Journal of Agricultural and Resource Economics 44(1):16–31 ISSN 1068-5502

The Influence of Genetic Modification Technologies on U.S. and EU Crop Yields

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Over 90% of U.S. corn and soybeans are planted with genetically modified (GM) seed varieties. We use a flexible, nonlinear functional form to investigate yield differences for corn, soybeans, and wheat between the United States and the European Union (which bans the use of GM technologies). U.S. corn and soybean yields increased relative to EU yields since the introduction of GM technologies. EU wheat yields (for which GM technologies are not commercially available in either region) continue to increase relative to the United States. Thus, the EU ban on GM technologies has likely increased the difference between corn and soybean yields between the two regions.

Key words: crop yields, genetically modified technology, nonlinear trends

Introduction

The World Health Organization (2014) defines genetically modified (GM) crops as plants in which DNA has been altered in a way that does not occur naturally through plant breeding. The process transfers selected genes within or across plant species using genetic engineering to produce plants that are resistant to insects, viruses, and specific herbicides. The technology reduces the need for insecticides and fungicides to control insects and viruses. A relatively new GM trait improves the drought tolerance of corn. In some cases, several GM traits are "stacked" into a single crop variety.

Over the past 20 years, most GM crops have generally been engineered to resist the effects of glyphosate herbicides, which has greatly increased the efficacy of weed controls. A glyphosate-resistant GM crop will not die when sprayed with a specific glyphosate, while all other plants that exist within the application (i.e., weeds) will die. This approach to weed control is much more effective than traditional herbicide applications.

GM seed varieties were first introduced in the United States in 1996 and are currently available for corn, cotton, soybeans, sugar beets, canola, and alfalfa. Although GM adoption rates were initially modest, over 90% of U.S. corn, cotton, and soybean acreage (as well as 100% of U.S. sugar beets and almost 100% of Canadian canola) were planted with GM seed in 2017. This high adoption rate is perhaps surprising given that GM seed varieties are 2–4 times more expensive than conventional (and widely available) seed varieties. Consequently, it must be that agricultural producers have received increased value from the adoption of this technology. The increased value could be generated by reduced chemical applications, improved weed control, less mechanical tillage, labor savings, and/or improved yields.

A recent *New York Times* article considers the impact of GM crops in the United States (and Canada) by comparing crop yield outcomes in these two countries with those in the European

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We acknowledge the support provided by the Montana Agricultural Experiment Station, and Watts and Associates, Inc.
Review coordinated by Darren Hudson.

Union, which has banned GM technologies (Hakim, 2016). The article asserts that although the United States has been using GM crops for 2 decades, yield trends between the two regions do not differ. Several other reports appear to echo similar concerns regarding an apparent lack of yield benefits from GM technology (e.g., Bunge, 2016; Foley, 2014; Gurian-Sherman, 2009). However, such assertions run counter to research that indicates GM technologies have the potential to increase yields through a combination of increased plant populations and reduced rotational impacts at the lower end of yield distributions (Chavas, Shi, and Lauer, 2014), and improved pest control (Nolan and Santos, 2012).

Yield-increasing technologies are especially important for the agricultural sector. Technological advances have allowed increased food production, lower food prices, and more efficient use of labor. Technologies that increase yields while reducing the use of land, water, and other resources are particularly valuable to society. While GM technologies have faced much scrutiny since their introduction in the United States, other advances in agricultural technologies have caused similar concerns in the past. Consequently, there is a long history of research into the effects of induced technological change in agriculture. Griliches (1958) investigated the impacts of research expenditures on the development of hybrid corn (a plant modification that occurs through the selective movement of DNA material contained in pollen across plants within a species) and related innovations. He estimated the social rate of return on public and private funds used to develop this technology. Hayami and Ruttan (1970) examined the impact of technology on agricultural productivity and argued that a continuous sequence of induced innovations can yield increased agricultural output, even for regions with different relative factor endowments and prices. They note that the important factor in sustaining productivity is allowing such technologies to be transferred between regions so that each can economize on their most limiting input factor. Olmstead and Rhode (1993) investigated induced technological change in U.S. agriculture and noted that changing crop patterns and investments in biological technologies explain much of the changes in relative input usage between 1880 and 1980.

We quantify differences between U.S. and EU corn and soybean yield trends over the past 6 decades to determine whether GM crop technologies have altered historical relationships between the two regions. In addition, we estimate yield trends using a generalized sigmoid functional form that nests a variety of possible yield trend outcomes ranging from linear to highly nonlinear. This highly flexible functional form allows for the use of F-tests of linear restrictions to determine the best-fitting function to represent crop yield trends. The procedure requires the use of a nonlinear least squares algorithm. However, many modern nonlinear search routines struggle to converge because they use a single search direction at each iteration. Therefore, we develop a search routine that simultaneously searches in multiple directions at each iteration. Although the search routine is not as computer-efficient as others, it has the important virtue of solving nonlinear searches with fewer convergence problems.

Identifying the Causes of Yield Differences

The issue of yield outcomes resulting from GM crop technologies is complex when comparisons are made across countries/regions. For instance, U.S. corn acreage expanded from 70 million acres in 2005 to almost 87 million acres in 2016. Much of this expansion was the result of higher corn prices and the availability of GM seed technologies. Consequently, corn acreages have extended into areas that previously were not prime corn production land. Lusk, Tack, and Hendricks (2016) note that the impact of GM technologies on average U.S. corn yields may be understated because of weather and soil-type heterogeneity.

Potential yield increases are only one benefit that may be generated by GM technologies. For example, Perry, Moschini, and Hennessy (2016) note that GM technologies have reduced the use of mechanical tillage, which consequently reduces CO_2 emissions, soil compaction, and soil erosion. But while GM crop varieties have reduced the use of many production inputs, most weed and insect problems were effectively controlled prior to the use of GM seeds—albeit with the use of more toxic chemicals, labor, and machinery inputs (Kniss, 2017). Consequently, perhaps one should not expect large increases in yields as a result of GM technologies. Nonetheless, it seems reasonable that if a technology increases the efficacy of weed, pest, and disease control while reducing soil compaction, yields should respond accordingly.

