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Genetically Modified Corn Diffusion and Biofuel Usage: Impacts on Corn Belt Cropping Systems Changes

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GENETICALLY MODIFIED CORN DIFFUSION AND BIOFUEL USAGE:

IMPACTS ON CORN BELT CROPPING SYSTEMS CHANGES

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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GENETICALLY MODIFIED CORN DIFFUSION AND BIOFUEL USAGE:

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The adoption of genetically modified (GM) crops, the rise of ethanol production that produced an additional derived demand for corn, and the increasingly prominent position of corn and soybeans in crop rotations embody major changes in U.S. agriculture during the past decades. This study investigates the linkages among these developments in two ways. First, we look at how biotechnology and biofuels have influenced cropping system changes in the Corn Belt region of the United States, using state-level data from 2000 to 2019. Second, we investigate the determinants of corn acreage intensification levels and heterogeneity at the state level using data from 2000 to 2017 for the same eleven Corn Belt states. In order to analyze these interconnections, we employed a linear mixed model to generate robust regression results estimates. In assessing the role of biotechnology and biofuels on U.S. Corn Belt cropping pattern changes, we find that (1) during this time period, farmers began to abandon relatively complex cropping patterns in favor of simpler crop rotation approaches; and (2) the widespread use of GM corn for biofuel appears to have had a positive impact on the increase in corn acres planted, although the consequences of biotech breakthroughs on producer planting decisions vary by state. As a result, future policy changes affecting farm-level corn production decisions are also likely to be varied. Further, in investigating the determinants of corn acreage intensification levels and heterogeneity in U.S. Corn Belt states, we find that (1) using the base regression model, the proliferation of GM crops, the implementation of renewable fuel regulations in the early 2000s, and the first lag of the relative corn to soybean price ratio all have positive effects on state-level corn acreage intensity; and (2) cropland released from the Conservation Reserve Program (CRP), a simple measurement of economies of scale, and the development of the ethanol production infrastructure are key contributors of corn acreage heterogeneity at the state level, while real cropland values – which partially represent cropland quality improvements such as tile drainage and irrigated agricultural acres – do not explain state-level corn acreage heterogeneity. Among the 11 Corn Belt states, Iowa had the largest increase in corn intensity of 7.6 percent over the period examined. Findings of this thesis back up and help explain well-documented shifts in cropping patterns, such as the loss of small grains and marginal lands in favor of corn and soybeans. Over a roughly two-decade period, this research sheds light on the determinants of corn acreage intensity levels and heterogeneity in Corn Belt states.

Keywords: GM Corn Diffusion, Corn Production, Biofuel Policy, Crop Rotation Patterns, state heterogeneity, corn acreage intensification.

CHAPTER I
INTRODUCTION

U.S. agriculture has undergone major changes over the past decades, including the adoption of genetically modified (GM) crops, the expansion of ethanol production that created an additional derived demand for corn, and an increasingly dominant role of corn and soybeans in crop rotations. According to Wallander et al. (2011) farmers shifted their crops away from hay and small grains and toward corn and soybeans since the 1990s. The same time period also saw changes in biofuel policies and broad-based agricultural policy. In addition, consumer demands, producers' profit, and trade potential influence producers' decisions regarding their production practices and technology usage. This study seeks to assess determinants of cropping pattern changes. In particular, the study's objectives are to study the role of GM corn adoption, the passage of the renewable fuel laws in the early 2000s, market forces, cropland released from the Conservation Reserve Program (CRP), economies of scale, the development of the ethanol production infrastructure, and cropland prices on the increasing relative contribution of corn in crop rotations. Results of the study may provide insights for agricultural policy makers as they consider the impacts of the adoption of possible future technological advancements, as well as those of biofuel, agricultural, and conservation policy changes on cropping pattern changes in the United States.

Chapter II examines the role of biotechnology and biofuels in cropping system changes in U.S. Corn Belt states. This chapter also seeks to investigate the impact of the increased adoption of GM corn varieties, corn-based biofuel production, and the resulting surge in derived demand for corn on corn acreage intensity in these states. The findings of this chapter shed light on the complex set of factors that affect cropping patterns changes, the widespread use of GM corn and the effects of biotechnological advances on producer planting decisions.

Chapter III focuses on exploring sources of the heterogenous impacts of federal policies and GM corn adoption on corn acreage intensity in Corn Belt states. This chapter not only expands the analysis of Chapter II by examining the degree to which corn acreage intensity was affected by GM corn adoption, changing federal biofuel policies, relative corn prices, but also further investigates the sources of the heterogenous impacts. The results of this chapter provide insights on the sources of state-specific impacts of the federal policies, market conditions, and GM corn adoption on corn acreage intensity.

The findings, conclusions, and implications from Chapters II and III are summarized in Chapter IV. While the findings of Chapters II and III are closely related to one another, Chapter III provides a more in-depth and expanded analysis and relies on a shorter period of analysis than that of Chapter II.

CHAPTER II

THE ROLE OF BIOTECHNOLOGY AND BIOFUELS IN THE U.S. CORN BELT CROPPING SYSTEM CHANGES

Abstract

Using state-level data from 2000 to 2019, the effects of transgenic corn usage and federal biofuel policies on state-level cropping trends in the U.S. Corn Belt region are investigated. We find that 1) producers shifted away from complex cropping patterns and toward simpler rotational practices during this period; 2) the spread of genetically modified corn for biofuel use appears to have had a positive influence on the intensification of corn acres planted, but the effects of biotech advances on producer planting decisions differ across states. As a result, future policy changes impacting corn production decisions at the farm level are likely to be diverse.

Introduction

Based on state-level data from 2000 to 2019, we examine links between increases in the adoption of genetically modified (GM) corn varieties, corn-based biofuel production, and the related surge in the derived demand for corn on corn acreage intensity in U.S. Corn Belt states. The objective of the study is to analyze how federal biofuel policies, relative corn (Zea mays) to soybean (Glycine max) prices, and farm-level GM corn adoption rates affected corn acreage intensity across 11 Corn Belt states over the 20-year period. This research adds to the current literature by considering the long-term effects of GM corn plantings and biofuel policy shifts on cropping patterns. The research also distinguishes the impact of changes in biofuel policies and technology on state-level cropping trends, which is a valuable contribution. Also, following Fausti et al. (2014) this study updates literature on U.S. corn belt cropping pattern changes using the span of our data. Our empirical findings indicate that increased ethanol production in response to biofuel policy changes influenced cropping patterns, which was aided by the spread of GM corn varieties and relatively high corn prices. While these factors led to an increase in corn production intensity in the Corn Belt as a whole, the effects varied by state. The impact of biofuel policy adjustments on crop rotation patterns at the state level is complicated by heterogeneity throughout states. Thus, heterogeneity across states has important policy implications for how biofuel policy changes will affect crop rotation patterns at the state level[1].

Literature Review

The Relationship Between GM Corn, Ethanol Production, and Corn Acreage Intensity.

Agricultural land use has been shifting toward more intensive processing activities for a long time. In the United States' Prairie Pothole Area, Johnston (2014) described how grasslands, wheat, and other small grains were converted to corn and soybean production (which partially overlaps with the northwestern part of the Corn Belt region). In the eastern part of the Northern Great Plains, Claassen et al. (2010) reported on the conversion of marginal production acres (grasslands and hay land) to cropland, while Wright and Wimberly (2013) recorded grassland conversions in the western Corn Belt. More generally, Wallander et al. (2011) found that corn and soybean acreage increased throughout the United States, along with an increase in double-cropping and hay land conversions.

[1] This work is currently under the review by *Renewable Agriculture and Food Systems* (RAFS).

Cropping systems in the United States are becoming more homogeneous, especially in the Midwest (Aguilar et al., 2015; Plourde et al., 2013). In recent decades, the number of crops participating in rotation cycles in the Corn Belt of the United States has decreased (Fausti, 2015; Johnston, 2014; Stigler, 2019; Wallander et al., 2011). Crop rotation practices that include multiple crops can help preserve soil fertility, minimize negative environmental impacts of agricultural production including soil erosion and nutrient discharge, reduce crop damage from weed and insect pests, and increase crop productivity (Bowles et al., 2020; Claassen et al., 2010; Hunt et al., 2020; Landis et al., 2008; Seifert et al., 2017). Producers are increasingly relying on chemical and genetic technologies to preserve soil fertility and keep agricultural pests at bay, rather than traditional rotation practices (Davis et al., 2012; Hunt et al., 2017; Sindelar et al., 2016). This may exacerbate externalities, including soil degradation and water pollution (Amundson et al., 2015; Turner & Rabalais, 2003).

The decline in crop diversity partially coincided with changes in U.S. energy and agricultural policies, the increased usage of GM crops, and the growth of the ethanol and agricultural seed industries. U.S. federal and state policies and programs wield much influence on cropping systems diversity, as evidenced by agricultural producers managing the majority of U.S. farmland in accordance with farm bill guidelines, incentives, and mandates to qualify for commodity payments or other farm program subsidies(Medicine & Council, 2015). Farm policy generally evolves slowly and unevenly but the 1996 farm bill embodied a major policy change, by expanding the number of crops qualifying for farm program payments. This increased farmers' ability to change crops, turn marginal lands into crop production, and switch from crop production to other agricultural uses while retaining program payments

(Claassen et al., 2010). Subsequent farm bills reversed some of this flexibility, but farmers retained much of their ability to respond directly to market signals, policy incentives, and technology changes (Mercier, 2011).

One aspect of technology change affecting agriculture over the past two decades is the widespread adoption of crops that were developed using genetic engineering, which offers tools and strategies to supplement traditional breeding techniques and can improve disease resistance, insect resistance, herbicide tolerance, and drought tolerance of crops (Vincelli, 2016). GM crop technology provides a host of benefits at the farm level, such as reducing labor requirements for crop production and increasing profits(Brookes & Barfoot, 2018; Fernandez-Cornejo, 2002). Since GM crop varieties were first introduced for commercial production in the United States in 1996, farmers rapidly adopted herbicide tolerance, insect resistance, and stacked (both traits). GM corn and soybean varieties in their cropping systems. U.S. adoption rates of all GM corn and soybeans varieties increased from zero in 1995 to 25 percent and 54 percent in 2000, to 86 percent and 93 percent in 2010, and to 92 percent and 94 percent in 2020, respectively (Economic Research Service, 2021b).

Numerous authors have studied the rapid adoption and diffusion of the types of GM crop varieties that enable crops to withstand herbicide applications or that are toxic to insect pests or both and documented an array of implications of the increased reliance on GM crop varieties(Benbrook, 2012; Brester et al., 2019; Cattaneo et al., 2006; Fernandez-Cornejo, 2002; Hutchison et al., 2010; Scandizzo & Savastano, 2010). A comprehensive study by the National Academies of Sciences - Engineering and Medicine (2016) did not find conclusive evidence of increased environmental risks of GM crops relative to crops bred using conventional methods, but the report's authors acknowledged the development of resistance to GM crop traits as a critical problem for crop production, attributed mainly to poor resistance-management strategies.

The case of target insect resistance development helps explain observed increases in the number of cropland acres treated with insecticides in selected locations – impacts that were unlikely to have been observed in the short run following the adoption and diffusion of GM crops – as reported by (Fausti et al., 2018). Whether a consequence of poor management practices or the technology itself, the example of target insect resistance development points to the need for considering the long-term effects of the adoption and diffusion of GM crops (Catacora-Vargas et al., 2018). One of the contributions of this study is a consideration of the long-term consequences of GM corn plantings on cropping patterns. Also, following Fausti et al. (2014), this study updates literature on U.S. corn belt cropping pattern changes using the span of our data.

