access to irrigation (e.g., western Nebraska, Kansas, Oklahoma, and Texas).

In sum, the relative economic importance of adjustments between crop, tillage, and acreage is highly variable. Our results confirm the importance of relative prices, especially for corn and soybeans. The choice of winter wheat and winter wheat acreage are influenced more by economic factors, soil and land characteristics, and lack of irrigation sources than climate conditions. Nitrogen prices create an additional link between optimal choices of crop, tillage, and acreage. Although the relationship between nitrogen prices and climate are less clear, increases in nitrogen prices could favor shifts toward less nitrogen-intensive crops, such as soybeans. This is because soybeans receive lower nitrogen applications and also fix nitrogen.

4.6 Conclusion

A growing body of empirical work in agricultural and environmental economics indicates that changes in short-run weather and long-term climate patterns will impact crop production, contingent on farmers' mitigation or adaptation behavior. We extend the literature by answering the following questions. How does climate impact the choice of crop-tillage combinations in the central US? How does climate impact planted acreage, after correcting for selection into crop and tillage practices? What are the economic implications of climate change on cropland use and allocation?

Using pooled cross-sectional field data on several thousand Midwest and Northern and Southern Plains farms, we estimate a two-step selection model that controls for management practices, local soil characteristics, and output and input prices. We find that early-season and late-season temperatures and rainfall have significant effects on crop and tillage choices. Sensitivity to extreme heat and intense precipitation varies substantially within season and across crops. Crop switching may occur under mild climate change, given price changes and available technologies. However, there are intermediate adaptation strategies that may take place before crop switching, such as adoption of no-till practices or drought-tolerant seeds. No-till practices boost field organic matter, providing more nutrients to plants, better drainage, and reduced erosion. If intra-seasonal rainfall becomes more concentrated in short and intense events, then there will be large adaptation gains by curtailing nutrient leaching, runoff, and soil erosion.

There are important economic and policy implications. First, estimated relationships between crop-tillage selection and late-season temperatures suggest relatively small impacts on crop choice. Nearly all climate models predict that adverse outcomes (e.g., more extreme temperatures, increased occurrence of drought, and more frequent heat waves) will intensify later in the century. Therefore, the geographic distribution and allocation of major crops in the central US is not likely to dramatically change in the near term.

Second, adoption of no-till practices and modern technologies, such as drought-tolerant seeds, advanced information technologies, and high-efficiency irrigation systems in some areas, may limit the downside impacts of climate change. The role of technological innovation is sometimes omitted in climate studies, partly because innovations are difficult to forecast. To the extent that biotechnology firms persist in innovation and farmers continue to adopt new technologies, estimated long-term impacts of climate studies could be overstated.

Third, our econometric results highlight the continued importance of economic factors, improved management, and soil and land characteristics. Climate change analyses should carefully consider the role of input and output prices and soil inputs when considering potential adaptation strategies.

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Table 4.1: Crop Choice across Seasons

Crop	Spring	Fall
Corn, Tilled	5,083	–
Corn, No-Till	2,202	–
Soybeans, Tilled	3,650	–
Soybeans, No-Till	2,929	–
Winter Wheat, Tilled	–	835
Winter Wheat, No-Till	–	531
Other, Tilled and No-Till	2,551	771
Total	16,415	2,137

Each entry indicates the number of fields for a particular crop-tillage combination across the two seasons. There are more unique fields than unique farms across the spring and fall samples (see Section 4.4.2).

Table 4.2: Mean Field Acreage and Tillage

Crop	Tilled	No-Till
Corn	57	63
Soybeans	66	63
Winter Wheat	86	76
Other Spring	70	122
Other Fall	48	47

Each entry indicates mean field size for a particular crop across the choice of tillage. See Section 4.4.2 for additional details.

