Environmental and Economic Concerns Surrounding Restrictions on Glyphosate Use in Corn

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Glyphosate

- An herbicide dominating the corn herbicide market in the U.S., China, and across the world, also known as Roundup.

Glyphosate debate: Buttefly population reduction?

- Evidence is divided on whether glyphosate contributes to monarch butterfly population reduction; indirectly through the loss of milkweed, on which monarchs lay their eggs and its larvae feed.

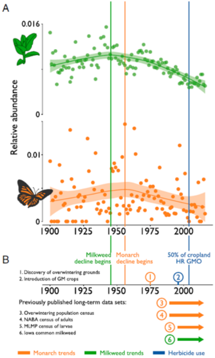
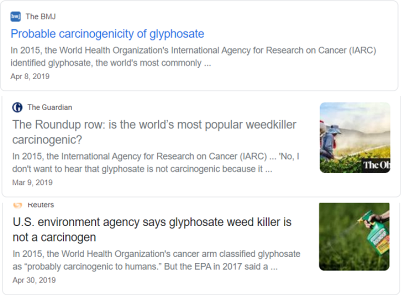


Figure: Adapted from Fig. 1., Boyle et al.(2019)

Glyphosate debate: Carcinogenic?

- In 2015, WHO IARC (International Agency for Research on Cancer) has classified glyphosate as “probable carcinogenic to humans”; yet conclusion remains undetermined.

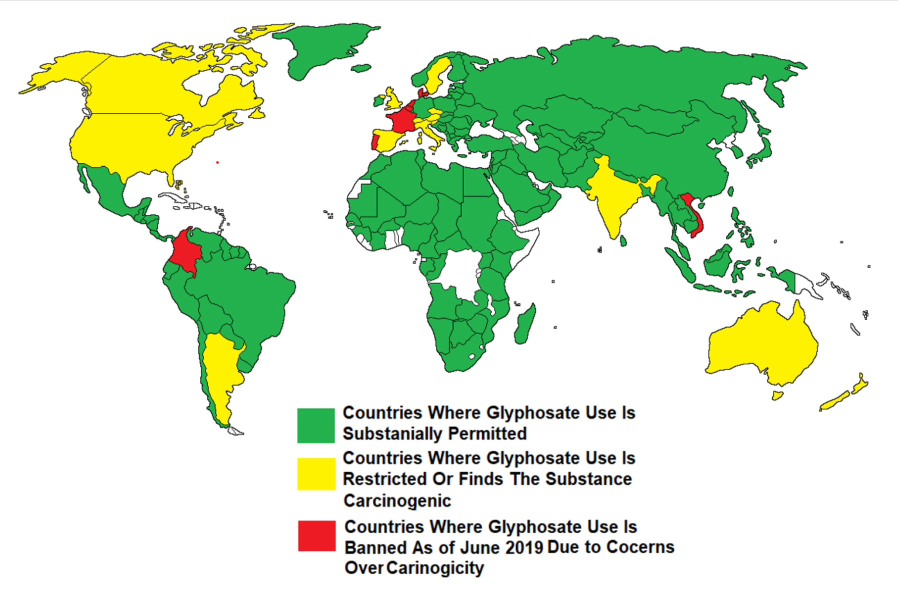


The BMJ
Probable carcinogenicity of glyphosate
In 2015, the World Health Organization's International Agency for Research on Cancer (IARC) identified glyphosate, the world's most commonly ...
Apr 8, 2019

The Guardian
The Roundup row: is the world’s most popular weedkiller carcinogenic?
In 2015, the International Agency for Research on Cancer (IARC) ... 'No, I don't want to hear that glyphosate is not carcinogenic because it ...
Mar 9, 2019

Reuters
U.S. environment agency says glyphosate weed killer is not a carcinogen
In 2015, the World Health Organization's cancer arm classified glyphosate as “probably carcinogenic to humans.” But the EPA in 2017 said a ...
Apr 30, 2019

Glyphosate restriction policies around the world



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- Glyphosate is ubiquitous in US corn production
  $\rightarrow$ unintended consequences?

