2015

Three essays on biofuel, weather and corn yield

Yixing Peng
Iowa State University

Three essays on biofuel, weather and corn yield

by

Yixing Peng

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

Program of Study Committee:
Bruce A. Babcock, Major Professor
John R. Schroeter
John C. Beghin
Chad E. Hart
Sebastien Pouliot

Iowa State University

Ames, Iowa

2015

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to take this opportunity to express my deepest gratitude and appreciation to those who helped me with my study and research at Iowa State University.

First and foremost, I sincerely thank my major professor, Bruce Babcock, who has guided and advised me from the very beginning of this research. Thanks for his kind supervision, comprehensive insight, valuable inputs, continuous support and patience throughout all stages of this research. Without his persistent help this dissertation would not have been possible. I would also like to thank my committee members, John Schroeter, John Beghin, Chad Hart, and Sebastien Pouliot, for their guidance, support and valuable suggestions throughout this research.

In addition, I would also like to thank Chen Wang, Christopher Anderson, Philip Gassman, and Todd Campbell for their contribution and help with my research. I am very grateful for my friends, colleagues, the department faculty and staff for making my time at Iowa State University a wonderful experience.

Finally, I would like to thank my parents, my brother and my boyfriend for their great love and support.

ABSTRACT

This dissertation is to study the competition of biofuels to meet the U.S. renewable fuels standards (RFS) and its impact on biofuel and corn prices, and the impacts of weather and soil moisture on corn yield in the Midwest. Chapter 2 illustrates the hierarchical competition of U.S. corn ethanol, Brazilian sugarcane ethanol and biodiesel to meet the RFS mandates and explained the evidenced two-way trade of ethanol between the U.S. and Brazil using a computable trade model of ethanol related markets between the U.S. and Brazil. And we estimate the impact of RFS on biofuel prices, agricultural commodity prices using a stochastic partial equilibrium model. Chapter 3 develops a linear spline fixed effect model to estimate the impact of climate variables on corn yield by adding in soil moisture as an explanatory variable. Recent two drought years 2011 and 2012 are included that facilitates estimation of corn yield response to extreme conditions. Daily soil moisture data in the Upper Mississippi River Basin Area from 1980 to 2012 is simulated from the crop model EPIC, which has very comprehensive interactions between hydrology, weather, soil, crop and plant environment controls. Bayesian Markov Chain Monte Carlo approach is applied to estimate the parameters and the thresholds simultaneously. Including recent two drought years 2011 and 2012 to have more drought observations in the modern eras, Chapter 4 revisits previous literature using the our extended data and then constructs yield response functions allowing the yield deviation from weather variables to change over time. Null hypotheses that the marginal and total weather impacts of adverse weather conditions remain constant are then tested.

CHAPTER 1. INTRODUCTION

The United States and Brazil are the two largest ethanol producers, accounting for more than 85% of the world's ethanol production, with the principal feedstock being corn in the U.S. and sugarcane in Brazil. The biofuels market in the U.S. and Brazil depends on government policies, the world gasoline price and feedstock prices and the demand of blended gasoline. It is imperative to develop a comprehensive model incorporating all interrelated biofuel market, feedstock markets and trade between the U.S. and Brazil to help understand the economic impacts of Renewable Fuel Standard (RFS).

The RFS established in the Energy Policy Act of 2005 and considerably expanded in the Energy Independence and Security Act of 2007 mandates minimum volumes of specific renewable fuels use in the U.S., which is a primary source of the expansion of the biofuel market. RFS establishes a three-level mandate hierarchy for renewable fuels based on the minimum lifecycle greenhouse gases emissions reduction of renewable fuels pathways: overall mandate as the broadest level; advanced biofuels mandate at the second level, which counting towards overall mandate, can be met by biomass-based diesel (biodiesel), cellulosic biofuels, and Brazilian sugarcane ethanol; within the advanced mandate, there existing the biodiesel and cellulosic biofuels sub-mandates at the narrowest level. EPA developed the Renewable Identification Number (RIN) market to facilitate compliance with the RFS. The hierarchy structure of the RFS mandates induce competition between sugarcane ethanol and biodiesel to meet the U.S. advanced mandate and the competition between corn ethanol and sugarcane ethanol to meet the U.S. conventional mandate. This also raises many important questions: Which and how much of corn ethanol, sugarcane ethanol and biodiesel will be used to meet the RFS mandates? How much sugarcane ethanol is required to meet the advanced mandate? How are the biofuel RINs priced? What is the impact of RFS on the market of corn, ethanol and gasoline markets?

Chapter 2 "Competition of Biofuels to Meet the RFS Mandates" presents a computable trade model of ethanol related markets between the U.S. and Brazil. Equilibrium conditions are specified under scenarios: with all RFS mandates, with conventional mandate only and with no mandates. Through the model, we illustrate the evidenced two-way trade of ethanol between the U.S. and Brazil induced by biofuel mandates. The supply curves of conventional biofuels RINs and advanced biofuels RINs are constructed, which can be used to illustrate and simulate the hierarchical competition of U.S. corn ethanol, Brazilian sugarcane ethanol and biodiesel, and to project all biofuels RINs prices. Moreover, we calibrate the demand and supply curves of corn, soybean, and biofuels, and simulate the equilibrium prices and quantities for marketing year 2013/14, using a stochastic partial equilibrium model. The model is applied to four scenarios: with all RFS mandates, with conventional mandate only, with RFS advanced mandate restricted to be met by sugarcane ethanol and with no mandates. Results indicate that RFS mandates induce the two-way trade of ethanol across the U.S. and Brazil and the possibility of two-way trade would increase with the other advanced mandate. Biodiesel helps reduce this potentially trade, but could not eliminate this whole impact on trade without subsidies.

Due to the expansion of renewable fuel industry, agriculture and energy are closely correlated with each other. In the U.S., corn is the primary feedstock used to produce ethanol so that corn supply is critical to determine the biofuel production and energy policy effectiveness. Due to the drought weather condition in 2012, corn yields were projected to be 123.4 bushels per acre in 2012 by U.S. Department of Agriculture (USDA), which decreased by 16% comparing with previous year. Together with the sharp decrease in corn production, corn price increased by 68 cents (11%). And this shortage in corn production also brought concerns on the whole agriculture and biofuel industries. In the first essay, we assumed that corn yields are stochastic following the historical distribution. The second essay focuses on investigating the impact of adverse weather conditions on corn yield in the Midwest. Not limited to the two frequently used weather variables in existing literature, temperature and rainfall, we add soil moisture as an explanatory variable into the corn yield response function. Daily soil moisture data in the Upper Mississippi River Basin Area (UMRB) from 1980 to 2012 is simulated from the crop model Environmental Policy Integrated Climate (EPIC), which has very comprehensive interactions between hydrology, weather, soil, nutrients, crop and plant environment controls. Recent two drought years 2011 and 2012 are included in the estimation dataset to facilitate estimation of corn yield response to extreme conditions.

Chapter 3 "Impact of Weather and Soil Moisture on Corn Yield in the US Midwest" develops a linear spline fixed effect model to estimate the impact of climate and soil variables on corn yield. Bayesian Markov Chain Monte Carlo approach is applied to estimate the parameters and the thresholds simultaneously. Results suggest corn yield effects from high temperature and plant water availability cannot be meaning fully isolated from one another. The percent yield reduction from high temperature is 15 to 20 percentage points greater under low compared to high water availability. The determinant factors for corn yield losses vary across the Corn Belt region. Excessive spring rainfall is damaging to corn yield in

Illinois and Iowa, however, during hot and dry summers, excessive spring rainfall is important for reducing yield loss through the soil moisture effect. In Wisconsin, too little spring rainfall is more damaging than too much.

In existing literatures, weather impacts on corn yield have been well studied and the results are very consistent. But there are still a lot of debates on whether corn is becoming more drought tolerant over time. Yu and Babcock (2010) examines how drought tolerance of corn and soybeans changed over time in the U.S. using a constructed drought index. Their results indicate that corn yield losses from a drought of a given severity have decreased over time in both absolute and percentage terms. However, very few drought incidents after 1990 comparing with the 1980s make their conclusions less convincing. Moreover, using field data on maize and soybean in the central U.S. for 1995-2012, Lobell, et al. (2014) concludes that drought sensitivity in maize, in particular sensitivity to high vapor pressure deficits (VPD), has steadily increased over the period from 1995-2012. Chapter 4 revisits Yu and Babcock (2010) using the dataset developed in Chapter 3 with more drought incidents in the modern era and simulated soil moisture. We construct models to allow the weather impact to change over time and test the hypotheses that the impacts remain constant over time under our hypothetical adverse weather conditions. Our results show that yield losses due to drought conditions increases over time in absolute yield terms but remains constant in percentage terms due to increase in base yield over time. Corn yield is becoming less sensitive to July-August precipitation which reduces yield losses under modest drought level.

Finally in Chapter 5, a summary of general conclusions is presented.

CHAPTER 2. COMPETITION OF BIOFUELS TO MEET RFS MANDATES

Abstract

This paper constructs a computable trade model of ethanol related markets between the U.S. and Brazil. Equilibrium conditions are specified under RFS biofuels mandates. Through the model, we illustrated the evidenced two-way trade of ethanol between the U.S. and Brazil. The supply curves of conventional biofuels RINs and advanced biofuels RINs are constructed, which can be used to demonstrate and simulate the hierarchical competition of U.S. corn ethanol, Brazilian sugarcane ethanol and biodiesel, and to project all biofuels RINs prices. Moreover, we calibrated the demand and supply curves of corn, soybean, and biofuels, and simulated equilibrium prices and quantities for marketing year 2013/14, using a stochastic quantitative model. The average values are used to estimate the impacts of RFS mandates on U.S. biofuels market. Our results showed that RFS mandates induced the two-way trade of ethanol across the U.S. and Brazil and the possibility of two-way trade would increase with the other advanced mandate. Competition from Biodiesel to meet the advanced mandate helped reduce this potentially two-way trade, but could not eliminate this whole impact on trade without subsidies.

Introduction

Concerns about growing dependency on foreign oil supplies, and greenhouse gases (GHGs) emissions have motivated the development of biofuels, such as the ethanol and biomass-based diesel, as substitutes of gasoline. The United States and Brazil are the two largest ethanol producers, accounting for more than 85% of the world's ethanol production, with the principal feedstock being corn in the U.S. and sugarcane in Brazil. U.S. ethanol production has increased rapidly from1.63 billion gallons (BG) in 2000 to 13.9 BG in 2011. The U.S. surpassed Brazil as the largest producer of ethanol in 2006.

The U.S. had been an importer of ethanol since 2004, almost all from Brazil, directly or through Caribbean Basin Initiative (CBI) countries. Starting from 2010 till present, it began to export corn ethanol, a large portion to Brazil. Meanwhile, the U.S. still keeps importing ethanol from Brazil. Ethanol exports even exceeded ethanol imports in 2011 (Figure 2.1). The major driver for this two way trade is the U.S. biofuel mandates.

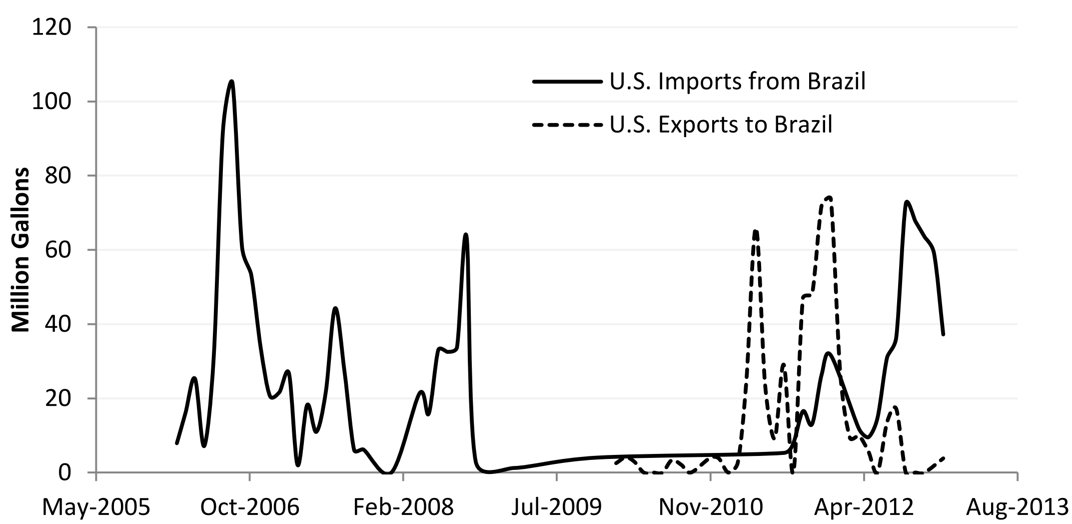

Figure 2.1: Trade of ethanol between the U.S. and Brazil

Data Sources: U.S. Energy Information Administration (EIA).

U.S. ethanol subsidy programs as volumetric ethanol excise tax credit[1] and ethanol tariff[2] expired in the end of 2011. These policies promoted the development of the ethanol

[1] Volumetric ethanol excise tax credit program is that gasoline suppliers who blend ethanol with gasoline are eligible for a tax credit of 45 cents per gallon of ethanol (Congressional Research Service 2012).

industry. But they didn't help differentiate U.S. corn ethanol and Brazilian sugarcane ethanol. Renewable Fuels Standard (RFS) established in the Energy Policy Act of 2005 mandated minimum volumes of specific renewable fuels use in the U.S., which was considerably expanded and increased by the Renewable Fuel Standard (RFS2) of the Energy Independence and Security Act of 2007. RFS establishes a three-level mandate hierarchy for renewable fuels based on the minimum lifecycle GHG emissions reduction of renewable fuels pathways[3]: overall mandate as the broadest level; advanced biofuels mandate at the second level, which counting towards overall mandate can be met by biomass-based diesel (biodiesel), cellulosic biofuels, and Brazilian sugarcane ethanol; within the advanced mandate, there existing the biodiesel and cellulosic biofuels sub-mandates at the narrowest level. The rest of the advanced mandate is named as the other advanced mandate (Thompson et al. 2010). Excluding the advanced mandate, the rest of the overall mandate is conventional mandate. This setting differentiates U.S. corn ethanol and Brazilian sugarcane ethanol in the way that corn ethanol can only be used to meet the overall mandate, while sugarcane ethanol also meets the criteria of advanced mandate.

We construct a stylized trade model between the U.S. and Brazil taking into account of U.S. corn and soybean markets, U.S. ethanol and biodiesel market, Soybean meal and oil markets and Brazilian sugarcane ethanol market, and apply the RFS mandates on the U.S. ethanol market. We specify the equilibrium conditions, through which the equilibrium prices and quantities can be calculated.

---

[2] All imported ethanol is subject to a 2.5% ad valorem tariff; fuel ethanol is also subject to a most-favored-nation added duty of 54 cents per gallon (with some exceptions) (Congressional Research Service 2012).

[3] According to U.S. Environmental Protection Agency (EPA), the lifecycle GHG emissions reduction threshold for renewable fuel is 20%, 50% for advanced biofuels, 50% for biomass-based diesel, and 60% for cellulosic biofuel (Congressional Research Service 2013).

Moreover, we investigate how RFS mandates are implemented through Renewable Identification Numbers (RINs) and the determinations of RIN prices of various biofuels. Starting from a hypothetic case that there is no advanced mandate in place, we explore the supply of advanced RINs from sugarcane ethanol. This analysis allows us to get insights of the different RIN prices from the trade pattern of ethanol between the U.S. and Brazil and the state whether mandates are binding or not. We then extend the model to consider biodiesel as an alternative to meet the other advanced mandate, and discuss the possibility to use both biodiesel and sugarcane ethanol to meet the other advanced mandate. This competence from biodiesel might help reduce U.S. dependence on imported sugarcane ethanol from Brazil to meet the other advanced mandate.

Specifically, following Babcock et al. (2010), with stochastic gasoline prices and feedstock yields, we calibrate the biofuels markets to solve for market clearing prices and quantities. The average values are used to estimate the impacts of RFS on U.S. biofuels market in the situation of marketing year[4]2013/14. We also explore the sensitivity of our results to U.S. gasoline price, Brazil ethanol production and U.S. corn yield levels.

This paper provides insight into how the RFS mandates induce the two-way trade between the U.S. and Brazil and how the RFS mandates affect the biofuels and related commodities markets through RINs. Moreover, this study constructs demand and supply curves of RIN to help understand how the RIN market works. Our result also shows U.S. biodiesel could help meet the other advanced mandate to some extent, but currently still could not eliminate U.S. dependence on imported sugarcane ethanol to meet the RFS mandates.

[4] Marketing year for corn and soybean starts from September 1st.

The Model

In this section, we establish a simple trade model to show the possibility of two-way trade in ethanol between the U.S. and Brazil. With concerns that the U.S. and Brazil accounting for over 85% of the world's ethanol production, U.S. imports of ethanol almost all from Brazil, directly or through CBI countries, and Brazil ethanol imports mostly from the U.S., we only include the U.S. and Brazil in the ethanol industry in our model. In the U.S., ethanol is mainly produced from corn, while Brazil uses sugarcane as the feedstock for ethanol. We have three commodities: a numeraire composite good, corn as food or feeds, and fuels including gasoline, U.S. produced corn ethanol and Brazil produced sugarcane ethanol. Corn ethanol and sugarcane ethanol have the same energy content. They are perfect substitutes as fuels.

Assume a representative consumer has a quasi-linear preference with utility function:

$$U = D_0 + f(D_c) + g(D_g + \theta D_e) \tag{2.1}$$

D_0, D_c, D_g and D_e represent consumption of numeraire, corn, gasoline and ethanol[5], respectively. $f(\cdot)$ and $g(\cdot)$ are increasing concave functions, while θ includes the factor that converts ethanol to gasoline energy equivalent amount[6], also reflects the constraints on blend rate of ethanol into gasoline[7]. As consumers cannot differentiate corn ethanol and sugarcane ethanol, the less expensive ethanol would be used to blend with gasoline. Maximizing the utility function, we could get the demand function of corn, gasoline and ethanol. The

---

[5] When ethanol is not specified as corn or sugarcane ethanol, it represents general ethanol and includes both.

[6] The energy content of ethanol is about 2/3 of gasoline, according to National Renewable Energy Laboratory (2008).

[7] In the U.S., conventional vehicles can only use gasoline blended with up to 10% of ethanol (E10). Small amounts of flex-fuel cars use fuels more than 10% and capped at 85% (E85). Another restriction hampering sales of E85 flex vehicles and E85 is the limited infrastructure available to sell E85 to the public. According to Renewable Fuels Association (RFA), as of mid-2012, there were only about 2904 E85 retail stations in the U.S., with a great concentration in the Corn Belt states, away from major fuels consumption states, also limited to the major Flex-fuel vehicle population (on the coasts).

demand of ethanol depends on the price ratio of ethanol to gasoline. Denote the prices facing consumers as p_c for corn, p_g for gasoline and p_e^D for ethanol.

The major elements of our model are as followings:

1. U.S. demand for corn as food/feed, $D_c(p_c)$
2. U.S. corn supply, $S_c(p_c)$
3. U.S. demand for ethanol, $D_e(p_e^D, p_g)$
4. U.S. corn ethanol supply, $S_e(p_e)$
5. U.S. demand for gasoline, $D_g(p_e^D, p_g)$
6. Brazilian demand for ethanol, $D_e^{BR}(p_e^{BR})$
7. Brazilian sugarcane ethanol supply, $S_e^{BR}(p_e^{BR})$

p_e denotes the ethanol supply price.[8] Corn supply equals the corn production plus the corn stocks. U.S. corn utilization includes domestic food and feed use, use for stocks, net export, and use for ethanol. In the U.S., ethanol is mainly produced from corn. We assume a constant return to scale production process following Cui et al. (2011).

$$x_{ce} = \min\{\alpha x_c, i_e\} \tag{2.2}$$

where x_{ce} represents corn ethanol output in gallons, x_c is corn feedstock input in bushels, i_e is the amount of other inputs or costs used in the production process, α is the number of gallons of ethanol produced from one bushel of corn.

Equilibrium

As U.S. ethanol excise tax credit and ethanol tariff expired in the end of 2011, we assume that the only policy instrument is the RFS mandates on ethanol. In order to

---

[8] Because we need to differentiate the ethanol demand and supply price when we consider the biofuels mandates, we use different notation from the beginning. But when there are no government interventions, the demand ethanol price just equal to the ethanol supply price at equilibrium.

emphasize the trade in ethanol, we set the gasoline price as exogenous, and make it stochastic in the calibration.[9] Also, we assume that corn ethanol is only produced in the U.S., sugarcane ethanol only in Brazil, and their trade of ethanol with other countries is set to be exogenous.[10] We assume that the transportation cost for the trade of ethanol between the U.S. and Brazil is positive, denoted as c.

First, we specify the market equilibrium conditions with no policy instrument:

$S_c(p_c) = D_c(p_c) + D_c^{other}(p_c) + \alpha \cdot S_e(p_e)$	U.S. corn market equilibrium	(2.3)
$S_e(p_e) + I_e - X_e = D_e\left(p_e^D, p_g\right)$	U.S. ethanol market equilibrium	(2.4)
$S_e^{BR}(p_e^{BR}) - I_e + X_e = D_e^{BR}(p_e^{BR})$	Brazilian ethanol market equilibrium	(2.5)
$p_e = \dfrac{p_c}{\gamma} + c_e$	Zero profit condition in ethanol industry	(2.6)

where $D_c^{other}(p_c)$ in equation (2.3) denotes corn demand for stock and net exports, and c_e in equation (2.6) is the cost of other inputs per unit of corn ethanol produced. Considering the valuable byproducts in the ethanol production process, dried distiller grains with solubles (DDGS) which is correlated with the corn price, we adjust the parameter α and denote as γ.

The arbitrage relationships in ethanol between the U.S. and Brazil are as follows:

$\lvert p_e - p_e^{BR} \rvert < c$	No trade in ethanol between the U.S. and Brazil	
$p_e = p_e^{BR} + c$	The U.S. imports sugarcane ethanol from Brazil	(2.7)
$p_e = p_e^{BR} - c$	The U.S. exports corn ethanol to Brazil	

[9] To make the gasoline price endogenous, we would also need to specify U.S. domestic production and imports of crude oil, and the oil refining section to make the model complete.

[10] We omit the amount of their trade of ethanol with other countries in the specification of the model equilibrium. They are set to be constant and adjusted to the corresponding demand in our model calibration.

When no government interventions present, specifically no policies differentiating corn ethanol and sugarcane ethanol[11], ethanol demand price equals to ethanol supply price, and there would be no trade between the U.S. and Brazil, or one way trade with U.S. either importing sugarcane ethanol from Brazil or exporting corn ethanol to Brazil. Whether any trade would happen and in which direction depends on the demand and supply parameters of the U.S. and Brazil. This result is consistent with the fact that the U.S. has been an importer of sugarcane ethanol before the implementation of the RFS in 2009.

Combining equations (2.3) to (2.7), we can solve for the equilibrium prices (p_c, p_e, p_e^{BR}) and the equilibrium ethanol consumption, imports and exports.

Equilibrium with RFS Mandates

We now bring in U.S. RFS mandates into the model. First, we introduce the nested structure of these renewable fuels mandates. RFS was established in the Energy Policy Act of 2005 and expanded in the Energy Independence and Security Act of 2007. It places mandates on the consumptions of different renewable fuels based on their minimum lifecycle GHG emissions reduction level. It has an overall mandate on all renewable fuels, which include conventional fuels (corn ethanol) and advanced fuels. Within this overall mandate, there is a sub-mandate on the consumption of advanced fuels (cellulosic biofuels, biodiesel, and other advanced fuels). Furthermore, RFS also requires minimum quantities of cellulosic biofuels and biodiesel uses individually. Taking into account of the mandates on cellulosic biofuels and biodiesel, there is a residue of the advanced mandate (other advanced mandate), for which sugarcane ethanol, biodiesel and cellulosic biofuels can compete.

[11] Overall renewable biofuels mandate only cannot induce two-way trade in ethanol either.

The cellulosic biofuels mandate has been set to near zero, and it cannot compete with biodiesel and sugarcane ethanol at this stage. We don't consider it in our model. In this section, we consider the equilibrium that the other advanced mandate is met by sugarcane ethanol. And we will relax this assumption to include biodiesel in the following section.

Let Q^M be the leftover overall mandate excluding the advanced mandate, and $Q_{adv}{}^M$ represents the other advanced mandate. Then the overall mandate for ethanol would be Q^M + $Q_{adv}{}^M$. When there is policy intervention, the supply and demand prices of ethanol might differ, which depends on whether these mandates are binding or non-binding. When both mandates are non-binding, the U.S. would import more than the other advanced mandate, $I_e > Q^M$, and $p_e = p_e{}^{BR} + c$ at equilibrium. Conditions (2.3) to (2.6) still apply and ethanol supply price equals ethanol demand price. When both mandates are binding, U.S. ethanol demand is exogenously set to be $Q^M + Q_{adv}{}^M$, and $I_e = Q_{adv}{}^M$. Together with conditions (2.3) to (2.7), equilibrium prices and quantities can be calculated. When only the other advanced mandate is binding, only U.S. ethanol imports would be set to $Q_{adv}{}^M$, but $p_e = p_e{}^D$. Here the ethanol supply price is for the conventional ethanol. Next we show how these mandates are implemented and how conventional and advanced biofuels markets are separated through the compliance scheme.