The widespread adoption of GM crops was previously linked to the intensification of specific crops in the Midwest (Heinemann et al., 2014). Cap and Malach (2012) also reported changes in land use patterns elsewhere and in particular in Argentina, Brazil, Paraguay, and Bolivia, involving increased areas planted to soybeans in general and GM soybeans. More broadly, in assessing impacts of GM crop technology across the globe based on farm-level data from 1996 through 2016, Brookes and Barfoot (2018) noted increased production areas of the four main GM crops (soybean, corn, cotton, and canola), especially of corn and soybeans.

Partially overlapping with the increased use of GM crops is the rise of biofuels. On the supply side, the development of corn and soybean-based biofuel conversion technology enabled the use of biofuels for transportation purposes. California’s decisions to ban methyl tert-butyl ether (MTBE) as a gasoline additive in

2002 and replace it with ethanol provided the initial impetus for the nationwide phase-out of MTBE and its replacement by ethanol. The nationwide conversion from MTBE to ethanol led to a rapid increase in the demand for ethanol and an expansion of the ethanol industry (Bracmort, 2020).

Biofuels were also upheld as an important energy source for the domestic economy to reduce the U.S. reliance on oil imports from abroad. To encourage the development of biofuel markets, U.S. energy policies include programs that set minimum requirements for biofuel usage blended with other transportation fuels. The two primary pieces of legislation are the 2005 Energy Policy Act, amended by the Energy Independence and Security Act of 2007. The latter's Renewable Fuel Standard (RFS) statute sets minimum targets for renewable fuel volumes that increase each year, from 9 billion gallons in 2008 to 36 billion gallons in 2022. The RFS further prescribes sub-mandates for four broad-based biofuel categories (cellulosic, biomass-based diesel, undifferentiated-advanced, and renewable energy), but it is subject to waivers that reduce the minimal usage of specific types of biofuels. For example, while the RFS statute requires using 30 billion gallons of renewable fuel in 2020, just over 20 billion gallons of total renewable fuel are used in practice, which corresponds to 11.6 percent of the total volume of the transportation fuel used. Due to the insufficient development of advanced biofuels, cornstarch-based ethanol remains the largest renewable fuel component, with annual maximum use of 15 billion gallons by 2022 (Bracmort, 2020).

According to the Renewable Fuels Association (2021), the United States produced 175 million gallons of ethanol in 1980. Since then, annual production levels initially grew relatively slowly to 1.6 billion gallons in 2000, but subsequently increased eight-fold to 13.3 billion gallons by 2010, and thereafter enlarged again much more slowly to 15.8 billion gallons of ethanol in 2019. Correspondingly, the United States produced 9.9 billion bushels of corn in 2000, which increased to 12.4 billion bushels in 2010 and 13.6 billion bushels by 2019 (National Agricultural Statistics Service, 2019). The ethanol industry consumed 0.5, 4.5, and 6.5 percent of the U.S. corn crop in 1980, 1990, and 2000, respectively, which increased to 38.5 percent in 2010, before dropping to 34.8 percent of the total U.S. corn supply in 2019 (Economic Research Service, 2021a).

As growing shares of the total corn output in the United States were used for ethanol production, the corn-based ethanol industry grew to a major industry over fewer than 15 years (Cai & Stiegert, 2014). The expansion phase of the ethanol industry coincided with corn price increases that sent positive market signals to row crop producers to increase their corn production (Fausti, 2015).

This study reports on the overlapping developments of GM corn use increases, changing federal farm policies, federal biofuel laws that mandated ethanol usage in transportation fuels, and their impacts on changing cropping patterns in the U.S. Corn Belt region, based on state-level data from 2000 to 2019. Given differences by state in terms of climate and soil conditions as well as state policies, understanding the effects of changes in policy and technology on state cropping patterns must account for state-level characteristics, which we accomplish by using a mixed modeling approach that incorporates both random and fixed effects. An additional contribution of our study is that we consider the combined and separate impacts of these distinct but overlapping developments on cropping system changes. Given the 20-years period, our analysis takes a long-run view of factors affecting cropping system changes. Our results indicate that the intensification of corn acres planted was influenced by the spread of GM corn for biofuel usage, which likely contributed to moving toward simpler rotational practices. We further find that the impacts of advancements in biotechnology on producer planting decisions varied across states.

Data and Methodology

For each year between 2000 and 2019, we used secondary state-level data on crop acres planted and GM corn coverage in eleven northern Corn Belt states – Iowa, Illinois, Indiana, Nebraska, Kansas, Michigan, Minnesota, Missouri, Ohio, South Dakota, and Wisconsin – resulting in a total of 220 observations. Data on annual crop acres planted were obtained from the National Agricultural Statistics Service (2019), and annual GM crop adoption rates from the (Economic Research Service, 2019). State-level data on GM crop adoption levels from before 2000 are not fully compatible with those of subsequent years, so they were not included in our analysis (Economic Research Service, 2019). A policy dummy variable was created to reflect the passage of the 2005 Energy Policy Act and the Energy Independence and Security Act of 2007 with a value of one for the years 2005 to 2019, zero otherwise. Annual average corn and soybean prices were collected from the (National Agricultural Statistics Service, 2019).

Using annual data, we apply a linear mixed regression modeling approach to estimate a fixed-effects model with random intercepts by states to investigate the effects of GM corn adoption and the enactment of ethanol policies on changes in state-level corn acreage intensity. The dependent variable is the ratio of corn acres planted to total acres planted, referred to as corn acreage intensity (CAI). Explanatory variables include the ratio of corn prices to soybean prices (PR), a 2005 ethanol policy dummy variable (RFS=1 for years from 2005 to 2019), and the state-level ratio of corn acres planted with GM corn (GMCS). State dummy variables were created to measure the random effects of corn acreage intensity by state (with Michigan as the base state). Using the above predictors, the random intercept model provides estimates for corn acreage intensity by state, over the 20-year transition period. The random intercept model was estimated with the repeated effect option in the SAS proc mixed procedure to account for possible state-level heterogeneity (SAS Institute, 1999). To account for possible endogeneity issues, the corn to soybean price ratio (PR) was lagged by one year (period t-1). We expect that data on acres planted are clustered due to the heterogeneity of individual state characteristics – such as climate, soil, landscape, and state agricultural and biofuel policies – leading to dissimilar responses to the introduction of biotechnology and bioenergy policies during the period covered by our study. Clustered data refer here to attributes associated with an individual state's agricultural sector, such as climate, soil type, landscape, and state-level agricultural policies that would result in a clustering of similar cropping patterns over geographically related states.

The renewable fuel laws' implementation is expected to have a positive relationship with corn acreage intensity, as outlined earlier. Also, the corn to soybean price ratio is expected to have a positive relationship with corn acreage intensity, because a decrease in the relative price of corn to soybeans would be expected to lessen corn acreage intensity (as soybean prices rise at the expense of corn prices, CAI decreases, and as corn prices rise at the expense of soybean prices, CAI increases). Lastly, the relationship between the ratio of total corn acres planted to GM corn acres planted and corn acreage intensity is expected to be mixed, in the sense that – while corn acreage intensity is expected to increase as the proportion of GM corn out of total corn acres grows during the period when the GM share increases – it has little or no impact in the long run. The price ratio variable captures the market valuation of corn relative to other crops, the GM corn variable reflects the supply-side impact of genetically engineered corn on total corn production, and the renewable fuels policy dummy variable (RFS) captures the increased demand for corn due to corn-based ethanol production policy incentives.

The standard assumptions associated with the linear mixed model (LMM) are listed in equations 1-4. Using the standard vector notation provided on page 121 in the SAS/Stat 9.3 User Guide (SAS Institute, 2011), we define the general structure of the model:

1. $CAI = \mathrm{X}\beta + Z\gamma + \varepsilon,$
2. $\gamma \sim N(O, G),$
3. $\varepsilon \sim N(O, R),$ and
4. $COV(\gamma, \epsilon) = 0.$

The dependent variable CAI (corn acreage intensity) denotes the vector of dependent variable observations. Matrix X is the design matrix associated with β, which represents the vector of unknown fixed-effects parameters. Matrix Z is the design matrix associated with Υ, representing the vector of unknown random-effects parameters. We specified the *repeated* statement option in our model because we do not want to assume that R is equal to $\sigma^2 I$. The error term, ε, reflects an unknown random error. Equation 4 states that Υ and ε are independent, which implies that following SAS Institute (1999), the variance of CAI can be defined as:

5. $VAR[CAI] = ZGZ^T + R,$

where G and R are the covariance matrices associated with Υ and ε, respectively. The superscript notation "T" denotes the transpose matrix operation. Examining the correlation between the model's residuals and the exogenous variables showed correlation coefficients of less than 0.01, suggesting exogeneity. The model design suggests the only predictor potential for endogeneity to be an issue is with the corn-soybean price ratio. To avoid this issue, the corn-soybean price ratio was lagged for one period. The default covariance structure for the mixed procedure is variance components (SAS Institute, 1999). While other covariance structures for *G* and *R* were investigated, the variance component structure was selected based on the "Null Model Likelihood Ratio Test." The LMM procedure in SAS provides flexibility when dealing with regression diagnostic issues (SAS Institute, 1999). We first employed a "sandwich estimator" approach to produce robust standard errors associated with β (Diggle et al., 1994; SAS Institute, 1999)

The linear form of the general model to be estimated is

6. $CAI_{it} = \alpha + \sum_{j=1}^{3} \beta_j X_{jit} + \sum_{i=1}^{11} \gamma_i Z_{it} + \varepsilon_{it},$

$$where\ i = 1\ to\ 11, j = 1\ to\ 3, and\ t = 1\ to\ 20$$

Parameter α is the fixed intercept, subscript "*i*" denotes the state, "*j*" refers to the explanatory variables, and "*t*" denotes time. The other parameters in equation 6 have been already explained above.

Empirical Results

Table 1 reports on the acres planted by a major crop over two periods in the Corn Belt from 1996 to 2019. Table 1 shows that the 11 U.S. Corn Belt states collectively experienced a major shift away from small grains, wheat (Triticum) and hay, toward corn and soybeans, in terms of annual crop acreage averages between a base period spanning from 1996 to 2004 and the 2005 to 2019 period. Between the first and second periods, the regional average of the proportion of corn and soybean acres planted out of total acres planted increased from 36.3 percent to 40.5 percent, and from 32.3 percent to 33.4 percent, respectively. The increase in corn acres planted over the two periods took place at the expense of cropland planted to barley, oats, wheat, and other crops. This pattern confirms the broad assertion by Wallander et al. (2011) that an increase in corn and soybean acreage across the United States, which coincided with an increase in double-cropping and hay land conversion.

Table 1: Acres planted by a major crop over two periods in the Corn Belt, 1996 to 2019

Crops (planted acres)	Avg. (1996-2004) Period 1		Avg. (2005-2019) Period 2		Change Period 2 vs. 1	
	1,000 acres	%	1,000 acres	%	1,000 acres	%
Corn	64,283	36.3	71687	40.5	7404	11.5
Soybean	57,103	32.3	59075	33.4	1972	3.5
Barley*	524	0.3	193	0.1	-331	-63.2
Oats*	2,077	1.2	1348	0.8	-729	-35.1
Wheat	22,331	12.6	18350	10.4	-3981	-17.8
Other	30627	17.3	26221	14.8	-4406	-14.4
Total Area	176945	100	176874	100	-71	-0.04

* Oats: Avena sativa; Barley: Hordeum vulgare. Source: Compiled from USDA data, https://quickstats.nass.usda.gov/.

