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The Effect of Biotechnology and Biofuels on U.S. Corn Belt Cropping Systems: Updated Version

by

Scott Fausti, Evert Van der Sluis,

Bashir Qasmi and Jonathan Lundgren

SDSU

Department of Economics

South Dakota State University

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Abstract

The effects of transgenic crop and federal biofuel policy on state-level cropping patterns in the Corn Belt region are investigated (2000-2012). The literature links the expansion of corn acreage to the supplanting of small grain and hay acreage in this region. Empirical evidence generated by a random intercept model with fixed effects indicates that the intensification of corn acres planted was positively impacted by biotech advancements in energy and agriculture. This suggests producers are moving away from diverse cropping patterns and the rotational practices associated with a diverse crop planting strategy. However, the empirical evidence suggests that the effects of these biotech advancements on producer planting decisions are heterogeneous across states. Thus, future policy changes affecting producer corn production decisions will not be uniform across States.

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*Scott Fausti (scott.fausti@sdstate.edu) is a Professor of Economics; Evert Van der Sluis (evert.vanderslus@sdstate.edu) is a Professor of Economics; Bashir A. Qasmi (bashir.qasmi@sdstate.edu) is an Associate Professor; and Jonathan Lundgren (jonathan.lundgren@sdstate.edu) is with the Agricultural Research Service. All are associated with South Dakota State University, Contact: Department of Economics, Box 504 Scobey Hall, Brookings, SD (605-688-4141).

The Effect of Biotechnology and Biofuels on U.S. Corn Belt Cropping Systems

1. Introduction:

An empirical investigation into the linkage between the usage of genetically-enhanced crops in production agriculture, bioenergy produced from these crops, and their combined effects on cropping patterns at the state level in the U.S. Corn Belt region is conducted based on annual data from 2000 to 2012. The United States experienced dramatic changes in row crop production practices during this period, particularly in the Corn Belt region, as documented by, for example, Wallander et al. 2011.

The objective of this study is to identify how ethanol (ethyl alcohol) policy, relative corn (Maize) to soybean (Glycine max**)** prices, and adoption rates of genetically modified (GM) corn affect corn acreage intensity differences across States. Our findings suggest that the effects of changes in bioenergy policy, relative crop prices, and the ability of GM technology to continue to provide pest protection (Landis et al. 2008; Hutchison et al. 2010; Gassmann et al. 2011) on producer cropping decisions vary by state across the Corn Belt region. Hence, future agricultural policy decisions need to recognize that producer reaction to changes in the above factors will be depended on geographical location (Van der Sluis et al. 2002).

We investigate the relationship between the rapid increase in the reliance on GM varieties in corn production, the simultaneous upsurge in corn-based biofuel production and the associated increase in the derived demand for corn on state-level corn acreage intensity. Our empirical results suggest cropping patterns were affected by the rapid increase in ethanol production due to biofuel policies, facilitated in part by the increased reliance on genetically-enhanced corn varieties, and the increased profitability of growing corn relative to other crops. These factors have contributed significantly to the increase in the proportion of corn acres planted in the U.S. Corn Belt region, but our analysis shows that the effect on corn production intensity varies between states.

2. Linking GM Corn Production, Ethanol Production, and Corn Acreage Intensity

The evolution of agricultural practices in the eleven states of the Corn Belt region (IA, IL, IN, NE, KS, MI, MN, MO, OH, SD, and WI) over the last quarter-century has resulted in a movement away from conventional row crop production practices. These conventional cropping practices helped maintain soil fertility (crop rotation effect) and reduce the damage associated with weed and insect pests that negatively impact crop productivity. Today, the U.S. crop production system relies heavily on chemical and genetic technology to maintain soil fertility and keep agricultural pests at bay. This transition has been supported by changes in U.S. energy and agricultural policy decisions, and advancements in biotechnology that, in turn, have fostered the growth of the ethanol and agricultural seed industries.

2.1 U.S. Agricultural and Energy Policies

The period between 1996 and 2012 has been identified in the literature as a transitional one in American agriculture. During this period, row crop producers have moved away from conventional crop rotation practices to a more crop-intensive production system, especially for corn and soybean production (Wallander et al. 2011; Johnston 2014). Claassen et al. (2010), maintain that changes in U.S. cropping decisions by producers were facilitated primarily by policy changes embodied in the 1996 Farm Bill (P.L. 104-127), commonly referred to as the "Freedom to Farm Act" (FFA), which decoupled the income support system for row crop producers and removed the set-aside requirements for support payments (Mercier 2011). Claassen et al. (2010) assert that these policy changes allowed agricultural producers to respond more directly to market signals, policy incentives, and changes in technology. The latter include the use of GM crops, which enabled farmers to reduce labor requirements for crop production during the planting season, as first documented by Fernandez-Cornejo and McBride (2002).

