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Genetically engineered varieties and applied pesticide toxicity in U.S. maize and soybeans: Heterogeneous and evolving impacts

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ABSTRACT

The extensive adoption of genetically engineered (GE) varieties in U.S. agriculture has dramatically changed the patterns of pesticide use. How this process ultimately affects environmental risk remains an open question. Previous studies have typically relied on aggregate trends to infer the impact of GE crop adoption on pesticide use, which fails to address selection bias and unobserved heterogeneity. We overcome this limitation by analyzing applied pesticide toxicity using farm-level fixed effects models, estimated with rich plot-level data on >200,000 seed and pesticide choices by U.S. maize and soybean farmers during the 1998–2016 period. We find that applied toxicity was, on average, lowered by the adoption of GE varieties across four target organism groups: mammals, birds, fish, and honey bees. However, most of the toxicity benefits conferred by GE adoption dissipated over time. For herbicide tolerant varieties, this was due to the increased use of old-line herbicides by GE adopters, a likely consequence of the growing problem of glyphosate weed resistance. Applied honey bee toxicity saw the sharpest increase during the GE era, but most of this increase was driven by the adoption of neonicotinoid seed treatments, rather than GE insect resistant traits.

1. Introduction

One of the recognized features of the widespread commercial success of genetically engineered (GE) seed varieties is that first-generation GE traits have a direct impact on pesticide use (Moschini, 2008; Barrows et al., 2014). Herbicide tolerance complements (and thereby increases) the use of glyphosate, which in turn substitutes for other herbicides. Insect resistance directly substitutes for the need to apply insecticides. This complex set of interactions has elicited considerable debate on how the diffusion of GE crops has impacted pesticide use patterns, non-target species, and the environment (National Research Council (NRC), 2010; National Academies of Sciences, Engineering, and Medicine (NASEM), 2016; Zilberman et al., 2018). Despite more than two decades of research on these questions, previous studies have been inconclusive because of two major problems: the measures used to quantify pesticide use are often uninformative, and the unit of analysis is typically unsuited to identify the causal impact of GE crops on pesticide use.

The first of these problems stems from the need to aggregate widely different pesticides into a single metric. Previous research has typically employed simple quantity-based measures (Osteen and Fernandez-Cornejo, 2013; Larsen and Noack, 2017), or adjusted such measures by the environmental impact quotient (EIQ), which accounts for toxicity heterogeneity across pesticides (Kleter et al., 2007; Perry et al., 2016a; Brookes and Barfoot, 2020). Both approaches have major limitations. The quantity-based measures (e.g., total kilograms per hectare or per year) do not account for the varying toxicity levels of individual pesticides, often resulting in misleading conclusions (NASEM, 2016; Möhring et al., 2019). The EIQ, which combines several aspects of toxicity and environmental health, was developed for the purpose of providing an overall and more accurate assessment of risk from different pesticides (Kovach et al., 1992). However, this metric has been criticized for its inaccuracies with respect to both insecticides (Peterson and Schleier III, 2014) and herbicides (Kniss and Coburn, 2015).

The second problem arises from using aggregate pesticide use trends to infer the impacts of GE trait adoption (Benbrook, 2012; Klümper and Qaim, 2014; Coupe and Capel, 2016). This approach can, at best, uncover correlations, but is ill-suited for establishing causality. This is particularly the case for the impact of GE crop adoption. Inferring what the counterfactual pesticide use patterns of GE adopters would be from the average usage patterns of non-GE adopters is potentially misleading

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because the pool of non-GE adopters is likely unrepresentative of GE adopters (Fernandez-Cornejo et al., 2014a, 2014b; Kniss, 2017). For example, a farm that uses only non-GE crops is more likely to have lower weed densities. Farm-level panel data can overcome this problem by permitting a comparison of pesticide use patterns for the same farm with and without GE crops (Kouser and Qaim, 2011; Kathage and Qaim, 2012).

This study expands on previous work by addressing both methodological problems and by applying the analysis to a unique and large farm-level dataset for U.S. maize and soybean production. Concerning the issue of how to measure pesticide use, we rely on the risk quotient (Peterson, 2006), a toxicity-based metric consistent with the guidelines set forth by the U.S. Environmental Protection Agency. This measure has been used in recent studies to provide a better understanding of the environmental impact of pesticides (Kniss, 2017; Perry and Moschini, 2020; Schulz et al., 2021). Furthermore, our measure of applied pesticide toxicity is computed at the plot level, where we also observe the specific GE traits of the planted seed. This feature permits the analysis to uncover the impact of GE trait adoption on the use of pesticides, thereby allowing a more nuanced assessment of the environmental impacts of first-generation GE traits.

The use of farm-level data and panel methods to assess the static and temporal impacts of GE crops has proved effective in previous work (e.g., Kathage and Qaim, 2012). In particular, Kouser and Qaim (2011) and Krishna and Qaim (2012) found that adoption of Bt cotton varieties significantly reduced pesticide use in India and these benefits persisted over time. The only study to analyze the impact of GE variety adoption on pesticide use using farm-level data in the United States is Perry et al. (2016a). However, their measure of pesticide use (the EIQ) is inadequate, and their analysis relies on farm-level data that only extends to 2011, thereby missing the more recent period when the negative consequences of pest adaptation have become more severe (Gould et al., 2018).

In this article, we draw on a farm-level dataset of pesticide and seed choices by U.S. maize and soybean farmers, assembled by Kynetec USA, Inc. The dataset is constructed from annual surveys, representative at the crop reporting district (CRD) level and spans the period from 1998 to 2016. The data include an average of 5154 maize farmers and 4863 soybean farmers per year (SI Appendix Table S1). We construct our sample by matching plot-level observations on the type of seed trait used, planted acres, and the types and amounts of pesticides used. A substantial portion of farmers in the sample are observed over multiple plots, which permits us to conduct a nuanced fixed-effects regression analysis. We provide results for GE herbicide tolerant (HT) soybeans, GE glyphosate tolerant (GT) maize, and GE insect resistant (IR) maize.

To evaluate the environmental impact of pesticide use, we compute five different measures of applied pesticide toxicity. The first measure is, simply, kilograms per hectare. Due to the limitations noted above, this measure is only provided for comparison purposes and is not considered a viable indicator of pesticide toxicity. The main set of pesticide metrics of interest are based on the risk quotient method (Peterson, 2006). A risk quotient is calculated by taking the ratio of an environmental exposure value to a target toxicity value. In this study, for each pesticide, exposure is measured as quantity applied (kg/ha) and toxicity is given by the lethal dose 50% (LD50); that is, the dose of an active ingredient that is lethal to 50% of the target population (Kniss, 2017; Perry and Moschini, 2020; Nelson and Bullock, 2003; Gardner and Nelson, 2008). The toxicity associated with the application of multiple pesticides is calculated as the sum of their individual risk quotients, which we term the total risk quotient (TRQ). We report results for four different organism groups: mammals, birds, fish, and honey bees.

