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The role of biotechnology and biofuels in US Corn Belt cropping system changes

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Abstract

The effects of transgenic corn use and federal biofuel policies on state-level cropping patterns in the US Corn Belt region are investigated using state-level data from 2000 to 2019. During this time, producers moved away from diverse cropping patterns and toward simpler rotational practices. Empirical evidence indicates that the intensification of corn acres planted was positively impacted by the spread of genetically modified (GM) soybeans—used as a proxy for GM corn for biofuel usage—but the effects of biotech advancements on producer planting decisions vary across states. This suggests that future policy changes affecting corn production decisions at the farm level will also be heterogeneous across states.

Introduction

We investigate linkages between increases in the adoption of genetically modified (GM) corn varieties, corn-based biofuel production, and the associated surge in the derived demand for corn on corn acreage intensity (CAI) in US Corn Belt states, based on state-level data between 2000 and 2019. We analyze how federal biofuel policies, relative corn (*Zea mays*) prices to soybean (*Glycine max*) prices, and farm-level GM soybean adoption—a surrogate variable for GM corn adoption—rates affected CAI across 11 Corn Belt states over the 20-year period. Results of our empirical analyses suggest cropping patterns were affected by ethanol production increases in response to biofuel policy changes, facilitated by the spread of GM crop varieties and relatively high corn prices. While these factors contributed to an overall increase in corn production intensity in the Corn Belt, the effects were heterogeneous across states. In turn, these disparate impacts have varying impacts on crop rotation practices across states, and thus may have differing policy implications.

Linking GM crop production, ethanol production, and corn acreage intensity

Agricultural land usage has long moved toward increasingly intensive production practices. Johnston (2014) detailed the conversion of grasslands, wheat, and other small grains toward corn and soybean production in the US Prairie Pothole Region (which partially overlaps with the northwestern part of the Corn Belt region). Claassen *et al.* (2010) reported on the conversion of marginal production acres (grasslands and hay land) to cropland in the eastern part of the Northern Great Plains, and Wright and Wimberly (2013) documented grassland conversions in the western Corn Belt. More broadly, Wallander *et al.* (2011) documented an increase in corn and soybean acreage across the United States, which coincided with an increase in double-cropping and hay land conversion. These developments are reflected in Table 1, which shows that the 11 US 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 to 40.5%, and from 32.3 to 33.4%, 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.

US cropping systems are on a path toward increased homogeneity, particularly in the Midwest (Plourde *et al.*, 2013; Aguilar *et al.*, 2015). The number of crops involved in rotation cycles declined in the US Corn Belt in recent decades (Wallander *et al.*, 2011; Johnston, 2014; Fausti, 2015; Stigler, 2019). Reduced rotations lead to decreased biodiversity in insect populations inhabiting corn fields and provide opportunities for corn pest population increases (Lundgren and Fausti, 2015). Crop production expansion has negative consequences for critical wildlife habitat and other ecosystem services provided by wetland and grassland, including increased soil erosion, additional nutrient runoff, which in turn leads to increased

Table 1. Acres planted by a major crop over three periods in the Corn Belt, 1996–2019

	Avg. (1996–2004) period 1		Avg. (2005–2019) period 2		Change period 2 *vs* 1	
Crops (planted acres)	1000 acres	%	1000 acres	%	1000 acres	%
Corn	64,283	36.3	716,87	40.5	7404	11.5
Soybean	57,103	32.3	59,075	33.4	1972	3.5
Barley[a]	524	0.3	193	0.1	−331	−63.2
Oats[a]	2077	1.2	1348	0.8	−729	−35.1
Wheat	22,331	12.6	18,350	10.4	−3981	−17.8
Other	30,627	17.3	26,221	14.8	−4406	−14.4
Total area	176,945	100	176,874	100	−71	−0.04