Table 4.3: Summary Statistics, Spring (N=16,415)

Variable	Mean	St. Dev.	Min	Max
Climate Conditions				
May GDD	249	61	79	592
June GDD	384	58	153	633
July GDD	467	56	216	668
August GDD	437	60	193	671
May HDD	0.03	0.20	0	3.7
June HDD	0.38	0.70	0	10.4
July HDD	1.20	1.87	0	17.9
August HDD	1.06	1.95	0	20.4
May Mean Prec (in)	3.7	0.9	0.6	6.3
June Mean Prec (in)	3.6	0.7	0.5	6.0
Jul Mean Prec (in)	3.3	0.6	0.8	5.0
August Mean Prec (in)	3.1	0.8	0.8	4.8
May Intense Prec (integer)	0.73	0.36	0	2.12
June Intense Prec (integer)	0.73	0.32	0	1.88
July Intense Prec (integer)	0.64	0.29	0	1.56
August Intense Prec (integer)	0.63	0.31	0	1.48
Economic Variables				
Corn Exp. Price ($/bu)	4.66	1.07	2.96	6.64
Soybeans Exp. Price ($/bu)	10.06	2.76	5.92	14.81
W. Wheat Exp. Price ($/bu)	5.97	1.69	2.77	9.17
Nitrogen Price ($/lb)	0.22	0.03	0.15	0.29
Management				
Previous Spring Corn (0-1)	0.45	0.50	0	1
Previous Spring Soybeans (0-1)	0.30	0.46	0	1
Double-Crop (0-1)	0.14	0.34	0	1
Years Operated Field (integer)	19.1	14.0	–	–
Soil Characteristics and Cropland				
Highly Erodible Soil (0-1)	0.12	0.33	0	1
Wetlands (0-1)	0.04	0.20	0	1
Slope (%)	2.10	1.89	0.08	16.19
T Factor (integer)	1.73	1.04	0.11	4.86
Root Zone Depth (cm)	123	30	9	151
Root Zone AWS (mm)	214	48	13	338
Sand (%)	9.5	9.5	0	87
Silt (%)	22.6	18.3	0	71
Sat. Hydraulic Conductivity (μm/s)	4.9	6.3	0	92
K Factor (t.ha.h/ha.MJ.mm)	0.14	0.10	0	0.44
Organic Matter (%)	1.3	0.9	0	5.7
County Cropland (10,000 ac)	22.9	14.2	0.05	94.1

Table 4.4: Summary Statistics, Fall (N=2,137)

Variable	Mean	St. Dev.	Min	Max
Climate Conditions				
April GDD	152	57	29	417
May GDD	288	69	78	551
September GDD	343	68	134	575
October GDD	182	61	48	465
April HDD	0.01	0.04	0	0.73
May HDD	0.18	0.46	0	3.70
September HDD	0.66	0.99	0	5.83
October HDD	0.01	0.03	0	0.37
April Mean Prec (in)	2.8	1.0	0.3	4.7
May Mean Prec (in)	3.8	1.0	0.6	6.2
September Mean Prec (in)	2.7	0.9	0.8	5.2
October Mean Prec (in)	2.6	0.8	0.8	5.0
April Intense Prec (integer)	0.55	0.32	0	1.64
May Intense Prec (integer)	0.85	0.41	0	2.04
September Intense Prec (integer)	0.62	0.32	0	1.64
October Intense Prec (integer)	0.55	0.29	0	1.64
Economic Variables				
Corn Prev. Price ($/bu)	3.52	0.87	1.84	5.47
Soybeans Prev. Price ($/bu)	8.19	2.07	5.35	13.35
W. Wheat Prev. Price ($/bu)	4.72	1.04	2.95	7.58
Nitrogen Price ($/lb)	0.21	0.03	0.15	0.29
Management				
Previous Fall W. Wheat (0-1)	0.29	0.45	0	1
Double-Crop (0-1)	0.67	0.47	0	1
Years Operated Field (integer)	18.1	14.7	–	–
Soil Characteristics and Cropland				
Highly Erodible Soil (0-1)	0.15	0.35	0	1
Wetlands (0-1)	0.02	0.15	0	1
Slope (%)	2.17	1.88	0.08	16.19
T Factor (integer)	1.73	0.85	0.35	4.63
Root Zone Depth (cm)	115	35	9	151
Root Zone AWS (mm)	201	47	80	338
Sand (%)	10.5	9.9	0	87
Silt (%)	22.4	16.5	0	71
Sat. Hydraulic Conductivity (μm/s)	5.2	6.0	0	92
K Factor (t.ha.h/ha.MJ.mm)	0.15	0.10	0	0.44
Organic Matter (%)	1.1	0.8	0	4.7
County Cropland (10,000 ac)	18.9	11.8	0.11	92.5

