CROP BIOTECHNOLOGY: ECONOMICS, ENVIRONMENT, AND POLICY

By

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ABSTRACT

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Crop biotechnology has been one of the most prominent technological advances in agriculture in recent decades. The first generation of biotech crops since the mid-1990s has protected plants from biotic stresses such as insects (insect-resistant crops) and weeds (herbicide-tolerant crops), while the newly emerged second-generation aims to protect crops from abiotic stress like drought, and improves quality, among other things. A central theme of this dissertation is the economic and environmental implications of crop biotechnology, whether direct or indirect through associated markets, as well as the role of policy in balancing the benefits and risks to effectively accommodate these innovations. The dissertation comprises three essays on three representative biotech crops in maize production in the United States: (the herbicide glyphosate complementary to) the glyphosate-tolerant (GT) crop, the rootworm-resistant Bt crop, and the drought-tolerant (DT) crop.

The first essay investigates the economic and environmental consequences of legislation restricting the use of glyphosate, the most commonly used herbicide in U.S. corn production because of its complementarity with glyphosate-tolerant crops. A monetary framework comprising economic, human health, and environmental welfare analysis is developed to examine the welfare consequence of a hypothetical glyphosate tax, given the currently available alternative herbicides. The results suggest substantial economic loss with only minor gains in human health and environmental welfare.

The second essay evaluates the regulatory needs for balancing short-term rootworm control benefits with long-term costs of lost pest susceptibility in rootworm-Bt corn planting. Changes in

Bt efficacy are related to historical Bt planting to determine the empirical long-term cost, which is then incorporated into a dynamic game of Bt planting to align it with current pest damage and risk of Bt efficacy erosion and propose counterfactual changes for sustainable use to benefit producers. Our findings indicate the necessity for region-specific regulation strategies, with the East significantly lowering rootworm Bt planting and the West adopting a more integrated management strategy.

The third essay assesses the climate adaptation value of drought-tolerant corn in the context of crop insurance. Using a county-level panel dataset in the Corn Belt of the United States, we found that yield implications of DT crops differ by region: drought-related yield risks, measured using insurance claims data, are found to be lower with higher DT planting rates for Western Corn Belt but not the Eastern counties. Further quantile analysis and simulations for the rainfed Western Corn Belt counties suggest that insurance premiums need to be reduced to reflect the yield protection value of DT innovation and be actuarially fair.

I would like to dedicate this dissertation to Mx. Music.
I appreciate your company and the pleasure you gave along the way.

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KEY TO ABBREVIATIONS

AES	Allen-Uzawa Elasticity of Substitution
APE	Average Partial Effects
Bt	Bacillus thuringiensis (Crop)
CDF	Cumulative Distribution Function
CRD	Crop Reporting District
CRE	Correlated Random Effect
DSCI	The Drought Severity and Coverage Index
DT	Drought-tolerant (Crop)
EDM	Equilibrium Displacement Model
EIQ	Environmental Impact Quotient
EPA	The Environmental Protection Agency
GDD	Growing Degree Days
GE	Genetically Engineered (Crop)
GT	Glyphosate-tolerant (Crop)
HH-E	Human Health and Environment
HT	Herbicide-tolerant (Crop)
IARC	The International Agency for Research on Cancer
LCR	Loss-cost Ratio
NASS	The National Agricultural Statistics Service
PDF	Probability Density Function
PEA	Pesticide Environmental Accounting

PRISM	The Parameter-elevation Regression on Independent Slopes Model
R&D	Research and Development
SDD	Stress Degree Days

CHAPTER 1 Introduction

Crop biotechnology, which emerged in the late 1980s, has been a game-changer in human food production history. Unlike traditional breeding, which involves more randomness and uncertainty, biotech crops are purposefully designed to confer desirable qualities in a much shorter breeding time. The main impetus has been advancements in molecular genetic technologies, particularly molecular breeding and genetic engineering. The first generation of biotech crops deals with biotic stresses like insects (insect-resistant traits) and weeds (herbicide-tolerant traits), whereas the current second-generation – some commercialized, more in the pipeline – focuses on abiotic stresses like drought (drought-tolerant traits), quality, and nutrition.

The biotech story for maize production in the United States, which we focus on in this dissertation due to its economic importance to the world food supply, began with the introduction of insect-resistant Bt hybrids in 1996. This was quickly followed by the development of herbicide-tolerant corn resistant to the herbicide glyphosate. These first-generation crops, which are increasingly being stacked, have had enormous market success, with adoption rates above 90% since 2013. Second-generation hybrids, particularly drought-tolerant (DT) hybrids, have emerged on the market in recent years. Unlike its genetically modified predecessors, conventionally bred hybrids account for the vast majority of the DT market. Nonetheless, this newcomer is experiencing a comparable adoption rate. More traits are predicted to emerge in the future as breeding technology advances and computational power improves to support long-term food security for the world's rising population under climate change (Zaidi et al. 2019; Steinwand and Ronald 2020).

These unprecedented innovations have improved productivity and lowered commodity prices while also providing major environmental and health benefits, including reducing food contamination (Huang et al. 2005; Wu 2006; Yu et al. 2020; see Barrows et al. 2014 for a review).

The policy is also an indispensable aspect of the biotechnology story. Unlike in the past, the majority of modern biotech crops are produced and commercialized by the private sector, with public sector efforts focusing on early-stage R&D. The continuing biotech controversy is accompanied by public resistance as well as government regulations (Wu 2004; Potrykus 2010). Before commercialization, the benefits and risks of biotech crops are evaluated in field trials, and regulatory approvals are required to import or use these crops, particularly for the genetically engineered hybrids.

However, the role of policy and regulations is not confined to premarket authorization and sometimes concerns related markets, resulting in significant economic and environmental implications. The value of biotechnology innovations is not solely a scientific issue; rather, it involves trade-offs between benefits and risks, economic and environmental aspects, and today versus tomorrow – and thus is dependent in part on regulatory efforts to strike a balance and accommodate the technology within the agronomic system and agricultural policy environments, such as the federal crop insurance program. This is what the three essays in this dissertation seek to demonstrate.

The first essay concerns the restrictive policy on glyphosate, an herbicide complementary to glyphosate-tolerant (GT) crops. Since the commercialization of transgenic glyphosate-tolerant (GT) crops, glyphosate has become the dominant herbicide for weed management in corn in the United States and elsewhere. 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 trade-offs: human health and environmental (HH-E) impacts versus market economic impacts, as well as 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 the first 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 $6 million US per annum; but also a net market economic loss of $98 million US 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.

In the second essay, we investigated whether a paradigm shift in rootworm-targeting Bt corn planting is needed. Corn rootworm is a prominent pest in the Corn Belt of the United States. Larvae feed below-ground on corn roots, lowering grain output and causing over one billion dollars in losses each year. The rootworm-active Bt corn expressing insecticidal protein was first released in 2003 and has since gained widespread adoption. Although non-Bt host refuges are planted to delay resistance, Bt efficacy has been declining as the pest evolves resistance, incurring the long-term cost of lost pest susceptibility. To empirically assess the cost of Bt efficacy erosion in the context of rootworm control, we link root damage data from Bt and non-Bt experimental fields with regional Bt planting data in 10 Corn Belt states from 2005 to 2016. The Bt treatment reduces root injury by around 1.3 nodes on average, but much of the Bt efficacy is lost if the cornfield had a history of Bt planting in the preceding year. Intertemporal suppression can somewhat offset the efficacy loss induced by Bt history, but the net cost is still equivalent to a 12% reduction in Bt efficacy. A dynamic game analysis of Bt planting that considers the long-term cost suggests that states in the West and East require different regulatory strategies. Because the East has low pest incidence, a low Bt planting level will benefit the region while also conserving the technology, or the susceptibility resource, for the future, whereas the West has higher pest pressure, which results in relatively high short-term benefits and justifies a high Bt planting level, so a more integrated management strategy synthesizing different technologies may be warranted.

The final essay evaluates the climate adaptation value of drought-tolerance (DT) technology in the context of the federal crop insurance program. Drought-related crop insurance claims account for about half of all indemnity payments in the United States, owing to an increase in the frequency and severity of drought incidents. Drought-resistant crops are seen as a promising technology for reducing drought sensitivity and adapting to warmer climates. Tolerance to abiotic conditions such as drought, in contrast to biotic stresses, involves more physiological processes and genes. Despite promising field trial findings, the use of this second-generation biotech maize in large-scale commercial production is still unknown. Using a unique panel dataset on seed use in U.S. Corn Belt from 2001 to 2016, we empirically assess the yield implications of commercially marketed DT crops, characterizing the technology across the entire continuum of environmental stress. We found that counties in the Western Corn Belt with higher DT planting rates have lower drought-related yield risk, as measured by indemnified payments divided by total liability, but otherwise for the Eastern counties, likely due to seed companies prioritizing the western market in research and development and selecting hybrids suitable for growing conditions in the region. Further investigations in the rainfed Western Corn Belt show no yield penalty but a slight yield advantage under favorable conditions, and that the DT innovations qualify as a climate adaptation technology with greater benefits in a more stressful environment. Simulations of actuarially fair crop insurance premiums suggest that large reductions are needed to accommodate the new technology in the existing Western Corn Belt farming system.

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CHAPTER 2 Environmental and Economic Concerns Surrounding Restrictions on Glyphosate Use in Corn

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Introduction

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 (IARC 2015), linking glyphosate exposure to increased risk of certain blood cancers. Although IARC's hazard assessment had produced different results from those conducted by other institutions (NTP 1992; JECFA 1998; EFSA 2015; JMPR 2016; EPA 2017; Andreotti 2018), 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 \$63 billion US, consented to pay \$10 billion US to settle tens of thousands of lawsuits linking its glyphosate-containing herbicide Roundup to non-Hodgkin's lymphoma (NHL) among applicators (Cohen 2020). Despite the lack of scientific consensus on the actual carcinogenicity of glyphosate, three trials in 2018-2019 favored plaintiffs who had attributed glyphosate exposure to non-Hodgkin's lymphoma.

Concerns regarding IARC's scientific evaluation have been discussed extensively in EPA (2017), Andreotti et al. (2018), 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 (BHAG 2020), 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 (Böcker and Finger 2016; Anderson 2017), and the animal product tax proposed to account for antibiotic use externalities (Giubilini et al. 2017). 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 vs. 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 or GT) transgenic crops, especially corn and soybean in the 1990s. Because 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 (Barber et al. 2021).

Although glyphosate and other herbicides have allowed growers to reduce their reliance on tilling fields when controlling weeds (Carpenter and LP Gianessi 1999; Swinton and Deynze 2017), 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 (Livingston et al. 2015) and tillage use (Deynze et al. 2018) choices.

Over the period 1998-2016, 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 2010-2016, the market has been dominated by four chemicals - glyphosate, atrazine, acetochlor, and S-metolachlor - with a total market share of approximately 90%, and more than 50 chemicals accounting for the residual 10% (**Figure 2.1** A). Therefore, we restrict our study period to 2010-2016 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 (**Figure 2.1** 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 about 2011. A similar time trend is observed for conventional tillage, likely due to the onset of weeds that have evolved resistance to glyphosate (Deynze et al. 2018) (**Figure 2.1** C). While the last twenty years 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 (**Figure 2.1** D).

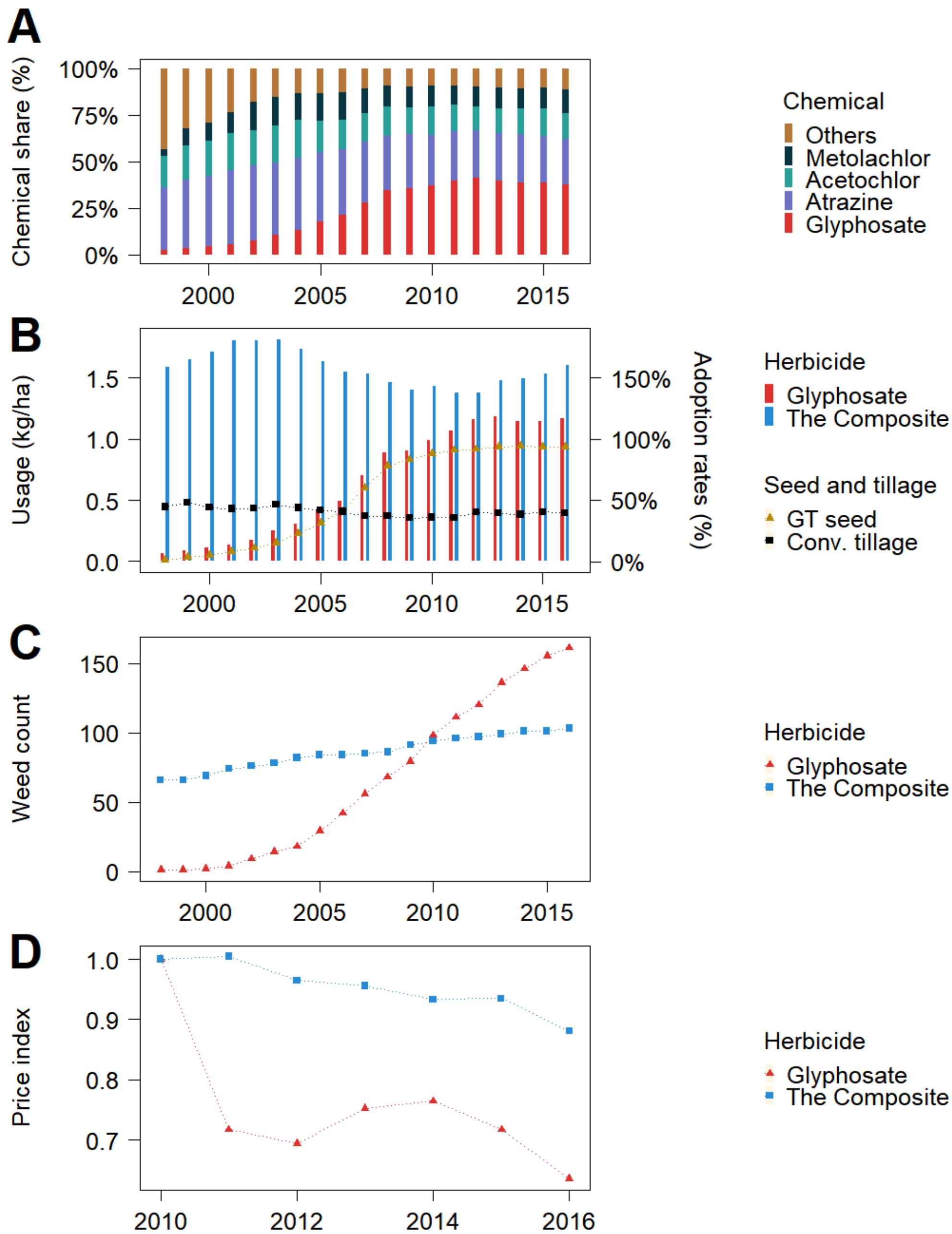

Figure 2.1 Time trend of herbicide use, seed choice, tillage practice, weed resistance, and herbicide prices in U.S. corn production, 1998-2016.

