Environmental and economic concerns surrounding restrictions on glyphosate use in corn

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Since the commercialization of transgenic glyphosate-tolerant (GT) crops in the mid-1990s, glyphosate has become the dominant herbicide to control weeds in corn, soybean, and other crops in the United States and elsewhere. However, recent public concerns over its potential carcinogenicity in humans have generated calls for glyphosate-restricting policies. Should a policy to restrict glyphosate use, such as a glyphosate tax, be implemented? The decision involves two types of tradeoffs: human health and environmental (HH-E) impacts versus market economic impacts, and the use of glyphosate versus alternative herbicides, where the alternatives potentially have more serious adverse HH-E effects. Accounting for farmers' weed management choices, we provide empirical evaluation of the HH-E welfare and market economic welfare effects of a glyphosate use restriction policy on US corn production. Under a glyphosate tax, farmers would substitute glyphosate for a combination of other herbicides. Should a 10% glyphosate tax be imposed, then the most conservative welfare estimate is a net HH-E welfare gain with a monetized value of US$6 million per annum but also a net market economic loss of US$98 million per annum in the United States, which translates into a net loss in social welfare. This result of overall welfare loss is robust to a wide range of tax rates considered, from 10 to 50%, and to multiple scenarios of glyphosate's HH-E effects, which are the primary sources of uncertainties about glyphosate's effects.

cost–benefit analysis | economic tradeoffs | genetically modified organisms | weed control | toxicity

Glyphosate, the most commonly used herbicide to control weeds worldwide, has until recently been assumed to pose low risks to human health and the environment. Recently, however, the International Agency for Research on Cancer (IARC) has classified glyphosate as a Group 2A probable human carcinogen (1), linking glyphosate exposure to increased risk of non-Hodgkin's lymphoma (NHL). Although IARC's hazard assessment had produced different results from those conducted by other institutions (2–7), the economic consequences of the IARC evaluation have been severe. In 2020, Bayer, the company that in 2018 purchased the longtime glyphosate patent holder Monsanto at US$63 billion, consented to pay US$10 billion to settle tens of thousands of lawsuits linking its glyphosate-containing herbicide Roundup to NHL among applicators (8). Despite the lack of scientific consensus on the actual carcinogenicity of glyphosate, three trials in 2018 to 2019 favored plaintiffs who had attributed glyphosate exposure to NHL.

Concerns regarding IARC's scientific evaluation have been discussed extensively in Environmental Protection Agency (EPA) (6), Andreotti et al. (7), and elsewhere. We focus, instead, on potential behavioral, environmental, and market economic impacts if farmers choose not to use glyphosate; whether because they are concerned about health risk or because a tax or other type of regulatory constraint is imposed on glyphosate use. Indeed, many countries have already banned glyphosate or imposed restrictions since the 2015 classification (9), while a critical question remains largely unaddressed: Would the substitutions for glyphosate be preferable from health, environmental, or market economic standpoints?

In this paper, we use economics models to evaluate the effects of a "proxy" regulation implemented in the United States: imposing taxes of various sizes on glyphosate use so that farmers may be incentivized to substitute glyphosate for alternative herbicides to control weeds. While command-and-control type regulations are still common in practice, market-based incentive policies are increasingly being applied in the human health and environmental policy arena, such as the pesticide and fertilizer taxes implemented in some of the European countries (10, 11) and the animal product tax proposed to account for antibiotic use externalities (12). In economics terms, taxes can be considered as having similar effects to restrictive regulations, except that the decisions to use products are decentralized: it is up to farmers to determine their choice set based on different prices for glyphosate versus other herbicides. In addition to estimating direct market economic impacts, we also estimate human health and environmental (HH-E) impacts in a pecuniary framework, thereby evaluating the overall welfare effects of glyphosate regulation given the set of currently available alternative herbicides.

Glyphosate and Weed Control: Background

Glyphosate is a broad-spectrum phosphonate herbicide that acts by inhibiting a plant phosphate synthase enzyme. It is used widely in agriculture to kill broadleaf weeds and grasses that compete with crop plants for soil and water nutrients. First commercialized in 1974 under the name Roundup by Monsanto Company, it is used extensively in agriculture worldwide, particularly since the introduction of Roundup Ready (glyphosate-tolerant [GT]) transgenic crops, especially corn and soybean in the 1990s. Because

Significance

Since IARC classified glyphosate as a Group 2A probable human carcinogen in 2015, multiple regulations restricting glyphosate use have emerged worldwide. One question that has been insufficiently addressed is how weed-control alternatives to glyphosate compare in terms of health, environmental, and market effects. Our study analyzes these effects by enacting hypothetical glyphosate taxes at varying levels in US field corn. We find that, despite reducing the net toxicological burden on human health and the environment from herbicide substitution, any level of glyphosate tax would result in a net social welfare loss, mostly driven by the increased cost of corn production. Our results suggest that caution is warranted when regulating glyphosate, if only because replacement herbicides may cause more harm.

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these GT crops could tolerate glyphosate application while the adjacent weeds could not, glyphosate has been applied broadly and efficiently to corn and soybean fields without harming the crops. However, extensive use of glyphosate has now led to glyphosate-resistant weeds in the United States and elsewhere, further threatening the effectiveness of other herbicides such as glufosinate (13).

Although glyphosate and other herbicides have allowed growers to reduce their reliance on tilling fields when controlling weeds (14, 15), tillage remains an important means of weed control. In brief: tillage is the practice of digging, stirring, or overturning soil on fields for several purposes, including weed burial and mechanical disruption. Therefore, seed type (GT or conventional) and tillage decisions (conventional or otherwise) are expected to be key drivers of substitution between glyphosate and alternative herbicides. Additionally, chemical efficiency alters the relative economic benefits from alternative herbicide choices and thereby affects the substitution. One major determinant of chemical efficiency is weed resistance, which is reshaping equilibrium herbicide (16) and tillage use (17) choices.