We consider the impact of GM technologies on crop yields by estimating U.S. and EU corn and soybean yield trends while allowing for both linear and nonlinear trend specifications. The results indicate that EU corn and soybean yield trends have declined relative to U.S. yield trends over the past 2 decades. Nonetheless, it is certainly possible that factors other than the EU ban on GM technologies could be responsible for these changes. Clearly, U.S. and EU production environments, agricultural policies, and regulatory issues differed both prior to and after the introduction of GM technologies in the United States. However, prior to 1996, virtually all agricultural technologies could be transferred between the two regions. While crop yields have increased markedly in developed countries over the past several decades, continued increases are not *fait accompli* (Pardey et al., 2015). That is, yields only increase if new technologies are developed and adopted. In the absence of human efforts, the combination of biology, disease, weed, and insect pressures would cause yield trends to be, at best, horizontal and, at worst, declining over time.[1]

Identifying the factor(s) that has caused relative changes in corn and soybean yield trends between the United States and the European Union is problematic. Given that a direct measure of the impact of GM technologies (outside of field plot trials) does not exist for aggregated data, we provide a counterfactual as evidence of the impact of GM technologies by considering yield differences for a major non–GM crop that is produced in both regions—wheat. It seems reasonable that if factors other than the ban on GM technologies have caused EU corn and soybean yields to decline relative to U.S. yields, then those same factors should cause EU wheat yields to do the same. Our research, however, finds that the opposite has occurred. EU wheat yields have continued to increase relative to U.S. wheat yields over the past 2 decades. Hence, it appears that GM technologies have had a substantial effect on U.S. crop yields.

Trend Analyses

Recent discussions regarding U.S. and EU yield comparisons have been flawed for two reasons: i) the use of visual rather than statistical examinations of relatively short time series data and ii) the assumption that yield trends are linear. Certainly, the starting point for any trend analysis is often ambiguous. Although GM seed research was conducted throughout the 1980s, GM technologies were not commercially available until 1995. In addition, the adoption rate was, initially, modest. It was not until 2005 that 50% of corn acreage was planted to a GM variety. Consequently, GM technologies probably did not substantially influence average annual U.S. corn yields until a majority of acreage was planted using GM seed varieties.

Estimating trends over short time periods (in this case, the 11 years between 2005, when 50% of acreage was planted to GM varieties, and 2016) is fraught with error. The selected initial year can change trend differences from being inconsequential to substantial. As the time period for trend analyses is lengthened, however, the influence of starting (or ending) points is reduced.

A second problem occurs if one assumes *a priori* that yield trends are linear. Because of adoption rates and learning processes, nonlinear functional forms could be more relevant for approximating changing yield trends. Ultimately, the choice of functional form becomes an empirical issue. We present a method for comparing linear functional forms to a variety of nonlinear functional forms when estimating yield trends.

[1] Between 1866 and 1940 (prior to the widespread production and use of commercial nitrogen fertilizer after World War II), U.S. corn yields averaged 32 bu/acre, with a trend slope of 0.

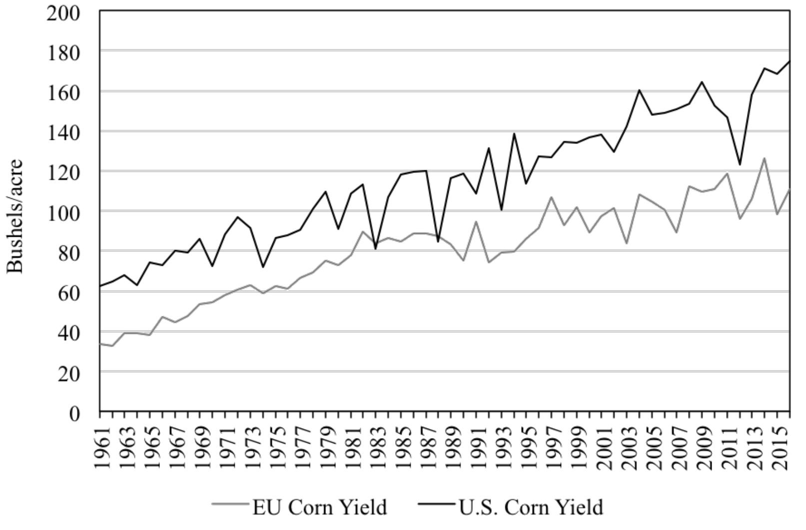

Figure 1. U.S. and EU Corn Yields, 1961–2016

A Closer Look at the Data

Linear Corn Yield Trends

USDA Foreign Agricultural Service's Production Supply and Disposition website (https://apps.fas.usda.gov/psdonline) provides crop yield data for most countries, including the United States and the European Union. Figure 1 presents corn yields for the EU-28 and the United States between 1961 and 2016.

Prior to considering the potential for nonlinear trends, we first estimate a Seemingly Unrelated Regression (SUR) of the following two-equation model in which corn yields for each region (Y) are regressed onto a linear time trend (t), which is a 4-digit number corresponding to the years 1961–2016:[2]

$$
\begin{aligned}
Y_t^{US} &= \beta_o + \beta_1 t + \varepsilon_t^{US} \\
Y_t^{EU} &= \gamma_o + \gamma_1 t + \varepsilon_t^{EU}.
\end{aligned} \tag{1}
$$

Equation (1) is estimated using the **R** programming package "systemfit" (Henningsen and Hamann, 2007). The coefficient estimates are presented in Table 1 and show that the value of the U.S. slope parameter is 1.83 and the value of the EU slope parameter is 1.35. The null hypothesis that $\beta_1 = \gamma_1$ is clearly rejected with a χ^2 statistic of 18.31 and a 0.05-level critical value of 3.84. Consequently, there is strong evidence that the U.S. corn yield trend has almost a 0.5 bu/acre advantage over the EU yield trend for the 56-year period.

However, it is possible that yield trend differences have occurred between the two regions since the introduction of GM technologies in 1996. As a test, we estimated a second SUR for the model:

$$
\begin{aligned}
Y_t^{US} &= \beta_o + \beta_1 t + \beta_2 D96 + \beta_3 (t \times D96) + \varepsilon_t^{US} \\
Y_t^{EU} &= \gamma_o + \gamma_1 t + \gamma_2 D96 + \gamma_3 (t \times D96) + \varepsilon_t^{EU},
\end{aligned} \tag{2}
$$

[2] A SUR model is used to facilitate hypothesis testing of the equality of cross-equation parameter estimates. Although SUR estimates will be more efficient than ordinary least squares (OLS) estimates if cross-equation correlations exist in the error structures, SUR and OLS results are identical if the regressors are the same in the equations being considered—as in equation (1) (Kmenta, 1989).