Panel: (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. 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 U.S. 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 2010-2016 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 panel C, and AgroTrak®, GfK Kynetec for other panels.)

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 "sufficient evidence" in animal experiments and "limited evidence" for human carcinogenicity; specifically, non-Hodgkin's lymphoma (NHL) (IARC 2015; Guyton et al. 2015a; Guyton et al. 2015b).

The paucity of data on individual-level glyphosate exposure has resulted in limited human evidence on the association (Gillezeau et al. 2019); however, more recent comprehensive cohort studies have provided little support for IARC's determination of probable human carcinogenicity (Andreotti et al. 2018; Leon et al. 2019). The Agricultural Health Study, a collaboration between the US National Institutes of Health (NIH) and Environmental Protection Agency (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 (Andreotti et al. 2018; Tarazona et al. 2017).

Although much remains unresolved about how glyphosate interacts with insect physiology (Motta et al. 2018; Farina et al. 2019; Vázquez et al. 2020), it is considered to have low environmental toxicity (Meftaul et al. 2020). 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. (Brower et al. 2012), 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 glyphosate-tolerant seed adoption and correspondingly extensive glyphosate use (Pleasants and Oberhauser 2013; Pleasants 2017; Saunders et al. 2018). Using museum collection data of monarch specimens, however, a more recent PNAS study (Boyle et al. 2019) 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 glyphosate-tolerant crops. A lively debate has ensued regarding the merits of the museum data collection methodology (Wepprich 2019; Ries et al. 2019; Boyle et al. 2019).

Modeling Approach

From the social welfare perspective of pesticide regulation (Cropper et al. 1992), 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 towards alternative herbicides (Böcker et al. 2018; Böcker et al. 2020). 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 (Zilberman and Millock 1997; Böcker and Finger 2016), we first develop a 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 2010-2016. 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:

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

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 represent the set of conditioned covariates in the equation, including: $\ln P_{c[i],t}$, 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 represents 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 **Figure 2.2**.

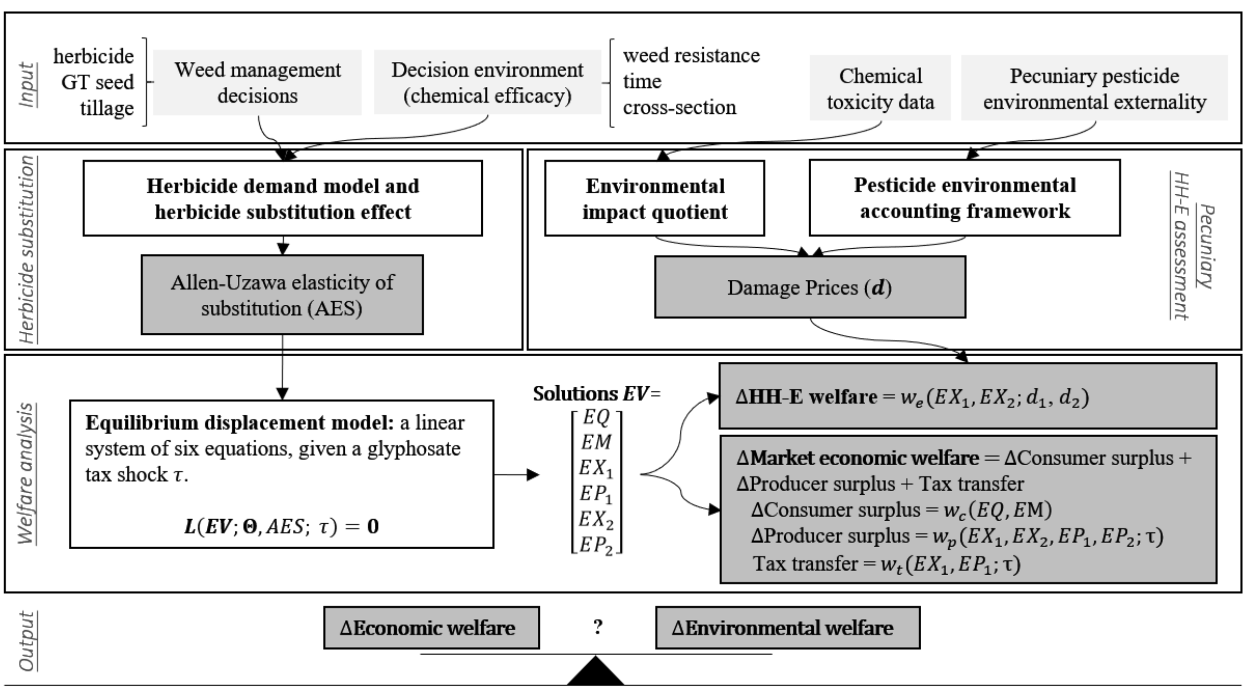

Figure 2.2 Model schematic for quantifying welfare effects of glyphosate policies.

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 Allen-Uzawa elasticity of substitution (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 human health and environmental (HH-E) welfare, consumer surplus, producer surplus, and tax transfer, respectively.

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 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 $\hat{v}$ (Papke and Wooldridge 2008).

In our analysis, we estimate a set of models with various endogeneity hypotheses. For

Models 1-3, 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 2.1** presents the second-step coefficient estimation results for the glyphosate demand equation (see Appendix, **Table 2.A4** for the first-step regression results, and **Table 2.A5** 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.

Table 2.1 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	
	Coeff.	APEs	Coeff.	APEs	Coeff.	APEs	Coeff.	APEs	Coeff.	APEs
$\ln P$	0.151[a]	0.058[a]	0.152[a]	0.058[a]	0.177[a]	0.062[a]	0.176[a]	0.062[a]	0.148[a]	0.057[a]
	(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[c]	-0.010[c]	-0.034[b]	-0.012[b]	-0.032[c]	-0.011[c]		
	(-1.62)	(-1.63)	(-1.70)	(-1.72)	(-2.38)	(-2.40)	(-1.85)	(-1.85)		
GT	0.424[a]	0.162[a]	0.439[a]	0.168[a]	1.074[a]	0.376[a]	1.072[a]	0.377[a]		
	(3.82)	(3.79)	(4.29)	(4.28)	(22.40)	(25.73)	(19.00)	(22.91)		
$Till$	-0.374	-0.143	-0.083[a]	-0.032[a]	-0.426[a]	-0.149[a]	-0.097[a]	-0.034[a]		
	(-1.42)	(-1.42)	(-5.03)	(-5.12)	(-2.79)	(-2.78)	(-5.35)	(-5.43)		
$\hat{v}_1$	1.052[a]		1.037[a]							
	(8.68)		(9.02)							
$\hat{v}_2$	0.285				0.332[b]					
	(1.08)				(2.17)					
CRE	Yes		Yes		Yes		Yes		Yes	
CF	Yes		Yes		Yes		No		No	
F-statistic										
GT	50.27		100.6							
Till	16.59				31.77					
Overidentification test										
			0.805		0.861					

Notes: $N \times T$*=29,711.* z statistics in parentheses. Statistical significance is marked with superscripts a-c (^{a} $p < 0.01$, ^{b} $p < 0.05$, ^{c} $p < 0.10$). 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. Standard errors 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. 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 (Stock and Yogo 2005), and the F-statistic for GT in Model 2 is also close to the threshold of 104.7 suggested in more recent research (Lee et al. 2020), 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.

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 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 Allen-Uzawa elasticity of substitution (AES) between glyphosate and other commonly used herbicides ("composite") with a value of 0.739 (See 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 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 (Fernandez-Cornejo et al. 1998; Böcker and Finger 2017), 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 (Just 2006; Popp et al. 2013; Fernandez-Cornejo et al. 2014).

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 simulated damage scenarios are (A) neither effects; (B) carcinogenic effects only; (C) monarch butterfly effects only; and (D) both effects. Using the Pesticide Environment Accounting framework (Leach and Mumford 2008; Leach and Mumford 2011) combined with the Environmental Impact Quotient approach (Kovach et al. 1992; Brookes and Barfoot 2012; Beckie et al. 2014; Perry et al. 2016a) which accounts for a range of HH-E effects, damage prices per gallon of herbicide are calculated. See Appendix, Section D for a discussion on methods and Appendix, **Table 2.A7-2.A8** 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)-(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 2010-2016 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 vs. other herbicides corn growers would use if glyphosate use were restricted. A log-linear equilibrium displacement model (EDM) is developed to analyze the effects of a glyphosate tax on HH-E and market economic welfare (Muth 1964; Alston and Scobie 1983; Mullen et al. 1988). We calibrate our model by combining various sources of information (See Appendix, **Table 2.A11** for sources). Most of the parameter calibrations are drawn from previous studies or are computed from data sources, except the Allen-Uzawa elasticity of substitution (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 (Just 2006; Norton et al. 2008). 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.

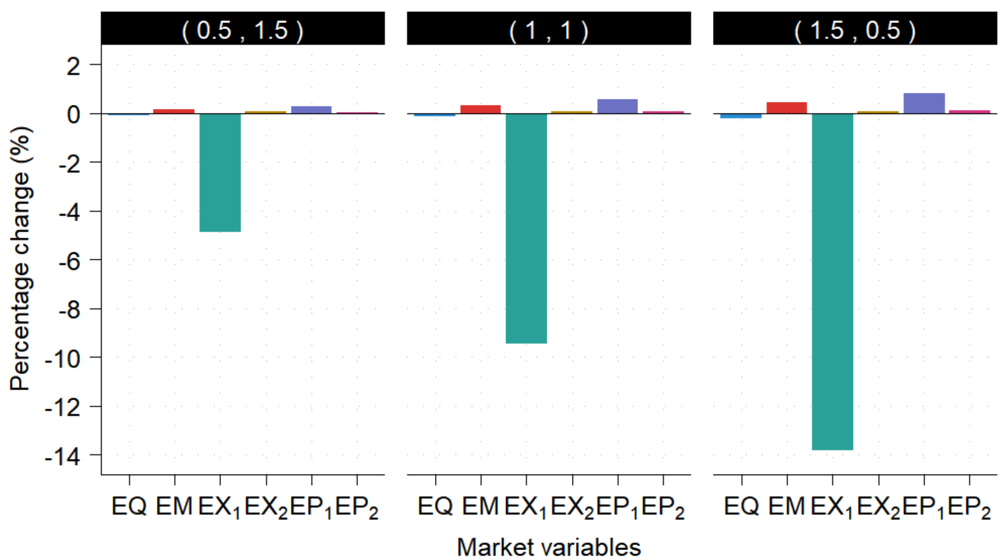

Figure 2.3 Percentage changes in market variables at 10% glyphosate tax.

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).

The simulation results for equilibrium solutions and welfare effects are presented in **Figure 2.3-2.4**. 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 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 (**Figure 2.3**).

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 non-linear 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 (**Figure 2.4**). 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 non-linearity 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.

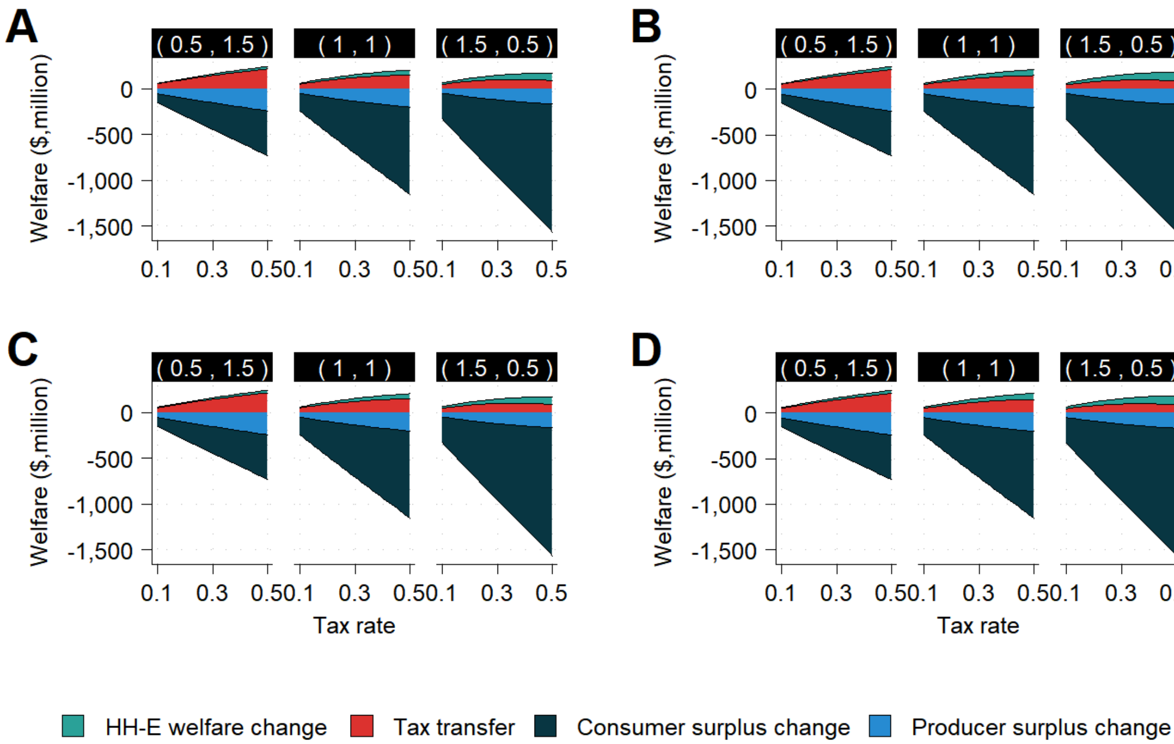

Figure 2.4 Nation-level welfare effects.

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 human health and environmental (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 (Böcker et al. 2018; Böcker et al. 2020) or taxes that reduce farmers' incentives to use this herbicide (Zilberman and Millock 1997; Böcker and Finger 2016). Hence, farmers who previously used glyphosate on corn fields might turn to alternative herbicides, or increase tilling, or follow a combination of these strategies to control weeds; instead of using glyphosate. Ours is the first analysis that 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 2010-2016), the annual HH-E costs associated with glyphosate and the composite herbicide applications range from $308 million 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. (2016b) 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. (2019) 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 (Fernandez-Cornejo and Pho 2002; Hanlon 2015) 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 (Smith et al. 2005) and to insecticides (Gassman et al. 2014; Wan et al. 2017), 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 (Dayan 2019). Yet the development of weed resistance to glyphosate has reinvigorated research into weed management, leading to significant recent advances (Kahlau et al. 2020). 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 2010-2016) 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 the Appendix, Section C.3 to investigate the sensitivity to grouping chemicals.