Table 4.5: Spring Crop Choice: Average Marginal Effects

	(Corn, Tilled)	(Corn, No-Till)	(Soybeans, Tilled)	(Soybeans, No-Till)	(Other, Tilled and No-Till)
May GDD	−0.001***	−0.002***	0.002***	0.0007***	0.0006***
June GDD	0.001***	0.001***	−0.001***	−0.0004***	−0.0009***
July GDD	−0.001***	−0.0002	0.001***	0.0003**	−0.0001
August GDD	0.0005**	0.002***	−0.002***	0.0001	−0.0006***
May HDD	0.05	−0.05	0.007	−0.11*	0.05**
June HDD	0.03***	0.01	−0.02**	−0.02***	0.02***
July HDD	−0.02***	0.001	−0.01**	0.01***	0.003
August HDD	0.0***	−0.01***	0.002	−0.01***	0.006***
May Mean Prec	0.01**	0.01***	0.001	−0.001	−0.02***
June Mean Prec	0.03***	0.003	−0.02***	−0.02***	0.003
July Mean Prec	0.03***	0.01*	−0.01***	−0.01***	0.003
August Mean Prec	0.005	0.002	0.005	−0.005	−0.01***
May Intense Prec	−0.01	−0.006	−0.004	0.007	0.01**
June Intense Prec	−0.02	−0.008	0.03***	0.008	0.002
July Intense Prec	−0.01*	−0.007	0.005	0.01	0.002
August Intense Prec	0.01	−0.02**	−0.007	0.004	0.01*
Corn Exp. Price	0.07***	0.06***	−0.17***	−0.14***	0.11***
Soybeans Exp. Price	−0.08***	−0.06***	0.10***	0.08***	−0.04***
W. Wheat Exp. Price	0.09***	0.05***	−0.06***	−0.04***	−0.01**
Nitrogen Price	0.12	0.002	−0.15*	0.26*	−0.33***
Previous Spring Corn	−0.03**	−0.01	0.16***	0.18***	−0.08***
Previous Spring Soybeans	0.14***	0.11***	−0.06***	−0.005	−0.04***
Double-Crop	−0.19***	−0.001	0.03**	−0.002	0.25***
Years Operated Field	< 0.000	< 0.000	< 0.000	< 0.000	< 0.000***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Standard errors are calculated using the delta method. Soil characteristics and county cropland controls are included in all regressions.

Table 4.6: Spring Acreage: Second-Step Regression Estimates

	(Corn, Tilled)	(Corn, No-Till)	(Soybeans, Tilled)	(Soybeans, No-Till)	(Other, Tilled and No-Till)
May GDD	0.27*	−0.05	0.67***	0.70***	0.63**
June GDD	−0.23	−0.09	−0.10	−1.24***	−1.39***
July GDD	−0.02	1.13**	0.06	1.09***	0.23
August GDD	0.12	−0.83	−0.72**	−0.41	0.42
May HDD	−59.97***	−5.46	−77.99	21.37	1.22
June HDD	41.87***	27.06	14.11	19.24	7.30
July HDD	−5.47	−10.95	8.00	−5.04	−0.36
August HDD	−0.70	8.01	−3.42	−2.74	0.79
May Mean Prec	−23.21***	−21.95***	0.33	−17.95***	−4.41
June Mean Prec	9.52**	20.40***	10.14*	14.23***	8.68
July Mean Prec	−15.28***	−18.35*	−11.64***	2.20	−29.61***
August Mean Prec	−10.01**	−3.25	−6.15	−1.53	14.57**
May Intense Prec	13.48*	21.85	22.11**	17.64*	−20.48
June Intense Prec	1.76	−7.95	−6.20	4.55	−1.56
July Intense Prec	29.12***	22.86***	2.32	2.75	52.86***
August Intense Prec	24.27***	−1.92	2.94	−0.71	−27.2*
Corn Exp. Price	14.97***	−4.60	−10.71***	−12.66***	−9.65
Soybeans Exp. Price	−2.30	−1.68	−1.46	2.35	−3.04
W. Wheat Exp. Price	−3.13	8.57***	11.26***	4.62**	10.85***
Nitrogen Price	58.52**	25.65	−48.13	−30.63	−12.68
Double-Crop	−5.32	−13.67	−28.84***	−17.33***	1.60
Years Operated Field	−0.42***	−0.45***	−0.18**	−0.13**	−0.59***
S_{-j_1}	42.24***	−35.45	−29.35***	−35.57***	−44.80*
S_{-j_2}	−47.54***	44.34	−41.52*	−3.87	29.12
S_{-j_3}	0.19	−40.72**	67.52***	23.84	8.55
S_{-j_4}	−4.19	40.13*	3.72	23.62	8.84