2. Background and data

GE crops represent the successful implementation of modern biotechnology in agriculture, resulting from the insertion of one or a few foreign genes into the germplasm of common crops by using recombinant DNA techniques. The addition of these genes endows varieties from elite germplasm with additional valuable traits. For maize and soybeans, to date, these traits primarily consist of two general types of attributes: herbicide tolerance (HT) and insect resistance (IR) (Ciliberto et al., 2019). Most commercial HT crops confer tolerance to the herbicide glyphosate, a powerful, broad-spectrum herbicide originally marketed by Monsanto under the tradename Roundup®. IR crops, on the other hand, embed one or more genes from the bacterium *Bacillus thuringiensis* (hence the label of *Bt* crops), which permit plants to express proteins that are toxic to certain insects. In maize, earlier GE varieties contained a single IR trait, which conferred resistance to the European corn borer. Later varieties also included *Bt* genes that provided resistance to some species of corn rootworm. Furthermore, the trend has been to combine HT and IR traits in commercial varieties, such that at present most farmers plant maize varieties that embed multiple GE traits.

GE varieties have achieved fast and widespread diffusion in several leading crops (chiefly maize, soybeans, cotton, and canola) and in a number of countries—a notable exception being the European Union. The commercial success of GE crops with farmers arises because they offer cost-reducing and/or yield-enhancing benefits. By their very nature, the adoption of GE traits has had major repercussions on the use of pesticides. GT crops are essentially a cost-reducing innovation that permits farmers to adopt an extremely simplified weed control system: it uses glyphosate instead of multiple narrow-spectrum herbicides, and removes the need for mechanical tillage (Perry et al., 2016b). The use of IR varieties, on the other hand, provides farmers with a novel method of insect control, removing the need to use insecticides. This solution can be cost effective for farmers and, insofar as the affected pests were not properly controlled by insecticides, IR traits can also increase expected yields.

Given the foregoing, it is clear that GE traits enrich the set of inputs used in farm production and potentially substitute and/or complement other inputs. Thus, a major research agenda has been to empirically ascertain how, and to what extent, GE traits impact the use of other inputs. This is particularly relevant for farmers' use of pesticides which, beyond the profitability features of interest to farmers, also have externality effects that impact human health, non-target species, and the environment at large. In the case of HT varieties, farmers predictably use more glyphosate and less of other herbicides. However, the pattern and magnitude of this substitution process are empirical questions, and the impacts are prone to change over time as farmers respond to changes in their environment (e.g., glyphosate weed resistance). The dynamic for IR varieties is perhaps more straightforward: they potentially substitute for the need to apply conventional insecticides. Here again, however, the nature and extent of this substitution remains an unsettled issue, and the impacts may change over time if insect resistance develops, or new insect pests emerge.

2.1. Data

The primary data source for this study is AgroTrak, a rich proprietary farm-level data set, assembled by the agricultural market research company Kynetec USA, Inc. We note at this juncture that AgroTrak also provides the primary source of information for the widely used pesticide estimates assembled by the U.S. Geological Survey (Thelin and Stone, 2013). The data consists of annual surveys from U.S. maize and soybean farmers in all 48 contiguous states, sampled to be representative at the CRD level, where a CRD is a multi-county, sub-state region identified by the U.S. Department of Agriculture National Agricultural Statistics Service.

Because pesticide use and the associated toxicity measures are our main objects of interest, we focus on the subset of AgroTrak data that provides information on pesticide use, which encompasses, on average, 5154 maize farmers per year and 4863 soybean farmers per year during the period 1998–2016. The AgroTrak data provide information on plot size, seed trait, and tillage practice, along with pesticide use. The analysis is thus structured to the smallest unit of land that can distinguish this relevant information. Specifically, we define a plot as a combination of the tillage type (conventional, conservational, or no-till), seed trait (e.g., GT maize), and seed company. Based on the 19-year period sample, maize farmers and soybean farmers have 1.83 plots per year and 1.24 plots per year, respectively. SI Appendix Table S1 reports some general summary statistics for the AgroTrak data. AgroTrak stopped reporting insecticide seed treatments in 2015, and thus the empirical analysis for maize insecticides does not include data from 2015 and 2016.

To assess the environmental impact of GE traits, in this paper we rely on toxicity-based metrics based on the LD50 value (the lethal dose that kills 50% of a target animal population) of the individual active ingredients of farmers' applied pesticides. As noted earlier, we separately track toxicity four four target organism groups. Rat LD50 values were used for mammals; for herbicides these values are obtained from Kniss (2017), and the LD50 values for insecticides are as reported in Perry and Moschini (2020). The herbicide LD50 values for birds, fish and honey bees are collected from several different sources (SI Appendix Table S2).

3. Applied pesticide toxicity

Pesticides are highly heterogenous in their toxicity. Thus, simple quantity-based measures are regarded as uninformative at best, and misleading at worst (NASEM, 2016). Hence, in this paper our analysis relies on risk-based metrics of applied toxicity. For comparison purposes, however, we also compute a simple use rate (kg/ha) measure as follows: given a plot i of size L_i, let q_{ik} denote the applied amount of commercial product k, and let a_{jk} be the amount of active ingredient j contained in commercial product k. The quantity per hectare of pesticide type P (soybean herbicides, maize herbicides, or maize insecticides) applied on plot i is computed as follows

$$Q_i^P = \frac{1}{L_i}\sum_{k\in P}\sum_{j} a_{jk}q_{ik} \tag{1}$$

Following Kniss (2017) and Perry and Moschini (2020), for an improved assessment of the human and environmental risks associated with pesticide use, we compute toxicity-based metrics based on the risk quotient method. Broadly, a risk quotient for an individual pesticide is a ratio of exposure to toxicity, where the measures of exposure and toxicity can take different forms depending on the goals and context of a study (Peterson, 2006). In this study, exposure is measured as the applied quantities of the various pesticides, and toxicity is measured by the LD50. These values, of course, depend on the target organism, and our analysis considers lethal dose measures for four different subject organisms: mammals, birds, fish, and honey bees. Specifically, we use oral LD50 values for mammals and birds, contact LD50 values for honey bees, and lethal concentration (LC50) values for fish.

An alternative measure to the risk quotient is the regulatory threshold level, which has recently been used in this context by Schulz et al. (2021). We elected to use risk quotients as the basis for our measure of applied toxicity primarily for data availability reasons. The regulatory threshold level is unavailable for many important active ingredients, such as cyanazine, alachlor, glyphosate, and atrazine, to name a few, which were not included in the applied pesticide metrics used in Schulz et al. (2021). Given that the focus of our study is on the impact of GE crops, it was imperative we include major pesticides such as glyphosate.

The total risk quotient (TRQ) from applied pesticides of type P on plot i, for organism group m, is computed as (Kniss, 2017; Perry and Moschini, 2020):

$$TRQ_{im}^P = \frac{1}{L_i}\sum_{j\in P}\frac{\sum_k a_{jk}q_{ik}}{LD50_{jm}} \tag{2}$$

where $LD50_{jm}$ is the acute LD50 value for active ingredient j with respect to organism group m (mammals, birds, fish, or honey bees).[1] The TRQ in Eq. (2) thus represents the number of LD50 doses per hectare for organism group m summed over all pesticide products of type P (we separately consider soybean herbicides, maize herbicides, or maize insecticides).