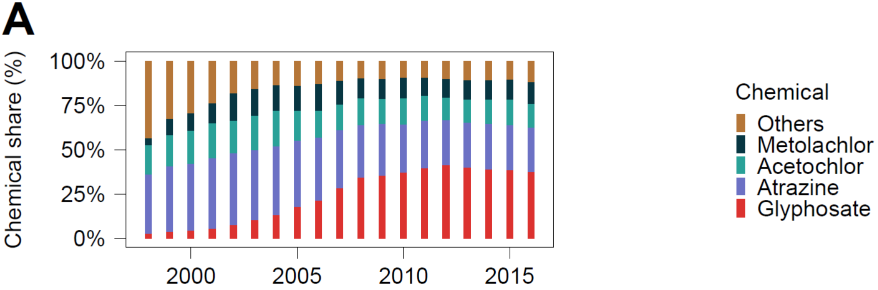

Figure: Chemical share, calculated as individual chemical use (kg/ha) divided by total herbicide chemical use (kg/ha). Adapted from Fig. 1. of this paper.

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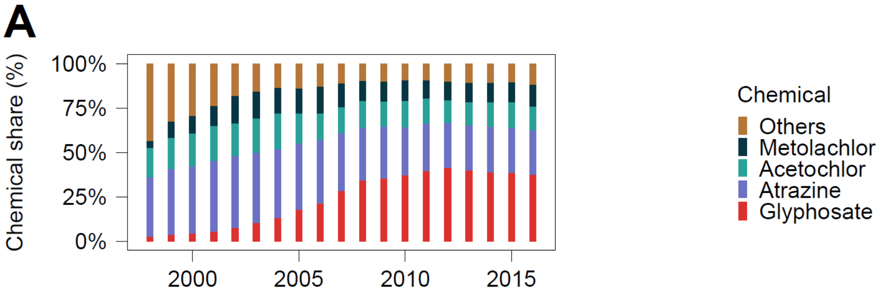
- Research question:Is a glyphosate-restricting policy preferable from a social welfare standpoint, given the substitution possibility?
  $\rightarrow$ economic, as well as human health and the environment



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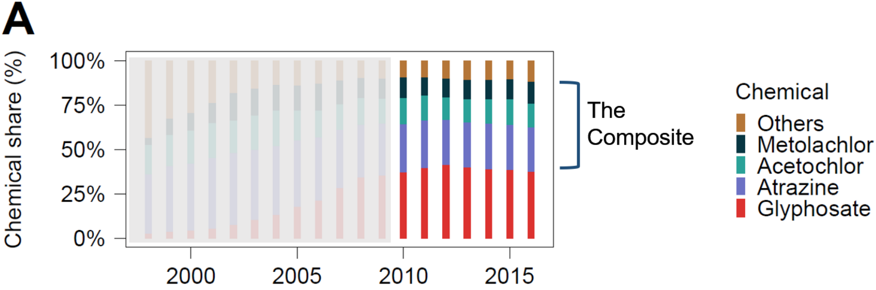

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Interdisciplinary Modeling Approach

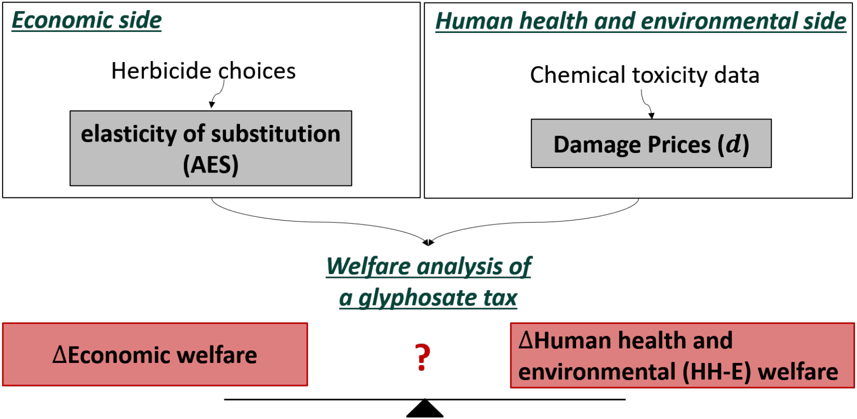

Figure: Adapted from Fig.2. of this paper.