RIN Prices

The mandated volumes of biofuels are enforced by the Environmental Protection Agency (EPA) through the market for biofuel Renewable Identification Numbers, which is a 38-character numeric code that is assigned to a volume of biofuel through the distribution system and ownership changes. Once the biofuel is blended, the RIN may be separated and used for compliance of the mandate. Obligated parties, including individual gasoline and diesel producers and importers, are required to meet their volume obligations set by EPA, which are based on their annual production and imports of gasoline. Obligated parties can choose to buy biofuel, blend it, and keep the RIN, or they can enter the RIN market to buy RINs from others.[12] This compliance scheme distinguishes conventional corn ethanol and imported sugarcane ethanol, and makes it possible to price different biofuels separately.

Following Babcock (2010), the price of RIN represents the gap between the supply price and the demand price at any given amount of biofuel.

$$RIN_{con} = p_e - p_e^D \tag{2.8}$$

If consumption of a biofuel within a calendar year begins to lag behind the pace needed to meet the annual mandated volume, then the demand for RINs would increase, which pushes up RIN prices. The increase in RIN prices increases biofuel prices received by the producers, who will then increase biofuels production and the following blending pace.

Figure 2.2 shows the equilibrium RIN prices with non-binding or binding ethanol mandates. The upward sloping curve S denotes U.S. ethanol supply, while downward sloping curve D represents U.S. ethanol demand. The market clearing price and quantity are given by P^* and Q^*. The vertical line indicates the mandated quantity. In panel (a), the mandate is not binding, with equilibrium quantity larger than the mandate, so the conventional RIN price (denoted by RIN_{con}) equals zero. In panel (b), the mandate is binding. The demand for ethanol is set exogenously to the mandate. RIN_{con} equals the gap between the supply and demand prices at the quantity of the mandate.

[12] RINs created in one year can also be carried over to the next year. But obligated parties can use only up to 20% of carry-over RINs to meet their present mandate. And RINs are only valid for two years. We don't consider carry-over RINs in our model. When the carry-over RINs are used to meet the present mandate, the demand for RINs would decrease, and the RIN price goes down. That would be one of the reasons why our RIN prices are higher than those from others study.

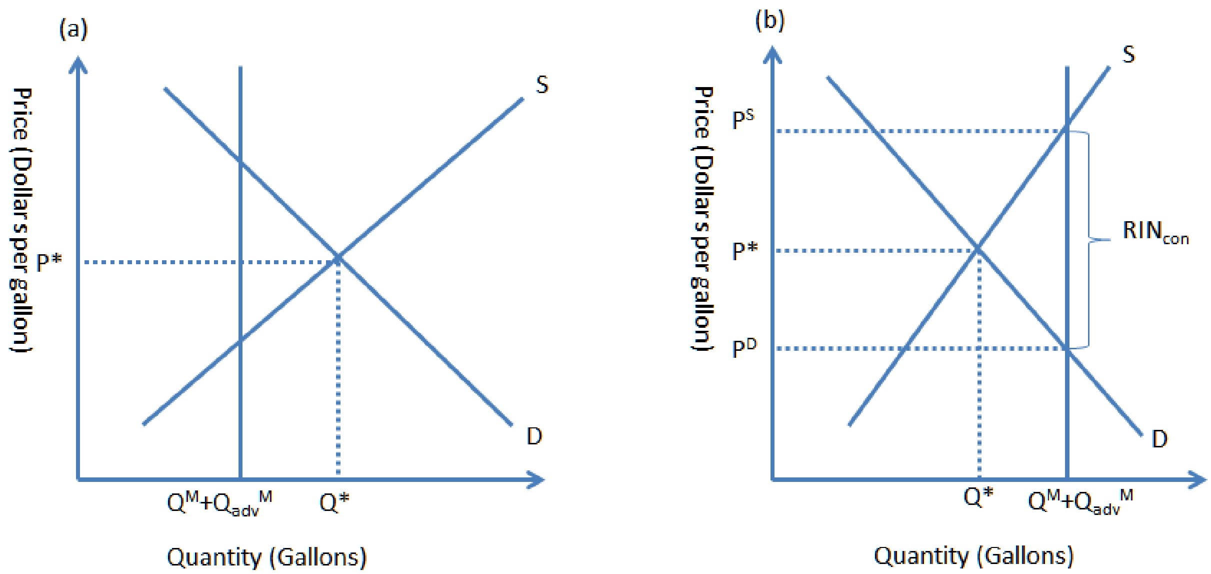

Figure 2.2: Determinations of RIN price when the mandate is (a) non-binding and (b) binding.

With the assumption that using sugarcane ethanol to meet the advanced mandate, the U.S. will always import sugarcane ethanol from Brazil, at least an amount equal to the other advanced mandate. So the supply price of the advanced biofuel and the corresponding advanced biofuel RIN price RIN_{adv} should satisfy:

$$p_{adv}^{S} = p_e^{BR} + c \tag{2.9}$$

$$RIN_{adv} = p_{adv}^{S} - p_e^{D} \tag{2.10}$$

Advanced RIN Supply from Sugarcane Ethanol

In the above section, we illustrate the equilibrium conditions for the conventional and advanced biofuels RIN prices, given the assumption that the other advanced biofuels mandate is met by sugarcane ethanol imported from Brazil. Here we discuss the advanced RIN supply from the sugarcane ethanol market.

We start the discussion from a hypothetical case that there is no advanced mandate, $Q_{adv}{}^{M}= 0$.The market equilibrium is indexed by superscript *0*, ($I_e{}^0$, $X_e{}^0$, $RIN_{con}{}^0$).We divide our analysis into three scenarios based on U.S. ethanol trade pattern under the hypothetical case.

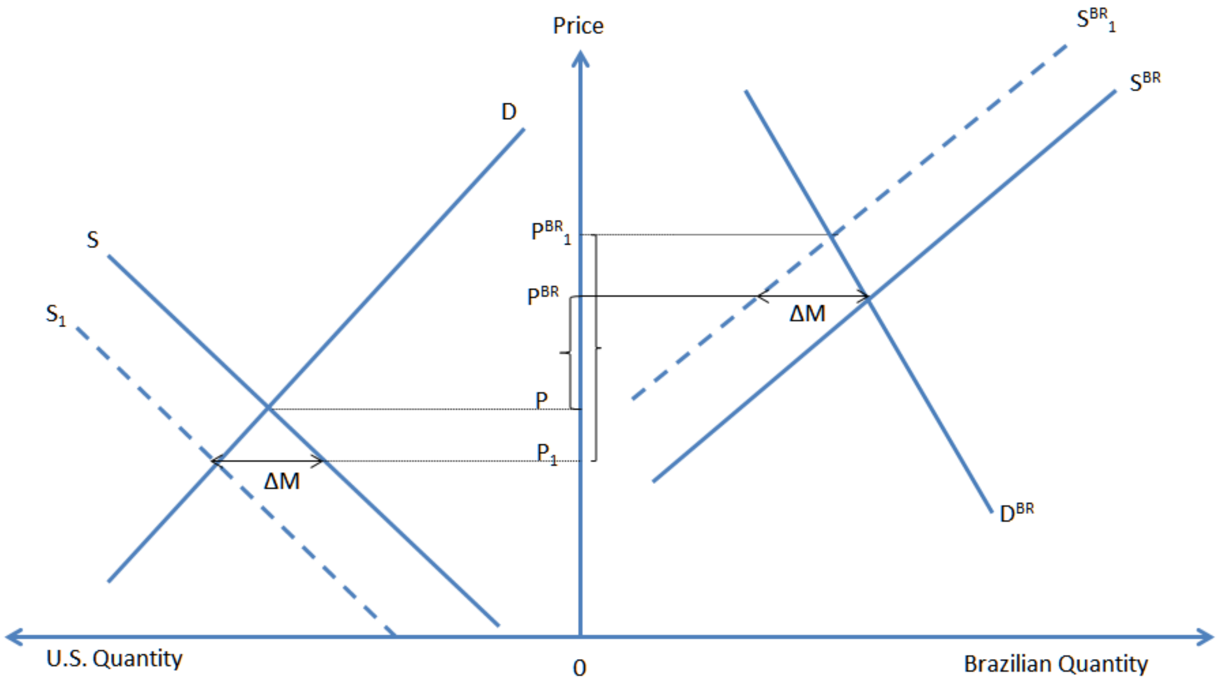

Figure 2.3: Comparative static analyses of the impacts of the other advanced mandate on U.S. and Brazilian markets when the U.S. has to import sugarcane ethanol to meet the other advanced mandate

For scenarios that U.S. imports amount is less than that of the other advanced mandate in the hypothetical case, the comparative static analysis of the impact of adding other advanced mandate is depicted in Figure 2.3. U.S. demand and supply are given by *D* and *S*, D^{BR} and S^{BR} for Brazil. Corresponding market clear equilibrium prices are *P* and P^{BR}. To satisfy the other advanced mandate, the U.S. has to import the shortage ΔM from Brazil. Then the domestic supply in the U.S. increases from *S* to S_1, while Brazilian domestic supply decreases from S^{BR} to $S^{BR}{}_{1}$. U.S. ethanol equilibrium price drops to P_1 and Brazilian ethanol price increases to $P^{BR}{}_{1}$. Then it is potential for the U.S. to start exporting or export more, due to the increase in U.S. excess supply and Brazilian excess demand.

Scenario 1: U.S. Exports to Brazil when $Q_{adv}{}^{M} = 0$

If the U.S. exports corn ethanol to Brazil under the hypothetical case, $X_e{}^0 > I_e{}^0 = 0$, adding the other advanced mandate induces the U.S. to import an amount of $Q_{adv}{}^{M}$ sugarcane ethanol. Ethanol imports enlarge the ethanol price between the U.S. and Brazil, which promotes more exports to Brazil. Therefore, the U.S. imports an amount of $Q_{adv}{}^{M}$ sugarcane ethanol from Brazil, and at the same time exports corn ethanol to Brazil, which forms a two-way trade in ethanol between the U.S. and Brazil. At equilibrium, $I_e = Q_{adv}{}^{M}$, $X_e > 0$, and $p_e = p_e{}^{BR} - c$. And the advanced RIN price is always more than the conventional RIN price by an amount of two times transportation, because

$$RIN_{adv} = p_{adv}^{S} - p_e^D = p_e^{BR} + c - p_e^D = p_e - p_e^D + 2c = RIN_{con} + 2c \tag{2.11}$$

When the mandate is binding under the hypothetical case, $RIN_{con}{}^{0} > 0$, after adding the other advanced mandate, the conventional ethanol mandate still binds. Combining U.S. and Brazilian ethanol market equilibrium conditions, $D_e(p_e{}^D, p_g) = Q^M + Q_{adv}{}^{M}$ and $p_e = p_e{}^{BR} - c$, we have

$$S_e(p_e) + S_e^{BR}(p_e + c) = Q^M + Q_{adv}^M + D_e^{BR}(p_e + c) \tag{2.12}$$

$$\frac{dp_e}{dQ_{adv}^M} = \frac{1}{\frac{dS_e}{dp_e} + \frac{dS_e^{BR}}{dp_e^{BR}} - \frac{dD_e^{BR}}{dp_e^{BR}}} > 0 \tag{2.13}$$

Where $dS_e/dp_e > 0$, $dS_e{}^{BR}/dp_e{}^{BR} > 0$, and $dD_e{}^{BR}/dp_e{}^{BR} < 0$. Equation (2.13) implies that the supply price of ethanol in the U.S. increases with $Q_{adv}{}^{M}$. The demand price decreases with the other advanced mandate. Then the conventional RIN price increases as the other advanced mandate increases, as depicted in panel (a) of Figure 2.4.

When the mandate is not binding under the hypothetical case, RIN_{con}^{0} =0, U.S. imports of sugarcane ethanol will squeeze out the same amount of corn ethanol from the domestic market. So when the other advanced mandate is less than U.S. excess domestic supply beyond Q^M, the conventional mandate is still non-binding. As the other advanced mandate increases, the conventional mandate will eventually bind and the relationship between the RIN prices and the other advanced mandate is identical to the binding case, as shown in panel (b) of Figure 2.4.

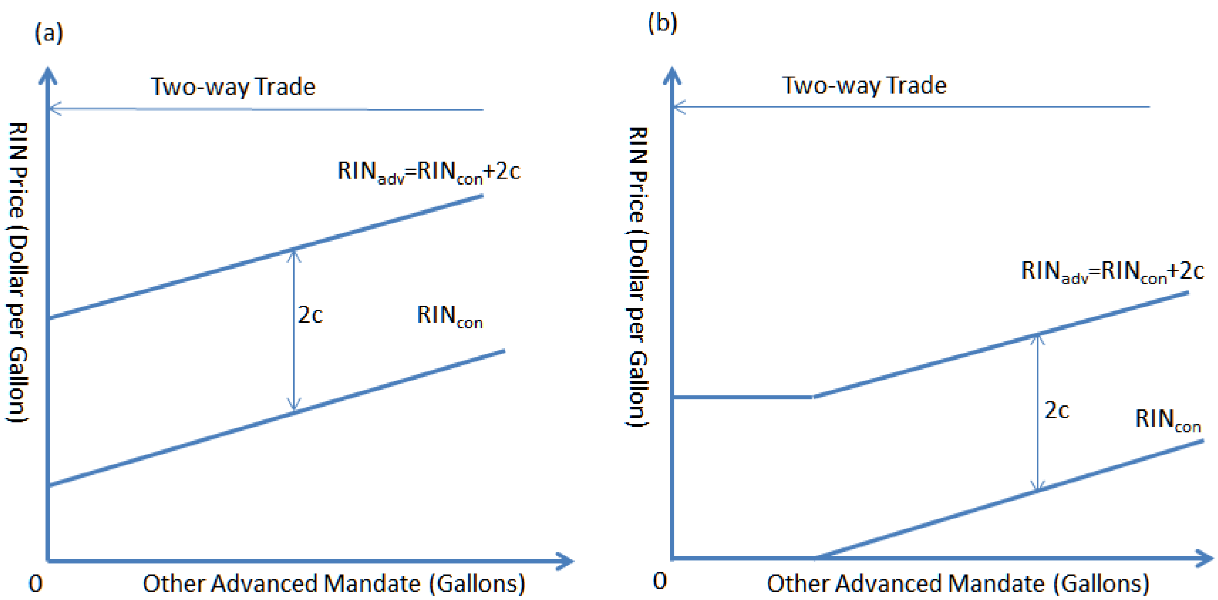

Figure 2.4: The relationship between RINs prices and the other advanced mandate when the U.S. exports to Brazil with (a) binding conventional mandate and (b) non-binding conventional mandate under the hypothetical case that no advanced mandate exists.

Scenario 2: no trade between U.S. and Brazil when $Q_{adv}^M = 0$

If there is no trade in ethanol between the U.S. and Brazil under the hypothetical case, $X_e^0 = I_e^0 = 0$, similar as scenario 1, adding the other advanced mandate induces the U.S. to import an amount of Q_{adv}^M sugarcane ethanol, which increases the likelihood of U.S. exports.

When the mandate is binding under the hypothetical case, $RIN_{con}^0 > 0$, after adding the other advanced mandate, the conventional ethanol mandate continues to be binding. U.S. imports of sugarcane ethanol increase its potential to export corn ethanol to Brazil. When the other advanced mandate is too small to incentive the U.S. to export, there would be a one-way trade from Brazil to the U.S., $I_e= Q_{adv}^M$ and $X_e = 0$. Together with $D_e(p_e^D,p_g) = Q^M + Q_{adv}^M$, we have

$$S_e(p_e) + Q_{adv}^M = Q^M + Q_{adv}^M = D_e(p_e^D) \tag{2.14}$$

So U.S. ethanol supply price remains the same, while U.S. ethanol demand price decreases with the other advanced mandate. For Brazil, domestic supply decrease pushes up the ethanol price. Therefore, both conventional and advanced RIN prices increases with the other advanced RIN mandate. But the gap between RIN_{con} and RIN_{adv} is less than $2c$, because

$$RIN_{adv} = p_e^{BR} + c - p_e^D = RIN_{con} + c + p_e^{BR} - p_e < RIN_{con} + 2c \tag{2.15}$$

where $|p_e^{BR} - p_e^S| < c$ is due to the condition that there is no trade in corn ethanol between the U.S. and Brazil. However, increases in the other advanced mandate will eventually induce the U.S to export corn ethanol to Brazil, and the gap between the conventional and advanced RIN price will then remain at $2c$ as in Figure 2.5 (a).

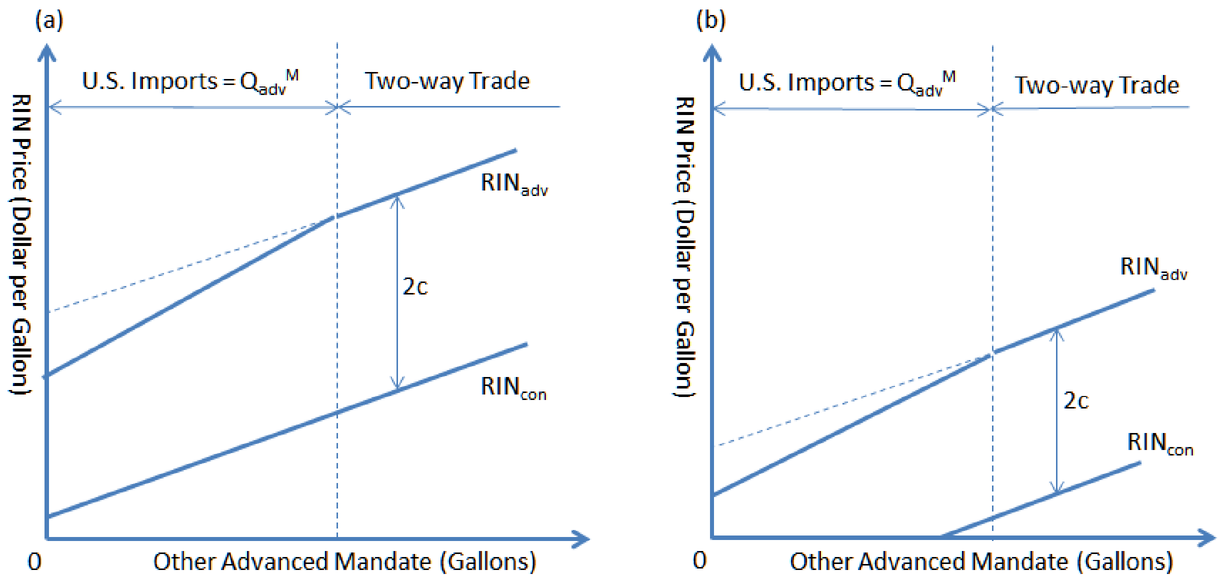

Figure 2.5: The relationship between RINs prices and the other advanced mandate when there is no trade between U.S. and Brazil with (a) binding conventional mandate and (b) non-binding conventional mandate under the hypothetical case that no advanced mandate exists.

When the mandate is not binding under the hypothetical case, $RIN_{con}^{0} = 0$, if the other advanced mandate is so small that the conventional mandate continues to be non-binding, then RIN_{con} remains at 0, while RIN_{adv} would be positive but less than $2c$, and increasing with the other advanced mandate. But eventually, increases in the other advanced mandate will lower U.S. demand enough to make the conventional mandate bind (Figure 2.5 (a)). It is also possible that increases in the other advanced mandate induce the U.S. to export to Brazil with U.S. conventional mandate still non-binding, which instead creates the situation in Figure 2.4 (b).

Scenario 3: U.S. Imports from Brazil when $Q_{adv}^{M} = 0$

When the U.S. imports from Brazil under the hypothetic case, $I_e^0 > X_e^0 = 0$, with the advanced mandate, imported sugarcane ethanol is used to meet the advanced mandate first.

When the mandate is binding under the hypothetical case, $RIN_{con}{}^{0} > 0$, imports are diverted to meet the other advanced mandate, so the conventional mandate still binds. U.S. ethanol supply price would increase to encourage more production and imports to meet the conventional mandate. As long as the U.S. uses sugarcane ethanol to meet the conventional mandate, the conventional RIN price equals the advanced RIN price as the following:

$$RIN_{adv} = p_e^{BR} + c - p_e^{D} = RIN_{con} \quad (2.16)$$

Demand price decreases to reach the increased overall mandate. So both RIN prices are positive and increasing with the other advanced mandate. However, increase in the other advanced mandate will eventually result in all imported sugarcane ethanol being used to meet the other advanced mandate. Further increase will lower U.S. domestic supply price and increase Brazilian ethanol price, which makes it non-profitable for the U.S. to import more than the other advanced mandate. Then the advanced RIN price will exceed the convention RIN price, as shown in Figure 2.6 (a).

When the mandate is not binding under the hypothetic case, $RIN_{con}{}^{0} = 0$, if the other advanced mandate can be met by the imported sugarcane ethanol and the conventional mandate is still non-binding, both the conventional and advanced RIN prices are zero. However, as the other advanced mandate increases, if U.S. imports more than the amount of the other advanced mandate, the conventional mandate will eventually bind. Then both RIN prices become positive and increase with the other advanced mandate, as illustrated in Figure 2.6 (b). It is also possible that as the other advanced mandate increases the advanced mandate binds with the conventional mandate non-binding. Then the U.S. will not import more than the other advanced mandate, as the situation in Figure 2.5 (b).

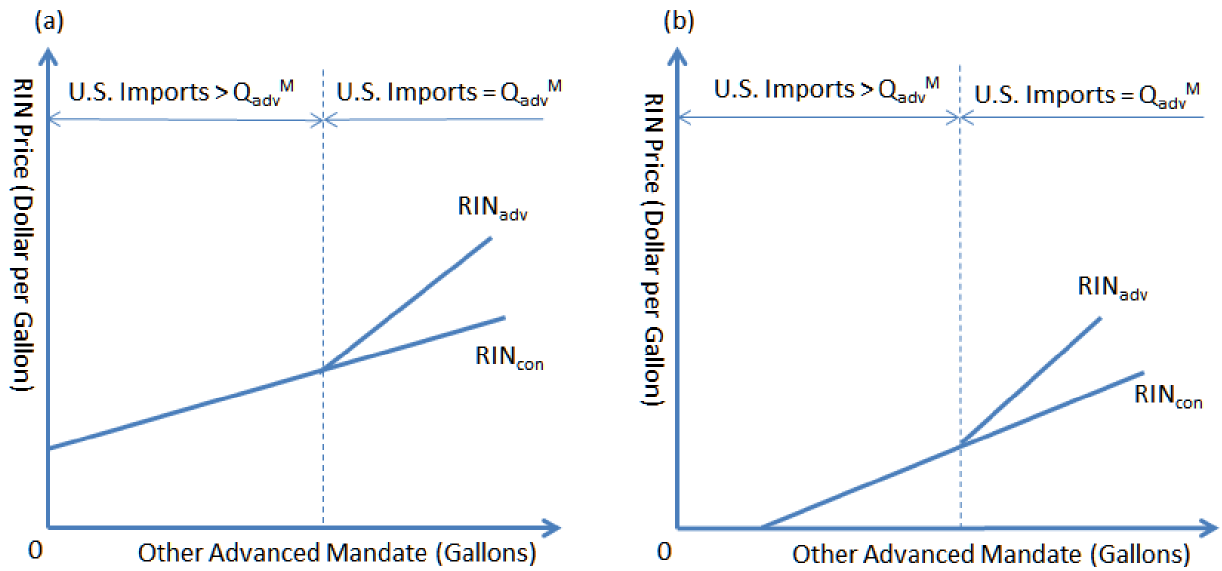

Figure 2.6: The relationship between RINs prices and the other advanced mandate when the U.S. imports from Brazil with (a) binding conventional mandate and (b) non-binding conventional mandate under the hypothetical case that no advanced mandate exists.

