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

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The objective of this paper is to investigate the linkage between the use of genetically-enhanced crops in production agriculture, bioenergy produced from these crops, and their combined effects on cropping patterns in the U.S. Corn Belt. Specifically, we investigate the relationship between the rapid increases in the production of genetically modified corn, the simultaneous upsurge in corn-based ethanol production, and the resulting increase in the derived demand for corn. We empirically investigate the effect of genetically modified crop adoption and the enactment of ethanol policies on state-level corn acreage intensity. Our empirical results suggest that the rapid increase in ethanol production due to biofuel policies – facilitated in part by the reliance on genetically-enhanced corn varieties – exacerbated the long-standing trend toward reducing the ratio of total corn acres to total acres planted.

Linking Genetically Modified Corn Production, Ethanol Production, and Corn Acreage Intensity

The period between 1996 and 2012 has been identified in the literature as one of a transition away from conventional crop rotation practices used in the Corn Belt, as documented by Wallander et al. (2011) and others. Genetically modified (GM) crop varieties were first introduced for commercial production in the United States in 1996. Since then, farmers have rapidly adopted herbicide tolerance (HT), insect resistance (Bt), 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. For example, Cattaneo (2006) analyzed the impacts of using transgenic cotton on biodiversity, pesticide use, and yield. Also, an earlier study by Van der Sluis et al. (2002) reported on economic costs, benefits, and risks involved with agricultural biotechnology at the farm and market levels, as well as for the farm and food system overall. The authors argued that the analysis of the merits of GM products should not only include technical aspects, but other stakeholder concerns as well, such as those living in developing nations, environmental groups, and consumers.

The development of corn and soybean-based biofuel conversion technology as an alternative 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. While there is no explicit mandate for corn-based ethanol, corn is by far the main source of biofuel production because of its comparative cost advantage relative to alternative biofuels.

While agricultural practices change continuously in response to a variety of factors (Wardlow and Egbert, 2002), U.S. biofuel policies have had particularly far-reaching consequences. The rapid adoption and diffusion of GM crops in combination with the increase in corn-based biofuel production have led to major changes in the types of crops planted and their cropping patterns. This was confirmed by Kurkalova et al. (2012) and Marshall (2011), who found that corn demand, driven by increased corn-based ethanol production, influenced producer crop rotation patterns in the U.S.

The Corn Belt region in particular has seen a major shift away from wheat and hay, as illustrated in Table 1. According to Claassen et al. (2010), the combined corn and soybean acreage nearly doubled from 20 percent to close to 40 percent of cultivated cropland over the ten-year period between 1997 and 2007. The authors suggest that the move toward increased corn and soybean plantings was facilitated primarily by policy changes embodied in the 1996 Farm Bill (P.L. 104-127), commonly referred to as the “Freedom to Farm” bill, which decoupled the income support system for row crop producers and removed the set-aside requirements for support payments (Mercier, 2011). These policy changes allowed agricultural producers to respond more directly to market signals, policy incentives, and changes in technology. The latter includes 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 issue of GMO diffusion linked to specific crop intensification goes 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.

Recent studies provide further confirmation of the finding that GM crop variety adoption rates may be linked to changes in agricultural producer production practices. For example, Fausti et al. (2012) found that the production of corn, hay, and sunflowers in South Dakota experienced an intensification of insecticide use in 2007, relative to levels reported in previous U.S. Census of Agriculture reporting years. The authors note the positive correlation between the amount of cropland treated with insecticides and the amount of cropland planted to GM crops. The authors document that other Midwestern states – which also had an increase in cropland acres planted to GM corn – saw an increase in cropland treated with pesticides as well.

In their analysis of adoption and diffusion decisions and patterns, Scandizzo and Savastano (2010) noted that once farmers adopt GM crops in their production systems, it is costly to switch back to conventional crop varieties. The difficulty to return to conventional crops is due in part because farmers have incomplete information about pest pressures at the time of planting. Also, learning and experimenting with new technologies involves sunk costs, and adopting GM crops requires making investments specific to the new technology. 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. 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 crop plantings and cropping patterns. The loss of biodiversity was also a focus of Atwell et al. (2009), who noted that market incentives have contributed to an increased reliance on row crops in general. While not unique to GM crops, the increased intensification of agriculture enhanced by the use of GM crops is associated with natural variability loss, and a rise in ecological imbalances.