Table 1. SUR and OLS Estimates of U.S. and EU Corn Yields, 1961–2016

Parameters	Equation (1)	Equation (2)	Equation (3)
		Estimated Coefficients	
U.S. intercept (β_o)	62.30	64.04	
	(21.91)	(17.42)	
U.S. trend (β_1)	1.83	1.71	
	(21.06)	(9.60)	
U.S. D96 (β_2)		−1.88	
		(−0.10)	
U.S. trend × D96 (β_3)		0.14	
		(0.33)	
EU intercept (γ_o)	41.84	37.20	32.02
	(18.04)	(13.27)	(10.26)
EU trend (γ_1)	1.35	1.65	2.36
	(19.05)	(12.12)	(9.37)
EU D96 (γ_2)		25.49	
		(1.84)	
EU trend × D96 (γ_3)		−0.78	
		(−2.41)	
EU trend × trend (γ_4)			−0.018
			(−4.15)
χ^2 statistic (χ^2_1)	18.31	9.87	
χ^2 critical value (0.05,1)	3.84	3.84	
System/adjusted R^2	0.87	0.88	0.90
Degrees of freedom	108	104	53

Notes: Numbers in parentheses are t-values.

where the term $D96$ is an intercept shifter using a binary variable that is equal to 1 beginning in 1996 (and 0 otherwise) and a slope shifter ($t \times D96$), which represents the trend term (t) multiplied by the 1996 binary variable. Table 1 presents the regression results. Note that the U.S. intercept shift coefficient ($\hat{\beta}_2$) and the slope shift coefficient ($\hat{\beta}_3$) are not significantly different from 0, indicating that the U.S. corn yield trend has continued on its upward linear path (as estimated in equation 1) since the introduction of GM technologies. However, the EU intercept shift coefficient ($\hat{\gamma}_2$) of 25.49 has a p-value of 0.07, and the slope shift coefficient ($\hat{\gamma}_3$) equals −0.78 and is statistically different from 0. The null hypothesis that $\beta_1 = \gamma_1 + \gamma_3$ (i.e., the U.S. trend line slope and the EU trend line slope since 1996) of equation (2) is rejected with a χ^2 statistic of 9.87 and a 0.05-level critical value of 3.84. The estimates from equation (2) indicate that the EU corn yield trend has been 0.87 (i.e., 1.65 − 0.78) bu/acre lower since the introduction of GM technologies in the United States, which is 0.96 bushels less than the U.S. trend estimated using equation (1). While the EU corn yield trend was only about 0.5 bu/year less than the U.S. trend prior to 1996, the EU trend line has been almost 1 bu/year less since 1996.

Because technological change is often gradual and influenced by learning processes, the EU corn yield slope change indicated by the parameter estimates of equation (2) is likely more gradual than that indicated by a binary shift variable. Hence, a common approach to investigating such a change is to include a quadratic trend term such that:

$$Y_t^{EU} = \gamma_o + \gamma_1 t + \gamma_4 t^2 + \varepsilon_t^{EU}. \tag{3}$$

Equation (3) was estimated using OLS, and the results are reported in the last column of Table 1. The results indicate that the per acre EU corn yield trend is likely nonlinear.

A Flexible Yield Trend Functional Form

The estimation of yield trends has been the subject of previous research (e.g., Bianchi, Boyle, and Hollingsworth, 1999; Kruse, 1999). A critical component for estimating yield trends is the selection of a functional form; it is unclear whether such trends should be estimated using linear or nonlinear functions. Consequently, we allow for both linear and nonlinear trends and then test nested models to determine the best-fitting functional form. For example, consider a generalized version of the sigmoid function:

(4) $$Y_t = \alpha_o + \frac{\alpha_1\, t^{\alpha_2}}{1 + \alpha_3 t^{\alpha_4}},$$

where Y_t is per acre yield in period t, t represents annual time periods, and the α_i represent parameters to be estimated. Equation (4) represents a relatively flexible functional form in which the simplest model occurs when $\hat{\alpha}_1 = 0$, at which point the estimated equation becomes

(5) $$\hat{Y}_t = \hat{\alpha}_o.$$

In this case, the trend has no slope and is simply equal to the mean of the yield data series.

If $\hat{\alpha}_2 = 1$, and $\hat{\alpha}_3 = 0$, then the estimated model becomes

(6) $$\hat{Y}_t = \hat{\alpha}_o + \hat{\alpha}_1 t,$$

which indicates that the yield data follow a linear trend with slope $\hat{\alpha}_1$ (which could be positive or negative).

If $\hat{\alpha}_2 \neq 0$ and $\hat{\alpha}_3 = 0$, then the estimated model becomes

(7) $$\hat{Y}_t = \hat{\alpha}_o + \hat{\alpha}_1 t^{\hat{\alpha}_2},$$

which indicates that the yield trend is monotonically increasing if $\hat{\alpha}_1 > 0$ or monotonically decreasing if $\hat{\alpha}_1 < 0$. The trend could be changing at increasing or decreasing rates depending on the size of $\hat{\alpha}_2$.

If $\hat{\alpha}_1 \neq 0$ and $\hat{\alpha}_2 = \hat{\alpha}_4$, then the estimated yield trend model becomes

(8) $$\hat{Y}_t = \hat{\alpha}_o + \frac{\hat{\alpha}_1\, t^{\hat{\alpha}_2}}{1 + \hat{\alpha}_3 t^{\hat{\alpha}_2}} = \hat{\alpha}_o + \frac{\hat{\alpha}_1}{\hat{\alpha}_3 + t^{-\hat{\alpha}_2}},$$

which results in a sigmoid functional form for which the maximum yield trend approaches $(\hat{\alpha}_o + \hat{\alpha}_1/\hat{\alpha}_3)$ as t becomes large.[3] The value of $\hat{\alpha}_2$ is directly related to the steepness of the yield trend, while the value of $\hat{\alpha}_3$ is directly related to the length of the initial flatter portion of the sigmoid function. If $\hat{\alpha}_2 \neq \hat{\alpha}_4$, then the functional form can represent a wide variety of shapes including declining yields and permanently upward sloping values.