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

sedimentation and leaching to surface and ground water, and may increase risk and vulnerability to extended periods of drought in the absence of long periods of rainfall (Claassen *et al.*, 2010; Wright and Wimberly, 2013; Johnston, 2014). Crop rotation practices involving multiple crops can help maintain soil fertility, reduce negative environmental impacts of agricultural production such as soil erosion and nutrient discharge, reduce crop damage associated with weed and insect pests, and increase crop productivity (Landis *et al.*, 2008; Claassen *et al.*, 2010; Seifert *et al.*, 2017; Bowles *et al.*, 2020; Hunt *et al.*, 2020). Instead of using conventional rotation practices, producers increasingly rely on chemical and genetic technology for maintaining soil fertility and keeping agricultural pests at bay (Davis *et al.*, 2012; Sindelar *et al.*, 2016; Hunt *et al.*, 2017). This may exacerbate externalities, including soil degradation and water pollution (Turner and Rabalais, 2003; Amundson *et al.*, 2015).

The decline in crop diversity partially coincided with changes in US energy and agricultural policies, the increased usage of GM crops, and the growth of the ethanol and agricultural seed industries. US federal and state policies and programs wield much influence on cropping systems diversity, as evidenced by agricultural producers managing the majority of US farmland in accordance with farm bill guidelines, incentives, and mandates to qualify for commodity payments or other farm program subsidies (National Research 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 (Fernandez-Cornejo and McBride, 2002; Brookes and Barfoot, 2018). 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. US adoption rates of all GM corn and soybean varieties increased from zero in 1995 to 25 and 54% in 2000, to 86 and 93% in 2010, and to 92 and 94% in 2020, respectively (Economic Research Service, 2021*b*).

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 (e.g., Cattaneo *et al.*, 2006; Hutchison *et al.*, 2010; Scandizzo and Savastano, 2010; Benbrook, 2012; Fernandez-Cornejo *et al.*, 2014; Brester *et al.*, 2019). 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 vast majority of these studies focus on the intensive margin effects of GM crops over a relatively short time period, whereas our work also considers the extensive margin effects over a relatively long period of two decades.

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 crop plantings on cropping patterns.

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 in particular. More broadly, in assessing the 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 subsequent 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 US reliance on oil imports from abroad. To encourage the development of biofuel markets, US 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 required using 30 billion gallons of renewable fuel in 2020, just over 20 billion gallons of total renewable fuel were used in practice, corresponding to 11.6% 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 an annual maximum use of 15 billion gallons through 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 eightfold 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% of the U.S. corn crop in 1980, 1990, and 2000, respectively, which increased to 38.5% in 2010, before dropping to 34.8% of the total U.S. corn supply in 2019 (Economic Research Service, 2021*a*).

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 and 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 crop 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 US 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-year 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 soybeans—as a proxy for 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

Our analysis is based on secondary state-level data on crop acres planted and GM soybean coverage in 11 northern Corn Belt states—Iowa, Illinois, Indiana, Nebraska, Kansas, Michigan, Minnesota, Missouri, Ohio, South Dakota, and Wisconsin—for each year between 2000 and 2019, 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). Ethanol production data were obained from the Energy Information Administration (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, 2021*a*, 2021*b*). 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 2005–2019, zero otherwise. Annual average corn and soybean prices were collected from the National Agricultural Statistics Service (2019).

Methodology

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 crop adoption and the enactment of ethanol policies on changes in state-level CAI. This approach enables separating fixed effects (which are constant across the individual states) from the random effects (which vary by state). The dependent variable is the ratio of corn acres planted to total acres planted, referred to as CAI. This variable captures the increased prominence of the combination of GM corn and non-GM corn acreage at the expense of small grains and marginal croplands. Explanatory variables include the ratio of corn prices to soybean prices (PR), which captures changing national and international market conditions as well as changes in commodity and conservation programs. We also include a 2005 ethanol policy dummy variable (RFS = 1 for years from 2005 to 2019) to capture structural changes in commodity markets due to the implementation of the RFS. A caveat of including the dummy variable is that it would also capture other structural changes associated with other forces occurring during the same period, such as the increased use of precision agriculture and other forms of substituting capital for labor at the farm level. In addition, we include the state-level ratio of soybean acres planted with GM soybeans. We use that latter as a proxy for corn acres

Table 2. Variance components statistics and global fit statistics

Random intercept model: simple	Covariance parameter estimate	Fit statistics
Random intercept	0.01363** (0.006125)	
Residual	0.000498*** (0.000073)	
AR(1)[a]	0.4849*** (0.07783)	
ICC[b]		96.47%
−2 Log likelihood		−1025.4
AIC		−1019.4
BIC		−1018.2