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Standard errors are calculated as the standard deviation of the coefficients from 1,000 bootstrap samples with replacement. Soil characteristics and county cropland controls are included in all regressions.

Table 4.7: Fall Crop Choice: Average Marginal Effects

	(Winter Wheat, Tilled)	(Winter Wheat, No-Till)	(Other, Tilled and No-Till)
April GDD	0.0002	−0.0001	−0.0002
May GDD	−0.0004***	−0.0001	0.0001*
September GDD	0.0002**	0.0001*	−0.0001
October GDD	0.0002*	0.0001*	−0.0001
April HDD	−0.007	−0.19**	0.16***
May HDD	0.007	−0.002	−0.002
September HDD	0.02***	0.005	0.008*
October HDD	−0.26***	0.04	0.05
April Mean Prec	−0.008***	−0.002	−0.0005
May Mean Prec	0.0006	−0.0001	−0.0009
September Mean Prec	−0.0003	−0.001	−0.001
October Mean Prec	−0.001	−0.002	0.003*
April Intense Prec	0.006	−0.007***	−0.0005
May Intense Prec	−0.002	0.004	−0.002
September Intense Prec	0.007	−0.003	−0.002
October Intense Prec	0.007	0.001	−0.001
Corn Prev. Price	−0.02***	−0.01**	0.01***
Soybeans Prev. Price	−0.004*	0.002	0.001
W. Wheat Prev. Price	0.006**	0.01***	−0.006***
Nitrogen Price	−0.14***	−0.13***	0.05
Previous Fall W. Wheat	0.04***	0.03***	−0.02***
Double-Crop	0.18***	0.22***	0.54***
Years Operated Field	0.0003**	0.0003***	−0.0006***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Standard errors are calculated using the delta method. Soil characteristics and county cropland controls are included in all regressions.

Table 4.8: Fall Acreage: Second-Step Regression Estimates

	(Winter Wheat, Tilled)	(Winter Wheat, No-Till)	(Other, Tilled and No-Till)
April GDD	1.45	1.50**	0.61
May GDD	−0.60	−0.42	0.60
September GDD	−0.10	−0.61	0.15
October GDD	−0.15	−0.54	−1.54*
April HDD	11.13	−242.22	300.7*
May HDD	5.50	87.74	66.87*
September HHD	−2.50	40.26**	20.56*
October HDD	−95.0	−1431.6	−1349.6**
April Mean Prec	−14.70	−9.21	1.86
May Mean Prec	−25.34	−20.04	−3.19
September Mean Prec	27.58	−42.28**	−23.37**
October Mean Prec	−41.58*	11.44	−2.78
April Intense Prec	5.83	38.33	4.11
May Intense Prec	22.09	23.87	17.73
September Intense Prec	35.38	50.78	24.80
October Intense Prec	30.02	17.88	−6.80
Corn Prev. Price	−11.01	−1.66	1.10
Soy Prev. Price	−2.15	−1.20	5.26*
W. Wheat Prev. Price	−9.91	−3.58	−2.33
Nitrogen Price	25.79	−77	55.34
Double-Crop	−39.5**	−20.8	31.80*
Years Operated Field	−0.62**	0.25	−0.28*
S_{-j_1}	52.91	−16.94	49.97
S_{-j_2}	−105.97*	26.73	−52.93

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Standard errors are calculated as the standard deviation of the coefficients from 1,000 bootstrap samples with replacement. Soil characteristics and county cropland controls are included in all regressions.