Nested Model Estimation and Selection

The functional forms presented in equations (5)–(8) are each nested within the model presented in equation (4). Because the models are nested, model selection involves an iterative process. That is, the first iteration involves estimating the restricted equation (Model 1):

(9) $$\text{Model 1: } Y_t = \alpha_o,$$

[3] The second term in equation (8) is obtained by rearranging the equation as

$$Y_t = \alpha_o + \frac{\frac{\alpha_1\, t^{\alpha_2}}{t^{\alpha_2}}}{\frac{1+\alpha_3\, t^{\alpha_2}}{t^{\alpha_2}}} = \alpha_o + \frac{\alpha_1}{\frac{1}{t^{\alpha_2}} + \alpha_3} = \alpha_o + \frac{\alpha_1}{\alpha_3 + t^{-\alpha_2}},$$

which facilitates the nonlinear estimation of this version of the model.

and the unrestricted equation (Model 2):

(10) $$\text{Model 2: } Y_t = \alpha_o + \alpha_1 t.$$

If an F-test of the null hypothesis that $\hat{\alpha}_1 = 0$ cannot be rejected, then Model 2 is rejected in favor of Model 1. The critical value is an F-statistic with $j = 1$ restrictions and $t - k$ degrees of freedom, where k is the number of parameters in the unrestricted model. If the null hypothesis is rejected, then Model 2 is selected over Model 1.

If Model 2 is selected, then a second nested test is conducted in which Model 2 becomes the restricted model and Model 3 is estimated as the following unrestricted model:

(11) $$\text{Model 3: } Y_t = \alpha_o + \alpha_1 t^{\alpha_2},$$

in which the null hypothesis of the single restriction of $\hat{\alpha}_2 = 1$ is tested using an F-test. If the null hypothesis cannot be rejected, Model 2 is selected over Model 3. However, if the test rejects the null hypothesis, then Model 3 is selected.

Model 3 is nested within Model 4 if $\hat{\alpha}_3 = 0$ such that

(12) $$\text{Model 4: } \mathrm{Y_t} = \alpha_\mathrm{o} + \frac{\alpha_1 \, \mathrm{t}^{\alpha_2}}{1 + \alpha_3 \, \mathrm{t}^{\alpha_2}}.$$

If an F-test of the null hypothesis that $\hat{\alpha}_3 = 0$ cannot be rejected, then Model 4 is rejected in favor of Model 3. However, if the test rejects the null hypothesis, then Model 4 is selected.

The final nested test occurs with the unrestricted estimation of Model 5 (which is equation 4):

(13) $$\text{Model 5: } \mathrm{Y_t} = \alpha_\mathrm{o} + \frac{\alpha_1 \, \mathrm{t}^{\alpha_2}}{1 + \alpha_3 \mathrm{t}^{\alpha_4}},$$

and Model 4 is nested within Model 5 if the restriction $\hat{\alpha}_2 = \hat{\alpha}_4$ is imposed. Consequently, Model 4 is the restricted model and can be tested against Model 5 (the unrestricted model) with an F-test of the single restriction $\hat{\alpha}_2 = \hat{\alpha}_4$. If the null hypothesis cannot be rejected by the F-test, then Model 4 is selected over Model 5. If the null hypothesis is rejected, then Model 5 is selected over Model 4.

Nonlinear Estimation Issues

The nested model estimation and selection process is accomplished using the **R** programming language and a nonlinear least squares algorithm used in combination with **R**'s nonlinear least squares (NLS) estimation function.[4] Given the sensitivity of NLS to starting values, we develop a nonlinear least squares **R** program that builds on a procedure developed by LaFrance (1979). The **R** search routine uses a standard "gradient method" (see Greene, 2008, Appendix E) but searches in multiple directions at each iteration. The algorithm updates each parameter estimate using $\theta_{i+1} = \theta_i + \lambda_i W_i g_i$, where θ_i is the current parameter estimate at iteration i, λ_i is a step length at iteration i, W_i is a positive definite matrix, and g_i is the gradient evaluated at point θ_i. The search directions ($d_i = W_i g_i$) include both a "Hessian"-based direction, $d_i = -H_i^{-1} g_i$, and a gradient-based direction, $d_i = I g_i$, in addition to a user-specified number of convex combinations of the two directions (i.e., $d_i = \phi\left(-H_i^{-1} g_i\right) + (1 - \phi) I g_i$ for $\phi \in [0, 1]$.).[5] If H_i is not negative definite in a given iteration i, the Greenstadt (1967) procedure is used to convert H_i to a negative definite matrix. The conversion is accomplished using $H_i^\pi = \sum_{k=1}^{p} - |\pi_k| \, c_k c_k^{'}$, where π_k and c_k are the kth eigenvalue and eigenvector of H_k, respectively, and H_k^π is used in lieu of H_k when computing directions (Greene,

[4] The programming code and estimation examples are available from the authors upon request.

[5] The function also allows the user to specify additional directions in the individual partial derivative directions $\frac{\partial f}{\partial \theta_j}$.

2008, p. 1071). For each iteration, a direction is chosen that provides the maximum increase in the objective function. Then θ_{i+1} is reset using the chosen direction and the process is repeated. If none of the directions with step length λ_i results in an improved objective value, λ_i is reduced and the process is repeated until a larger objective value is found or λ_i is reduced to a very "small" level. The algorithm is considered to have converged if either the gradient or λ_i is approximately 0. A further check for convergence involves using the estimated parameters as starting values for **R**'s NLS function. The resulting NLS output also provides estimated standard errors of the parameter estimates.

Parameter Starting Values

Parameter estimates obtained from nonlinear estimation procedures are often sensitive to starting values. Given that the lower-dimension yield trend models are nested in higher-dimension models, we use the estimated parameters from each of the lower-dimension models as starting values for estimating each higher-dimension model. For example, Model 3 was estimated twice using parameter estimates from Model 1 and Model 2. Similarly, Model 4 was estimated three times using the parameter estimates from Models 1, 2, and 3 as starting values. The minimal SSE and associated parameter estimates obtained using the four sets of starting values were used as the "solution" for the given model.