Herbicide Demand System Estimation

Following the conceptual model we develop (see 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 (Binswanger 1974). 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 (Papke and Wooldridge 1996). The model is further extended to control for farm heterogeneity using the correlated random effects method, and for endogeneity using the control function approach (Papke and Wooldridge 2008; Wooldridge 2019). 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 Appendix, Section 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 2010-2016. 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. Data are representative at the Crop Reporting District level across the main US corn-growing states and have been used in our previous studies (Perry et al. 2016a; Yu et al. 2020). The data contain information on chemical and mechanical weed control practices, as well as seed varieties, for about 4,337 farms annually. See the 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 the Appendix, Section B.

Environmental Accounting and Scenario Simulation

We combine the Pesticide Environmental Accounting (PEA) framework (47) with the Environmental Impact Quotient (EIQ) approach (49) 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 non-toxic) 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 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 (47), 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 non-herbicide 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 (Appendix, **Table 2.A9**). 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 (Appendix, **Table 2.A10-2.A11**). In general, the parameter calibration uses information from periods that largely overlap with our study period 2010-2016.

APPENDIX

APPENDIX

A Herbicide substitution model: formulation and specification

A.1 Conceptual model

A conceptual model of herbicide demand is developed, assuming a cost-minimizing farmer. Suppose there exists a twice differentiable production function for corn production of an individual farm as follows:

$$Y = F(X, K, A), \tag{1}$$

where Y is output, X is a vector of herbicide inputs, K is a vector of other inputs that affect weed control, and A is a vector of all other inputs. If the weed control inputs (X, K) are homothetically weakly separable (Chambers 1988) from all other inputs then, the production function can be written as

$$Y = H(W(X, K), A), \tag{2}$$

where $W(\cdot)$, the aggregate weed control input, is a homothetic function.[1] The solutions to (X, K) can be equivalently obtained from solving

$$\min_{X,K} \quad C = XP_x + KP_k$$
$$subject\ to\colon\ \overline{W} = W(X, K),$$

where $\overline{W}$ denote the weed control target. A farmer is assumed to make weed control decisions in two stages where the optimal K is decided in the first stage and is denoted by $\overline{K}$. Then, taking $\overline{K}$

[1] The validity of this homothetic weak separability assumption is an empirical question. However, in our case, data for other inputs are not available.

as given, X is chosen in the second stage. The minimization problem is hence solved backward as follows:

Stage II: Taking $\bar{K}$ as given, a farmer obtains optimal herbicide choice $X^* = X(P_x, \bar{K})$ by solving

$$\begin{aligned} \min_{X} \quad & C = XP_x \\ & subject\ to\colon\ \bar{W} = W(X, \bar{K}). \end{aligned}$$

There exists a minimum cost function dual to the weed control input function $W(\cdot)$:

$$\tilde{C}^* = J(\bar{W}, P_x, \bar{K}), \tag{3}$$

where $\tilde{C}^*$ is the total cost of herbicide inputs and $\bar{W}$ is the aggregate weed control input. If $W(\cdot)$ is a positive, nondecreasing, linear homothetic (constant returns to scale), and concave function (Chambers 1988), then the cost function can be written as

$$\tilde{C}^* = \bar{W}G(P_x, \bar{K}), \tag{4}$$

where $G(\cdot)$ is a unit cost function satisfying the same regularity conditions and is a function of weed control inputs. The minimum unit cost function for the optimizing farmer is thus written as

$$C^* = G(P_x, \bar{K}). \tag{5}$$

Stage I: Knowing that $X^* = X(P_x, \bar{K})$, a farmer solves the first stage

$$\begin{aligned} \min_{\bar{K}} \quad & C = X(P_x, \bar{K})P_x + \bar{K}P_k \\ & subject\ to\colon\ \bar{W} = W(X(P_x, \bar{K}), \bar{K}), \end{aligned}$$

to obtain the optimal choice vector $\bar{K}^* = K(P_x, P_k, \bar{W})$.

A.2 Empirical model: the Translog cost function approach

There are generally two approaches to estimating an input demand system (Thijssen 1992; Chakir and Thomas 2003). The primal approach specifies separate factor demand equations and then undertakes joint estimation. The dual approach is more commonly used because it is easier to estimate in a way that complies with theoretical considerations. Furthermore, and directly relevant for our purposes, estimates are more readily used for policy applications. The dual approach specifies a flexible functional form for the cost (or profit) function and then derives the associated supply and demand factor equations. Following Binswanger (1974), a Translog cost function is employed to implement the dual approach. No *a priori* restrictions are imposed on elasticities of substitution in the Translog cost function. The Translog specification provides a second-order approximation to an arbitrary functional form. In avoiding a particular production function specification, the Translog specification gives more robust results. In our context, there are two herbicide inputs of interest: glyphosate and the composite herbicide, i.e., $X = (x_1,\ x_2)$, and $P_x = (p_1,\ p_2)$, with the subscripts 1 and 2 corresponding to glyphosate and the composite herbicide, respectively. The other weed control inputs that we consider as affecting the control function are GT seed and tillage, i.e., $\bar{K} = (\bar{k}_1, \bar{k}_2)$, where the subscripts 1 and 2 denote GT seed and tillage, respectively. Rewrite the minimum cost function in eq. (5) in natural logarithms:

$$\ln\,(C^*) = f\big(\ln(p_1), \ln(p_2), \bar{k}_1, \bar{k}_2\,\big). \tag{6}$$

Then the Taylor Series expansion is as follows:

$$\begin{aligned} \ln C^* \quad &= \textstyle\sum_{m=1}^{2} \alpha_m \ln(p_m) + \frac{1}{2}\sum_{m=1}^{2}\sum_{j=1}^{2} \beta_{m,j} \ln(p_m)\ln(p_j) \\ &+ \textstyle\sum_{m=1}^{2} \psi_m\, \bar{k}_m + \frac{1}{2}\sum_{m=1}^{2}\sum_{j=1}^{2} \vartheta_{m,j}\, \bar{k}_m \bar{k}_j \\ &+ \textstyle\sum_{m=1}^{2}\sum_{j=1}^{2} \gamma_{m,j} \ln(p_m)\, \bar{k}_j + \alpha_0 + remainder. \end{aligned} \tag{7}$$

Note that

$$\begin{aligned} \frac{\partial \ln C^*}{\partial \ln(p_m)} \quad &= \frac{\partial C^*}{\partial p_m} \cdot \frac{p_m}{C^*} = \frac{x_m}{\overline{W}} \cdot \frac{p_m}{C^*} = \frac{p_m x_m}{\tilde{C}^*} \\ &= \frac{p_m x_m}{\sum_{k=1}^{2} p_k\, z_k} = s_m, \end{aligned} \tag{8}$$

where x_m ($m \in \{1, 2\}$) represents the cost-minimizing input demand, s_m is the cost-share for input m, and the second equality holds because by Shepard's lemma we have

$$\frac{\partial \tilde{C}^*}{\partial p_m} = \frac{\partial \bar{W} \cdot C^*}{\partial p_m} = \bar{W} \cdot \frac{\partial C^*}{\partial p_m} = x_m. \tag{9}$$

Also, note that

$$\frac{\partial \ln C^*}{\partial \ln p_m} = \alpha_m + \sum_{j=1}^{2} \beta_{m,j} \ln(p_j) + \sum_{j=1}^{2} \gamma_{m,j} \bar{k}_j. \tag{10}$$

Hence the system of latent cost shares equations can be obtained as follows

$$s_m = \alpha_m + \sum_{j=1}^{2} \beta_{m,j} \ln(p_j) + \sum_{j=1}^{2} \gamma_{m,j} \bar{k}_j. \tag{11}$$

The standard assumed properties of the cost function (symmetry, homogeneity of degree one in prices), from neoclassical production theory, require the following parametric restrictions to be fulfilled:

$$\beta_{m,j} = \beta_{j,m}; \sum_{m=1}^{2} \beta_{m,j} = 0. \tag{12}$$

The second restriction (homogeneity) is fulfilled by the use of normalized prices. In estimation, the dataset excludes the farms that use neither glyphosate nor the composite. This is a simplification to ensure that the two cost-share equations sum to one and so to avoid unnecessary complications in econometric treatment. Empirically, the portion of excluded farms is very small, consisting of only 641 out of 30,362 observations (**Table 2.A1**). Following that, we drop the composite herbicide equation, and thus subscript m is dropped thereafter for notation simplicity. Then, the equation of interest is given by

$$\begin{aligned} s_{i,t} = \alpha + \beta_1 \ln P_{c[i],t} + \gamma_1 Resist_{s[i],t} + \gamma_2 GT_{i,t} \\ +\gamma_3 Till_{i,t} + \chi_t + \iota_s + \varpi_s Trend, \end{aligned} \tag{13}$$

where $s_{i,t}$ is the cost-share of glyphosate for farm i in year t. The variable $\ln P_{c[i],t}$ denotes the ratio of glyphosate price to the composite herbicide price in Crop Reporting District (CRD) c associated with farm i in year t. The weed resistance to glyphosate that varies at the state level and year is represented as $Resist_{s[i],t}$. The variables $Till_{i,t}$ and $GT_{i,t}$ denote the conventional tillage rate and GT adoption rate at the farm level. Symbols ξ_t, ς_s and $\alpha_s Trend$ represents year dummies, state dummies, and state-specific time trends capturing general technical changes across time and states.

A.3 Econometric model: extending fractional response approach

The fractional response approach is adopted to estimate the glyphosate cost-share equation, i.e., eq. (13). Developed by Papke and Wooldridge (1996), the fractional response approach models fractional variables that range from zero to one inclusive, and thus is a natural approach to estimating the glyphosate cost-share equation. Unlike Tobit-type models, the fractional response model does not impose a distribution on the dependent variable conditional on the independent variables. Instead, it directly specifies the conditional mean function as a probit function, i.e.,

$$E(s_{i,t}|x_i) = \Phi(x_{i,t}b), \tag{14}$$

where $\Phi(\cdot)$ denotes the standard cumulative density function while $x_{i,t}$ and b represent, respectively, the stacked covariates in eq. (13) and stacked coefficients. Note that the coefficients in eq. (13) are not identical to the coefficient vector b in eq. (14). The model can then be estimated using the quasi-maximum likelihood (QMLE). To the best of our knowledge, there have been few applications of the fractional response model to cost-share equation estimation, but Kölling (2012; 2018) has applied this idea in estimating the cost-share equations derived from a Translog cost function.

Heterogeneity and endogeneity with unbalanced panels. The above basic model is an idealized presentation without any econometric complications. However, our data structure gives rise to three technical issues: unobserved farm heterogeneity, potential endogeneity in the tillage and GT variables, and an unbalanced panel. Therefore, we extend the basic model to accommodate these complications.

We first consider unobserved farm heterogeneity. Letting c_i represent the farm heterogeneity, then we extend the conditional mean model in eq. (14) to become

$$E\left(\mathrm{s}_{i,t} \middle| \mathrm{x}_i, c_i\right) = \Phi\left(\mathrm{x}_{i,t} b + c_i\right). \tag{15}$$

The time-constant farm heterogeneity is potentially correlated with explanatory variables, GT and tillage variables in particular. A common practice to control for such correlations is the fixed effect. However, in nonlinear models, it is well-known that cross-sectional fixed effects will generally result in the so-called "incidental parameter problem", that is, with fixed periods and a large number of cross-sectional units that goes to infinity, the coefficient and average partial effect estimates will be inconsistent (Neyman and Scott 1948; Wooldridge 2010). An alternative approach is the correlated random effects (CRE) method, implemented through the Chamberlain-Mundlak device (Mundlak 1978; Chamberlain 1984; Papke and Wooldridge 2008). Concretely, assume

$$c_i | x_i \sim Normal(\theta + \bar{x}_i \zeta, \sigma_c^2),$$

where $\bar{x}_i$ are the time-averaged variables and unity is excluded from $x_{i,t}$. Then we have

$$E\left(\mathrm{s}_{i,t} \middle| x_i, \varepsilon_i\right) = \Phi\left(\theta + x_{i,t} b + \bar{x}_i \zeta + \epsilon_i\right), \tag{16}$$

where $\epsilon_i \equiv c_i - (\theta + \bar{x}_i \zeta)$ has a conditional normal distribution $\epsilon_i | x_i \sim Normal(0, \sigma_c^2)$. From the law of iterated expectations, the conditional mean model that is extended for farm heterogeneity becomes

$$E(\mathrm{s}_{i,t}|x_i) = E[(\mathrm{s}_{i,t}|x_i, \varepsilon_i)|\mathrm{x}_i] = \Phi(\tilde{\theta} + x_{i,t}\tilde{b} + \bar{x}_i\tilde{\zeta}), \tag{17}$$

where the coefficients in eq. (16) are scaled by $(1 + \sigma_c^2)^{-1/2}$ and become $(\tilde{\theta}, \tilde{b}, \tilde{\zeta})$. Intuitively, the correlated random effects method is a middle ground between the fixed effects (FE) and random effects (RE) methods that are commonly applied to panel data. While the FE allows for arbitrary dependence between c_i and x_i, and the RE assume independence between c_i and x_i, with the CRE we specify a parametric model for the conditional distribution of c_i to allow for its dependence on x_i in a restrictive way.

Although the CRE approach is commonly seen in nonlinear model applications, extending it from balanced to unbalanced panels is a nontrivial matter and needs additional treatment. Assuming that the unbalancedness, or time period selection, is not systematically associated with unobserved errors, Wooldridge (2019) has proposed a strategy to achieve the extension. Concretely, assume that c_i follows a normal distribution, and model the conditional mean and variance of c_i to depend on the covariates as well as time period selection, i.e.,

$$E(c_i|w_i) = \sum_{r=1}^{T} \theta_r \lambda_{ir} + \sum_{r=1}^{T} \lambda_{ir}\bar{x}_i\zeta_r\,;$$

$$Var(c_i|w_i) = \exp\left(\omega + \sum_{r=1}^{T-1} \lambda_{ir}\varphi_r\right).$$

where w_i denotes the set of conditioning variables, T is the maximum number of time periods in the panel, T_i denotes the number of periods some farm i is present in the dataset, and $\lambda_{ir} \equiv 1[T_i = r]$ is a time period selection indicator. Here ω denotes the variance parameter for $T_i = T$, and the φ_r parameters provide deviation of variance from $\exp(\omega)$ as T_i varies. Therefore, the distribution assumption on c_i for unbalanced panels is analogous to that for balanced panels, but is extended such that the coefficients vary with the number of periods indicated by λ_{ir}. Equivalently, we can write c_i as

$$c_i = \sum\nolimits_{r=1}^{T} \theta_r \lambda_{ir} + \sum\nolimits_{r=1}^{T} \lambda_{ir} \bar{x}_i \zeta_r + \epsilon_i \,,$$

where $\epsilon_i | w_i \sim Normal(0, \exp(\omega + \sum_{r=1}^{T-1} \lambda_{ir} \varphi_r))$. Then we obtain the following:

$$E\big(s_{i,t} \big| x_{i,t}, w_i\,\big) = \Phi\left(\frac{x_{i,t1}\tilde{b} + \sum_{r=1}^{T} \tilde{\theta}_r \lambda_{ir} + \sum_{r=1}^{T} \lambda_{ir} \bar{x}_i \tilde{\zeta}_r}{[\exp(\sum_{r=2}^{T} \lambda_{ir} \tilde{\varphi}_r)]^{\frac{1}{2}}}\right), \tag{18}$$

where we follow Wooldridge (2019) and re-parameterize, analogously to the balanced panel case. The new parameters are denoted by re-specifying with the upper tilde notation.