3.1. Observed patterns of GE variety adoption and pesticide use

Trends in GE variety adoption and pesticide use provide an initial glimpse of their evolution over the period of study. Fig. 1-(A) separately depicts the share of land planted for GT soybeans, GT maize, and IR maize and shows rapid adoption of these traits during the observed period. For GE maize, the GT trait is frequently stacked with IR traits. Fig. 1-(A) also shows that GT soybean adoption has plateaued at near complete adoption since the mid-2000s, whereas GT and IR maize plateaued (at lower rates) more recently.

Fig. 1 (B)–(D) display pesticide use trends. Following Perry et al. (2016a), the bars report average total pesticide use rates (the ratio of total kilograms of all active ingredients to total hectares planted), whereas the TRQ values are reported by line graphs. To facilitate comparison between unweighted amounts of pesticides and the TRQ values, we normalize each TRQ index such that its overall mean is set equal to the overall mean for the quantity-based amount (kg/ha).

Several interesting patterns in pesticide use are worth noting. Overall, the TRQ trends are considerably different from the total quantity trends. For herbicide use in soybeans (Fig. 1-(D)), applied toxicity has a distinctive U-shaped trend during the sample period for mammals, birds, and honey bees, while for fish there is a general decline. The simple quantity measure, on the other hand, shows a slow but steady increase. The main reason for this increase is the massive increase in glyphosate use, a direct outcome from the adoption of GT varieties. The early downward trend for the risk-based measures coincides with the rapid increase of glyphosate use, which displaced other herbicides with higher toxicity rates (Kniss, 2017). It is apparent, however, that the TRQ for all organism groups other than fish have increased since 2006, when GT adoption reached a plateau of about 95%. As shown in Fig. 1-(B), while the use of glyphosate per hectare has changed little in the latter half of the sample, the use of other herbicides has increased considerably. From 2007 to 2018 the share of glyphosate in the total amount of applied herbicides (kg/ha) decreased from 90% to 52%, possibly a consequence of the diffusion of glyphosate-resistant weeds (Heap, 2014; Livingston et al., 2015; Kniss, 2018; Ye et al., 2021; Van Deynze et al., 2022).

Trends for herbicide use in maize are quite different (Fig. 1-(C)). The total amount of herbicide per hectare has been relatively flat, as glyphosate use increased later in maize than in soybeans and is generally lower. The resurgence of old-line herbicides in the last few years is also less pronounced in maize. The TRQs are characterized by a common drop across all organism groups in the first half of the sample. Much of the initial dramatic decline in the mammal TRQ can be attributed to the phase-out of the highly toxic chemicals alachlor and cyanazine.[2] These chemicals constituted 61% of the mammal hazard quotient in 1998 versus just 1.9% in 2016 (SI Appendix Table S16).

The quantity of insecticides used in maize production, and the corresponding four toxicity-weighted measures, exhibit a general decreasing tendency. As was the case for herbicides, there was a significant reduction even prior to the commercialization of GE varieties, a consequence of farmers using less toxic insecticides. Nearly all TRQs fell further during the GE era, suggesting an insecticide-saving effect (NRC,

[1] As in Perry and Moschini (2020), TRQ values are rescaled to be thousands of LD50 mg/kg/ha for mammals and birds, millions of LC50 μg/L/ha for fish, and millions of contact LD50 μg/bee/ha for honey bees.

[2] The voluntary deregistration of cyanazine by DuPont was approved by the EPA on 1-6-2000.

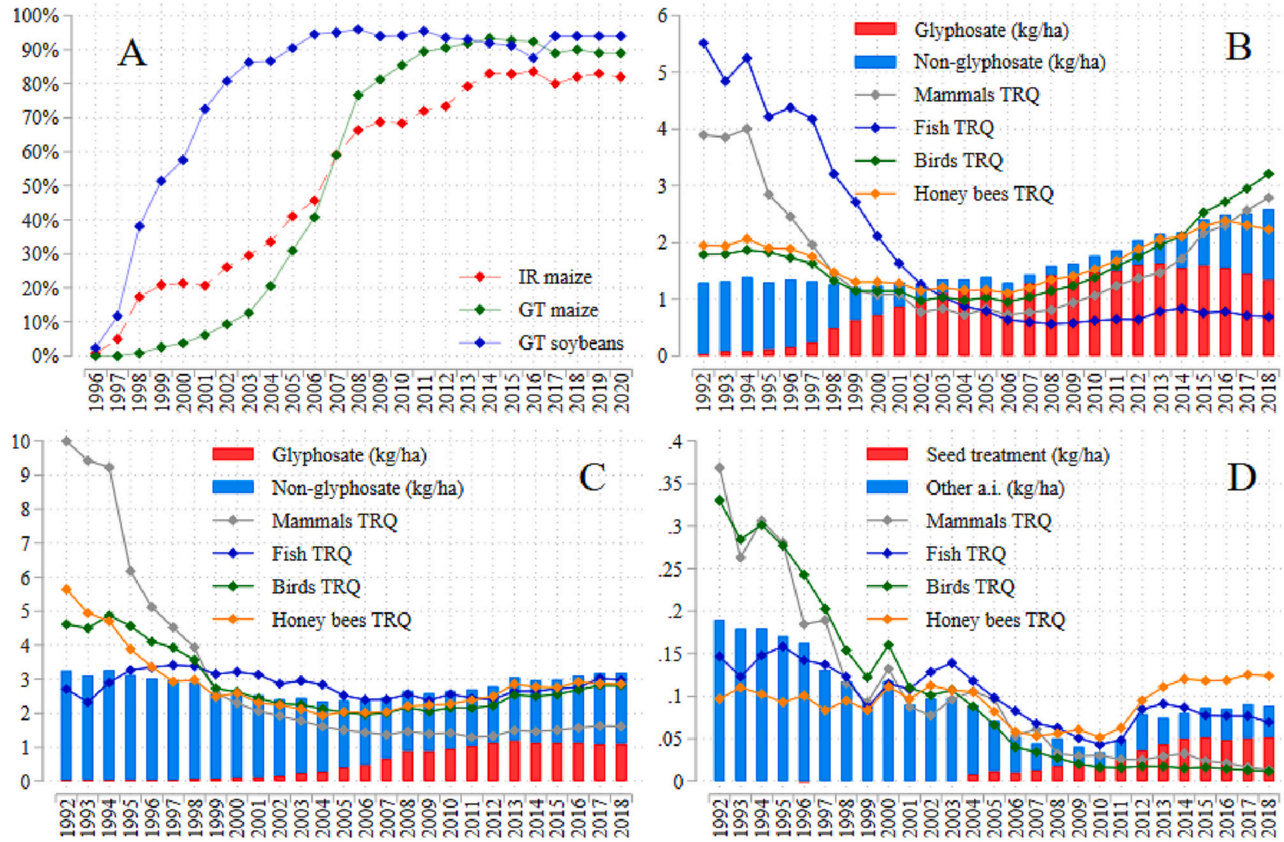

Fig. 1. GE variety adoption and pesticide use in U.S. Maize and Soybeans, 1998–2016.
Note: (A) Adoption rates for GT soybeans, GT maize, and IR maize (in which one or more genes from *Bacillus thuringiensis* are embedded), 1996–2020; (B) Herbicide use in soybeans (kg/ha and total risk quotients (TRQs)), 1992–2018; (C) Herbicide use in maize (kg/ha and TRQs), 1992–2018; (D) Insecticide use in maize (kg/ha and TRQs), 1992–2018. For panel (A), national adoption rates are computed from AgroTrak data for the period 1996–2016, and from USDA data for 2017–2020. For panel (D), AgroTrak discontinued the reporting of seed treatment data after 2014. For the purpose of this chart, we impute the missing amounts (kg/ha) for the period 2015–2018 from the average usage rate for neonicotinoids in 2014.