Heteroskedasticity

Each of the selected model results was checked for heteroskedasticity. If the null hypothesis of homoskedasticity was rejected, the entire set of models for each commodity was re-estimated using iterative weighted nonlinear least squares. The heteroskedastic adjustment was needed for 4 of 8 commodity/difference specifications. Given that results from these more complicated estimation procedures caused almost no changes in the estimated trend lines, we report the original estimates below.

Time Trends

The higher-order, nonlinear models include powers of the time trend variable. When such variables are coded using 4-digit year values, the time trend indicator becomes relatively large and reduces the efficacy of the search routine. To improve convergence performance, the time trend variable is rescaled using the difference between the 4-digit value for each year (e.g., 1961) and a base year that immediately precedes the first observation. The difference is then divided by 10. For example, if the first year of the data is 1961, then the following formula is used to rescale the value of t for each annual observation:

$$\tilde{t} = \frac{Year_t - 1960}{10}, \; t = 1,\, 2,\, \ldots,\, n. \tag{14}$$

Therefore, the term $\tilde{t}$ is substituted for t when estimating equations (10)–(13).

Nonlinear Corn Yield Trends

The initial trend estimates presented above provide solid evidence that U.S. and EU corn yield trends have diverged since the introduction of GM technologies in the United States. Therefore, we estimated equation (4) using the data for the 1961–2016 period and a trend variable as calculated in equation (14). Each nested model was tested iteratively, and Table 2 reports the results. For U.S. corn yields, we tested Model 1 (a more restricted, nested version of Model 2) against Model 2. The F-statistic of the null hypothesis that $\hat{\alpha}_1 = 0$ was rejected (F-statistic of 443.7, critical value of

Table 2. F-Statistics for Nested Model Selection

	Model 2 vs. Model 1	Model 3 vs. Model 2	Model 4 vs. Model 3	Model 5 vs. Model 4
Critical F-Values	$F_{0.05}(1,54) =$ **4.019**	$F_{0.05}(1,53) =$ **4.023**	$F_{0.05}(1,52) =$ **4.027**	$F_{0.05}(1,51) =$ **4.030**
Region and Commodity	**F-Statistics**			
U.S. corn	443.731	0.049	0.445	0.002
EU corn	363.018	19.309	0.818	1.112
U.S. − EU corn	20.547	7.083	1.146	0.049
U.S. soybeans	365.002	4.304	0.900	0.650
EU soybeans	147.907	6.630	26.619	0.026
U.S. − EU soybeans	14.108	6.987	14.752	14.299
U.S. wheat	344.086	1.496	1.430	1.959
EU wheat	606.833	31.763	12.804	0.477
EU − U.S. wheat	196.356	14.520	14.878	0.011

4.019) at the 0.05 probability level. Thus, the rejection of the null hypothesis that $\hat{\alpha}_1 = 0$ indicates that Model 1 is rejected in favor of an alternative. Because Model 1 was rejected, the next nested test involves testing the restriction that $\hat{\alpha}_2 = 0$ in Model 2 (which is a more restrictive, nested version of Model 3). In this case, the null hypothesis that $\hat{\alpha}_2 = 0$ cannot be rejected given the F-statistic of 0.049 and a critical value of 4.023. Consequently, Model 2 cannot be rejected. The remaining tests also indicate rejections of higher-order models.

Table 3 presents the parameter estimates and their t-statistics. Figure 2 presents the predicted values of the linear trend. The slope of the trend line is 1.83.[6] Using predictions from the trend line and starting in 1996 when GM technologies were first introduced, U.S. corn yields increased 28.5%, or 37 bu/acre, by 2016.[7]

We conducted a similar selection process for the EU corn yield data presented in Figure 3. Similar to the U.S. results, the restriction implied by Model 1 was rejected (F-statistic of 363.0, critical value of 4.019). Hence, Model 1 was rejected in favor of Model 2. The second nested test indicates that the restriction implied by Model 2 was rejected (F-statistic of 19.3, critical value of 4.023). Consequently, Model 3 is selected over Model 2. However, the restrictions implied by Model 3 could not be rejected (F-statistic of 0.818, critical value of 4.027). Hence, Model 3 is selected and the estimated nonlinear trend is presented in Figure 4. The EU trend is increasing, but at a decreasing rate.

The use of binary variables and linear trends indicated that U.S. and EU corn yield trends have diverged since GM technologies were introduced. Allowing for nonlinear trends, however, indicates that EU corn yields are declining relative to those of the United States by even more than those indicated using linear trend analyses. The European Union's nonlinear trend line predicts a 19 bu/acre increase between 1996 and 2016 which represents a 20.5% increase in yields. Because GM technologies are not used in the European Union, these yield increases must be caused by other factors such as better weather, improved conventional seed technologies, changes in input or output prices, and/or improved production practices. These same factors could also be responsible for yield increases in the United States. However, the difference of 18 bu/acre between the two regions since 1996 may be attributable to the U.S. adoption of GM technologies.

[6] The parameter estimate in Table 3 is 18.28 and was estimated using $\tilde{t}$, as indicated in equation (14). The slope of the linear trend line is, therefore, calculated by dividing the parameter estimate by 10. This is virtually identical to the parameter estimate of the linear trend reported in Table 1.

[7] We report the sequential model selection process F-statistics. However, other model combinations are possible. For example, if Model 2 were rejected when tested against Model 3, and then Model 3 could not be rejected relative to Model 4, it is possible that Model 2 might not be rejected relative to Model 4 (i.e., the sequential model selection process need not be transitive). We checked all possible model combinations and did not find any intransitive outcomes.

Table 3. Parameter Estimates for Selected Models

	Parameter Estimates				
Region and Commodity	$\hat{\alpha}_o$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{\alpha}_4$
U.S. corn	62.30	18.28			
	(21.91)	(21.07)			
EU corn	14.35	41.63	0.49		
	(1.30)	(3.68)	(4.88)		
U.S. − EU corn	26.31	0.16	3.05		
	(9.13)	(0.46)	(2.34)		
U.S. soybeans	24.77	2.25	1.38		
	(23.54)	(2.98)	(7.13)		
EU soybeans	16.81	0.001	0.00004	−12.12	
	(15.06)	(0.28)	(0.28)	(−2.90)	
U.S. − EU soybeans	10.58	−0.07	5.42	0.00006	8.82
	(8.89)	(−0.43)	(2.10)	(0.53)	(4.45)
U.S. wheat	25.47	3.80			
	(37.90)	(18.55)			
EU wheat	28.95	13.95	0.21	−1.69	
	(12.94)	(3.89)	(5.86)	(−5.68)	
EU − U.S. wheat	5.98	4.62	0.15	−2.91	
	(3.27)	(1.73)	(2.03)	(−4.05)	

Notes: Numbers in parentheses are t-values.