Table 4.9: Inequality of Intense Precipitation on Crop Choice across Tillage

	(1)	(2)	(3)	(4)
	May	June	July	August
Corn	12.03***	0.95	16.57***	2.52
Soybeans	2.30	1.95	0.84	0.37
	April	May	September	October
Winter Wheat	0.60	0.20	1.18	1.67

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Each table entry contains the Wald test statistic of the null hypothesis that the difference in regressor coefficients is zero for the tilled and no-till crop in each row. The χ^2_1 critical value at the 5% significance level is 3.84.

APPENDIX C. CROP CHOICE AND CLUSTERING

For purposes of analyzing sensitivity to the preferred estimates in Tables 4.5-4.9, we address two conceptual econometric issues. First, the main results drop all field-year observations for which no crop is planted. This is innocuous for the spring analysis as very few random fields in the ARMS surveys happen to not be in use. However, the fall sample size is reduced by several thousand observations as a result of dropping field-years with nothing planted. This also tends to shift the location of the fall analysis away from prime corn-growing areas and precludes discussion of fall cover crop decisions. To analyze sensitivity to this "control crop," we include all observations with nothing planted and add this category to the choice set.

Second, the climate regressors, prices, soil characteristics, and cropland controls vary at the county level, despite the field-year dependent variables varying at a much finer spatial resolution. As such, the effective sample size is closer to the total number of counties, and standard errors may be underestimated. The conventional remedy to this potential inference problem is to cluster the standard errors at the highest level of aggregation, i.e., county (Kloek, 1981; Moulton, 1986). Standard errors associated with parameter estimates contained below have been clustered by county. There are 1,123 counties in the spring dataset and 1,120 counties in the fall dataset.

Table C.1 provides estimates of the relative-risk ratios for the spring crop choice analysis with clustered standard errors and the additional "nothing planted" choice. Because the choice set has expanded by one alternative and the standard errors have been corrected, there are naturally some differences in statistical significance and effect sizes between the results in Tables 4.5 and C.1. Direct comparisons are also difficult because the latter results must be interpreted with respect to the "other crops" base category. However, we find that many of the climate coefficients retain significance and the expected sign. For example, July HDD reduce the relative odds of selecting tilled corn and tilled soybeans relative to other crops (0.84 and 0.88), with larger effects on no-till corn and soybeans (0.93 and 0.99). Similarly, May intense precipitation reduces the relative odds of choosing tilled soybeans over other crops (0.83), while there is no significant impact on no-till soybeans. Unlike Table 4.5, climate conditions appear to have similar effects on corn and soybeans because of estimation with respect to the base choice.

Patterns among the price effects and management practices are also intuitive and similar to the main results. Expected corn prices have relatively larger effects on choice of corn than choice of soybeans (0.40-0.59 vs. 0.04-0.05), and expected soybean prices have relatively larger effects on choice of soybeans than choice of corn (4.03-4.06 vs. 0.71-0.94). Nitrogen prices are significant but improbably large, perhaps the result of measurement error and small variation in the data. Turning to management practices, we find that fields planted to corn in the previous season are 9.1-13.5 times more likely to be planted to soybeans currently, while fields previously planted to soybeans are 3.4-5.2 times more likely to be planted to corn. Double-cropping also has significant effects. Also similar to the main results, years of field operation are significant but have no practical effect on the choice of any crops relative to other crops.