Table 2 summarizes changes in cropping patterns in the 11 Corn Belt states between 1996 and 2019, divided over two sub-periods: 1996-2004, and 2005-2019. The table shows that each state experienced an increase in corn acres planted from the first to the second period, measured as a proportion of total acres planted, as described earlier. However, with the exception of Iowa and Illinois, all the other nine states experienced an increase in soybean acres planted from the first to the second period. This may be because Iowa and Illinois had the largest percent of the corn acres planted.

Table 2: Changes in crop area shares in the Corn Belt, by state, 1996 to 2019

State/ Region	Period	Corn Acres Planted	Soybean Acres Planted	Barley Acres Planted	Oats Acres Planted	Wheat Acres Planted	Other crops Acres Planted
		********* *As a Percent of Total Principal Crop Area*********					
Iowa	1996-04	49.8	42.4	0.0	1.0	0.1	6.6
	2005-19	55.3	39.4	0.0	0.6	0.1	4.6
Illinois	1996-04	47.2	44.0	0.0	0.3	4.4	4.1
	2005-19	52.4	41.9	0.0	0.2	3.1	2.4
Nebraska	1996-04	44.3	22.5	0.0	0.8	10.1	22.3
	2005-19	48.8	26.1	0.0	0.6	7.90	16.6
Minnesota	1996-04	36.1	34.9	1.5	1.9	10.4	15.2
	2005-19	40.7	36.7	0.5	1.2	7.90	12.9
Indiana	1996-04	45.7	44.1	0.0	0.3	4.4	5.6
	2005-19	47.2	44.6	0.0	0.1	3.2	4.8
South Dakota	1996-04	23.8	22.5	0.6	2.4	19.7	31.0
	2005-19	30.5	26.5	0.2	1.6	15.9	25.3
Wisconsin	1996-04	45.3	16.8	0.8	5.1	2.2	29.8
	2005-19	49.2	21.8	0.4	3.3	3.4	21.9
Ohio	1996-04	32.4	43.6	0.0	1.0	10.4	12.7
	2005-19	35.2	46.3	0.0	0.6	7.4	10.5
Kansas	1996-04	13.1	11.3	0.0	0.5	44.5	21.6
	2005-19	19.7	16.6	0.1	0.4	39.2	24
Missouri	1996-04	20.7	36.2	0.0	0.3	8.0	34.8
	2005-19	24.3	39.1	0.0	0.2	5.9	30.5
Michigan	1996-04	34.6	29.5	0.3	1.3	8.8	25.5
	2005-19	37.0	31.0	0.2	1.0	9.1	21.7
Corn Belt	1996-04	36.3	32.3	0.3	1.2	12.6	17.3
	2005-19	40.5	33.4	0.1	0.8	10.4	14.8

Source: Compiled from USDA data, https://quickstats.nass.usda.gov/.

Table 3 provides summary statistics of the main variables used in our analyses. From 1996 through 2019, the mean corn and soybean acres planted in the 11 Corn Belt states are 6,265 and 5,303, respectively. Also, the minimum and the maximum values for all the field crops denote that corn has a wider range of its coverage than the other crops. Again, on the average, GM corn has a bit higher coverage than GM corn varieties, however, both traits have the same range of approximately 98 percent. The prices for corn, soybean and wheat also indicate that the prices of soybean are higher than the other two crops. This is evidenced in the mean and the maximum values for soybean in Table 3.

Table 3: Descriptive statistics (1996-2019)

Variable	Units	N	Mean	St Dev	Minimum	Maximum
Corn	1,000 acres	264	6265	3521.8	2,150	14,300
Soybean	1,000 acres	264	5303	2695.0	930	11,000
Barley	1,000 acres	264	28.8	69.4	0	600
Oats	1,000 acres	264	147.4	122.0	0	530
Wheat	1,000 acres	264	1804	2,609.7	0	11,800
Total acres	1,000 acres	264	16082	6,163.4	460	25,021
GM corn	Percent	264	58.9	35.8	0	98
GM soybean	Percent	264	73.0	34.1	0	98
Corn prices	USD/bu	264	3.4	1.4	1.7	6.7
Soybean prices	USD/bu	264	8.4	2.9	4.4	14.1
Wheat prices	USD/bu	264	4.3	1.5	1.8	8.1

Table 4 lists the fit statistics and the estimated Intraclass Correlation Coefficients (ICC) for each model. The ICC estimates exceed 90 percent for the random intercept model, suggesting that the effects of biotech advancements on producer planting decisions are heterogeneous across states. Regression diagnostic analyses confirmed that the mixed model approach was more robust than a simple fixed effects model. A restricted maximum likelihood estimation procedure was employed. To gauge the goodness of fit of the mixed model approach, we ran a simple fixed effect-only model. Furthermore, the variance components estimating procedure found that the variance associated with matrix G's contribution to the variance of matrix V (the covariance matrix of corn acreage intensity) was significant at the five percent level or less for the random intercept model (Table 4). Regression diagnostics confirm the decision to select a variance-covariance structure that corrects for serial correlation in the model (Table 4). The --existence of clustered data results in biased standard errors. Clustering was confirmed, and a process for correcting it was implemented (ICC statistics reported in Table 4).

Table 4: Variance Components Statistics and Global Fit Statistics

Random intercept model: Simple	Covariance Parameter estimate	Fit Statistics
Random intercept	0.01374**	
	(0.006174)	
Residual	0.000501***	
	(0.000074)	
AR(1)†	0.4910***	
	(0.000501)	
ICC‡		96.5%
-2 Log Likelihood		-1024.7
AIC		-1018.7
BIC		-1017.5

Notes: ***, **, and * indicate significance at 0.01, 0.05, and 0.10 levels, respectively; and standard errors in parentheses; † AR(1) is the autoregressive (1) diagnostic to account for serial correlation and state-level heterogeneity; ‡ ICC is the Intraclass Correlation Coefficient, given by the ratio of the random intercept to the sum of the random intercept and the residual, expressed in percentage points.

Table 5 reports on the random intercept model estimates for corn acreage intensity, by state from 2000 to 2019. The random intercept model provides estimates for the fixed effects and random effects parameter estimates at the regional and state levels, respectively. All fixed effects parameter estimates are statistically significant at the one percent level, except for GM corn which is statistically significant at about 5.4 percent. These findings suggest that an increase in the lagged corn to soybean price ratio, the adoption and diffusion of GM corn technology, and the passage of the biofuels acts of 2005 and 2007 each positively affected corn acreage intensity in the Corn Belt region. The fixed effects intercept has a value of 0.2851, which can be interpreted as an estimate of the regional average of the proportion of corn acres to total acres planted, indicating that over the 20-year span of our data, corn acreage intensity averaged 29 percent. The random intercept coefficients reflect the deviation from the regional average. The coefficients for Kansas, Missouri, and South Dakota are statistically significant and negative, implying that these states' intercepts are smaller than the regional average intercept. The coefficients for Minnesota, Ohio, and Michigan are not statistically significant, implying that these states' intercepts are at the regional average. The random intercept coefficients of the remaining five states (Iowa, Illinois, Nebraska, Indiana, and Wisconsin) are statistically significant and positive, which implies that these states' intercepts are above the regional average. The simple mixed model confirms that the GM corn adoption rate, relative crop prices, and biofuel policy all contributed to an increase in corn acreage intensity in the eleven states. Furthermore, the random intercept estimates confirm heterogeneity in cropping decisions across states due to individual state attributes, including those related to agricultural production and state-specific policies.

Synopsis of Empirical Results

The parameter estimate for the fixed effects intercept component of the model of 0.2851 reflects the proportion of corn acres planted at the regional level assuming that GM corn diffusion and biofuel policies were unchanged. The random intercepts are interpreted as the state-specific deviation from the fixed effects intercept for the region as a whole, so states without a statistically significant random intercept (Minnesota, Ohio, and Michigan) had a proportion of corn acres planted equal to the regional average. Statistically significant positive random intercept terms indicate states whose proportions of corn acres planted were above the regional average prior to the significant increase in GM corn adoption and implementation of biofuel policies (Iowa, Illinois, Nebraska, Indiana, and Wisconsin). Conversely, states with statistically significant and negative coefficients represent those with less corn intensity than the regional average before the widespread diffusion of GM corn and implementation of biofuel policy incentives (Kansas, Missouri, and South Dakota).

Table 5: Random intercept model estimates for corn acreage intensity, by state, 2000-2019

Random intercept model	Coefficients estimate
Fixed Effects	
Intercept	0.2851***
	(0.03372)
GM corn	0.0341*
	(0.01759)
RFS	0.0240***
	(0.004651)
Price Ratio	0.1560***
	(0.02013)
Random Effects	
Iowa	0.1466***
	(0.03619)
Illinois	0.1221***
	(0.03619)
Nebraska	0.0824**
	(0.03620)
Minnesota	0.0048
	(0.03620)
Indiana	0.0797**
	(0.03621)
South Dakota	-0.1041***
	(0.03625)
Wisconsin	0.0922**
	(0.03619)
Ohio	-0.0395
	(0.03625)
Kansas	-0.2055***
	(0.03620)
Missouri	-0.1529***
	(0.03619)
Michigan	-0.0258
	(0.03620)

Notes: ***, **, and * indicate significance at 0.01, 0.05, and 0.10 levels, respectively; standard errors in parentheses; type 3 test for fixed effects indicated the interaction coefficient in Models 1-4 are significant (P-value < 0.01); parameter estimates rounded to 4 decimal places.

Discussion

As the proportion of corn and soybean acres out of total crop acres planted increased between the pre-and post-RFS periods, total acres planted to small grains and hay declined and producers moved away from conventional rotation practices in the region. Based on the empirical evidence produced by a random intercept model with fixed effects, biotechnology advances in energy and crop production, as well as previous government policy decisions in the areas of energy and agriculture, appear to have had a positive impact on the intensification of corn acres planted in the Corn Belt region. The results also suggest that state-level corn acreage intensification due to the introduction of GM corn and biofuel technology was heterogenous across the eleven-state region during the 20-year period of this study. This suggests that possible changes in energy policies, relative crop prices, and the ability of GM technology to continue providing pest protection will therefore also likely affect crop rotation patterns differently from state to state.

Cropping pattern shifts in general, as well as corn's increasing dominance in the eleven states' crop production systems, had a slew of anticipated and unforeseen consequences. For example, the relatively high corn prices experienced in the years following the passage of the renewable fuels standards led to a drop in other crop production, global price rises for other crops, and a rise in the cost of growing livestock Corn production intensification, aided in part by the use of GM varieties, resulted in improved corn pest resistance (Gassmann et al., 2011) and insecticide coverage of planted acreage (Fausti et al., 2012). At the outset of crop biotechnology's widespread use, neither the degree of pest resistance nor the resulting rise in insecticide acreage coverage was expected.

The findings of this study, though focused on data collected in the eleven-state Corn Belt region, may be applicable to other parts of the country. Corn production has increased not only as a result of widespread adoption of GM corn varieties and biofuel policies but also as a result of other factors such as climate change and advancements in plant breeding technology. Therefore, the issues raised in our research pose a challenge to agriculture in the United States and are crucial to its future success.