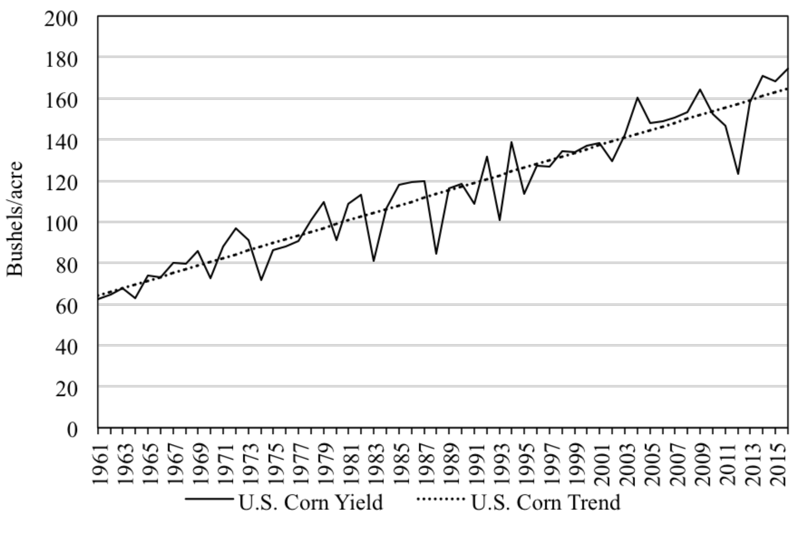

Figure 2. U.S. Corn Yield and Trend, 1961–2016

A more direct approach to test for divergent annual yields is to consider the difference between U.S. and EU corn yields using the data presented in Figures 2 and 3. The model selection process described above was applied to annual yield differences (Table 2) and the parameter estimates for the selected model (Model 3) are presented in Table 3 (the row labeled U.S. − EU Corn). Note that the t-value associated with $\hat{\alpha}_1$ is not statistically different from 0. However, estimated coefficients in nonlinear models do not have the same marginal interpretation as in linear models. That is, the non-nested tests presented in Table 2 clearly reject the null hypothesis that $\hat{\alpha}_1 = 0$.

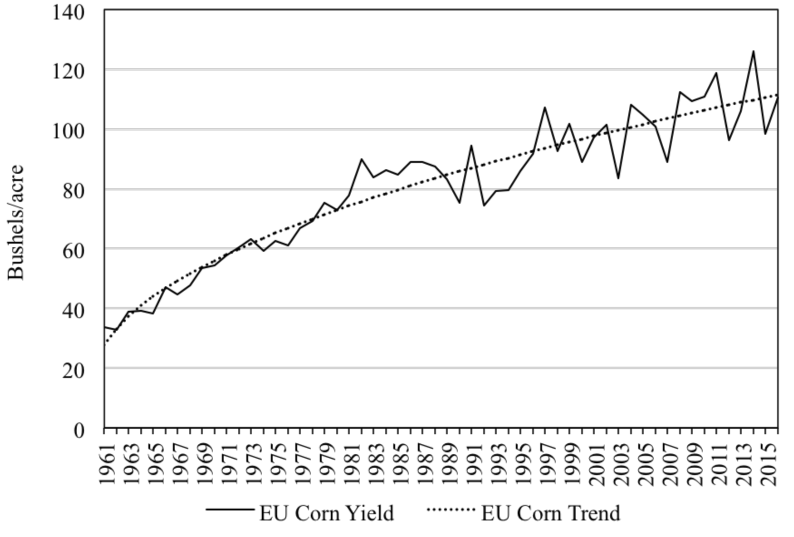

Figure 3. EU Corn Yield and Trend, 1961–2016

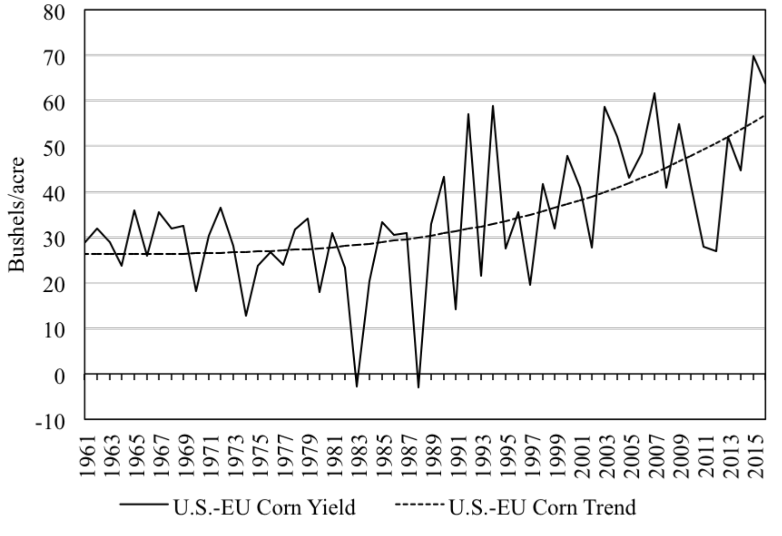

Figure 4. U.S. Minus EU Corn Yield and Trend, 1961–2016

The nonlinear model illustrated in Figure 4 (Model 3) presents the results of the model selection process. The difference between U.S. and EU corn yields has been increasing at an increasing rate. It appears that much of the increase has occurred over the past 2 decades—the time period in which GM corn has been almost completely adopted in the United States but banned in the European Union. The trend line predictions show that the predicted difference between U.S. and EU corn yields in 1996 (34.2 bu/acre) increased to 56.8 bu/acre in 2016. The 22.6 bu/acre increase in the difference between U.S. and EU corn yields since 1996 is similar to that noted above when viewing the trends in levels.