2010). The major exception concerns the TRQ for honeybees (Fig. 1-(D)), which initially declined but then increased significantly from 2010 to 2018. This trend coincides with the substantial increase in the use of neonicotinoids as seed treatments, which are highly toxic to honey bees (NRC, 2010; Osteen and Fernandez-Cornejo, 2013; Perry et al., 2016a; Perry and Moschini, 2020; Schulz et al., 2021; Fernandez-Cornejo et al., 2014a).

4. Empirical analysis

The foregoing descriptive statistics are informative, but they do not account for confounding factors that might affect farmers' decisions on seed choices and pesticide use, which prevents conclusive inferences about the actual impacts of GE trait adoption on pesticide use. To determine these impacts, we take advantage of the panel structure of the data. In particular, by including region-specific time trends, farmer fixed effects, and year fixed effects, we estimate a GE trait impact model that controls for farm heterogeneity and other omitted factors that may potentially influence both seed and pesticide choices.

4.1. Regression models

To estimate the impact of GE variety adoption on applied pesticide toxicity, we run fixed-effects regression models. Specifically, we estimate the following regression equation:

$$y_i = \alpha_{t[i]} + \beta_{t[i]} G_i + \gamma_{r[i]} T_{t[i]} + \phi_{f[i]} + e_i \tag{3}$$

where i=1,2,…,N indexes the plot. The plot-level left-hand-side variable y_i takes one of five forms: the simple quantity-based metric of Eq. (1) or the toxicity-based metric of Eq. (2), which is specific to organism group m (mammals, birds, fish, or honey bees). On the right-hand-side of the estimating equation, $\alpha_{t[i]}$ is a time fixed effect; G_i is an indicator variable that equals 1 if the relevant GE trait (HT for soybean herbicides, GT for maize herbicides, and IR for maize insecticides) was adopted on plot i; $\gamma_{r[i]} T_{t[i]}$ are CRD-specific time trends; $\phi_{f[i]}$ is a farmer fixed effect; and, e_i is an unobservable error term. The subscript notation follows the convention in Gelman and Hill (2007), so that $t[i]$ indicates the year associated with plot i, $r[i]$ indicates the CRD associated with plot i, and $f[i]$ identifies the farm associated with plot i.

Regression models of the type we propose can typically be viewed as reduced-form representations of conditional input demand functions (Perry and Moschini, 2020). A standard concern with this approach is the potential for simultaneity bias—farmers simultaneously choose which GE traits to adopt and the types and amounts of pesticides. This is most apparent when the left-hand-side variable is the simple quantity-based metric of Eq. (1), a model we use for comparison purposes only. For our core analysis, however, the left-hand-side variable pertains to the toxicity-based metric of Eq. (2), and thus is not a direct choice by the farmer. Precisely because these measures are meant to capture externality (pollution) effects, they may not be particularly salient in farmers' profit maximization decision. In any event, the two recognized responses to endogeneity issues, which also arise in estimating production functions, are fixed effects and instrumental variables. As exemplified in Eq. (3), here we take the fixed effects approach by including separate farmer and year fixed effects, as well as regional-specific trends.

The key identifying assumption for the model's parameters is that the adoption of GE trait G_i is exogenous to the unobservable component, conditional on other covariates: $E[e_i|G_i] = 0$. The same rationale of Perry et al. (2016a) can be invoked here. First, through the farmer fixed effects, our model can control for heterogeneous farm characteristics (e.g., location, weed density, farmer's education, and age) on pesticide use and the GE adoption decision. Second, time fixed effects account for year-specific factors that are common across plots in the same year (e.g., expected crop prices, various input prices). Third, regional trends (i.e., CRD-specific time trends) control for other unobservable spatiotemporal factors. By conditioning on these components, our model rules out most potential confounding factors.

To the extent that confounding factors remain, we believe the estimated coefficients will be biased toward indicating that GE traits increase, rather than decrease, pesticide use. An important unobserved aspect of farmers' input choices is expected pest pressure. Generally, if a farmer expects greater pest pressure (insect pressure or weed pressure) on a given plot, denoted by R_i, they will be more likely to use GE traits *and* pesticides. Thus, there will be a positive correlation between pest pressure, GE trait adoption, and pesticide use, that is $corr(G_i, R_i) \geq 0$ and $corr(y_i, R_i) \geq 0$. These considerations suggest that the GE trait coefficients may be biased toward indicating a pesticide-increasing effect–intuitively, farmers that adopt GE traits appear to use more pesticides than non-adopters because of greater pest pressure, rather than the traits themselves.

In addition to pest pressure, other unobserved factors may potentially affect the estimated GE impacts. Thus, in the results section below, we conduct several checks to investigate the robustness of our results.

4.2. Results

The pesticide use data consists of plot-level observations that span the period from 1998 to 2016 (for maize insecticides, the sample period is 1998 to 2014 because plot-level neonicotinoid use is not available for the last two years), which nearly covers the entire diffusion phase of GE traits. Using a fixed-effects regression model, outlined above, we estimate how farmers change their pesticide use when adopting GE varieties. We report the estimated coefficients separately for soybean herbicides, maize herbicides, and maize insecticides. For herbicide use, GE soybean varieties are defined as herbicide-tolerant (HT) varieties that embed either the GT trait or glufosinate-tolerance (i.e., the LibertyLink (LL) trait), while GE maize varieties are defined as varieties that include the GT trait. The LL trait is not included in the definition of GE HT maize because the adoption of the LL trait mainly resulted from the introduction of stacked traits containing both GT and LL, rather than maize farmers' intentional choice to apply glufosinate. Indeed, since 2011, the data show that fewer than 5% of plots planted with maize possessing the LL trait report using glufosinate (SI Appendix Table S15).

For an initial assessment, the effect of GE adoption on pesticide use is held constant over time. That is, in Eq. (3) we set $\beta_t = \beta$, $\forall t$, and thus estimate the average impact of GE adoption during the entire period of study. Table 1 reports the estimated coefficients for the impact of GE variety adoption on all five measures of herbicide use separately for soybeans and maize. For soybeans, HT variety adoption is associated with an increased usage rate of about 0.30 kg/ha (an increase of about 27% compared to non-adopters). By contrast, the risk-based measures indicate that GE adoption significantly lowered applied herbicide toxicity for all four organism groups. For mammals and fish, HT soybean adoption reduced applied toxicity by about 32% and 54% (relative to non-adopters), respectively. For birds and honey bees, HT adoption was associated with a lower TRQ of 18% and 14%, respectively.

As noted, both the GT and LL traits are included in the definition of HT soybeans. Because the LL trait has recently been a substitute for the GT trait in soybeans (unlike maize, stacked traits were not commercialized for soybeans over the period of study), in an additional set of regressions, we separately identify the impacts of GT and LL trait adoption on herbicide use (SI Appendix Table S10). In terms of total amount, GT adopters applied more herbicide than non-adopters whereas LL adopters used less herbicide than non-adopters. However, across all organism groups, both GT adoption and LL adoption reduced applied toxicity. In terms of magnitude, both traits had similar reducing effects, except for honey bees, where LL adopters displayed a higher toxicity reduction than GT adopters.