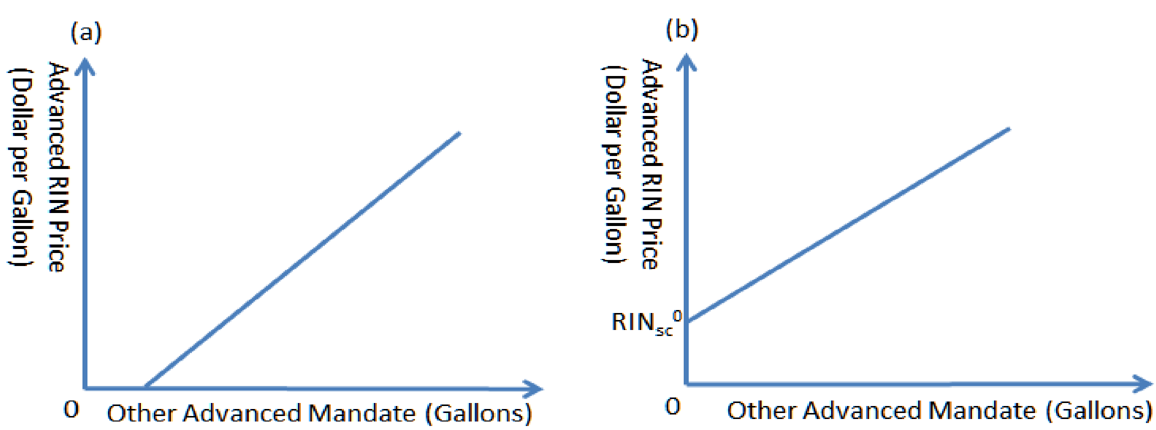

Figure 2.7: Advanced RIN supply from sugarcane ethanol when (a) the U.S. imports from Brazil with a non-binding mandate and (b) other situations, under the hypothetical case that no advanced mandate exists

In summary, both the conventional and advanced RIN prices are non-decreasing with the other advanced mandate. We also get insights of the biofuels RIN prices from the trade pattern between the U.S. and Brazil. The price gap between the conventional and advanced RIN is two times transportation cost when there is two-way trade. When the U.S. only imports from Brazil the amount of the other advanced mandate, the price gap is less than $2c$. As long as the U.S. imports more than the other advanced mandate, the conventional RIN price equals the advanced RIN price.

In the next section, we take into account of the competence from an alternative source of advanced biofuels, biodiesel. For ease of comparison, we simplify the above discussion about the advanced RIN supply from imported sugarcane ethanol. When the U.S. imports from Brazil with non-binding conventional mandate in the hypothetical case, the advanced RIN price starts from zero and becomes positive as the other advanced mandate increases (Figure 2.7 (a)). Otherwise, the advanced RIN price is always positive and non-decreasing with the other advanced mandate (Figure 2.7 (b)). In the latter case, denote RIN_{sc}^{0} as the hypothetic minimum advanced RIN price.

Advanced RIN Supply from Biodiesel

In the above model, we assume that the other advanced mandate is met with imported sugarcane ethanol. Actually, multiple fuels are certified as advanced biofuels that can be used to meet the advanced mandate. The most important biofuel that qualifies is biodiesel made from soybean oil, animal fats or waste grease, which means that it is a substitute for sugarcane ethanol in meeting the other advanced mandate[13]. A complication of including biodiesel is that it also has a mandate that only it can meet before any volume is available to meet the advanced mandate. We first examine the biodiesel market with only the sub-

[13] According to RFS, Biodiesel could also compete with corn ethanol to meet the conventional mandate. But currently the biodiesel RIN price is still much higher than conventional RIN price. Biodiesel has little advantage to compete with corn ethanol to meet the leftover overall mandate. We omit this possibility in our model.

mandate just for the biodiesel (denoted as $Q_{bd}{}^{M}$). Then add in the other advanced mandate and analyze the advanced RIN supply from biodiesel.

With only the biodiesel sub-mandate, market clearing condition and corresponding biodiesel RIN prices are shown in Figure 2.8. Biodiesel demand and supply curves are denoted as D and S, with equilibrium price and quantity (P^{**}, Q^{**}). The vertical solid line is the amount of the biodiesel sub-mandate. If the biodiesel mandate is not binding, with $Q^{**} > Q_{bd}{}^{M}$, the biodiesel supply price $P_{bd}{}^{S}$ equals the biodiesel demand price $P_{bd}{}^{D}$, and biodiesel RIN price $RIN_{bd}{}^{0}$ is zero. If the biodiesel mandate is binding, the demand for biodiesel is exogenously set to $Q_{bd}{}^{M}$. The biodiesel RIN price is positive and equals the gap between the biodiesel supply and demand prices, represented by a - b.

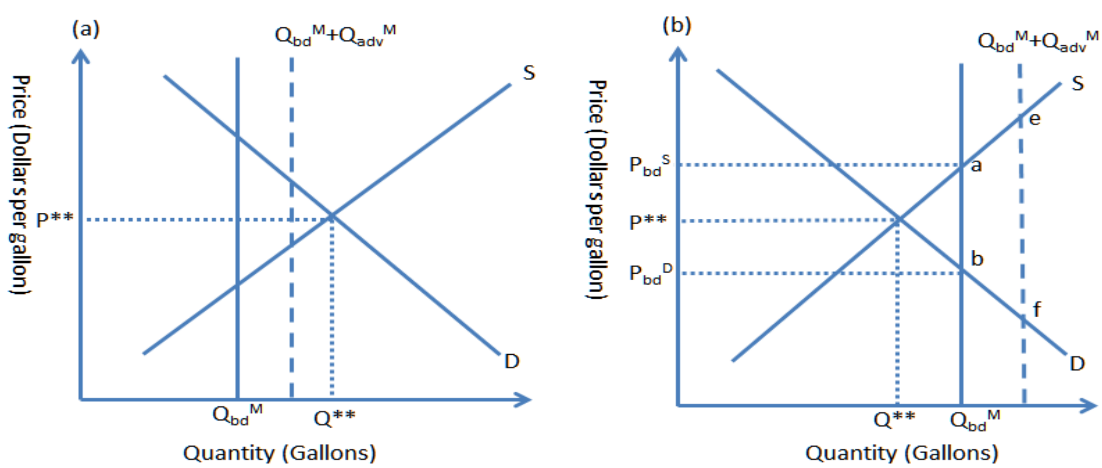

Figure 2.8: Determinations of biodiesel RIN price when the biodiesel sub-mandate is (a) non-binding and (b) binding.

Next, we consider the case with the other advanced mandate met by biodiesel. Adding the other advanced mandate works as an increased biodiesel mandate. If the biodiesel sub-mandate is binding, $RIN_{bd}{}^{0} > 0$, it remains binding with the other advanced mandate.

The increased mandate leads to a higher supply price and a lower demand price as depicted in Figure 2.8 (b). The dotted vertical line is the summed mandate. The advanced RIN price exceeds the initial biodiesel RIN price, because the price gap increases from $a - b$ to $e - f$. So when the biodiesel sub-mandate is binding, the advanced RIN price is always positive and increasing with the other advanced mandate (Figure 2.9(b)). If the biodiesel sub-mandate is non-binding, $RIN_{bd}^0 = 0$, when the other advanced mandate is small enough that the increased mandate is still non-binding, the advanced RIN price would be zero (Figure 2.8 (a)). But as the other advanced mandate increases, it will eventually bind and the advanced RIN price will become positive and increase with the other advanced mandate (Figure 2.9 (a)).

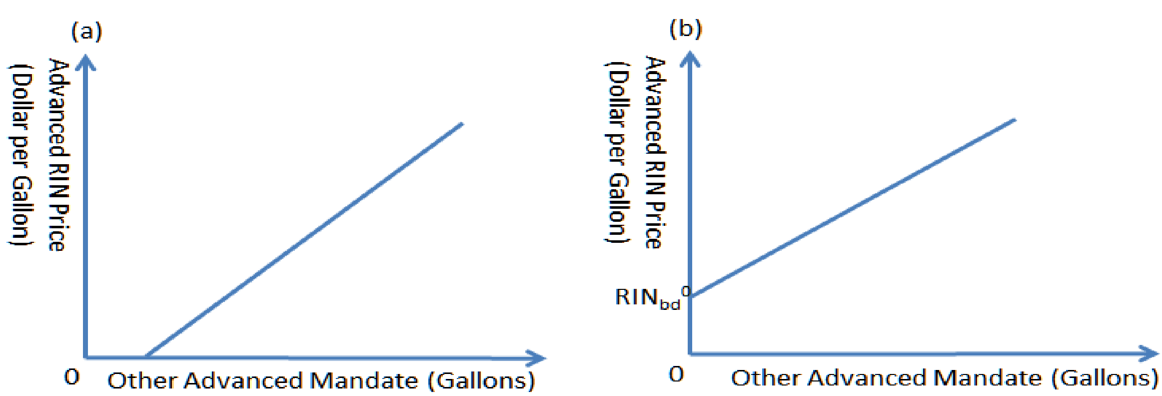

Figure 2.9: Advanced RIN supply from biodiesel when (a) biodiesel sub-mandate is non-binding and (b) biodiesel sub-mandate is binding.

Equilibrium for the Advanced RIN with Biodiesel

Considering the competition between biodiesel and imported sugarcane ethanol to meet the other advanced mandate, there are three possibilities to meet the other advanced mandate: (1) use sugarcane ethanol only; (2) use biodiesel only; (3) use both sugarcane ethanol and biodiesel. If only use one fuel to meet the other advanced mandate, the advanced RIN price must not be greater than that of using any of the other fuel. Otherwise, both fuels would be used to meet the other advanced mandate. The conditions for interior solutions are:

$$Q_{sc} + Q_{bd} = Q_{adv}^{M} \tag{2.17}$$

$$RIN_{adv} = RIN_{sc} = RIN_{bd} \tag{2.18}$$

where Q_{sc} and Q_{bd} are the corresponding amounts of the other advanced mandate that are met by sugarcane ethanol and biodiesel. RIN_{sc} is the advanced RIN price when hypothetically using sugarcane ethanol to meet an amount of Q_{sc} advanced mandate. Similarly, RIN_{bd} is the advanced RIN price using biodiesel to meet an amount of Q_{bd} advanced mandate.

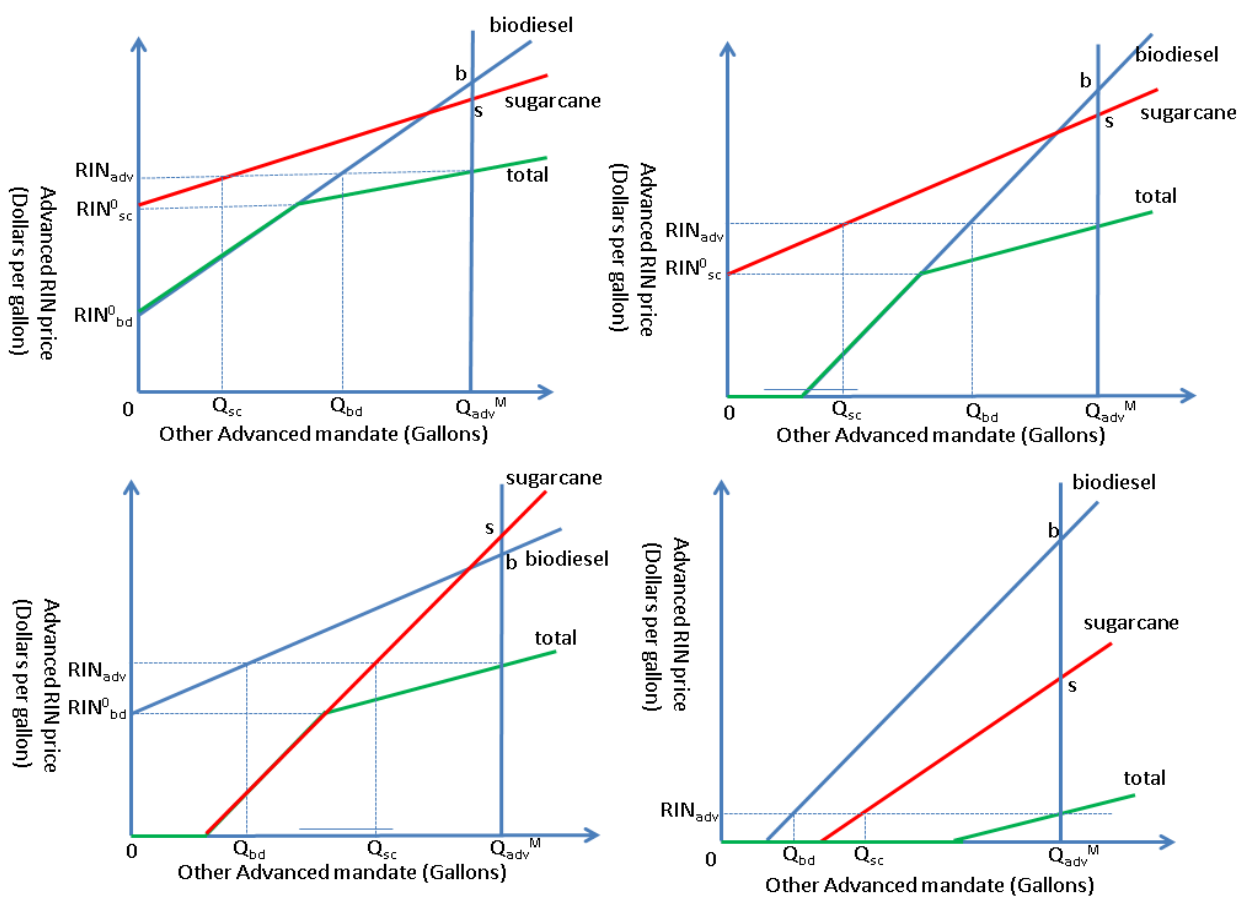

Figure 2.10: Advanced RIN supply when both sugarcane ethanol and biodiesel are qualified as advanced biofuels.

Here, we also show the determination of the shares of the other advanced mandate met by sugarcane ethanol and biodiesel by graphs. There are four possible configurations of the total advanced RIN supply from biodiesel and sugarcane ethanol, shown in the four panels of Figure 2.10. The advanced RIN supply from sugarcane ethanol and biodiesel are noted as 'sugarcane' and 'biodiesel', respectively. At each given advanced RIN price, the total supply of the advanced RIN (denoted as 'total'), is the horizontal sum of the supply from sugarcane ethanol and biodiesel. RIN_{adv} is the advanced RIN price when the total supply equals the other advanced mandate, and Q_{sc} and Q_{bd} are determined by the intersections of the equilibrium advanced RIN price with the supplies of advanced RINs from sugarcane ethanol and biodiesel. Interior solutions are depicted in Figure 2.10, but it is easy to see how a decrease in the other advanced mandate would result in only one of the fuels being used to meet the advanced mandate.

To some extent, U.S. domestic produced biodiesel can decrease U.S. dependence on the imports of sugarcane ethanol to meet the other advanced mandate, and then reduce the possibility of two-way trade. If U.S. biodiesel is competitive, the U.S. might not have to induce more imports just because of the mandates. Competence from biodiesel to meet the other advanced mandate could also reduce the advanced RIN price. In Figure 10, the advanced RIN prices using only one fuel, corresponding to points *s* and *b*, are at least as much as the advanced RIN price using both fuels, RIN_{adv}.

Calibration

We simulate the model for the marketing year 2013/14 to estimate the potential impacts of RFS biofuels mandates on the ethanol trade pattern between the U.S. and Brazil, various RIN prices and related commodity prices. Our simulation method for U.S. and

Brazilian ethanol market mainly follows Babcock et al. (2010). To account for the uncertainties in the feedstock yields, gasoline prices in the U.S., we take values of all these variables from our projected distributions. Given 500 randomly combination of draws of all these variables, we calculate the equilibrium prices and quantities. The averages are then used to show the impacts of RFS mandates in 2013/14.

U.S. Corn Market

Corn supply equals beginning stocks plus the product of yield and harvested acreage. We fix the amount of corn harvested area at 87.7 million acres as in November 11, 2012 World Agricultural Supply and Demand Estimates (WASDE)[14] projections for the marketing year 2012/13. Corn beginning stock equals the projection for 2012/13 ending stock, 647 million bushels. We simulate corn yield distribution from U.S. historical corn yield data from 1980 to 2011, which is from the database of National Agriculture Statistics Service (NASS)[15]. We fit the linear de-trended data to a beta distribution, with a mean of 161.6 bushels per acre (bu/ac), a standard deviation of 11.6 bu/ac, a maximum of 185 bu/ac, and a minimum of 100 bu/ac.

Food, feed and net export demand of corn are calibrated to linear functions, with elasticities -0.096, -0.25 and -0.6, respectively (Babcock et al. (2010)). With evidence of the poor yield in 2012, these demands are calibrated to fit WASDE[16] prices and quantities for the normal year 2010/11. Corn storage demand is modeled using a beta distribution based on the relationship between corn prices and ratios of corn storage demand to corn production.

[14] See http://www.usda.gov/oce/commodity/wasde
[15] See http://www.nass.usda.gov/
[16] We assume that the substitution effect of the dried distillers grains with solubles (co-product of ethanol produced from corn) as feeds use if accounted for in the WASDE projections.

Resulting parameters are p = 1.8 and q = 1.1. Data we use are from 2000/01 and 2010/11, with the ratio constrained between 5% to 25% and corn price bounded by $8/bushel.

U.S. Ethanol Market

According to the RFA, we assume that all U.S. corn ethanol plant produce 2.8 gallons of ethanol and 17.5 pounds of DDGS per bushel of corn, $\alpha = 2.8$.[17] Following Babcock et al. (2010), we assume the price of DDGS is 85% of the corn price. The other operating cost is 74 cents per gallon ethanol produced, which is calculated from zero profit condition and assumed to be constant. $\gamma = 2.8/(1- 17.5/56*0.85) = 3.8$.[18]

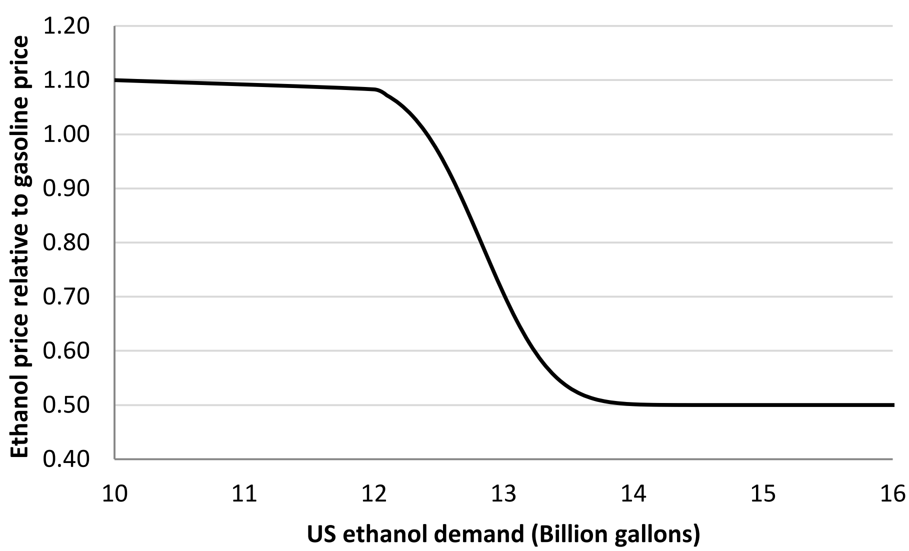

Figure 2.11: U.S. ethanol demand

[17] According to the RFA, dry mill facilities represent nearly 90% of U.S. total ethanol production and a modern dry mill ethanol refinery produce approximately 2.8 gallons of ethanol and 17.5 pounds of DDGS from a bushel of corn.

[18] We assume 1 bushel corn weights 56 lbs.

The demand of ethanol is calibrated using a beta distribution based on its relationship with the relative price of ethanol to gasoline.[19] The relative price of ethanol to gasoline is constrained between 0.5 and 1.1, and the maximum consumption of ethanol is assumed to be 20 BG at the price ratio lower than 0.5 indicating that low enough ethanol price might induce investments and use of E85. As in Figure 2.11, when the wholesale price ratio of ethanol to gasoline is 0.9, ethanol demand is about 12.4 BG; when the price ratio decreases to 0.6, ethanol demand increases to 13.2 BG. The resulting parameters are p = 180.39 and q = 322.35.

Gasoline price is simulated as a lognormal distribution with a mean of \$2.55/gallon and a standard deviation of \$0.62/gallon. We estimate the mean as the average of the 2013/14 gasoline RBOB futures prices at NYMEX,[20] and the standard deviation from the average implied volatility of gasoline RBOB options at NYMEX.

Brazilian Ethanol Market

Following Babcock et al. (2010), Brazilian ethanol demand is modeled from Brazilian auto fleet size. In Brazil, ethanol vehicles use hydrous ethanol with 5% water; gasoline vehicles use gasoline blended with anhydrous ethanol; flex-fuel vehicles (FFVs) can switch between two forms of fuel. The demand for fuel ethanol is:

$$D_e^{BR} = N_e L_e + \beta N_f L_e + \delta L_g (N_g + (1 - \beta) N_f) \qquad (2.19)$$

N_e, N_f and N_g denote the ethanol, flex-fuel and gasoline vehicles fleet size, respectively. L_e and L_g are the volumes of fuel consumed by a vehicle per year. β is the average share of FFVs that using ethanol per year. δ is the mandatory blend level in Brazil,

[19] Anderson (2011) also finds that ethanol demand as a substitute of gasoline is sensitive to the relative price of ethanol to gasoline.
[20] See http://nymex.com/index.aspx

which is assumed to be 25%.[21] The fleet size in 2013/14 is calibrated to the weighted average of the linear trend level in 2013 and 2014. The historical data is from Brazilian Sugarcane Industry Association (UNICA). Three motorcycles are treated as one car. The resulting values are 15.7 million for gasoline vehicles, 0.74 million for ethanol vehicles and 21.8 million for FFVs. Annual ethanol consumption per car (L_e) is modeled as a constant elasticity (-0.04) function of the ethanol to gasoline price ratio and adjusted to anhydrous in gallons. Coefficients are derived by fixing ethanol consumption per vehicle per year at 1885 liters at a price ratio of 0.7.[22] Considering that ethanol has only 2/3 energy content of gasoline, blended gasoline consumption per year satisfies $L_e = L_g$*(0.25*1.05 + 0.75*1.5). For FFVs owners, whether to use gasoline or ethanol depends on the relative price of ethanol to gasoline. The relationship between δ and the relative price is modeled as a standard beta distribution with p = 2.6987, and q = 1.3579.[23] And the transportation cost from U.S. plant to Brazilian plant is assumed to be $0.38/gallon[24].

Brazilian ethanol supply is modeled as a constant elasticity function of ethanol to gasoline price ratio. The short-run elasticity is set to 0.04 to reflect the flexibility of Brazilian sugar mills to switch between producing sugar and ethanol based on the relative prices. The

[21] In Brazil, the blend rate was lowered from 25% to 20% in October 2011, due to tight ethanol supplies. But it is expected to be back up to 25% on May 1st, 2013.

[22] According to USDA, the Brazilian light vehicle fleet of 18 million units consumes 4.2 billion gallons per year of gasoline and 3.1 billion gallons per year of hydrated and anhydrous ethanol, and gasoline is blended with 23% anhydrous ethanol. We construct L_e by adding the ethanol consumption to the hydrous ethanol energy equivalent amount of the gasoline consumption.

[23] In Babcock, Barr, and Carriquiry 2010, coefficients p and q are derived from two calibration points. In 2009, at the price ratio 0.56, the share of FFVs using ethanol was determined by UNICA to be 0.7. When price ratio rose to 0.73 in January and February, the share declined to about 0.44.

[24] Crago, Khanna, Barton, Giuliani, and Amaral (2010) estimated the average transportation cost from Brazil refinery to U.S. port to be 0.18 Reals per liter. With our assumption of exchange rate at 2.05 Reals per Dollar, it is $0.33/gallon. We include a moderate cost from U.S. port to places for blending.

coefficient is calibrated to the point with 26 billion liters ethanol production at the ethanol to gasoline price ratio 0.7.[25]

Soybean and Soybean Products Market

As the U.S., Brazil and Argentina account for about 80% of the production, and more than 85% of the exports of soybean, about 80% of the exports of soybean products, we only consider these three countries in the world supply. According to projections for 2012/13, November, 2012 WASDE report, we fix U.S. soybean harvested area at 75.7 million acres, 27.5 million hectors (ha) for Brazil and 19.7 million hectors for Argentina[26]. U.S. Soybean beginning stock is 140 million bushels, 17.17 million metric ton (mt) for Brazil, and 21.65 million metric ton for Argentina. Similar as corn yield, we simulate all soybean yields as beta distributions using NASS and USDA Foreign Agricultural Service (FAS)[27] historical yield data. U.S. soybean yield has a mean of 44.7 bu/ac (3.05 t/ha for Brazil, 2.77 t/ha for Argentina), a standard deviation of 2.8 bu/ac (0.18 t/ha for Brazil, 0.26 t/ha for Argentina), a maximum of 51 bu/ac (3.5 t/ha for Brazil, 3.2 t/ha for Argentina), and a minimum of 34 bu/ac (2.5 t/ha for Brazil, 2 t/ha for Argentina).

Soybean utilization includes crush, storage, net exports, and other demands. Crushing productivity parameters are derived through dividing soybean meals and oil productions by soybean crush quantities. Crush demands are modeled as linear function of the crush margin, which are calculated by subtracting cost of one bushel soybean from revenues of soybean meals and soybean oil produced. Storage and other demand are calibrated as linear functions of soybean price. Prices and quantities used to derive the parameters are from November,

[25] The calibration point is according to 2013 Brazilian ethanol production projection in USDA GAIN report.
[26] We report their original units in the study, and adjust the units in our calculation.
[27] Brazilian and Argentine historical yields data is from USDA Foreign Agricultural Service.