Conclusion

This study explores the overlapping developments of the increased GM corn acreage as a share of total corn acreage, changing federal agricultural policies, the implementation of federal biofuel laws mandating ethanol usage in transportation fuels, and their impacts on changing cropping patterns in the U.S. Corn Belt region, based on state-level data from 2000 to 2019. Agricultural land use has long moved toward increased intensity. This study reports on developments over the past two decades that involved an expansion of corn and soybean acreage at the expense of small grain acreage and an acceleration of grassland conversions to cropland. The increased homogeneity in cropland usage corresponded with a steady move toward simpler crop rotations with associated soil health concerns and an increased reliance on chemicals to hold pests at bay. The past two decades have also seen changes in renewable fuel policies, increased corn production for ethanol use, and a near-complete spread of GM corn as a proportion of total corn acres.

The study found that the spread of GM corn for biofuel use influenced the intensification of corn acres planted, and the impacts differed across states, using a mixed modeling approach with both random and fixed effects. As a result, potential policy changes impacting corn production decisions at the farm level are likely to be inconsistent across states.

A key contribution of this study to the existing literature is that it considers the long-term consequences of GM corn plantings and biofuel policy changes on cropping patterns. An additional contribution is that the study distinguishes the effects of changes in biofuel policies and technology on state-level cropping patterns. This research could pave the way for future studies examining the direct effects of GM crop adoption, federal biofuel rules, and federal agricultural policies on crop rotations. Future research may be able to disaggregate the disparate effects of federal policies and GM corn adoption at the state level.

CHAPTER III

DETERMINANTS OF CORN ACREAGE INTENSIFICATION LEVELS AND HETEROGENEITY IN U.S. CORN BELT STATES

Abstract

The determinants of corn acreage intensification levels and heterogeneity in the U.S. Corn Belt states are explored using state-level data from 2000 to 2017 by employing a linear mixed model that includes both fixed and random effects. We find that (1) the proliferation of GM crops, the introduction of renewable fuel laws in the early 2000s, and the first lag of the relative corn to soybean price ratio all have positive effects on state-level corn acreage intensity, using the base regression model; (2) cropland released from the Conservation Reserve Program (CRP), as simple approximation of economies of scale, and the development of the ethanol production infrastructure are key contributors of corn acreage heterogeneity at the state level, while real cropland values – as a proxy for cropland quality improvements by way of tile drainage and irrigated agricultural acres – do not explain state-level corn acreage heterogeneity. Among the 11 Corn Belt states, Iowa had the largest increase in corn intensity of 7.6 percent between 2000 and 2017.

Introduction

U.S. agriculture underwent major changes over the past decades, including but not limited to the adoption of genetically modified (GM) crops, the expansion of ethanol production that created an additional derived demand for corn, and an increasingly dominant role of corn and soybeans in crop rotations. Chapter II showed that the prominence of corn acres as a share of total cropland planted was positively influenced by the spread of GM corn for biofuel use in the Corn Belt region between 2000 and 2019, but the effects varied across states. This study seeks to build on the previous study by exploring the sources of the heterogenous impacts of federal policies and GM corn adoption on corn acreage intensity in Corn Belt states. In particular, this study's objectives are to assess the influences of GM corn adoption, the passage of the renewable fuel laws in the early 2000s, market forces, cropland released from the Conservation Reserve Program (CRP), a simple approximation of economies of scale in production agriculture, the development of the ethanol production infrastructure, and real cropland values on the increased prevalence of corn in crop rotations.

A striking change in cropland usage in the United States over the past two decades is the increased predominance of corn acres as a share of total cropland acreage. At the national level, Wallander et al. (2011) documented an increase in corn and soybean acreage across the United States at the expense of cotton acreage and uncultivated hay land over the first decade in the 21^{st} century. Similarly, Susanto et al. (2008) found that corn acreage expansion took place at the expense of other crops such as soybeans, wheat, and cotton, as well as part of the cropland enrolled in the Conservation Reserve Program (CRP).

The increase in corn acres planted as a proportion of total cropland acres planted – which we refer to as corn acreage intensity – may be partially attributed to the expansion of ethanol production in the United States (Elobeid et al., 2007; Lin & Henry, 2016; Westcott, 2007), but other factors may have contributed as well. In their assessment of the likely effects of U.S. ethanol production on agricultural markets, Elobeid et al. (2007) noted a significant increase in demand for corn resulting in growing crops on increasingly marginal areas, and observed an increased prevalence of continuous corn production facilitated by transgenic varieties. Further, in studying agricultural expansion and crop rotation patterns in nine Corn Belt states (IA, IL, MO, NE, SD, OH, MN, IN, and KS) from 2006 to 2013, Lin and Henry (2016) observed a continuous acreage expansion of corn and soybeans while most other crops underwent a decline in areas planted. With a net loss of 3.9 million acres, the authors noted that grassland took the largest loss. The authors found that rising agricultural commodity prices, spurred by ethanol production and a variety of socioeconomic factors had a substantial impact on land use and agronomic practices in the United States. Further research by Westcott (2007) also showed an increased role of corn as the most prevalent feedstock for ethanol production.

The U.S. agricultural sector has undergone a series of additional changes, including but not limited to modifications in agricultural policies, the rapid and widespread increase in GM crop adoption, the implementation of biofuel policies, variations in market conditions, as well as changes in the scale of agricultural production operations. This study explores the influence of these developments on corn acreage intensity. In particular, the aim of the study is to investigate the degree to which corn acreage intensity was affected by GM corn adoption, changing federal biofuel policies, fluctuating corn prices relative to other commodity prices, federal programs in the form of CRP, ethanol production infrastructure, irrigated acres of land, average cropland values, and economies of scale in production agriculture. In doing so, the study elucidates sources of the heterogenous impacts of this set of factors on corn acreage intensity by state.

Chapter II focused on factors contributing to the increased share of corn acres out of total cropland acres, including the increased production of corn-based ethanol that created a derived demand for corn, broad agricultural and ethanol policy changes, relative crop price changes, and the increased usage of GM crops, based on secondary data on 11 Corn Belt states from 2000 to 2019. This research builds on the previous study by investigating how relative corn prices, agricultural and biofuel policies, the adoption of GM corn affect state-level corn acreage intensity. The current research also seeks to explore heterogenous impacts on corn acreage intensity due to the aforementioned factors based on data from the same 11 Corn Belt states from 2000 to 2017. The findings of this research are important for agricultural producers and policy makers because they enable policymakers and agricultural producers to make informed decisions about factors affecting cropping patterns.

Cropping System Changes

U.S. corn and soybean acres increased from 79,551 and 74,266 thousand acres to 90,819 and 83084 thousand acres, respectively, between 2000 and 2020, while other crop acres decreased from 174,868 to 136,211 thousand acres over the same period. That is, corn and soybean acres in the United States increased by 14.2% and 11.9 percent, respectively, while other crop acres declined by 22.1 percent between 2000 and 2020 (National Agricultural Statistics Service, 2021a). Figure 3 in the Appendix shows the increase in corn and soybean acres relative to other crops from 2000 to 2020.

Arora and Wolter (2018) argued that the origins of cropland conversions and cropping pattern changes are unclear and attributed inconsistencies to the different time periods that researchers use to investigate these linkages. However, other authors ascribe the increase in corn and soybean area to converting CRP land toward crop production (Johnston, 2014; Wimberly et al., 2017), and again others attribute it to the conversion of marginal grasslands (Lark et al., 2015; Wright & Wimberly, 2013).

Johnston (2014) showed that crop rotation practices underwent a reduction in complexity and became increasingly dominated by corn and soybeans over the past decades. In their analysis of cropping pattern changes in the North Dakota and South Dakota, O'Brien et al. (2020) found that a combination of grassland conversions, the return of CRP land to crop production, and crop rotation simplification resulted in an increase in total cropland area and a rapid spread of corn and soybean rotation systems. Our focus differs from the latter study in the sense that we analyze cropping pattern changes in eleven Corn Belt states and investigate the sources of state-level corn acreage heterogeneity.

While not a direct focus of this study, the growth in corn and soybean acres at the expense of small grains and grassland acres contributed to a series of related issues such as a rise in the number of acres treated with insecticide (Fausti et al., 2018; Fausti et al., 2012; Gassmann et al., 2011). Neither the extent of pest resistance nor the subsequent increase in the number of acres treated with insecticides was unanticipated at the onset of the widespread use of crop biotechnology.

The Spread of GM Corn

GM crop varieties have become widely adopted in the United States since their introduction for use in agricultural production in the 1990s. The three most important GM crop varieties – corn, soybeans, and cotton – are each planted on well over 90 percent of their respective total crop areas in the United States (Economic Research Service, 2021b). Agricultural producers have become reliant upon GM crop varieties for maintaining pest control, reducing their labor input, and increasing overall output.

This has provided them with net economic benefits and reduced input and output uncertainty (Benbrook, 2012; Brester et al., 2019; Brookes & Barfoot, 2018; Cattaneo et al., 2006; Fernandez-Cornejo et al., 2014). Scandizzo and Savastano (2010) noted that the process of adopting GM crops is largely irreversible, in the sense that farmers find it difficult to return to growing conventional, non-GM, crops.

Numerous authors studying the impacts of GM crops have raised concerns about their effects on a variety of aspects. For example, Anyshchenko (2019); Prakash et al. (2011); Wilkinson and Ford (2007) expressed concerns about the environmental effects of growing GM crops. However, an extensive report published by the National Academies of Sciences - Engineering and Medicine (2016) found no conclusive evidence of increased environmental risks from GM crops when compared to crops bred using traditional methods. The report's authors acknowledged the development of resistance to GM crop traits as a critical problem for crop production, but attributed the resistance to poor resistance-management strategies. They further indicated that new varieties – whether GM or traditionally produced – be subjected to safety assessments if they contain unexpected traits or potential risks. The report's authors noted that producers who embraced GM soybean, cotton, or corn generally experienced positive economic outcomes, although results vary depending on insect abundance, farming practices, and agricultural infrastructure.

Due to its rapid and widespread adoption since the 1990s, we include a focus on GM corn as a possible contributing factor to the increase in corn acreage intensity in the eleven Corn Belt states over the past two decades.

Market Forces

Claassen et al. (2010) documented that agricultural producers were encouraged to respond more directly to the market signals, policy incentives, and technological changes as a result of agricultural policy changes of the late 1990s than had been the case before. Figure 4 in the Appendix shows the changes in U.S. commodity prices from 2000 to 2020 for three common crops in the Corn Belt: corn, soybeans, and wheat. Between 2000 and 2012, prices of all three commodities rose to historically very high levels, but subsequently fell. Even in the face of large annual and seasonal variations, U.S. corn prices rose from $1.85 to $4.3 per bushel, while soybean prices increased from $4.54 to $11.15 per bushel between 2000 and 2020, corresponding to price increases of 132 percent for corn and 146 percent for soybeans (National Agricultural Statistics Service, 2021a).