Over the period 1998 to 2016, the US corn herbicide market has experienced significant changes. Glyphosate treatment grew dramatically to become the most applied herbicide in corn in 2008, while other herbicides fell from use. Specifically, during 2010 to 2016, the market has been dominated by four chemicals—glyphosate, atrazine, acetochlor, and S-metolachlor—with a total market share of ~90% and more than 50 chemicals accounting for the residual 10% (Fig. 1*A*). Therefore, we restrict our study period to 2010 to 2016 and construct a "composite" herbicide composed of the latter three as the only alternative herbicide to glyphosate.

Glyphosate application grew almost in lockstep with the GT seed adoption rate since the commercialization of GT corn in 1998 in the United States (Fig. 1*B*). As of 2016, only about 10% of corn acres were planted with non-GT seed. In contrast, composite herbicide applications have been decreasing since 2003, until a reversal in trend commenced in about 2011. A similar time trend is observed for conventional tillage, likely due to the onset of weeds that have evolved resistance to glyphosate (17) (Fig. 1*C*). While the last 20 y have seen minimal changes in documented weed resistance to the composite herbicide, documented resistance to glyphosate has increased steadily. Over the study period, the composite herbicide price index has remained stable, but fluctuations have been observed for the glyphosate price index (Fig. 1*D*).

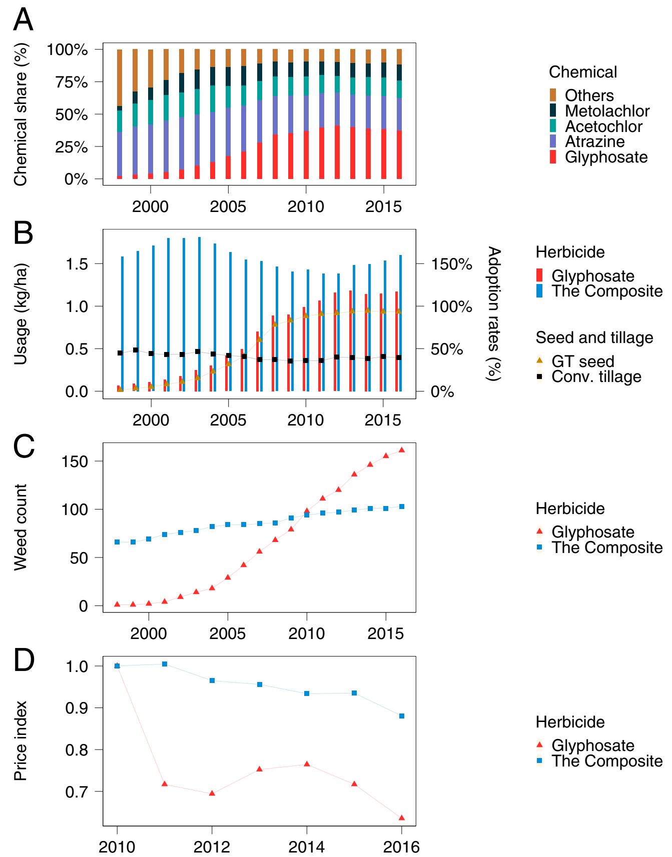

Fig. 1. Time trend of herbicide use, seed choice, tillage practice, weed resistance, and herbicide prices in US corn production, 1998 to 2016. (*A*) Chemical share, calculated as individual chemical use (kg/ha) divided by total herbicide chemical use (kg/ha). (*B*) Herbicide use, GT seed adoption, and conventional tillage adoption. The adoption rates are calculated as the percentage of planted acres. (*C*) Weed resistance, calculated as the cumulative count of documented resistant weed species summed across all US states. "Resist" is calculated as the count difference between glyphosate and the composite herbicide. (*D*) Herbicide prices, measured by the Fisher price index. The indexes are constructed for the study period of 2010 to 2016 using the mean of the entire study period as the base. For comparison, the indexes are rescaled to equal 1 for the year 2010. (Data source: International Survey of Herbicide Resistant Weeds for *C* and AgroTrak, GfK Kynetic for *A*, *B*, and *D*).

Contentions on Health and Environmental Effects of Glyphosate

Until recently, it was generally accepted that glyphosate toxicity was low; hence, minimal HH-E effects were expected from glyphosate exposure. In 2015, however, IARC classified glyphosate as "probably carcinogenic to humans" (Group 2A) based on "limited evidence" in humans for NHL and "sufficient evidence" in animals of carcinogenicity (1, 18, 19).

The paucity of data on individual-level glyphosate exposure has resulted in limited human evidence on the association (20); however, more recent comprehensive cohort studies have provided little support for IARC's determination of probable human carcinogenicity (7, 21). The Agricultural Health Study, a collaboration between the US NIH and EPA with farmworker data over decades, has shown that glyphosate exposure is associated with increased risks of these cancers only among farmworkers in the highest exposure group. Nevertheless, these associations are not statistically significant, and glyphosate carcinogenicity remains controversial (7, 22).

Although much remains unresolved about how glyphosate interacts with insect physiology (23–25), it is considered to have low environmental toxicity (26). The main environmental concern related to glyphosate does not arise from any direct effect but rather from its indirect impact on monarch butterfly populations; through the loss of milkweed (a common weed in US agricultural fields), on which monarchs lay their eggs and its larvae feed. Brower et al. (27), among others, observed that the monarch butterfly population at the overwintering site in Mexico is in decline. Several studies have linked the decline with milkweed loss in the Midwest caused by GT seed adoption and correspondingly extensive glyphosate use (28–30). Using museum collection data of monarch specimens, however, a more recent PNAS study (31) provides evidence that the observed decline in recent years is part of a long-term trend that had already begun in the 1950s, long prior to commerce in glyphosate and GT crops. A lively debate has ensued regarding the merits of the museum data collection methodology (32–34).