The development of corn and soybean-based biofuel conversion technology as alternatives to fossil fuels allowed U.S. energy policy to include programs that require using minimal levels of biofuels blended in with transportation fuels. The overall goal of these mandates is to have biofuels become an important source of energy for the U.S. economy. The two primary legislative mandates are the 2005 Energy Policy Act and the Energy Independence and Security Act of 2007. The legislation sets minimum annual consumption levels in four broad-based biofuel categories: cellulosic, biomass-based diesel, undifferentiated-advanced, and renewable energy. The mandate for all biofuels in 2022 is set at 36 billion gallons. Currently, the corn-starch based ethanol production cap is set to reach 15 billion gallons in 2015, and remain fixed going forward (Schnepf and Yacobucci 2013). However, corn-based ethanol is by far the main source of biofuel production because of its cost advantage relative to alternative biofuels. Given the current state of production technology for non-corn-starch based ethanol alternatives, the 36 billion gallon ethanol mandate is unrealistic unless the 15 billion gallon cap is removed from corn-starch based ethanol production.

2.2 Biofuel Commercialization

According to the Renewable Fuels Association (2014) the U.S. produced 175 million gallons of ethanol in 1980, 848 million gallons in 1990, and 1.622 billion gallons in 2000. In 2000, the U.S produced 9.97 billion bushels of corn which indicates that the ethanol industry consumed about 6.5 percent of the U.S. corn crop that year. Thus, in the first 20 years of its existence, only a small percentage of the annual corn crop flowed into the ethanol industry.

California's decision to ban the use of MTBE (methyl tertiary-butyl ether) and use ethanol as a gasoline additive substitute provided the initial increase in demand that fueled expansion of the ethanol industry. Passage of the 2005 Energy Policy Act created a renewable fuel standards policy in the United States that imposed ethanol mandates and spurred refiners nationwide to increase their demand for ethanol as the U.S. made a rapid conversion from MTBE to ethanol (EPA, 2014).

Statistics provided by the Renewable Fuels Association (2014) indicate that 95 ethanol plants produced 3.9 billion gallons in 2005. In the same year, the U.S. produced 11.1 billion bushels of corn. The estimated share of the 2005 corn production consumed by the ethanol industry reached 12.9

percent in 2005.[1] By the end of 2013, the number of ethanol plants in the United States had increased to 210, with a total capacity of 15 billion gallons, and a total production of 13.3 billion gallons per year. In 2013, the U.S. produced 13.9 billion bushels of corn. Using a FAPRI 2012 conversion rate of 2.77, the ethanol industry consumed approximately 34 percent- of the 2013 corn crop. The corn-based ethanol industry has grown from a minor to a major industry in less than 15 years (Cai and Stiegert 2014). This rapid expansion contributed to corn price increases which, in turn, sent a positive market signal to row crop producers to substantially increase their corn production. Changes in the agricultural production policies due to the 1996 Freedom to Farm Act allowed producers to increasingly shift production practices toward corn after corn, corn and soybean rotations, double cropping, and move away from planting other conventional crops in a rotation. To accomplish this switch, producers made a rapid transition from planting conventional to GM seed.

2.3 *Commercialization of GM Seed Technology for Corn and Soybeans*

GM crop varieties were first introduced for commercial production in the United States in 1996. Since then, farmers have rapidly adopted herbicide tolerance (HT: glufosinate), insect resistance (Bt: Bacillus thuringeiensis), and stacked (both traits) GM corn and soybean varieties. The U.S. adoption rates of GM corn and soybeans increased from zero in 1995, to 25 percent and 54 percent in 2000, and to 90 percent and 93 percent in 2013, respectively (Economic Research Service, 2014).

Numerous authors have noted the rapid adoption and diffusion of GM crops, and various studies provide documentation of an array of implications of the increased reliance on GM crop varieties (e.g. Benbrook 2004; Cattaneo et al. 2006, Benbrook 2009; Fernandez-Cornejo et al. 2014). In their analysis of adoption and diffusion decisions and patterns, Scandizzo and Savastano (2010) suggest that once farmers begin to adopt GM crops in their production systems, producers reach a point where it becomes too costly to switch back to conventional crop varieties (pp.144-145). The authors provide

[1] We used the Food and Agricultural Policy Research Institute (FAPRI) 2005 conversion rate of 2.71 gallons per bushel to estimate corn production usage by the ethanol industry for 2005.

several reasons for why irreversibility may occur. They argue that producers find it difficult to return to conventional crops because they have incomplete information about pest pressures at the time of planting. Learning and experimenting with new technologies involves sunk costs. Adopting GM crops requires making investments specific to the new technology (among other things, increased use of larger scale specialized, and no-till equipment, etc.). The authors suggest that GM crop adoption and diffusion may reduce biodiversity, enhance pest resistance, and cause irreversible biological effects due to the spread of genes to non-target wild species (p.145). Thus, the irreversibility of the adoption of GM crops and their high diffusion rates represent a dramatic change in the types of agriculture observed, including the types of crops planted and cropping patterns.

