

# Genetically engineered crops and pesticide use in U.S. maize and soybeans

Edward D. Perry,<sup>1</sup> Federico Ciliberto,<sup>2</sup> David A. Hennessy,<sup>3</sup> GianCarlo Moschini<sup>4\*</sup>

2016 © The Authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. Distributed under a Creative Commons Attribution NonCommercial License 4.0 (CC BY-NC). 10.1126/sciadv.1600850

The widespread adoption of genetically engineered (GE) crops has clearly led to changes in pesticide use, but the nature and extent of these impacts remain open questions. We study this issue with a unique, large, and representative sample of plot-level choices made by U.S. maize and soybean farmers from 1998 to 2011. On average, adopters of GE glyphosate-tolerant (GT) soybeans used 28% (0.30 kg/ha) more herbicide than nonadopters, adopters of GT maize used 1.2% (0.03 kg/ha) less herbicide than nonadopters, and adopters of GE insect-resistant (IR) maize used 11.2% (0.013 kg/ha) less insecticide than nonadopters. When pesticides are weighted by the environmental impact quotient, however, we find that (relative to nonadopters) GE adopters used about the same amount of soybean herbicides, 9.8% less of maize herbicides, and 10.4% less of maize insecticides. In addition, the results indicate that the difference in pesticide use between GE and non-GE adopters has changed significantly over time. For both soybean and maize, GT adopters used increasingly more herbicides relative to nonadopters, whereas adopters of IR maize used increasingly less insecticides. The estimated pattern of change in herbicide use over time is consistent with the emergence of glyphosate weed resistance.

## INTRODUCTION

One of the most salient developments in global agriculture in the past 20 years has been the introduction of genetically engineered (GE) crop varieties (1–5). In the United States in 2015, GE varieties accounted for 94% of planted soybean and 93% of planted maize (6). Adoption of this new technology was rapid: First introduced in 1996, GE soybean varieties embedding the glyphosate-tolerant (GT) trait have exceeded 80% of planted hectares since 2003. The share of planted maize using GE varieties—embedding GT and/or insect-resistant (IR) traits—has exceeded 80% since 2008. GT varieties are complementary inputs with glyphosate, and their adoption has inevitably led to substitution away from other herbicides (7). Conversely, IR varieties can substitute for the use of insecticides, conceivably leading to lower pesticide use. Because pesticides have implications for human health and ecological diversity, factors that affect their use are of considerable policy interest (8–10). However, the nature and extent of the impact of GE variety adoption on pesticide use remain open questions.

The prevailing consensus is that IR crops have significantly reduced insecticide use, but for herbicides, the literature is divided (11, 12). Because most studies have lacked extensive survey data (11), a key issue has been how to impute counterfactual herbicide use for GE adopters. Some have used rates based on recommended conventional herbicide programs (13–15). However, these recommended rates are much larger than the average observed herbicide usage rates before the advent of GE crops (9, 10), so that unsurprisingly, this method suggests large reductions in herbicide use due to GE adoption. Studies that instead rely on observed herbicide usage rates have hitherto been limited to 1 or 2 years of data, and in the earlier stages of GE crop adoption (16–18). Hence, the generality of their results is limited, and they cannot shed light on whether the impact of GE variety adoption on pesticide use has changed

over time. In particular, there have been little data to assess whether the recent development of glyphosate-resistant weeds has eroded whatever herbicide use benefits there may have been from GT crops (11).

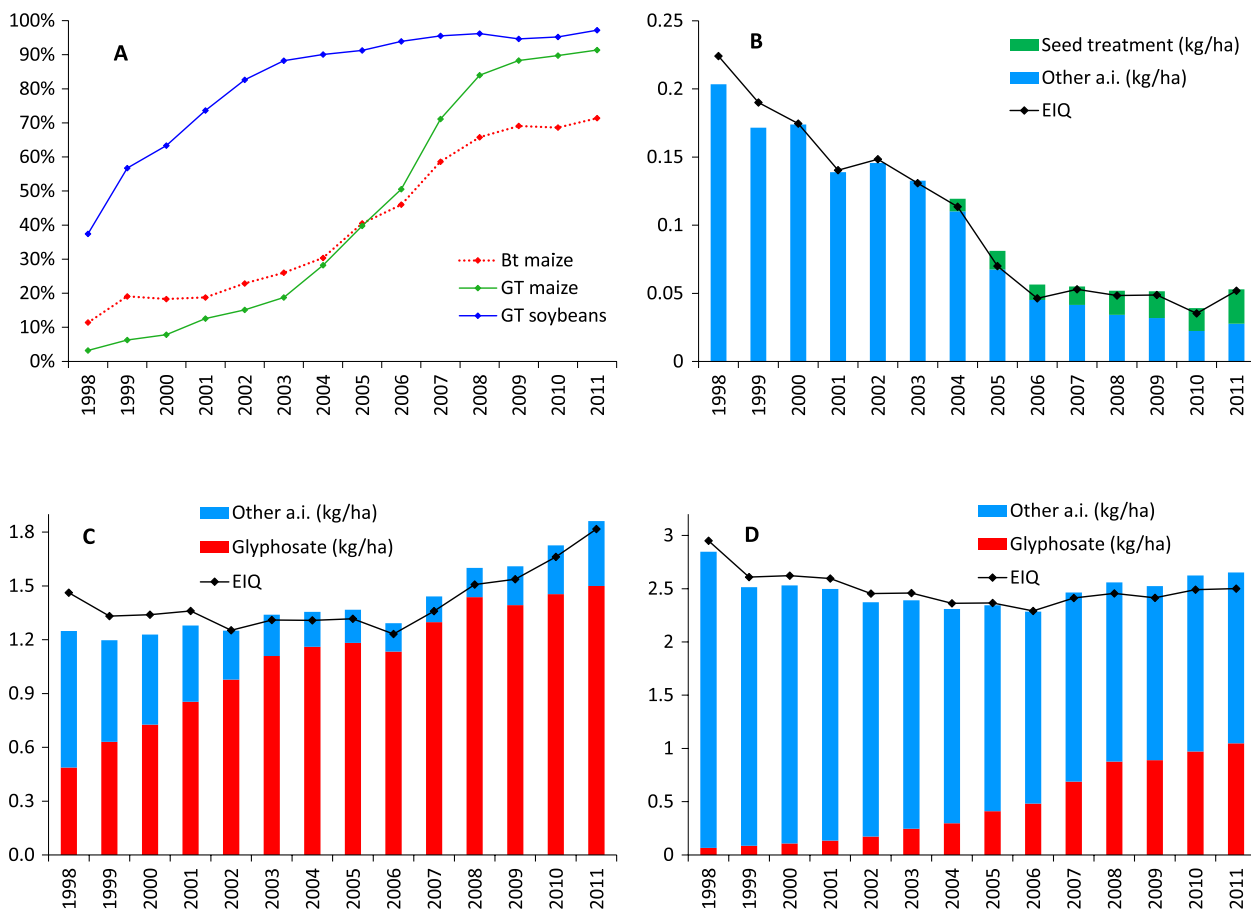
Our analysis relies on a unique, large farm-level data set that spans the period 1998–2011. The data have been assembled annually by GfK Kynetec, a unit of a major market research organization that specializes in the collection of agriculture-related survey data. For each year, the samples are designed to be representative at the crop reporting district (CRD) level and include an annual average of 5424 farmers for maize and 5029 farmers for soybeans (table S1). On the basis of these data, for each farmer, we match the amount of pesticide used with the size of the corresponding plot and the attributes of the seed planted on that plot (including the type of GE traits embedded). Some farmers make more than one chemical/seed choice in any 1 year (that is, they have more than one plot), and some (but not all) are observed for more than 1 year (fig. S1). Thus, we can estimate the impact of GE crops on pesticide use by means of a fixed-effects regression analysis with observations on a large number of individual plot-level choices.