Modeling Approach

From the social welfare perspective of pesticide regulation (35), inconclusiveness in the policy debate around glyphosate pertains to primarily two issues. First, there is a lack of understanding regarding how farmers would substitute between glyphosate and other herbicides. When using municipal-level data, previous papers modeling glyphosate ban effects in Germany have suggested modest substitution toward alternative herbicides (36, 37). However, glyphosate is more ubiquitous in the US context. More importantly, given the nature of herbicide substitution, the matter is best studied at the farm level so as to sufficiently control for the effects of other interrelated farm-level weed management decisions, especially of seed and tillage. Second, despite accumulating scientific studies, links between glyphosate application and suspected HH-E effects are not well established, which complicates the evaluation.

To quantify HH-E and market economic welfare impacts of a glyphosate tax as a policy decision (10, 38), we first develop an herbicide demand model. The model will allow us to estimate the empirical Allen–Uzawa elasticity of substitution (AES), a measure of substitutability, between glyphosate and alternative herbicides (i.e., the composite herbicide). The herbicide demand model is estimated using a unique, large farm–level dataset on US corn production spanning 2010 to 2016. Our model controls for weed management decisions related to herbicide options, as well as factors that shape the decision-making environment through affecting chemical efficacy, such as weed resistance; thereby allowing for more accurate characterization of herbicide substitution. Specifically, we estimate the following fractional probit model for glyphosate demand specified as a cost share:

$$E(s_{i,t}|x_i) = \Phi(b_0 + b_1 \ln P_{c[i],t} + b_2 Resist_{s[i],t} + b_3 GT_{i,t} + b_4 Till_{i,t} + \xi_t + \varsigma_s + \alpha_s Trend), \quad [1]$$

where $\Phi(\cdot)$ denotes a probit function, $s_{i,t}$ is the cost share of glyphosate for farm i in year t, defined as glyphosate expenditures divided by the total expenditures on glyphosate and the composite herbicide, and x_i represents the set of conditioned covariates in the equation, including the following: $\ln P_{c[i],t}$, which denotes the ratio of glyphosate price index to the composite herbicide price index in Crop Reporting District c associated with farm i in year t; $Resist_{s[i],t}$, which represents the weed resistance to glyphosate that varies at the state level represented by $s[i]$ and year; $Till_{i,t}$ and $GT_{i,t}$, which denote conventional tillage rate and GT adoption rate at farm level; and lastly ξ_t, ς_s and $a_s Trend$, which represent year dummies, state dummies, and state-specific time trends capturing general technical changes across time and states.

Second, we combine the Pesticide Environmental Accounting (PEA) and Environmental Impact Quotient (EIQ) approaches to assess herbicide-related HH-E risks in a pecuniary framework and then translate HH-E damage into a "damage price" monetary measure. We further adjust the damage prices under alternative damage scenarios to capture uncertainties in the contentious HH-E effects associated with glyphosate.

Finally, we develop an equilibrium displacement model (EDM) in the herbicide–corn market setting and then apply the AES parameter and damage prices to estimate welfare effects. While the herbicide demand model admits the characterization of herbicide substitution at a fixed corn production level, the EDM allows for changes in corn production in response to the glyphosate tax. Specifically, the solutions to the EDM (i.e., the percentage changes in market variables induced by the tax) are applied to compute the net HH-E and market economic welfare changes, with the last being the sum of consumer surplus change, producer surplus change, and tax transfer. The modeling approach is illustrated in Fig. 2.

Results

Weed Control: Seed and Tillage Choices and Herbicide Substitution. In estimating the glyphosate demand equation (Eq. **1**), we hypothesize that *GT* and *Till* are correlated with omitted factors in the equation. This correlation is also referred to as "endogeneity" in economic terms because the tillage and seed variables are endogenously determined by the system, as opposed to being exogenous to the system. A prominent source of omitted factors is unobserved farm-specific weed pressure, which potentially affects tillage, seed, and herbicide decisions, simultaneously. Ignoring endogeneity would lead to bias in the effect estimates. To address this concern, a two-step control function approach (CF; see *SI Appendix*, section A.3) is taken. In the first step, the suspected endogenous variable is regressed on all exogenous variables to isolate the endogenous variations captured by the residual term $\hat{v}$, and in the second step, we extend Eq. **1** to directly control for $\hat{v}$ by including it as a covariate. Consequently, an endogeneity test is obtained from assessing the test statistics on $\hat{v}$ (39).

In our analysis, we estimate a set of models with various endogeneity hypotheses. For Models 1 to 3, we assume, respectively, that both variables, only *GT*, and only *Till* is endogenous. The residual term for *GT* and *Till* is denoted by $\hat{v}_1$ and $\hat{v}_2$, respectively. For comparison, we also estimate Model 4, which assumes exogeneity for *GT* and *Till*, and Model 5, which excludes control variables. Table 1 presents the second-step coefficient estimation results for the glyphosate demand equation (see *SI Appendix*, Table S4 for the first-step regression results, and *SI Appendix*, Table S5 for the full estimates of the second-step regressions). The Models 2 and 3 results show that both variables are endogenous when they are tested separately because the coefficient estimates for $\hat{v}_1$ and $\hat{v}_2$ are statistically different from zero in the two models, respectively. However, when the two variables are tested simultaneously in Model 1, the coefficient estimate for $\hat{v}_2$ becomes insignificant even at the 10% level, although that for $\hat{v}_1$ remains statistically significant. A possible reason is that GT and conservation tillage are themselves complements in weed control and so are correlated, and the source of endogeneity for the two factors are also concordant, so the correlation between $\hat{v}_1$ and $\hat{v}_2$ results in a lower level of significance. Therefore, we choose Model 1 for our analysis.

Coefficient estimates are interpreted through average partial effects (APE); that is, partial effects averaged across all observations to characterize the direction and size of effects (See *SI Appendix*, section A.4 for the partial effect formula). The APEs for *GT* and *Till* are estimated to be 0.162 and −0.143, respectively. The results suggest that adopting conservation tillage and GT seed would increase the share of glyphosate in a farmer's herbicide portfolio. Moreover, the APE for *Resist* is negative and statistically significant with a value of −0.011, suggesting that relatively more weed resistance to glyphosate would result in reduced use of glyphosate on those fields.