Now, since our specification involves two potentially endogenous variables, we further extend the model to control and explicitly test for endogeneity. We make some necessary notation changes: let $z_{i,t1}$ denote the exogenous variables in the estimation equation, i.e., the cost-share equation, $y_{i,t1}$ denote a potentially endogenous variable, $\mathrm{z_{i,t2}}$ denote the excluded exogenous variables as the instrumental variables, and write the complete set of exogenous variables as $z_{i,t} \equiv (z_{i,t1}, z_{i,t2})$. Similarly, denote the time averages of $z_{i,t}$ as $\bar{z}_i$. The conditional mean model is now expressed as

$$E\big(s_{i,t} \big| z_{i,t}, y_{i,t1}, c_i, u_{i,t}\,\big) = \Phi\big(z_{i,t1}\eta + \mu_1 y_{i,t1} + c_i + u_{i,t}\big), \tag{19}$$

where $u_{i,t}$ is the time-varying omitted factor that is potentially correlated with $y_{i,t1}$. We control for the endogeneity by applying the two-step control function approach (Papke and Wooldridge 2008; Rivers and Vuong 1988; Blundell and Powell 2003; 2004). This can be seen as an extension of Papke and Wooldridge (2008) for balanced panels to the unbalanced panels case. In contrast to the usual instrumental variables approach (two-stage least squares, in particular), which eliminates endogeneity through replacing the endogenous variable term with a linear projection on exogenous variables, the control function approach controls for the endogenous variation part of the endogenous variable. Importantly, the first approach will result in inconsistent estimates in non-linear models in general, so we adopt the latter. Concretely, assume

$$y_{i,t1} = \tau_1 + z_{i,t}\delta_1 + \sum\nolimits_{r=2}^{T} \tilde{\theta}_r \lambda_{ir} + \sum\nolimits_{r=2}^{T} \lambda_{ir} \bar{z}_i \tilde{\zeta}_r + v_{i,t1}; \tag{20}$$

$$\varepsilon_{i,t} = \rho_1 v_{i,t1} + e_{i,t1};$$

where $\varepsilon_{i,t} \equiv \epsilon_i + u_{i,t}$, and $e_{i,t1}$ is independent of $(z_{i,t}, v_{i,t1})$. The correlation between $u_{i,t}$ and $y_{i,t1}$ is thus captured by ρ_1. Then the conditional mean expression in eq. (18) is further extended to:

$$E\left(s_{i,t} \middle| z_{i,t}, y_{i,t1}, v_{i,t1}, w_i\right) = \Phi\left(\frac{z_{i,t1}\tilde{\eta} + \tilde{\mu}_1 y_{i,t1} + \tilde{\rho}_1 v_{i,t1} + \sum_{r=1}^{T} \tilde{\theta}_r \lambda_{ir} + \sum_{r=1}^{T} \lambda_{ir} \bar{z}_i \tilde{\zeta}_r}{\left[\exp\left(\sum_{r=2}^{T} \lambda_{ir} \tilde{\varphi}_r\right)\right]^{\frac{1}{2}}}\right). \tag{21}$$

Following that, a two-step procedure is straightforward:

(1) Step 1: obtain the pooled OLS residuals $\hat{v}_{i,t1}$ from regressing $y_{i,t1}$ on (1, $z_{i,t}$, $\lambda_{i2},\ldots,\lambda_{iT}$, $\lambda_{i2}\bar{z}_i,\ldots,\lambda_{iT}\bar{z}_i$);

(2) Step 2: estimate the fractional probit model in eq. (21) to obtain estimates for ($\tilde{\eta}$, $\tilde{\mu}_1$, $\tilde{\rho}_1$, $\tilde{\theta}_2,\ldots,\tilde{\theta}_T$, $\tilde{\zeta}_2,\ldots,\tilde{\zeta}_T$, $\tilde{\varphi}_2,\ldots,\tilde{\varphi}_T$). Denote the estimates as ($\hat{\eta}$, $\hat{\mu}_1$, $\hat{\rho}_1$, $\hat{\theta}_2,\ldots,\hat{\theta}_T$, $\hat{\zeta}_2,\ldots,\hat{\zeta}_T$, $\hat{\varphi}_2,\ldots,\hat{\varphi}_T$).

The control function approach provides a convenient test for endogeneity: the null that $\rho_1 = 0$ corresponds to $y_{i,t1}$ being exogenous. Moreover, although one endogenous variable is assumed here for illustration purposes, the model can be easily extended to allow for plural endogenous variables. For example, with an additional endogenous variable $y_{i,t2}$, simply add $y_{i,t2}$ and $\rho_2\hat{v}_{i,t2}$, where $\hat{v}_{i,t2}$ is obtained from a similar first step regression. For identification, there should not be perfect linearity among elements of $z_{i,t}$, while there should be time variation in $z_{i,t1}$ and $z_{i,t2}$. Vector $z_{i,t}$ may include time-constant variables, but their partial effect estimates may not be consistently identified. Time dummies may also enter $z_{i,t}$. Although for CRE with balanced models time dummies are excluded from $\bar{z}_i$, they are included for the unbalanced panel case, because the number of time periods varies so that the time dummy averages are no longer constant (Wooldridge 2019).

The asymptotic standard errors obtained from second-stage estimation are incorrect due to the two-step procedure, so panel bootstrapping is used, which resamples only the cross-sectional units but not years within each unit (Papke and Wooldridge 2008; Wooldridge 2019). The standard errors are clustered at CRD (Crop Reporting District) level to capture potential spatial correlation among farms within the same CRD because the data are collected to be representative at the CRD level. A similar estimation framework and application can be found in Bluhm et al. (2018).

A.4 Coefficient interpretation

Since the model is nonlinear, the coefficient estimates are interpreted through the Average Partial Effects (APE) statistics and through elasticities. Following Papke and Wooldridge (2008), we average across time and cross-section to estimate the APE. Define

$$m_{i,t} \equiv \left[\exp\left(\sum_{r=2}^{T-1} \lambda_{ir}\hat{\varphi}_r\right)\right]^{-\frac{1}{2}} \times \phi\left(\frac{z_{i,t1}\hat{\gamma} + \hat{\alpha}_1 y_{i,t1} + \hat{\rho}_1 \hat{v}_{i,t1} + \sum_{r=1}^{T} \hat{\theta}_r \lambda_{ir} + \sum_{r=1}^{T} \lambda_{ir}\bar{z}_i\hat{\zeta}_r}{[\exp(\sum_{r=2}^{T} \lambda_{ir}\hat{\varphi}_r)]^{\frac{1}{2}}}\right); \qquad (22)$$

$$\bar{m} \equiv (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} m_{i,t}\,; \qquad (23)$$

where $\phi(\cdot)$ denotes the standard normal density function. Then, for continuous variables $(z_{i,t1}, y_{i,t1})$, the APE is the coefficient estimate multiplied by $\bar{m}$. For example, the APE for $z_{i,t1}$ is $\bar{m}\hat{\gamma}$. For elasticities, formulas are given by

$$\kappa_{m,j} \quad = \frac{\partial \ln(x_m)}{\partial \ln(p_j)} = \frac{\partial \ln(s_m)}{\partial \ln(p_j)} + s_j = \frac{1}{s_m} \frac{\partial s_m}{\partial \ln(p_j)} + s_j; \tag{24}$$

$$\kappa_{m,m} \quad = \frac{\partial \ln(x_m)}{\partial \ln(p_m)} = \frac{\partial \ln(s_m)}{\partial \ln(p_m)} + s_m - 1 = \frac{1}{s_m} \frac{\partial s_m}{\partial \ln(p_m)} + s_m - 1; \tag{25}$$

$$AES_{m,j} \quad = \frac{\eta_{m,j}}{s_j} = 1 + \frac{1}{s_m s_j} \frac{\partial s_m}{\partial \ln(p_j)}; \tag{26}$$

where $\kappa_{m,j}$ is cross-price elasticity between input m and j, $\kappa_{m,m}$ is own-price elasticity, and $AES_{m,j}$ is the Allen-Uzawa elasticity of substitution (AES) (Berndt and Wood 1975). Then the average elasticities are obtained by averaging across the sample (both time and unit) the estimates of elasticities using the following formulas:

(1) glyphosate own-price elasticity = $m_{i,t}\hat{\gamma}_1/\hat{s}_{i,t} - 1 + \hat{s}_{i,t}$;

(2) composite own-price elasticity = $m_{i,t}\hat{\gamma}_1/(1 - \hat{s}_{i,t}) - \hat{s}_{i,t}$;

(3) glyphosate-composite cross-price elasticity = $-m_{i,t}\hat{\gamma}_1/\hat{s}_{i,t} + 1 - \hat{s}_{i,t}$;

(4) composite-glyphosate cross-price elasticity = $-m_{i,t}\, \hat{\gamma}_1/(1 - \hat{s}_{i,t}) + \hat{s}_{i,t}$;

(5) Allen-Uzawa elasticity of substitution = $1 - m_{i,t}\, \hat{\gamma}_1/[\hat{s}_{i,t}\, (1 - \hat{s}_{i,t})]$;

where the predicted glyphosate cost-share $\hat{s}_{i,t}$ is given by

$$\Phi\left(\frac{z_{i,t1}\hat{\eta} + \hat{\mu}_1 y_{i,t1} + \hat{\rho}_1 \hat{v}_{i,t1} + \sum_{r=1}^{T} \hat{\theta}_r \lambda_{ir} + \sum_{r=1}^{T} \lambda_{ir} \bar{z}_i \hat{\zeta}_r}{[\exp(\sum_{r=2}^{T} \lambda_{ir} \hat{\varphi}_r)]^{\frac{1}{2}}}\right). \tag{27}$$

B Data and Variables

B.1 The AgroTrak® survey

The AgroTrak® survey data, on which we primarily rely for the analysis, is a large continuous panel dataset that collects plot-level information on crop protection chemical usage in the US on an annual basis. The survey is conducted by GfK Kynetec, a market research company that specializes in agricultural market research, and is representative at the CRD level. Rigorous procedures and extensive quality control measures are taken to ensure representativity. For example, to establish a comprehensive sample base, the respondents are obtained from exhaustive sources, including government lists from the USDA and the FSA, agricultural publication subscription lists, and agricultural association lists. Data collected are reviewed and verified by specially trained personnel and Kynetec USA analysts in terms of accuracy, completion level, internal consistency, and compatibility with external information. In addition, previous studies that use the AgroTrak® survey data have conducted external validation. For instance, Perry et al. (2016a) has cross-validated the genetically-engineered variety adoption information using the USDA National Agricultural Statistics Service (NASS) survey data. More information regarding the AgroTrak® survey data can also be found in the Supplementary text of Perry et al. (2016a).

The AgroTrak® raw data is at the field level, consisting of 77,802 field-level observations during 2010-2016, and each observation is associated with a farm identifier. The survey is designed such that a proportion of farms participating in previous years are followed. As a result, a subset of farms is sampled repeatedly across years. **Table 2.A2** provides an overview of the repeated farm-level sampling. The table shows that around 50% of farms are repeatedly sampled. In addition, there are 30,362 farm-year observations and 14,382 unique farms, so a farm is sampled for 2.1 years on average. We extract and use for analysis herbicide use and expenditure, seed trait (whether the planted seed contains GT trait), tillage practice, and planting area information for each plot. While the AgroTrak® data identifies the same farms across time periods, it does not identify whether two plots are identical in different years.

For the main analysis, we aggregated the plot-level raw data to the farm level in order to circumvent further complications in the already-complex econometric model. For example, the field-level analysis will involve controlling for discrete, as opposed to continuous, endogenous variables. Doing so is challenging for nonlinear models such as the fractional response model in Section A.3 (Wooldridge 2010). Analyzing data at the farm level is also reasonable because a farmer allocates resources for the entire farm when making production decisions. In total, 30,362 farm-level observations are available over the 2010-2016 interval. However, as discussed in Section A.2 above, we exclude all 641 observations that use neither glyphosate nor the composite herbicide. The final sample for analysis drops ten additional observations due to missing covariate values. As a result, the final sample for analysis consists of 29,711 observations. Panel A of **Figure 2.A1** illustrates our sample's geographical distribution.

B.2 Variables

This section describes the variables in more detail, devoting particular attention to excluded instruments.

Excluded instrument variables. For GT we use the GT seed price (*pgt*) and the Bt seed adoption rate (*Bt*) as instruments, while for $Till$ we use the diesel fuel price (*pfuel*) and soil erodibility (*hel8*). GT seed price is included because higher price decreases the relative benefit of planting GT seed and thus GT varieties become less preferable. The GT seed price is exogenously determined by the market and does not directly relate to herbicide decisions. Similarly, Bt adoption is assumed to correlate with GT adoption but does not directly affect herbicide choice. Biotech companies have been developing multi-traits seed products (Que et al. 2010), and GT trait has been increasingly stacked with other genetically engineered traits such as Bt, a genetic trait that provides crop protection from pests. As a result, if a farmer adopts Bt, then the marginal cost of adopting GT is reduced and so GT is more likely to be adopted. **Figure 2.A2** illustrates the trend in trait stacking. In recent years, around 95% of planting areas use GT seed where about 10% of plant varieties embed only GT traits and the rest are stacked with the Bt trait. **Figure 2.A2** also shows that GT trait is stacked with other HT (herbicide-tolerant) traits. By the same logic, other-HT seed adoption is also presumably correlated with GT**.** However, it is unlikely to be exogenous as it directly affects the benefits of alternative herbicides and thus of herbicide choice. On the contrary, the Bt adoption decision is associated with pest control rather than with weed control choice.