## RESULTS

Data on pesticide use and GE crop adoption in U.S. soybeans and maize are shown in Fig. 1. For maize, the share of varieties containing the GT trait (whether alone or stacked with IR traits) is reported separately from the share of varieties embedding one or more IR traits (henceforth Bt maize) (Fig. 1A). The rate of use of insecticides applied to maize fell from 0.2 kg/ha in 1998 to about 0.05 kg/ha in 2011, a 75% decrease (Fig. 1B). Since 1998, the most striking trend has been an increase in the use of glyphosate (Fig. 1, C and D). By 2011, glyphosate dominated the soybean herbicide market with just over 80% of total herbicide applied, and in maize, it accounted for nearly 40% of applied herbicide (a near 20-fold increase from 1998). Increased glyphosate use came at the expense of other herbicides, although for soybeans there was also an increase in total herbicide use that began in 2007 and steadily rose through 2011.

<sup>1</sup>Department of Agricultural Economics, Kansas State University, Manhattan, KS 66506, USA. <sup>2</sup>Department of Economics, University of Virginia, Charlottesville, VA 22904, USA. <sup>3</sup>Department of Agricultural, Food, and Resource Economics, Michigan State University, East Lansing, MI 48824, USA. <sup>4</sup>Department of Economics and Center for Agricultural and Rural Development, Iowa State University, Ames, IA 50011, USA.

\*Corresponding author. Email: moschini@iastate.edu



**Fig. 1. GE variety adoption and pesticide use, maize and soybeans in the United States, 1998–2011.** (A) Adoption rates of GT soybeans, GT maize, and Bt maize (embedding one or more genes from *Bacillus thuringiensis*). (B) Insecticide use in maize (kg/ha and EIQ weights). (C) Herbicide use in soybeans (kg/ha and EIQ weights). (D) Herbicide use in maize (kg/ha and EIQ weights). Adoption rates and active ingredient (a.i.) use (kg/ha) are reported in tables S12 and S13.

The average rates in Fig. 1 are constructed by adding the amount of active ingredients of a large number of different chemicals. A concern with this (common) procedure is that the total weight associated with a bundle of heterogeneous chemicals is a poor measure of environmental impact (19, 20). There is no agreed-upon superior procedure to aggregate heterogeneous pesticides. Following other studies (13, 14, 21), we use the environmental impact quotient (EIQ) (22) as an alternative benchmark. Specifically, each active ingredient is weighted by its EIQ value (23), and the resulting weighted sum is normalized so as to have the same overall mean as the unweighted total. Despite certain shortcomings (24), the EIQ’s appeal in our context is that it converts an array of attributes specific to each pesticide into a single value meant to summarize the toxicity of the chemical. In general, reweighting chemicals by their EIQ score does not significantly affect overall trends in pesticide use, except for soybeans where, from 1998 to 2005, the herbicide rate slightly increased but declined in the EIQ-weighted amount (Fig. 1).

To further investigate the impact of GE variety adoption on pesticide use, we use our plot-level data to estimate the fixed-effects regression model outlined in Materials and Methods. We consider two different measures of the amount of pesticides per unit of land applied by growers: unweighted sum of all active ingredients used (kg/ha) and EIQ-weighted sum. The model is estimated separately for soybean her-

bicides, maize herbicides, and maize insecticides. For soybeans, we have a total of 86,736 plot-level observations, whereas for maize we have a total of 134,264 observations.

To assess the average impact over the entire 1998–2011 period, we first estimate the fixed-effects model under the restriction that the impact of GE varieties is constant over time, that is,  $\beta_t = \beta, \forall t$  (Table 1; full results in table S2). Overall, GT soybeans increased the quantity of herbicides used by 0.30 kg/ha (a 28% increase relative to the average use by non-GT growers over the entire period). When herbicides are weighted by their EIQ score, however, the coefficient of the adoption variable is not significantly different from zero, reflecting the relatively lower EIQ values for glyphosate. For maize, GT adopters used about 0.03 kg/ha less herbicide (a 1.2% decline relative to the average overall use by non-GT growers). In EIQ terms, the savings were larger at 9.8%, again reflecting the relatively low EIQ values for glyphosate. With respect to insecticides, GE adopters of IR varieties used about 0.013 kg/ha less insecticide than nonadopters (an 11.2% decline relative to the average overall use by non-Bt adopters), a difference that is essentially unaffected by EIQ weighting.