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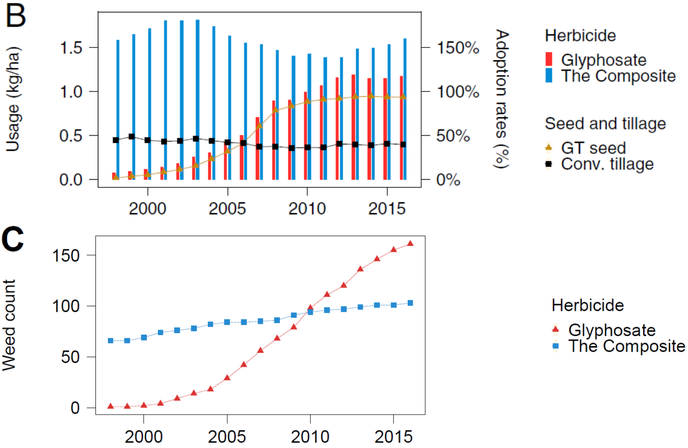
What drives herbicide substitution?

- Non-price drivers of substitution between glyphosate and it alternative herbicides, namely "the composite": **Glyphosate-tolerant (GT) corn adoption, tillage, and weed resistance** (Figure adapted from Fig. 1. of this paper).



Empirical model specification

Derived from the underlying Translog cost function, the herbicide demand equation is specified as:

$$s = b_0 + \boxed{b_1 lnP} + b_2 Resist + b_3 GT + b_4 Till + \Psi + \epsilon \qquad (1)$$

Notations:

- s: herbicide cost share of glyphosate, varies by farm and year;
- lnP: logarithm of price index ratio of glyphosate to the composite; The AES will be recovered from b_1 estimate.
- *Resist*: weed resistance to glyphosate relative to the composite;
- *GT*: GT adoption rate;
- *Till*: conventional tillage rate;
- Ψ: year dummies, state dummies, and state-specific time trends.

Three econometric issues

- **Issue 1**: Fractional dependent variable, bounded between 0 and 1: *fractional response approach*

$$E(s|\bullet) = \Phi(b_0 + b_1 lnP + b_2 Resist + b_3 GT + b_4 Till + \Psi) \qquad (2)$$

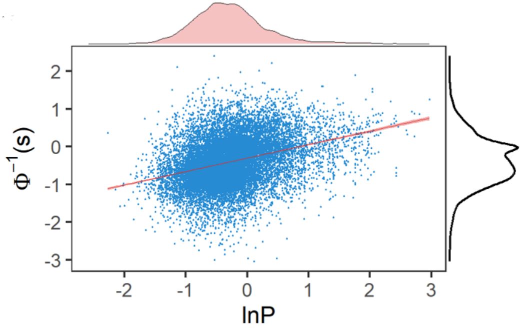


Figure: Visualization of fractional response model.

Three econometric issues, continue

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- **Extending eq. (2) and setting up the estimation equation as follows:**

$$E(s_{it}|z_{it}, y_{1,it}, c_i, u_{it}) = \Phi(z_{1,it}\eta + \mu_1 y_{1,it} + \boxed{c_i} + \boxed{u_{it}}) \tag{3}$$

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  - z_{it}: exo. variables, consisting of included exo. variables z_1 and excluded exo. variables $z_{2,it}$; $y_{1,it}$: endo. variables (GT and Till)

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  - c_i: time-invariant farm heterogeneity, modeled to depend on not only all exogenous variables but also time period selection denoted by λ_{ir} to account for unbalancedness.