Table 1
Estimated average impact of GE adoption on herbicide use, 1998–2016.

	Total quantity (a.i. kg/ha)	Total Risk Quotient (LD50s/ha)			
		Mammals	Birds	Fish	Honey Bees
Soybean herbicides					
β	0.298*** (0.0105)	−0.258*** (0.0241)	−0.126*** (0.00762)	−0.941*** (0.0309)	−3.281*** (0.258)
Non-adopter mean	1.112	0.800	0.682	1.743	23.281
GE adopters Δ%	26.8%	−32.2%	−18.4%	−54.0%	−14.1%
N	132,788	132,788	132,788	132,788	132,788
R^2	0.571	0.489	0.596	0.589	0.557
Maize herbicides					
β	0.0150 (0.0145)	−0.297*** (0.0194)	−0.158*** (0.00916)	−0.101*** (0.00639)	−0.513 (0.289)
Non-adopter mean	2.555	1.654	1.287	0.583	27.890
GE adopters Δ%	0.59%	−18.0%	−12.3%	−17.3%	−1.84%
N	206,558	206,558	206,558	206,558	206,558
R^2	0.563	0.541	0.546	0.562	0.518

Notes: This table reports the estimated parameters of the GE adoption variables in Eq. (3) under the assumption $\beta_t = \beta$, $\forall$ t. For each pesticide group (soybean herbicides or maize herbicides), five models are estimated, each with a different left-hand-side variable as given by Eqs. (1) and (2). Oral LD50 values are used for the mammal and bird TRQs, LC50 values for the fish TRQ, and contact LD50 values for the honey bee TRQ. Each regression also includes year fixed effects, farmer fixed effects, and CRD-specific trends (full estimation results are reported in the SI Appendix Tables S3 and S4). For each regression, the estimated β coefficient is used to compute the percent difference in pesticide use of GE adopters relative to non-adopters. Standard errors are reported in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

For maize herbicide use, Table 1 shows GT variety adoption was associated with a general reduction in applied toxicity during the study period. Compared to non-adopters, the applied pesticide toxicity for GT adopters was lower by 18%, 12%, and 17% for mammals, birds, and fish, respectively. The adoption of GT maize did not have a statistically significant impact on use rates (a.i. kg/ha) or on toxicity for honeybees.

Adoption of IR maize varieties, on the other hand, is associated with a significant reduction in applied toxicity for all organism groups, as well as a reduction in the quantity metric. As reported in Table 2, the TRQs for mammals, birds, fish, and honeybees were lower by 16%, 12%, 18%, and 8%, respectively, for IR maize adopters compared to non-adopters.

Allowing for the impacts of GE adoption on applied pesticides to vary over time permits an assessment of whether there have been temporal changes. For these regression analyses, the GE coefficient β_t in Eq. (6) is allowed to vary over four time intervals: 1998–2001, 2002–2006, 2007–2011, and 2012–2016. The estimated coefficients for the time-specific GE impacts are displayed in four sets of charts on the basis of organism group and separately for each pesticide category (Fig. 2) (the full regression results corresponding to Fig. 2 are reported in SI Appendix Tables S6–S8). Specifically, the left y-axes in Fig. 2 report the difference in applied toxicity between GE and non-GE adopters for herbicides and the right y-axes display the difference in applied toxicity for maize insecticides.

For soybeans, the general finding is that HT adopters initially

Table 2
Estimated average impact of GE adoption on maize insecticide use, 1998–2014.

	Total quantity (a.i. kg/ha)	Total Risk Quotient (LD50s/ha)			
		Mammals	Birds	Fish	Honey Bees
β	-0.0134^{***} (0.00141)	-1.734^{***} (0.171)	-1.032^{***} (0.179)	-1.221^{***} (0.0795)	-124.1^{***} (16.40)
Non-adopter mean	0.124	10.805	8.559	6.660	1457.7
GE adopters Δ%	−10.8%	−16.1%	−12.1%	−18.3%	−8.51%
N	173,332	173,332	173,332	173,332	173,332
R^2	0.466	0.477	0.400	0.495	0.465

Note: This table reports the estimated parameters of the GE adoption variables in Eq. (3), for maize insecticides, under the assumption $\beta_t = \beta, \forall\, t$. Five models are estimated, each with a different left-hand-side variable as given by Eqs. (1) and (2). Oral LD50 values are used for the mammal and bird TRQs, LC50 values for the fish TRQ, and contact LD50 values for the honey bee TRQ. Each regression also includes year fixed effects, farmer fixed effects, and CRD-specific trends (full estimation results are reported in the SI Appendix Table S5). For each regression, the estimated β coefficient is used to compute the percent difference in pesticide use of GE adopters relative to GE non-adopters. Standard errors are reported in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

exhibited a lower applied toxicity compared to non-adopters, but over time these savings dissipated. In the first two sub-periods, HT soybean adoption was associated with statistically significant lower applied toxicity rates for all organism groups. In the final two sub-periods, there was no statistical difference between HT adopters and non-HT adopters for mammals and birds, whereas HT adoption still significantly reduced the TRQ for fish. For honeybees, on the other hand, the impact of HT adoption is not statistically significant in the third sub-period and is reversed in the 2012–2016 period when HT adopters exhibited higher honey bee toxicity compared to non-adopters. Similar findings pertain to GT maize. In particular, the TRQs for adopters and non-adopters of GT maize are not statistically different in the last sub-period for mammals, birds, and fish, whereas for honeybees, GT maize adopters had a significantly higher toxicity impact relative to non-adopters in the final two sub-periods. Additional evidence in the Kynetec data indicates that the increased use of 2,4-D by GE adopters in later periods was responsible for the rise in honey bee toxicity.

Although the foregoing estimated regression models are not directly informative about why the impacts changed over time, the herbicide results are consistent with a decreasing efficacy of glyphosate applications, possibly a consequence of the emergence of glyphosate-resistant weeds (Gould et al., 2018; Heap, 2014; Livingston et al., 2015; Kniss, 2018; Ye et al., 2021; Van Deynze et al., 2022; Powles, 2008; Norsworthy et al., 2012; Gilbert, 2013; Perotti et al., 2020). This conjecture is supported by decomposing sub-period specific herbicide applications into a glyphosate component and non-glyphosate component. **Fig. S1** in the SI Appendix reports the estimated differences, based on fixed-effects regressions, in herbicide use (kg/ha) between plots planted with GE varieties and plots planted with non-GE varieties separately for glyphosate and non-glyphosate herbicides. The positive red bars indicate that GE adopters use more glyphosate per hectare than non-GE adopters, as expected. Correspondingly, the negative blue bars indicate that GE adopters use less of all other herbicides—this is the basic substitution effect one expects. The main finding that emerges from **Fig. S1** for both maize and soybeans is that the effectiveness of this substitution effect has waned over time—GE adopters are increasingly relying on old-line