The issue of the diffusion of GM crops linked to the intensification of the same crops extends beyond the borders of the U.S. For example, Cap and Malach (2012) reported on changes in land use patterns due to the increased area planted to soybeans in general, and the increased reliance on GM soybeans in particular, in four South American nations. The authors found that the commercial availability of glyphosate-tolerant soybean varieties contributed to an increase in the area planted to soybeans in three of the four main South American soybean-producing nations.

2.4 Cropping Pattern over time

Corn Belt states have experienced a significant change in crop production patterns since the passage of the FFA in 1996. In particular, these states experienced a major shift away from small grains, wheat (Triticum), and hay, toward corn and soybeans (Table 1). According to Johnston (2014), Wallander et al. (2011), and Claassen et al. (2010), the cropping system in the Corn Belt and Eastern Northern Plains underwent substantial change since the mid-1990s. Johnston (2014) has documented the conversion of grasslands in the Prairie Pothole Region (PPR) of the U.S. into corn-soybean acreage. Johnston presents data indicating that this change in the cropping pattern has resulted in the supplanting of wheat and other small grains in the PPR. Claassen et al. (2010) identifies a significant conversion of marginal production acres (grasslands, hay-land) to cropland in the Eastern Northern Plains. Wallander et al. (2011) note that the increase in the U.S. corn and soybean acreage over the past decade has coincided with the increased incidence of double cropping, the conversion of hay land, and a reduction in cotton (Gossypium hirsutum) acreage.

The extensive literature on changing cropland patterns has linked the emergence of corn-based ethanol production to changes in cropping patterns in general. However, no econometric analyses have been conducted on the role of federal ethanol policies, relative crop prices, and GM seed adoption in state-level cropping patterns using a "mixed model" approach. Given the heterogeneous nature of individual State climate and soil conditions, understanding the effects of policy and technology on state cropping patterns must account for state-level characteristics. To capture the heterogeneity between states, a mixed modeling approach that incorporates both random and fixed effects was adopted.

3. Data

Our analysis is based on secondary state-level data on crop acres planted and GM corn coverage in eleven northern Corn Belt states for each year between 2000 and 2012, resulting in a total of 143 observations. In particular, our data set includes state-level cropland acres planted for IA, IL, IN, NE, KS, MI, MN, MO, OH, SD, and WI between 1996 and 2012, collected from the National Agricultural Statistics Service (2014). We also collected annual GM crop adoption rates for the eleven northern Corn Belt states from the Economic Research Service (2014) from 2000 to 2012 (genetically modified crop adoption rates for years prior to 2000 were not available). A policy dummy variable was created based on the passage of the 2005 Energy Policy Act and the Energy Independence and Security Act of 2007. The dummy variable has a value of one for the years 2005 to 2012, zero otherwise. Annual average corn and soybean prices were collected from the National Agricultural Statistics Service (2014).

4. Methodology

Given the nature of our state-level pooled time series/cross-sectional data set, we adopted a linear mixed modeling approach to investigate the effect of GM corn adoption and the enactment of ethanol policies on changes in state-level corn acreage intensity. Our objective is to investigate how corn acreage planted as a proportion of total cropland acres planted in the eleven-state region has changed during this transition period. We hypothesize that agricultural sector heterogeneity between states – for example, differences in climate, soil, landscape, and state agricultural policies – has resulted in dissimilar responses to the introduction of biotechnology and bioenergy policy during the transition period covered in our study.

Using annual data, we apply a mixed regression modeling approach to estimate a fixed effects model with a random intercept by state. Four models were estimated: a) no interaction terms (the simple model), b) the GMCS/State interaction term model; c) the RFS/State interaction term model, and d) the PR/State interaction term model. We hypothesize that data on acres planted are clustered due to the heterogeneity of individual state characteristics.[2] The dependent variable is the ratio of corn acres planted to total acres planted, or corn acreage intensity (CAI) by state. Explanatory variables include the ratio of annual corn to soybean prices (PR); an ethanol policy dummy variable (RFS=1 for years from 2005 to 2012); and the state-level percentage of corn acres planted with GM corn seed (GMCS). We assume each of these explanatory variables has a positive relationship with CAI. We also created fixed effects interaction terms designed to identify the effect of GMCS adoption rates, RFS policy on state-level CAI, and the effect of the change in the relative price of corn to soybeans on State level CAI.[3] The price ratio variables captures the market valuation of corn relative to other crops, the GMCS variable

[2] Clustered data refer 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 between geographically related states. The existence of cluster data will result in biased standard errors. Clustering was verified and a correction procedure was implemented.