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- u_{it}: time-varying omitted factor correlated with $y_{1,it}$

Estimation procedure

After a few steps of derivation, eq. (3) becomes

$$E(s_{it}|z_{it}, y_{1,it}, v_{1,it}, \lambda_{ir}) = \Phi(\frac{z_{1,it}\tilde{\eta} + \tilde{\mu}_1 y_{1,it} + \tilde{\rho}_1 v_{1,it} + \Sigma_{r=1}^{T}\tilde{\theta}_r\lambda_{ir} + \Sigma_{r=1}^{T}\tilde{\zeta}_r\lambda_{ir}\bar{z}_i}{exp(\Sigma_{r=2}^{T}\lambda_{ir}\tilde{\phi}_r)^{0.5}}) \quad (4)$$

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- step 1: obtain the OLS residuals $\hat{v}_{1,it}$ from eq. (5)
- step 2: estimate he fractional probit model in eq. (4) where $\hat{v}_{1,it}$ enters the regression.
- Standard errors are bootstrapped to adjust for the first-stage estimation.

Econometric model schematic

- IVs for *GT*: *pgt*, GT seed price; *Bt*, Bt seed adoption rate.
- IVs for *Till*: *pfuel*, diesel fuel price; *hel*8, soil erodibility.

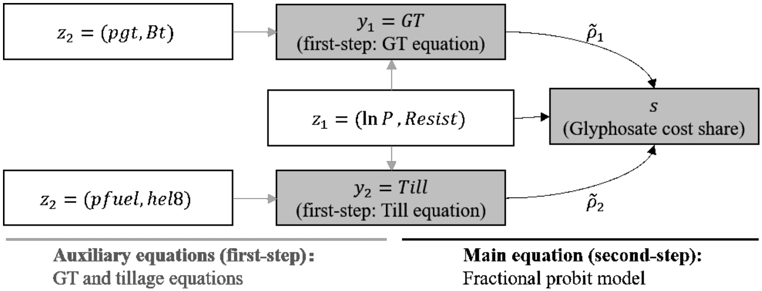

Figure: Adapted from Fig.S3 of the SI Appendix.

Data and variables

Survey data on weed control practices

- 2010-2016 (1998-2016)
- collected annually by Gfk Kynetec, a market research company
- annual average of more than 4000 farmer observations
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Complementary data sources

- $Resist$: the International Survey of Herbicide Resistant Weeds (ISHRW)
- $hel8$: the National Reserve Inventory (NRI); equals 1 if highly erodible, 0 otherwise
- $pfuel$: the U.S. Energy Information Administration

Key results: AES

Estimates for the coefficient of lnP, i.e., b_1

- $\hat{b}_1$=0.151***(std. err.=2.76)
- Average partial effect $A\hat{P}E$=0.058***(std. err.=2.80)

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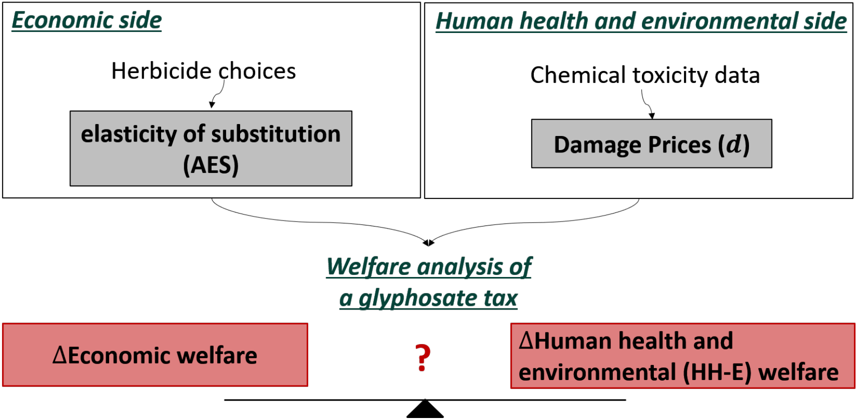
Allen-Uzawa elasticity of substitution (AES)=0.739 >0, so glyphosate and the composite are substitutes on average.

Recall the overall modeling approach



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Monetizing toxicity into damage prices

Combine the Environmental Impact Quotient (EIQ) approach (Kovach et al. 1992) and the Pesticide Environmental Accounting Framework (PEA)(Leach and Mumform 2008).