The EIQ index is composed of three subcomponents: farmworker EIQ, which accounts for farmer exposure to dermal and chronic toxicity; consumer EIQ, which captures exposure to chronic toxicity and

**Table 1. Estimated impact of GE varieties on pesticide use, average impact over 1998–2011 (assumes  $\beta_t = \beta, \forall t$ ).  $N$  = number of observations. SEs (in parentheses) are clustered at the farmer level. The model includes time fixed effects, CRD-specific time trends, and individual (farmer) fixed effects. \* $P < 0.05$ , \*\* $P < 0.01$ , \*\*\* $P < 0.001$ . a.i., active ingredient.**

	Soybean herbicides		Maize herbicides		Maize insecticides	
	a.i. kg/ha	EQ kg/ha	a.i. kg/ha	EQ kg/ha	a.i. kg/ha	EQ kg/ha
$G_i$	0.3021*** (0.0097)	0.0045 (0.0122)	-0.0329* (0.0150)	-0.2590*** (0.0156)	-0.0129*** (0.0014)	-0.0122*** (0.0014)
$N$	86,736	86,736	134,264	134,264	134,264	134,264
$R^2$	0.067	0.028	0.022	0.027	0.039	0.051

**Table 2. Estimated impact of GE varieties on the farmer, consumer, and ecology components of EIQ-weighted pesticide use, average impact over 1998–2011 (assumes  $\beta_t = \beta, \forall t$ ).  $N$  = number of observations. SEs (in parentheses) are clustered at the farmer level. The model includes time fixed effects, CRD-specific time trends, and individual (farmer) fixed effects. \* $P < 0.05$ , \*\* $P < 0.01$ , \*\*\* $P < 0.001$ .**

	Soybean herbicide EIQ			Maize herbicide EIQ			Maize insecticide EIQ		
	Farmer	Consumer	Ecology	Farmer	Consumer	Ecology	Farmer	Consumer	Ecology
$G_i$	-0.0081*** (0.0021)	-0.0281*** (0.0013)	0.0407*** (0.0091)	-0.0301*** (0.0024)	-0.0534*** (0.0017)	-0.1755*** (0.0116)	-0.0019*** (0.0003)	-0.0003*** (0.0001)	-0.0100*** (0.0011)
$N$	86,736	86,736	86,736	134,264	134,264	134,264	134,264	134,264	134,264
$R^2$	0.034	0.051	0.027	0.029	0.048	0.025	0.041	0.027	0.053

potential groundwater effects; and ecology EIQ, which captures the impacts of chemicals on fish, birds, bees, and beneficial arthropods (22). To gain further insight into the EIQ result in Table 1, we decompose the  $G_i$  coefficient into these three subcomponents. For all soybean herbicides, corn herbicides, and maize insecticides, the farmworker and consumer components were lower on account of GE variety adoption. For the ecology component, maize herbicides and insecticides were improved by GE adoption, but for soybean herbicides, GE adoption had a detrimental effect (Table 2). Because leaching potential and dermal toxicity are specific to the farmworker and consumer components, these results are broadly consistent with previous work that finds that herbicide usage patterns associated with GE varieties are beneficial (16, 18).

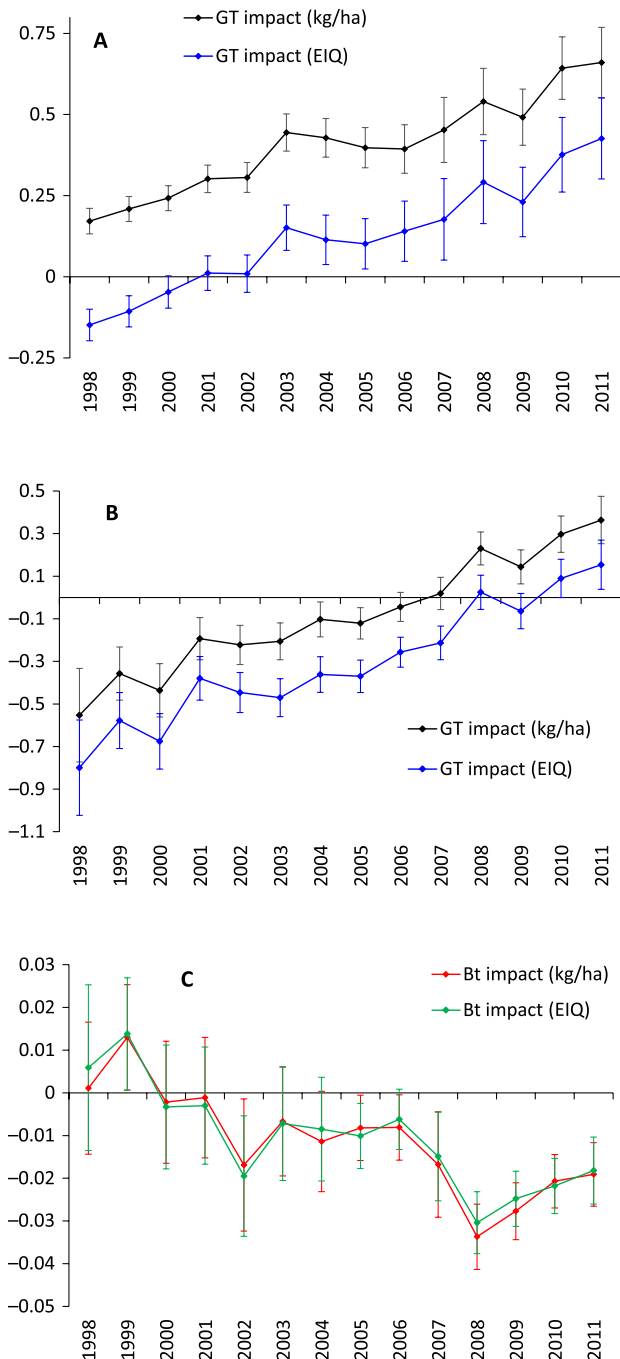
Next, we estimate the model where the  $\beta_t$  parameters are allowed to vary over time. The full results are reported in table S3; here, we graph the estimated  $\beta_t$  coefficients, along with their 95% confidence interval (Fig. 2). The impact of GT variety adoption on herbicide use has changed markedly over time. In all periods, GT soybean adopters used more herbicide than nonadopters, and this difference increased considerably over time. By 2011, the amount applied by GT adopters was 0.66 kg/ha greater than nonadopters, an increase of 0.49 kg/ha from 1998. Moreover, although the total amount applied by a GT user was initially less harmful (as measured by the EIQ), from 2003 onward, the reverse applied. The estimated trend for the impact of GT adoption for maize herbicides shows a similar pattern: Over time, GT adopters gradually used more herbicide relative to conventional users, and by 2008, this difference was positive and statistically significantly greater than zero. Even when weighted by the EIQ impact, by 2011, GT adopters used more herbicide per hectare than nonadopters.

As for the impact of GE maize varieties embedding Bt traits, GE adopters used less insecticide than conventional growers for all years since 2000 (Fig. 2). The reduction in insecticide use attributable to the adoption of GE varieties increases (in absolute value) and becomes more significant (statistically) over time, possibly because of the diffusion of GE maize varieties with multiple Bt traits (for example, conveying resistance to corn rootworm, in addition to the European corn borer). In interpreting these results, however, one should bear in mind the possibility that Bt adoption might reduce the need for insecticide use by nonadopters as well, via an area-wide suppression effect, a conjecture supported by some evidence (25, 26).