This short review of the literature suggests that the rapid adoption and diffusion of genetically modified crops in combination with a high rate of increase in corn-based ethanol production has led to a variety of changes in production agriculture. The focus of our study is on analyzing changes in cropping patterns due to the increased reliance on genetically modified crops and the growth in the derived demand for corn stemming from the increased ethanol production since the mid-1990s.

Data

Our analysis is based on secondary state-level data on crop acres planted, GM crop coverage, and crop prices in eleven northern Corn Belt states for each year between 2000 and 2012. A total of 143 observations were used in the analysis. We collected state-level cropland acres planted for IA, IL, IN, NE, KS, MI, MN, MO, OH, SD, and WI for the years 1996 to 2012 from the National Agricultural Statistics Service (2013) Web site. We collected annual GM crop adoption rates for the eleven northern Corn Belt states from the Economic Research Service Web site (2013) 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.

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 GMO adoption and the enactment of ethanol policies on changes in state-level corn acreage intensity. Our objective is to investigate how the proportion of corn acreage across northern Corn Belt states changed during this transition period. We hypothesize that agricultural sector heterogeneity between states – for example, differences in climate, soil, landscape, and state agricultural policies – result 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 effect model with a random intercept by state. We hypothesize that data on acres planted are clustered due to the heterogeneity of individual state characteristics.[1] The dependent variable (CSR) is the ratio of total corn acres to total acres planted, or corn acreage intensity by state. Explanatory variables include the ratio of annual corn to soybean prices (price ratio); an ethanol policy dummy variable (Reg=1 for years from 2005 to 2012); and the state-level percentage of corn acres planted with GMO seed (GECorn). We assume each of these explanatory variables has a positive relationship with CSR. We also created interaction terms designed to identify the effect of GMO adoption rates and the RFS policy on state-level CSR.[2] We believe this set of explanatory variables captures the market valuation of corn relative to other crops, the supply side impact of biotechnology on corn production, and the effect of the increased demand for corn due to policy incentives associated with corn-based ethanol production increases.

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[1] 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 differences in cropping patterns between states. The existence of cluster data will result in biased standard errors.

[2] We tested both GECorn and RFS for random verses fixed effects. Both random effect hypotheses were rejected at the 5 percent level. Thus, the interaction terms capture individual state-level fixed effect coefficients for the explanatory variables GECorn and RFS. The fixed effect interaction terms are both significant at less than 1 percent.

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. $CRC = \mathrm{X}\beta + Z\gamma + \ \varepsilon,$

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

3. $\varepsilon \ \sim \boldsymbol{N}(O, R),$ and

4. $COV(\gamma, \epsilon) = 0.$

The dependent variable CRC denotes the vector of dependent variable observation. Matrix X is the design matrix associated with *β*, which represents the vector of unknown fixed effect parameters. Matrix Z is the design matrix associated with *Υ*, representing the vector of unknown random effect parameters. The error term, *ε*, reflects an unknown random error vector whose elements are not required to be homogenous and independent. Equation 4 states that *Υ* and *ε* are independent, which implies that the variance of CRC (SAS Institute, 1999: p. 2087) can be defined as:

5. $VAR[CRC] = ZGZ^T + \ R.$[3]

G and *R* are the covariance matrices associated with *Z* and *ε*, respectively.[4] 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). The mixed procedure requires the covariance matrices *G* and *R* to be specified. The specification of the covariance matrices *G* and *R* were then determined using the "Null Model Likelihood Ratio Test" with a test statistic that follows an asymptotic chi-square distribution with q-1 degrees of freedom, were q is the number of covariance parameters associated with the alternative covariance matrix structures being compared.

We estimated three models. The first model is a simple random intercept model containing

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[3] The superscript notation "T" denotes the transpose matrix operation.

[4] The default covariance structure for the Mixed procedure is variance components (SAS 1999: p. 2088)

fixed effects for the price ratio, GMO, and RFS. The second is a random intercept model with a GMO interaction term, where the simple model is extended by adding a fixed effect interaction term for state*GMO. The interaction variable's parameter estimate, δ, reflects each individual state's slope coefficient for the effect of each specific state's GMO 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 effect interaction term for state*RFS. The interaction variable's parameter estimate, δ, captures each individual state's fixed effect intercept adjustment coefficient for the effect of federal ethanol policy on each specific state's proportion of corn acres planted.[5] The linear form of the model to be estimated is:

$$6. CRS_{it} = \alpha + \beta X_{ijt} + \gamma Z_{it} + \delta Z_{it} X_{ijt} + \varepsilon_{it}, where\ i = 1\ to\ 11, j = 1\ to\ n, and\ t = 1\ to\ 13.$$

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. Furthermore, the variance components estimating procedure found that the variance associated with matrix Z's contribution to the variance of matrix V was significant at the one percent level. Regression diagnostics confirmed the presence of serial correlation in the GMO interaction model. The problem was corrected by specifying an AR(1) covariance structure for the R matrix defined in equation 3. Diagnostics confirm the AR(1) covariance structure was significant at the five percent level.