For tillage, conservation tillage generally requires less fuel (Triplett and Dick 2008), so fuel price will directly affect farmers' tillage decisions. We also include *hel8* as an excluded instrument for tillage. As is elaborated on in Perry et al. (2016b), a farm that grows crops on highly erodible land has stronger incentives to adopt conservation tillage in order to comply with conservation requirements for federal subsidies as laid down in the 1985 Farm Bill. Similarly, fuel price and land erodibility are exogenous to a farm and are unlikely to directly relate to herbicide use. A schematic for the econometric model specification is presented in **Figure 2.A3**.

Variable construction. Variables obtained from the AgroTrak® data are glyphosate cost share, herbicide prices, seed choices, and tillage choice. For each herbicide, i.e., glyphosate and the composite herbicide, prices are measured by the Fisher price index. For the base, we follow Perry et al. (2016b) and use the mean of the entire study period (2010-2016). The market for each herbicide is composed of a large number of subtly differentiated products, and the products available to and used in a county vary from county to county. For example, in our sample there are more than one hundred glyphosate products with different composition and prices, and a few products are pre-mixed with non-glyphosate chemicals such as 2, 4-D to enhance its efficacy, resulting in a price premium. This is similar for the composite herbicide. Therefore, we choose the fixed basket of products for constructing the price index by two criteria: first, the product mustn't be pre-mixed, that is, a glyphosate product will be excluded if it contains non-glyphosate active ingredients, and a composite product will be excluded if it contains active ingredients other than the three composite chemicals (atrazine, acetochlor, and S-metolachlor); and second, the share of its expenditure in the total expenditures should be no less than 5%. This gives us five products for glyphosate and six products for the composite herbicide as the basket. Following that, the variable $\ln P$ is defined as the log of the glyphosate price to composite price ratio. Herbicide prices are constructed at the CRD level, rather than farm level, to capture price homogeneity within a region.

For each farm, glyphosate cost-share s is calculated as glyphosate herbicide expenditure divided by total expenditures on glyphosate and the composite herbicide. For GT and Bt, We divide the area on which GT (Bt) seed (varieties that contain GT(Bt) trait) is planted by the farm's total planting area to obtain GT (Bt). Similarly, we use the conventional tillage acres divide by total planting acres of a farm to calculate $Till$.

The remaining variables are constructed from various sources. Weed resistance data come from the International Survey of Herbicide Resistant Weeds (ISHRW). Resistance is measured by the cumulative number of weed species that are identified to be resistant within a state in a year. The variable $Resist$ is defined as the difference between the glyphosate-resistant weed count and the sum of resistant weed counts across the composite herbicide components. A weed species is defined as being resistant to the composite herbicide if it is resistant to at least one of the three composite chemicals, namely atrazine, acetochlor, and S-metolachlor. The GT seed price is obtained from the TraitTrak™, another proprietary data product from GfK Kynetec, and varies at the state level. This dataset is also used by Perry et al. (22). The soil erodibility data come from the National Reserve Inventory (NRI). Indicator variable $hel8$ takes value 1 whenever the county average soil erodibility index associated with plot i is 8 or more (i.e., highly erodible), and value 0 otherwise. Lastly, diesel fuel prices are obtained from the U.S. Energy Information Administration (https://www.eia.gov/) and vary across the Petroleum Administration for Defense Districts (PPADs). We follow Perry et al. (2016b) and calculate the variable $pfuel$ by averaging diesel fuel prices from the prior September through to May of the year in question. **Table 2.A3** summarized the variables and data sources as well as providing summary statistics.

Variations in variables. As noted from previous sections that describe the data, identification is driven by temporal and spatial dimension variations in variables. **Figure 2.1** in the main text has provided a way to understand temporal variations in the explanatory variables. State-level maps of the main variables are also provided in **Figure 2.A1** to illustrate the spatial variations. Since the correlated random effect is applied to control for farm heterogeneity, we also present variations in the residualized variables in **Figure 2.A4**.

C Additional results

C.1 Full regression results

Table 2.A4 presents the first-step regression results for Models 1-3 in the main text, and the full estimates of the second-step regressions for Models 1-5 are provided in **Table 2.A5**. Both GT and $Till$ variables are assumed to be endogenous in Model 1. In Models 2 and 3 we assume that only GT and only $Till$ are endogenous, respectively. Model 4 assumes exogeneity of the two variables, and Model 5 excludes the control variables (GT, $Till$, $Resist$). **Table 2.A6** presents the complete set of average elasticity estimates which are obtained as described in Section A.4.

C.2 Notes on substitution

In our analysis, a critical step is to estimate the Allen-Uzawa elasticity of substitution (AES) from the herbicide demand model. As stated in the main text, the AES measures substitutability when holding output constant. Hence it is a metric for *net* substitution, as opposed to *gross* substitution where output is allowed to change. The AES can be expressed as the share-weighted cross-price elasticity for cost-minimizing input demand, thus the greater-than-zero estimate of AES suggests that glyphosate and the composite herbicides are *net* substitutes in the sense that the cost-minimizing input demand increases as the price of the other input increases. Although it is the AES estimate *per se* that is needed as a parameter for the equilibrium displacement model (EDM), in this section we provide additional results to show that the two herbicides are *gross* substitutes as well. This is equivalent to showing that the cross-price elasticities for profit-maximizing input demand are positive.

We first define a new set of parameters and variables that differ from those in the previous section. Let $x_i(p, \boldsymbol{w})$ denote the profit-maximizing factor demand, and $u_i(\boldsymbol{w}, y)$ the cost-minimizing factor demand, where $p, \boldsymbol{w}$, and y denote output price, input price vector, and output quantity. Sakai (1973) has provided decomposition equations of the total price effects into substitution and expansion effect, which connects the gross substitution that involves $\partial x_i(p, \boldsymbol{w})/\partial w_j$ and the net substitution that involves $\partial u_i(\boldsymbol{w}, y)/\partial w_j$. The decomposition is given by

$$\frac{\partial x_i(p, \boldsymbol{w})}{\partial w_j} = \frac{\partial u_i\big(\boldsymbol{w}, y(p, \boldsymbol{w})\big)}{\partial w_j} - \frac{\partial x_i(p, \boldsymbol{w})}{\partial p}\frac{\partial p}{\partial w_j} \tag{28}$$

The left-hand side is the gross change in input i in response to a change in input j's price. The first term on the right-hand side is the change in input i in response to input j's price change holding output prices constant, i.e., the substitution effect along the isoquant curve. The second term is the expansion effect and shows the response of input i to a change in input j's price through the effect of j's price on output price.

The compensated change in output price in this decomposition equation is in parallel to the compensated income change in Slutsky's equation in consumer's theory. Converting the decomposition equation into elasticity form gives

$$\epsilon_{i,j}(p, \boldsymbol{w}) = \epsilon_{i,j}(\boldsymbol{w}, y) - \epsilon_{i,p}(p, \boldsymbol{w})\epsilon_{p,j} \tag{29}$$

where

$$\epsilon_{i,j}(p, \boldsymbol{w}) = \frac{\partial \ln x_i(p, \boldsymbol{w})}{\partial \ln w_j}$$

$$\epsilon_{i,j}(\boldsymbol{w}, y) = \frac{\partial \ln u_i\big(\boldsymbol{w}, y(p, \boldsymbol{w})\big)}{\partial \ln w_j} = AES_{i,j} \cdot s_j$$

$$\epsilon_{i,p}(p, \boldsymbol{w}) = \frac{\partial \ln x_i(p, \boldsymbol{w})}{\partial \ln p}$$

$$\epsilon_{p,j} = \frac{\partial \ln p}{\partial \ln w_j}$$

Using this formula, we calibrate for $\epsilon_{i,j}(p, \boldsymbol{w})$ to investigate whether glyphosate and the composite herbicide are also *gross* substitutes, or equivalently, whether $\epsilon_{i,j}(p, \boldsymbol{w})$ is greater than zero. The value of the substitution effect, $\epsilon_{i,j}(\boldsymbol{w}, y)$, is obtained directly based on our estimates where AES is estimated to be 0.739. The predicted share of the composite herbicide is 0.501 and so $\epsilon_{i,j}(\boldsymbol{w}, y)$ is 0.370. For the expansion effect, we calibrate using the average herbicide as a reasonable approximation, due to data constraints. Lin et al. (1995) has estimated herbicide demand as a function of corn output prices and derived the elasticity to be around 0.55, which is used to approximate $\epsilon_{i,p}(p, \boldsymbol{w})$. For the output price response to herbicide price, a reference point could be established using the results under a perfectly competitive corn market where the total production cost should equal to corn price times yield. In that case, how output price changes with herbicide price change depend on the proportion of herbicide cost in the total cost. More specifically, $\epsilon_{p,j}$ should equal the herbicide cost share of total production cost. The largest proportion of corn production cost usually involves land, fertilizer, and equipment while herbicide takes up a relatively very small portion of the production cost. According to the cost estimate for corn production in Iowa,[2] the minimum and maximum proportions averaged over 2010-2016 are 2.8% and 4.1% respectively, so $\epsilon_{p,j}$ ranges from 0.028 to 0.041. Therefore, according to eq. (28), $\epsilon_{i,j}(p, \boldsymbol{w})$ is

[2] Iowa State University, https://www.extension.iastate.edu/agdm/crops/html/a1-20.html. Although corn production cost estimates are also available from alternative sources such as Purdue University and South Dakota State University, Iowa State University uniquely provides a separate cost estimate for herbicide instead of only pesticide or chemical cost as a whole, thus providing better precision.

calibrated to range from 0.347 to 0.355 and is positive, indicating a gross substitution relationship between glyphosate and the composite herbicide.

C.3 Robustness regressions

Alternative cost function specification. Various flexible functional forms have been tested that approximate cost functions without placing *a priori* restrictions on the elasticity of substitution. The two most commonly used in the literature are the Translog and the Generalized Leontief (GL). Evidence is divided on whether the choice of functional form is critical (Chalfant 1984; Borger 1992). For robustness purposes, we estimate the Generalized Leontief specification in this section.

While it is ideal to address the econometric issues in estimating the GL as we have done for the Translog, we are faced with technical difficulties caused by data availability. Specifically, our data do not provide the output information. Therefore, we have to rely on a unit cost function and transform the factor demand into shares in order to circumvent the need for the output variable in estimation. Recall that the cost-shares are obtained by differentiating the log cost with respect to log prices. The advantage of the Translog is that the cost function is in logarithmic form and thus the right-hand side expressions of the cost-share equations are linear in parameters. In contrast, the right-hand side expressions are generally nonlinear for other functional forms, including the GL. Therefore, we provide here the estimation of the GL without special treatment for the potential econometric issues, namely unobserved farm heterogeneity, endogeneity, and unbalancedness. The results should be viewed as a rough "benchmark" as a robustness check and should be interpreted with caution.

The unit cost function of the Generalized Leontief is given by

$$C^* = b_{11}p_1 + 2b_{12}(p_1p_1)^{\frac{1}{2}} + b_{22}p_2; \tag{30}$$

where p_1 and p_2 are glyphosate and composite herbicide, respectively, and C^* is the unit cost. The corresponding factor demands are then given by

$$x_1(p_1, p_2) = \frac{\partial C^*}{\partial p_1} = b_{11} + b_{12}\left(\frac{p_2}{p_1}\right)^{\frac{1}{2}}; \tag{31}$$

$$x_2(p_1, p_2) = \frac{\partial C^*}{\partial p_2} = b_{22} + b_{12}\left(\frac{p_1}{p_2}\right)^{\frac{1}{2}}. \tag{32}$$

Then we obtain the glyphosate cost-share equation as the following:

$$s_1 = \frac{p_1 x_1}{C^*} = \frac{b_{11}p_1 + b_{12}(p_1 p_2)^{\frac{1}{2}}}{b_{11}p_1 + 2b_{12}(p_1 p_1)^{\frac{1}{2}} + b_{22}p_2}. \tag{33}$$

Dividing by $b_{22}p_2$ in both nominator and denominator and transforming into logarithm form gives

$$\ln s_1 = \ln\left(b_1 \frac{p_1}{p_2} + b_2\left(\frac{p_1}{p_2}\right)^{\frac{1}{2}}\right) - \ln\left(b_1 \frac{p_1}{p_2} + 2b_2\left(\frac{p_1}{p_2}\right)^{\frac{1}{2}} + 1\right), \tag{34}$$

where $b_1 \equiv b_{11}/b_{22}$ and $b_2 \equiv b_{12}/b_{22}$. Adding the control variables, we estimate the following equation:

$$\ln s_1 = \ln\left(b_1 \frac{p_1}{p_2} + b_2\left(\frac{p_1}{p_2}\right)^{\frac{1}{2}}\right) - \ln\left(b_1 \frac{p_1}{p_2} + 2b_2\left(\frac{p_1}{p_2}\right)^{\frac{1}{2}} + 1\right) + r_0 Resist + r_1 GT + r_2 Till. \tag{35}$$

The equation is estimated using nonlinear least-squares. The Allen-Uzawa elasticity of substitution (AES) estimate is computed from the estimation results by averaging the value of elasticity across the sample. The AES estimate is 0.710, indicating a net substitution relationship between glyphosate and the composite herbicide, which is consistent with the economic implications from a Translog specification. The value is also close to the AES estimate from our main results (0.739).

Individual versus aggregated herbicide. In our analysis, the three alternative chemicals are aggregated to become the only alternative to glyphosate. One potential concern is that the three alternatives may respond differently to glyphosate reduction. For example, a possibility is that certain chemicals will decrease while others increase. Therefore, we conduct an additional analysis to investigate the sensitivity of our results to disaggregation.

Specifically, we use GT adoption as a glyphosate-related shock and analyze the response of the three individual alternative chemicals as well as the composite herbicide to it. We rely on the AgroTrak® data for analysis and estimate at the plot level for the period 2010-2016. The following equation is estimated for atrazine, acetochlor, S-metolachlor, and the composite herbicide, separately:

$$y_i = \alpha_{t[i]} + \beta_{t[i]} GT_i + \delta_{c[i]} T_{t[i]} + \theta_{f[i]} + u_i, \tag{36}$$

where the dependent variable is the active ingredient weight in pounds per acre applied on plot i when estimating for atrazine, acetochlor, and S-metolachlor, and is the product gallons per acre for the composite herbicide. The variable GT_i is a dummy variable which equals 1 whenever a plot is planted to GT corn and equals 0 otherwise. Parameter $\beta_{t[i]}$ is a time-specific coefficient, $\delta_{c[i]} T_{t[i]}$ represents CRD-specific trends, and $\theta_{f[i]}$ is the farm-level fixed effect. We are interested in the $\beta_{t[i]}$ parameter which captures the year-specific impacts of GT adoption on chemical use. However, as discussed in Section B.1, although a subset of farms is followed over time the plots on a farm are not necessarily identical across years and thus we can't control for unobserved plot heterogeneity through plot fixed effects. Consequently, plot-specific omitted factors that are correlated with GT_i, whether time-constant or time-varying, will cause bias. That the GT variable remains correlated with omitted factors after controlling for farm fixed effects in the main analysis suggests that GT is also highly likely to be endogenous in eq. (36). Therefore, we instrument it with GT seed price and whether Bt seed is used, similar to the approach taken in the main analysis (also see more details for the instruments in Section B.2). The tests also show that we can reject the exogeneity hypothesis at the 1% level, where the instruments pass the weak instrument and overidentification tests. We present the estimation results for $\beta_{t[i]}$ in **Figure 2.A5**. The results indicate that the response patterns are very similar across the three individual alternative chemicals as well as the composite herbicide. This provides indirect evidence that our results in the main analysis shall not be sensitive to the aggregation of the three alternative chemicals into one composite herbicide.