The $\ln P$ coefficient estimate carries little economic meaning on its own. It is, however, translated into the AES between glyphosate and other commonly used herbicides ("composite") with a value of 0.739 (See *SI Appendix*, section A.4 for formulas and procedures). Glyphosate and the composite are found to be net substitutes, since the AES measures the elasticity of substitution holding output constant and is positive (See *SI Appendix*, section C.2 for more discussions). The own-price elasticities for glyphosate and the composite are equal to −0.371 and −0.369, respectively. Although the relative inelasticity of herbicides is consistent with previous findings (40, 41), the elasticities estimated in this paper are somewhat higher than previous estimates. This underscores the significance of considering substitution possibilities between individual herbicides when estimating price elasticities, as has been recognized elsewhere (42–44).

Herbicide-Related Damage: Scientific Debates and Pecuniary Health and Environmental Accounting. Since the major controversies around glyphosate focus on its carcinogenicity and the indirect impact on monarch butterfly reduction, in addition to the status quo scenario, more extreme scenarios for these two effects are also simulated in order to represent the uncertainties in welfare analysis. The four

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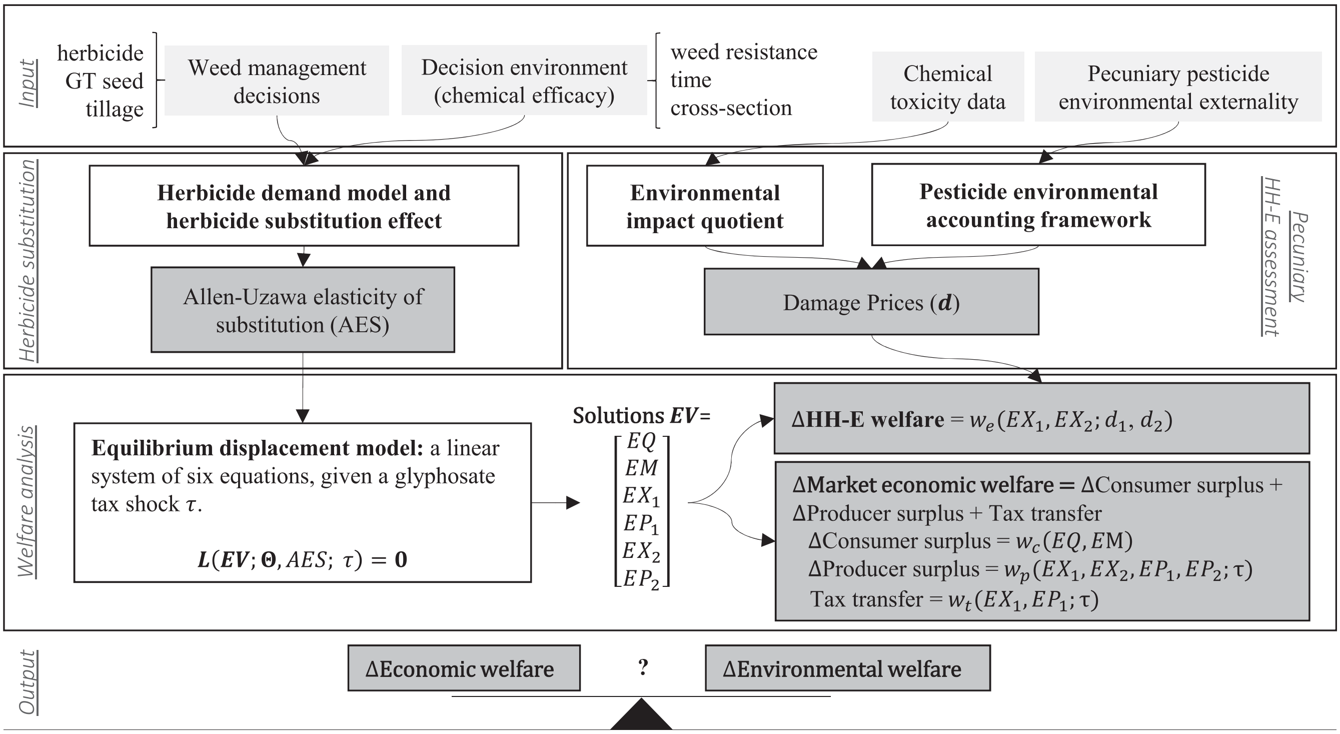

Fig. 2. Model schematic for quantifying welfare effects of glyphosate policies. Regarding notation, $L(\cdot)$ denotes a set of linear functions governing welfare effects under different farmer uses of glyphosate or alternative herbicides, $\boldsymbol{EV} = dln(\boldsymbol{V})$ is the percentage changes in $\boldsymbol{V}$, a vector of the six market variables: Q, X_1, X_2 denote quantities of corn, glyphosate, and the composite herbicide, and M, P_1, P_2 denote prices correspondingly. Vector $\boldsymbol{\Theta}$ represents market parameters other than the AES, while the operator Δ denotes the after-tax change, and $w_j(\cdot)$ ($j \in \{e, c, p, t\}$) denote the welfare effects as functions of the argument for HH-E welfare, consumer surplus, producer surplus, and tax transfer, respectively.

simulated damage scenarios are as follows: A) neither effects; B) carcinogenic effects only; C) monarch butterfly effects only; and D) both effects. Using the Pesticide Environment Accounting framework (45, 46) combined with the Environmental Impact Quotient approach (47–50), which accounts for a range of HH-E effects, damage prices per gallon of herbicide are calculated. See *SI Appendix*, section D for a discussion on methods and *SI Appendix*, Tables S7 and S8 for the calculation procedure.

The HH-E externalities due to glyphosate are monetized to equal \$2.82, \$3.41, \$2.91, and \$3.51 per kg a.i. ("a.i." denotes "active ingredient"), respectively, under scenarios A to D. Correspondingly, the damage prices for glyphosate herbicide (d_1) are \$4.68/gal, \$5.66/gal, \$4.83/gal, and \$5.83/gal, respectively, given that its average active ingredient content equals 1.66 kg a.i./gal. With the composite herbicide, the average active ingredient contents per gallon herbicide (kg a.i./gal) for atrazine, acetochlor, and S-metolachlor are 0.77, 0.42, and 0.33, respectively. The monetized HH-E externalities per kilogram active ingredient of the three components are the same and equal \$3.52/kg a.i., which translates into a damage price of \$5.35 per gallon of herbicide (d_2).