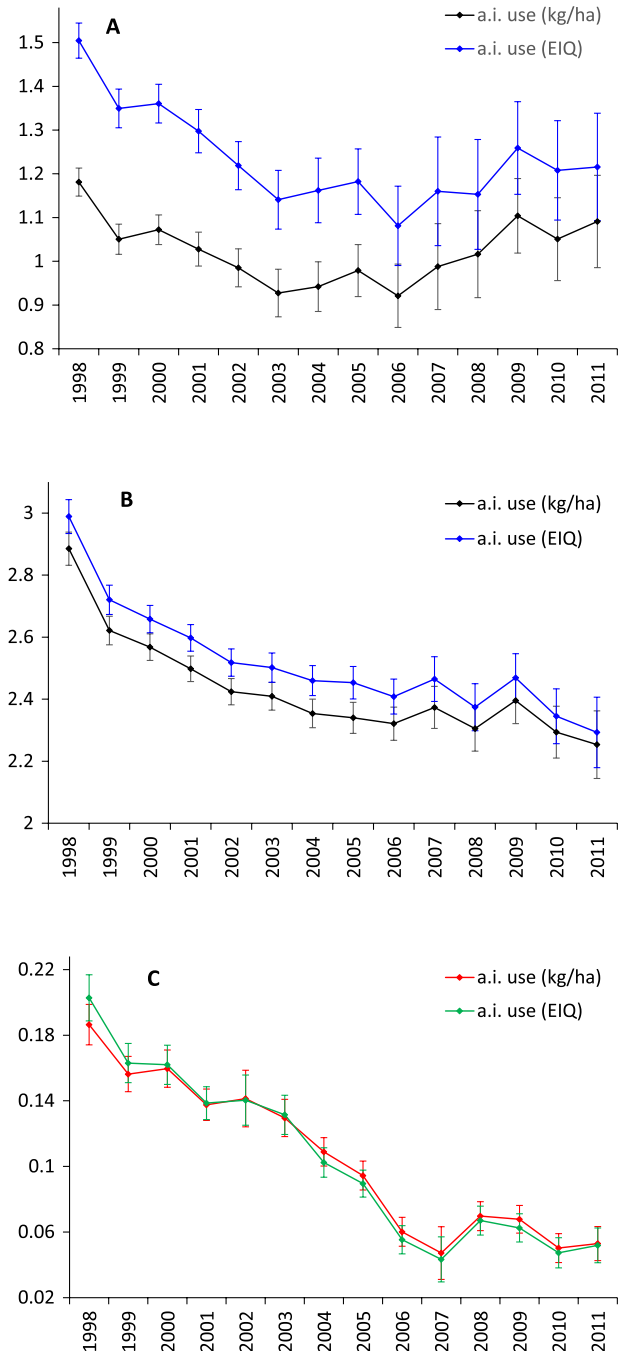
Whereas Fig. 2 illustrates the estimated differential pesticide use by GE adopters relative to nonadopters, it is also of interest to investigate the underlying time trend of pesticide use by nonadopters. This information is conveyed by the year-specific intercepts of the estimated model. Figure 3 graphs the estimated  $\alpha_t$  coefficients (full results are in table S3). For maize herbicides, there was a steady downward trend in herbicide use per hectare. Much of this downward trend can be explained by the decline of certain high-rate herbicides. For example, the active ingredient metolachlor was supplanted by the lower-rate S-metolachlor, and cyanazine was phased out by the U.S. Food and Drug Administration (in cooperation with DuPont) by 2002 (fig. S2). Other low-rate herbicides, such as mesotrione, also gained market penetration over the study period. For soybean herbicides, a downward trend also occurred early on, but the trend inverted in 2006. For maize insecticides, the use by nonadopters declined steadily up to 2007, stabilizing thereafter. This is broadly consistent with stylized facts concerning insecticide use in U.S. agriculture (8–10). More specifically, even before the introduction of Bt crops, there was a trend toward products with

lower application rates. Neonicotinoids, which are applied in the form of seed treatments, are one class of low-rate insecticides that have been widely adopted recently. By 2011, our data indicate that nearly 50% of applied weight in insecticides took the form of seed treatments (Fig. 1B).

The robustness of the results obtained from the baseline model was investigated by considering several variations: the alternative where farmers' heterogeneity is instead represented by a random-effect model (table S4), explicit accounting for the expansion of no-tillage practices (table S5), explicit representation of plot-specific weed pressure (table



**Fig. 2. Estimated  $\beta$ , parameters from the fixed-effects model. (A)** Year-specific impacts of GT soybeans on herbicide use (kg/ha and EIQ weights). **(B)** Year-specific impacts of GT maize on herbicide use (kg/ha and EIQ weights). **(C)** Year-specific impacts of Bt maize on insecticide use (kg/ha and EIQ weights). For all panels, vertical bars denote 95% confidence intervals.



**Fig. 3. Estimated  $\alpha$ , parameters from the fixed-effects model. (A)** Year-specific herbicide use by non-GT soybean adopters (kg/ha and EIQ weights). **(B)** Year-specific herbicide use by non-GT maize adopters (kg/ha and EIQ weights). **(C)** Year-specific insecticide use by non-Bt maize adopters (kg/ha and EIQ weights). For all panels, vertical bars denote 95% confidence intervals.