Table C.2 reports the relative-risk ratios for the re-estimated fall crop choice model. As in Table 4.7, many of the climate regressors are insignificant, again suggesting that winter wheat could play an important role under severe climate change. The revised results show that April and October HDD decrease the relative odds of planting tilled winter wheat over other fall crops, in contrast to the main results in Chapter 4. Further, importance shifts from climate conditions to economic factors and management practices for no-till winter wheat. Higher corn and nitrogen prices decrease the relative odds of planting no-till winter wheat, but higher winter wheat prices have positive effects on the relative odds of planting both tilled and no-till winter wheat. The impacts of management practices remain similar to those in the main paper. As with Table C.1, our general conclusion is that the fall crop choice results are robust to including the additional "nothing planted" category and clustering the standard errors.

Of final interest are the effects of climate, prices, management practices, and soil characteristics on the choice to not plant a crop. Both Tables C.1 and C.2 show that this decision is little influenced by any regressors in our analysis. Though several of the regressors in the fifth column of Table C.1 are significant, coefficients in both tables are generally close to one and so have little effect on the relative odds of choosing to plant nothing. This confirms that the "nothing planted" choice is economically uninteresting and is reasonably omitted from the analysis in the main paper. However, in upcoming years, the choice to plant nothing in the fall may become increasingly tied to decision making regarding fall cover crops. Future analysis could consider the impacts of expanding current state and federal subsidies of cover crops, with a potentially expanded role for cover crops in farmers' climate change adaptation strategies.

Table C.1: Spring Crop Choice: Multinomial Logit Relative-Risk Ratios

	(Corn, Tilled)	(Corn, No-Till)	(Soybeans, Tilled)	(Soybeans, No-Till)	(Nothing Planted)
May GDD	0.99***	0.97***	1.01***	1.01*	0.99***
June GDD	1.02***	1.02***	1.00	1.00*	1.02***
July GDD	1.00	1.00	1.01***	1.01***	0.99**
August GDD	1.01**	1.03***	0.99***	1.00	1.01***
May HDD	0.58	0.29**	0.39	0.16***	1.25
June HDD	0.93	0.89	0.65***	0.64***	0.69***
July HDD	0.84***	0.93*	0.88***	0.99	1.19***
August HDD	1.00	0.82***	0.92***	0.83***	0.93**
May Mean Prec	1.28***	1.34***	1.21***	1.20***	1.13**
June Mean Prec	1.13**	1.05	0.79***	0.78***	0.99
July Mean Prec	1.16**	1.10	0.89*	0.87*	0.84**
August Mean Prec	1.19***	1.12***	1.18***	1.12*	1.23***
May Intense Prec	0.78**	0.77***	0.83*	0.89	0.87
June Intense Prec	0.87	0.86	1.24**	1.13	0.87
July Intense Prec	0.89	0.88	1.03	1.07	1.01
August Intense Prec	0.89	0.73***	0.84	0.89	0.83*
Corn Exp. Price	0.40***	0.59***	0.05***	0.04***	0.92
Soybeans Exp. Price	0.94***	0.71***	4.06***	4.03***	1.24***
W. Wheat Exp. Price	2.12***	2.56***	0.70***	0.73***	0.92
Nitrogen Price	86.69***	58.66***	22.69***	355.20***	91.55***
Previous Spring Corn	2.34***	2.31***	9.13***	13.46***	0.14***
Previous Spring Soybeans	3.42***	5.24***	1.24	1.92***	0.33***
Double-Crop	0.12***	0.17***	0.28***	0.23***	–
Years Operated Field	1.01***	1.00***	1.01***	1.01***	1.01**

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Standard errors are clustered by county. Soil characteristics and county cropland controls are included in all regressions.