D Pecuniary environmental assessment model

D.1 EIQ: environmental damage measure

This section describes in detail the EIQ and PEA approach we apply in this paper, and the procedure for computing damage prices. This is followed by a discussion of the merits of these approaches as well as potential limitations as is relevant to the application. EIQ is adopted to measure the environmental and human health effects associated with the herbicides, with a higher score indicating greater environmental and human health impact. Generally, current pesticide risk assessment methods fall into three categories: the relative scoring method, the risk ratio method, and the fuzzy logit expert method. Among these methods, the EIQ approach (a relative scoring method) and the hazard quotient approach (a risk ratio method) are most commonly used in herbicide risk assessment. EIQ (Kovach 1992) has been widely used in the pesticide literature (Brookes and Barfoot 2012; Beckie et al. 2014; Brookes et al. 2017). The EIQ value of an individual pesticide is the average of farm-worker (applicator and picker), consumer (consumer and groundwater leaching), and ecological (fish, birds, bee, and beneficial insects) effects. In calculating the EIQ scores, the information about toxicity and the chemical's physical properties (e.g., plant surface half-life) are combined and weighted to reflect the risk from exposure. Alternatively, the hazard quotient approach (Nelson and Bullock 2003; Peterson and Hulting 2004) captures pesticide risk using the estimate of exposure (usually the amount of pesticide applied) divided by the toxicity endpoint of a pesticide (LD_{50} for acute toxicity, and NOAEL for chronic toxicity[3]) and has a direct interpretation as the number of LD50 or NOAEL values applied per unit of area.

Each of the approaches has its own merits and caveats. Some analysts have criticized scaling and weighting features of the EIQ, as well as its qualitative risk rating (Dushoff et al. 1994; Cox et al. 2005; Kniss and Coburn 2015; Leach and Mumford 2008). For example, its linearly additive nature implicitly assumes that the environmental damage is proportional to the amount of pesticide applied, but this is not fully scientifically grounded given that the dose-response curves for non-carcinogenic effects are usually non-linear. Moreover, impacts to only a small number of ecosystem species are taken into account, such as birds, fish, bees, and beneficial arthropods. Despite these shortcomings, the EIQ approach is more generally applicable and provides a convenient means of comprehensively summarizing a pesticide chemical using a single value. While the hazard quotient approach is free from many problems that EIQ has, it is less appropriate for this study for mainly two reasons. First, the units are not comparable across ecological receptors (e.g., fish, bees). Consequently, the hazard quotient has to be compared for each receptor separately, and

[3] LD_{50} (Lethal dose 50%) is defined as the dose that is lethal to 50% of a tested animal population such as rats, and NOAEL (No observed adverse effect level) is defined as the highest exposure/dose level at which there are no statistically or biologically significant increase in adverse effects when comparing an exposed to a non-exposed group.

monetizing the adverse effects for different receptors is challenging. Second, it uses the absolute value of toxicity endpoint, which makes adjustments for each of the carcinogenic and monarch butterfly effects more problematic. In contrast, the EIQ approach groups the toxicities into categories and rates each category on a scale from one to five, which facilitates simulation of the debated effects. In conclusion, despite potential limitations, EIQ remains a more appropriate measure of environmental and human health effects for our purpose.

D.2 PEA: monetary environmental accounting

To monetize the environmental damage, we adapt the Pesticide Environmental Accounting (PEA) framework developed by Leach and Mumford (2008). Essentially, we convert the absolute external cost of the average pesticide due to environmental damage into the external cost of an individual pesticide, based on its EIQ value. Given our specific study context, namely U.S. corn production, the external cost of the average pesticide in the United States is used. The original value presented in Pretty et al. (2001) was in pounds sterling, so we convert to US dollars using the average conversion rates from an online historical exchange rate database, OANDA rate® (https://www.oanda.com/) and also inflate to the year 2020 using the U.S. government Consumer Price Index (CPI) data (https://www.bls.gov/). Using the EIQ system, Leach and Mumford (2008) has distributed the average pesticide external effect across EIQ categories to obtain the external effect due to specific health and environmental effects. As shown in **Table 2.A7**, the externality cost per kilogram active ingredient (abbreviated as "a.i.") for the average pesticide in the U.S. is \$5.63, where \$0.77 is due to applicator effects.

For each EIQ category, the score is grouped into low, medium, and high to determine the weight that applies to the specific pesticide chemical, and the grouping procedure is described in

Leach and Mumford (2008). For example, the EIQ score of applicator effects for glyphosate is 5 under status-quo, which falls into the “low” range, so a weight of 0.5 is applied to obtain the applicator effect cost of glyphosate as $0.77*0.5=$0.39/kg a.i. Similarly, weights of 1 and 1.5 will be applied correspondingly for the medium and high ranges (Leach and Mumford 2008). Lastly, summing the externality costs of a herbicide across EIQ categories gives the total cost per kilogram active ingredient of the particular herbicide, and multiplying it by the average kilogram active ingredient per gallon product gives the damage price when measured in US dollar per gallon.

We recognize that the PEA framework we adopt is only as good as its underlying assumptions. First and foremost, it involves transferring the value of a point estimate when making use of the absolute external costs of average pesticides in the United States. It is a form of benefit transfer, which is a common approach in the environmental accounting literature but is usually considered more prone to transfer errors than its alternative, namely the function transfer approach (Rosenberger and Loomis 2003; Rosenberger and Stanley 2006; Boyle et al. 2010). Therefore, we have made several efforts to investigate the validity of such a transfer. In their original paper, Leach and Mumford (Leach and Mumford 2008) chose to transfer the point estimate from the Pretty et al. (2001) paper which has estimated the external cost of pesticides in the UK, Germany, and the USA. Careful considerations were put into the decision: upon analyzing several approaches, they chose that in Pretty et al. (2001) because the monitoring and remediation approach in that study is theoretically more robust than others that involve the variability of subjective valuations. The monitoring and remediation approach has also been applied in Pretty et al. (2000). Both Pretty et al. (2000) and Pretty et al. (2001) have been widely cited, supporting the soundness of the transferred study (Pretty et al. 2001). In addition, instead of using the average cost for three countries as is done in Leach and Mumford (2008), we transfer based on only the cost estimates in the United

States, in order to better match the contexts of the original study with the new application in terms of geographical area and population. In summary, the criteria for using a point estimate transfer (Rosenberger and Stanley 2006) have been largely met, so the concern over transfer error is mitigated.

Second, the framework is based on the EIQ approach and inevitably inherits the limitations of EIQ as discussed above, including its linear nature. Nevertheless, as is emphasized in the original Leach and Mumford (Leach and Mumford 2008) paper, the value of this framework is in providing a “simple tool that can quickly assess the indirect costs of individual pesticides based on their particular toxicological and environmental behavior”. Although several papers have estimated the environmental costs of pesticide application (Pretty et al. 2000; Pimentel 2005; Tegtmeier and Duffy 2004), these papers consider only the combined costs of all pesticides. To the best of our knowledge, the Leach and Mumford (2008) approach used here is the only tool available that provides a unified framework by which to transform the environmental damage into monetary measures for an individual pesticide, and it appears to be reasonably valid for conducting environmental accounting (Waterplot and Zilberman 2012; Praneetvatakul et al. 2013; Grovermann et al. 2013). **Tables 2.A7-2.A8** illustrate the procedure for computing damage prices for glyphosate and the composite herbicide, respectively. It is noted that the three chemicals in the composite herbicide - atrazine, acetochlor, and S-metolachlor - happen to have the same weight for each of the EIQ categories. This shows the comparatively similar toxicological properties of the three chemicals.

E Welfare analysis model

E.1 Equilibrium displacement model: formulation

The market equilibrium can be characterized by the following six equations:

(a) Consumer demand: $Q = f(M)$;

(b) Production: $Q = Q(X_1,\ X_2)$;

(c) Factor demand for input 1: $P_1 = MQ_1(X_1, X_2)$;

(d) Factor demand for input 2: $P_2 = MQ_2(X_1, X_2)$;

(e) Factor supply for input 1: $X_1 = g_1(P_1)$;

(f) Factor supply for input 2: $X_2 = g_2(P_2)$;

where the subscript is equal to 1 for glyphosate, and 2 for the composite herbicide. The system is composed of six endogenous variables: Q, the quantity of output corn; M, the price of corn; P_1 and P_2, the prices of glyphosate and the composite herbicide; X_1 and X_2, the quantity of glyphosate and the composite herbicide. Expressions $g_1(\cdot)$ and $g_2(\cdot)$ denote the supply functions for glyphosate and the composite herbicide, respectively, while $f(\cdot)$ denotes the demand function for corn. The production function, as a function of the two inputs, is $Q(\cdot)$ and is assumed to exhibit constant returns to scale so as to be consistent with long-run equilibrium conditions in a competitive industry. Expressions $Q_1(\cdot)$ and $Q_2(\cdot)$ denote the partial derivatives of $Q(\cdot)$, i.e., the marginal products of glyphosate and the composite herbicide.

Totally differentiating the equations above, converting to elasticities, and adding the exogenous shock of a glyphosate tax (modeled in the input supply equation) gives

(a’) $EQ = \zeta EM$

(b’) $EQ = \kappa_1 EX_1 + \kappa_2 EX_2$

(c’) $EP_1 = EM - (\kappa_2/\vartheta)EX_1 + (\kappa_2/\vartheta)EX_2$

(d’) $EP_2 = EM + (\kappa_1/\vartheta)EX_1 - (\kappa_1/\vartheta)EX_2$

(e’) $EX_1 = \epsilon_1[EP_1 - \tau]$

(f’) $EX_2 = \epsilon_2 EP_2$

where EX denotes dX/X, or $dln(X)$, ζ denotes the price elasticity of consumer demand for corn, κ_m ($m \in \{1, 2\}$ for glyphosate and the composite herbicide, respectively) is cost share of input m, and $\kappa_m \equiv P_m X_m$/(Total corn production cost), ϑ is the Allen-Uzawa elasticity of substitution (AES) between glyphosate and the composite herbicide, and ϵ_m denotes elasticity of supply for input m. Symbol τ represents a vertical shift in the supply of input 1, i.e., the glyphosate tax rate that is imposed.

E.2 Solutions and welfare effects

Solving the system of logarithmic differential equations yields a set of solutions expressed in terms of elasticity parameters and the exogenous supply shifter. The expressions are presented in **Table 2.A9**. Following that, welfare effects can be calculated using formulas presented in **Table 2.A10**. In the welfare calculation, other than the parameter calibrations that are given in the paper, baseline values for the endogenous variables are also needed. The baseline values and data sources are summarized in **Table 2.A11**.

Figures and Tables

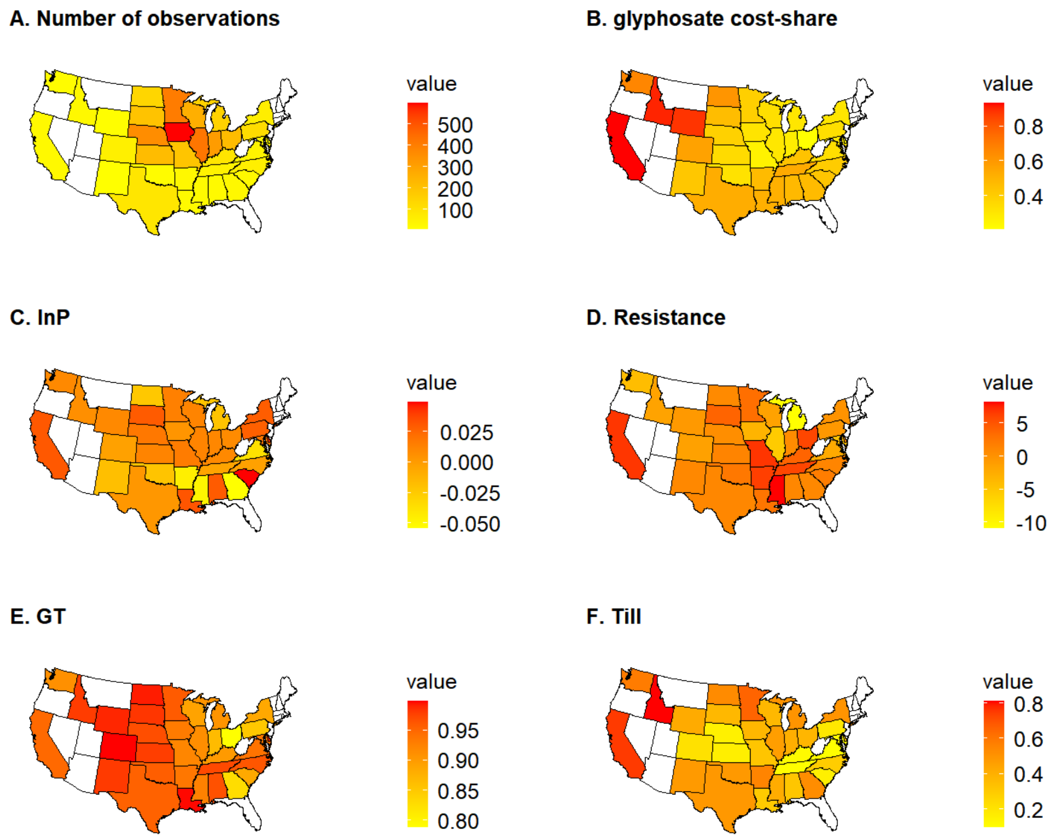

Figure 2.A1 State-level maps of main variables, averaged over 2010-2016.

Panel: (A) Number of farm-year observations. (B) Glyphosate cost-share, the dependent variables. (C)-(F) explanatory variables in the glyphosate cost-share equation. Our sample includes 34 states in the United States, and the unsampled states are represented by white color. (Data sources: International Survey of Herbicide Resistant Weeds for panel D, AgroTrak®, GfK Kynetic for other panels.)