The widening difference between U.S. and EU corn yields could be attributable to other factors such as changes in agricultural policy, environmental issues, or relative factor prices. For example, the European Union has increased regulations regarding the use of nitrogen fertilizers since the

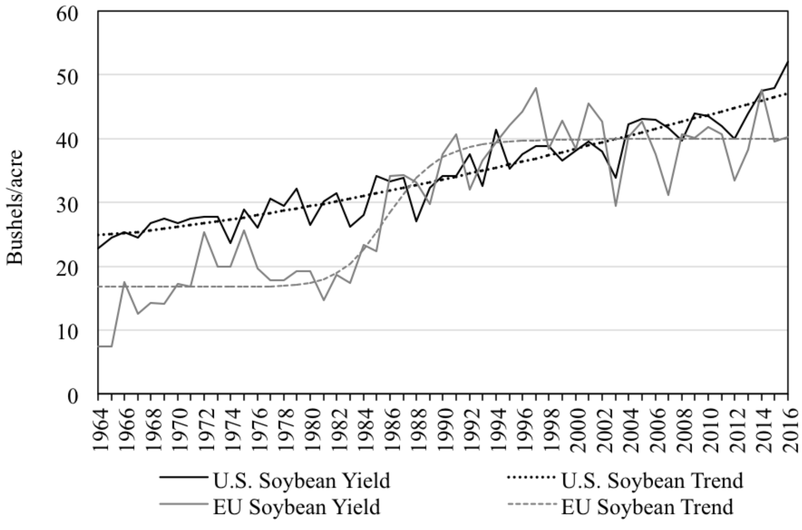

Figure 5. U.S. and EU Soybean Yields and Trends, 1964–2016

late 1980s while also reducing various agricultural support programs (van Grinsven et al., 2015). Hence, total nitrogen fertilizer use declined by about 30% in the early 1990s from record levels in the late 1980s. This is an important consideration given that corn production generally requires high nitrogen fertilizer inputs. Nitrogen fertilizer use in the United States has been relatively constant since the early 1980s, while nitrogen use in the European Union has been relatively constant since the early 1990s. Consequently, it does not appear that differences in environmental policies related to nitrogen fertilizers can explain the differences in corn yield trends over the past 2 decades.

Soybean Yield Trends

The GM technologies that help control weed and insect problems in corn have likely increased yields. However, weed control in corn—through a combination of broadleaf and grass herbicides and mechanical cultivation—was relatively effective prior to GM technologies. Nolan and Santos (2012) used experimental plot data to conclude that GM corn yield increases were more highly influenced by GM insect control traits than by herbicide tolerance traits.

Weed control in soybeans, however, was more difficult prior to GM technologies because selective broadleaf herbicides were only partially effective (Perry, Moschini, and Hennessy, 2016). Therefore, if GM technologies increase crop yields, it would likely be more apparent in crops for which traditional methods of weed control had lower efficacy. Figure 5 presents soybean yield data for the United States and the European Union between 1964 and 2016 (data on EU soybean yields are not available prior to 1964). In addition, only 10,000 acres of soybeans were planted in the European Union in 1964, as it was a new crop for that region. It was not until 1980 that close to 1 million acres were planted, and only 2 million acres were planted in 2016, compared to almost 83 million acres in the United States.

Model 3 could not be rejected for U.S. soybean yields. However, Model 4 was rejected. Nonetheless, the nonlinear U.S. soybean yield trend has only a small degree of curvature and is similar to a linear trend. Model 4 could not be rejected for EU soybean yields, which indicates that EU yields have followed a sigmoid functional form. Specifically, the EU yield trend has been almost flat since the mid-1990s. While U.S. soybean yields were increasing during the period in which GM soybean technologies were being adopted, there has been almost no upward trend in EU soybean yields.

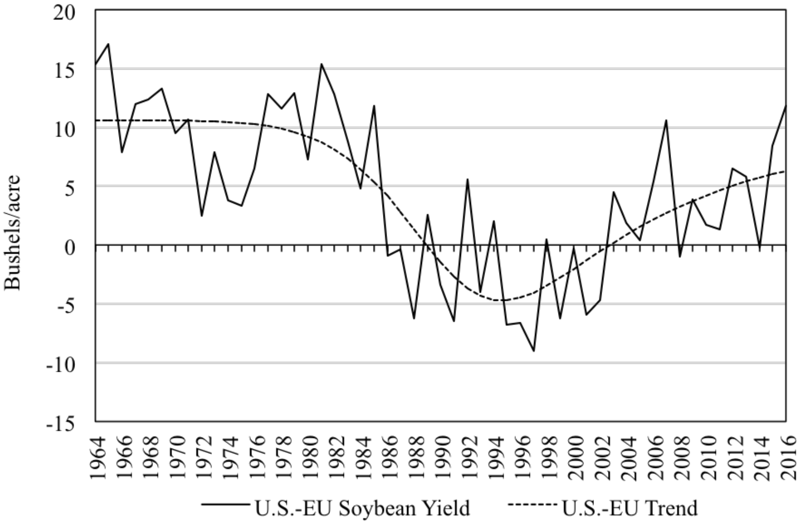

Figure 6. U.S. Minus EU Soybean Yield and Trend, 1964–2016

Figure 6 presents the annual differences between U.S. and EU soybean yields between 1964 and 2016. Between 1964 and the mid-1980s, U.S. soybean yields were larger than EU yields. Between 1986 and 2002, EU yields were generally larger than U.S. yields. Since 2002, U.S. soybean yields have been generally larger than those in the European Union. The restrictions on Model 4 were rejected (F-statistic of 14.299, critical value of 4.030), which indicates that Model 5 represents the functional form that best fits the soybean yield difference data. The trend line clearly indicates that the difference between U.S. and EU soybean yields has increased since 1996.

A Counterfactual: Wheat Yields

It is possible that factors other than GM technologies are responsible for differences in yields between regions or countries. For example, both the United States and the European Union have experienced major changes in agricultural policies over the past several decades. In addition, labor, food safety, or production scale differences may have developed over time. One way to determine whether the differences in corn and soybean yield trends noted above have been caused by factors other than GM technologies is to estimate yield trends for a major crop that is produced in both countries but is unaffected by GM technologies. Wheat—which is a major commodity for both regions and is not commercially produced using GM technologies—provides a reasonable metric for comparison.