Table C.2: Fall Crop Choice: Multinomial Logit Relative-Risk Ratios

	(Winter Wheat, Tilled)	(Winter Wheat, No-Till)	(Nothing Planted)
April GDD	1.01**	1.00	1.01
May GDD	0.99***	0.99	1.01
September GDD	1.00	1.00	0.99*
October GDD	1.01	1.01**	1.00
April HDD	0.005***	$<$ 0.00***	0.007
May HDD	1.25	1.03	1.03
September HDD	0.91	0.75	0.21***
October HDD	0.001**	0.98	13.86
April Mean Prec	0.95	0.99	1.47***
May Mean Prec	1.05	1.03	1.05
September Mean Prec	1.06	1.01	1.17
October Mean Prec	0.89	0.86	0.90
April Intense Prec	1.19	0.85	1.13
May Intense Prec	1.01	1.16	1.02
September Intense Prec	1.27	1.00	1.09
October Intense Prec	1.16	1.04	0.84
Corn Prev. Price	0.49***	0.51***	1.14
Soybeans Prev. Price	0.89	1.02	1.00
W. Wheat Prev. Price	1.27**	1.51***	0.86
Nitrogen Price	0.05*	0.01**	185.43**
Previous Fall W. Wheat	3.54***	3.79***	0.85
Double-Crop	0.13***	0.28***	–
Years Operated Field	1.03***	1.03***	1.02***

Significance is denoted as *p<0.1, **p<0.05, ***p<0.01. Standard errors are clustered by county. Soil characteristics and county cropland controls are included in all regressions.

CHAPTER 5. CONCLUSIONS

This dissertation explores two distinct but related areas: climate change impacts on components of agricultural supply, and information effects on consumer demand for genetically modified foods. One common thread throughout the three essays is that direct and indirect impacts of poorly-alleviated climate change will differentially affect markets for agricultural products. Estimating the influence of weather and climate on agricultural yields, crop-tillage choices, and land allocation, as well as identifying the role of information and environmental preferences on the demand for GM foods, has been the central focus. Differences between these demand- and supply-side topics necessarily invite distinct methods and data. To address these research questions, we have implemented Bayesian filters, two-step discrete-continuous models, and experimental auctions.

The first essay, "Climate Change, Technology, and US Corn Yields," seeks a better understanding of the long-term and short-term implications of climate change for corn, the most important US crop. Increasing yields in the past half-century have contributed to domestic food security, and more recently, created direct links with energy markets. A more complete understanding of the empirical relationship between yields and climate is of practical interest for concerned producers and essential for informed policymaking. Bayesian dynamic regressions are estimated for 770 non-irrigated counties during 1960-2011 and used to forecast corn yields over 2012-2031. Bayesian dynamic econometric models are useful time series methods for addressing structural change, obsolescence of early data, and outliers. For parsimony in out-of-sample forecasts, agricultural production is assumed to be Cobb-Douglas. We find that yields will increase 10-40% over current averages by 2031 for most counties. There is substantial spatial variability in the forecasts, but Corn Belt and Great Lakes counties will experience the greatest yield growth. We then estimate the long-run relationship between climate damages and Hicks-neutral technical change in yields from a cross section of county-level long differences. A standard inverse-quadratic damage function is generalized to include extreme temperatures and extreme precipitation, controlling for spatial variability in soil productivity. The long-run results indicate significant connections between climate damages and technical change and suggest adaptation possibilities for agriculture beyond 2031.

The second essay, "Valuing New (Varieties of) Goods: Evidence from Lab Auctions of Popular Foods Genetically Engineered to Reduce New Food Safety Concerns" examines consumer demand for genetically modified potatoes. New goods and new varieties of existing goods are central to improving consumer welfare. A new foodborne risk was recently discovered in starchy foods cooked at high temperatures. Acrylamide is a probable carcinogen forming naturally in potatoes and potato products cooked at high temperatures. Using experimental methods, we test the effects of food labels and packaged information on willingness-to-pay (WTP) for conventional potatoes and potato products using GM technology to reduce acrylamide levels. Random n^{th}-price auctions elicit WTP before and after each subject receives a randomly-assigned information treatment, consisting of one or two perspectives: an industry perspective on using biotechnology to reduce acrylamide levels, a scientific perspective on exposure to acrylamides, and/or an "environmental group" perspective on biotechnology. We find strong information effects: relative to the "environmental group" perspective, consumer WTP differences increase significantly for other information treatments. We show for the first time that consumers are willing to pay a premium for food safety obtained using biotechnology for two popular foods in the US diet. These results have practical significance for those interested in food safety and food marketing.