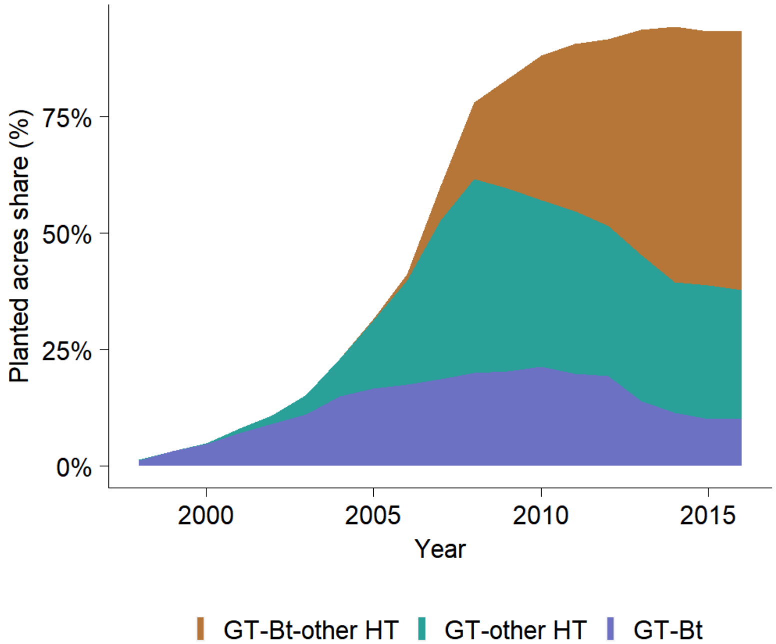

Figure 2.A2 Decomposition of GT (glyphosate-tolerant) seed adoption in US corn production (% of planted hectares), 1998-2016.

GT seeds consist of three types of stacking: GT only ("GT"), GT stacked with Bt ("GT-Bt"), and GT stacked with Bt and other HT ("GT-Bt-other HT). (Data source: AgroTrak®, GfK Kynetec.)

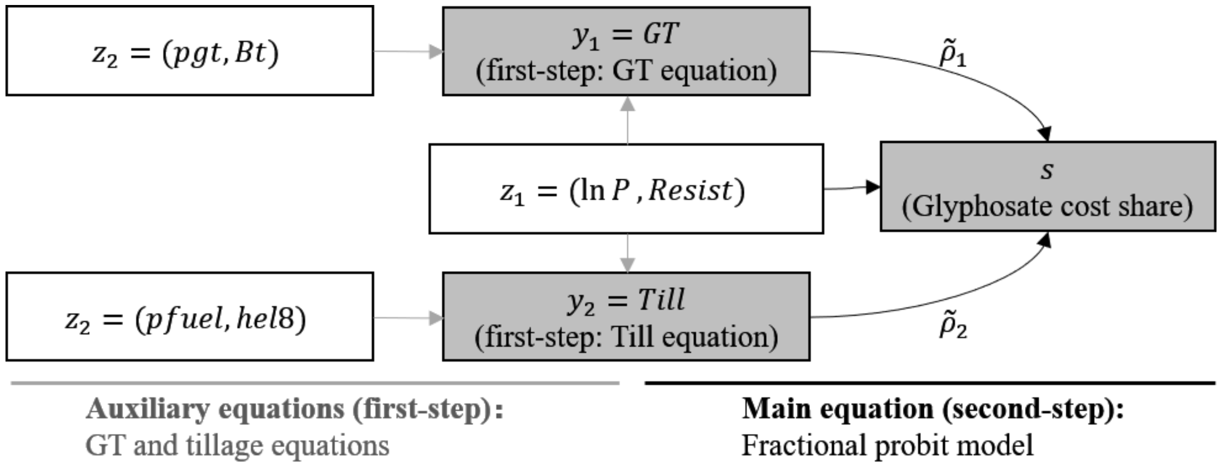

Figure 2.A3 Econometric model schematic for estimating the glyphosate cost-share equation.

For the main equation, i.e., the second-step fractional probit (eq. (21)), the main explanatory variables are $z_1 = (ln\, P, Resist)$, $y_1 = GT$, and $y_2 = Till$. The GT and $Till$ variables are hypothesized to be endogenous and thus are instrumented using first-step auxiliary equations (eq. (20)). The excluded instrumental variables for GT and $Till$ are (pgt, Bt) and $(pfuel, hel8)$, respectively. The residuals from the first-step regressions are $\hat{v}_1$ and $\hat{v}_2$. They enter the second-step regression as covariates. The main equation and auxiliary equations are connected through residual coefficients $\tilde{\rho}_1$ and $\tilde{\rho}_2$ which capture the correlation between the suspected endogenous variables and omitted factors.

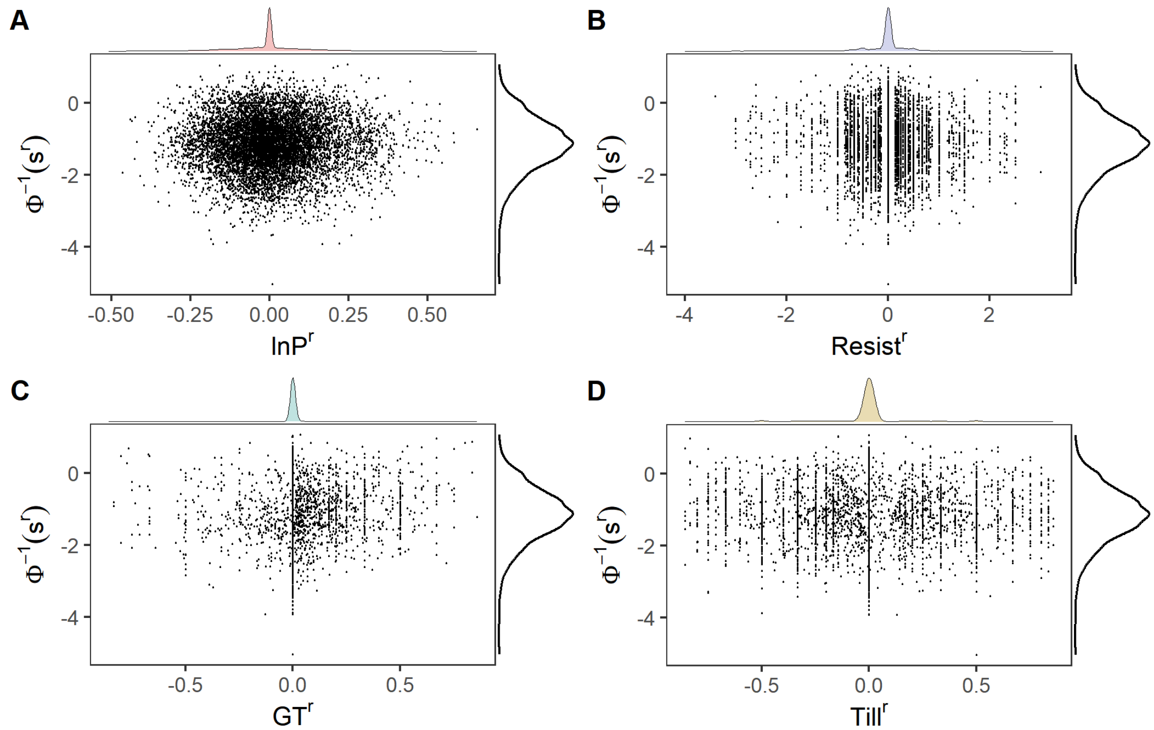

Figure 2.A4 Visualization of residualized variables.

Variables are residualized by subtracting the field averages (over the entire study period) from the observations to capture the within-field variation. The y-axis represents the inverse normal of the residualized glyphosate cost share, $\Phi^{-1}(s^r)$, across the four panels, and the x-axis variable is thus the residualized version of: log price ratio, $ln\,P^r$, for Panel (A); relative weed resistance to glyphosate, $Resist$, for Panel (B); GT seed adoption rate, GT^r, for Panel (C); and conventional tillage rate, $Till^r$, for Panel (D). In addition, the curve on the right is the marginal density of the y-axis variable, and the upper colored area illustrates the marginal density of the corresponding x-axis variable.

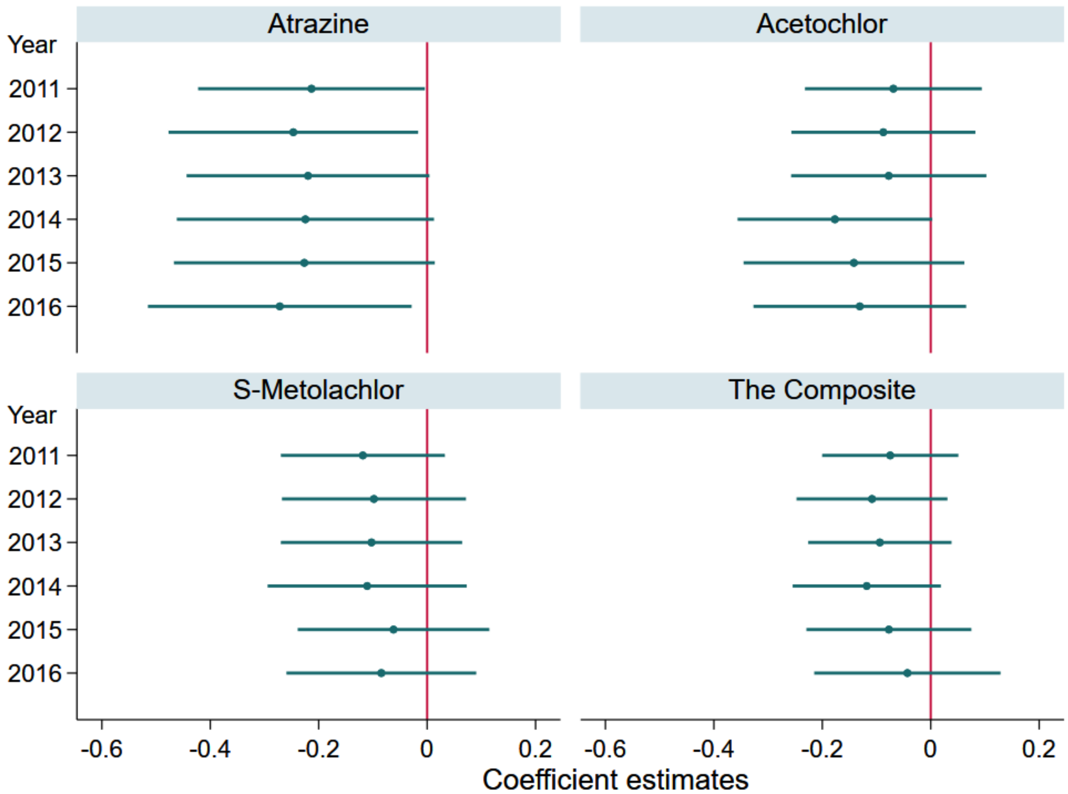

Figure 2.A5 Estimates for time-specific coefficients $\boldsymbol{\beta_{t[i]}}$, 2011-2016.

The points are coefficient estimates, and the horizontal bars denote the 95% confidence interval.

Table 2.A1 Decomposition of sample, by herbicide decisions

	Full dataset		Dataset after exclusion	
	Frequency	Percentage	Frequency	Percentage
Both	16,713	55.0%	16,713	56.2%
Glyphosate only	8,662	28.5%	8,662	29.1%
Composite only	4,346	14.3%	4,346	14.6%
Neither	641	2.1%	0	0.0%
Total	30,362	100.0%	29,721	100%

Notes: The dataset after exclusion is the full dataset less observations that use neither glyphosate nor the composite herbicide. The final sample further drops 10 observations due to missing covariate values, so the final sample we use in estimation consists of 29,711 farm-level observations.

Table 2.A2 Overview of farm-level repeated sampling

Number of sampled years	Number of unique farms	Percent
1	7,518	52.27
2	2,824	19.64
3	1,551	10.78
4	966	6.72
5	735	5.11
6	512	3.56
7	276	1.92
Total	14,382	100.00

Table 2.A3 Variable description, data source, and summary statistics

Variable	Definition	Data source	Mean	Std. Dev.	Min	Max
s	Glyphosate cost share	AgroTrak®	0.498	0.376	0.000	1.000
$\ln P$	Log price ratio (glyphosate divided by the composite price)	AgroTrak®	0.009	0.158	-0.619	0.725
$Resist$	Cumulative count of glyphosate-resistant weed minus composite-resistant weed	ISHRW	0.122	4.095	-11.000	10.000
GT	GT seed adoption rate	AgroTrak®	0.913	0.264	0.000	1.000
$Till$	Conventional tillage rate	AgroTrak®	0.396	0.479	0.000	1.000
pgt	GT seed price	TraitTrak®	103.45	27.26	55.46	256.20
Bt	Bt seed adoption rate	AgroTrak®	0.728	0.384	0.000	1.000
$pfuel$	Diesel fuel price	USDA-NASS	3.18	0.58	1.94	3.99
$hel8$	Whether growing crops on highly erodible land	NRI	0.363	0.481	0.000	1.000

Table 2.A4 First-stage regression results

	(1) Model 1: GT	(2) Model 1: $Till$	(3) Model 2: GT	(4) Model 3: $Till$
pgt	-0.0001	0.0000	-0.0001	
	(-0.42)	(0.03)	(-0.50)	
Bt	0.2246***	-0.0026	0.2260***	
	(14.08)	(-0.29)	(14.16)	
$pfuel$	-0.1230	-0.4140		-0.3810
	(-0.85)	(-1.63)		(-1.50)
$hel8$	-0.0087	-0.1691***		-0.1698***
	(-1.02)	(-7.89)		(-7.89)
$\ln P$	-0.0062	0.0004	-0.0066	0.0007
	(-0.54)	(0.01)	(-0.58)	(0.02)
$Resist$	0.0025	-0.0091	0.0023	-0.0091
	(0.77)	(-1.37)	(0.71)	(-1.38)
$Till$			-0.0141***	
			(-2.73)	
GT				-0.0521***
				(-3.15)
N	29711	29711	29711	29711

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the CRD level. Model 1 assumes both GT and $Till$ variables to be endogenous, and Model 2 and 3 assume only GT and only $Till$ is endogenous, respectively.