Renewable Fuel Policies Affecting the Demand for Corn

Solomon et al. (2007) documented that a key factor underlying the initial increase in ethanol production was the ban on methyl tertiary butyl ether (MTBE) as a fuel additive in the early 2000s. Following the ban, ethanol was used in its place as an oxygenate, which led to a strong increase in the demand for corn as its fuel stock. However, the main energy policy changes directly boosting the demand for ethanol and thus the derived demand for corn were the 2005 Energy Policy Act (EPA) and the 2007 Energy Independence and Security Act (EISA). These two laws called for the development of renewable fuel standards that mandated the blending of ethanol into transportation fuel. According to the Renewable Fuels Association (2021), the mandate of the 2005 EPA was to blend ethanol with gasoline annually through 2012, while the 2007 EISA extended the mandate through 2022. The largest renewable fuel component consists of cornstarch-based ethanol, with an annual maximum of 15 billion gallons through 2022 (Bracmort, 2020). While the Renewable Fuel Standard (RFS) statute sets minimum targets for renewable fuel volumes for each year, it is subject to reductions due to waivers of the RFS requirements. As a result of the two renewable fuel laws, corn-based ethanol has become a major source of fuel in the United States over the past decades.

In examining the implications of the U.S. ethanol mandate using data from 1960 through 2010, Roberts and Schlenker (2009) found that RFS policy changed the supply of ethanol-blended gasoline and influenced agricultural production costs. Related, in analyzing how ethanol refineries affect the likelihood that a field will be planted to a particular crop based on annual data from 2002 through 2012, Stevens (2015) found a significant impact of ethanol refineries on the cropland usage, especially in areas near ethanol processing plants. These issues are particularly valid for Midwestern states because of the region's high concentration of ethanol plants.

Linking CRP, Mean Cropland Asset Value, Irrigation and Corn Acreage Intensification

The Farm Service Agency (FSA) administers the Conservation Reserve Program (CRP). This federal program allows farmers to retire environmentally vulnerable farmland currently in crop production in exchange for annual rental payments (Farm Service Agency, 2021; National Agricultural Statistics Service, 2019). Enrollment contracts are typically signed for 10-15 years. Several studies report that during times of high commodity prices, cropland released from CRP has a significant role in land use shifts (Hendricks & Er, 2018; Ifft et al., 2019; Janssen et al., 2008; Secchi & Babcock, 2015). CRP's long-term purposes are to restore and maintain land cover in order to improve water quality, minimize soil erosion, and limit wildlife habitat loss.

However, as land is released from CRP and turned into crop production, we expect that a disproportionately large share of the released cropland will be used for planting corn. Therefore, we expect CRP acres as a share of total cropland acres to have a negative relationship with corn acreage intensity.

Another aspect of change in production agriculture involves investments in land quality improvements by way of tile drainage and irrigation. To the best of our knowledge, no comprehensive state-wide data exist on the number of acres that are drained by tile in the Corn Belt for the entire period of analysis used in this study. However, the number of acres having drainage tile was included in the last two Censuses of Agriculture, and showed that tile drainage in the United States increased from 48.6 million acres to 55.6 million acres between 2012 and 2017, representing an increase of 14.5 percent (National Agricultural Statistics Service, 2021b). During the same period, the irrigated farm acres increased by 13.9 percent.

Economies of Scale in Agriculture

Economies of scale are frequently associated with mechanization in agriculture, which allows for the employment of more powerful and high-performance machines. To assess the above claim, Delord et al. (2015) indicated that individual expenses differ significantly from one farm to the next, regardless of farm size, a feature that might lead to inefficiencies. Also, Paul et al. (2004) assessed the elements that influenced Corn Belt farms' scale economies and efficiency from 1996 to 2001 and found that the potential for significant scale and scope economies, as well as some increased technical efficiency, appear to drive trends toward larger farm sizes and decreased competitiveness of small family farms. Similarly, USDA reports the average U.S. farm size increased from 434 acres in 2000 to 444 acres in 2017 (National Agricultural Statistics Service, 2019).

A commonly-used empirical measure for skewness – defined as the third moment of the probability density function – is Pearson's second skewness coefficient (median skewness) also referred to as the Pearson 2 measure of skewness (Doane & Seward, 2011) is defined as (mean-median)/(standard deviation). Given that no data are available on the standard deviation, we assume that the mean minus the median provides a rough measure of the distribution of acres operated in a state, whereby a positive skewness value implies that large farms dominate acres operated in a state. We use the difference between average and median farm size as a proxy for economies of scale.

Farm Programs Effects

Agricultural producers generally use farm programs to help manage market risks, recover from possible calamities, and help conserve and maintain the country's natural resources Farm Service Agency (2021). A key component of environmental and agricultural policy in the United States centers on alleviating negative externalities. McGranahan et al. (2015) argued that the policy objective of reducing negative externalities is accomplished in two ways. One is that farmer involvement in voluntary conservation projects tends to fluctuate depending on policy and market conditions (Stuart & Gillon, 2013). The other fundamental purpose of U.S. farm policy is to help stabilize commodity prices and increase farm incomes (Claassen et al., 2008; Ribaudo et al., 2001). As documented by Johnston (2014); Secchi and Babcock (2015); Wright and Wimberly (2013) and others, increased commodity prices fueled the expansion of intensive agriculture in the United States. This contributed to a transformation of agricultural land use that took the forms of a reduction in agricultural diversification, a decrease in integrated animal agriculture, and a reliance on a few, high-input crops.

Program payments have long been skewed toward large farm operations and agricultural safety net program benefits are concentrated among the largest, wealthiest farms. This may have contributed to scale enlargement in farm operations and consolidation according to research conducted over the last 50 years (Bekkerman et al., 2019; MacDonald, 2013). We seek to explore how these factors may have affected corn acreage intensity heterogeneity at the state level.

While no single variable can directly capture the broad and diverse aspects of agriculture policy, we utilize a one-year lag of the corn to soybean price ratio to quantify program impacts, in part because agricultural commodities became increasingly subject to market pressures in the late 1990s. After the early 2000s, however, commodity markets once again increased their reliance on government subsidies, this time in the form of crop insurance indemnity payments. We expect that the lagged relative commodity prices has a positive influence on corn acreage intensity.

Conceptual Framework

Based on findings from Chapter II, we expect that the rapid adoption and diffusion of GM crops increased corn acreage intensity. However, because GM crop technologies were first introduced in the 1990s and subsequently replaced nearly all conventionally-bred corn planting over a span of little more than a decade, we expect the relationship between GM crops and corn acreage intensity to be increasingly less noticeable as time progresses, and so mixed over the nearly two decades period of analysis of the current study.

In the same way, due to the increased derived demand for corn linked to the expansion of corn-based ethanol production, about 40 percent of corn produced is used primarily for fuel production, leaving the remainder for other uses, including livestock feed and high-fructose corn sweeteners. Ceteris paribus the increased demand for corn increases the price of corn, which in turn encourages corn producers to increases their production and thus creates an upsurge in the amount of corn for ethanol production (Hanon, 2014). Hence, we expect the biofuel policy changes occurring in the early 2000s and relative corn prices to be positively associated with corn acreage intensity. Furthermore, given that climate and soil conditions vary geographically, understanding the effects of policy changes and technology improvements on cropping patterns must account for local characteristics. Thus, we expect the state-level corn acreage intensification due to the introduction of GM corn and biofuel technology to differ by state. This study seeks to investigate the sources of these heterogenous impacts.

Data

Annual data pertaining to the 11 Corn Belt states – Iowa, Illinois, Indiana, Nebraska, Kansas, Michigan, Minnesota, Missouri, Ohio, South Dakota, and Wisconsin – were collected for the period from 2000 through 2017, resulting in a total of 198 observations. Table 6 provides a description of the variables used and their data sources. The time period of the dataset was limited on one end by a lack of consistent data on GM corn for years prior to 2000, and on the other end by the unavailability of data on irrigated land and median farm size for years beyond 2017. Annual observations were available for all data, except for acres of irrigated land and median farm size, which were obtained from the Census of Agriculture for 1997, 2002, 2007, 2012, and 2017. For the intervening years, the data on these two components were approximated by way of linear interpolations. Besides the irrigated acres and median farm size data – as well as ethanol production data which were obtained from the U.S. Energy Information Administration (EIA) – all other data were obtained from NASS. A policy dummy variable was included to reflect the passage of the 2005 Energy Policy Act and the Energy Independence and Security Act of 2007, with a value of one for the years between 2005 and 2017, and zero otherwise.

Table 6: Variable definitions and data sources, state-level observations

Variable	Name	Definition	Units	Data Source
CAI	Corn acreage intensity	Corn acres planted as a share of total cropland acres	Ratio	NASS
CBratio	Lag of corn/soybean price ratio	Corn to soybean price ratio, 1-year lagged	Ratio	NASS
GEC	GM corn share	GM corn acres planted as a share of total corn acres planted (ratio)	Ratio	NASS
Ethanol	Lag of ethanol production	Ethanol production, 1-year lagged	1,000 barrels	EIA
CRP	CRP acreage intensity	CRP acreage as a share of total cropland acres including CRP acres	Ratio	NASS
IFA	Irrigated farm acres	Irrigated acres as a share of total cropland acres including CRP acres		Ag Census
Scale	Economies of scale proxy	Difference between the mean and median farm size	Acres	NASS, Ag Census,
Avgcrop	Mean cropland asset value	Average cropland value deflated by the CPI-U	$/acres	NASS, BLS
RFS	Renewable fuels standard policy	1 for 2005 to 2017, zero otherwise	Dummy	
	Total cropland	Sum of acres in corn, soybean, wheat, ….., and CRP	Acres	NASS
	Average farm size	Mean of farm size	Acres	NASS
	Median farm size	Median farm size	Acres	Ag Census

Table 7 provides descriptive statistics of the variables used in the analysis. The mean of corn acreage intensity (CAI) was nearly 37 percent, suggesting that the average proportion of corn acres planted out of total cropland acres was approximately 37 percent in the eleven Corn Belt states over the 18-years of analysis. Corn acreage intensity varied from approximately 11 to 54 percent over the period and states covered. The mean of the one-year lag of the corn to soybean price ratio (CBratio) in the 11 states was 0.40, and the average proportion of GM corn acres planted as a share of total corn acres planted was 68 percent, varying from a low of nine percent to a high of 98 percent. The one-year lag of ethanol production varied from zero to 95.5 thousand barrels. CRP intensity – defined as the number of acres enrolled in the CRP as a share of total cropland acres – had a mean of 5.8 percent, and varied between 1.8 percent and 12.6 percent. The number of irrigated farm acres out of total cropland acres averaged approximately 7.5 percent, with a range from 0.4 percent to 42.7 percent. The scale variable – defined as the difference between the median and the mean farm size acreage – had a mean of 306.8 acres, and a range from 64.4 to 1,042 acres. The scale variable provides a proxy for the presence of economies of scale. Finally, the Avgcrop variable, representing real cropland value per acre – calculated as the nominal cropland value per acre adjusted for inflation using the CPI-U – had a mean of $1,487 per acre and varied between $316 to $3,616 per acre. While imperfect, the Avgcrop variable was used to capture cropland quality improvements due to tile drainage.

Table 7: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CAI	198	0.368	0.115	0.111	0.543

CBratio	198	0.400	0.045	0.328	0.482
GEC	198	0.684	0.270	0.090	0.980
Ethanol	198	14.387	18.232	0	95.513
CRP	198	0.058	0.026	0.018	0.126
IFA	198	0.075	0.110	0.003	0.427
Scale	198	306.8	262.538	64.400	1,042
Avgcrop	198	1,487	719.016	316.492	3,616

Table 8 lists the Pearson correlation matrix, which shows that all bivariate correlations between the predictors are smaller than 0.5, except for those between the real cropland value per acre and ethanol production variables (0.65), and between the real cropland value per acre and the proportion of cropland in CRP variables (-0.62). To avoid multicollinearity, predictors with bivariate correlation coefficients greater than 0.5 were not included in one and the same model. Initial information based on the correlation coefficients suggests that the ethanol production, CRP intensity, real cropland value, and economies of scale variables may serve as good predictors of corn acreage intensity.