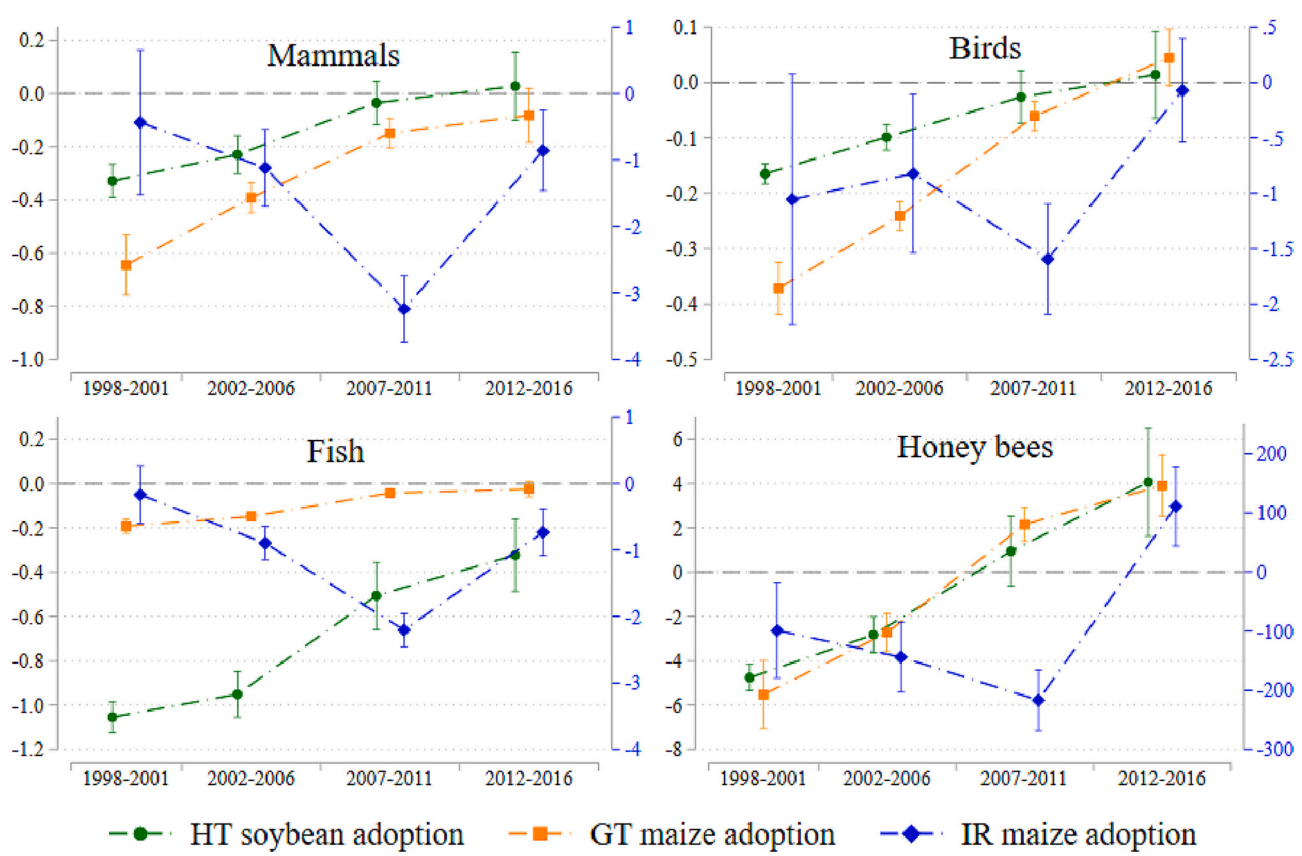

Fig. 2. Estimated time-specific impacts of GE varieties on pesticide use, 1998–2016.
Note: The vertical axes represent the estimated difference in the applied pesticide TRQ between GE adopters and non-GE adopters. The left y-axes provide scales for herbicides (soybean herbicides and maize herbicides) and the right y-axes correspond to the values for maize insecticides. Because plot-level data on neonicotinoid use in maize end in 2014, the last period for "Maize insecticides" is actually from 2012 to 2014.

herbicides to supplement glyphosate in their weed-control strategies (Heap and Duke, 2018).

The insecticide toxicity impacts of IR maize adoption are depicted by the blue lines in Fig. 2. As was the case for herbicides, the impacts have changed significantly over time. The TRQs for IR maize adopters were lower compared to non-adopters in the first three sub-periods, with the largest reducing effect occurring in the third sub-period (2007–2011). However, these effects sharply reversed in the final sub-period (2012–2014). IR maize adoption still reduced the mammal and fish TRQs in this period, but there was no statistical difference for the bird TRQ and honey bee toxicity was actually higher for adopters.

Two developments in maize production during this time frame can potentially explain the sudden rise in applied toxicity for IR maize adopters. The first development is the introduction and widespread diffusion of neonicotinoid seed treatments, which are used more frequently with IR varieties (Perry and Moschini, 2020). The toxicity of neonicotinoids varies significantly across organism groups—they are relatively less toxic to mammals and fish, whereas they are highly toxic to aquatic invertebrates and pollinators (e.g., honey bees) (Goulson, 2013). To further assess the role played by neonicotinoids in contributing to applied toxicity, we estimated a separate set of regressions with additional indicator variables for whether the planted seed was treated with a neonicotinoid insecticide (SI Appendix Table S11). After including these additional indicators, the impact of IR maize on honey bee toxicity is negative in the first three sub-periods and statistically insignificant in the final sub-period (and also small in magnitude). By contrast, neonicotinoids have a large and statistically significant positive impact on the honey bee TRQ in all sub-periods, with the largest impact in the final sub-period. The change in the estimated honey bee impact for IR maize after including the neonicotinoid indicators reflects the positive correlation between IR traits and neonicotinoids. Thus, part of the sharp increase in TRQs depicted in Fig. 2 was due to neonicotinoids, rather than IR trait adoption.

The second development was the evolved resistance by western corn rootworm to multiple *Bt* traits in GE maize, which was first documented in 2009 (Tabashnik et al., 2013; Gassmann et al., 2014). This pest adaptation reduced the efficacy of GE rootworm (RW) varieties and thereby potentially increased the need for farmers to supplement these varieties with additional insecticides (e.g., pyrethroids). The data employed in this study distinguish between varieties that confer resistance to the European corn borer (CB) and varieties that confer resistance to various species of rootworms. Thus, to explore this possibility, we ran additional regressions in which the IR indicator variable was replaced with separate indicators for whether the planted GE seed contained CB and/or RW traits (we also included the neonicotinoid indicators in these regressions). The results from these regressions show that, prior to the final sub-period (2012–2014), both CB and RW adopters had lower honey bee TRQs compared to non-adopters (SI Appendix Table S12). However, in the final sub-period, RW adoption had a statistically significant and positive impact on the honey bee TRQ (this impact was still just one-tenth of the neonicotinoid impact, however). Conversely, CB adoption was still associated with a lower honey bee TRQ in the final sub-period, although the impact was statistically insignificant. Overall, these regressions suggest that the evolved resistance by western corn rootworm led to a moderate increase in insecticide use for RW trait adopters.