The third essay, "US Climate Change Adaptation along the Intensive and Extensive Margins: A Field-Level Analysis," expands on the agriculture-climate links in the first essay by investigating the role of environmental inputs and climate on cropland use and allocation. As farmers respond to climate change, adjustments along both the intensive and extensive margins will be made. A two-step discrete-continuous model of crop-tillage combinations and acreage allocation is estimated using field data from the Agricultural Resource and Management Survey (ARMS). In the first step, a multinomial logit model is estimated to analyze the extensive margin. Farmers choose combinations of crops (corn, soybeans, winter wheat, and other) and tillage to maximize latent economic net returns.

In the second step, linear regressions quantify the impacts of climate, economic factors, management, and soil characteristics on crop acreage. Pooling field data over 2006-2012, we find significant impacts on choice of crop, tillage practices, and acreage. Growing Degree Days in nearly all months of the spring and fall growing seasons have substantial effects, as well as mean and intense precipitation. No-till practices may be an effective adaptation strategy to intense heat and precipitation in the short run. In the long run, farmers may adjust crop choice and planted acreage, depending on relative output prices and soil characteristics.

Modern agriculture in wealthy countries, such as the United States, is undergoing yet another deep and far-reaching transformation. The duration and expected consequences of this transformation are not known with certainty, but its general effects will be persistent because of sunk investments and limited reversibility. The most important features of this transformation include: (i). climate change and associated threshold effects, (ii). agricultural biotechnologies and the genomic revolution, (iii). site-specific and information technologies drawing on "big data," (iv). pest resistance and its relation to trait licensing, (v). increasing consumer interest in organic agriculture and traceability, (vi). continued market substitution of public R&D for private R&D, (vii). adjustment of producer incentives in new farm policy, and (viii). increasingly mobile agricultural labor supply and production. Although only the first two features have been treated in this dissertation, the analysis can be extended by considering parallels with - and feedback between - these other key aspects.

Amid the broader context of this transformation, what are the novel insights and general lessons learned from this analysis? First, deep uncertainty and risk (downside and upside) continue to pervade agricultural adaptation to climate and biotechnologies. The analysis has addressed this with novel applications of appropriate methodologies, producing a more reliable set of results. For example, forecasts of the economic impacts of climate change should not extend beyond reasonable time frames. The accelerating pace of technological innovations suggests that forecasts for year 2100 or beyond have little credibility in practice and limited theoretical purpose. Uncertainty regarding consumer demand for biotechnologies is also considerable, but the use of incentive-compatible mechanisms in experiments credibly reduces this uncertainty while retaining external validity. In the longer timer, greater flexibility in modeling and methods will permit better adjustment to the changing set of climate and biotechnology factors deemed important.

Second, expanded and up-to-date information sets have become more important for optimal decision making. In the context of climate change, a first step to adaptation is the recognition of fundamentally shifting growing conditions. Continued success of modern agriculture will require eroding a major asymmetry: high acceptance of biotechnologies among producers and climate change among consumers, and relatively lower acceptance of climate change among producers and biotechnologies among consumers. A key lesson from this analysis is that information provision has substantial impacts on consumer (and producer) economic behavior. Such information provision can be accommodated by both private- and public-sector "nudges." For example, notifying producers about average regional nitrogen use or informing consumers about peers' purchases of GM foods are low-cost tools that may help improve social welfare.

Third, the evolving structure of incentives is helping to accommodate many of the ongoing changes in US agriculture and food systems. Farmers adopt biotechnologies because they increase yields and decrease certain production costs. Given appropriate incentives, farmers will also respond to either the direct or indirect climate change impacts that affect their operations. In the near term, biotechnology-induced decreases in production costs will be reflected in gradually decreasing food prices, spurring greater demanded quantities of GM foods. The evolution of these market incentives hinge on climate uncertainty and adequate diffusion of information. Additional insights into uncertainty and risk, information provision, and incentives beyond those considered in this analysis will help US agriculture meet increasing global demand for feed, fiber, and fuel.