The results show that any indirect effects to monarch butterflies have little consequence in glyphosate's damage price, in contrast with the increased cancer risk from exposure to glyphosate, which results in much higher damage prices. When both human health effects and monarch butterfly effects are assumed, the damage price is about 25% higher than when assuming neither. Translating the damage prices in dollars per gallon into aggregate HH-E damages at the national level gives a sense of the damage magnitude: the sample averages of herbicide applied per corn acre over the period of 2010 to 2016 are 0.27 gal/ac and 0.39 gal/ac for glyphosate and the composite herbicide, respectively. The annual average corn acreage planted in the United States over the period is 92 million acres, so the HH-E damages caused by glyphosate herbicide range from \$116 to \$145 million and amount to \$192 million for the composite herbicide.

Social Welfare Analysis. Finally, we model the total comparative HH-E and market economic effects of glyphosate versus other herbicides corn growers would use if glyphosate use were restricted. A log-linear EDM is developed to analyze the effects of a glyphosate tax on HH-E and market economic welfare (51–53). We calibrate our model by combining various sources of information (See *SI Appendix*, Table S11 for sources). Most of the parameter calibrations are drawn from previous studies or are computed from data sources, except the AES, the damage prices (d_1 and d_2), and the herbicide supply elasticities. The first two are obtained from the preceding sections while the herbicide supply elasticities are assumed to be one following common practice in previous studies (42, 54). Lower (0.5) and higher (1.5) supply elasticity values are also examined to exhaust all possibilities for robustness purposes. We then simulate a wide range of tax rates, from 10 to 50% at the US national level. We also compare scenarios in which glyphosate carcinogenicity and monarch butterfly effects are assumed, either separately or in combination.

The simulation results for equilibrium solutions and welfare effects are presented in Figs. 3 and 4. We find that imposing even a small percentage tax would lead to substantial net market economic welfare loss resulting from a combination of corn production decline, higher corn price, and a significant decline in glyphosate use. On the contrary, even under scenarios where the composite herbicide is associated with more adverse HH-E effects (i.e., scenarios A and C), net HH-E welfare increases because the increase in composite herbicide use is small when compared to the decrease in glyphosate use. Nevertheless, the HH-E gain is outweighed by the market economic loss and thus the overall social welfare is compromised. For example, for the most conservative welfare loss

Table 1. Second-step estimation results for the glyphosate demand equation

	Model 1: Both		Model 2: *GT* only		Model 3: *Till* only		Model 4: Neither		Model 5: No control	
Variables	Coeff.	APEs	Coeff.	APEs	Coeff.	APEs	Coeff.	APEs	Coeff.	APEs
ln *P*	0.151***	0.058***	0.152***	0.058***	0.177***	0.062***	0.176***	0.062***	0.148***	0.057***
	(2.76)	(2.80)	(3.14)	(3.17)	(3.60)	(3.64)	(3.32)	(3.34)	(2.98)	(3.00)
Resist	−0.028	−0.011	−0.027*	−0.010*	−0.034**	−0.012**	−0.032*	−0.011*		
	(−1.62)	(−1.63)	(−1.70)	(−1.72)	(−2.38)	(−2.40)	(−1.85)	(−1.85)		
GT	0.424***	0.162***	0.439***	0.168***	1.074***	0.376***	1.072***	0.377***		
	(3.82)	(3.79)	(4.29)	(4.28)	(22.40)	(25.73)	(19.00)	(22.91)		
Till	−0.374	−0.143	−0.083***	−0.032***	−0.426***	−0.149***	−0.097***	−0.034***		
	(−1.42)	(−1.42)	(−5.03)	(−5.12)	(−2.79)	(−2.78)	(−5.35)	(−5.43)		
$\hat{v}_1$	1.052***		1.037***							
	(8.68)		(9.02)							
$\hat{v}_2$	0.285				0.332**					
	(1.08)				(2.17)					
CRE	Yes		Yes		Yes		Yes		Yes	
CF	Yes		Yes		Yes		No		No	
F-statistic (GT)	50.27		100.6							
F-statistic (Till)	16.59				31.77					
Overidentification test			0.805		0.861					

$N \times T = 29{,}711$. *z*-statistics are in parentheses. Time dummies, state dummies, and state-specific trends are included. Residual terms $\hat{v}_1$ and $\hat{v}_2$ correspond to *GT* and *Till*, respectively. SEs are obtained by panel bootstrapping with 1,000 replications and clustered at CRD level. Year dummies, state dummies, and state-specific time trends are included. Farm heterogeneity is controlled for using the correlated random effects method (CRE; see *SI Appendix*, section A.3). The first-stage *F*-statistics reported in the table are cluster robust and are all above the corresponding critical values for 5% estimation bias for which we conventionally follow Stock and Yogo (68), and the *F*-statistic for *GT* in Model 2 is also close to the threshold of 104.7 suggested in more recent research (69), addressing the weak instrument concerns. The *P* values for the overidentification test are reported in the last row of the table. The results show that the null hypothesis cannot be rejected, so the concern for instrument endogeneity is mitigated from a statistical standpoint. Statistical significance is marked with asterisks (***$P < 0.01$, **$P < 0.05$, and *$P < 0.10$).

estimate where a 10% glyphosate tax is imposed while supply elasticities are 0.5 and 1.5 for glyphosate and the composite herbicide, respectively, uses of glyphosate and the composite quantity would change by −4.86% and +0.06%, along with a −0.08% change in corn quantity and a +0.15% change in corn price, among other market variables (Fig. 3).