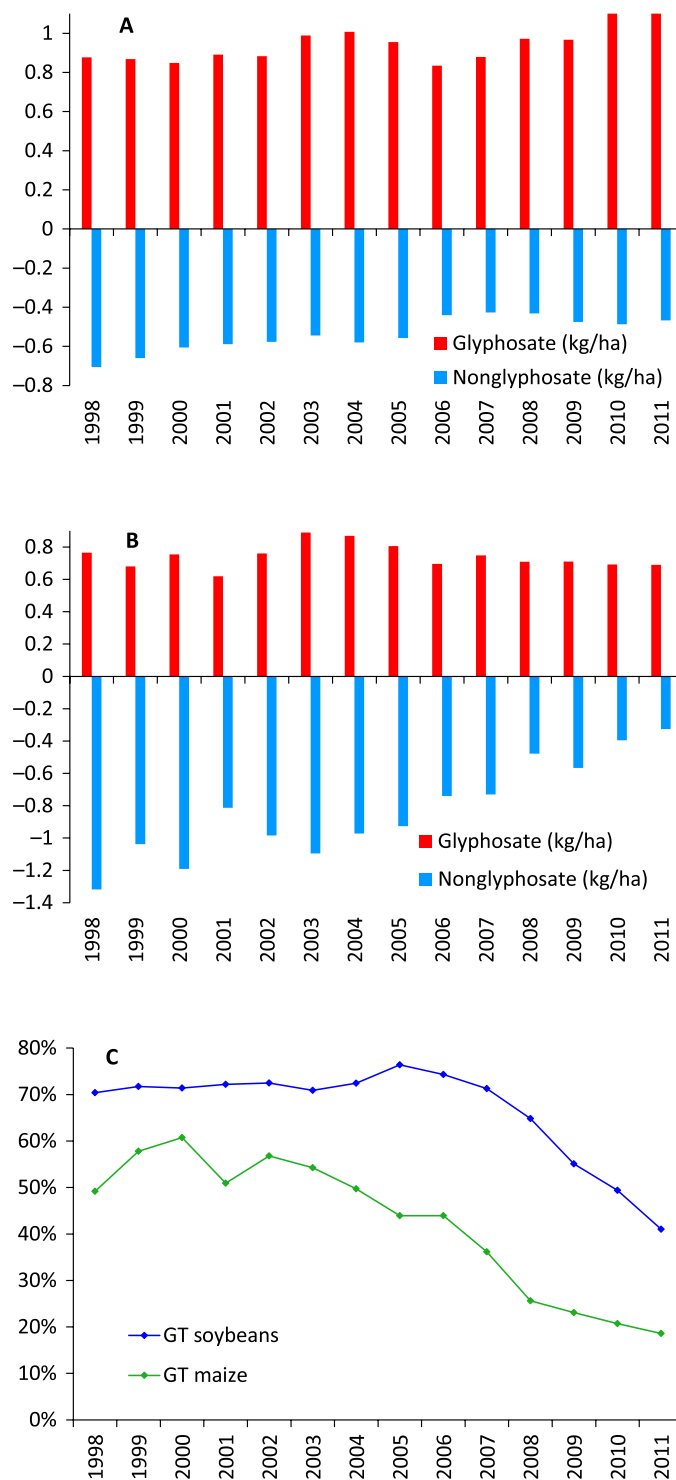
S6), accounting for selection bias due to the possible role of unobserved plot-level heterogeneity (tables S7 and S8), and omission of choices associated with zero pesticide use (tables S9 and S10). Details for each of these variations, and an additional discussion, are provided in the Supplementary Materials. Overall, the results of interest are essentially unchanged under these alternative specifications.

A clear result that emerges from our analysis is the change in differential herbicide use by GT adopters relative to non-GT adopters over time. What are the sources of such significant and persistent upward trends? Explanations such as the expansion of no-tillage practices or unobserved plot-level heterogeneity can be ruled out on the basis of the alternative specifications noted above. Part of the trend can be explained simply by the fact that non-adopters, particularly in maize, transitioned to lower-rate herbicides, but this cannot explain the sharp increase in later periods (specifically, 2007–2011). One explanation not ruled out by our investigations concerns the possible role of weed resistance. This is of particular interest, as glyphosate weed resistance has recently emerged as a significant concern (27–29). With GT crops, growers can apply glyphosate multiple times in a relatively short time span. Furthermore, the simultaneous availability of GT soybeans and GT maize has led to maize-soybean rotations that use glyphosate exclusively, thus significantly reducing the degree of chemical heterogeneity faced by weed populations (an important factor for preventing the emergence of herbicide tolerance) (29).

Making a direct link between our results and weed resistance is difficult because the data do not contain a plot-level variable that correlates with glyphosate weed resistance. To pursue an indirect inference route, however, we decompose the results in Fig. 2 by estimating the fixed-effects regressions separately for glyphosate and nonglyphosate herbicides. The underlying rationale for this procedure is that one of the early indicators of resistance would be a relative increase in the use of nonglyphosate herbicides by GE adopters. We find that for both soybeans and maize there has been a significant increase in nonglyphosate herbicides applied by GT adopters (relative to non-GT users) (table S11). In soybeans, a GT adopter in 1998 used about 0.71 kg/ha less in nonglyphosate herbicides relative to a conventional user; by 2011, the difference was just 0.48 kg/ha (Fig. 4A). In maize, GT adopters went from using 1.31 kg/ha less in nonglyphosate herbicides in 1998 to only 0.32 kg/ha less in 2011 (Fig. 4B). The role of glyphosate weed resistance is also supported by data on the fraction of GT plots that relied exclusively on glyphosate for weed control. Up to 2006, more than 70% of land planted with GT soybeans and more than 40% of land planted with GT maize were treated exclusively with glyphosate. However, since then, these rates have dropped significantly, reaching lows of 41% (soybeans) and 19% (maize) (Fig. 4C).

## DISCUSSION AND CONCLUSION

The role of GE crops in shaping the patterns of pesticide use remains a controversial topic. Over the period 1998–2011, our results show that GE variety adoption reduced both herbicide and insecticide use in maize, while increasing herbicide use in soybeans. However, weighting pesticides by the EIQ lowers the difference in herbicide use by GT soybean adopters (such that the estimated average impact over the study period is statistically indistinguishable from zero). Adoption of Bt maize, on the other hand, is associated with a clearer decline in insecticide use. This is broadly consistent with previous work (11–13, 17), although we find a smaller reduction. For herbicides, our results confirm the critical role of increased glyphosate use, but again, we come to



**Fig. 4. Decomposition of year-specific impacts of GE variety adoption.** (A) Differences in herbicide use between GT soybean adopters and nonadopters (kg/ha) (red bars, glyphosate; blue bars, all other herbicides). (B) Differences in herbicide use between GT maize adopters and nonadopters (kg/ha) (red bars, glyphosate; blue bars, all other herbicides). (C) Fraction of hectares planted to GT varieties that use exclusively glyphosate.



less optimistic conclusions than other studies (13–15). These differences reflect not only the data that we use but also the methodology of our study: Unlike much of the existing work, our analysis relies on directly observed herbicide use for plots using GE and non-GE varieties, rather than arbitrarily constructed counterfactual use rates.

The richness of the data that we use, together with the methodology that we propose—with year-specific GE adoption effects, while controlling for the possible confounding effects of omitted variables via farmer fixed effects, year fixed effects, and regional trends—also permits us to characterize the time path of the GE variety adoption effects. We find clear evidence of increasing herbicide use by GT variety adopters over time for both soybeans and maize, a finding that we attribute in part to the emergence of glyphosate weed resistance. No such pattern appears for maize insecticide use over time, consistent with the evidence that non-Bt maize refugia have been broadly effective as a means to prevent the onset of pest resistance (30).