4.3. Robustness

To ascertain the robustness of the GE impact coefficients, we estimated several alternative specifications of Eq. (3). A primary concern with the baseline estimated impacts is the potential bias arising from the existence of unobserved confounding factors. Although we include farmer fixed effects, year fixed effects, and CRD-specific trends, these may not fully control for spatio-temporal unobserved heterogeneity. Two such unobserved factors are the type of tillage practice and weed pressure. No-till is a practice whereby farmers leave all crop residues on the field. Previous research has shown that no-till is complementary to GE crop adoption (Perry et al., 2016b), and it may also affect pesticide use. To control for this, we added an indicator variable for whether a farmer used no-till to the baseline dynamic model (SI Appendix Table S17). Overall, the use of no-till is generally associated with higher TRQs in both crops, but the GE impacts are largely unaffected. As it concerns weed pressure, we do not observe this variable directly, but we do observe the main weed species a farmer targeted. Thus, for the herbicide models, we added indicator variables for nine different major weeds to the time-specific GE impact regression models (SI Appendix Table S18). As expected, the presence of a particular weed was associated with greater pesticide use. However, the GE impacts themselves remained largely unaffected.

An additional concern with respect to the baseline analysis is that some farmers plant both GE and non-GE crops within the same year. Given that the farmer fixed effects do not fully control for heterogeneity at the finer plot level, there may be unobserved plot-specific factors driving their adoption and pesticide decisions.[3] We investigate this issue by estimating the models with the sub-samples that exclude farmers who planted both GE and non-GE crops within a given year (SI Appendix Table S19). The estimated GE impacts in these models are essentially the same as the baseline estimated impacts.

Some farmers in the sample do not use any pesticides in any given year, which raises the question as to whether this is due to unmodeled specific reasons (e.g., organic crops, environmental concerns, etc.). To the extent that this is correlated with GE adoption, the coefficients would be biased. To address this concern, we report results for the subsample that excludes farmers that never used pesticides in a given year (SI Appendix Table S20). Overall, the estimated GE impacts are unaffected.

Beyond the factors already considered, there may still remain other sources of unobserved spatio-temporal unobserved heterogeneity. For example, there may be crop rotation effects or pest population dynamics related to the previous season. Of course, one cannot fully control for all these possibilities, but we can enrich the set of fixed effects by replacing the yearly fixed effects and CRD trends with CRD-by-year fixed effects. The results for these models are presented in Table S21 of the SI Appendix. Here again, the results are highly robust to the inclusion of these fixed effects.

In addition to the foregoing robustness checks, we explored whether there is heterogeneity in the estimated GE impacts across two additional dimensions. First, we created an indicator variable for whether a farmer resided in the Central Corn Belt (CCB), defined as the region consisting of Illinois, Indiana, and Iowa, and interacted this variable with the time-invariant GE indicator variables. The results for these models are presented in Table S22 of the SI Appendix. For the herbicide models, the GE impacts all remained negative, but the pesticide toxicity reducing effects of HT crop adoption were statistically significantly smaller in the CCB. Conversely, IR crop adoption in the CCB was associated with *larger* reductions in the TRQ compared to IR adoption in the non-CCB. Second, we allowed for the GE impacts to differ based on whether a farmer planted >500 acres in the respective crop (SI Appendix Table S23). In this case, there was less heterogeneity in the impacts. Larger operations that adopted the HT technology exhibited a slightly smaller pesticide reducing effect for mammals and birds in soybeans. In corn, there was a larger attenuation of the pesticide reducing effect for mammals and honey bees for HT adopters, whereas the insecticide reducing effect from IR adoption was increased with respect to mammals and fish.

[3] Recall that a plot is defined as a combination of the tillage type (conventional, conservational, or no-till), seed trait (e.g., GT maize), and seed company. While we observe decisions at this level, we do not have information on the physical location of a plot over time. A plot, as defined, is therefore best viewed as a "virtual" plot.

5. Discussion

The main advantage of the analysis presented here is that the estimated impacts are based on farm-level fixed-effects regressions. Thus, our results implicitly uncover the ceteris paribus differences in pesticide use between GE and non-GE adopters at the farm level. This approach contrasts with those used in other recent studies that instead rely on aggregate data to infer the impact of GE adoption on pesticide use. For example, Kniss (2017) provides aggregate acute and chronic applied toxicity trends for cotton, maize, soybeans, rice, and wheat and finds that acute rat toxicity trends for the main GE crops (cotton, maize, and soybeans) declined during the period 1990–2015. Despite this evidence, the study is not able to make definitive claims about the impact of GE adoption on pesticide use. As the author notes, the downward trend in applied toxicity could apply to both GE and non-GE crops. Moreover, the pool of non-GE adopters may be unrepresentative of GE adopters. Thus, a basic comparison of the average pesticide toxicity between each group would likely be misleading.

The most recent large-scale study to analyze trends in pesticide use is Schulz et al. (2021). Similar to the findings here, they report that applied pesticide toxicity has fallen for mammals, birds, and fish. To assess the toxicity impacts associated with GE crop adoption, they provide separate trends for three applied toxicity metrics in the two main GE crops: corn and soybeans. They show that pollinator and aquatic invertebrate toxicity increased over time in maize, and terrestrial plant toxicity increased in soybeans. However, they note that applied toxicity for *Bt* and *non-Bt* crops was equal on a per hectare basis. Similar to the limitations in Kniss (2017), the analysis in Schulz et al. (2021) relies on aggregated data, rather than a farm-level analysis. Overall, they were not able to make any definitive conclusions about the causal impact of GE crop adoption on pesticide use.

Several important findings emerge from our analysis. First, the adoption of HT soybeans and GT maize initially reduced applied toxicity with respect to birds, fish, mammals, and honey bees. However, by 2007, our estimates indicate there was no longer a difference in applied toxicity between GE and non-GE adopters for birds and mammals. Applied toxicity for fish remained lower for GT adopters relative to non-adopters, but was higher for honey bees. Thus, the pesticide use benefits conferred by HT varieties were in part transitory. Relatedly, our results suggest that glyphosate resistance was the reason these benefits dissipated—farmers had to supplement glyphosate with old-line herbicides.

Our results confirm the general finding that IR maize reduces the use of insecticides, both with respect to quantity and applied toxicity, and these savings occurred for the duration of the sample period considered. The exception to this is applied toxicity with respect to honey bees. Initially, IR maize reduced the honey bee TRQ, but by the final subperiod, it was associated with higher toxicity. As noted above, an important confounding factor is the adoption of neonicotinoid seed treatments, which are highly toxic to honeybees and became prevalent during the mid-2000s. When we account for neonicotinoid seed treatment adoption in the regressions, IR maize is no longer associated with higher honey bee toxicity. Thus, the primary source of increased honey bee toxicity in maize was the diffusion of neonicotinoid seed treatments, a finding consistent with previous work (Perry and Moschini, 2020).

This paper uses a similar methodology to Perry et al. (2016a), but there are some key differences in approach and findings. The data used here extend to 2016, rather than 2011, and we employ risk-based pesticide measures instead of the EIQ. The latter produced distinctively new conclusions. The estimated time impacts in Perry et al. (2016a) show that, after 2007, even the EIQ index for GE HT soybean and maize adopters exceeded the EIQ index for non-adopters. By contrast, here we find that, at worst, the applied toxicity associated with GE adoption is not statistically different from the applied toxicity associated with non-GE crops (the exception is for honey bees). This highlights a major deficiency in the EIQ, which is that it correlates too strongly with quantity-based measures. Our study also confirms the importance of using risk-based measures rather than quantity-based measures. The differences were especially stark for HT soybeans. All regression estimates show that GE adopters used *more* herbicides, in terms of weight, than non-GE adopters, but in nearly all cases the applied toxicity associated with GE plots was either lower than for non-GE plots or not statistically different. Finally, this study also accounts for the impact of neonicotinoid seed treatments, which was not considered in Perry et al. (2016a).