[3] The fixed effects interaction terms for GMCS and PR represent individual state slope coefficients for the explanatory variables.

reflects the supply side impact of biotechnology on corn production, and the RFS policy dummy variable captures the increased demand for corn due to corn-based ethanol production policy incentives.

The standard assumptions associated with the linear mixed model (LML) 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. $CAI = X\beta + Z\gamma + \varepsilon$,
2. $\gamma \sim \boldsymbol{N}(O, G)$,
3. $\varepsilon \sim \boldsymbol{N}(O, R)$, and
4. $COV(\gamma, \epsilon) = 0$.

The dependent variable CAI 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. The error term, *ε*, reflects an unknown random error. Equation 4 states that *Υ* and *ε* are independent, which implies that the variance of CAI (SAS Institute, 1999: p. 2087) can be defined as:

5. $VAR[CAI] = ZGZ^T + R.$[4]

G and *R* are the covariance matrices associated with *Υ* and *ε*, respectively.[5] The LML procedure in SAS provides great flexibility when dealing with regression diagnostic issues (SAS Institute, 1999). First, we employed a "sandwich estimator" approach to produce robust standard errors associated for *β* (SAS Institute, 1999, chapter 41; and Diggle et al., 1994).

We estimated four models. The first model is a simple random intercept model containing fixed effects for the PR, GMCS, and RFS variables. The second model is a random intercept model with a

[4] The superscript notation "T" denotes the transpose matrix operation. We also examined the correlation between the model's residuals and the exogenous variables. All correlation coefficients were less than 0.01. Thus, exogeneity is confirmed.
[5] The default covariance structure for the Mixed procedure is variance components (SAS 1999: p. 2088). Other covariance structures for *G* and *R* were investigated. The variance components structure was selected based on the "Null Model Likelihood Ratio Test."

GMCS interaction term, where the simple model is extended by adding a fixed effects interaction term for State*GMCS.[6] The interaction variable's parameter estimate, δ, is a slope coefficient, reflecting for the effect of each specific state's GM corn adoption rate on the proportion of corn acres planted. The third model is a random intercept model with the RFS interaction term, where the simple model is extended by adding a fixed effects interaction term for state*RFS. The interaction variable's parameter estimate, δ, captures each individual state's fixed effects intercept adjustment coefficient for the effect of federal ethanol policy on the same state's proportion of corn acres planted. The fourth model is a random intercept model with the PR interaction term, where the simple model is extended by adding a fixed effects interaction term for state*PR. The interaction variable's parameter estimate, δ, captures the state-specific fixed effects estimated slope coefficient for the effect of the change in the relative price of corn to soybeans on corn acres planted.[7] The linear form of the general model to be estimated is:

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

$$where\ i = 1\ to\ 11, j = 1\ to\ 3, and\ t = 1\ to\ 13.$$

The parameter α is the fixed intercept, the subscript "*i*" denotes the state, "*j*" denotes explanatory variables, and "*t*" denotes time. Regression diagnostic analyses confirmed that the mixed model approach was more robust than a simple fixed effects model.[8] Furthermore, the variance components estimating procedure found that the variance associated with matrix G's contribution to the variance of matrix V (covariance matrix for CAI) was significant at the five percent level or less in all four models (Table 4). Regression diagnostics confirmed the absence of serial correlation in all four models.

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[6] A test for random versus fixed slope model specification was conducted for the GMCS adoption rate. The random slope assumption was rejected at the 5 percent level.
[7] Note, due to multicollinearity, the interaction effects needed to be modeled separately.
[8] A restricted maximum likelihood estimation procedure was employed. To gauge goodness of fit of the mixed model approach, we ran a simple fixed effects only model. The log likelihood statistic for this comparison model is – 458.8. The Null Model Likelihood Ratio test rejects the null hypothesis that the two models are equivalent at P< 0.001.

5. Empirical Results

5.1 Summary Statistics

Tables 1 through 3 summarize changes in cropping patterns in the northern Corn Belt between 1996 and 2012, divided over the first part (1996-2004) and the second part (2005-2012) of the period. The tables indicate that, relative to the first period, each state in our sample experienced an increase in corn acres planted in the second period, both in absolute terms as well as measured as a proportion of total acres planted. From the first to the second period, the regional average of the proportion of corn acres planted out of total acres planted increased from 35.8 percent to 40.2 percent, while the proportion of soybean acres out of total acres planted remained unchanged at about 32 percent. This indicates that the increase in corn acres planted between the two periods took place at the expense of areas planted to wheat, hay, and other crops. Furthermore, the increase in corn acre intensity suggests that producers moved away from conventional crop rotation practices that included not only corn and soybeans but other crops as well. These results are consistent with the findings of Wallander et al. (2011).