Table 8: Correlation Matrix

	CAI	CBratio	GEC	Ethanol	CRP	IFA	Scale	Avgcrop
CAI	1							
CBratio	0.05791	1						
GEC	0.07319	0.08658	1					
Ethanol	0.48173	0.04196	0.47997	1				
CRP	-0.6388	-0.0453	0.06747	-0.07700	1			
IFA	0.03281	-0.0005	0.14403	-0.13934	0.07182	1		
Scale	-0.2916	-0.0107	0.35614	0.05035	0.27019	0.36055	1	
Avgcrop	0.67087	0.08454	0.34782	0.64606	-0.6199	-0.2147	-0.3923	1

Methodology

For analyzing the data, we used a mixed regression modeling approach to estimate a fixed-effects model with a random intercept by state. We estimated six alternative models to capture conditions that vary by state pertaining to GM crop plantings, renewable fuel usage, and the relative price of corn and to further investigate the sources of these heterogenous impacts. Model 1 is the base model that includes the variables GM corn, biofuel policies and the lag corn to soybean price ratio, with random intercept terms that capture the state-specific effects. Models 2 through 6 add variables to the base model one at a time, and also seek to assess the state-specific heterogenous impacts.

The aim of the six regression models is to investigate the contribution of each additional predictor. The dependent variable is corn acreage intensity (defined as the ratio of corn acres planted to total acres of cropland including cropland in CRP). Explanatory variables of the base model include the one-year lag of the ratio of corn to soybean prices, a dummy variable capturing ethanol policy changes, and the share of GM corn acres out of total corn acres. The additional predictors included in Models 2-6 are the CRP intensity (acres enrolled in CRP divided by total cropland acres including CRP acres), economies of scale, irrigated land (acres of irrigated land divided by total cropland including CRP acres), the one-year lag of ethanol production, and real cropland value (nominal cropland value deflated by the CPI-U).

We performed a likelihood ratio test to validate the use of each additional variable relative to the base model. The price ratio variable represents the market valuation of corn relative to that of soybeans. We used a one-year lag of the relative crop price to account for possible endogeneity between corn acreage intensity and relative crop prices. Further, the GM corn variable captures the supply-side effect of biotechnology on the production of corn, and the renewable fuels standard policy dummy variable reflects the demand for corn due to policies affecting the corn-based ethanol industry.

Considering the nature of the state-level cross-sectional dataset, a stationarity test was conducted to avoid spuriousness. We used the Phillips-Perron unit root test and found that our variables were stationary (the *p*-values of the tau test statistic are greater than 0.05), suggesting the variables need to be in their levels, not their first difference.

The six models estimated are as follows. Model 1 serves as the base regression model. Model 2 adds the CRP variable, and in its place Models 3-6 include the scale economies, irrigation, first lag of ethanol production and mean cropland values to the base model, respectively.

Due to different climate and soil conditions by region, the nature of the agricultural sector varies by state. The assumptions of our mixed modeling approach are given by the equations below. We define the generic form of our model following the standard notation of the SAS user guide as:

$$CAI = \mathrm{X}\alpha + Z\tau + \varepsilon \tag{1}$$

$$\tau \sim N(O, G) \tag{2}$$

$$\varepsilon \sim N(O, R) \tag{3}$$

$$COV(\tau, \varepsilon) = 0 \tag{4}$$

Taking the variance of equation 1 and using the conditions in equations 2, 3, and 4, equation 1 is rewritten as equation 5:

$$Var(CAI) = Var(\mathrm{X}\alpha + Z\tau + \varepsilon)$$

$$Var(CAI) = Var(Z\tau + \varepsilon)$$

$$Var(CAI) = Var(Z\tau) + Var(\varepsilon) + 2Cov(Z\tau, \varepsilon)$$

$$Var(\ CAI) = ZVar(\tau)Z^T + Var(\ \varepsilon\ ) + 2ZCov\ (\tau, \varepsilon\ )$$

$$Var(\ CAI) = ZGZ^T +\ R \qquad (5)$$

In equation 2, the dependent variable CAI_E is the corn acreage intensity and measures the vector of dependent variable observations for all four models. Vector Xα measures the unknown fixed effects estimates and matrix X is the design matrix associated with α. Vector $Z\tau$ measures the unknown random-effects estimates and matrix Z is the design matrix associated with $'\tau'$. Because equations 3 and 4 are normally distributed, this implies that equation 5 holds. Following SAS Institute, 1999: p. 2087, the variance of corn acreage intensity is given by equation 6 above. The linear mixed model (LMM) in SAS is flexible in that it helps do a robust check using the sandwich estimator. It also allows for conducting a robustness check of the model by employing a maximum likelihood estimation procedure.

Transforming equation 2 gives a specific form of the LMM as shown in equation 6 below.

$$CAI_{it} =\ \omega +\ \sum_{j=1}^{3}\ \alpha_j\ X_{jit} +\ \sum_{i=1}^{11} \tau_i\ Z_{it} +\ \varepsilon_{it}\ , \qquad (6)$$

$where\ i = 1\ to\ 11, j = 1\ to\ j_{k+1}, and\ t = 1\ to\ 18.$

In equation 6, ω is the fixed intercept parameter and subscripts i, j, and t denote state, explanatory variables, and time, respectively, while *k* represents the predictors added in Models 2-5.

Models 1-6 are estimated as follows:

$CAI\ \ = f\ (GEC, RFS, CBratio)$ *Model 1*

$CAI\ \ = f\ (GEC, RFS, CBratio,\ CRP)$ *Model 2*

$CAI\ \ = f\ (GEC, RFS, CBratio,\ Scale)$ *Model 3*

$CAI\ \ = f\ (GEC, RFS, CBratio, IFA)$ *Model 4*

$CAI\ \ = f\ (GEC, RFS, CBratio,\ Ethanol)$ *Model 5*

$$CAI = f\ (GEC, RFS, CBratio, Avgcrop) \qquad \textit{Model 6}$$

The dependent variable for all six models, CAI, corn acreage intensity, is a function of the explanatory variables. $GEC, RFS, CBratio$ are the share of GM crops out corn acres planted with GM corn, the Renewable Fuel Standard Policy dummy variable, and the lagged relative price of corn to soybeans, respectively.

Results

Table 9 reports the variance components and global fit statistics of the estimated regression models. As noted above, Model 1 is the base model, and Models 2-6 are the extended models with the inclusion of the CRP, scale economies, irrigation, ethanol production, and real cropland value variables, respectively. The Table also shows the estimated Intraclass Correlation Coefficients (ICC) and autoregressive (1) diagnostics. For all six models, the ICC estimates exceed 90 percent, suggesting the models perform well and fit the data. Based on the ICC estimates, Model 3 performs better than the other five models, suggesting that the differing impacts of the biofuel laws and the adoption of GM corn on producer planting decisions across states can largely be attributable to the presence of economies of scale in the agricultural sector (Model 3).

Table 9: Variance Components Statistics and Global Fit Statistics (II)

	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
	Base model	CRP effect	Economies of scale effect	Irrigation effect	Ethanol effect	Average cropland effect
Covariance Parameter	Covariance Parameter estimate	Covariance Parameter estimate	Covariance Parameter estimate	Covariance Parameter estimate	Covariance Parameter estimate	Covariance Parameter estimate
Random Int.	0.01362**	0.01084**	0.01940**	0.01439**	0.01285**	0.01253**

Residual	0.000418***	0.000320***	0.000359**	0.000509***	0.000399***	0.000407***
AR(1)*	0.4324***	0.1862**	0.3310***	0.4376***	0.4058***	0.4125***
ICC**	97.0%	97.1%	98.2%	96.7%	96.9%	96.9%
Fit Statistics						
-2 Log Likelihood	-934.5	-947.7	-923.0	-933.7	-923.6	-915.0
AIC	-928.5	-941.7	-917.0	-927.7	-917.6	-909.0
BIC	-927.4	-940.5	-915.8	-926.5	-916.4	-907.8

Notes: * AR(1) is the autoregressive (1) diagnostic to account for serial correlation and state-level heterogeneity; and ** ICC is the Intraclass Correlation Coefficient, given by the ratio of the random intercept to the sum of the random intercept and the residual, expressed in percentage points.

Table 10 lists the results of the six models by state. As in Chapter II, the share of corn acres out of total cropland acres increased at the expense of small grains, grazing lands, as well as CRP land. Model 1, the base regression, shows that corn acreage intensification is positively linked to the adoption of GM corn, the one-year lag of the corn-soybean price ratio, and the passage of the renewable fuel laws. Further, some states have corn acreage intensities that are consistently above (IA, IL, NE, IN, and WI), while others are below (SD, KS, MO), and the remaining ones (MN, OH, and MI) are no different from the regional average. Overall, the simple mixed model (base model) confirms that the GM corn adoption rate, relative crop prices, and biofuel policies each contributed to an increase in corn acreage intensity in the region overall. Furthermore, the random intercept estimates confirm heterogeneity in cropping decisions across states. These differences are likely due to individual state attributes, including those related to agricultural production and state-specific policies, as explored below.

Regression Models 2-6 reported in Table 10 seek to explore factors accounting for corn acreage intensity differences by state. The intercept term of Model 2 provides an estimate of the regional average of the proportion of corn acres to total acres planted of nearly 32 percent in the Corn Belt between 2000 and 2017. The fixed effects parameter estimates for RFS, the CRP variable, and the lagged corn-soybean price ratio are statistically significant at the one percent level, but the GM corn estimate is not significant. These findings suggest that an increase in the lagged corn to soybean price ratio and the passage of the biofuels laws of 2005 and 2007 positively affected corn acreage intensity in the Corn Belt overall. The negative impact of the CRP variable on corn acreage intensity indicates that as cropland was converted from CRP to crop production, the proportion of corn acres planted out of total cropland acres increased, i.e., a disproportionate amount of the released CRP acres were planted to corn.

Comparing the base regression model to Model 2 suggests that released CRP acres not only contributed to corn acreage intensity, but also help explain why some states are consistently above, below or at the regional intercept of corn acreage intensity. In particular, the coefficients for KS, MO, and SD are statistically significant and negative, implying that these states' corn acreage intensities were below the regional average of 32 percent. The coefficients for MN, OH, and MI are not statistically significant, suggesting these states' corn acreage intensities were at the regional average. Finally, the coefficients of the remaining five states (IA, IL, NE, IN, and WI) are statistically significant and positive, intimating these states' corn acreage intensities exceeded the regional average.

Similarly, the intercept term of Model 3 provides an estimate of the regional average of the proportion of corn acres to total acres planted of nearly 22 percent in the Corn Belt between 2000 and 2017. The fixed effects parameter estimates for RFS, economies of scale, and the lagged price ratio are statistically significant at the one percent level, and the GM corn estimate is significant at the ten percent level. These findings suggest that an increase in the lagged corn to soybean price ratio and the passage of the biofuels acts of 2005 and 2007, economies of scale, and GM corn adoption positively affected corn acreage intensity in the Corn Belt overall. Further, the measure of economies of scale has a positive impact on corn intensity, indicating that as farm size skewness increases, the proportion of corn acres planted out of total cropland acres increases. A comparison between the base regression model and Model 3 indicates that economies of scale helps explain why some states are consistently above, below or at the regional corn average intercept. The only difference between Model 3 and the base model is that the coefficient of NE is now insignificant.