2012 WASDE. Soybean net exports equal the beginning stock plus the production and excluding the crush, storage and other demands. U.S. crush, storage and other demands elasticities we use are 0.3, -0.65 and -0.1 (0.23, -0.65 and -0.03 for Brazil, and 0.2, -0.65 and -0.25 for Argentina), respectively.

Soybean meals and soybean oil beginning stocks are also from WASDE projections for storage demands in 2012/13. Soybean meals are utilized to domestic, storage and net export demands. Domestic and storage demands are calibrated as linear functions of the soybean meals price. Domestic and storage demands elasticities are -0.25 and -0.65 for all three countries. Soybean oil is utilized to domestic (non-biodiesel), biodiesel use, storage, and net export demands in the U.S., while in Brazil and Argentina we don't differentiate use for biodiesel. Elasticities for domestic and storage demands are -0.1 and -0.65, respectively. Data for all calibration points is from WASDE, and the share of soybean oil used for biodiesel is from U.S. Energy Information Administration (EIA).[28] Net exports equal supplies from soybean subtracting domestic and storage demands.

World demand and supply of soybean, soybean meals and soybean oil are calibrated as linear functions of the world prices. Elasticities are -0.1, -0.1, -1 for soybean and soybean meals and soybean oil, respectively. Quantities are the sum of the net exports of the U.S., Brazil and Argentina, and we use U.S. prices as the world prices. All data is from WASDE.

[28] The share of soybean oil for biodiesel use comes from U.S. bioenergy statistics table 6 "Soybean oil supply, disappearance and share of biodiesel use". See www.era.usda.gov

U.S. Biodiesel Market

We fix U.S. biodiesel production from sources other than soybean oil at 680 million gallons.[29] According to Paulson and Ginder (2007), one pound of feedstock can produce 0.982 pound of biodiesel. Given there are 7.4 pounds in a gallon, we have 7.55 pounds soybean oil to produce one gallon of biodiesel. The biodiesel margin per gallon equals the price of biodiesel minus the cost of required soybean oil and other costs ($0.4/gallon)[30]. We derive the supply curve of biodiesel from soybean oil indirectly through the relationship between biodiesel production and the biodiesel margin. It is simply modeled as a linear function. Data for the share of soybean oil used for biodiesel from 2008/09 to 2010/11 is from EIA, and divide by 7.55 to get the biodiesel production from soybean oil. Annual average biodiesel margins data is collected from Center for Agricultural and Rural Development (CARD).

The U.S. biodiesel net export is assumed to be zero.[31] And assume that biodiesel mandate is always binding.

RFS Mandates

In 2013 the RFS mandates total U.S. biofuel consumption of 16.55 billion gallons. Of this volume 2.75 BG is required to be met by advanced biofuels, and the rest 13.8 BG is mandated on renewable biofuels (conventional mandate in our study). The 2.75 BG advanced mandate includes 1.28 BG mandate on biodiesel. Because biodiesel has about 50% more energy content than ethanol, each gallon of biodiesel counts as 1.5 gallons of ethanol

[29] This assumption follows EPA final rules about 2013 biomass-based diesel renewable fuel volume. And we assume this will not change in 2014.

[30] Again, using the cost estimations in Paulson and Ginder (2007), we define other costs as the sum of the costs of other inputs, operating expenses and capital costs minus the credits from co-products.

[31] According to EIA, exports of biodiesel peaked in 2008 largely due to a perverse effect of a biodiesel tax credit in the European Union. Exports then dropped to near zero after the effect was eliminated.

equivalent. So multiplying 1.28 BG by 1.5, biodiesel mandate counts as 1.92 BG towards the advanced mandate, which leaves an amount of 0.83 BG advanced mandate (other advanced mandate in our study) to be met by sugarcane ethanol from Brazil or U.S. biodiesel. The cellulosic mandate has been set to near zero, so we neglect cellulosic ethanol in our analysis. In 2014, the total biofuel mandate increases to 18.15 BG, of which 14.4 BG mandates to be met by conventional biofuels, and 3.75 BG met by advanced biofuels. We assume that biodiesel mandate remains the same in 2014. It leaves an amount of 1.83 BG mandate to other advanced biofuels. The weighted averages of mandates in 2013 and 2014 are used for the marketing year 2013/14. The resulting conventional mandate is 14.2BG, 1.28 BG for biodiesel, and 1.5 BG for other advanced mandate. All mandates used in our study are illustrated in Table 2.1.

Table 2.1: Assumptions of U.S. Renewable Fuels Mandates (BG)

Year	Conventional Renewable	Advanced Biofuels	Cellulosic Biofuels	Biomass-Based Diesel	Other Advanced	Total RFS
2013	13.8	2.75	0	1.28	0.83	16.55
2014	14.4	3.75	0	1.28	1.83	18.15
2013/14	14.2	3.42	0	1.28	1.5	17.62

Note: See http://www.ethanolrfa.org for the RFS mandates. *Other advanced biofuel mandates are ethanol energy equivalent volumes.

Simulation Results for 2013/14

Given the assumptions of the exogenous parameters and the distributions of the stochastic variables, we now consider alternative policy scenarios for the marketing year 2013/14. These scenarios are as follows:

1. Conventional mandate.

2. All mandates (Constrained), other advanced mandate can only be met by sugarcane ethanol.

3. All mandates, other advanced mandate can be met by both sugarcane ethanol and biodiesel.

4. No Mandates.

Table 2.2 represents the number of observations of no trade, one-way trade or two-way trade in ethanol out of our 500 simulations for each scenario. For all scenarios, we report in Table 2.3 the implied mandates and average results of key variables. In Table 2.4, results for interior solutions that using both sugarcane ethanol and biodiesel to meet the other advanced mandate are reported. Our results show that RFS mandates, especially the other advanced mandate that could differentiate U.S. corn ethanol and Brazilian sugarcane ethanol, help induce the two-way trade between the U.S. and Brazil. U.S. biodiesel could help meet part of the other advanced mandate, which then reduce U.S. imports of sugarcane ethanol to meet the RFS mandates. But this effect is far from eliminating U.S. dependence on imports from Brazil.

Table 2.2: Impacts of RFS mandates on the trade of ethanol between the U.S. and Brazil

	Conventional Mandate	All Mandates (Constrained)	All Mandates	No Mandates
No Trade	192	0	0	97
U.S. Imports from Brazil	9	43	60	1
U.S. Exports to Brazil	299	0	0	402
Two-way Trade	0	457	440	0

Note: All results are expresses in number of observations out of our 500 simulations.

Conventional Mandate

In this scenario, there exist the 14.2 BG conventional mandate and 1.28 BG biodiesel mandate. We assume that biodiesel is not as competitive as corn ethanol to meet the conventional mandate, the ethanol and biodiesel markets are solved separately, given exogenous gasoline price. The second column of Table 2.2 reports the number of observations of different trade patterns of ethanol, given there is only conventional mandate in the ethanol market. Out of our 500 draws, there are 299 observations with the U.S. exporting corn ethanol to Brazil, 192 with no trade, and 9 with the U.S. importing from Brazil. Without the advanced mandate to differentiate U.S. corn ethanol and Brazilian sugarcane ethanol, only one-way trade or no trade of ethanol could happen between the U.S. and Brazil. Large domestic demand of ethanol in Brazil pushes up Brazilian ethanol price to $2.41/gallon, which makes it profitable for the U.S. to export corn ethanol to Brazil even paying the transportation cost. Moreover, for 96% of the simulations, the conventional mandate is binding, mainly due to the inelastic ethanol demand assumption.

The second column of Table 2.3 represents the overall average results with the conventional and biodiesel sub-mandate. The average ethanol price in the U.S. is $2.03/gallon, 27 cents below Brazilian ethanol Price. Average U.S. production is 14.59 BG, with 0.35 BG exporting to Brazil. The average conventional RIN price is $0.75/gallon. The average biodiesel RIN price is $1.77/gallon, high above the conventional RIN price. Because of U.S. increased production of soybean and large export demands from Brazil and Argentina, the soybean and soybean meals prices are very low in our study, while the demand for soybean oil for biodiesel use keeps the soybean oil price high.

Table 2.3: Average Results for Alternative Biofuels Mandate Scenarios in 2013/14

	Conventional Mandate	All Mandates (Constrained)	All Mandates	No Mandates
Conventional Mandate (BG)	14.2	14.2	14.2	0
Biodiesel Sub-Mandate (BG)	1.28	1.28	1.28	0
Other Advanced Mandate Met by Sugarcane Ethanol (BG)	0	1.5	1.41	0
Other Advanced Mandate Met by Biodiesel (BG)	0	0	0.09	0
Corn Price ($/bushel)	4.93	5.35	5.33	4.34
U.S. Ethanol Plant Price ($/gallon)	2.03	2.14	2.14	1.88
Brazilian Ethanol Price ($/gallon)	2.3	2.51	2.49	2.22
Soybean Price ($/bushel)	8.63	8.63	8.67	8.23
Soybean Oil Price (cents/lb)	56.55	56.55	57.43	47.36
Soybean Meals Price ($/short ton)	237.65	237.65	235.63	258.91
U.S. Ethanol Production (BG)	14.59	15.44	15.4	13.42
U.S. Ethanol Exports (BG)	0.35	1.22	1.18	0.61
U.S. Ethanol Imports (BG)	0	1.5	1.41	0
Conventional RIN price ($/gallon)	0.75	0.86	0.86	0
Biodiesel RIN price ($/gallon)	1.77	1.77	1.79	0
Advanced RIN price ($/gallon)	0	1.61	1.59	0

All Mandates (Constrained)

In this scenario, we assume that all RFS mandates in place, but the other advanced mandate can only be met by the imported sugarcane ethanol. Reported in column three of Table 2.2, there are 43 observations with the U.S. importing more than the other advanced mandate, with low corn yield (122.4 bu/ac) and high gasoline price ($3.53/gallon). Comparatively higher demand of ethanol together with shortage of supply induces the U.S. to import more than the other advanced mandate to meet the conventional mandate. The rest 457 observations present two-way trade in ethanol between the U.S. and Brazil. The U.S. has to import sugarcane ethanol to meet the other advanced mandate, and at the same time, the U.S. exports the corn ethanol to Brazil due to the excess supply of corn ethanol in the U.S.

together with increasing domestic demand of ethanol in Brazil. Almost all of the mandates become binding, with an amount of 15.7 BG ethanol demand in the U.S.

The overall average results are shown in the third column of Table 2.3. With the other advanced mandate constrained to be met by the sugarcane ethanol, U.S. imports of sugarcane ethanol increase to 1.5 BG, which induces the U.S. to export more corn ethanol. U.S. ethanol exports increase by 0.87 BG. Increased export demand causes U.S. ethanol price to increase by 11 cents/gallon. U.S. production increased from 14.59 BG to 15.44 BG. In Brazil, ethanol price increases 21 cents/gallon because of the positive net export demand. The average conventional RIN price increases by 11 cents/gallon, which implies that the conventional mandate becomes more binding, and the advanced RIN price is 75 cents, almost equal to two times transportation cost, more than the conventional RIN. All results for the soybean, soybean products, and biodiesel markets remain the same. As an average, the advanced RIN price is still lower than the biodiesel RIN price.

Table 2.4: RIN Prices for Scenarios with All Mandates

	Percentage*	Conventional RIN Price	Advanced RIN Price	Biodiesel RIN Price
Other Advanced Mandate Met by SC	0.75	0.83	1.58	1.85
Other Advanced Mandate Met by SC and BD	0.25	0.94	1.63	1.63

Note: *Percentage of observations out of our 500 simulations. All RIN prices are in ethanol equivalent unit. SC = Sugarcane Ethanol, BD = Biodiesel.

All Mandates

This scenario illustrates the impacts of RFS mandates on the U.S. and Brazil biofuels market. Sugarcane ethanol and biodiesel can compete as the other advanced biofuels. There are 60 observations with the U.S. importing from Brazil and 440 with two-way trade. Biodiesel can help meet 0.09 BG of the other advanced mandate, which reduces U.S. dependence on imported sugarcane ethanol to meet the other advanced mandate, and then decreases the possibility of two-way trade. But this effect is somehow very small. The U.S. still depends on imports to meet the RFS other advanced mandate.

Table 2.4 reports the percentage of corner and interior solutions and corresponding average RINs prices. There are 75% of our observations only using sugarcane ethanol to meet the other advanced mandate. Across these observations, the average conventional RIN price is \$0.83/gallon, and the average advanced RIN price is \$1.58/gallon, lower than the biodiesel RIN price. This implies that sugarcane ethanol has an absolute advantage as the other advanced biofuels. The rest 25% observations use both sugarcane ethanol and biodiesel to meet the other advanced mandate, such that the advanced RIN price equal to the biodiesel RIN price. And no observation uses only biodiesel. The overall average advanced RIN price is \$1.59/gallon. Comparing with the case with constrained all mandates, alternative source of other advanced biofuels leads to a small decrease in the average corn price, ethanol production, ethanol exports and soybean meal price, while increases in average soybean, soybean oil prices.

No Mandates

To be complete, this scenario assumes a waiver of all biofuels mandates. There are 402 out of 500 observations with the U.S. exporting to Brazil, and 97 with no trade between the U.S. and Brazil. The conventional mandate reduces the probability for the U.S. to export to Brazil by 20%. However, RFS mandates induce two-way trade between the U.S. and Brazil, and increase the exports of the U.S.

If RFS mandates are waived, U.S. average ethanol demand drops from 15.63 BG to 12.8 BG, and U.S. ethanol production declines by 1.98 BG. The decrease in export demand leads to a drop of 12.1% in the U.S. ethanol price, and a drop of 10.8% in Brazilian ethanol price. The corn price decreases by 18.6% (or 99 cents/bushel). The average soybean and soybean oil prices decline by 5% and 17.5%, respectively. Soybean meals price increases by 10%. The large impacts of removing all mandates rely on the assumption that no carry-over RINs are used to meet the obligations.

Sensitivity Analysis

In this section, we investigate the robustness of our results to U.S. gasoline price and Brazil ethanol production. We vary the two variables one at a time and re-run the model for the marketing year 2013/14. And then compare the results for the scenario with all RFS mandates. Moreover, we also consider the sensitivity of our results to U.S. corn yield, which could imply the effects of shocks in U.S. ethanol supply.

U.S. Gasoline Price

We calculate the equilibriums for three fixed gasoline prices: a low gasoline price of \$1.5/gallon, the average price of \$2.55/gallon, and a high price of \$3.5/gallon.[32] The results for the scenario with all RFS mandates are shown in Table 2.5.

[32] These gasoline prices used are just to show the effects of gasoline prices on our average results. They do not provide any information of the distribution of the gasoline price.

U.S. gasoline price has a small effect with all RFS mandates in place, which is away from the results in Thompson, Meyer and Westhoff (2008) due to the assumption of the inelastic demand of ethanol in the U.S. Because of the difficulty of the U.S. to blend more than 10% ethanol into its auto fleets, and the limitations in the investments in E85 and sales of flex-fuels vehicles, even with a high gasoline price to promote consumers' willingness to consume ethanol, the RFS mandates are still almost binding. But RFS mandates still help induce two-way trade between the U.S. and Brazil.

Table 2.5: Market Effects of U.S. Gasoline Price

Gasoline Price	1.5$/gallon	2.55$/gallon	3.5$/gallon
Percentage with Two-way Trade[1]	0.9	0.88	0.87
Percentage using both fuels[2]	0.1	0.22	0.4
Corn Price ($/bushel)	5.33	5.32	5.3
U.S. Ethanol Plant Price ($/gallon)	2.14	2.14	2.13
Brazil Ethanol Price [3]($/gallon)	2.5	2.49	2.48
Soybean Price ($/bushel)	8.65	8.67	8.7
Soybean Oil Price (cents/pound)	56.85	57.3	58.06
Soybean Meals Price ($/short ton)	236.96	235.39	234.18
U.S. Ethanol Production (BG)	15.41	15.39	15.35
U.S. Ethanol Exports (BG)	1.21	1.19	1.14
U.S. Ethanol Imports (BG)	1.47	1.43	1.35
Conventional RIN Price ($/gallon)	1.39	0.86	0.38
Biodiesel RIN Price ($/gallon)	2.43	1.79	1.23
Advanced RIN Price ($/gallon)	2.13	1.6	1.11

Note: All results are reported in the regular units in the market. All RIN prices are in ethanol equivalent unit. 1Percentage of observations with the U.S. exporting corn ethanol to Brazil, and importing sugarcane ethanol from Brazil simultaneously.2Percentage of observations using both sugarcane ethanol and biodiesel to meet the other advanced mandate.3Brazilian domestic wholesale anhydrous ethanol price, with exchange rate at 2.05 reals per dollar.

With U.S. biodiesel as an alternative source of the other advanced biofuels, when the gasoline price increases, biodiesel becomes comparatively more competitive. At the gasoline price of $3.5/gallon, the percentage using both fuels to meet the other advanced mandate increases by 18%. But in general, biodiesel is still more expensive. There is only an amount of 0.08 BG decrease in the U.S. imports. But the increase in the gasoline price leads to significant drops in the RINs prices through increasing the demand prices, 55.8% in the conventional RIN price, 31.3% in the biodiesel RIN price, and 30.6% in the advanced RIN price. When the gasoline price decreases, the effects are inversed as shown in Table 2.5.

Brazilian Ethanol Production

With concerns about the sensitivity of our results to Brazilian ethanol production, we vary the calibration point of Brazil ethanol supply curve in our model. Shocks of Brazilian ethanol supply could also come from variations in the sugarcane yield in Brazil and changes in world sugar price. But these effects on the average results are similar as our analysis in this section. When the price ratio of ethanol to gasoline is 0.7 in Brazil, Brazilian ethanol production is recalibrated from the average 26 billion liters to a low production level of 22 billion liters and a high production level of 30 billion liters. The average results are illustrated in Table 2.6.

When ethanol production is low, 97% of our observations have two-way trade happening between the U.S. and Brazil, 9% more than the case with ethanol production about 26 billion liters. Facing high domestic demand, Brazilian ethanol price increases by 10 cents and imports demand of corn ethanol from the U.S. increase by nearly 50% (0.63 BG). U.S. ethanol price also increases by 9 cents to entice enough production to meet the increased demand from Brazil. U.S. ethanol production increases by 0.63 BG and the corn price rises by 5.8%.

Table 2.6: Market Effects of Brazilian Ethanol Production

	22 billion liters	26 billion liters	30 billion liters
Percentage with Two-way Trade[1]	0.97	0.88	0.75
Percentage using both fuels[2]	0.38	0.25	0.05
Corn Price ($/bushel)	5.64	5.33	5.04
U.S. Ethanol Plant Price	2.22	2.14	2.06
Brazil Ethanol Price [3]($/gallon)	2.59	2.49	2.38
Soybean Price ($/bushel)	8.71	8.67	8.64
Soybean Oil Price (cents/pound)	58.2	57.43	56.7
Soybean Meals Price ($/short ton)	233.84	235.63	237.3
U.S. Ethanol Production (BG)	16.03	15.4	14.82
U.S. Ethanol Exports (BG)	1.81	1.18	0.6
U.S. Ethanol Imports (BG)	1.34	1.41	1.49
Conventional RIN Price ($/gallon)	0.94	0.86	0.78
Biodiesel RIN Price ($/gallon)	1.83	1.79	1.77
Advanced RIN Price ($/gallon)	1.7	1.59	1.48

Note: All results are reported in the regular units in the market. All RIN prices are in ethanol equivalent unit. 1Percentage of observations with the U.S. exporting corn ethanol to Brazil, and importing sugarcane ethanol from Brazil simultaneously.2Percentage of observations using both sugarcane ethanol and biodiesel to meet the other advanced mandate.3Brazilian domestic wholesale anhydrous ethanol price, with exchange rate at 2.05 reals per dollar.

The percentage using both sugarcane ethanol and biodiesel to meet the other advanced mandate increases by 13%, and U.S. ethanol imports drop by 0.07BG, which implies the shortage of sugarcane ethanol from Brazil makes U.S. biodiesel more competitive as the other advanced biofuels. This also confirms that U.S. biodiesel could reduce U.S. dependence on imports to meet RFS mandates in some extent. Soybean and soybean oil prices increase, while soybean meals price drops. The average conventional RIN price increases by 8 cents, with the average advanced RIN price two times of the transportation cost more than the conventional RIN price. The effects are inversed for a high level of ethanol production in Brazil, shown in Table 2.6.

U.S. Corn Yield

Low corn yield due to bad weather conditions is one of the most important shifter of U.S. ethanol supply. We compare the average market results from low, moderate and high corn yields[33], with results reported in Table 2.7.

When U.S. corn yield is as low as 143.8 bu/ac, only 40% of 100 observations have two-way trade between the U.S. and Brazil, with the U.S. exports 0.12 BG corn ethanol to Brazil, while imports 1.26 BG sugarcane ethanol from Brazil. The exports decrease by 1.53 BG from those with the moderate corn yield (162.9 bu/ac). A shortage in corn supply leads to a high corn price at $6.83/bushel, and it could go higher if the corn yield further decreases as in 2012 that U.S. corn prices goes above $8/bushel with the extreme low corn yield at 122.8 bu/ac. Comparing with the case with the moderate corn yield, U.S. ethanol production from corn decreases by 1.37 BG and U.S. ethanol price drops by 27.8% ($0.55/gallon). Brazilian ethanol price also goes up by $0.43/gallon due to the decreased exports of corn ethanol to Brazil.

Poor corn yield also increases the competitiveness of biodiesel as the other advanced mandate, 67% of 100 observations use both fuels to meet the other advanced mandate. Biodiesel helps meet 0.24 BG of the other advanced mandate, increased from 0.01 BG in the moderate corn yield case. Soybean, soybean meals and soybean oil prices all rises due to the demand for biodiesel, and also due to the comparatively low soybean yield.[34] All RINs prices increase because of the increased supply prices.

[33] We sort our draws by corn yield, then compare the first, middle and last quintiles and report the average results.

[34] As corn and soybean in the U.S. are usually grown in the same area, and then experience the same weather conditions. Corn yield and Soybean yield has a positive correlation. We impose the correlation on the draws of these two yields. The correlation is derived from the historical data.

Table 2.7: Market Effects of U.S. Corn Yield

U.S. Corn Yield	143.8 bu/ac	162.9 bu/ac	176.3 bu/ac
Percentage with Two-way Trade[1]	0.4	1	1
Percentage using both fuels[2]	0.67	0.04	0.09
Corn Price ($/bushel)	6.83	4.73	4.71
U.S. Ethanol Plant Price ($/gallon)	2.53	1.98	1.97
Brazil Ethanol Price [3]($/gallon)	2.79	2.36	2.35
Soybean Price ($/bushel)	9.97	8.34	8.15
Soybean Oil Price (cents/pound)	61.26	56.12	55.93
Soybean Meals Price ($/short ton)	263.49	229.54	224.09
U.S. Ethanol Production (BG)	14.32	15.69	15.77
U.S. Ethanol Exports (BG)	0.12	1.65	1.65
U.S. Ethanol Imports (BG)	1.26	1.49	1.47
Conventional RIN Price ($/gallon)	1.22	0.69	0.69
Biodiesel RIN Price ($/gallon)	1.91	1.73	1.72
Advanced RIN Price ($/gallon)	1.86	1.45	1.45

Note: All results are reported in the regular units in the market. All RIN prices are in ethanol equivalent unit. 1Percentage of observations with the U.S. exporting corn ethanol to Brazil, and importing sugarcane ethanol from Brazil simultaneously.2Percentage of observations using both sugarcane ethanol and biodiesel to meet the other advanced mandate.3Brazilian domestic wholesale anhydrous ethanol price, with exchange rate at 2.05 reals per dollar.

Conclusions

In this paper, we construct a stylized trade model between the U.S. and Brazil, and illustrate the equilibrium conditions. We apply the RFS biofuels mandates to the U.S. ethanol market in our model, and use this policy to understand the competition between corn ethanol and Brazilian sugarcane ethanol to meet the conventional RFS mandate and also the competition between Brazilian sugarcane ethanol and biodiesel to meet the other advanced mandate.

We then explore the determinations of various RINs prices and the relationship between these RIN prices. Starting from a hypothetic case that there is no advanced mandate in place, we derive the supply of advanced RINs from sugarcane ethanol. We also get insights of the RINs prices from the ethanol trade pattern between the U.S. and Brazil. Both the conventional and advanced RIN prices are non-decreasing with the other advanced mandate. With two-way trade between the U.S. and Brazil, the advanced RIN price is two times transportation cost more than the conventional RIN price. When the U.S. imports an amount of the other advanced mandate, the conventional and advanced RIN price gap is less than two times transportation cost. When the U.S. imports more than the other advanced mandate, the conventional RIN price equals the advanced RIN price. The model is then extended to take into account of U.S. biodiesel as an alternative to meet the other advanced mandate, and discuss the possibility to use both biodiesel and sugarcane ethanol to meet the other advanced mandate.