## MATERIALS AND METHODS

### Data

The data used in this study came from AgroTrak, a large, farm-level commercial data set assembled by GfK Kynetec. Iowa State University acquired limited access to these proprietary data via a marketing research agreement with GfK Kynetec. Each year, GfK Kynetec conducts surveys throughout the United States of randomly sampled farmers about decisions pertaining to seed and pesticide choices. The samples constructed for AgroTrak are representative at the CRD level. Each CRD is a multicounty area identified by the National Agricultural Statistics Service of the U.S. Department of Agriculture (USDA) (fig. S3). AgroTrak is widely considered to be the most comprehensive source for these data and has been used in several other studies (31–33).

The subset of AgroTrak used in this analysis pertains to pesticide use by U.S. soybean and maize farmers during the 14-year period 1998–2011. Over this period, on average, the surveys included 5029 farmers per year for soybeans and 5424 farmers per year for maize. For each crop, respondents indicated how much land was planted, with what seed trait, and the type of tillage used. A grower’s land planted with the same seed trait (for example, GT soybeans) and with the same tillage method (conventional, conservational, or no till) defines a “plot” for the purpose of our analysis. Over the 14-year period, we identified a total of 86,736 plots for soybeans and 134,264 plots for maize. For each of these plots, AgroTrak provides sufficient information to reconstruct the amount of all commercial pesticide products applied by the farmer. Using the table that provides each product’s active ingredient, also in the data set, we calculated the total amount of pesticides used on each plot.

We used two measures of pesticide use for each plot. The first measure was the total amount of all active ingredients used on the plot. Specifically, if  $Q_i^k$  denotes the quantity of commercial product  $k$  applied on plot  $i$ , with a per-unit content  $a_j^k$  of active ingredient  $j$ , and  $L_i$  denotes the land size of plot  $i$ , our first plot-level measure of pesticide use (kg/ha) is defined as

$$y_i^A = \frac{1}{L_i} \sum_k \sum_j Q_i^k a_j^k \quad (1)$$

The second measure of total pesticide use per plot was meant to address the composition heterogeneity of commercial pesticides by

weighing active ingredients by their EIQ values. The latter were obtained from the list in the study of Eshenaur *et al.* (23), updated in 2012. Specifically, if  $E_j$  is the EIQ value associated with active ingredient  $j$ , the EIQ measure of plot-level pesticide use is defined as

$$y_i^E = \frac{\kappa}{L_i} \sum_k \sum_j Q_i^k E_j a_j^k \quad (2)$$

where  $\kappa$  is a normalizing constant chosen such that  $y_i^E$  and  $y_i^A$  have the same overall mean (this facilitates comparison of regression coefficients obtained from these two alternative measures of pesticide use).

Table S1 and fig. S1 contain some summary statistics of the structure of the AgroTrak data used in this study. An important feature of the GfK data set is that it contains repeated observations across time for a subset of the growers. Of the 38,693 farmers in the sample, more than 50% were sampled for at least 2 years, and more than 30% were sampled for at least 3 years. This was a key element that permitted us to estimate a model that controlled for the possible impact of unobserved farmer-level heterogeneity.

### Model

The main results of the analysis were based on the following fixed-effects regression model, which was estimated separately for herbicides and insecticides as well as for each of the two crops of interest (maize and soybeans)

$$y_i = \alpha_{t[i]} + \beta_{t[i]} G_i + \gamma_{r[i]} T_{t[i]} + \phi_{f[i]} + e_i, \quad i = 1, 2, \dots, N \quad (3)$$

where  $i$  indexes the plot,  $N$  is the total number of observations (thus,  $N = 86,736$  for soybeans and  $N = 134,264$  for maize),  $t[i]$  identifies the year in which data for plot  $i$  are observed,  $r[i]$  denotes the region (that is, the CRD) of the plot, and  $f[i]$  indicates the farmer to whom the plot belongs [the notation follows that of Gelman and Hill (34)]. As noted, we considered two different measures for the dependent variable, and thus, either  $y_i = y_i^A$  or  $y_i = y_i^E$ . The main independent variable of interest,  $G_i$ , is a binary variable that equals 1 if plot  $i$  was planted with a GE variety, and 0 otherwise. For soybean and maize herbicides,  $G_i = 1$  if the variety embeds a GT trait, and for maize insecticide,  $G_i = 1$  if the variety contained one or more IR traits (that is, Bt maize). The year-specific  $\beta_t$  parameters, our main focus, captured the impact of adopting GE crops on pesticide use. This impact was estimated relative to the underlying benchmark of pesticide use on non-GE plots captured by the time fixed effects  $\alpha_t$ . The remaining terms are grower-specific effects, denoted by  $\phi_f$ , and CRD-specific time trends, denoted by  $\gamma_r T_t$  (here,  $T_t$  is a linear time trend, suitably demeaned so that the estimated  $\alpha_t$  could be interpreted as the average use of pesticide on non-GE plots).

The identifying assumption for estimation was that—conditional on the fixed effects and regional trends— $G_i$  is exogenous with respect to  $e_i$ , that is,  $E[e_i | G_i] = 0$ . We justified this assumption based on the following. First, the presence of grower-specific fixed effects in the model controlled for unobserved factors, idiosyncratic to the decision maker (for example, location, education, and age), that were correlated with both the adoption and pesticide use decisions. Second, the presence of time-specific fixed effects controlled for the impact of excluded factors that conceivably affect pesticide use but that may be presumed reasonably constant within a given year (such as prices of the various pesticides and the expected crop prices). Third, the CRD-specific time trends controlled for unobserved

location and time-specific factors that affect both the adoption and pesticide use decisions. Together, these components ruled out much of the potentially confounding effects of omitted variables. In addition, the results provided in the Supplementary Materials demonstrate that the baseline results were robust to alternative specifications and the explicit accounting of some additional factors.

## SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at <http://advances.sciencemag.org/cgi/content/full/2/8/e1600850/DC1>

Supplementary Text

fig. S1. Number of years sampled for growers in AgroTrak data set.

fig. S2. Maize herbicide use by non-GT adopters (selected herbicides, kg/ha).

fig. S3. Crop reporting districts.

fig. S4. Trends in glyphosate and expected crop output prices, 1998–2011.

table S1. Summary statistics for AgroTrak data set.

table S2. Full results corresponding to Table 1.

table S3. Full results corresponding to Figs. 2 and 3.

table S4. Random effects replace farmers fixed effects.

table S5. Model estimates with the no-till binary variable included.

table S6. Targeted weeds and impact of GE variety adoption on herbicide use (kg/ha of active ingredient).

table S7. Model excludes growers that plant both GE and non-GE varieties within a given year.

table S8. Model excludes growers that plant both GE and non-GE varieties within a given year.

table S9. Model excludes farmers that never used pesticides (on any of their plots).

table S10. Model excludes farmers that never used pesticides (on any of their plots).

table S11. Full set of results corresponding to Fig. 4.

table S12. GE adoption rates (% of planted hectares), 1998–2011.

table S13. Pesticide rates (kg/ha), 1998–2011.

table S14. Correlation between state-level GE adoption rates from USDA and GfK data.

table S15. Summary statistics by adoption choice.

References (35–45)

## REFERENCES AND NOTES

- M. Qaim, D. Zilberman, Yield effects of genetically modified crops in developing countries. *Science* **299**, 900–902 (2003).
- G. Moschini, Biotechnology and the development of food markets: Retrospect and prospects. *Eur. Rev. Agric. Econ.* **35**, 331–355 (2008).
- J. Kathage, M. Qaim, Economic impacts and impact dynamics of Bt (*Bacillus thuringiensis*) cotton in India. *Proc. Natl. Acad. Sci. U.S.A.* **109**, 11652–11656 (2012).
- Z. Xu, D. A. Hennessy, K. Sardana, G. Moschini, The realized yield effect of genetically engineered crops: US maize and soybean. *Crop. Sci.* **53**, 735–745 (2013).
- G. Barrows, S. Sexton, D. Zilberman, Agricultural biotechnology: The promise and prospects of genetically modified crops. *J. Econ. Perspect.* **28**, 99–120 (2014).
- U.S. Department of Agriculture, Economic Research Service, Genetically engineered varieties of corn, upland cotton, and soybeans, by State and for the United States, 2000–15; [www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-us.aspx](http://www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-us.aspx).
- J. Fernandez-Cornejo, S. Wechsler, M. Livingston, L. Mitchell, *Genetically Engineered Crops in the United States* (U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2014).
- National Research Council, *Impact of Genetically Engineered Crops on Farm Sustainability in the United States* (National Academies Press, Washington, DC, 2010).
- C. D. Osteen, J. Fernandez-Cornejo, Economic and policy issues of U.S. agricultural pesticide use trends. *Pest Manag. Sci.* **69**, 1001–1025 (2013).
- J. Fernandez-Cornejo, R. Nehring, C. Osteen, S. Wechsler, A. Martin, A. Vialou, *Pesticide Use in US Agriculture: 21 Selected Crops, 1960–2008* (U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2014); [www.ers.usda.gov/publications/eib-economic-information-bulletin/eib124.aspx](http://www.ers.usda.gov/publications/eib-economic-information-bulletin/eib124.aspx).
- J. E. Carpenter, Peer-reviewed surveys indicate positive impact of commercialized GM crops. *Nat. Biotechnol.* **28**, 319–321 (2010).
- W. Klümper, M. Qaim, A meta-analysis of the impacts of genetically modified crops. *PLOS One* **9**, 111629 (2014).
- G. Brookes, P. Barfoot, Environmental impacts of genetically modified (GM) crop use 1996–2013: Impacts on pesticide use and carbon emissions. *GM Crops Food* **6**, 103–133 (2015).
- G. A. Kleter, R. Bhula, K. Bodnaruk, E. Carazo, A. S. Felsot, C. A. Harris, A. Katayama, H. A. Kuiper, K. D. Racke, B. Rubin, Y. Shevah, G. R. Stephenson, K. Tanaka, J. Unsworth, R. D. Wauchope, S.-S. Wong, Altered pesticide use on transgenic crops and the associated general impact from an environmental perspective. *Pest Manag. Sci.* **63**, 1107–1115 (2007).
- S. R. Johnson, S. Strom, K. Grillo, *Quantification of the Impacts on US Agriculture of Biotechnology-Derived Crops Planted in 2006* (National Center for Food and Agricultural Policy, Washington, DC, 2007).
- M. Qaim, G. Traxler, Roundup Ready soybeans in Argentina: Farm level and aggregate welfare effects. *Agric. Econ.* **32**, 73–86 (2005).
- M. G. Cattaneo, C. Yafuso, C. Schmidt, C.-. Huang, M. Rahman, C. Olson, C. Eilers-Kirk, B. J. Orr, S. E. Marsh, L. Antilla, P. Dutilleul, Farm-scale evaluation of the impacts of transgenic cotton on biodiversity, pesticide use, and yield. *Proc. Natl. Acad. Sci. U.S.A.* **103**, 7571–7576 (2006).
- A. Wossink, Z. S. Denaux, Environmental and cost efficiency of pesticide use in transgenic and conventional cotton production. *Agr. Syst.* **90**, 312–328 (2006).
- J. Carpenter, GM crops and patterns of pesticide use. *Science* **292**, 637–638 (2001).
- S. O. Duke, S. B. Powles, Glyphosate: A once-in-a-century herbicide. *Pest Manag. Sci.* **64**, 319–325 (2008).
- T. A. Brimmer, G. J. Gallivan, G. R. Stephenson, Influence of herbicide-resistant canola on the environmental impact of weed management. *Pest Manag. Sci.* **61**, 47–52 (2005).
- J. Kovach, C. Petzoldt, J. Degni, J. Tette, A method to measure the environmental impact of pesticides. *N. Y. Food Life Sci. Bull.* **139**, 1–8 (1992).
- B. Eshenaur, J. Grand, J. Kovach, C. Petzoldt, J. Degni, J. Tette, *Environmental Impact Quotient: A Method to Measure the Environmental Impact of Pesticides* (New York Integrated Pest Management Program, Cornell Cooperative Extension, Cornell University, 1992–2015); [www.nysipm.cornell.edu/publications/EIQ/](http://www.nysipm.cornell.edu/publications/EIQ/).
- A. R. Kniss, C. W. Coburn, Quantitative evaluation of the environmental impact quotient (EIQ) for comparing herbicides. *PLOS One* **10**, e0131200 (2015).
- W. D. Hutchison, E. C. Burkness, P. D. Mitchell, R. D. Moon, T. W. Leslie, S. J. Fleischer, M. Abrahamson, K. L. Hamilton, K. L. Steffey, M. E. Gray, R. L. Hellmich, L. V. Kaster, T. E. Hunt, R. J. Wright, K. Pecinovsky, T. L. Rabaey, B. R. Flood, E. S. Raun, Area-wide suppression of European corn borer with Bt maize reaps savings to non-Bt maize growers. *Science* **330**, 222–225 (2010).
- Y. Lu, K. Wu, Y. Jiang, Y. Guo, N. Desneux, Widespread adoption of Bt cotton and insecticide decrease promotes biocontrol services. *Nature* **487**, 362–365 (2012).
- S. B. Powles, Evolved glyphosate-resistant weeds around the world: Lessons to be learnt. *Pest Manag. Sci.* **64**, 360–365 (2008).
- N. Gilbert, Case studies: A hard look at GM crops. *Nature* **497**, 24–26 (2013).
- M. Livingston, J. Fernandez-Cornejo, J. Unger, C. Osteen, D. Schimmelpfennig, T. Park, D. Lambert, *The Economics of Glyphosate Resistance Management in Corn and Soybean Production* (U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2015); [www.ers.usda.gov/publications/err-economic-research-report/err184](http://www.ers.usda.gov/publications/err-economic-research-report/err184).
- B. E. Tabashnik, Delaying insect resistance to transgenic crops. *Proc. Natl. Acad. Sci. U.S.A.* **105**, 19029–19030 (2008).
- S. Gangwal, D. M. Reif, S. Mosher, P. P. Egeghy, J. F. Wambaugh, R. S. Judson, E. A. C. Hubal, Incorporating exposure information into the toxicological prioritization index decision support framework. *Sci. Total Environ.* **435–436**, 316–325 (2012).
- G. P. Thelin, W. W. Stone, *Estimation of Annual Agricultural Pesticide Use for Counties of the Conterminous United States, 1992–2009* (U.S. Geological Survey, Reston, VA, 2013).
- P. D. Mitchell, Market-level assessment of the economic benefits of atrazine in the United States. *Pest Manag. Sci.* **70**, 1684–1696 (2014).
- A. Gelman, J. Hill, *Data Analysis Using Regression and Multilevel/Hierarchical Models* (Cambridge Univ. Press, Cambridge, 2007).
- M. Qaim, The economics of genetically modified crops. *Annu. Rev. Resour. Econ.* **1**, 665–694 (2009).
- M. Qaim, A. De Janvry, Bt cotton and pesticide use in Argentina: Economic and environmental effects. *Environ. Dev. Econ.* **10**, 179–200 (2005).
- S. Bonny, Genetically modified glyphosate-tolerant soybean in the USA: Adoption factors, impacts and prospects. A review. *Agron. Sustain. Dev.* **28**, 21–32 (2008).
- J. Fernandez-Cornejo, C. Klotz-Ingram, S. Jans, Farm-level effects of adopting herbicide-tolerant soybeans in the U.S.A. *J. Agric. Appl. Econ.* **34**, 149–164 (2002).
- C. M. Benbrook, Impacts of genetically engineered crops on pesticide use in the U.S.—The first sixteen years. *Environ. Sci. Eur.* **24**, 24 (2012).
- G. Brookes, J. Carpenter, A. McHughen, *A Review and Assessment of 'Impact of Genetically Engineered Crops on Pesticide Use in the US—The First Sixteen Years: Benbrook C (2012)'; [www.ask-force.org/web/Pesticides/Brookes-Carpenter-Hughes-Rebuttal-Benbrook-2012.pdf](http://www.ask-force.org/web/Pesticides/Brookes-Carpenter-Hughes-Rebuttal-Benbrook-2012.pdf) [accessed March 5, 2016].*
- O. Sydorovych, M. C. Marra, A genetically engineered crop's impact on pesticide use: A revealed-preference index approach. *J. Agric. Resour. Econ.* **32**, 476–491 (2007).
- G. C. Nelson, D. S. Bullock, Simulating a relative environmental effect of glyphosate-resistant soybeans. *Ecol. Econ.* **45**, 189–202 (2003).