5.2 Regression Results

Four models were estimated: (a) Model-1, Simple Random Intercept Model, (b) Model-2, Random Intercept Model with GMCS/State interaction terms, (c) Model-3, Random Intercept Model with RFS/State interaction terms, and d) Model-4, Random Intercept Model with Price-Ratio/State interaction terms. The fit statistics and regression results for the four estimated models used in our analysis are provided in Tables 4 and 5. We provided estimated Intraclass Correlation Coefficients (ICC) for each model (Table 4). The ICC estimates are greater than eighty percent for all four models. This statistical evidence supports our conclusion that the effect of biotech advancements on producer planting decisions are heterogeneous across states.

5.21 Model-1

Model-1 provides estimates for the fixed effects parameter estimates at the regional level. All fixed effects parameter estimates are statistically significant at the one percent level. These findings suggest that an increase in the corn-to-soybean price ratio, the adoption and diffusion of GM corn technology, and the passage of the biofuels acts of 2005 and 2007 all positively affected corn acreage intensity in the Corn Belt region. The fixed effects intercept has a value of 0.266, which can be interpreted as an estimate of the regional average of the proportion of corn acres to total acres planted. The random intercept coefficients reflect the deviation from the regional average. The coefficients for KS, MO, and SD are statistically significant and negative, implying that these states' intercepts are smaller than the regional average intercept. The coefficients for MN, OH, and MI are not statistically significant, implying that these states' intercepts are at the regional average. The random intercept coefficients of the remaining five states are statistically significant and positive, which implies that these states' intercepts are above the regional average. The simple mixed model confirms that GMCS adoption rate, relative crop prices, and biofuel policy each 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.

5.22 Model-2

In an effort to capture the state-specific effects of the adoption and diffusion of GM corn technology on cropping pattern changes, we dropped the GMCS fixed effects variable and introduced interaction terms (Model-2). The positive state-specific fixed effects slope coefficients for the GMCS/State indicate that corn acreage intensity in all states was positively impacted by the intensification of GM corn adoption. However, comparison of the state-specific GMCS interaction coefficients in Model-2 with the GMCS coefficient (0.060) in Model-1 shows that in seven of the Corn Belt states (IA, IL, KS, NE, MN, SD, and WI) the adoption and diffusion of transgenic corn varieties disproportionately contributed to the increased corn acreage intensity in comparison to the region as a whole. In the remaining four states (IN, OH, MO, and MI) the spread of GM corn varieties had a smaller impact on corn acreage intensity relative to the regional average as estimated in Model-1. With respect to the regional intercept and individual state random intercept estimates, the only noteworthy change was that NE's random intercept became insignificant. Regional fixed effects estimates for RFS and PR remained positive and significant.

5.23 Model-3

Similarly, to assess the impact of the federal biofuel policy on cropping pattern changes by state, we dropped the RFS as a regional explanatory variable and instead introduced state-specific RFS interaction terms (Model-3). Comparing the state-specific fixed effects interaction coefficients in Model-3 with the RFS coefficient (0.0136) in Model-1 helps identify those states where the RFS policies intensified corn acreage plantings and where the effects are above the regional average.[9] The results indicate that the two federal biofuel laws had a disproportionately stronger impact on corn production patterns in IA, IL, NE, and SD relative to the region overall. On the other hand, the impacts of federal biofuel laws on cropping patterns in MN and WI were slightly below the regional average estimate provided by model-1. This perhaps is due to state-level policies favoring biofuels production and usage prior to the passage of federal regulations. The parameter estimates for the states in which the biofuel laws had a particularly strong impact on changing cropping patterns (IA, IL, NE, and SD) were highly significant, while those for the two states for which the biofuel laws had a slightly smaller impact than for the northern Corn Belt region as a whole (MN and WI) were statistically significant at the five percent level. The parameter estimate for KS was equal to that of the region overall, and was significant at five percent. The parameter estimates for the remaining biofuel-state interaction terms (IN, MI, MO,

[9] Given that RFS is a bivariate dummy variable, the parameter estimate for this variable represents a shift in the intercept for the 2005-2012 period relative to the 2000 to 2004 period. In addition, an individual state's intercept is a function of the regional fixed effects intercept plus the state's individual random intercept estimate. Thus, the RFS interaction term provides an estimate of the shift in an individual state's intercept due to biofuel legislation in the post 2004 period, relative to the pre-2004 period.

and OH) were not statistically significant. This implies that federal biofuel policy did not alter corn acreage levels in these states relative to the 2000-2004. The unevenness of the effect of federal biofuel policy on the proportion of corn acres planted suggests state-level idiosyncratic attributes played a role in federal policy effectiveness. Regional fixed effects estimates for GMCS and PR remained positive and significant.