Specifically, with stochastic gasoline prices and feedstock yields from our projected distribution, we calibrate the demands and supplies of all related products to solve for market clearing prices and quantities for the marketing year 2013/14. The average values are used to estimate the impacts of RFS on U.S. biofuels market. Our results consistently show that RFS biofuels mandates motivate the two-way trade between the U.S. and Brazil. U.S. biodiesel could help meet the other advanced mandate to some extent, but currently still could not eliminate U.S. dependence on imported sugarcane ethanol to meet the RFS mandates. Variation in U.S. gasoline price, Brazil ethanol production and U.S. corn yield levels would change the magnitude of U.S. exports to the Brazil, and also impact the comparative competiveness of U.S. biodiesel as the source of the other advanced biofuels. With the difficulty to blend more than 10% ethanol into gasoline, the U.S. ethanol demand is very inelastic and constrains the impacts of high gasoline price and high corn yield on commodities prices. And the RFS mandates also constrain the impacts of downside gasoline price change. With a poor corn yield as in 2012, RFS mandates could help explain the increase in all commodities prices and all RIN prices, and the decrease in the U.S. exports of corn ethanol.

References

Anderson, S. T. (2011). The demand for ethanol as a gasoline substitute. *Journal of Environmental Economics and Management*, 63(2): 151-168.

Babcock, B. A. (2010). Mandates, tax credits, and tariffs: Does the U.S. biofuels industry need them all? Center for Agricultural and Rural Development Policy Brief 10-PB1.

Babcock, B. A., Barr, K. J. and Carriquiry, M. (2010). Costs and benefits to taxpayers, consumers, and producers from U.S. ethanol policies. Center for Agricultural and Rural Development Staff Report 10-SR-106.

Cui, J., Lapan, H. E., Moschini, G., and Cooper, J. (2011).Welfare impacts of alternative biofuel and energy policies. *American Journal of Agricultural Economics*, 93(5): 1235-1256.

Crago, C. L., Khanna, M., Barton, J., Giuliani, E., and Amaral, W. (2010). Competitiveness of Brazilian sugarcane ethanol compared to U.S. corn ethanol. *Energy Policy*, 38(11): 7404-7415.

Federal Register. (2012). Regulation of fuels and fuel additives: 2013 Biomass-Based Diesel renewable fuel volume: final rule.

Paulson, N. D., Ginder, R. G. (2007). Growth and direction of the Biodiesel industry in the United States. Center for Agricultural and Rural Development Working Paper 07-WP-448.

Schnepf, R. and Yacobucci, D. B.(2013). Renewable Fuel Standard (RFS): Overview and issues. Congressional Research Service.

Thompson, W., Meyer, S., and Westhoff, P. (2009). How does petroleum price and corn yield volatility affect ethanol markets with and without an ethanol use mandate? *Energy Policy* 37: 745-749.

Thompson, W., Meyer, S., and Westhoff, P. (2010). The new markets for Renewable Identification Numbers. *Applied Economic Perspectives and Policy* 32(4): 588-603.

USDA. 2012. World agricultural supply and demand estimates.WASDE-512. November.

USDA. 2012. Brazil Biofuels Annual. USDA Foreign Agricultural Service Gain Report.

Yacobucci, D. B. (2012). Biofuels incentives: A summary of federal programs. Congressional Research Service.

CHAPTER 3. IMPACT OF WEATHER AND SOIL MOISTURE ON CORN YIELD IN THE US MIDWEST

Abstract

In this study, a linear spline fixed effect model is constructed to estimate the impact of climate variables on corn yields by adding in soil moisture as an explanatory variable into the corn yield response function. Recent two drought years 2011 and 2012 are included in the estimation dataset that facilitates estimation of corn yield response to extreme conditions. The daily soil moisture data in the Upper Mississippi River Basin Area from 1980 to 2012 is simulated from the crop model EPIC, which has very comprehensive interactions between hydrology, weather, soil, nutrients, crop and plant environment controls. Bayesian Markov Chain Monte Carlo (MCMC) approach and Metropolis-Hasting algorithm are applied to estimate the two-knot spline models. Our results suggest that the effects of high temperature on corn yield should be evaluated together with water availability. The yield reduction from high temperature is 15 to 20 percentage points greater under low compared to average water availability. With increased spring rainfall projection, it is reasonable to question that whether the effects of high temperature have been overlooked in recent studies. Moreover, our findings indicate that the determinant factors for corn yield losses vary across the U.S. Midwest. Excessive spring rainfall in Iowa and Illinois is damaging to corn yield, however, could help reduce yield losses during hot and dry summers through the soil moisture effect. In Wisconsin, too little spring rainfall is more damaging than too much.

Introduction

Numerous studies have focused on the impact of climate change on crop yields. Most confirm that it can significantly impact the agricultural production, especially focusing on the negative effects of high temperature (Schlenker and Roberts 2006, 2009, Hatfield et al. 2011, Lobell et al. 2013). A shortage of agricultural supply then has the potential to push up the food and fuel prices, and may even trigger food crisis and social problems in some poor countries. In 2012, extreme heat and lack of precipitation sharply decreased the corn and soybean productions in the United States, which accounts for about 40% of the world's corn production. Together with the demand from biofuels industry, the average corn price in the marketing year 2012/13 was pushed up to about $7.8/bushel, with U.S. corn exports decreased by 40% comparing with 2010/11. Future globe warming could further exaggerate this situation (Lobell et al. 2011). Thus, it is imperative to clearly understand how climate change would impact the crop yields.

Most studies of the crop yield response to the climate change use econometric regression models to identify the effects of temperature and precipitation on crop yields from historical data. Using panel data of corn yield, temperature, and precipitation from 1950 to 2004 in 2000 counties of the U.S., Schlenker and Roberts (2006) find that corn yields are increasing in temperature for moderate temperature, but significantly decreasing once temperature exceeds 30°C.Yu and Babcock (2011) estimate impacts of both rainfall and temperature on corn yields across states in the U.S. Corn Belt by fitting a linear spline model with endogenous thresholds to avoid the symmetric restriction of quadratic functional form. However, studies consider soil moisture factors are limited. Exceptional increase in rainfall in the U.S. Midwest (Kunkel et al. 2013, Anderson et al. 2013) makes it more important to consider the soil moisture effect to project the climate impact on corn yield. Several studies use a number of soil quality variables as controls in their regression equations (Schlenker et al. 2006, Deschenes and Greenstone 2007). With data from 1954 to 1988 in central Iowa, Carlson (1990) includes July 1st and August 1st plant-available soil moisture variables into his linear regression model, and finds significant positive correlations with corn yields. Roberts et al. (2012) includes the vapor pressure deficit derived from temperatures into their regression, which is closely related to relative humidity, and influences evapotranspiration and soil moisture.

Our study estimates the corn yield response function by adding soil moisture as an explanatory variable. Soil moisture reflects the long-run accumulated soil water storage for crops and the information of the initial state of the soil water condition. During periods of high temperature, more soil moisture may help resist the drought and moderate potential damages, while less soil moisture can exaggerate the damaging effects and induce more yield losses. Daily soil moisture data in the Upper Mississippi River Basin area (UMRB, Figure 3.1)[35]from 1980 to 2012 is simulated from crop model Environmental Policy Integrated Climate (EPIC).These models usually have comprehensive theory background, and are constructed to include the interactions of hydrology, weather, soil, nutrients and plant environment controls. Izaurralde et al. (2003) assess the impact of future climate change on U.S. corn and wheat yields by simulations using the Environmental Policy Integrated Climate (EPIC) model (Williams, 1995). The widely used drought indices Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) are derived in Narasimhan and Srinivasan (2005) based respectively on weekly soil moisture deficit and evapotranspiration

[35] Upper Mississippi River Basin includes large parts of Illinois (85 counties), Iowa (76 counties), Minnesota (72 counties), Missouri (37 counties), and Wisconsin (55 counties), and small areas in Indiana (13 counties), Michigan (1 county), and South Dakota (6 counties).

deficit using the distributed hydrologic model Soil and Water Assessment Tool (SWAT). These models are also widely used to simulate the impacts of projected climate change and the benefits and costs of alternative environmental policies (Thomson et al. 2002, Feng et al. 2007).

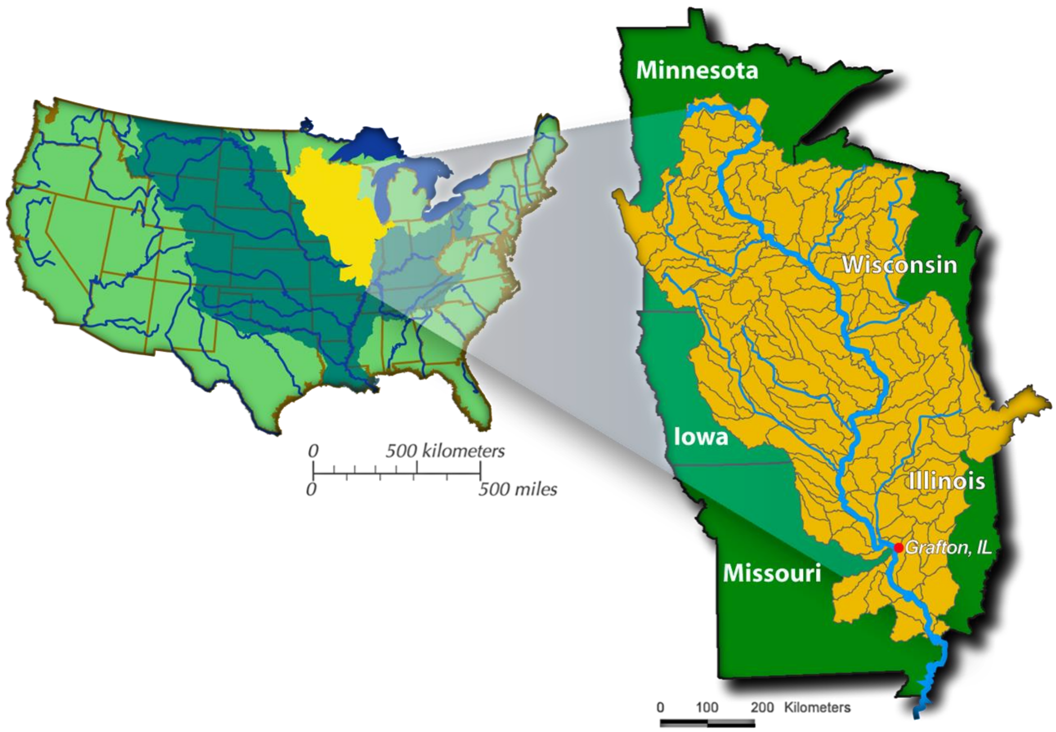

Figure 3.1 Upper Mississippi River Basin

Source: Feng et al. 2007

Recent two drought years 2011 and 2012 are included in the estimation dataset to facilitate estimation of corn yield response to extreme conditions. Bayesian Markov Chain Monte Carlo approach in Yu and Babcock (2010) is applied to estimate the parameters and the thresholds of the two-knot spline yield response functions simultaneously. Our results suggest that the effects of high temperature on corn yield should be evaluated together with water availability. The yield reduction from high temperature is 15 to 20 percentage points greater under low compared to average water availability. With increased spring rainfall projection, it is reasonable to question that whether the effects of high temperature have been overstated in recent studies. Soil water availability could play an important role and it could not be reasonably described using growth season precipitation only. Moreover, our findings indicate that the determinant factors for corn yield losses vary across the U.S. Midwest. Excessive spring rainfall in Iowa and Illinois is damaging to corn yield, however, could help reduce yield losses during hot and dry summers through the soil moisture effect. In Wisconsin, too little spring rainfall is more damaging than too much.

Data

In this study, we estimate the impacts of temperature, precipitation and soil moisture on corn yield. The data is a balanced panel of counties across major states in the Upper Mississippi River Basin ranging from 1980 to 2012. We have a total of 8547 observations including 2508 from 76 Iowa counties, 2508 from 76 Illinois counties, 2013 from 61 Minnesota counties, and 1518 from 46 Wisconsin counties. All counties with yield data in all years from 1980 to 2012 are included.[36] Counties in UMRB rely mainly on rainfall for soil moisture, which helps to focus on the weather and soil moisture impacts.

Corn yield is constructed as corn production divided by planted acres. County-level corn production and planted acreage data is collected from the U.S. Department of Agriculture's National Agricultural Statistics Service (USDA-NASS).

[36] There are 9 counties in Illinois with missing corn yield data, 11 in Minnesota, 14 in Missouri, and 9 in Wisconsin.

We use the same 1/8 degree gridded daily data for the maximum temperature, minimum temperature and precipitation as in Maurer et al. (2002)[37], and extend it to span the period 1979-2012.The soil moisture data is simulated using the EPIC model, version 1102-64 (Izaurralde et al. 2006).[38] EPIC simulations are carried out at a field-scale level for areas homogeneous in weather, soil, land-scape, crop rotation, and management system parameters using a continuous daily time step for 34 years from 1979 to 2012. The Natural Resource Inventory database provides information on the natural resource characteristics of the landscape, soil, crop rotation and other input data for the simulations. The daily maximum and minimum temperatures and precipitation data is used as weather inputs in EPIC. Each field in EPIC runs is matched with the nearest 1/8th degree weather grid point. The simulated data for 1979 is omitted to minimize the starting effects.

In our regression, we include May to August as corn growth season. Because extreme heat always happens in July and August and water requirement for corn growth in July and August is higher than in May and June (Evans et al. 1996), we divide the growth season into two time intervals May to June (MJ, planting and early vegetative growth) and July to August (JA, pollination and grain fill).Daily maximum and minimum temperatures, precipitation and root zone soil water content for each field are averaged for each time interval. The arithmetic mean of the maximum and minimum temperatures is used as the average temperature. The area-weighted average over all fields within a county is constructed to obtain county-level data.

[37] In Maurer et al. (2002), daily precipitation totals from the National Oceanic and Atmospheric Administration Cooperative Observer (Co-op) stations were assigned to each day based on the time observation for the gauge. The precipitation gauge data were gridded to the 1/8 resolution using the synergraphic mapping system algorithm. The gridded daily precipitation data were then scaled to match the long-term average of the Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation climatology. The minimum and maximum daily temperature data from Co-op stations were gridded using the same algorithm as for precipitation, and were lapsed to the grid cell mean elevation.

[38] Additional information concerning EPIC can be found in Gassman et al. 2004.

The mean and standard errors of corn yield, temperature, precipitation, and soil moisture for Illinois, Iowa, Minnesota, and Wisconsin are summarized in Table 3.1. The temperature in July and August is about 4°C higher than in May and June. And the soil moisture in July and August is much lower than that in May and June. Iowa and Illinois have more spring rainfall compared to Minnesota and Wisconsin. Soil moisture reservoir is deepest in Illinois, slightly less in Iowa, and substantially less in Minnesota and Wisconsin.

Table 3.1: Yield, Weather and Soil Moisture Statistical Mean and Standard Errors

	Illinois	Iowa	Minnesota	Wisconsin
Number of Observation	2508	2508	2013	1518
Corn Yield (bushels per planted acre)	130.81	133.04	116.54	94.44
	(33.45)	(31.88)	(37.11)	(28)
Temperature in May and June (°C)	19.66	18.30	16.81	16.34
	(1.53)	(1.33)	(1.43)	(1.30)
Temperature in July and August (°C)	23.86	22.63	21.28	20.90
	(1.63)	(1.53)	(1.37)	(1.41)
Precipitation in May and June (mm)	3.59	3.91	3.28	3.34
	(1.46)	(1.52)	(1.16)	(1.29)
Precipitation in July and August (mm)	3.08	3.59	3.24	3.48
	(1.23)	(1.59)	(1.15)	(1.19)
Soil Moisture on May 1st(mm)	210.16	171.27	142.87	145.52
	(39.11)	(45.45)	(48.28)	(38.00)
Soil Moisture on July 1st(mm)	144.56	124.59	105.74	97.95
	(45.29)	(53.69)	(51.34)	(41.35)

Note: Standard errors are in the parenthesis.

The Model

Impacts of weather and soil water on corn yield for major states in UMRB are estimated individually. We are following Yu and Babcock (2010) to use two-knot spline yield response functions and Bayesian Markov Chain Monte Carlo approach to estimate the parameters and thresholds simultaneously. This method captures the nonlinear and asymmetric features of weather impacts on corn yield and has the advantage of high computational efficiency.

Log corn yield is specified to be composed of a linear trend and two-knot spline functions of temperature, precipitation and soil moisture variables. In our regression models, we have the average daily temperature, and precipitation across May to June, and July to August and also May 1st and July 1st soil moisture variables.

The Control Model

The control model only includes the two most frequently used weather variables temperature and precipitation so that it is comparable with existing literatures and also could be the base case for us to study the role of soil moisture in response to corn yield. The control model is as follows:

$$\begin{aligned} 100 * \log(Y_{i,t}) = \quad & \alpha_i + \beta_0 Year \\ & + \sum_{j=MJ,JA} (\beta_{T,1}^j \min(0, T_{i,t}^j - T_{low}^j) + \beta_{T,2}^j T_{i,t}^j + \beta_{T,3}^j \max(0, T_{i,t}^j - T_{high}^j)) \\ & + \sum_{j=MJ,JA} (\beta_{P,1}^j \min(0, P_{i,t}^j - P_{low}^j) + \beta_{P,2}^j P_{i,t}^j + \beta_{P,3}^j \max(0, P_{i,t}^j - P_{high}^j)) \\ & + \epsilon_{i,t} \end{aligned}$$

Subscripts *i*, *t* denote county and year, respectively. *j* represents different time interval, either May to June or June to August. *Y* denotes corn yield. *Year* is the time trend variable. *T* and *P* represent the average temperature and precipitation. α_i is the county fixed-effect parameter, which absorbs all unobserved time-invariant and county-specific determinants of corn yield. T_{low} and T_{high} are the low and high thresholds that divide the average temperature into three ranges, P_{low} and P_{high} for the average precipitation. These thresholds are estimated together with the coefficients α and β.

The percentage marginal effects of the average temperature and precipitation are measured as follows:

$$\beta_{T,s}^{j} = \begin{cases} \beta_{T,low}^{j} = \beta_{T,1}^{j} + \beta_{T,2}^{j} & \text{if } T_{i,t}^{j} \leq T_{low}^{j} \\ \beta_{T,med}^{j} = \beta_{T,2}^{j} & \text{if } T_{low}^{j} \leq T_{i,t}^{j} \leq T_{high}^{j} \\ \beta_{T,high}^{j} = \beta_{T,2}^{j} + \beta_{T,3}^{j} & \text{if } T_{i,t}^{j} \geq T_{high}^{j} \end{cases}$$

$$\beta_{P,s}^{j} = \begin{cases} \beta_{P,low}^{j} = \beta_{P,1}^{j} + \beta_{P,2}^{j} & \text{if } P_{i,t}^{j} \leq P_{low}^{j} \\ \beta_{P,med}^{j} = \beta_{P,2}^{j} & \text{if } P_{low}^{j} \leq P_{i,t}^{j} \leq P_{high}^{j} \\ \beta_{P,high}^{j} = \beta_{P,2}^{j} + \beta_{P,3}^{j} & \text{if } P_{i,t}^{j} \geq P_{high}^{j} \end{cases}$$

Subscript s denotes the state of the weather condition, where $\beta_{T,low}$ ($\beta_{P,low}$) represents the marginal effects of average temperature (precipitation) when the temperature (precipitation) falls below the lower threshold, $\beta_{T,med}$ ($\beta_{P,med}$) for the range between the lower and upper thresholds, $\beta_{T,high}$ ($\beta_{P,high}$) for the range above the upper threshold. This model specification allows the weather effects to vary with the weather conditions, which shows the nonlinear and asymmetric impacts of weather variables and also improves the model interpretability.[39] One degree increase in summer temperature might result in more damages to corn yield in drought years than in cool years.

[39] The variable mean may not necessarily fall between the two thresholds.

The Dry-Hot Model

The Dry-Hot model adds the two-knot spline functions of May 1st and July 1st soil moisture. Moreover, to illustrate the soil moisture effect of water availability on yield losses from heat, we also incorporate the interactions of July-August high heat, July-August low precipitation and July 1st low soil moisture. The model is as follows:

$$\begin{aligned} 100 * \log(Y_{i,t}) = \; & \alpha_i + \beta_0 Year \\ & + \sum_{j=MJ,JA} (\beta_{T,1}^{j} \min(0, T_{i,t}^{j} - T_{low}^{j}) + \beta_{T,2}^{j} T_{i,t}^{j} + \beta_{T,3}^{j} \max(0, T_{i,t}^{j} - T_{high}^{j})) \\ & + \sum_{j=MJ,JA} (\beta_{P,1}^{j} \min(0, P_{i,t}^{j} - P_{low}^{j}) + \beta_{P,2}^{j} P_{i,t}^{j} + \beta_{P,3}^{j} \max(0, P_{i,t}^{j} - P_{high}^{j})) \\ & + \sum_{j=May1,Jul1} (\beta_{S,1}^{j} \min(0, S_{i,t}^{j} - S_{low}^{j}) + \beta_{S,2}^{j} S_{i,t}^{j} + \beta_{S,3}^{j} \max(0, S_{i,t}^{j} \\ & \qquad - S_{high}^{j})) \\ & + \beta_{TP}^{JA} \max\left(0, T_{i,t}^{JA} - T_{high}^{JA}\right) * \min(0, P_{i,t}^{JA} - P_{low}^{JA}) \\ & + \beta_{TS}^{JA} \max\left(0, T_{i,t}^{JA} - T_{high}^{JA}\right) * \min(0, S_{i,t}^{Jul\,1} - S_{low}^{Jul\,1}) \\ & + \beta_{PS}^{JA} \min(0, P_{i,t}^{JA} - P_{low}^{JA}) * \min(0, S_{i,t}^{Jul\,1} - S_{low}^{Jul\,1}) + \epsilon_{i,t} \end{aligned}$$

S denotes soil moisture in the root zone, with two thresholds S_{low} and S_{high}. For May-June temperature and precipitation and May 1st soil moisture, the percentage marginal impacts are similar as the control model. With the interaction terms, the percentage marginal effects of July-August temperature and precipitation and July 1st soil moisture are conditional on all three variables. For example, one degree increase in summer temperature could result in different amount of change in corn yield in dry years than in normal or wet years; more rainfall might be more helpful when soil water availability is limited than abundant. Specifically,

$$\beta_{T,s}^{JA} = \begin{cases} \beta_{T,low}^{JA} = \beta_{T,1}^{JA} + \beta_{T,2}^{JA} & \text{if } T_{i,t}^{JA} \leq T_{low}^{JA} \\ \beta_{T,med}^{JA} = \beta_{T,2}^{JA} & \text{if } T_{low}^{JA} \leq T_{i,t}^{JA} \leq T_{high}^{JA} \\ \beta_{T,high}^{JA} = \beta_{T,2}^{JA} + \beta_{T,3}^{JA} + \beta_{TR}^{JA} * \min\left(0, R_{i,t}^{JA} - R_{low}^{JA}\right) & \\ \qquad + \beta_{TS}^{JA} * \min(0, S_{i,t}^{Jul\,1} - S_{low}^{Jul\,1}) & \text{if } T_{i,t}^{JA} \geq T_{high}^{JA} \end{cases}$$

$$\beta_{P,s}^{JA} = \begin{cases} \beta_{P,low}^{JA} = \beta_{P,1}^{JA} + \beta_{P,2}^{JA} + \beta_{TP}^{JA} * \max\left(0, T_{i,t}^{JA} - T_{high}^{JA}\right) & \\ \qquad + \beta_{PS}^{JA} * \min(0, S_{i,t}^{Jul\,1} - S_{low}^{Jul\,1}) & \text{if } P_{i,t}^{JA} \leq P_{low}^{JA} \\ \beta_{P,med}^{JA} = \beta_{P,2}^{JA} & \text{if } P_{low}^{JA} \leq P_{i,t}^{JA} \leq P_{high}^{JA} \\ \beta_{P,high}^{JA} = \beta_{P,2}^{JA} + \beta_{P,3}^{JA} & \text{if } P_{i,t}^{JA} \geq P_{high}^{JA} \end{cases}$$

$$\beta_{S,s}^{JA} = \begin{cases} \beta_{S,low}^{Jul1} = \beta_{S,1}^{Jul1} + \beta_{S,2}^{Jul1} & \\ \qquad + \beta_{TS}^{JA} * \max\left(0, T_{i,t}^{JA} - T_{high}^{JA}\right) + \beta_{PS}^{JA} & \text{if } S_{i,t}^{Jul1} \leq S_{low}^{Jul1} \\ \qquad * \min(0, P_{i,t}^{JA} - P_{low}^{JA}) & \\ \beta_{S,med}^{Jul1} = \beta_{S,2}^{Jul1} & \text{if } S_{low}^{Jul1} \leq S_{i,t}^{Jul1} \leq S_{high}^{Jul1} \\ \beta_{S,high}^{Jul1} = \beta_{S,2}^{Jul1} + \beta_{S,3}^{Jul1} & \text{if } S_{i,t}^{Jul1} \geq S_{high}^{Jul1} \end{cases}$$

Estimation Results

We followed Yu and Babcock (2010) to use Bayesian approach to estimate the parameters and thresholds simultaneously. 20,000 iterations are simulated with the first 5000 as the burn-in period. The mean and the standard deviation of the posterior distributions are calculated based on the 15,000 draws for each parameter.