Correspondingly, the market economic loss is estimated to be $98 million per annum in the United States, and the HH-E gain for the status-quo damage scenario (i.e., scenario A) is only $6 million, about one-sixteenth of the market economic loss. Even when assuming the most extreme damage scenario for glyphosate, which expands the HH-E benefit to $7 million, the tax still results in a net social welfare loss of $91 million at the US national level. Due to the nonlinear nature of the welfare formula in terms of the tax rate, the estimates for a 50% tax rate are also informative. Switching to a 50% tax rate while keeping other parameters fixed, the percentage changes in market variables would increase fivefold because these percentage changes are linear in the tax rate. This translates into a market economic loss of $516 million, HH-E gains that range from $28 to $35 million, and net social welfare loss of $481 million per annum at a minimum (Fig. 4). The ratio of net social welfare loss between the 50 and 10% tax rate cases under the same circumstances exceeds the tax ratio of 5, illustrating the nonlinearity of glyphosate tax consequences on social welfare. The largest social welfare loss, at $1,398 million per annum, occurs when a 50% tax is imposed, status-quo damage scenario A is assumed, and supply elasticities are 1.5 and 0.5, respectively, for glyphosate and the composite herbicide. Thus, the negative social welfare result is robust to a wide range of tax rates and alternative glyphosate damage scenarios, as well as a reasonable range of supply elasticities.

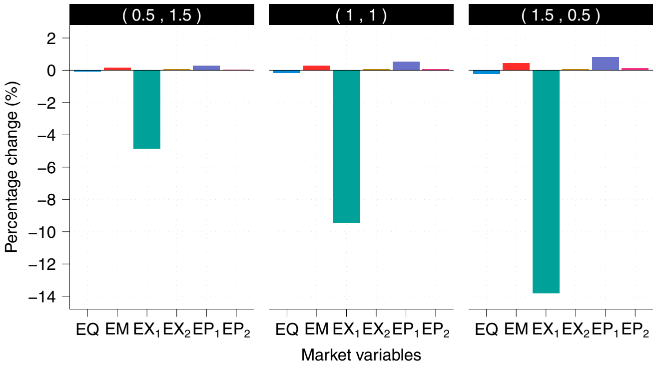

Fig. 3. Percentage changes in market variables at 10% glyphosate tax. Market variables Q, X_1, X_2 denote quantities of corn, glyphosate, and the composite herbicide, and M, P_1, P_2 denote prices, correspondingly. E denotes percentage change. Percentage changes in market variables are identical across glyphosate damage scenarios and are linear in the tax rate. We present three combinations of glyphosate (*Left*) and the composite (*Right*) herbicide supply elasticity, namely, (0.5, 1.5), (1, 1), and (1.5, 0.5). The three combinations are selected because, all else equal, the (0.5, 1.5) combination corresponds to the most conservative estimate of welfare loss (lower bound), and (1.5, 0.5) corresponds to the most extreme loss (upper bound).

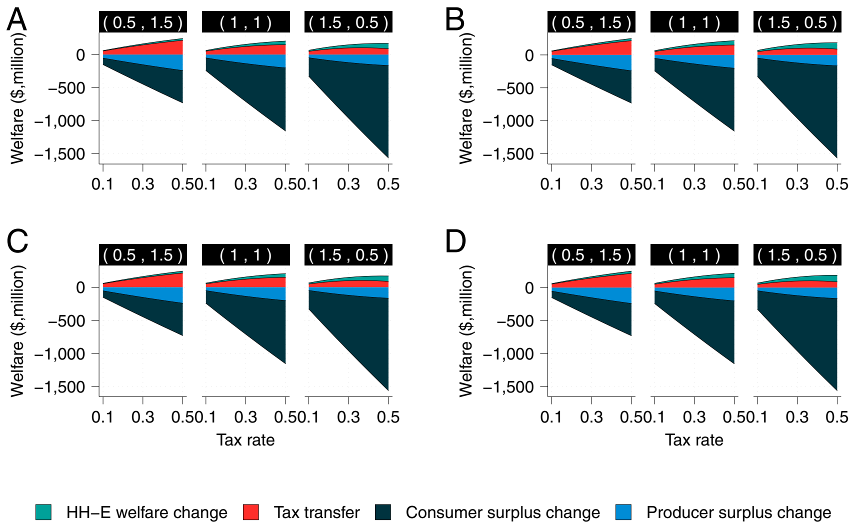

Fig. 4. Nation-level welfare effects. Welfare changes for a glyphosate tax ranging from 10 to 50% in the United States under four glyphosate damage scenarios: (*A*) no carcinogenic effect and no monarch butterfly effects, (*B*) carcinogenic effects only, (*C*) monarch butterfly effects only, and (*D*) both effects are assumed. Across scenarios, market economic welfare is identical, but HH-E welfare differs. Within each scenario, we present three combinations of glyphosate (*Left*) and the composite (*Right*) herbicide supply elasticity, namely, (0.5, 1.5), (1, 1), and (1.5, 0.5). The three combinations are selected because, all else equal, the (0.5, 1.5) combination gives the most conservative estimate of welfare loss (lower bound), while (1.5, 0.5) gives the most extreme welfare loss (upper bound). Market economic welfare change = consumer surplus change + producer surplus change + tax transfer.

Discussion

Following the 2015 IARC Monograph that classified glyphosate as a Group 2A probable human carcinogen, political jurisdictions enacted multiple regulations that in effect restricted glyphosate use in agriculture, while Bayer/Monsanto faced multiple lawsuits about suspected cancer cases linked to glyphosate exposure. Glyphosate use restrictions could come in the form of outright bans (36, 37) or taxes that reduce farmers' incentives to use this herbicide (10, 38). Hence, farmers who previously used glyphosate on corn fields might turn to alternative herbicides, increase tilling, or follow a combination of these strategies to control weeds instead of using glyphosate. Our analysis comprehensively addresses the effects of a glyphosate use restriction policy on food producers, consumers, human health, and the environment.