The coefficients for KS, MO, and SD are statistically significant and negative, implying that these states' corn acreage intensities were below the regional average of 22 percent. The coefficients for MN, OH, NE, and MI are not statistically significant, implying that these states' corn acreage intensities were at the regional average. Finally, the coefficients of the remaining five states (IA, IL and WI) are statistically significant and positive, suggesting these states' corn acreage intensities exceeded the regional average. These findings are the same as those of the base random intercept regression model, except for NE coefficient.

In Model 4, the additional variable had no meaningful influence relative to the base model, suggesting that state-level irrigated acres do not aid in the explanation of why some states are consistently above, below or at the regional corn average intercept. The fact that irrigation is a costly and long-term investment with pay-offs spread over time may help explain the statistical insignificance of this variable.

Except for the irrigation variable, the fixed effects estimates are statistically significant in the same way as the base regression model.

The intercept term of Model 5 provides an estimate of the regional average of the proportion of corn acres to total acres planted of nearly 27 percent in the Corn Belt between 2000 and 2017. The fixed effects parameter estimates for RFS, the first lag of ethanol production, and the first lag of the price ratio are statistically significant at the one percent level, and the GM corn estimate is significant at the ten percent level. These findings suggest that an increase in the lagged corn to soybean price ratio and the passage of the biofuels acts of 2005 and 2007, ethanol production in the previous year and the share of GM corn acres positively affected corn acreage intensity in the Corn Belt overall. The first lag of ethanol production has a positive impact on corn intensity, suggesting that ethanol production in the preceding year may have influenced farmers' decisions to grow more corn, thus increasing corn acreage intensity. When comparing the findings of the base regression model and those of Model 5, it appears that the previous year’s ethanol production level is a factor in explaining why some states are continuously above, below, or at the regional corn average intercept. This is justified by the random intercept coefficients in Model 5 and the base model (the significance of the random effects for Model 5 and the base model are consistent).

Specifically, the coefficients for KS, MO, and SD are statistically significant and negative, implying that these states’ corn acreage intensities were below the regional average of 22 percent. Those for MN, OH, and MI are not statistically significant, implying that these states’ corn acreage intensities were at the regional average, while the coefficients of the remaining five states (IA, IL, NE and WI) are statistically significant and positive, suggesting these states’ corn acreage intensities exceeded the regional average. The results of the random intercepts model with the base regression are the same.

Finally, in Model 6, adding a variable to the underlying model had no discernible effect, suggesting that state-level real cropland values – partially representing quality improvements including in the form tile drainage – do not explain why some states are continuously above, below, or above the regional corn average intercept. This may be because real cropland value is not a perfect proxy for tile drainage and is also affected by other factors such as investment demand and financial portfolio diversification. The fixed effects coefficients in the base regression model and Model 6 show that the first lag of the corn to soybean price ratio and the RFS estimate have positive impacts on corn acreage intensity. For both the base model and Model 6, the random effects intercepts are fairly consistent.

Table 10: Random intercept model estimates for corn acreage intensity, by state, 2000-2017 (II)

	Model 1 Base model	Model 2 CRP effect	Model 3 Economies of scale effect	Model 4 Irrigation effect	Model 5 Ethanol effect	Model 6 Average cropland effect
Fixed Effects						
Intercept	0.2686***	0.3220***	0.2240***	0.2599***	0.2700***	0.2646***
GEC	0.04399**	0.01959	0.03383*	0.04162**	0.03057*	0.02843
RFS	0.01995***	0.02868***	0.01693***	0.01985***	0.02027***	0.02008***
CBratio	0.1364***	0.1482***	0.1458***	0.1385***	0.1396***	0.1341***
CRP		-0.8342***				
Scale			0.000163***			
IFA				0.1272		
Ethanol					0.000631**	
Avgcrop						0.000010
Random Effects						
IA	0.1306***	0.1392***	0.1509***	0.1394**	0.1150***	0.1247***
IL	0.1276***	0.1137***	0.1377***	0.1345**	0.1234***	0.1198***
NE	0.07426**	0.07210**	0.02607	0.03271	0.07620***	0.07814**
MN	-0.00553	0.009001	0.01391	0.001154	-0.00558	-0.00273
IN	0.09526***	0.06442**	0.1153***	0.1004**	0.09490***	0.08842**
SD	-0.1048***	-0.0934***	-0.2085***	-0.09762**	-0.1028***	-0.0950***
WI	0.08758**	0.08387***	0.1214***	0.09100**	0.09004***	0.08634**
OH	-0.02379	-0.05130	0.005640	-0.01519	-0.02222	-0.03070

KS	-0.2110 ***	-0.173***	-0.2454***	-0.2147***	-0.2070***	-0.2007***
MO	-0.1541***	-0.1285***	-0.1301***	-0.1547***	-0.1497***	-0.1508***
MI	-0.01611	-0.03568	0.01314	-0.01685	-0.01222	-0.01738

Notes: ***, **, and * indicate significance at 0.01, 0.05, and 0.10 levels, respectively; type 3 test for fixed effects indicated the interaction coefficient in Models 1-4 are significant (P-value < 0.01); parameter estimates rounded to 4 decimal places.

Model Comparison

Table 11 reports on the Likelihood Ratio test (LRT) statistics. The LRT is a hypothesis test that aids in determining which of two nested models is the best. The full model should have more parameters than the reduced model, according to the LRT criterion (Wright & Charlesworth, 2004). The null hypothesis states that the simplified model is significant, in contrast to the alternative premise that the model requires more terms. With the exception of Model 4, the p-values suggest rejecting the null hypothesis for all of the models and including the extra terms.

Table 11: Likelihood Ratio test

Models	DF	Dev1	Dev2	Chi-square	p-values
1 & 2	1	-934.5	-947.7	13.2	0.00028
1 & 3	1	-934.5	-923	11.5	0.000696
1 & 4	1	-934.5	-933.7	0.8	0.37109
1 & 5	1	-934.5	-923.6	10.9	0.000962
1 & 6	1	-934.5	-915	19.5	1.01E-05

Notes: For all models, dev1 and dev2 are the -2 loglikelihood test statistic values. The degrees of freedom are denoted by DF, while the goodness of fit test statistic is denoted by chi-square.

Predicting Corn Acreage Intensity

Expected corn acreage intensity is depicted in Figures 1 and 2. Figure 1 provides a comparison of the proc means procedure estimates to the estimates of the corn intensity for all five models. Only the fixed effects coefficients are used to predict corn intensity for each model. For each predictor, it is derived by multiplying the fixed effects coefficients by the proc means procedure mean, and then summing. Model 3 predicts 36.6 percent corn acreage intensity for the fixed effects coefficients, as shown in Figure 1, higher than the other four models.

Figure 2 shows the individual or the random effects predicted corn acreage intensity for each of the eleven states. As with the use of the fixed effects coefficients, Model 3 predicts the highest level of corn intensity among the models analyzed. Model 3 also has the largest ICC estimate, suggesting it accounts for the majority of variability in corn acreage intensity. Figure 2 shows that IA, IL, IN, and WI have higher anticipated corn acreage intensities than the other states. Because these states' intercepts are positive and statistically significant at the five percent level, their corn acreage intensities are positively impacted. Similarly, states like SD, KS, and MO have a greater anticipated corn intensity, but it is negative, suggesting that corn intensity is adversely affected in these three states. However, MN, OH, MI, and NE have an extremely low expected corn intensity, meaning that these states will have very little corn intensity relative to the states in the Corn Belt region as a whole.

Figure 1: Predicted Corn acreage intensity for all the six Models

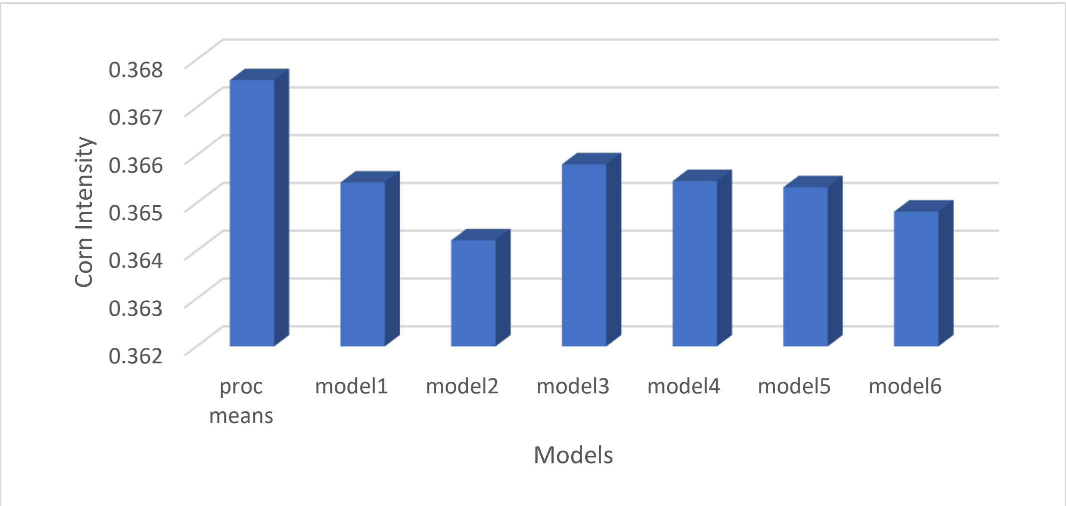
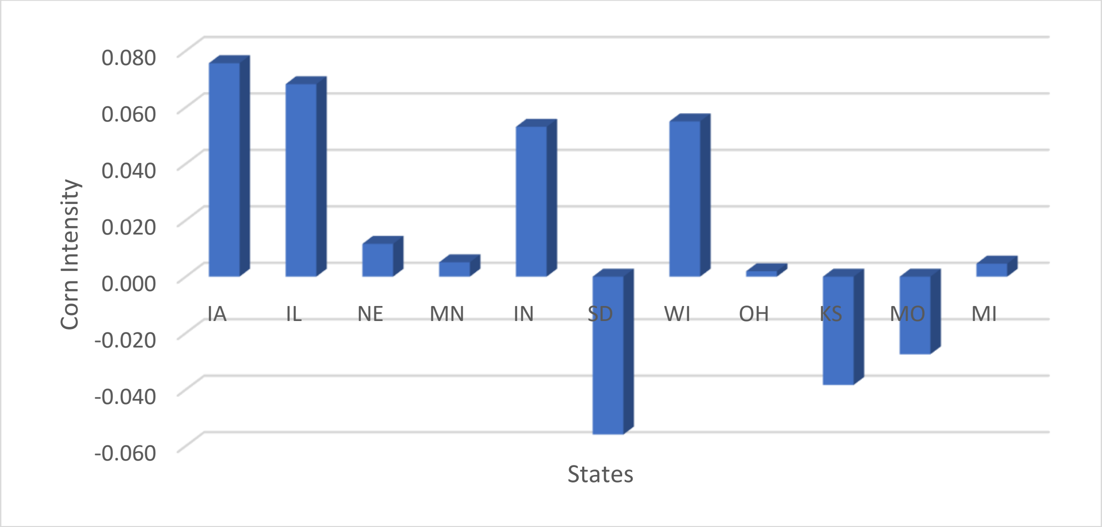


Figure 2: Predicted corn acreage intensity for all states using Model 3



Simulating Corn Acreage Intensity

The results of the six models are largely consistent and robust. The average proportion of corn acres planted at the state level is approximately 27 percent assuming that GM corn adoption, biofuel policies, market forces as reflected by the one-year lag of the corn/soy price ratio and all other factors are held constant, as represented in the base regression model. States without a statistically significant random intercept (MI, MN, and OH) have levels of corn acreage planted equal to the regional average (as does NE for Models 2, 5 and 6 at the five percent significance level). Similarly, states with statistically significant positive (negative) random intercept terms reflect those where the proportions of corn acres planted were above (below) the regional average before the widespread adoption of GM corn and implementation of biofuel policy incentives. At the five percent significance level, IA, IL, IN and WI had positive coefficients, while KS, MO and SD had a negative coefficient for the random intercept estimates in all six models.