Results for the Control Model

Table 3.2 presents the posterior mean and standard deviation of the parameters of the control model. The linear trend estimates are all positive and statistically significant in all four states, ranging from 1.34% increase in corn yield per year in Illinois to as high as 2.1% increase per year in Minnesota. Table 3.3 shows the lower and upper thresholds for all four weather variables across the four states.

For each weather variable, the first coefficient measures the difference between the percentage marginal impact on corn yield when it is below the lower threshold and the percentage marginal impact when it is between the two threshold; the third is the difference between the percentage marginal impact on corn yield when it is between the two threshold and the marginal impact when it is above the threshold. To better illustrate the percentage marginal impact of weather variables on corn yield. Using the 15,000 draws of the coefficients, we simulate the percentage impact of each variable. The mean and standard deviation are illustrated in Table 3.4.

$\beta^{JA}_{T,low}$, $\beta^{JA}_{T,high}$, $\beta^{MJ}_{P,low}$, $\beta^{MJ}_{P,high}$and $\beta^{JA}_{P,low}$ are statistically significant across all four states. The percentage marginal impact of July-August temperature is negative in Iowa and Illinois and positive in Wisconsin and Minnesota, which might be explained by the spatial variation in temperature. Historical average July-August temperature in Iowa and Illinois is at least 1.4°C higher than in Minnesota and Wisconsin. The marginal impacts of July-August temperature almost all become negative when the temperature increases above the lower threshold. And the impact magnitudes increase significantly when July-August temperature is over the upper threshold, which indicates additional heat in July-August is more harmful for corn yield in dry summer than in normal condition. When above the upper threshold, one

Table 3.2: Posterior Mean and Standard Deviation of Coefficients of the Control Model

	Illinois	Iowa	Minnesota	Wisconsin
β_0	1.34*	1.47*	2.10*	1.53*
	(0.04)	(0.03)	(0.05)	(0.06)
$\beta_{T,1}^{MJ}$	7.30	7.08*	8.42*	8.17*
	(3.84)	(2.97)	(1.42)	(2.64)
$\beta_{T,2}^{MJ}$	-5.96	-1.51	-2.88*	-0.94
	(4.12)	(4.00)	(1.24)	(2.64)
$\beta_{T,3}^{MJ}$	13.95*	-1.24	-10.82*	-4.35
	(6.58)	(5.06)	(3.45)	(4.27)
$\beta_{T,1}^{JA}$	5.81*	6.61*	9.68*	15.14*
	(0.94)	(0.88)	(3.08)	(3.35)
$\beta_{T,2}^{JA}$	-10.62*	-9.10*	-1.21	-3.71*
	(0.89)	(0.69)	(0.70)	(0.77)
$\beta_{T,3}^{JA}$	-21.23*	-20.30*	-11.67*	-9.42*
	(2.41)	(1.93)	(1.75)	(1.94)
$\beta_{P,1}^{MJ}$	10.30	15.26*	20.45*	28.27*
	(5.17)	(3.24)	(5.76)	(3.81)
$\beta_{P,1}^{MJ}$	1.38	3.78*	-3.82*	3.57
	(6.02)	(0.89)	(1.18)	(3.71)
$\beta_{P,1}^{MJ}$	-3.72	-10.97*	-26.24*	-10.73*
	(6.74)	(0.89)	(2.99)	(3.41)
$\beta_{P,1}^{JA}$	7.69*	5.82*	7.38	7.53
	(3.37)	(1.44)	(4.09)	(5.12)
$\beta_{P,2}^{JA}$	4.42	2.46*	-0.88	4.16
	(3.10)	(1.23)	(4.00)	(4.76)
$\beta_{P,3}^{JA}$	-5.07	-14.88*	0.26	-3.70
	(3.00)	(1.37)	(4.52)	(4.85)

Note: Standard errors are in the parenthesis. Asterisk (*) denotes estimates significant at 5%.

degree increase in July-August temperature results in about 30% corn yield losses in Illinois and Iowa and about 13% in Minnesota and Wisconsin.

Table 3.3: Estimated Thresholds of the Control Model

	Illinois	Iowa	Minnesota	Wisconsin
Lower threshold of May-June Temperature	21.11	17.93	16.98	16.05
Upper threshold of May-June Temperature	22.17	19.50	19.22	17.81
Lower threshold of July-August Temperature	23.46	22.57	18.91	18.54
Upper threshold of July-August Temperature	26.05	24.98	22.2	21.84
Lower threshold of May-June Precipitation	2.48	1.74	2.48	2.30
Upper threshold of May-June Precipitation	4.12	4.02	5.2	3.55
Lower threshold of July-August Precipitation	2.76	3.33	2.87	3.41
Upper threshold of July-August Precipitation	3.89	5.30	3.94	4.36

The marginal impacts of May-June and July-August precipitation are all positive when they are below the lower thresholds, which indicates that drought in the growing seasons is always harmful for corn growth. When May-June precipitation is below the lower threshold, one millimeter per day decrease in precipitation will lead to about 12% yield losses in Illinois, 19% in Iowa, 17% in Minnesota and 32% in Wisconsin. It is similar in July and August. When July-August precipitation is below the lower threshold, one millimeter decrease per day in precipitation will decrease corn yield by about 12% in Illinois, 8% in Iowa, 7% in Minnesota and 12% in Wisconsin. The lower thresholds are almost all between the mean and one standard deviation below mean, which are not extreme low levels. The significantly negative marginal impact of high May-June precipitation indicates that too much water in the planting and early vegetative growing period is harmful. The results of the control model are very consistent with existing literatures so that it could be used as a base model for our soil moisture impact analysis.

Table 3.4: Percentage Marginal Effects of Weather Variables in the Control Model

	Illinois	Iowa	Minnesota	Wisconsin
$\beta^{MJ}_{T,low}$	1.34	5.56	5.53*	7.24*
	(0.76)	(2.95)	(1.02)	(2.70)
$\beta^{MJ}_{T,med}$	-5.96	-1.51	-2.88*	-0.94
	(4.12)	(4.00)	(1.24)	(2.64)
$\beta^{MJ}_{T,high}$	7.99*	-2.76	-13.70*	-5.28
	(3.28)	(1.66)	(2.94)	(3.13)
$\beta^{JA}_{T,low}$	-4.81*	-2.49*	8.47*	11.43*
	(0.79)	(0.50)	(2.78)	(3.15)
$\beta^{JA}_{T,med}$	-10.62*	-9.10*	-1.21	-3.71*
	(0.89)	(0.69)	(0.70)	(0.77)
$\beta^{JA}_{T,high}$	-31.84*	-29.40*	-12.88*	-13.13*
	(2.42)	(1.72)	(1.65)	(1.83)
$\beta^{MJ}_{P,low}$	11.69*	19.04*	16.63*	31.84*
	(3.92)	(2.98)	(6.49)	(3.32)
$\beta^{MJ}_{P,med}$	1.38	3.78*	-3.82*	3.57
	(6.02)	(0.89)	(1.18)	(3.71)
$\beta^{MJ}_{P,high}$	-2.34*	-7.19*	-30.06*	-7.16*
	(1.16)	(0.64)	(2.53)	(1.14)
$\beta^{JA}_{P,low}$	12.10*	8.28*	6.50*	11.69*
	(1.19)	(0.93)	(2.63)	(1.89)
$\beta^{JA}_{P,med}$	4.42	2.46*	-0.88	4.16
	(3.10)	(1.23)	(4.00)	(4.76)
$\beta^{JA}_{P,high}$	-0.66	-12.42*	-0.62	0.46
	(1.15)	(0.76)	(1.31)	(1.42)

Note: Standard errors are in the parenthesis. Asterisk (*) denotes estimates significant at 5%.

Results for the Dry-Hot Model

Including May 1st and July 1st soil moisture variables and the interaction terms improves the fit of the control model. The value of adjusted-R^2 increases by 0.02 in Minnesota and up to 0.07 in Iowa. F tests with null hypothesis that these two models have the same effect are all significantly rejected. Table 3.5 presents the posterior mean and standard deviation of coefficients of the Dry-Hot model. Coefficients of the trend variable remain positive and statistically significant and increase by 0.07 in Iowa and 0.05 in Wisconsin.

Table 3.5: Posterior Mean and Standard Deviation of Coefficients of the Dry-Hot Model

	Illinois	Iowa	Minnesota	Wisconsin
β_0	1.35*	1.56*	2.10*	1.6*
	(0.03)	(0.03)	(0.05)	(0.05)
$\beta_{T,1}^{MJ}$	9.23*	7.98*	0.03	9.45*
	(4.19)	(2.09)	(10.95)	(3.47)
$\beta_{T,2}^{MJ}$	-5.63	1.1	0.89	1.52
	(4.16)	(1.95)	(6.65)	(2.82)
$\beta_{T,3}^{MJ}$	17.51*	0.43	-3.19	1.31
	(6.61)	(3.91)	(8.10)	(3.79)
$\beta_{T,1}^{JA}$	5.67*	3.1	9.79*	15.23*
	(1.00)	(1.85)	(3.18)	(3.15)
$\beta_{T,2}^{JA}$	-8.54*	-6.44*	-1.47*	-2.25*
	(0.50)	(1.70)	(0.70)	(0.74)
$\beta_{T,3}^{JA}$	-1.14	14.85*	-6.13*	3.16
	(3.23)	(3.95)	(1.86)	(2.03)
$\beta_{P,1}^{MJ}$	7.00	17.62*	12.06*	18.63*
	(4.17)	(3.34)	(2.15)	(4.76)
$\beta_{P,2}^{MJ}$	-2.61	1.90*	-2.48*	1.67

Table 3.5 Continued

	(4.22)	(0.86)	(1.09)	(4.45)
$\beta_{P,3}^{MJ}$	-0.16	-7.85*	-24.56*	-8.92*
	(5.03)	(0.86)	(2.84)	(4.28)
$\beta_{P,1}^{JA}$	3.94	10.59*	1.40	6.14
	(3.39)	(3.54)	(6.52)	(4.01)
$\beta_{P,2}^{JA}$	-0.34	-15.37*	4.58	-1.29
	(3.23)	(3.45)	(2.47)	(3.75)
$\beta_{P,3}^{JA}$	1.14	6.06	-5.18*	-0.11
	(3.63)	(3.79)	(2.58)	(4.27)
$\beta_{S,1}^{May1}$	1.089	1.206	0.822	-0.253
	(0.905)	(1.801)	(1.148)	(0.972)
$\beta_{S,2}^{May1}$	-1.180	-1.226	-0.789	0.037
	(0.902)	(1.802)	(1.145)	(0.886)
$\beta_{S,3}^{May1}$	1.358	1.199	0.753	-0.189
	(0.910)	(1.811)	(1.144)	(0.909)
$\beta_{S,1}^{Jul1}$	0.935	2.193*	0.390*	3.599
	(1.781)	(0.927)	(0.130)	(2.793)
$\beta_{S,2}^{Jul1}$	-0.852	-2.372*	-0.092*	-3.520
	(1.775)	(0.927)	(0.030)	(2.787)
$\beta_{S,3}^{Jul1}$	0.836	2.491*	-0.296*	3.507
	(1.798)	(0.926)	(0.129)	(2.794)
β_{TP}^{JA}	8.984*	6.751*	3.043	8.407*
	(1.266)	(0.764)	(6.859)	(1.432)
β_{TS}^{JA}	0.133*	0.086*	0.541*	0.248*
	(0.033)	(0.013)	(0.124)	(0.036)
β_{PS}^{JA}	-0.193*	-0.102*	-2.350	-0.112*
	(0.019)	(0.005)	(1.822)	(0.027)

Note: Standard errors are in the parenthesis. Asterisk (*) denotes estimates significant at 5%.

Since Dry-Hot model only includes the interactions of July-August temperature, July-August precipitation and July 1st soil moisture, the percentage marginal effects of May-June temperature, May-June precipitation and May 1st soil moisture are estimated in the same way as the control model. The mean and standard deviation are shown in Table 3.6. For May-June temperature, the coefficients are still consistent with the control model in Illinois, Iowa and Wisconsin. Warm weather is beneficial for corn growth in the early stage, especially in cool spring years. For Illinois and Iowa, this beneficial effect becomes much more significant in the Dry-Hot model might due to the high soil moisture in Illinois and decrease in the lower threshold in Iowa as shown in Table 3.7. May-June precipitation coefficients are consistent with the control model across all four states with the same signs and significance levels. But most of the impact magnitudes become smaller in $\beta_{P,low}^{MJ}$, with the most decrease by 10 percent points in Wisconsin. May 1st soil moisture is insignificant in almost all four states.

With the interaction terms, the interpretation of July-August temperature, precipitation and July 1st soil moisture impacts becomes more complicated. But it is still comparable with the control model when July-August temperature is below the upper threshold or July-August precipitation and July 1st soil moisture are above the lower threshold as shown in Table 3.8. When July-August temperature is below the upper threshold, the coefficients are very consistent with the control model, even though the thresholds are lower in the Dry-Hot model in Illinois and Iowa. The conditional high July-August temperature even has positive marginal impact might result from few observations of hot but wet summers in Iowa. When July-August precipitation is above the lower threshold, precipitation impacts remain insignificant in Illinois and Minnesota. $\beta_{P,med}^{JA}$ becomes significantly negative in Iowa. This big change is because the two thresholds are too close and one knot specification gives similar and a little flatter prediction without the jump. The large marginal impact of July 1st soil moisture between the two thresholds in Iowa is also due to too close thresholds. Except for Minnesota, July 1st soil moisture marginal impacts are all insignificant in Illinois, Iowa and Wisconsin. But for Minnesota, excessive moisture is the dominant factor for yield losses.

Table 3.6: Percentage Marginal Effects of May-June Temperature, Precipitation and May 1st Soil Moisture in the Dry-Hot Model

	Illinois	Iowa	Minnesota	Wisconsin
$\beta_{T,low}^{MJ}$	3.59*	9.09*	0.92	10.97*
	(0.44)	(1.97)	(4.8)	(2.98)
$\beta_{T,med}^{MJ}$	-5.63	1.10	0.89	1.52
	(4.16)	(1.95)	(6.65)	(2.82)
$\beta_{T,high}^{MJ}$	11.88*	1.53	-2.3	2.82
	(3.22)	(2.52)	(2.48)	(2.27)
$\beta_{P,low}^{MJ}$	4.39*	19.51*	9.58*	20.30*
	(1.84)	(3.11)	(2.18)	(2.35)
$\beta_{P,med}^{MJ}$	-2.61	1.90*	-2.48*	1.67
	(4.22)	(0.86)	(1.09)	(4.45)
$\beta_{P,high}^{MJ}$	-2.78*	-5.96*	-27.03*	-7.25*
	(1.32)	(0.60)	(2.49)	(0.93)
$\beta_{S,low}^{May1}$	-0.090*	-0.021	0.033	-0.216
	(0.021)	(0.023)	(0.048)	(0.200)
$\beta_{S,med}^{May1}$	-1.180	-1.226	-0.789	0.037
	(0.902)	(1.802)	(1.145)	(0.886)
$\beta_{S,high}^{May1}$	0.179	-0.027	-0.037	-0.152
	(0.192)	(0.041)	(0.131)	(0.127)

Note: Standard errors are in the parenthesis. Asterisk (*) denotes estimates significant at 5%.

Table 3.7: Estimated Thresholds of the Dry-Hot Model

	Illinois	Iowa	Minnesota	Wisconsin
Lower threshold of May-June Temperature	21.51	17.40	16.05	15.33
Upper threshold of May-June Temperature	22.19	19.45	17.69	17.03
Lower threshold of July-August Temperature	22.58	22.17	18.91	18.52
Upper threshold of July-August Temperature	25.70	23.70	22.16	21.41
Lower threshold of May-June Precipitation	2.69	1.62	2.82	2.45
Upper threshold of May-June Precipitation	4.45	4.04	5.23	3.28
Lower threshold of July-August Precipitation	3.70	5.51	1.86	3.98
Upper threshold of July-August Precipitation	4.52	6.13	3.21	4.68
Lower threshold of May 1^{st} Soil Moisture	231.74	172.49	171.59	143.20
Upper threshold of May 1^{st} Soil Moisture	245.53	181.18	192.48	169.71
Lower threshold of July 1^{st} Soil Moisture	146.68	198.06	42.71	113.20
Upper threshold of July 1^{st} Soil Moisture	170.82	200.32	177.93	114.97

It is notable that the coefficients of the interaction terms are all statistically significant in Illinois, Iowa and Wisconsin as shown in the last three rows of Table 3.5. The coefficients of the interaction term of high July-August temperature and low July-August precipitation and the interaction of high July-August temperature and low July 1^{st} soil moisture are significantly positive, which indicate that in drought condition, one degree increase in temperature results in more yield losses when there is less water availability. Water availability could help reduce yield losses in drought years. The coefficients of the interaction of low July-August precipitation and low July 1^{st} soil moisture are significantly negative. This shows when there is more soil moisture in the ground, the marginal impact of precipitation would be smaller. Soil moisture and precipitation could be substitutes to some extent.

Table 3.8: Percentage Marginal Effects of July-August Temperature, Precipitation and July 1st Soil Moisture in the Dry-Hot Model

	Illinois	Iowa	Minnesota	Wisconsin
$\beta^{JA}_{T,low}$	-2.88*	-3.34*	8.32*	12.98*
	(0.95)	(0.73)	(2.87)	(2.94)
$\beta^{JA}_{T,med}$	-8.54*	-6.44*	-1.47*	-2.25*
	(0.5)	(1.70)	(0.70)	(0.74)
$\beta^{JA}_{T,high}{}^{\#}$	-9.68*	8.41*	-7.61*	0.91
	(3.15)	(2.74)	(1.58)	(1.78)
$\beta^{JA}_{P,low}{}^{\#}$	3.60*	-4.78*	5.98	4.85*
	(0.67)	(0.62)	(5.50)	(1.20)
$\beta^{JA}_{P,med}$	-0.34	-15.37*	4.58	-1.29
	(3.23)	(3.45)	(2.47)	(3.75)
$\beta^{JA}_{P,high}$	-1.48	-9.30*	-0.60	-1.40
	(1.10)	(0.86)	0.86)	(1.43)
$\beta^{July1\#}_{S,low}$	-0.083*	-0.178*	0.297*	0.080
	(0.032)	(0.020)	(0.137)	(0.049)
$\beta^{July1}_{S,med}$	-0.852	-2.372*	-0.093*	-3.519
	(0.902)	(0.927)	(0.030)	(2.787)
$\beta^{July1}_{S,high}$	0.179	0.120	-0.389*	-0.012
	(0.192)	(0.074)	(0.131)	(0.050)

Note: Standard errors are in the parenthesis. Asterisk (*) denotes estimates significant at 5%. $^{\#}$ means they are conditional marginal impacts. $\beta^{JA}_{T,high}{}^{\#}$ is the marginal impact when July-August precipitation and July 1st soil moisture are above their lower thresholds. $\beta^{JA}_{P,low}{}^{\#}$ is the marginal impact when July-August temperature is below the upper threshold and July 1st soil moisture is above the lower threshold. $\beta^{July1\#}_{S,low}$ is the marginal impact when July-August temperature is below the upper threshold and July-August precipitation is above the lower threshold.

To better illustrate the impact of water availability on the yield effects of high July-August temperature, we calculate the marginal effect of high July-August temperature under different July-August precipitation and July 1st soil moisture conditions using the 15,000 simulations of parameters. The average marginal effects are shown in Table 3.9. Minnesota is excluded due to limited high temperature effects.

Table 3.9: Percentage Marginal Effects of High July-August Temperature under Different July-August Precipitation and July 1st Soil Moisture Conditions

July 1st Soil Moisture	Jul-Aug Precipitation	Illinois	Iowa	Wisconsin
μ	μ	-15.57	-10.89	-6.88
μ-σ	μ	-21.50	-15.52	-17.16
μ	μ-σ	-26.62	-21.62	-16.80
μ-σ	μ-σ	-32.54	-26.25	-27.07

Note: μ denotes the historical mean of the variable in the column. σ is the corresponding standard deviation.

The first row shows the yield losses due to high July-August temperature when July-August precipitation and July 1st soil moisture are both at historical mean levels. The last row shows the yield losses when July-August precipitation and July 1st soil moisture are both at one standard deviation below mean. If both July-August precipitation and July 1st soil moisture move from one standard deviation below mean to mean level, yield losses from high July-August temperature decrease from 32.54% to 15.57% in Illinois, 26.25% to 10.89% in Iowa and 27.07% to 6.88% in Wisconsin. This indicates that soil moisture and rainfall could reduce yield losses from hot summer. Without considering the soil moisture conditions, the feared yield losses from high temperature might be overstated, especially when high temperature is accompanied with increased soil moisture. Moreover, one standard deviation increase in July-August precipitation reduces more yield losses from high July-August temperature than one standard deviation increase in July 1st soil moisture in Illinois and Iowa. The impact is about the same in Wisconsin. For example in Illinois, when July-August precipitation is at mean, increasing July 1^{st} soil moisture from one standard deviation below mean to mean reduces yield losses by about 6 percent points. But when July 1^{st} soil moisture is at mean, increasing July-August precipitation from one standard deviation below mean to mean reduces yield losses by over 10 percent points.

Similarly, when July-August temperature is high, the percentage marginal effect of low July-August precipitation decreases from 12.75% to 4.01% if July 1^{st} soil moisture increase from one standard deviation from mean to mean in Illinois, from 8.19% to 2.71% in Iowa and from 11.19% to 6.56% in Wisconsin. Precipitation has a larger impact on corn yield when soil moisture is low in the summer. This clearly shows the substitution between July 1^{st} soil moisture and July-August precipitation.

Illustration Using 1980-1992 and 2000-2012

Studies show that increase of greenhouse gases has accelerated the increase of precipitation since 1990s and hot and dry summer is less frequent in recent years. (Kunkel et al. 2013, Janssen et al. 2014) When high temperature is accompanied with high precipitation and high soil moisture, yield losses might be much less than predicted without taking into account of water availability. For simplicity, we use our existing dataset to show the impact of this climate shift.

We take two periods 1980-1992 and 2000-2012 from our dataset for Illinois, Iowa and Wisconsin.[40] The mean value of each variable for each period is shown in Table 3.10 with the p-value for the test that the mean value is different between the two periods. May-Jun precipitation and July 1^{st} soil moisture increased significantly in 2000-2012, which is

[40] Minnesota is excluded due to limited high temperature effects.

consistent with existing literatures that annual rainfall increased since 1990s and was driven by warm season rainfall. (Kunkel et al. 2013) Moreover, May-June temperature significantly decreased in the later period in Iowa and Wisconsin.

Table 3.10: Mean of Each Predictor for Periods 1980-1992 and 2000-2012

	T^{MJ}	P^{MJ}	S^{May1}	T^{JA}	P^{JA}	S^{Jul1}
Illinois						
1980-1992	19.71	3.16	206.2	23.83	3.09	132.6
2000-2012	19.76	3.71	207.6	23.94	3.16	142.3
p-value	0.41	0	0.41	0.13	0.22	0
Iowa						
1980-1992	18.65	3.39	171.2	22.76	3.57	108.5
2000-2012	18.17	4.12	165.2	22.61	3.60	122.1
p-value	0	0	0	0.03	0.74	0
Wisconsin						
1980-1992	16.55	2.82	145.0	20.90	3.54	90.2
2000-2012	16.17	3.69	142.4	21.00	3.33	97.6
p-value	0	0	0.25	0.15	0	0

We evaluate the average yield given the variables taking values at the mean of each period. And derive the yield change by subtracting estimated yield in 1980-1992 from yield in 2000-2012. The total yield change is presented in the second column of Table 3.11. Corn yield slightly decreased in Illinois by 1.97 bushels/acre and increased by 2.33 bushels/acre in Iowa. The change is more substantial in Wisconsin by 6.12 bushels/acre. Columns 3 to 8 of Table 3.11 show the contribution of each variable to this yield change.

In Illinois and Wisconsin, the primary driver of the yield reduction is increased May-June precipitation (-4.22 bushels/acre in Illinois, -4.34 bushels/acre in Wisconsin). In Illinois, this yield reduction is offset by yield increase from higher July 1st soil moisture. This benefit is smaller in Wisconsin. And the yield reduction is exaggerated by yield losses from lower July-August precipitation. The yield change in Iowa is modest with the primary yield increase from higher July-August temperature.