Empirical Results

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 (2005-20012) of the period. The tables

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[5] Note, due to multicollinearity, the two interaction effects needed to be modeled separately.

indicate that all of the Corn Belt states in our sample experienced an increase in corn acres planted as well as an increase in the proportion of acres planted to corn in the second period, relative to the first. During this period, the proportion of corn acres planted increased from 35.8 percent to 40.2 percent, while the proportion of soybean acres remained unchanged at about 32 percent. One interesting statistic is that the total acres under all crops declined after 2004 by about 2 percent. After 2004, the increase in corn acres planted took place at the expense of areas planted to wheat, hay, and other crops. This suggests that the increased corn area led producers to move away from conventional crop rotation practices.

Regression Results

Three models were estimated: (a) Model-1, Simple Random Intercept Model, (b) Model-2, Random Intercept Model with GMO/State interaction terms, and (c) Model-3, Random Intercept Model with RFS/State interaction terms. The fit statistics and regression results for the three estimated models used in our analysis are provided in Tables 4 and 5. Model-1 provides estimates for the fixed effect parameter estimates at the regional level. All fixed effect parameter estimates are statistically significant at one percent level. These findings suggest that an increase in the corn-to-soybean price ratio, the adoption and diffusion of GMO technology, and the passage of the biofuels acts of 2005 and 2007 all affected corn acreage intensity in the northern Corn Belt region.

In an effort to capture the state-specific effects of the adoption and diffusion of GMO technology on cropping pattern changes, we dropped the GMO fixed effect variable and introduced interaction terms (Model-2). The positive state-specific slope coefficients indicate that corn acreage intensity in all states was positively impacted by the intensification of GMO adoption. However, comparison of the state-specific GMO interaction coefficients in Model-2 with the GMO coefficient in Model-1 show 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.

Similarly, to assess the impact of the federal biofuel policy on cropping pattern changes by state, we dropped the RFS as explanatory variable, and introduced state-specific RFS interaction terms (Model-3). Comparing state-specific fixed effect interaction coefficients in Model-3 with the RFS coefficient in Model-1 helps identify the states where the RFS policies intensified corn acreage plantings. 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 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 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 was significant at five percent. The parameter estimates for the remaining biofuel-state interaction terms (IN, MI, MO, 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 period. 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 policy effectiveness.

The parameter estimates of the random intercept component for the three models are highly consistent, as are those of the fixed effect intercepts, which range from 0.255 to 0.266. This range reflects the proportion of corn acres planted at the state level assuming that GMO diffusion and biofuel policies were unchanged. The random intercept is interpreted as the state-specific deviation from the fixed effect 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. States with statistically significant positive intercept terms indicate that theses states' proportion of corn acres planted were above the regional average prior the introduction of GMO 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 GMO and implementation of biofuel policy incentives.

One interesting insight gleaned from the parameter estimates is that IN, MI, MO and OH each had GMO 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. Thus, these results suggest that the sensitivity of corn intensity to GMO adoption is a factor that affects biofuel policy effectiveness. Thus we believe that the results indicate that there is a statistically positive relationship between increased GMO diffusion and increasing corn acre intensity due to the passage of biofuel policies.

These results suggest that variables not captured in our analysis, including state-level policies and agronomic characteristics, may also have affected corn planting increases at the state level. In particular, corn planting intensities in states with proactive biofuels policies, such as Minnesota, may have been more affected by state-level policies than by federal policies.

Discussion

The empirical results presented in our study demonstrate that the corn planting intensification due to the introduction of GMOs and biofuel technology varied by state between 2000 and 2012. The evidence also suggests that the significant increase in corn acreage intensity over the period of analysis is linked to biofuel policies and GMO adoption. Furthermore, the proportion of soybean acres has remained stable in the pre- and post-RFS periods, indicating a decline in the acres planted to other 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. This suggests that the effects of using GMO 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 GMO on corn acres planted. These four states were also the states where biofuel policy had no effect on corn intensity. The identification of the heterogonous factors across states may provide insights on how cropping patterns will change in the future.