[a]AR(1) is the autoregressive (1) diagnostic to account for serial correlation and state-level heterogeneity.
[b]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.
*** and ** indicate significance at 0.01 and 0.05 levels, respectively; and standard errors in parentheses.

planted with GM corn because the dependent variable is defined as the sum of GM corn and non-GM corn acres planted as a share of total crop acres planted, which would make the use of GM corn as a predictor problematic. The use of GM soy to total soy acreage as a proxy for GM corn is justified because the adoption of the two GM crop varieties largely overlapped in the Corn Belt, as indicated by the high correlation coefficient (0.828) between GM corn and GM soybeans, although the widespread GM soybean adoption process preceded that of GM corn. State dummy variables were created to measure the random effects of CAI by state (with Michigan as the base state). Using the above predictors, the random intercept model provides estimates for CAI 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 similar cropping patterns over geographically related states. The existence of clustered data results in biased standard errors. Clustering was verified and a correction procedure was implemented (see the Intraclass Correlation Coefficients (ICC) statistics reported in Table 2).

The renewable fuel laws' implementation is expected to have a positive relationship with CAI, as outlined earlier. Also, the corn to soybean PR is expected to have a positive relationship with CAI, because a decrease in the relative price of corn to soybeans would be expected to lessen CAI (as soybean prices rise relative to corn prices, CAI decreases, and as corn prices rise relative to soybean prices, CAI increases). Lastly, the relationship between the ratio of GM soybean acres planted over total soybean acres planted and CAI is expected to be mixed, in the sense that—while CAI is expected to increase as the proportion of GM soybean acres 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 PR variable captures the market valuation of corn relative to other crops, the GM soy variable indirectly reflects—in the sense that GM soy is used as a proxy for GM corn—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:

$$\mathrm{CAI} = X\beta + Z\gamma + \varepsilon, \tag{1}$$

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

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

$$\mathrm{COV}(\gamma, \ \varepsilon) = 0. \tag{4}$$

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 γ, 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 γ and ε are independent, which implies that the variance of CAI (SAS Institute, 1999, p. 2087) can be defined as:

$$\mathrm{VAR}[\mathrm{CAI}] = ZGZ^{\mathrm{T}} + R, \tag{5}$$

where G and R are the covariance matrices associated with γ 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 <0.01, suggesting exogeneity. Model design suggests the only predictor potential for endogeneity to be an issue is with the corn–soybean PR. To avoid this issue, the corn–soybean PR was lagged one period. The default covariance structure for the mixed procedure is variance components (SAS Institute, 1999, p. 2088). 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, Chapter 41).

The linear form of the general model to be estimated is:

$$\mathrm{CAI}_{it} = \alpha + \sum_{j=1}^{3} \beta_j X_{jit} + \sum_{i=1}^{11} \gamma_i Z_{it} + \varepsilon_{it}, \tag{6}$$

where $i = 1–11$, $j = 1–3$, and $t = 1–20$.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.

Table 3. Changes in crop area shares in the Corn Belt, by state, 1996–2019

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/.

Empirical results

Table 3 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.

Table 4 provides summary statistics of the main variables used in our analyses, and Table 2 lists the fit statistics and the estimated ICC for the model. The ICC estimates exceed 90% 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 goodness of fit of the mixed model approach, we ran a simple fixed effect only model. The log likelihood statistic for this comparison model is −1025.4. The Null Model Likelihood Ratio test rejects the null hypothesis that the two models are equivalent at $P < 0.001$. 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 CAI) was significant at the 5% level or less for the random intercept model (Table 2). Regression diagnostics confirm the decision to select a variance-covariance structure that corrects for serial correlation in the model (Table 2).