Our findings show that any level of glyphosate tax is likely to decrease overall social welfare. This is because the market economic loss from restricted weed control outweighs any decreased risks to human health and the environment from switching to alternative herbicides. In light of the divided scientific evidence on the human carcinogenic and monarch butterfly effects of glyphosate, we consider a set of HH-E damage scenarios for glyphosate and evaluate the HH-E effects in each scenario using a pecuniary framework. We find that the total HH-E damage is priced at $5.35/gal for the composite herbicide, and this damage price is exceeded by that of glyphosate only if human carcinogenicity is assumed. This finding confirms the overall low environmental toxicity for glyphosate but also highlights glyphosate carcinogenicity as a primary source of uncertainty in the glyphosate policy debate. Correspondingly, at the current level of chemical use (averaged over 2010 to 2016), the annual HH-E costs associated with glyphosate and the composite herbicide applications range from $308 to $337 million.

Critical to evaluating the tradeoffs between glyphosate and the alternative herbicide is their substitutability in weed control operations, which is absent from previous studies largely due to data limitations. In our estimation, we control for other interrelated farm-level weed management decisions to obtain a more appropriate characterization of the substitution relationship. Our results show that they substitute on average, indicating a potential increase in the alternative herbicide use in response to glyphosate restrictions. However, in calibrating our corn-herbicide market equilibrium model we find that the increase is relatively small when compared to glyphosate reduction as a result of glyphosate taxation. Consequently, the overall human health and environmental burden to society is reduced, albeit rather marginally when compared to the aggregate externality. We estimate that the HH-E gain due to a 10% tax ranges from $6 to $7 million per annum. However, the HH-E gain comes at a high market economic cost to society. Given current availabilities in the corn-herbicide market, corn producers will be restricted to more expensive alternatives, and the increased production cost is transmitted in part to consumers, resulting in a small but economically significant drop in corn quantity at the market equilibrium. Therefore, both consumer welfare and producer welfare decline. Our most conservative estimate of the market economic loss caused by a 10% tax is $98 million annually, with a higher tax rate causing disproportionately greater loss.

The estimated social welfare loss from restricting glyphosate would increase were we to also consider the possibility of farmers switching back to mechanical weed control alternatives. Perry et al. (55) have shown that glyphosate, together with the glyphosate tolerance seed trait in soybeans, has facilitated reduced tillage cultivation and so has saved on soil erosion as well as on carbon emissions from disturbed soils and fossil fuels consumed during this energy-intensive process. In turn, Deines et al. (56) provide evidence that lower tillage intensity increases yields in US Corn Belt corn and soybean production.

Our analysis has revealed that the most likely substitutions for reduced glyphosate use would be less efficient at weed control in US cornfields from a social welfare standpoint. If glyphosate-related inhibition policies are to be enforced in the United States and worldwide, then our work points toward the need to translate fundamental research in the biological sciences into weed management technologies that have minimal adverse consequences for humans and the environment so as to ensure that the HH-E gain from restricting glyphosate comes at low cost.

Induced innovation (57, 58) in weed management is likely an important feature of our setting, especially if we consider a closely related issue: weed resistance to herbicides. Compared to resistance to antimicrobials (59) and to insecticides (60, 61), resistance to herbicides has received less attention and has not until recently been viewed as important by researchers and policymakers. Possibly because glyphosate's success left little opening for profit or because of regulatory burdens and cancellation risks, no new classes of herbicides were commercially developed between the middle 1980s and 2020, and scientific inquiry in the area wilted (62). Yet the evolution of weed resistance to glyphosate has reinvigorated research into weed management, leading to significant recent advances (63). A similar induced innovation impetus should follow glyphosate-restricting policies. Accounting for resistance might increase the calculated value of a glyphosate curtailment intervention even if damage from resistance is eventually tempered by innovation. This is because the accounting would recognize a modified rate of resistance development. However, the benefit from managing resistance will diminish when the use of the herbicide is severely restricted because there is little benefit in reducing resistance to a chemical that is not widely used. Further model development will be needed when improved resistance data becomes available. Until that time, our analysis serves to highlight the tradeoffs to human health, the environment, and corn productivity in the US if glyphosate use is restricted and points out countervailing risks from alternative methods of weed control in US agriculture.

Materials and Methods

To avoid unnecessary methodological complications, we group atrazine, acetochlor, and S-metolachlor into a conceptual herbicide—the composite herbicide—and omit chemicals other than these three plus glyphosate. This simplification is justified by the almost constant market share of the other chemicals (about 10% during our study period of 2010 to 2016) as well as the similarity in toxicity properties among the three composition chemicals (atrazine, acetochlor, and S-metolachlor). Moreover, the three chemicals are commonly mixed to form herbicide products—such as Lexar and Harness XTRA—while glyphosate is not typically mixed with other chemicals for products. Additional analysis is included in *SI Appendix*, section C.3 to investigate the sensitivity to grouping chemicals.

Herbicide Demand System Estimation. Following the conceptual model we developed (*SI Appendix*, section A.1), the herbicide demand system is framed as a two-stage decision, where tillage and GT decisions are taken as given and thus are modeled as right-hand side variables in herbicide cost-share equations. The equations for each herbicide are derived from a Translog cost function (64). The system consists of two cost-share equations, one for glyphosate and the other for the composite herbicide. We drop the latter and estimate only the glyphosate equation, as the two shares always sum to one.