These findings indicate that GM corn adoption, relative price changes, and biofuel policies affected corn acreage intensity. They further show that Iowa has the highest predicted corn intensity (about 7.6%). Overall in the eleven Corn Belt states, the CRP, economies of scale factors, and ethanol production are the key sources of state-level corn acreage intensity.

Summary and Conclusions

This study addresses the determinants of cropping pattern changes at the state level. In particular, we explore the effects of GM corn adoption, the enactment of the renewable fuel laws in the early 2000s, market forces, cropland released from the Conservation Reserve Program (CRP), changes in economies of scale in agricultural production, the development of the ethanol production infrastructure, and cropland prices on the increased prevalence of corn in crop rotations. We also address the sources of state-level heterogeneity, which aids in identifying the state-specific features affecting cropping patterns. Results of the study are expected to increase awareness among policymakers and agricultural producers about changing cropping patterns and their implications for long-term sustainability, as well as help them make informed decisions about ways to mitigate these long-term term trends and their potentially negative environmental effects.

Using state-level data of eleven Corn Belt states from 2000 to 2017, we applied a linear mixed model with both fixed and random effects to investigate these linkages. We estimated six models – a base regression model and five additional ones, with each adding a predictor to the base model in an effort to assess their individual contribution to corn acreage intensity. A log likelihood ratio test was used to examine the importance of each model relative to the base model. Based on their ICC scores, we then used the preferred model to predict each state's corn acreage intensity.

Findings of the base model indicate that state-level corn acreage intensities are positively impacted by the spread of GM crops, the passage of the renewable fuel laws in the early 2000s, and the first lag of the relative corn to soybean price ratio. In addition, the main sources of heterogeneity of corn acreage intensity at the state level are cropland released from the CRP, a simple approximation of economies of scale in production agriculture, and the development of the ethanol production infrastructure. However, real cropland values – a proxy for cropland quality improvements including factors such as tile drainage – and irrigated farm acres do not represent sources of state-level heterogeneity in corn acreage intensity. Utilizing Model 3 (the preferred model, based on its ICC value), we predicted that Iowa would have the highest corn intensity of 7.6 percent among the eleven Corn Belt states.

This research adds to the body of knowledge on cropping pattern changes by identifying factors that contributed to changes in cropping patterns at the state level. By and large, the same states exhibit levels of corn acreage intensity that are consistently above, below, or at the regional average. Our study sheds light on the determinants of corn acreage intensity levels for the Corn Belt region as a whole and for state-level heterogeneity over a nearly two-decade period. Our findings provide support for, and help explain, the well-documented changes in cropping patterns involving loss of acreage of small grains and marginal areas in favor of corn and soybeans.

A caveat of our work is that data on the median farm size and irrigated acres are only available for census years, so the time period of analysis was constrained due to a method for integrating these data with the survey data. Also, because comparable data on GM corn was not available for years prior years, our analysis is based on annual data starting in 2000. Further, while factors such as tile drainage may be closely associated with cropping pattern changes and may help explain differences in corn acreage intensity by state, data limitations prohibited us from a full exploration of the role of tile drainage in affecting corn acreage intensity. Future studies may be able to incorporate a reliable proxy for measuring tile drainage.

An additional consideration for further research is whether elements of our analysis can be disaggregated to the county level. Another area worth exploring is the use of nonlinear models to further investigate the determinants of cropping pattern changes. Lastly, future research may consider interacting the RFS dummy variable with key independent variables of interest, which in effect splits the data into time periods before and after the Renewable Fuels Laws, while maintaining sufficient degrees of freedom.

CHAPTER IV
CONCLUSIONS

This thesis first examined the role of biotechnology and biofuels on cropping system changes in 11 U.S. Corn Belt states. Second, we assessed the determinants of corn acreage intensification levels and heterogeneity among the same states. Based on state-level data from 2000 to 2019, results from Chapter II show the overlapping developments of increased GM corn acreage as a share of total corn acreage, changing federal agricultural policies, the implementation of federal biofuel laws mandating ethanol usage in transportation fuels, and their impacts on changing cropping patterns in the U.S. Corn Belt region. The study examined trends observed over at the past two decades, including an increase in corn and soybean acreage at the expense of small grains acreage and a conversion of grasslands to crop production. The findings of this study add to the existing literature by considering the long-term effects of GM corn plantings and biofuel policy changes on cropping patterns. An additional valuable contribution of this study is that it distinguishes the impact of changes in biofuel policies and agricultural biotechnology on state-level cropping patterns.

Results of Chapter III show that cropland released from the CRP, a simple proxy for economies of scale in production agriculture, and the development of the ethanol production infrastructure are key sources of variation in corn acreage intensity at the state level. However, real cropland values – partially representing cropland quality improvements by way of tile drainage – and irrigated farm acres are not identified as causes of state-level heterogeneity in corn acreage intensity. This study adds to the corpus of knowledge on cropping pattern changes by identifying factors impacting changes in cropping patterns at the state level. The study sheds light on the determinants of corn acreage intensity levels for the Corn Belt region as a whole and for state-level variation over a nearly two-decade period. Findings show that the same states have corn acreage intensity levels that are consistently above, below, or equal to the regional average. Findings also support and explain well-documented shifts in cropping patterns, such as the loss of small grain and marginal land in favor of corn and soybeans.

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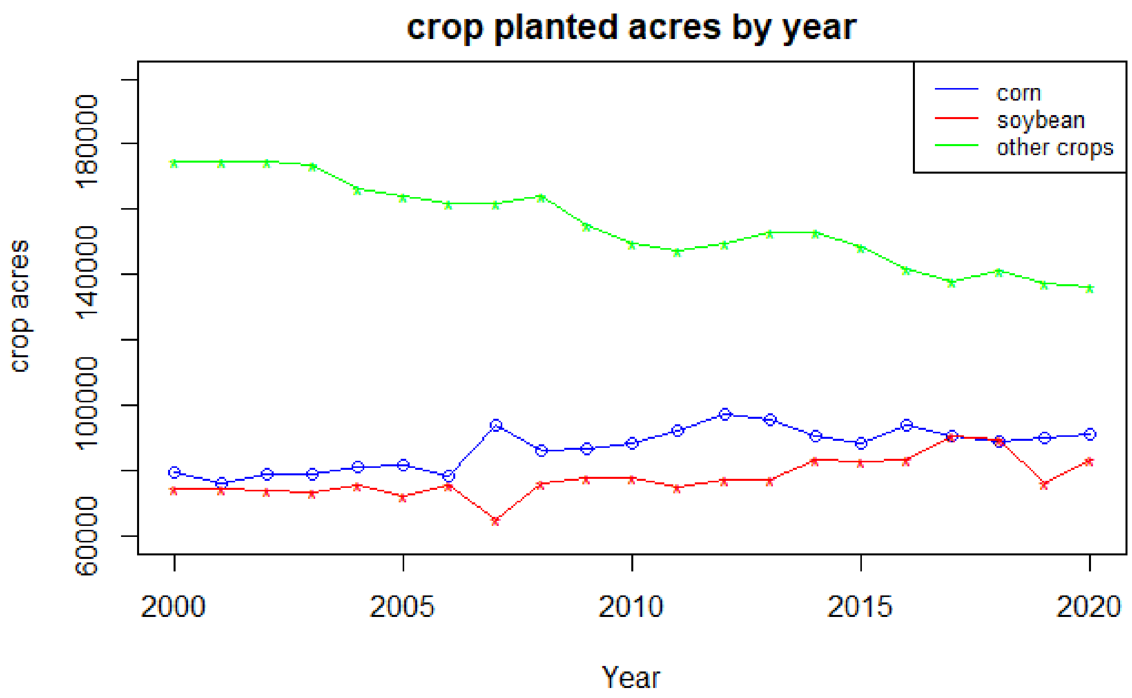
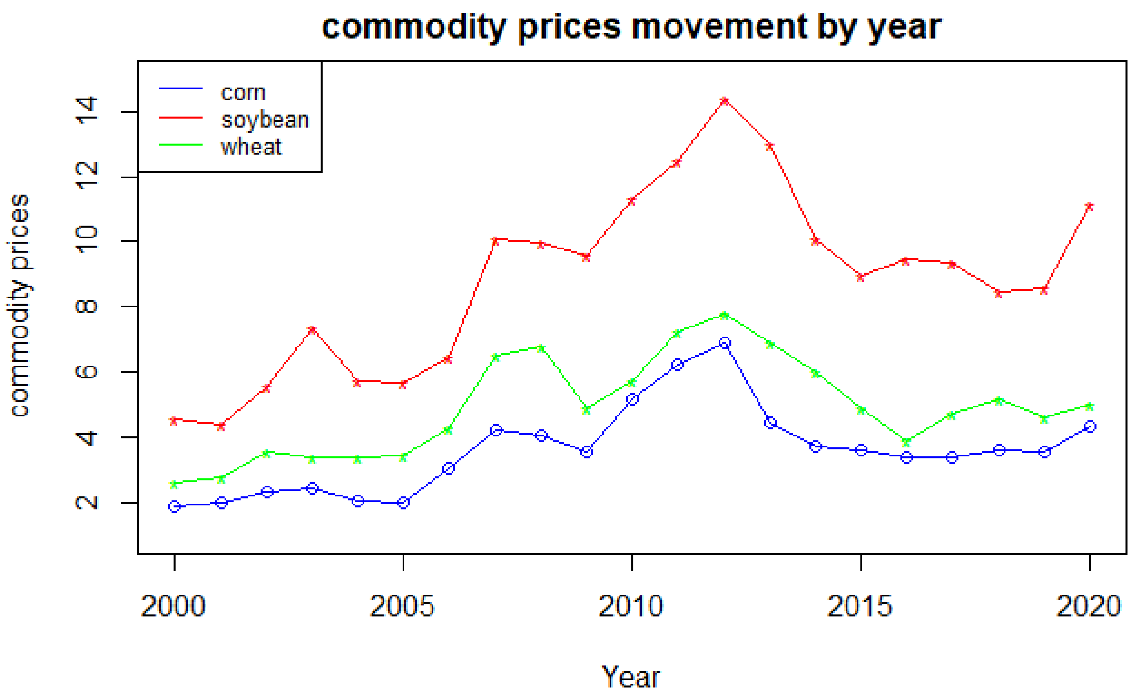
APPENDIX

Figure 3: U.S. Cropping pattern changes (2000 to 2020)



Source: NASS https://quickstats.nass.usda.gov/

Figure 4: U.S. commodity prices movement (2000 to 2020)



Source: NASS https://quickstats.nass.usda.gov/