Table 3.11: Mean Yield Change when Variables Change from Mean Values of 1980-1992 to Mean Values of 2000-2012

	Total	T^{MJ}	P^{MJ}	S^{May1}	T^{JA}	P^{JA}	S^{Jul1}
Illinois	-1.97	0.31	-4.22	-0.22	-1.64	0.77	3.35
Iowa	2.33	-0.70	0.58	0.41	1.64	-0.17	0.51
Wisconsin	-6.12	-0.86	-4.34	0.38	-0.30	-2.59	1.28

To illustrate the yield change under extreme conditions, we take the subset of observations with July-August temperature above the upper threshold from each period and calculate the variable means as shown in Table 3.12. In Illinois and Iowa, July-August temperature decreased significantly which is consistent with the evidence of fewer drought incidences in recent years. Same as the average case, May-June precipitation and July 1st soil moisture are higher in 1990-2012. And July-August precipitation also increased in Illinois and Iowa.

The yield change of the two subsets from periods 1980-1992 and 2000-2012 is presented in Table 3.13. Comparing with the period average case, the yield change is more substantial under high temperature condition. Yield reduction decreased significantly in Illinois and Iowa (23.32 bushels/acre in Illinois, 25.31 bushels/acre in Iowa). In Illinois and

Iowa, the reduction in yield losses is due to lower July-August temperature, higher July-August precipitation and more July 1st soil moisture. In Wisconsin, the yield loss reduction is much smaller, mainly due to more July 1st soil moisture. The contribution of July-August rainfall and July 1st soil moisture is less than July-August temperature but still substantial and cannot be neglected.

Table 3.12: Mean of Each Predictor for Periods 1980-1992 and 2000-2012 when July-August Temperature Is Above the Upper Threshold

	T^{MJ}	P^{MJ}	S^{May1}	T^{JA}	P^{JA}	S^{Jul1}
Illinois						
1980-1992	20.42	2.74	229.2	26.62	2.10	116.6
2000-2012	21.51	3.51	222.1	26.32	2.44	127.8
p-value	0	0	0.08	0	0	0.06
Iowa						
1980-1992	19.42	3.12	171.5	24.92	2.87	101.8
2000-2012	19.28	4.18	175.6	24.42	3.53	118.2
p-value	0.27	0	0.47	0	0	0
Wisconsin						
1980-1992	17.20	2.52	151.3	22.41	3.60	86.6
2000-2012	16.79	3.42	150.3	22.18	3.58	96.9
p-value	0	0	0.8	0	0.91	0

Table 3.13: Mean Yield Change when Variables Change from Mean Values of 1980-1992 to Mean Values of 2000-2012 when July-August Temperature Is Above the Upper Threshold

	Total	T^{MJ}	P^{MJ}	S^{May1}	T^{JA}	P^{JA}	S^{Jul1}
Illinois	23.32	3.98	-2.03	0.68	9.09	6.09	6.13
Iowa	25.31	0.02	0.77	-0.17	12.63	11.90	4.47
Wisconsin	4.71	-0.81	-0.98	0.12	2.60	-0.28	4.77

Conclusion

We construct a log yield response function with two-knot linear spline functions of temperature, precipitation variables and also the interactions of high heat and low precipitation and low soil moisture terms. Bayesian Monte Carlo approach is applied to estimate the parameters and thresholds simultaneously using a balanced panel dataset from 1980 to 2012 over the Upper Mississippi River Basin. Our results show that the impact of high temperature on corn yield cannot be estimated without taking into account the water availability. Yield losses from high July-August temperature reduced by 15 to 20 percentage points under average water availability than under low water availability. Soil water availability could play an important role and it could not be reasonably described using growth season precipitation only. July 1st soil moisture and July-August precipitation are substitutes. But one standard deviation increase in precipitation reduces more yield losses from high temperature than one standard deviation increase in soil moisture.

Moreover, our findings indicate that the determinant factors for corn yield losses vary across the U.S. Midwest. Excessive spring rainfall in Iowa and Illinois is damaging to corn yield, however, could help reduce yield losses during hot and dry summers through the soil moisture effect. In Wisconsin, too little spring rainfall is more damaging than too much.

We also illustrate the possible climate shift impact on corn yield using the historical periods' average values of weather and soil moisture variables. The data shows high heat and low water availability are less frequent in the later period. More May-June precipitation increases yield losses but offsets by the increase in July 1st soil moisture. Under average weather conditions, the change in yield is modest. But under hot condition, yield losses decrease significantly due to cool weather and more water availability. However, using a more reliable source of climate projections would give a better picture of the yield impact than using historical data.

Reference

Andresen, J., et al. (2012). Historical climate and climate trends in the Midwestern USA. US National Climate Assessment Midwest Technical Input Report: 1-18.

Carlson, R. E. (1990). Heat stress, plant-available soil moisture, and corn yields in Iowa: A short- and long-term view. *Journal of Production Agriculture*, 3: 293-297.

Deschenes, O. and Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97: 354-385.

Evans, R. O., Cassel, D. K. and Sneed, R. E. (1996). Soil, water, and crop characteristics important to irrigation scheduling. North Carolina Cooperative Extension Service. AG 452-1.

Feng, H., Kurkalova, L. A. , Kling, C. L. and Gassman, P. W. (2007). Transfers and environmental co-benefits of carbon sequestration in agricultural soils: Retiring agricultural land in the Upper Mississippi River Basin. *Climatic Change*, 80(1-2): 91-107.

Gassman, P. W., Williams, J. R., Benson, V. R., Izaurralde, R. C., Hauck, L. M., Jones, C. A., Altwood, J. D., Kiniry, J. R., and Flowers, J. D. (2004). Historical development and applications of the EPIC and APEX models. American Society of Agricultural Engineers. Paper No. 042069.

Green W. H. 2008. Econometric analysis. New Jersey: Prentice Hall, Inc. Upper Saddle River, New Jersey.

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., et al (2011). Climate impacts on agriculture: implications for crop production. Agronomy Journal, 103(2): 351-370.

Izaurralde, R. C., Rosenberg, N. J., Brown, R. A., and Thomson, A. M.. (2003). Integrated assessment of Hadley center climate change projections on water resources and agricultural productivity in the conterminous United States. II. regional agricultural productivity in 2030 and 2095.Agricultural and Forest Meteorology, 117(2003): 97-122.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., Quiroga Jakas, M.C. (2006). Simulating soil C dynamics with EPIC: model description and testing against long-term data, Ecological Modelling, 192(3-4): 362–384.

Hanssen, E., Wuebbles, D. J., Kunkel, K. E., Olsen, S. C., and Goodman, A. (2014). Observational and model-based trends and projections of extreme precipitation over the contiguous United States. *Earth's Future*, 2(2): 99-113.

Kunkel, K. E., Stevens, L. E., Stevens, S. E., Sun, L., Janssen, E., Wuebbles, D., and Dobson, J. G. (2013). Regional climate trends and scenarios for the U.S. national climate assessment: Part 9. Climate of the contiguous United States. NOAA Technical Report NESDIS 142-9: 85, National Oceanic and Atmospheric Administration, National environmental satellite, data, and information service, Washington, D.C.

Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, 333(6042): 616-620.

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., and Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, 3: 497-501.

Maurer, E. P., Wood, A. W., Adam, J. C., Lettenmaier, D. P., and Nijssen, B. (2002). A long-term hydrologically-based data set of land surface fluxes and states for the conterminous United States. *Journal of Climate*, 15: 3237-3251.

Roberts, M. J., Schlenker, W., and Eyer., J. (2012). Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics*, 95: 236-243.

Schlenker, W., Hanemann, W. M. and Fisher, A. C. (2006). The impact of global warming on U.S. agriculture: An econometric analysis of optimal growing conditions. *Review of Economics and Statistics*, 88(1): 113-125.

Schlenker, W. and Roberts, M. J. (2006). Nonlinear effects of weather on corn yields. *Review of Agricultural Economics*, 28(3): 391-398.

Schlenker, W., and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crops under climate change. Proceedings of the National Academy of Sciences, 106(37): 15594-15598.

Thompson, A. M., Brown, R. A., and Ghan, S. J. (2002). Elevation dependence of winter wheat production in eastern Washington State with climate change: A methodological study. *Climate Change*, 54(1-2): 141-64.

Williams, J. R. (1995). The Epic model in computer models of watershed hydrology. Water Resources Publications: 909-1000.

Yu, T. and Babcock, B. A. (2011). Estimating non-linear weather impacts on corn yield-A Bayesian approach. Center of Agricultural and Rural Development. Working Paper 11-WP 522.

CHAPTER 4. CORN YIELD SENSITIVITY CHANGE TO DROUGHT CONDITIONS SINCE 1980

Abstract

We construct yield response functions to allow the yield deviation driven by weather variables to change over time. The model is estimated using a balanced panel dataset for from 1980 to 2012, including two recent drought years 2011 and 2012 with more drought incidences in the modern eras. Then we test the hypotheses that the marginal and total impacts of weather variables remain constant under our hypothetical drought weather conditions. Our results show that yield losses due to drought conditions increases over time in absolute yield terms but remains constant in percentage terms due to increase in base yield over time. Corn yield is becoming less sensitive to July-August precipitation which reduces yield losses under modest drought level. Yield losses from one degree increase in July-August temperature increase since 1980 in bushels per acre but remains constant in percentage. July-August precipitation marginal impact decreases over time in percentage terms because corn yield is becoming less sensitive to summer precipitation and precipitation is also becoming less helpful to reduce yield losses from high heat over time. The substitution effect between July-August precipitation and July 1st soil moisture is greater since 1980. Beside of the substitution effect, the marginal impact of July 1st soil moisture is unchanged.

Introduction

Numerous studies have focused on the impacts of weather conditions in the growing season on corn yield, especially the impact of growing spring rainfall, high temperature and limited water availability in the summer. However, there are still debates on whether the impact of weather conditions is constant or changing over time. And few observations of dry and hot summer conditions during 1990-2010 make the previous results less convincing. Moreover, the sensitivity of corn yield to weather condition has an important implication on the determination of premium rates for crop insurance. Risk Management Agency (RMA) uses the actual corn yield history to determine their crop insurance guarantees, which cannot differentiate the impact of few drought events and increased yield sensitivity to adverse weather conditions in an increased corn yield record. So it is imperative to have a clear understanding of the evolving impact of weather on corn yield. In this chapter, we investigate the impact of weather conditions on corn yield allowing the weather effects to change with time. And then test the hypothesis that the total and marginal effects remain constant over time in both absolute and percentage terms.

The weather impact on corn yield is well studied. Their results show that moderate heat is beneficial to corn growth but when the temperature is above some threshold yield declines sharply, and an increase in precipitation benefits corn yield but is harmful when it is too much (Lobell and Asner, 2003; Schlenker and Roberts, 2006; Deschenes and Greenstone, 2007; Yu and Babcock, 2011). For example, using panel data of corn yield, temperature, and precipitation from 1950 to 2004 in 2000 counties of the U.S., Schlenker and Roberts (2006) finds that corn yields are increasing in temperature for moderate temperature, but significantly decreasing once temperature exceeds 30°C.Yu and Babcock (2011) shows concave relationship between corn yield and rainfall and temperature across states in the U.S. Corn Belt by fitting a linear spline model with endogenous thresholds. But they all use constant trend effect which is not flexible to take into consider change in weather impact over time.

Unlike the consistency in the weather impacts on corn yield in existing literatures, there are debates on the research about the changing impact of weather conditions especially drought on corn yield over time. By constructing a drought index capturing the presence of both unusually hot and unusually dry conditions, Yu and Babcock (2010) indicates that corn has indeed become more drought tolerant since 1980 in terms of both bushels and percentage losses. On the other hand, comparing the results of cross-sectional and time series regression analysis for period from 1950 to 2005, Schlenker and Roberts (2009) states weather impacts don't change over time and there is little adaption to weather changes. But too few drought events after 1990 make their results less convincing. And the drought in 2011 and 2012 provides us more observations to compare the weather impact between the modern eras with 1980s. Using field data on maize and soybean in the central U.S. for 1995-2012, Lobell, et al. (2014) concludes that drought sensitivity in maize, in particular sensitivity to high vapor pressure deficits (VPD), has steadily increased over the period from 1995-2012, although yields have increased in yield value under all levels of stress for both crops. In this chapter, we revisit the model of Yu and Babcock (2010) and show the result changes due to including two recent drought year observations, using the county-level weather and corn yield data from 1980 to 2012 in Iowa and Illinois. We then construct corn yield response functions with the flexibility allowing the weather impact to change over time and test the hypotheses that the marginal and total weather impacts on corn yield remain constant over time since 1980 under our hypothetical adverse weather conditions, especially for July-August temperature, July-August precipitation and July 1st soil moisture. The weather impact on corn yield in 1980 is consistent with the results in Chapter 3. Our results show that yield losses due to drought conditions increase over time in absolute yield terms but remain constant in percentage terms due to increase in base yield over time. Corn yield is becoming less sensitive to July-August precipitation which reduces yield losses under modest drought level.

The rest of this chapter is organized as follows: in section 2 we describe the dataset we use in this study. We revisit the existing literature using our dataset and compare the results in section 3. In section 4, we construct a yield response function with the flexibility to allow weather impact on corn yield to change over time and present the estimated result. The hypothesis that marginal impact of weather variables on corn yield is constant over time is tested in section 5. Section 6 explores the change in the total weather impact on corn yield. In the last section, a general conclusion is presented.

Data Selection

In this study, we estimate the changing impacts of temperature, precipitation and soil moisture on corn yield over time. We use the same 1/8 degree gridded daily data for the maximum temperature, minimum temperature and precipitation as in Maurer et al. (2002),[41] and extend it to span the period 1979-2012. All counties in Iowa and Illinois with yield data in all years from 1980 to 2012 are included.[42]

[41] In Maurer et al. (2002), daily precipitation totals from the National Oceanic and Atmospheric Administration Cooperative Observer (Co-op) stations were assigned to each day based on the time observation for the gauge. The precipitation gauge data were gridded to the 1/8 resolution using the synergraphic mapping system algorithm. The gridded daily precipitation data were then scaled to match the long-term average of the Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation climatology. The minimum and maximum daily temperature data from Co-op stations were gridded using the same algorithm as for precipitation, and were lapsed to the grid cell mean elevation.

[42] There are 9 counties in Illinois with missing corn yield data.

Corn and soybean yields are constructed as production divided by planted acres. County-level production and planted acreage data is collected from the U.S. Department of Agriculture's National Agricultural Statistics Service (USDA-NASS).

The soil moisture data is simulated using the EPIC model, version 1102-64 (Izaurralde et al. 2006).[43] EPIC simulations are carried out at a field-scale level for areas homogeneous in weather, soil, land-scape, crop rotation, and management system parameters using a continuous daily time step for 34 years from 1979 to 2012. The Natural Resource Inventory database provides information on the natural resource characteristics of the landscape, soil, crop rotation and other input data for the simulations. The daily maximum and minimum temperatures and precipitation data is used as weather inputs in EPIC. Each field in EPIC runs is matched with the nearest 1/8th degree weather grid point. The simulated data for 1979 is omitted to minimize the starting effects.

In our regression, we include May to August as corn growth season. We divide the growth season into two time intervals May to June (MJ, planting and early vegetative growth) and July to August (JA, pollination and grain fill). Daily maximum and minimum temperatures, precipitation and soil moisture for each field are averaged for each time interval. The arithmetic mean of the maximum and minimum temperatures is used as the average temperature. The area-weighted average over all fields within a county is constructed to obtain county-level data.

[43] Additional information concerning EPIC can be found in Gassman et al. 2004.

Revisit Previous Study

In order to see the impact of including more drought events in the modern eras, we revisit the model in Yu and Babcock (2010) estimating their model and also estimate their model using our dataset including data from 1980-2012.

They define a drought index (DI) as follows:

$$DI_{i,t} = -\max(0, CLDD_{i,t}^{Stand}) * \min(0, TPCP_{i,t}^{Stand}) \tag{4.1}$$

Where *CLDD* and *TPCP* are standardized average cooling degree days and total monthly precipitation with *i* and *t* as the county and year index. Their model is specified as:

$$\begin{aligned} Y_{i,t} = \beta_{cons} + \alpha_i + \sum_{r=1}^{R} \gamma_r (CRD_r * T) + \beta_{di} DI_{i,t} + \beta_{dit} DIT_{i,t} \\ + \beta_{disq} DISQ_{i,t} + \beta_{disqt} DISQT_{i,t} + \varepsilon_i \end{aligned} \tag{4.2}$$

Where *t*, *i* and *r* denote time, county and crop reporting districts (CRDs), respectively. *R* is the number of crop reporting districts. *Y* denotes crop yield. α_i is the county-specific fixed effect parameter. *T* is a trend variable taking values 0 to 32 for years 1980 to 2012. *DIT* = *DI* * T*, *DISQ* = *DI* **DI*, *DISQT* = *DI* * *DI* * *Q*.

We first apply their data selection criteria on our dataset for the same period as their study to guarantee the weather data is consistent. By choosing only those counties in CRDs that have at least two drought incidents with an index larger than 2 or at least three drought incidents with an index larger than 1.5 since 2000, we get the same number of CRDs as their paper. But we don't have weather data for Indiana. Our estimation and hypothesis tests results are also very consistent. Corn yield losses from mild and moderate drought have decreased over time in both absolute and percentage terms.

Then we use the dataset from 1980 to 2012 with the same data selection criteria to estimate the model. The resulted data includes 1 more CRD in Illinois and 3 more CRDs in Iowa due to the recent drought years 2011 and 2012. The coefficients of *DIT*, *DISQ* and *DISQT* are quite different in both signs and statistical significance. And we fail to reject the hypothesis that corn yield losses remain constant under moderate drought condition in both absolute and percentage terms. Yield losses increase over time in bushels but remain constant in percentage. Also the marginal yield losses from drought also increase over time. This comparison provides evidence that two few drought incidents in the modern eras and without considering the soil moisture level before drought make the result less convincing. We then construct a model using the weather variables directly rather than using the drought index. This can differentiate the impact of individual weather variables and also test the total yield deviation due to weather.

The Model

The soil moisture data is only available for the Upper Mississippi River Basin Area, which includes 76 counties in Illinois, 76 counties in Iowa, 61 counties in Minnesota and 46 counties in Wisconsin. Since there are even fewer drought conditions in Minnesota and Wisconsin, we only use data for Iowa and Illinois counties in the UMRB and estimate our model by pooling Iowa and Illinois together. So we have a balanced panel dataset with 5016 observations.

We construct corn yield to be composed of county-specific fixed effect parameter, a deterministic time trend variable, function of weather variables and interactions of time trend with weather variables to allow weather impact to change over time. Specifically,

$$
\begin{aligned}
Y_{i,t} = \quad & \alpha_i + \beta_0 * T + \beta_w * f\left(W_{i,t}\right) + \beta_{wT} * f(W_{i,t}) * T + \varepsilon_i \qquad (4.3) \\
f(W) = \quad & Temp^{MJ} + (Temp^{MJ})^2 + Temp^{JA} + (Temp^{JA})^2 + Prep^{MJ} \\
& +(Prep^{MJ})^2 + Prep^{JA} + (Prep^{JA})^2 + SM^{May1} + (SM^{May1})^2 \\
& +SM^{Jul1} + (SM^{Jul1})^2 + Temp^{JA} * Prep^{JA} + Temp^{JA} * SM^{Jul1} \\
& +Prep^{JA} * SM^{Jul1}
\end{aligned}
$$

Y represents corn yield. α_i is the fixed effect parameter which absorbs time-invariant and county-specific determinants of corn yield. *T* is time trend variable taking values of 0 to 32 for years 1980 to 2012. *Temp* and *Prep* denote the average temperature and precipitation across the indexed period, respectively. *MJ* and *JA* are the period indices for May-June and July-August. *SM* denotes soil moisture on May 1st or July 1st. β_0, β_w and β_{wT} are coefficients to be estimated. ε_i is the error term.

All weather variables are re-centered to have zero mean by subtracting the historical mean from each observation. When all weather variables take values at their historical mean levels, α_i measures the average corn yield for county *i* in 1980. β_0 measures a deterministic trend yield due to factors not related to weather conditions. It is assumed to be constant across all the counties. The function of weather variables $f(W_{i,t})$ is specified as the sum of quadratic functions of all the weather variables and also includes the interactions of July-August temperature, precipitation and July 1st soil moisture to take into account of the soil moisture effect on corn yield and yield trend.

Without the interaction terms with time trend, it illustrates the weather impact in 1980. Interaction term of weather and time trend variable $f(W_{i,t}) * T$ gives the model the flexibility to capture the possible changes in weather impact on corn yield over time.

Moreover, the quadratic and interaction terms of weather variables allow the marginal impact of weather variables to vary for different weather conditions.

In order to minimize the parameters to be estimated and keep significant factors in the yield response function, we selectively add and remove terms so that to minimize Bayesian information criteria (BIC). The resulting model is as follows:

$$\begin{aligned} Y_{i,t} = \quad & \alpha_i + \beta_0 * T + \beta_1 * Temp^{MJ} + \beta_2 * Temp^{JA} + \beta_3 * (Prep^{MJ})^2 \\ & + \beta_4 * Prep^{JA} + \beta_5 * (Prep^{JA})^2 + \beta_6 * SM^{May1} + \beta_7 * (SM^{Jul1})^2 \\ & + \beta_8 * Temp^{JA} * Prep^{JA} + \beta_9 * Temp^{JA} * SM^{Jul1} \\ & + \beta_{10} * Prep^{JA} * SM^{Jul1} + \beta_{11} * Temp^{MJ} * T + \beta_{12} * (Temp^{JA})^2 * T \\ & + \beta_{13} * (Prep^{JA})^2 * T + \beta_{14} * Prep^{JA} * SM^{Jul1} * T + \varepsilon_i \end{aligned} \tag{4.4}$$

The stepwise-BIC approach only keeps the interaction of time trend with May-June temperature, July-August temperature and precipitation, and July 1st soil moisture. May 1st soil moisture or May-June precipitation impact on corn yield per year only changes through the soil moisture impact of July 1st soil moisture. The model specification is straightforward to test whether weather impact on corn yield measured in bushels per acre has varied over time.

To investigate the percentage impact of weather variables and also to test whether the percent yield impact of weather variables has changed over time, we have 100*log(Y) on the left-hand side of the regression function. So the coefficients present the percent yield change due to changes in the predictors. Using the same selection method, the model is specified as in equation (4.5). Here, *b*'s are the parameters to be estimated as β's in model (4.4). γ_i is the corresponding county-specific fixed effect parameters.

$$
\begin{aligned}
100 * \log(Y_{i,t}) = \quad & \gamma_i + b_0 * T + b_1 * Temp^{MJ} + b_2 * Temp^{JA} \\
& + b_3 * (Temp^{JA})^2 + b_4 * Prep^{MJ} + b_5 * \left(Prep^{MJ}\right)^2 \\
& + b_6 * Prep^{JA} + b_7 * (Prep^{JA})^2 + b_8 * SM^{May1} \\
& + b_9 * SM^{Jul1} + b_{10} * (SM^{Jul1})^2 + b_{11} * Temp^{JA} * Prep^{JA} \\
& + b_{12} * Temp^{JA} * SM^{Jul1} + b_{13} * Prep^{JA} * SM^{Jul1} \\
& + b_{14} * Temp^{MJ} * T + b_{15} * Temp^{JA} * T \\
& + b_{16} * (Temp^{JA})^2 * T + b_{17} * (Prep^{JA})^2 * T \\
& + b_{18} * Temp^{JA} * Prep^{JA} * T \\
& + \varepsilon_i
\end{aligned} \tag{4.5}
$$

The error term absorbs the impact of all other yield determinants. It could be heteroskedastic and serial correlated among counties or over time. The coefficients are still consistent with the presence of heteroskedastic but the standard errors are underestimated. The null hypotheses that the estimated variance of residuals from our fixed effect models is equal across all counties are rejected at the 1% significance level using Breusch-Pagan test (Breusch and Pagan, 1979). The null hypotheses that there are no serial correlations in the error terms are also significantly rejected using Breusch-Godfrey test (Godfrey, 1978). Arellano type variance matrix is adopted to obtain the standard errors, which are robust to heteroskedasticity and serial correlation for fixed number of years and large number of observations. (Arellano, 1987)

Estimation Results

Models (4.4) and (4.5) are estimated using the panel data of county-level corn yield, average temperature, precipitation in May-June and July-August and soil moisture on May

1st and July 1st. Table 4.1 provides coefficients estimates and robust standard errors for all selected variables in model (4.4). All coefficients are significant at 5% significance level.