Several econometric issues arise in the estimation. First of all, the glyphosate cost share, s, is a fractional variable bounded on the unit interval. Response coefficients in a standard linear regression that ignores the nonlinearity are likely to be biased toward zero. Second, farm heterogeneity is likely to be present. Like other farm-level decisions, herbicide decisions are also expected to be conditional on unobserved time-constant farm and farmer characteristics, such as farmers' education level. Third, seed choice GT and tillage practice $Till$ are likely to be endogenous, as discussed in previous sections. Therefore, we adopt the fractional response framework, a nonlinear approach, to model the glyphosate cost share as given in Eq. **1** [i.e., to specify the conditional mean of glyphosate cost share as a probit function (65)]. The model is further extended to control for farm heterogeneity using the correlated random effects method and for endogeneity using the control function approach (39, 66). In particular, GT is instrumented with the GT seed price and Bt seed adoption rate, while $Till$ is instrumented with the diesel fuel price and soil erodibility. These instruments isolate exogenous variations in the endogenous variables, thereby allowing for the identification of their causal effects on the cost share in the glyphosate demand equation. The extended final model is estimated following a two-step procedure: first, regress the suspected endogenous variable on all exogenous variables to obtain residuals (denoted by $\hat{v}_1$ for GT and $\hat{v}_2$ for $Till$); second, estimate a fractional probit model where $\hat{v}_1$ and $\hat{v}_2$ are included as covariates. Then the coefficients for $\hat{v}_1$ and $\hat{v}_2$ in the second-step estimation capture the correlation between suspected endogenous variables and the omitted factors in the glyphosate cost-share equation and thereby provide a direct test for endogeneity. See *SI Appendix*, sections A.3 and B.2 for more details on econometric modeling and a discussion on instrumental variables.

We compile a farm-level unbalanced panel that spans 2010 to 2016. The primary data source is the AgroTrak survey, a unique, large-field–level survey dataset. This dataset has been collected annually by the market research company GfK Kynetec, which specializes in the collection of agriculture-related survey data (https://www.kynetec.com). Data are representative of the Crop Reporting District levels across the main US corn-growing states and have been used in our previous studies (50, 67). The data contain information on chemical and mechanical weed control practices, as well as seed varieties, for about 4,337 farms annually. See *SI Appendix*, section B.1 for more descriptions on the AgroTrak survey. Weed resistance data are obtained from the International Survey of Herbicide Resistant Weeds (ISHRW). Each year, the ISHRW records the weed species identified to have become resistant to a certain chemical for the first time in a state. More detailed descriptions of data and variables can be found in *SI Appendix*, section B.

Environmental Accounting and Scenario Simulation. We combine the PEA framework (45) with the EIQ approach (47) to compute the damage prices of herbicides and, in particular, to simulate the four damage scenarios for glyphosate.

For each herbicide, the PEA framework provides the monetary external cost (in \$/kg a.i.) for each of eight HH-E effect categories in the EIQ system, namely applicator, picker, consumer, groundwater, aquatic, bird, bee, and beneficial insect effects. Higher EIQ scores indicate more adverse effects, and herbicides with higher EIQ are given higher external costs. The damage price (in \$/gallon) is then obtained by summing over category-specific external costs and multiplying by the average kilogram active ingredient per gallon herbicide product. Hence, the value of human life and other ecological receptors have been implicitly incorporated into the damage price measure.

In simulated scenarios, the hypothesized additional effects of glyphosate (i.e., carcinogenic and monarch butterfly effects) are captured by higher EIQ scores and damage prices. Specifically, for scenarios involving human carcinogenicity, the chronic health effect parameter in the EIQ formula is adjusted. It is assigned the smallest value 1 for the status quo, which corresponds to little or no long-term negative health effects, and is adjusted to the largest value 5 for carcinogenic scenarios to represent the most extreme human health effects by carcinogenicity. The monarch butterfly effects are more problematic because glyphosate is not directly associated with the two parameters involved in the beneficial insect effects, namely plant surface half-life and beneficial arthropod toxicity. Nevertheless, adjusting the value of the beneficial arthropod toxicity parameter from 1 (relatively nontoxic) to 5 (highly toxic) is an equivalent way of accounting for the population reduction impact under the most extreme monarch butterfly effects. The damage prices for simulated scenarios can then be computed based on the adjusted EIQ scores (see *SI Appendix*, section D.2 for details). Original EIQ data are obtained from the framework website (available at https://nysipm.cornell.edu/eiq, updated version in 2017). Other relevant data sources include Leach and Mumford (45) and the AgroTrak dataset for computing the sample average active ingredient per gallon herbicide.

Equilibrium Displacement Model. We model equilibrium displacement in a one-output (corn), two-input (glyphosate and the composite herbicide) structure, and competitive industries are assumed where farmers are price takers in the three markets. It is implicitly assumed that prices of inputs other than herbicides do not change in response to a glyphosate tax. As a result, the inclusion of nonherbicide inputs would be unaffected and so are excluded from the model. In this way, the model is simplified to focus on only the herbicide inputs. The model consists of six market variables endogenously determined in the system, namely corn quantity (Q), corn price (M), glyphosate herbicide quantity (X_1), glyphosate herbicide price (P_1), the composite herbicide quantity (X_2), and the composite herbicide price (P_2). Solving the model gives the percentage changes in these market variables expressed in terms of tax rates (linearly) and the set of parameters that characterize the market structure (*SI Appendix*, Table S9). Market economic and HH-E welfare changes can then be computed using the percentage changes, baseline values of the market variables, damage prices, and calibrated parameters (*SI Appendix*, Tables S10 and S11). In general, the parameter calibration uses information from periods that largely overlap with our study period of 2010 to 2016.

Data Availability. All data used are publicly accessible except the data from GfK Kynetec. Kynetec data were purchased and are protected by a non-third-party disclosure agreement, but variables from of the AgroTrak and TraitTrak (in *SI Appendix*) surveys may be obtained through crop subscriptions services (contact at https://www.kynetec.com/contact). Weed resistance data come from the International Herbicide-Resistant Weed Database (available at http://www.weedscience.org). Environmental Impact Quotient (EIQ) data come the EIQ website (available at https://nysipm.cornell.edu/sites/nysipm.cornell.edu/files/shared/documents/EIQ-values-May-2020.xlsx). Data used in *SI Appendix* are from several sources: soil erodibility are obtained from the National Resource Inventory (available upon request: https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/technical/nra/nri/; contact at nri@wdc.usda.gov), fuel prices data from the US Energy Information Administration (available at https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_m.htm), crop production and price data are obtained from National Agricultural Statistics Service (available at https://quickstats.nass.usda.gov/). Extracted data and codes have been deposited in GitHub (https://github.com/resdata/glyphosate_analysis) and datasets used are available here.

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