A few caveats are in order, at this juncture. First, only acute toxicity (i.e., LD50) is considered in our analysis. Chronic toxicity may also be of interest, and chronic toxicity measures (e.g., no observable effect level) do not necessarily correlate with acute toxicity (Kniss, 2017). Thus, extrapolating our results to long-term effects could lead to erroneous conclusions. Second, following the convention of existing literature, we have defined total pesticide toxicity by summing up the toxicity of each active ingredient in pesticides, essentially assuming independence of the individual effects. For future research, considering the potential super additivity of risks that could arise from the combined toxicity of several active ingredients may be desirable (Topping et al., 2020). Third, although we consider four different organism groups, other groups such as daphnia, algae, and earthworms have been analyzed in previous work (e.g., Kudsk et al., 2018).[4]

Another potentially important aspect not considered in this study is the existence of area-wide effects. Previous work has shown that non-*Bt* users benefit from *Bt* adopters through area-wide suppression effects (Hutchison et al., 2010). By suppressing insect populations in an entire area, *Bt* users confer both yield and insecticide saving benefits to non-*Bt* users (the free riders). Our estimates do not capture this potential benefit and may therefore underestimate the insecticide saving benefits of both IR traits and neonicotinoid seed treatments. Conversely, in the case of HT crops, there is potential for negative spillover effects if non-HT users, who may still employ glyphosate prior to planting, must resort to alternative weed control strategies in the face of glyphosate resistant species. Identification of area-wide effects requires precise information on the location of plot, which goes beyond the capabilities of our data, and we therefore leave it to future work.

6. Conclusion

Concerns about the use of pesticides in agriculture remain a major topic of interest for environmental and agricultural policy around the world. Whereas it is recognized that chemical inputs have made a major contribution to food security over the last several decades, it is also clear that pesticides present nontrivial risks for human health and the environment (Tang et al., 2021). Ensuring adequate food supply for a growing world population, while protecting human health and ecosystems from unwanted risks, requires policies that deal with complex and thorny issues. There are no silver bullets or simple choices for a socially optimal pesticide policy, and several facets need to be addressed in a holistic fashion (Möhring et al., 2020). Among the possible innovation strategies that could help in this setting, an enticing avenue is offered by the development of plants endowed with increased resistance to pest pressure. As noted by (Möhring et al., 2020), however,"… *the link between the value of advanced plant breeding and the reduction of pesticide use is often neglected in public discussions* …".

The application of biotechnology in agriculture, and specifically the development and widespread adoption of first-generation GE varieties, has radically changed the ability of breeders to develop crop varieties resistant to pest and environmental stresses. Going forward, gene editing tools such as CRISPR-Cas offer the potential of newer and more powerful approaches to improving the pest resistance of crops. The experience

[4] Their analysis also accounts for factors such as soil half-life, which may alter the estimated toxic load for a bundle of heterogeneous chemicals.

with first-generation GE traits can be very instructive in this setting. The widespread adoption of GE varieties embedding HT and IR traits has had a significant, and at times subtle, impact on pesticide use patterns. The overall environmental impact attributable to GE crop varieties remains controversial, however.

Several factors complicate a conclusive assessment of the impact of GE crops on pesticide use. The impacts are not static, and several perspectives may be of interest—short-term or long-term impacts, actual or potential impacts, and whether the impacts are reversible or irreversible (Wesseler et al., 2011). The use of appropriate toxicity metrics is essential in this setting. As discussed extensively in this article, popular aggregate measures—such as total unweighted volume of applied pesticides, or the EIQ-weighted measure—are clearly deficient. Furthermore, as noted, relying on aggregate measures of pesticide use trends, even when disaggregated regionally, provides a framework that is particularly ill-suited to uncover the causal impacts of GE crop adoption on applied pesticides, relative to conventional crops. The data and analysis presented in this paper, therefore, by using a large body of farm-level data over a relatively long time period, and by relying on suitable risk-based metrics, offers one of the most comprehensive assessments, to date, on the environmental consequences of GE variety adoption and applied pesticide toxicity.

Some policy implications follow from our findings. A common goal of policymakers is to reduce overall agricultural pesticide use without significantly sacrificing productivity and economic gains (Finger and Möhring, 2022). The rise in glyphosate use that has accompanied the proliferation of GE herbicide tolerant crops has been met with calls to ban HT crops or restrict the use of glyphosate itself (Ye et al., 2021). Our research suggests that removing or limiting the use of GE crops in the current environment, as some have suggested, would likely reduce the overall quantity of herbicides used but would not confer benefits in terms of applied toxicity with respect to mammals, bird, and fish. Farmers would return to using traditional crop systems that rely more heavily on old-line herbicides and tillage for weed control (Perry et al., 2016b).

There are also clear lessons to be learned from the temporal patterns in pesticide use by GE adopters. The applied toxicity benefits of HT crop adoption could possibly have been preserved had there been earlier efforts to prevent the development of glyphosate weed resistance (Norsworthy et al., 2012; Davis and Frisvold, 2017; Green, 2018). These efforts could have consisted of the occasional supplementation of glyphosate with older herbicides, as is done now, but to a lesser degree. The toxicity benefits of HT adoption would have been moderated but would have persisted over time. In addition, recent years have seen new GE herbicide tolerant traits come to market, such as dicamba-tolerant soybeans (Johnson et al., 2010; Werle et al., 2018; Wechsler et al., 2019). To the extent that these new traits confer applied toxicity benefits, it is important to take measured efforts to prevent further weed resistance issues.

Resistance has also been an on-going concern with respect to IR traits (Gassmann et al., 2014; Tabashnik et al., 2013), especially with respect to RW traits. Our results show that the insecticide saving effects of GE IR traits were attenuated for most species groups in the final sub-period of our sample (2012–2016), a partial consequence of resistance. To address insect resistance, the industry has promoted the use of non-*Bt* maize refuges, and this appears to have been partially successful in forestalling further resistance. However, root worm resistance has persisted and threats to additional resistance remain. Recent research has shown that farmers can decrease the negative impacts of resistance by rotating maize with other crops and by diversifying the planted variety of GE IR maize (Carrière et al., 2020). In addition, some evidence suggests that the widespread use of neonicotinoids can offset the benefits of non-*Bt* maize refuges by killing non-resistance insects. Thus, the occasional use of maize not treated with neonicotinoids may also be warranted. Going forward, it will be essential to employ all of these strategies, not only in the United States, but also in other countries where the adoption of Bt maize has not plateaued.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The farm-level data used in the study are proprietary, a commercial product assembled and marketed by Kynetec USA, Inc. We do not have the right to grant access to the raw data to others. Interested parties can obtain the data directly from the vendor. The LD50 values used to compute the risk quotients, and mean application rates for each observed active ingredient in U.S. maize during the 1998–2016 period, are reported in the Supplementary Information.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2023.107873.

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