5.24 Model-4

The final model investigates the effect of a change in relative crop price (PR) on a State's corn acreage intensity. In this model, we dropped the regional relative crop price variable and replaced it with a State*PR interaction term. Similar to model 2, the interaction parameter estimates reflect individual state fixed effects slope coefficients. The positive state-specific fixed effects slope coefficients indicate that corn acreage intensity in nine of the states was positively impacted by an increase the market price of corn relative to the price of soybeans. OH and MO had insignificant parameter estimates, suggesting that corn acreage intensity was not affected by the PR ratio.

A comparison of the state-specific PR interaction coefficients in Model-4 with the PR coefficient (0.1858) in Model-1 indicates that five of the states (IA, NE, MN, SD, and WI) had a significantly stronger positive response to a change in relative price, as compared to the regional average with respect to corn acre intensity. In four states (KS, MO, MI, and OH) the parameter estimates indicate a very weak corn acreage response to a change in relative price compared to the regional average. The parameter estimates for IL and IN indicate they had a similar acreage response to a change in relative prices in comparison to the regional average. State heterogeneity also appears to be a viable explanation for the variation in producer planting decision response to a change in relative crop price.

The Price-Ratio model's regional fixed effects estimates for the intercept, the GMCS and RFS parameters are very similar to simple model estimates. The random intercept assumption continued to be statistically justified with a p-value less than 0.04 (the weakest of the four models). However, the random intercept estimates for NE, WI, and MO became insignificant. Otherwise, the random intercept estimates for Model-4 are consistent with Model-1.

5.3 Synopsis of Empirical Results

The parameter estimates of the random intercept component for the models 1-3 are highly consistent, as are those of the fixed effects intercepts, which range from 0.254 to 0.266. This range reflects the proportion of corn acres planted at the state level assuming that GM corn diffusion and biofuel policies were unchanged. The random intercept is interpreted as the state-specific deviation from the fixed effects intercept for the region as a whole. All states **not** having a statistically significant random intercept reflect a proportion of corn acres planted equal to the regional average. These states include MI, MN, and OH for all four models. Model-2 also includes NE and model-4 adds WI and MO. States with statistically significant positive random intercept terms indicate that the proportions of corn acres planted in these states were above the regional average prior the introduction of GM corn seed and implementation of biofuel policies. The states with statistically significant and negative coefficients represent those with less corn intensity than the regional average prior to the widespread diffusion of GM corn and implementation of biofuel policy incentives.

One interesting insight gleaned from the parameter estimates for IN, MI, MO and OH is that each of these states had GMCS/state interaction parameter estimates below the regional average estimate provided in Model-1. These same states also were the only ones with insignificant RFS interaction parameter estimates and these states were also less sensitive to changes in relative price as compared to the regional state average. We conclude that these results suggest that the sensitivity of corn acreage intensity to GMCS adoption and relative price changes are factors that affect biofuel policy effectiveness in terms of changing corn acreage intensity. Thus we believe that the results indicate that there is a positive relationship between increased GM corn diffusion and increasing corn acre intensity due to the passage of biofuel policies. These results suggest that the sensitivity of corn acreage intensity to the GM corn adoption contributed to the success of biofuel policy with respect to corn-starch based ethanol production goals.

6. Discussion

Empirical evidence generated by a random intercept model with fixed effects indicates that the intensification of corn acres planted was positively impacted by biotech advancements in energy and agriculture. This suggests producers are moving away from diverse cropping patterns and the rotational practices associated with a diverse crop planting strategy. As a result, total acres planted in small grains, and hay has declined in the Corn Belt region. We conclude that corn acreage intensification can be linked to past government policy decisions in the areas of energy and agriculture.

The empirical results presented demonstrate that state-level corn acreage intensification due to the introduction of GM corn and biofuel technology was not homogenous across the eleven-state region during the 13 year transition period covered in this study. The empirical results suggest that producer corn acreage response to agriculture and energy policy decisions varies by geographical location. Thus, future changes in ethanol energy policy, relative crop prices, and the ability of GM technology to provide pest protection will also have a heterogeneous effect on producer cropping decisions. Future agricultural policy decisions need to recognize that producer reaction to changes in the above factors will depend on geographical location.

The evidence also suggests that the significant increase in corn acreage intensity over the period of analysis is linked to biofuel policies and GM corn adoption. Furthermore, the proportion of soybean acres has remained stable in the pre- and post-RFS periods. This indicates a decline in the acres allocated to alternative crops used in conventional rotation practices in the region (Table 1). Empirical evidence also indicates that five of the eleven states (IA, IL, KS, MO, and SD) experienced a double-digit percentage increase in corn acres planted between the two periods. This suggests that the effects of using GM corn technology on the production side and biofuel policies on the demand side vary by state. Empirical evidence suggests that IN, MI, MO, and OH experienced a below-average boost from the use of GM corn on corn acres planted. These four states were also the one where biofuel policy had no effect on corn intensity. The identification of the heterogonous factors across states may provide additional insights on how cropping patterns will change in the future in response to policy changes.