Step 1: EIQ - Toxicity evaluation

Step 2: PEA - From EIQ to monetary externality (damage prices)

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- damage price: the monetary value of externality per gallon of a pesticide product.

Simulating for alternative glyphosate toxicity scenarios

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	No monarch butterfly effect	Monarch butterfly effect
No carcinogenic effect	**(a): status-quo** [C=1, B=1]	**(c): Butterfly effect only** [C=1, B=5]
Carcinogenic effect	**(b): Cancer effect only** [C=5, B=1]	**(d): Both effects** [C=5, B=5]

Simulating for alternative glyphosate toxicity scenarios

- To capture the uncertainties around glyphosate toxicity and its HH-E impacts: carcinogenic and monarch butterfly effects are the most debated - thus four scenarios.
- Simulate through adjusting two key parameters in EIQ evaluation equation:
  - C: long-term health effect (farm worker & consumer effect)
  - B: beneficial arthropod toxicity (beneficial insect effect)

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Key results: damage prices

Damage prices for the composite and glyphosate under four scenarios (status-quo + 3 extreme scenarios)

	Glyphosate herbicide				The composite herbicide
	(a) Neither	(b) Cancer	(c) Butterfly	(d) Both	
Environmental externality ($/kg a.i.)	2.82	3.41	2.91	3.51	3.52
Average a.i. of herbicide (kg a.i./gal)	1.66				1.52
Damage price ($/gal)	4.68	5.66	4.83	5.83	5.35

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- confirms the overall low environmental toxicity for glyphosate
- highlights glyphosate carcinogenicity as a primary source of uncertainty in the glyphosate policy debate

Recall the overall modeling approach

Economic side

Herbicide choices

elasticity of substitution (AES)

Human health and environmental side

Chemical toxicity data

Damage Prices (d)

Welfare analysis of a glyphosate tax

ΔEconomic welfare

?

ΔHuman health and environmental (HH-E) welfare

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EDM Overview

An equilibrium displacement model (EDM) is a system of supply and demand equations linking market variables of corn and herbicide market, parameters, and exogenous shocks.

- *Market variables*: price and quantity of corn, glyphosate, and alternative herbicides - 6 variables
- *Key parameters*: AES, damage prices
- *Policy shock*: glyphosate tax (10%-50%)

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- *Policy shock*: glyphosate tax (10%-50%)

Outcome:

- percentage change in market variables at the post-shock equilibrium
- welfare changes (HH-E welfare; market economic welfare=consumer welfare+producer welfare+tax transfer)

key results: equilibrium changes

- Three panels for robustness: examine across an exhaustive range of herbicide supply elasticities, i.e., assuming to be combinations of 0.5, 1.0, or 1.5.

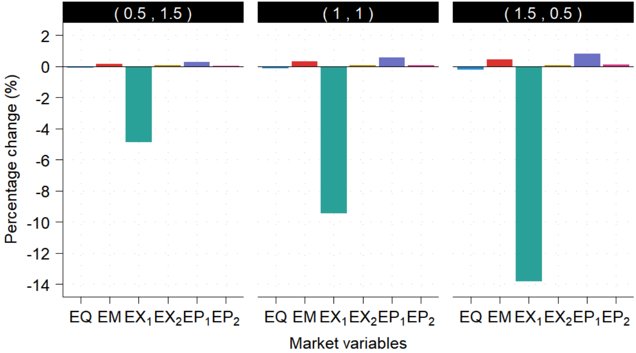
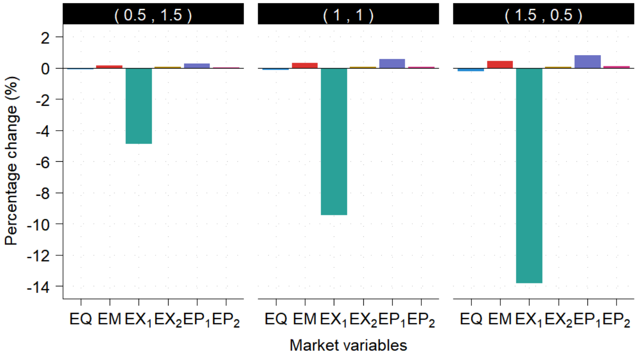


Figure: Percentage changes in market variables at 10% glyphosate tax.

key results: equilibrium changes

- a glyphosate tax will decrease glyphosate use but increase its alternative herbicide use (substitution effect overrides expansion effect) at the same time.