Cropping pattern changes in general and the growing dominance of corn in U.S. crop production systems in the northern Corn Belt have introduced a host of expected and unexpected consequences. For example, the relatively high corn prices experienced over the past several years contributed to price increases of other crops globally, a decline in the production of other crops, and an increase in the cost of raising livestock. The corn production intensification facilitated in part by the reliance on GM varieties also resulted in increased corn pest resistance and increased insecticide usage. Both the extent of the pest resistance and the subsequent relatively rapid increase in pesticide use were unanticipated at the onset of the widespread use of crop biotechnology.

The result of our study build on the general consensus drawn from the literature that the rapid increase in corn-based ethanol production has in part been facilitated by the increased use of GM corn varieties, and vice versa, the increased ethanol production – in part made possible by supportive federal and state policies – contributed to a prolonged period of high corn prices and thereby further facilitated the full-scale adoption and diffusion of the use of GM corn varieties.

We hypothesize that the combination of the shift in the demand for corn due to the increased corn-based ethanol production, and the corn supply shift caused by the rapid adoption and diffusion of GM corn varieties in agricultural production was facilitated by an agricultural policy environment that encouraged agricultural producers to respond to price incentives. In turn, the positive feedback loop between corn-based ethanol production and the increased reliance on GM corn varieties in agricultural production embodied a crop management paradigm shift in the northern Corn Belt. While different from state-to-state, our research indicates that overall crop production patterns, the use of genetically modified technology in agricultural production, the reliance on ethanol markets as an outlet for corn production, and crop rotation patterns each has changed dramatically and interactively in the Corn Belt since the late 1990s.

While based on data collected in the northern Corn Belt, the 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 genetically modified 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

	Avg. (1996-2004)		**Avg. (2005-2012)**		**Change in Area**	
Crops	**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, Planted Acres	524	0.3%	226	0.1%	-297	-57%
Oats, 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%	176751	100%	-2829	-2%

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 Random Int. Model: Simple	**Model-2** Random Int. Model: GMO/State	**Model-3** Random Int. Model: RFS/State
Covariance Par Est.			
Random Int.	Z=2.34: P-Value <0.01	Z=2.32: P-Value <0.02	Z=2.33: P-Value <0.01
Residual	Z=8.12: P-Value <0.01	Z=8.02: P-Value <0.01	Z=8.12: P-Value <0.01
AR(1)	N/A	Z= -2.01: P-Value <0.05	N/A
Fit Statistics			
-2 Log Likelihood	-674.3	-707.6	-692.6
AIC	-662.3	-673.6	-660.6
BIC	-659.9	-666.8	-654.3

Table 5. Random intercept estimates for corn acreage intensity, by state, 2000-2012

	Model-1 Random Int. Model: Simple	**Model-2** Random Int. Model: GMO/State	**Model-3** Random Int. Model: RFS/State
Fixed Effect			
Intercept	0.266***	0.255***	0.266***
GMO	0.060***		0.065***
RFS	0.014***	0.009***	
Price Ratio	0.186***	0.191***	0.182***
Interaction Term			
IA		0.118***	0.031***
IL		0.094***	0.027***
NE		0.101**	0.021**
MN		0.075***	0.011***
IN		0.029***	-0.007
SD		0.120***	0.026***
WI		0.084***	0.013**
OH		0.021***	-0.005
KS		0.084***	0.014**
MO		0.047***	0.001
MI		0.052**	0.001
Random Effect			
IA	0.145***	0.120***	0.133***
IL	0.140***	0.134***	0.130***
NE	0.074**	0.057**	0.068**
MN	-0.003	-0.002	-0.003
IN	0.100***	0.125***	0.110***
SD	-0.121***	-0.158***	-0.130***
WI	0.091***	0.091***	0.091**
OH	-0.026	0.001	-0.015
KS	-0.222***	-0.227***	-0.224***
MO	-0.157***	-0.139***	-0.150***
MI	-0.018	-0.002	-0.010

Note: ***, and ** indicate significance at 0.01 and 0.5 levels, respectively. Type 3 test for Fixed Effects indicated the interaction coefficient in Models 2 and 3 are significant (P-value < 0.001).

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