Following Gujarati and Porter (2009, p. 704), we performed a Hausman test for endogeneity in two steps. First, we regressed the GM soy to total soy acreage ratio (our proxy for the adoption and diffusion of GM corn technology at the farm level) on all independent variables, including the state dummy variables. We then obtained the residual ($V^{\wedge}$) and the predicted value of the GM soy to total soy acreage ratio from stage 1. In the second stage, we regressed the CAI variable on the renewable fuels dummy variable, the lag of the corn to soybean PR, the state

Table 4. Descriptive statistics (1996–2019)

Variable	Units	*N*	Mean	St Dev	Minimum	Maximum
Corn	1000 acres	264	6265	3521.8	2150	14,300
Soybean	1000 acres	264	5303	2695.0	930	11,000
Barley	1000 acres	264	28.8	69.4	0	600
Oats	1000 acres	264	147.4	122.0	0	530
Wheat	1000 acres	264	1804	2609.7	0	11,800
Total acres	1000 acres	264	16,082	6163.4	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	US$/bu	264	3.4	1.4	1.7	6.7
Soybean prices	US$/bu	264	8.4	2.9	4.4	14.1
Wheat prices	US$/bu	264	4.3	1.5	1.8	8.1

dummies, and both $V^{\wedge}$ and the predicted value of the GM soy to total soy acreage ratio from step 1. We then tested for the significance of $V^{\wedge}$ using the OLS regression from step 2. Using a heteroskedasticity-robust *t*-test, if the coefficient of $V^{\wedge}$ is statistically different from zero, then the GM soy to total soy acreage ratio is indeed endogenous. Our estimation results show that the coefficient on $V^{\wedge}$ is not statistically different from zero, so we conclude that GM soybeans is not endogenous.

Wooldridge (2019, p. 516) and Pindyck and Rubinfeld (1998) suggest an alternative approach by using the actual value of the GM soy to total soy acreage ratio to fit the OLS regression in step 2. We also followed this approach. Results show that the coefficient of $V^{\wedge}$ is not statistically different from zero, implying that the GM soy to total soy acreage ratio is not endogenous. We did not include GM corn in step 2, because we used GM soybeans as the instrument for GM corn.

Table 5 reports on the random intercept model estimates for CAI, 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 1% level. These findings suggest that increases in the lagged corn to soybean PR, in the GM soy to total soy acreage ratio (our proxy for the adoption and diffusion of GM corn technology at the farm level), and the passage of the biofuels acts of 2005 and 2007 each positively affected CAI in the Corn Belt region. The fixed-effects intercept has a value of 0.2498, 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, CAI averaged 24.9% in the 11 Corn Belt states. The random intercept coefficients reflect the deviation of CAI 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 soybean adoption rate (representing GM corn adoption), relative crop prices, and biofuel policy all contributed to an increase in CAI in the 11 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 0.2498 reflects the proportion of corn acres planted at the regional level, assuming that GM soybean plantings as a share of total soybean acres planted (our proxy for GM corn diffusion), biofuel policies, and the PR were unchanged. That is, the intercept is interpreted as the value of the dependent variable when all the covariates are set to zero. The positive and significant parameter estimate of GM soybeans suggests that an increase in the number of acres planted to GM soybeans planted as a share of total soybean planting—and by proxy, an increase in GM corn—positively impacted CAI. Similarly, the positive and significant parameter estimate of the RFS dummy variable suggests that implementation of the renewable fuels standard contributed to CAI increases compared to the base period prior to 2005. Finally, the positive and significant parameter estimate of the PR variable indicates that an increase in the price of corn relative to the price of soybeans also had a positive impact on CAI in the Corn Belt overall. Because the two continuous variables are both expressed as ratios, it is difficult to compare their relative impacts, but the magnitudes of the two parameter estimates suggest that a one percentage increase in the PR has a larger impact on CAI than a one percentage increase in GM soybean plantings as a share of total soybean plantings.