Figure 7 presents U.S. and EU wheat yields between 1961 and 2016. Note that EU wheat yields exceed those of the United States in every year. An iterative trend model selection process was conducted on these data, and a linear trend model for the U.S (Model 2) could not be rejected with a slope of 0.38 (i.e., $3.80 \div 10$). The restrictions for Model 4 could not be rejected for EU wheat yields (F-statistic of 0.477, critical value of 4.030). Consequently, EU wheat yields have followed a sigmoid functional form since 1961. Note that EU wheat yields have continued to increase over the past several years, albeit at a decreasing rate.

Another way to evaluate these changes is to estimate a trend for the difference between EU and U.S. wheat yields. The row in Table 2 denoted "EU − U.S. Wheat" shows that the restrictions implied by Model 4 could not be rejected (F-statistic of 0.011, critical value of 4.027). Figure 8 indicates that the difference between EU and U.S. wheat yields has continued to widen, although at a decreasing rate. Hence, if factors other than GM technologies have been responsible for widening

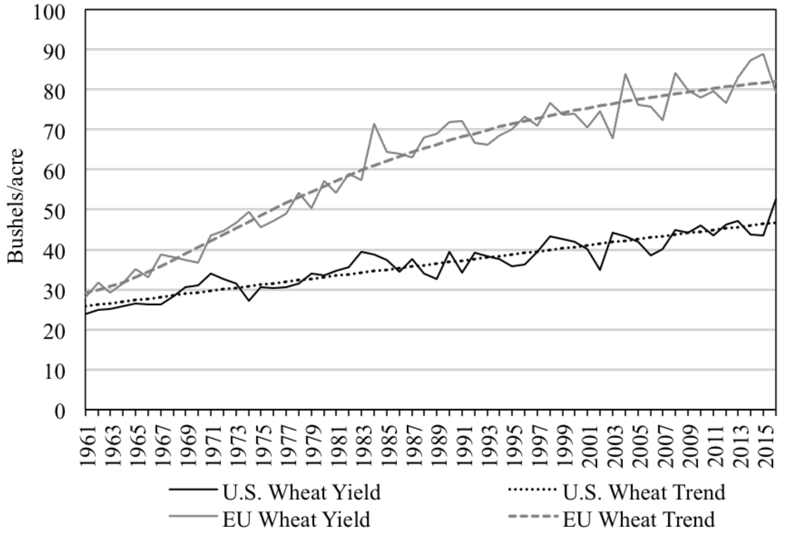

Figure 7. U.S. and EU Wheat Yields and Trends, 1961–2016

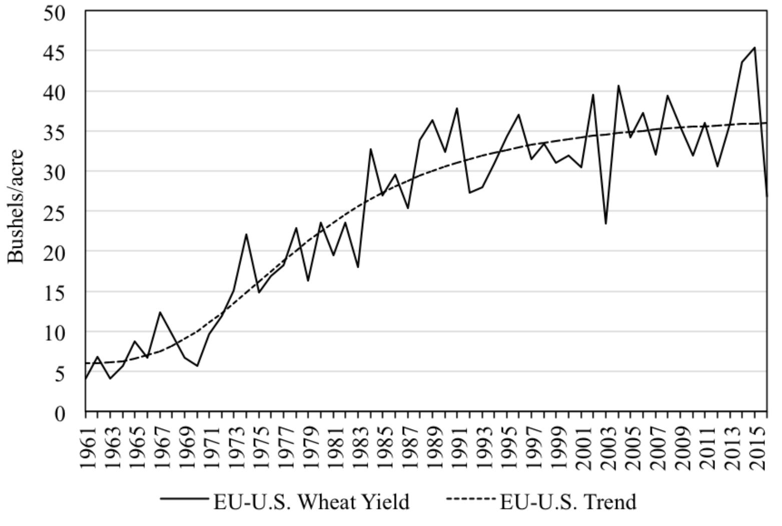

Figure 8. EU Minus U.S. Wheat Yield and Trend, 1961–2016

U.S. and EU corn and soybean yield trends, they have not had a similar effect on U.S. and EU wheat yield trends.

Summary

Although it is common to estimate yield trends using linear functional forms, such trends may be nonlinear. We develop a nonlinear search routine that simultaneously searches in multiple directions at each iteration, which greatly reduces nonlinear least squares convergence problems. Our results show that, for the United States, a linear trend for corn yields best fits the data and indicates that U.S. corn yields have increased 37 bu/acre (28.5%) since the introduction of GM technologies in 1996. The EU corn yield trend is best described by a nonlinear functional form, which indicates that

EU corn yields have flattened over the past 2 decades. Between 1996 and 2016, the EU corn yield trend increased by 19 bu/acre (20.5%). U.S. corn yields have increased by 23 bu/acre relative to EU yields since the adoption of GM varieties. This represents an 18% increase in U.S. yields, which is similar to the GM effect estimated by Lusk, Tack, and Hendricks (2016) using county-level data and Nolan and Santos (2012) using experimental plot data but smaller than that estimated by Xu et al. (2013) using county-level data from the Central Corn Belt.

Soybean yields may be even more influenced by GM technologies than corn yields because weed control is less effective for non–GM soybeans than for non–GM corn. The estimated trends show that the United States had a substantial yield advantage over the European Union until the mid-1980s. For the next 20 years, EU soybean yields usually exceeded those of the United States. However, since the introduction of GM soybean technologies, EU soybean yields have remained flat, while U.S. yields have increased and now exceed those of the European Union.

Factors other than GM technologies could be responsible for flattening EU corn and soybean yield trends. However, it seems reasonable that such factors would also affect other crops, including those for which GM technologies are not commercially available in the United States. Trend analyses shows that EU wheat yields continue to increase relative to those of the United States.

Agricultural yield trend increases are not *fait accompli*. The remarkable sustained crop yield gains experienced in developed countries over the past 6 decades have occurred because of the development of new technologies. Although some yield gains may be realized through the better use of previously developed technologies, increasing yield trends can only occur if new technologies are adopted. Banning yield-enhancing technologies will alter a region's productivity relative to historical trends, with the ultimate effect that food production will be lower than its full potential.

[Received January 2018; final revision received May 2018.]

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