Cropping pattern changes in general and the growing dominance of corn in U.S. crop production systems in the eleven states have shed light on host of expected and unexpected consequences. For example, the relatively high corn prices experienced over the past several years 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 planted acre coverage with insecticide (Fausti et al. 2012). Both the extent of the pest resistance and the subsequent increase in insecticide-acreage-coverage were unanticipated at the onset of the widespread use of crop biotechnology.

While based on data collected in the eleven-state region sometimes referred to as the U.S. Corn Belt, this study is also of interest to other regions of the United States. Corn production has expanded not only in response to the widespread adoption of GM corn varieties and biofuel policies, but also as a consequence of 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.

Table 1. Changes in principal crops area in the Corn Belt, 1996 to 2012

Crops	Avg. (1996-2004)		Avg. (2005-2012)		Change in Area	
	1,000 acres	**%**	**1,000 acres**	**%**	**1,000 acres**	**%**
Corn, Planted Acres	64283	35.8	71044	40.2	6760	11
Soybean, Planted Acres	57103	31.8	56651	32.1	-452	-1
Barley[1], Planted Acres	524	0.3	226	0.1	-297	-57
Oats[1], Planted Acres	2077	1.2	1378	0.8	-699	-34
Wheat, Planted Acres	22331	12.4	20053	11.3	-2278	-10
Hay, Harvested Acres	24375	13.6	21454	12.1	-2921	-12
Others	8886	4.9	5945	3.4	-3727	-41.9
Total Planted Area	179580	100.0	176751	100.0	-2829	-2

[1] Oats: Avena sativa; Barley: Hordeum vulgare.

Source: Compiled from USDA data, http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1000).

Table 2. Changes in area under different crops in the Corn Belt, by state, 1996-2012

State/ Region	Units	Corn Acres Planted	Soybeans Acres Planted	Barley Acres Planted	Oats Acres Planted	Wheat Acres Planted	All Hay Acres Harvested	Total[1] Planted Area
		********* Avg.(2005-2012) compared to the Avg.(1996-2004)*********						
IA	1000 Acres	1292	-844	0	-92	-4	-209	-88
	(in)	10.5	-8.0	-	-35.3	-11.7	-24.8	-0.4
IL	1000 Acres	1318	-1245	0	-30	-239	-50	-556
	(in)	11.8	-12.0	-	-41.2	-23.1	-7.3	-2.4
NE	1000 Acres	638	518	-8	-47	-207	-301	-134
	(in)	7.5	12.1	-100	-30.1	-10.8	-18.4	-0.7
MN	1000 Acres	606	21	-205	-130	-380	-252	-395
	(in)	8.4	0.3	-65.8	-34.5	-18.1	-8.4	-2.0
IN	1000 Acres	169	-250	0	-17	-129	-163	-320
	(in)	2.9	-4.5	-	-49.0	-23.3	-13.5	-2.5
SD	1000 Acres	824	202	-53	-156	-268	-294	-299
	(in)	20.1	5.2	-52.4	-38.2	-7.9	-13.3	-1.7
WI	1000 Acres	259	249	-24	-117	116	-135	-9
	(in)	7.1	18.3	-36.6	-28.5	66.1	-3.3	0.1
OH	1000 Acres	183	-40	-1	-32	-180	-443	-311
	(in)	5.4	-0.9	-33.8	-32.3	-16.8	-14.3	-3.0
KS	1000 Acres	1049	724	4	-40	-767	-129	-497
	(in)	34.5	27.4	41.5	-32.1	-7.4	-10.2	-2.1
MO	1000 Acres	349	240	0	-17	-261	-540	13
	(in)	12.3	4.8	-	-41.7	-23.9	-13.1	0.1
MI	1000 Acres	73	-26	-10	-20	42	-406	-235
	(in)	3.1	-1.3	-43.8	-22.5	7.0	-18.1	-3.5
Corn Belt	1000 Acres	6760	-452	-297	-699	-2278	-2921	-2829
	(in)	10.5	-0.8	-56.8	-33.7	-10.2	-12.0	-1.6

[1] Totals do not match because areas under other crops are not listed.
Source: Compiled from USDA data, http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1000).