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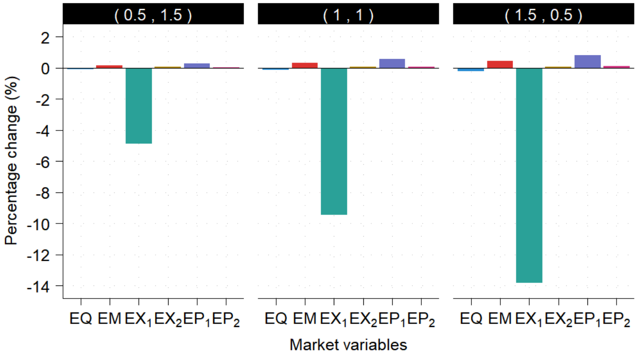
- a glyphosate tax will decrease glyphosate use but increase its alternative herbicide use (substitution effect overrides expansion effect) at the same time.
- How do the two counter-forces translate into welfare effects?



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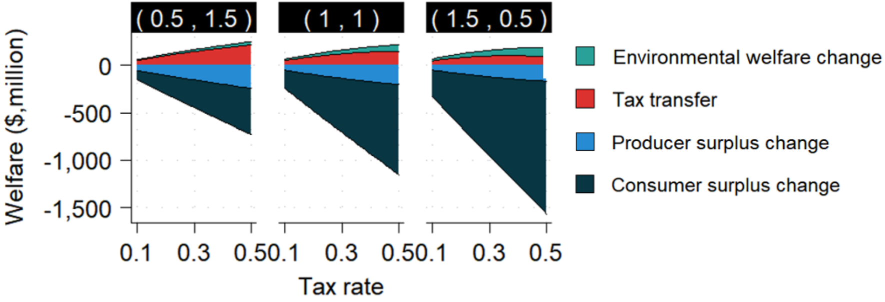
Key results: welfare effects assuming cancer & butterfly effects



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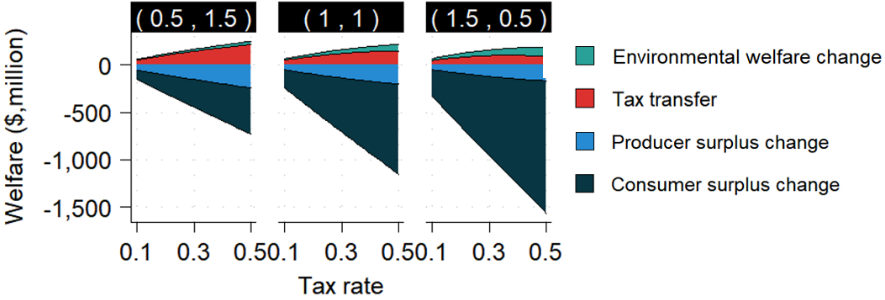

- Environmental gain is outweighed by economic loss, even when assuming the most adverse human health and environmental effects of glyphosate.