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 soy 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

Table 5. Random intercept model estimates for corn acreage intensity, by state, 2000–2019

Random intercept model	Coefficients estimate
Fixed effects	
Intercept	0.2498*** (0.03360)
GM soybean	0.0577*** (0.01702)
RFS	0.0286*** (0.003470)
Price ratio	0.1700*** (0.01940)
Random effects	
Iowa	0.1466*** (0.03604)
Illinois	0.1229*** (0.03605)
Nebraska	0.0824** (0.03605)
Minnesota	0.0080 (0.03604)
Indiana	0.0749** (0.03604)
South Dakota	−0.1020*** (0.03606)
Wisconsin	0.0920** (0.03604)
Ohio	−0.0419 (0.03606)
Kansas	−0.2051*** (0.03605)
Missouri	−0.1527*** (0.03604)
Michigan	−0.0251 (0.03606)

*** and ** indicate significance at 0.01 and 0.05 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.

than the regional average before the widespread diffusion of GM soy and implementation of biofuel policy incentives (Kansas, Missouri, and South Dakota).

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. The empirical evidence generated by a random intercept model with fixed effects indicates that the intensification of corn acres planted in the Corn Belt region was positively impacted by biotechnology advancements in energy and crop production and past government policy decisions in the areas of energy and agriculture. The results also suggest that state-level corn acreage intensification due to the introduction of GM crops and biofuel technology was heterogeneous across the 11-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 changes in general and the growing dominance of corn in US crop production systems in the 11 states had a host of expected and unexpected consequences. For example, the relatively high corn prices experienced in the years following the passage of the renewable fuels standard contributed to a decline in the production of other crops, price increases of other crops globally, and an increase in the cost of raising livestock. Corn production intensification facilitated in part by the reliance on GM varieties also resulted in increased corn pest resistance (e.g., Gassmann *et al*., 2011) and increased coverage of planted acres with insecticide (Fausti *et al*., 2012, 2018). Neither the extent of the pest resistance nor the subsequent increase in insecticide-acreage-coverage were anticipated at the onset of the widespread use of crop biotechnology.

While based on data collected in the 11-state Corn Belt region, the results of this study may be of relevance to other areas of the United States. Corn production has expanded not only in response to the widespread adoption of GM crop varieties and biofuel policies, but also due to other forces such as climate change and plant breeding technology improvements. Thus, the issues addressed in our study represent a challenge for and are of critical importance to agriculture in the future throughout the United States.

Concluding comments

This study explores the overlapping developments of the increased GM crop acreage as a share of total planted acres, 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 US Corn Belt region, based on state-level data from 2000 to 2019. Agricultural land use has long moved toward increased intensity, and numerous studies have documented a variety of intensive margin effects of GM crop adoption at the farm level. In contrast, our study emphasizes the extensive margin effects by reporting 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 varieties of corn and soybeans as a proportion of total corn and soybean acres, respectively.

Using a mixed modeling approach with both random and fixed effects, results of the study indicate that the intensification of corn acres planted was affected by the spread of GM soybean varieties. While we are unable to make a direct link between the increased prominence of GM corn as a share of total corn acres and CAI, the high correlation coefficient (0.828) between GM corn and GM soy acres suggests that the spread of GM corn is strongly associated with CAI. Furthermore, these impacts varied across states, implying that future policy changes affecting corn production decisions at the farm level will likely be heterogeneous across states as well.

A key contribution of this study to existing literature is that it considers long-term consequences of GM soybean plantings (as a proxy for 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. Furthermore, our findings suggest that the spread of GM crops, biofuel policies, and relative crop prices contributed to encouraging expansion of corn production onto marginal lands. These slippage effects—unintended program impacts bringing relatively marginal lands into crop production—resulted in adding land with relatively low yield potential for use in crop production, and may help explain why the rapid adoption of GM crops is not associated with large yield and income gains at the aggregate level.

This work may lay the foundation for possible future studies assessing the impacts GM crop adoption, the implementation of federal biofuel laws, and federal agricultural policies on crop rotations directly. Possible future studies may also be able to further disaggregate the heterogeneous state-level impacts of federal policies and GM corn and soybean variety adoption. Also, future work may be able to further explore the influences of GM corn adoption, the passage of the renewable fuel laws in the early 2000s, as well as market forces in the context of changing commodity programs—including cropland acres released from the Conservation Reserve Program (CRP), developments in the structure of production agriculture—including the role of the substitution of capital for labor and economies of scale in production agriculture, alterations in the structure of the food manufacturing industry—which utilizes corn as an input in food production, variations in the derived demand for feed grains—stemming from meat production, and changes in real cropland values—in part as a result of outside investments.

Data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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