43. J. Fernandez-Cornejo, S. Jans, Quality-adjusted price and quantity indices for pesticides. *Am. J. Agric. Econ.* **77**, 645–659 (1995).
44. J. Fernandez-Cornejo, C. Hallahan, R. Nehring, S. Wechsler, A. Grube, Conservation tillage, herbicide use, and genetically engineered crops in the United States: The case of soybeans. *AgBioForum* **15**, 231–241 (2012).
45. E. D. Perry, G. Moschini, D. A. Hennessy, Testing for complementarity: Glyphosate tolerant soybeans and conservation tillage. *Am. J. Agric. Econ.* **98**, 765–784 (2016).

### Acknowledgments

**Funding:** This research was partly supported by the National Institute of Food and Agriculture and USDA (grant no. 2015-67023-22954). **Author contributions:** D.A.H. and G.M. acquired the data and conceived the broad project's objectives. E.D.P., F.C., and G.M. developed the analytical framework. E.D.P. analyzed the data. E.D.P. and G.M. wrote the paper with contributions

from F.C. and D.A.H. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials. Additional data related to this paper may be requested from the authors. The data from GfK Kynetec are proprietary and cannot be shared by the authors; they may be acquired directly from the vendor.

Submitted 21 April 2016

Accepted 5 August 2016

Published 31 August 2016

10.1126/sciadv.1600850

**Citation:** E. D. Perry, F. Ciliberto, D. A. Hennessy, G. Moschini, Genetically engineered crops and pesticide use in U.S. maize and soybeans. *Sci. Adv.* **2**, e1600850 (2016).



## Genetically engineered crops and pesticide use in U.S. maize and soybeans

Edward D. Perry, Federico Ciliberto, David A. Hennessy and GianCarlo Moschini

*Sci Adv* 2 (8), e1600850.

DOI: 10.1126/sciadv.1600850

### ARTICLE TOOLS

<http://advances.sciencemag.org/content/2/8/e1600850>

### SUPPLEMENTARY MATERIALS

<http://advances.sciencemag.org/content/suppl/2016/08/29/2.8.e1600850.DC1>

### REFERENCES

This article cites 35 articles, 5 of which you can access for free  
<http://advances.sciencemag.org/content/2/8/e1600850#BIBL>

### PERMISSIONS

<http://www.sciencemag.org/help/reprints-and-permissions>

Use of this article is subject to the [Terms of Service](#)

---

*Science Advances* (ISSN 2375-2548) is published by the American Association for the Advancement of Science, 1200 New York Avenue NW, Washington, DC 20005. 2017 © The Authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. No claim to original U.S. Government Works. The title *Science Advances* is a registered trademark of AAAS.