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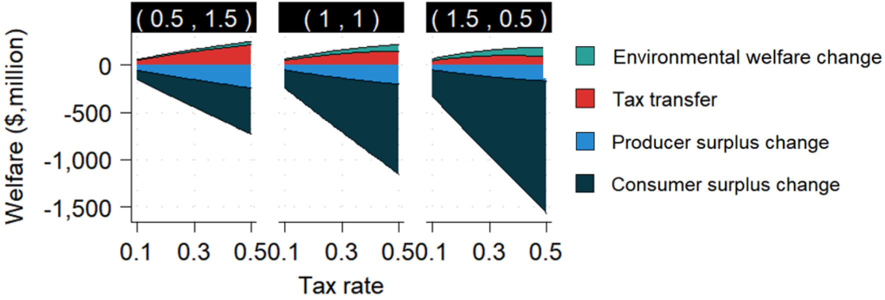
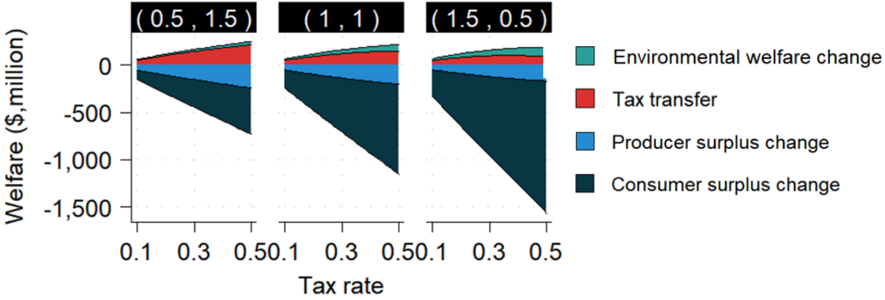


- A glyphosate tax will result in net social welfare loss.

Key results: welfare effects assuming cancer & butterfly effects



- This finding is robust to a wide range of tax rates and reasonable combinations of herbicide supply elasticities.

Summary

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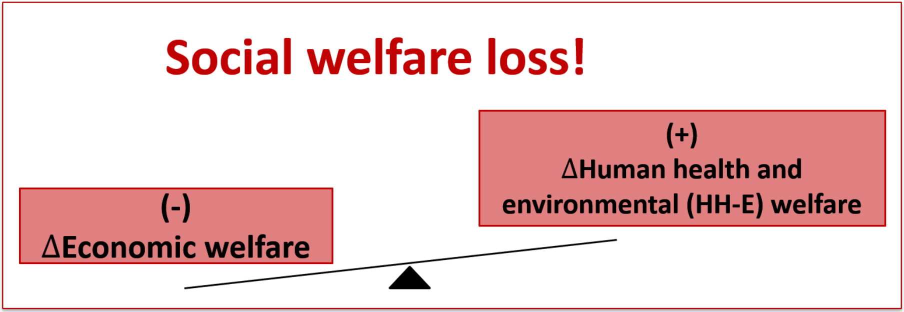
- The first analysis that rigorously and comprehensively addresses the effects of a glyphosate use restriction policy on food producers, consumers, human health, and the environment.
- Farmers who previously used glyphosate on corn fields might turn to alternative herbicides, leading to equilibrium changes.
- A glyphosate tax is likely to decrease overall social welfare, because the economic loss from restricted weed control outweighs any decreased risks to human health and the environment from switching to alternative herbicides.
- This conclusion holds despite the uncertainties around glyphosate's human health and environmental impacts.

Let's end where we begin!



Thank you!

Q & A

GT trait stacking

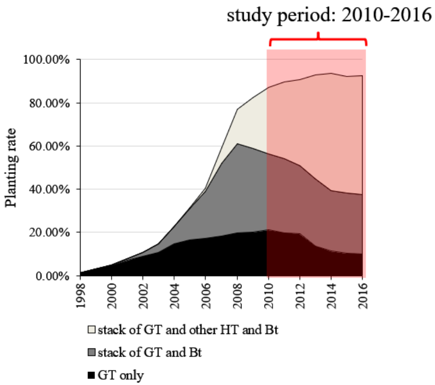


Figure: Adapted from Fig. S2 of the SI Appendix.

Step 1: Model formulation

One-output (corn), Two-input (glyphosate and the composite herbicide) model (assuming the prices of other inputs are constant in response to the tax change).