Table 3. Changes in crop area shares in the Corn Belt, by state, 1996 to 2012

State/ Region	Period	Corn Acres Planted	Soybeans Acres Planted	Barley Acres Planted	Oats Acres Planted	Wheat Acres Planted	All Hay Acres Harvested
		********* *As a Percent of Total Principal Crop Area*********					
IA	1996-04	49.8	42.4	0.0	1.0	0.1	3.4
	2005-12	55.2	39.1	0.0	0.7	0.1	2.6
IL	1996-04	47.2	44.0	0.0	0.3	4.4	2.9
	2005-12	54.1	39.7	0.0	0.2	3.5	2.7
NE	1996-04	44.3	22.5	0.0	0.8	10.1	8.6
	2005-12	47.9	25.4	0.0	0.6	9.0	7.1
MN	1996-04	36.1	34.9	1.5	1.9	10.4	14.8
	2005-12	39.8	35.7	0.5	1.3	8.7	13.9
IN	1996-04	45.7	44.1	0.0	0.3	4.4	9.5
	2005-12	48.3	43.2	0.0	0.1	3.5	8.5
SD	1996-04	23.8	22.5	0.6	2.4	19.7	12.9
	2005-12	29.1	24.1	0.3	1.5	18.4	11.4
WI	1996-04	45.3	16.8	0.8	5.1	2.2	50.2
	2005-12	48.5	19.9	0.5	3.6	3.6	48.6
OH	1996-04	32.4	43.6	0.0	1.0	10.4	29.8
	2005-12	35.2	44.5	0.0	0.7	8.9	26.3
KS	1996-04	13.1	11.3	0.0	0.5	44.5	5.4
	2005-12	18.1	14.8	0.1	0.4	42.2	5.0
MO	1996-04	20.7	36.2	0.0	0.3	8.0	30.1
	2005-12	23.3	37.9	0.0	0.2	6.1	26.2
MI	1996-04	34.6	29.5	0.3	1.3	8.8	33.1
	2005-12	36.9	30.1	0.2	1.1	9.8	28.1
Corn Belt	1996-04	35.8	31.8	0.3	1.2	12.2	13.6
	2005-12	40.2	32.1	0.1	0.8	11.3	12.1

Source: Compiled from USDA data, http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1000).

Table 4. Variance Components Statistics and Global Fit Statistics

	Model-1 Rand Int. Model: Simple	**Model-2** Rand Int. Model: GMCS/State	**Model-3** Rand Int. Model: RFS/State	**Model-4** Rand Int. Model: PR/State
Covariance Parameter	**Covariance Par Est. & Z statistic**	**Covariance Par Est. & Z statistic**	**Covariance Par Est. & Z statistic**	**Covariance Par Est. & Z statistic**
Random Int.	0.01541: Z=2.23	0.01544: Z=2.20	0.01505: Z=2.23	0.01386: Z=1.75
Residual	0.000329: Z=8.03	0.000329: Z=7.71	0.000311: Z=7.71	0.000337: Z=7.71
Intraclass Corr coef.	ICC = 82.4%	ICC = 84%	ICC = 83%	ICC= 80%
Fit Statistics				
-2 Log Likelihood	-648.6	-619.7	-594.9	-638.1
AIC	-644.6	-615.7	-590.9	-634.1
BIC	-643.8	-614.9	-590.1	-633.3

Table 5. Random Intercept Model Estimates for Corn Acreage Intensity, by State, 2000-2012

	Model-1 Rand Int. Model: Simple	**Model-2** Rand Int. Model GMCS/State	**Model-3** Rand Int. Model: RFS/State	**Model-4** Rand Int. Model: PR/State
Fixed Effects				
Intercept	0.266***	0.254***	0.266***	0.266***
GMCS	0.060***		0.065***	0.064***
RFS	0.014***	0.008**		0.012**
PR	0.186***	0.194***	0.182***	
Interaction Terms				
IA		0.120***	0.031***	0.272***
IL		0.096***	0.027***	0.180***
NE		0.103***	0.021***	0.421***
MN		0.079***	0.011*	0.197***
IN		0.031***	-0.007	0.160***
SD		0.120***	0.026***	0.262***
WI		0.086***	0.013*	0.295***
OH		0.022***	-0.005	0.009
KS		0.082***	0.014**	0.047**
MO		0.047***	0.001	0.022
MI		0.054***	0.001	0.140***
Random Effects				
IA	0.145***	0.120***	0.133***	0.110*
IL	0.140***	0.133***	0.130***	0.141**
NE	0.074**	0.057	0.068*	-0.019
MN	-0.003	-0.004	-0.003	- 0.009
IN	0.098***	0.124***	0.110***	0.107*
SD	-0.121***	-0.157***	-0.130***	-0.152**
WI	0.091**	0.090**	0.091**	0.048
OH	-0.026	0.001	-0.015	-0.041
KS	-0.222***	-0.225***	-0.224***	-0.171***
MO	-0.157***	-0.137***	-0.151***	-0.096
MI	-0.018	-0.002	-0.001	-0.001

Note: ***, **, 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 2-4 are significant (P-value < 0.01). Parameter estimates rounded to 3 decimal places.

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