Table 4.1: Estimates and Robust Standard Errors of Yield Model

	Estimates	Standard Errors
$Intercept$	114.27	(2.58)
T	2.00	(0.04)
$Temp^{MJ}$	3.82	(0.50)
$Temp^{JA}$	-8.69	(0.28)
$(Prep^{MJ})^2$	-1.47	(0.11)
$Prep^{JA}$	5.41	(0.30)
$(Prep^{JA})^2$	-1.78	(0.14)
SM^{May1}	-0.0239	(0.0078)
$(SM^{Jul1})^2$	-0.0007	(0.0001)
$Temp^{JA} * Prep^{JA}$	1.35	(0.16)
$Temp^{JA} * SM^{Jul1}$	0.0312	(0.0045)
$Prep^{JA} * SM^{Jul1}$	-0.0377	(0.0077)
$Temp^{MJ} * T$	-0.15	(0.03)
$(Temp^{JA})^2 * T$	-0.05	(0.01)
$(Prep^{JA})^2 * T$	0.03	(0.01)
$Prep^{JA} * SM^{Jul1} * T$	-0.0018	(0.0004)

Note: Coefficients and standard errors for soil moisture variables are rounded to four decimal places and others are rounded to two. All coefficients are statistically significant at 5%.

The intercept is a proxy of the average yield in 1980 given all weather variables taking values at their historical mean. It is estimated to be around 114 bushels per acre. The deterministic trend due to factors other than weather variables is significantly positive around

2 bushels per acre per year. Terms without interaction with time trend variable give an estimate of the weather impact in 1980.

The coefficient of May-June temperature is significantly positive. Warm spring is generally beneficial for corn growth. On the contrary, summer heat incurs yield losses. Given July-August precipitation and July 1st soil moisture at historical mean levels, one Celsius degree increase in July-August temperature will lead to 8.69 bushels yield losses. But increase in July-August precipitation or July 1st soil moisture will help reduce yield losses from high heat, which is consistent with the result in Chapter 3. For example, one standard deviation increase in July-August precipitation reduce yield losses from one degree increase in temperature by 1.95 bushels per acre; one standard deviation increase in July 1st soil moisture reduce yield losses by 1.58 bushels per acre, which is a little less than the impact from one standard deviation increase in precipitation. Above average May-June precipitation is harmful. Too much water in the planting period might delay the planting and be harmful for root development. This is similar for May 1st soil moisture. Assuming July-August temperature and July 1st soil moisture take their historical mean values, corn yield increases when July-August precipitation is1.52mm/day above its historical mean and decreases for higher values. Increase in July-August temperature increases the marginal impact of precipitation also extends the threshold to a higher value. Summer precipitation is more helpful in a wider range in hot summer. More July 1st soil moisture works in an opposite way as increase in July-August temperature due to the substitution effect. The impact of July 1st soil moisture is similar as July-August precipitation. All the results are generally consistent with Chapter 3. The potential change in the weather impacts on corn yield will be discussed in the next section.

Table 4.2: Estimates and Robust Standard Errors of Log-Yield Model

	Estimates	Standard Errors
$Intercept$	477.28	(2.37)
T	1.46	(0.04)
$Temp^{MJ}$	5.01	(0.51)
$Temp^{JA}$	-9.78	(0.42)
$(Temp^{JA})^2$	-0.73	(0.16)
$Prep^{MJ}$	-1.21	(0.14)
$(Prep^{MJ})^2$	-1.20	(0.11)
$Prep^{JA}$	4.56	(0.28)
$(Prep^{JA})^2$	-1.67	(0.15)
SM^{May1}	-0.0684	(0.0103)
SM^{Jul1}	0.0819	(0.0130)
$(SM^{Jul1})^2$	-0.0006	(0.0001)
$Temp^{JA} * Prep^{JA}$	2.33	(0.33)
$Temp^{JA} * SM^{Jul1}$	0.0418	(0.0058)
$Prep^{JA} * SM^{Jul1}$	-0.0604	(0.0040)
$Temp^{MJ} * T$	-0.19	(0.03)
$Temp^{JA} * T$	0.10	(0.02)
$(Temp^{JA})^2 * T$	-0.03	(0.01)
$(Prep^{JA})^2 * T$	0.03	(0.01)
$Temp^{JA} * Prep^{JA} * T$	-0.05	(0.02)

Note: Coefficients and standard errors for soil moisture variables are rounded to four decimal places and others are rounded to two. All coefficients are statistically significant at 5%.

Table 4.2 illustrates the estimates and robust standard errors of Log-Yield Model. All coefficients are still significant at 5%. Given the percent yield variation, more variables are determined to be relevant. The estimated average corn yield in 1980 is around 118 bushels per acre with a deterministic 1.46% trend per year. The impacts of the weather variables are similar to the result of the Yield Model. As a baseline in 1980, increase in May-June temperature benefits yield; too much water in May-June is harmful for corn growth; July-August temperature, precipitation and July 1st soil moisture all have a concave relationship with corn yield. One degree increase in July-August temperature reduces corn yield by 9.78% at round the historical mean temperature and the losses increase as the temperature increases, given average water availability. When July-August precipitation or July 1st soil moisture move from the historical mean to one standard deviation below the mean, the marginal yield losses for temperature around the mean are about 13% and 12%, respectively. July-August precipitation benefits corn yield in percentage up to 1.5mm/day above its historical mean. At historical mean, 1mm/day increase in precipitation increases corn yield by 4.56%. When July 1st soil moisture is one standard deviation below its historical mean, the marginal impact of precipitation increases to 7.62% due to the substitution effect. July 1st soil moisture increases yield when it is below 119mm, given July-August temperature and precipitation at mean values.

Terms without interaction with time trend variable provide a picture of the weather impacts in 1980. It is straightforward to use the estimation of the interactions terms with time trend to test whether the marginal and total impacts have changed over time in both absolute and percentage terms.

Marginal Impact of Weather Variables

Our model specification allows us to investigate the yield deviation driven by weather variables and also the change in the weather impacts over time. In the estimation results section, we discuss the baseline weather impact in 1980. This section we concentrate on weather variables that might have changing impact on corn yield. The marginal impact of weather variables and the change in the marginal impact can be expressed as linear functions of the model parameters. And due to the quadratic and interaction terms, the marginal impact might also depend on the variable itself and other weather variables.

Table 4.3 provides the reduced forms of the marginal effects of May-June temperature, July-August temperature, July-August precipitation and July 1st soil moisture in absolute terms. Based on the linear expressions shown in table 4.3, one can test the hypothesis that the marginal effects of these variables are constant over time.

For May-June temperature, the marginal benefit is decreasing over time since β_{11} is significantly negative. So on average the effect of May-June temperature is not very significant.

For July-August temperature, the expression shows that $\frac{\partial Y}{\partial Temp^{JA}}$ decreases as $Prep^{JA}$ and SM^{Jul1}decreases below the mean ($Prep^{JA} < 0, SM^{Jul1} < 0$) since the two coefficients are significantly positive. This indicates that water availability reduces the marginal yield losses due to high heat, on the other hand, dry weather condition exaggerate the damages of high heat in the summer. Change of the impact of July-August temperature is dependent on itself. When temperature is above the historical mean ($Temp^{JA} > 0$), the yield losses due to one degree increase in the July-August temperature increases over time since $\beta_{12} < 0$. Moreover, the increase speed is higher for higher temperature. Yield is becoming more and more sensitive to high heat. This is consistent with Lobel et al. (2014) that yield sensitivity to high heat has steadily increased and more severe under more adverse conditions. As the major factor that incurs corn yield losses, it is reasonable to doubt that the drought impact has decreased over time.

Table 4.3: Marginal Effects of Weather Variables of Yield Model and Their Change Over Time

Variables	Expressions
$Temp^{MJ}$	$\frac{\partial Y}{\partial Temp^{MJ}} = \beta_1 + \beta_{11} * T$
	$\frac{\partial^2 Y}{\partial Temp^{MJ} \partial T} = \beta_{11}$
$Temp^{JA}$	$\frac{\partial Y}{\partial Temp^{JA}} = \beta_2 + \beta_8 * Prep^{JA} + \beta_9 * SM^{Jul1} + 2 * \beta_{12} * Temp^{JA} * T$
	$\frac{\partial^2 Y}{\partial Temp^{JA} \partial T} = 2 * \beta_{12} * Temp^{JA}$
$Prep^{JA}$	$\frac{\partial Y}{\partial Prep^{JA}} = \beta_4 + 2 * \beta_5 * Prep^{JA} + \beta_8 * Temp^{JA} + \beta_{10} * SM^{Jul1} + 2 * \beta_{13} * Prep^{JA} * T + \beta_{14} * SM^{Jul1} * T$
	$\frac{\partial^2 Y}{\partial Prep^{JA} \partial T} = 2 * \beta_{13} * Prep^{JA} + \beta_{14} * SM^{Jul1}$
SM^{Jul1}	$\frac{\partial Y}{\partial SM^{Jul1}} = 2 * \beta_7 * SM^{Jul1} + \beta_9 * Temp^{JA} + \beta_{10} * Prep^{JA} + \beta_{14} * Prep^{JA} * T$
	$\frac{\partial^2 Y}{\partial SM^{Jul1} \partial T} = \beta_{14} * Prep^{JA}$

For July-August precipitation, the marginal impact depends on itself, July-August temperature and also July 1st soil moisture through the substitution effect. Marginal impact of precipitation through reducing yield losses from high heat is discussed previously. We now focus on the interaction between precipitation and soil moisture. First we consider that when July 1st soil moisture is at the historical mean level, the marginal effect decreases over time when precipitation is below average since $\beta_{13} > 0$. But on the other hand, corn yield increases with July-August precipitation when it is below the threshold $-\frac{\beta_4}{2*(\beta_5+\beta_{13}*T)}$. So the threshold increases over time. The marginal effect of July-August precipitation decreases over time when it is below average and precipitation benefits corn yield in a wider range. Increase in July-August temperature also extends the range in which more precipitation is beneficial for corn yield. Then we consider when July 1st soil moisture is below the average. We put our focus on the impact of drought weather conditions. Beneficial conditions have the opposite impact as the adverse condition. When soil moisture is below average, the marginal effect of precipitation increases over time since $\beta_{14} < 0$. The threshold also increases as July 1st soil moisture decreases below average. This indicates comparing with average soil moisture condition, decrease in precipitation incur more yield losses in a wider range under limited soil moisture environment.

For July 1st soil moisture, it increases yield when it is below average with other variables at mean. High temperature and low precipitation can increase this threshold. The marginal effect doesn't change over time when July-August precipitation remains at mean. However, when precipitation is below average, one mm/day decrease in soil moisture lead to more yield losses over time.

Table 4.4 illustrates the expressions of the marginal effects of May-June temperature, July-August temperature and precipitation in percentage points. The marginal effect of May-June temperature is similar as in the Yield model using bushels per acre.

For average July-August temperature ($Temp^{JA} = 0$), the average marginal percentage impact is $b_2 + b_{15} * T$ with $b_2 = -9.78$ and $b_{15} = 0.1$. So yield losses due to average heat decrease over time. Similar as the Yield model, increase in the water availability in the summer reduces percentage yield losses resulting from high heat since b_{11} and b_{12} are all positive. This benefit from July-August precipitation is decreasing over time because the coefficient of $Temp^{JA} * Prep^{JA} * T$ is significantly negative. For high July-August temperature ($Temp^{JA} > 0$), this declining trend decreases as temperature increases and it reaches zero when $Temp^{JA} = -\frac{b_{15}}{2*b_{16}} = 1.67$, given average July-August precipitation. For extreme heat, the percentage yield losses might increase over time. This is somehow consistent with our result using the model in Yu and Babcock (2010) that the percentage yield losses under modest drought reduce over time but failed to reject the constant sensitivity null hypothesis under moderate and extreme drought conditions.

Table 4.4: Marginal Effects of Weather Variables of Log-Yield Model and Their Change Over Time

Variable	Expressions	
$Temp^{MJ}$	$\frac{\partial 100 * \log(Y)}{\partial Temp^{MJ}} =$	$b_1 + b_{14} * T$
	$\frac{\partial^2 100 * \log(Y)}{\partial Temp^{MJ} \partial T} =$	b_{14}
$Temp^{JA}$	$\frac{\partial 100 * \log(Y)}{\partial Temp^{JA}} =$	$b_2 + 2 * b_3 * Temp^{JA} + b_{11} * Prep^{JA} + b_{12} * SM^{Jul1}$ $+ b_{15} * T + 2 * b_{16} * Temp^{JA} * T + b_{18} * Prep^{JA} * T$
	$\frac{\partial^2 100 * \log(Y)}{\partial Temp^{JA} \partial T} =$	$b_{15} + 2 * b_{16} * Temp^{JA} + b_{18} * Prep^{JA}$
$Prep^{JA}$	$\frac{\partial 100 * \log(Y)}{\partial Prep^{JA}} =$	$b_6 + 2 * b_7 * Prep^{JA} + b_{11} * Temp^{JA} + b_{13} * SM^{Jul1}$ $+ 2 * b_{17} * Prep^{JA} * T + b_{18} * Temp^{JA} * T$
	$\frac{\partial^2 100 * \log(Y)}{\partial Prep^{JA} \partial T} =$	$2 * b_{17} * Prep^{JA} + b_{18} * Temp^{JA}$

Similarly, percentage marginal impact of July-August precipitation is greater and benefits corn yield in a wider range under low than average soil moisture condition. Also the marginal effect of July-August precipitation through reducing yield losses from high temperature is declining over time. The decrease is faster for higher temperature. Assume July-August temperature and July 1st soil moisture are taking their historical mean values. The relationship between log yield and July-August precipitation is becoming less concave over time. The marginal impact of July-August precipitation decreases over time when it is below average because $b_{17} > 0$ and the threshold below which increase in July-August precipitation benefits corn yield increases over time.

Table 4.5: Marginal Effects Change Over Time since 1980

Variables Values			Marginal effects change over time.					
$Temp^{JA}$	$Prep^{JA}$	SM^{Jul1}	$Temp^{JA}$		$Prep^{JA}$		SM^{Jul1}	
			Yield	Log Yield	Yield	Log Yield	Yield	Log Yield
σ	0	0	Decrease	Constant	Constant	Decrease	Constant	Constant
σ	0	-σ	Decrease	Constant	Increase	Decrease	Constant	Constant
σ	-σ	0	Decrease	Constant	Decrease	Decrease	Increase	Constant
σ	-σ	-σ	Decrease	Constant	Constant	Decrease	Increase	Constant

Note: σ indicates one standard deviation above mean and similarly -σ is one standard deviation below mean. Other variables are taking historical mean values. Decrease/Increase/Constant means the marginal effects decrease/increase/unchanged over time. For July-August temperature, decrease in marginal effect means more yield losses.

Since the marginal effects of weather variables rely on the value of each other. We summarize the change of the marginal effects over time under several hypothetical weather conditions as shown in Table 4.5. And we focus on drought conditions which we have more concern. In general, yield losses from high July-August temperature increase over time in bushels per acre, but remain constant in terms of percentage. Marginal effect of July-August precipitation decreases under low precipitation level, but offsets by the increase through the substitution effect with soil moisture. In terms of percentage, the impact of July-August precipitation decreases. Marginal impact of July 1st soil moisture remains constant except that when July-August precipitation is low it increases due to the substitution effect.

Total Weather Impact

In previous section, we separately discuss the change in the impact of each weather variable over time, especially the impact of high July-August temperature, low July-August precipitation and July 1st soil moisture. This section we investigate the total impact of weather on corn yield and the change in the total weather impact over time. In the general expression, total weather impact on corn yield is simply $\beta_w * f\left(W_{i,t}\right) + \beta_{wT} * f(W_{i,t}) * T$. The change in the total weather impact over time is $\beta_{wT} * f(W_{i,t})$.

For the Yield model, the change in the total weather impact over time is:

$$\frac{\partial Y}{\partial T} = \beta_{11} * Temp^{MJ} + \beta_{12} * (Temp^{JA})^2 + \beta_{13} * (Prep^{JA})^2 + \beta_{14} * Prep^{JA} * SM^{Jul1} \tag{4.6}$$

This indicates that beside of the deterministic trend increase due to factors not related to weather variables, like technology and management, absolute trend yield might also change with weather variables like May-June temperature, July-August temperature and precipitation and July 1st soil moisture.

For the Log-Yield model, the change in the total weather impact in terms of percentage points over time is:

$$\frac{\partial 100 * \log(Y)}{\partial T} = \quad b_{14} * Temp^{MJ} + b_{15} * Temp^{JA} + b_{16} * (Temp^{JA})^2 \qquad (4.7)$$

$$+b_{17} * (Prep^{JA})^2 + b_{18} * Temp^{JA} * Prep^{JA}$$

For hypothetical weather conditions, we test the null hypotheses that yield deviation driven by weather variables remains constant over time. The result is illustrated in Table 4.6, in which Increase/Decrease/Constant indicates yield losses due to weather conditions increase/decrease/unchanged over time.

Table 4.6: Total Weather Effects Change Over Time since 1980

Variables Values			Change in Yield Losses due to Weather	
$Temp^{JA}$	$Prep^{JA}$	SM^{Jul1}	Yield	Log Yield
σ	0	0	Increase	Constant
σ	0	-σ	Increase	Constant
σ	-σ	0	Increase	Decrease
σ	-σ	-σ	Increase	Decrease
2 σ	-σ	-σ	Increase	Constant

Note: σ indicates one standard deviation above mean and similarly -σ is one standard deviation below mean. Other variables are taking historical mean values. Decrease/Increase/Constant means the marginal effects decrease/increase/unchanged over time.

In general, yield losses from adverse weather impact increase over time in terms of bushels per acre. This is mainly due to increased yield losses from the dominant factor July-August temperature. Expressed in percentage terms, we fail to reject that the marginal impact remains constant over time under most cases. The impact of July-August temperature remains constant under moderate heat condition. So when July-August precipitation is below average, the less sensitivity of yield to precipitation becomes the dominant factor and yield losses decline under these conditions. But when July-August temperature is 2 times standard deviation above the historical mean, the total weather impact returns to be constant. The increased benefit from precipitation is offset by the damage from high heat.

Moreover, the weather impact on trend is still well below the deterministic trend impact. Yield is still increasing over time. Although in absolute terms yield losses due to adverse weather increase over time, it remains about constant in percentage terms.

Conclusions

Weather plays an important role in predicting corn yield. Impacts of weather variables on corn yield have been well studied. The results are consistent that high temperature is the main factor for yield losses. Precipitation and soil moisture partially reduce the yield losses from high temperature. However, there are different opinions about whether corn yield is becoming more drought tolerant in absolute and percentage terms. We use a balanced panel dataset for 76 counties in Iowa and 76 counties in Illinois from 180 to 2012. Two recent drought years 2011 and 2012 are included to have more observations of adverse weather conditions in the modern eras. Average temperature, average precipitation in July and August and soil moisture simulated from crop model EPIC on May 1st and July 1st are adopted in our study.

We construct the yield response function as the sum of a deterministic time trend variable and yield deviations due to weather variables which are composed of quadratic functions of all the weather variables and interaction of July-August temperature, precipitation and July 1st soil moisture, and the interaction of time trend with all the weather terms. This specification allows us to capture the interaction of temperature and water availability in the summer and also the change of weather impact over time. We test the hypotheses that the marginal and the total impact of weather variables remain constant over time under our hypothetical adverse weather conditions in both absolute and percentage terms.

Our results suggest that yield sensitivity to adverse weather conditions increases over time since 1980 in bushels per acre. Yield losses increase over time primarily from high July-August temperature. But in general we fail to reject the null hypothesis that corn yield sensitivity remains constant over time in terms of percentage. This might result from the increase in the absolute yield level due to technology or management improvement. And yield losses might have decreased under modest drought conditions.

The marginal impact of July-August temperature decreases over time, which indicates that one degree increase in July-August temperature incurs more yield losses over time in bushels per acre. This change is not significant in terms of percentage. For July-August precipitation, the marginal impact increases over time when July 1st soil moisture is low and increases faster for lower July 1st soil moisture levels. This means the substitution effect is strengthening over time, especially when one source is limited and the other source is available. This is the same for July 1st soil moisture. Other than the substitution effect, the marginal impacts of precipitation and soil moisture are about constant over time in terms of absolute yield. July-August precipitation marginal impact decreases over time in percentage terms because corn yield is becoming less sensitive to summer precipitation and precipitation is also becoming less helpful to reduce yield losses from high heat over time. Our model estimates also show the marginal impact of July 1st soil moisture on corn yield in percentage terms is not changing with time.

To remove the possible bias in our model resulting from the weather trend, we also use the detrended weather variables to estimate our model. The major results are consistent with the model presented in this study.

References

Arellano, M. (1987). Computing robust standard errors for within-groups estimators. *Oxford Bulletin of Economics and Statistics*, 49 (4): 431-434.

Brusch, T. S. and Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47 (5): 1287-1294.

Deschenes, O. and Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97 (1): 354-385.

Gassman, P. W., Williams,J. R., Benson, V. R., Izaurralde, R. C., Hauck, L. M., Jones, C. A., Altwood, J. D., Kiniry, J. R., and Flowers, J. D. (2004). Historical development and applications of the EPIC and APEX models. *American Society of Agricultural Engineers*. Paper No. 042069.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica*, 46: 1293-1302.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., Quiroga Jakas, M.C. (2006). Simulating soil C dynamics with EPIC: model description and testing against long-term data, *Ecological Modeling*, 192(3-4): 362–384.

Lobell, D. B. and Asner, G. P. (2003).Climate and management contributions to recent trends in U.S. agricultural yields. *Science*, 299 (5609): 1032.

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., Hammer, G. L. (2014). Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. *Science*, 344 (6183): 516-519.

Maurer, E. P., Wood, A. W., Adam, J. C., Lettenmaier, D. P., and Nijssen, B. (2002). A long-term hydrologically-based data set of land surface fluxes and states for the conterminous United States. *Journal of Climate,* 15: 3237-3251.

Schlenker, W. and Roberts, M. J. (2006). Nonlinear effects of weather on corn yield. *Review of Agricultural Economics*, 28 (3): 391-398.

Yu, T. and Babcock, B. A. (2010). Are U.S. corn and soybeans becoming more drought tolerant? *American Journal of Agricultural Economics*, 92 (5): 1310-1323.

Yu, T. and Babcock, B. A. (2011).Estimating non-linear weather impacts on corn yield - A bayesian approach. Center for Agricultural and Rural Development, Working Paper 11-WP 522.

CHAPTER 5. CONCLUSIONS

Due to the expansion of renewable fuel industry, agriculture and energy are closely correlated with each other. In the U.S., corn is the primary feedstock used to produce ethanol so that corn supply is critical to determine the biofuel production and energy policy effectiveness. Weather conditions play an important role in predicting corn yield. This dissertation is composed by three topics with different focuses on biofuel, and weather impacts on corn yields.

Chapter 2 focuses on the biofuel market. We construct a computable trade model of ethanol related markets between the U.S. and Brazil. The supply curves of conventional biofuels RINs and advanced biofuels RINs are constructed, which can be used to illustrate and simulate the hierarchical competition of U.S. corn ethanol, Brazilian sugarcane ethanol and biodiesel, and to project all biofuels RINs prices. Moreover, we calibrate the demand and supply curves of corn, soybean, and biofuels, and simulate the equilibrium prices and quantities for marketing year 2013/14, using a stochastic partial equilibrium model. Results indicate that RFS mandates induce the two-way trade of ethanol across the U.S. and Brazil and the possibility of two-way trade would increase with the other advanced mandate. Biodiesel helps reduce this potentially trade, but could not eliminate this whole impact on trade without subsidies.

In chapter 2, we calibrate corn yield by fitting a beta distribution from historical data. Chapter 3 shifts to investigate the weather and soil moisture impact on corn yield, which is critical to predict corn yield. Not limited to use the two frequently used weather variables, temperature and precipitation; we add soil moisture as an explanatory variable into the corn yield response function. Daily soil moisture data in the Upper Mississippi River Basin Area from 1980 to 2012 is simulated from the crop model EPIC. Recent two drought years 2011 and 2012 are included in the estimation dataset to facilitate estimation of corn yield response to extreme conditions. We develop a fixed effect model with sum of linear spline function of weather variables and interactions of July-August variables. Bayesian Markov Chain Monte Carlo approach is applied to estimate the parameters and the thresholds simultaneously. Results suggest corn yield effects from high temperature and plant water availability cannot be meaning fully isolated from one another. The percent yield reduction from high temperature is 15 to 20 percentage points greater under low compared to high water availability. The determinant factors for corn yield losses vary across the Corn Belt region. Excessive spring rainfall is damaging to corn yield in Illinois and Iowa, however, during hot and dry summers, excessive spring rainfall is important for reducing yield loss through the soil moisture effect. In Wisconsin, too little spring rainfall is more damaging than too much.

In chapter 4, we focus on the topic that whether corn yield losses driven by weather conditions have reduced over time. With more observations under drought condition in 2011 and 2012, we revisit previous literature and find that corn yield losses from drought increase in bushels and remain constant rather than decreasing in percentage terms. We then develop yield response functions to allow the weather impact on corn yield to change over time and test the hypotheses that the impacts remain constant over time under our hypothetical adverse weather conditions. Our results show that yield losses due to drought conditions increases over time in absolute yield terms but remains constant in percentage terms due to increase in base yield over time. Corn yield is becoming less sensitive to July-August precipitation which reduces yield losses under modest drought level.