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- (a) output demand: $Q = f(M)$; Q, corn quantity; M, corn price
- (b) output production: $Q = Q(X_1, X_2)$; X_1 (X_2), glyphosate (the composite) herbicide quantity
- (c) input demand for glyphosate: $P_1 = MQ_1(X_1, X_2)$; P_1, glyphosate herbicide price
- (d) input demand for the composite: $P_1 = MQ_1(X_1, X_2)$; P_2, the composite herbicide price
- (e) input supply for glyphosate: $X_1 = g_1(P_1)$
- (f) input supply for the composite: $X_1 = g_1(P_1)$

Step 2: differentiation and derivation

Totally differentiating and converting to elasticities, and adding the exogenous shock of a glyphosate tax τ. Let EX denote percentage changes in X.

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- (a') $EQ = \zeta EM$; ζ, the price elasticity of consumer demand for corn
- (b') $EQ = \kappa_1 EX_1 + \kappa_2 EX_2$; κ_m, cost share of input m, and $\kappa_m = P_m X_m/(\text{Total corn production cost})$
- (c') $EP_1 = EM - (\kappa_2/\text{AES})EX_1 + (\kappa_2/\text{AES})EX_2$
- (d') $EP_2 = EM + (\kappa_1/\text{AES})EX_1 - (\kappa_1/\text{AES})EX_2$
- (e') $EX_1 = \epsilon_1(EP_1 - \tau)$
- (f') $EX_2 = \epsilon_2 EP_2$

Step 3: solutions

Solving the system gives the percentage change of the market variables as expressions of parameters.

Equations	Solutions	Signs
EQ	$[\{\vartheta + \epsilon_2(\kappa_1 + \kappa_2)\}\kappa_1\epsilon_1\zeta\tau]/D$	-
EM	$[\{\vartheta + \epsilon_2(\kappa_1 + \kappa_2)\}\kappa_1\epsilon_1\tau]/D$	+
EX_1	$-[\{-\zeta\vartheta + (\kappa_2\vartheta - \kappa_1\zeta)\epsilon_2\}\epsilon_1\tau]/D$	+
EX_2	$[\kappa_1(\vartheta + \zeta)\epsilon_1\epsilon_2\tau]/D$	Same sign as $\vartheta + \zeta$
EP_1	$[\{\kappa_1\vartheta - \kappa_2\zeta + \epsilon_2(\kappa_1 + \kappa_2)^2\}\epsilon_1\tau]/D$	+
EP_2	$[\kappa_1(\vartheta + \zeta)\epsilon_1\tau]/D$	Same sign as $\vartheta + \zeta$

Notes: Signs given assume that $\zeta < 0$, $\epsilon_1 > 0$, and $\epsilon_2 > 0$. D abbreviates $D = AES(\zeta + \kappa_1\epsilon_1 + \kappa_2\epsilon_2) - \zeta(\kappa_2\epsilon_1 + \kappa_1\epsilon_2) + \epsilon_1\epsilon_2(\kappa_1 + \kappa_2)^2 > 0$.

Step 3: solutions, continued

Subsequently, welfare changes from the shock of τ can be calculated using the following table:

Equations	Solutions	Definition
ΔCS	$-M_0 Q_0 EM(1 + 0.5EQ)$	Consumer surplus change
ΔPS_1	$P_{1,0} X_{1,0}(EP_1 - \tau)(1 + 0.5EX_1)$	Producer surplus change for input 1
ΔPS_2	$P_{2,0} X_{2,0} EP_2(1 + 0.5EX_2)$	Producer surplus change for input 2
ΔTax	$\tau P_{1,0} X_{1,0}(1 + EX_1)$	Tax transfer
ΔEnv	$-d_1 X_{1,0} EX_1 - d_2 X_{2,0} EX_2$	Environmental welfare change
ΔS	$\Delta CS + \Delta PS_1 + \Delta PS_2 + \Delta Tax + \Delta Env$	Social welfare change

Notes:The zeros in the subscripts denote the baseline values of these variables.

Step 4: calibration

Need to calibrate the parameters and baseline quantities % prices.

Combines various sources of information, including

- previous literatures (for corn price elasticity)
- AgroTrak data & corn budget estimates (for herbicide cost share in total corn production cost; and baseline herbicide quantities & prices)
- USDA National Agricultural Statistics Service (for baseline corn quantity & price)