Table 2.A5 Full estimates of second-step regression

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
$\ln P$	0.151***	0.151***	0.177***	0.176***	0.148***
	(3.22)	(3.23)	(3.30)	(3.32)	(2.98)
$Resist$	-0.028*	-0.027*	-0.034*	-0.032*	
	(-1.71)	(-1.68)	(-1.88)	(-1.85)	
GT	0.424***	0.438***	1.057***	1.072***	
	(4.90)	(5.05)	(18.53)	(19.00)	
$Till$	-0.374*	-0.098***	-0.424*	-0.097***	
	(-1.76)	(-5.92)	(-1.94)	(-5.35)	
$\hat{v}_1$	1.052***	1.037***			
	(11.71)	(11.60)			
$\hat{v}_2$	0.285		0.330		
	(1.33)		(1.50)		
$\lambda_2 \times \overline{\ln P}$	0.098	0.079	0.209	0.188	0.049
	(0.41)	(0.34)	(0.82)	(0.75)	(0.21)
$\lambda_3 \times \overline{\ln P}$	0.415	0.407	0.379	0.382	0.403
	(1.24)	(1.21)	(0.98)	(0.99)	(1.12)
$\lambda_4 \times \overline{\ln P}$	-0.933*	-0.978*	-0.975	-1.023*	-1.004*
	(-1.74)	(-1.85)	(-1.61)	(-1.71)	(-1.95)

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
$\lambda_5 \times \overline{\ln P}$	-0.223	-0.366	-0.185	-0.367	-0.234
	(-0.32)	(-0.55)	(-0.21)	(-0.43)	(-0.28)
$\lambda_6 \times \overline{\ln P}$	-0.394	-0.340	0.272	0.269	-0.625
	(-0.38)	(-0.33)	(0.24)	(0.24)	(-0.56)
$\lambda_7 \times \overline{\ln P}$	0.003	-0.218	-0.174	-0.436	0.004
	(0.00)	(-0.12)	(-0.09)	(-0.23)	(0.00)
$\lambda_2 \times \overline{Resist}$	0.007	0.005	0.004	0.001	
	(1.20)	(0.82)	(0.70)	(0.17)	
$\lambda_3 \times \overline{Resist}$	0.004	0.001	0.005	0.001	
	(0.60)	(0.19)	(0.70)	(0.23)	
$\lambda_4 \times \overline{Resist}$	0.006	0.003	0.008	0.006	
	(0.81)	(0.45)	(1.18)	(0.87)	
$\lambda_5 \times \overline{Resist}$	0.010	0.007	0.011	0.009	
	(1.44)	(1.04)	(1.51)	(1.31)	
$\lambda_6 \times \overline{Resist}$	-0.001	-0.008	-0.004	-0.009	
	(-0.16)	(-1.00)	(-0.46)	(-1.16)	
$\lambda_7 \times \overline{Resist}$	0.022*	0.016	0.025**	0.020*	
	(1.72)	(1.20)	(2.48)	(1.89)	

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
$\lambda_2 \times \overline{GT}$			0.354**	0.329**	
			(2.56)	(2.44)	
$\lambda_3 \times \overline{GT}$			0.564***	0.575***	
			(3.97)	(4.04)	
$\lambda_4 \times \overline{GT}$			0.319**	0.323**	
			(2.00)	(2.04)	
$\lambda_5 \times \overline{GT}$			0.738***	0.742***	
			(3.50)	(3.53)	
$\lambda_6 \times \overline{GT}$			0.326	0.311	
			(1.60)	(1.56)	
$\lambda_7 \times \overline{GT}$			0.094	0.109	
			(0.28)	(0.34)	
$\lambda_2 \times \overline{Till}$		0.004		0.010	
		(0.10)		(0.24)	
$\lambda_3 \times \overline{Till}$		-0.003		0.012	
		(-0.07)		(0.24)	
$\lambda_4 \times \overline{Till}$		0.047		0.035	
		(0.71)		(0.46)	

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
$\lambda_5 \times \overline{Till}$		0.090		0.115	
		(1.46)		(1.45)	
$\lambda_6 \times \overline{Till}$		-0.037		-0.020	
		(-0.54)		(-0.26)	
$\lambda_7 \times \overline{Till}$		-0.184		-0.219*	
		(-1.50)		(-1.73)	
$\lambda_2 \times \overline{pgt}$	0.002**	0.002**			
	(2.06)	(2.17)			
$\lambda_3 \times \overline{pgt}$	0.001	0.001			
	(0.81)	(0.94)			
$\lambda_4 \times \overline{pgt}$	-0.000	-0.001			
	(-0.23)	(-0.45)			
$\lambda_5 \times \overline{pgt}$	0.000	-0.000			
	(0.24)	(-0.39)			
$\lambda_6 \times \overline{pgt}$	0.003**	0.003*			
	(2.35)	(1.95)			
$\lambda_7 \times \overline{pgt}$	0.000	0.000			
	(0.10)	(0.00)			

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
$\lambda_2 \times \overline{Bt}$	-0.062	-0.056			
	(-0.97)	(-0.89)			
$\lambda_3 \times \overline{Bt}$	0.009	0.017			
	(0.11)	(0.22)			
$\lambda_4 \times \overline{Bt}$	-0.171**	-0.146*			
	(-2.19)	(-1.88)			
$\lambda_5 \times \overline{Bt}$	0.004	0.044			
	(0.04)	(0.44)			
$\lambda_6 \times \overline{Bt}$	-0.004	-0.014			
	(-0.03)	(-0.13)			
$\lambda_7 \times \overline{Bt}$	-0.203	-0.217			
	(-0.98)	(-1.07)			
$\lambda_2 \times \overline{pfuel}$	0.948		1.093		
	(1.45)		(1.54)		
$\lambda_3 \times \overline{pfuel}$	1.600**		1.575**		
	(2.13)		(1.96)		
$\lambda_4 \times \overline{pfuel}$	0.582		0.710		
	(0.62)		(0.67)		

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
$\lambda_5 \times \overline{pfuel}$	1.294		0.984		
	(1.48)		(0.95)		
$\lambda_6 \times \overline{pfuel}$	2.902**		2.709**		
	(2.27)		(2.07)		
$\lambda_7 \times \overline{pfuel}$	2.402		3.219		
	(0.97)		(1.34)		
$\lambda_2 \times \overline{hel8}$	-0.011		0.011		
	(-0.27)		(0.25)		
$\lambda_3 \times \overline{hel8}$	-0.042		-0.007		
	(-0.86)		(-0.13)		
$\lambda_4 \times \overline{hel8}$	-0.128**		-0.109		
	(-2.06)		(-1.59)		
$\lambda_5 \times \overline{hel8}$	-0.054		-0.045		
	(-1.06)		(-0.74)		
$\lambda_6 \times \overline{hel8}$	-0.107		-0.082		
	(-1.52)		(-1.06)		
$\lambda_7 \times \overline{hel8}$	-0.252**		-0.248**		
	(-2.57)		(-2.48)		

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
λ_2	-2.228	0.030	0.108	0.094	-0.147**
	(-1.64)	(-2.28)	(-1.85)	(1.29)	(-1.99)
λ_3	-3.368**	-0.103*	-3.814**	-0.603***	-0.061
	(-2.16)	(-1.87)	(0.54)	(-2.76)	(-0.02)
λ_4	-1.207	-0.086	0.046	-0.578*	-0.101
	(-0.63)	(-0.32)	(-0.87)	(0.55)	(-1.57)
λ_5	-2.782	-0.191	0.060	0.053	-0.246
	(-1.53)	(-0.69)	(-1.28)	(-2.21)	(-0.97)
λ_6	-6.026**	-0.171**	-0.059	-0.092	0.304
	(-2.26)	(-2.19)	(-2.08)	(-0.75)	(0.75)
Variance function					
λ_2	0.032	-0.302**	-2.730*	-0.462***	0.048
	(0.59)	(0.56)	(1.50)	(-2.81)	(0.57)
λ_3	-0.110**	-0.123	0.034	0.036	-0.003
	(-2.04)	(-0.64)	(-2.30)	(0.55)	(-0.76)
λ_4	-0.098	-0.105	-1.948	0.043	-0.270
	(-1.54)	(-1.62)	(0.58)	(-1.96)	(-1.19)

Table 2.A5 (cont'd)

Variables	Model 1: Both	Model 2: GT only	Model 3: $Till$ only	Model 4: Neither	Model 5: No control
λ_5	-0.172**	-0.178**	-2.704	-0.828**	-0.035
	(-2.14)	(-2.23)	(0.60)	(0.53)	(-0.32)
λ_6	-0.163**	-0.003	-5.672**	-0.074	-0.126
	(-2.04)	(-0.01)	(-0.59)	(-0.22)	(-1.05)
CRE	Yes	Yes	Yes	Yes	Yes
CF	Yes	Yes	Yes	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes
State-specific trends	Yes	Yes	Yes	Yes	Yes

Notes: Robust z-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Year dummies, state dummies, and state-specific time trends are included. Note that the standard errors in this table are not adjusted using bootstrap due to the large number of variables, but the differences between bootstrapped standard errors and the directly obtained standard errors are generally small. Model 1 assumes both GT and $Till$ variables to be endogenous, and Model 2 and 3 assume only GT and only $Till$ is endogenous, respectively. Model 4 assumes exogeneity of the two variables, and Model 5 excludes the control variables.

Table 2.A6 Average elasticities across the sample

	Glyphosate	The composite
Glyphosate price	-0.371	0.369
	(-7.73)	(7.71)
The composite price	0.371	-0.369
	(7.73)	(-7.71)
AES	0.739	
	(7.83)	

Notes: t statistics in parentheses. Standard errors are obtained by panel bootstrapping with 1,000 replications.

Table 2.A7 Damage price of glyphosate under four damage scenarios

EIQ system categories	U.S. average pesticide cost ($)/ kg a.i.	**(A) Neither effect**		**(B) Carcinogenic effect only**		**(C) Monarch butterfly effect only**		**(D) Both effects**	
		EIQ score	Low/medium /high weight	EIQ score	Low/medium /high weight	EIQ score	Low/medium /high weight	EIQ score	Low/medium /high weight
Applicator effects	0.77	5	0.5	25	1	5	0.5	25	1
Picker effects	0.43	3	0.5	15	1	3	0.5	15	1
Consumer effects	2.13	2	0.5	10	0.5	2	0.5	10	0.5
Ground water	0.60	1	0.5	1	0.5	1	0.5	1	0.5
Aquatic effects	0.80	5	0.5	5	0.5	5	0.5	5	0.5
Bird effects	0.19	6	0.5	6	0.5	6	0.5	6	0.5
Bee effects	0.52	9	0.5	9	0.5	9	0.5	9	0.5
Beneficial insect effects	0.19	15	0.5	15	0.5	75	1	75	1

Table 2.A7 (cont'd)

EIQ system categories	U.S. average pesticide cost ($)/ kg a.i.	**(A) Neither effect**	**(B) Carcinogenic effect only**	**(C) Monarch butterfly effect only**	**(D) Both effects**
Total cost ($)/ kg a.i.	5.63	**2.82**	**3.41**	**2.91**	**3.51**
Average a.i. per gallon product (kg a.i./gallon)			**1.66**		
Damage price per gallon ($/gallon)		**4.68**	**5.66**	**4.83**	**5.83**

Notes: The grey block represents the EIQ categories we adjust for each scenario. Scenario (A) maintains the current EIQ scores for glyphosate. For Scenario (B) we adjust for applicator, picker, and consumer effects to account for the carcinogenic effect of glyphosate. In Scenario (C) we adjust for insect effects to account for the monarch butterfly effect of glyphosate. In Scenario (D) both effects are accounted for by adjusting for applicator, picker, consumer as well as insect effects.

Table 2.A8 Damage price of the composite herbicide

EIQ system categories	U.S. average pesticide cost ($)/ kg a.i.	Atrazine			Acetochlor			S-metolachlor		
		EIQ score	Low/medium /high weight	Cost ($)/ kg a.i.	EIQ score	Low/medium /high weight	Cost ($)/ kg a.i.	EIQ score	Low/medium /high weight	Cost ($)/ kg a.i.
Applicator effects	0.77	5	0.5	0.39	7.50	0.5	0.39	7.50	0.5	0.39
Picker effects	0.43	3	0.5	0.21	3.15	0.5	0.21	4.50	0.5	0.21
Consumer effects	2.13	4	0.5	1.06	2.33	0.5	1.06	6.00	0.5	1.06
Ground water	0.60	3	1	0.60	3.00	1	0.60	3.00	1	0.60
Aquatic effects	0.80	9	1	0.80	15.00	1	0.80	9.00	1	0.80
Bird effects	0.19	12	0.5	0.10	4.65	0.5	0.10	12.00	0.5	0.10
Bee effects	0.52	9	0.5	0.26	6.30	0.5	0.26	9.00	0.5	0.26

Table 2.A8 (cont'd)

EIQ system categories	U.S. average pesticide cost ($)/ kg a.i.	**Atrazine**			**Acetochlor**			**S-metolachlor**		
		EIQ score	Low/medium /high weight	Cost ($)/ kg a.i.	EIQ score	Low/medium /high weight	Cost ($)/ kg a.i.	EIQ score	Low/medium /high weight	Cost ($)/ kg a.i.
Beneficial insect effects	0.19	23.55	0.5	0. 10	17.64	0.5	0.10	15.00	0.5	0. 10
Total cost ($)/ kg a.i.	5.63		**3.52**			**3.52**			**3.52**	
Average a.i. per gallon product (kg a.i./gallon)			**0.77**			**0.42**			**0.33**	

Table 2.A8 (cont'd)

Damage price per gallon ($/gallon)	**5.35**

Table 2.A9 Expressions for the solutions

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 $\epsilon_2 > 0$. Denominator D abbreviates $D = \vartheta(-\zeta + \kappa_1\epsilon_1 + \kappa_2\epsilon_2) - \zeta(\kappa_2\epsilon_1 + \kappa_1\epsilon_2) + \epsilon_1\epsilon_2(\kappa_1 + \kappa_2)^2 > 0$.

Table 2.A10 Formulas for welfare effects

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	$\Delta CS+\ \Delta PS_1+\ \Delta PS_2+\Delta Tax+$ ΔEnv	Social welfare change

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

Table 2.A11 Summary of baseline values for market variables and parameter calibration

Variable	Definition	Value	Source
Market variables			
Q_0	The baseline value of corn quantity	13,184	USDA NASS, corn production in million bushels, averaged over 2010-2016.
M_0	The baseline value of corn price	4.85	USDA NASS, corn price received by farmers in dollars per bushel, averaged over 2010-2016.
$X_{m,0}$	The baseline value of herbicide quantity	$X_{1,0}$ = 24.89, $X_{2,0}$ = 35.96	The unit is million gallons. Herbicide quantity used per acre is obtained from AgroTrak, as sample average of herbicide gallons used per acre, 2010-2016 (Result: 0.27 for glyphosate, and 0.39 for the composite herbicide). Corn acres planted is obtained from USDA NASS, as corn acres planted in million, averaged over 2010-2016 (Result: 92.20).
$P_{m,0}$	The baseline value of herbicide price	$P_{1,0}$ = 22.93, $P_{2,0}$ = 28.49	AgroTrak, sample average of herbicide prices in dollars per gallon, 2010-2016.

Table 2.A11 (cont'd)

Variable	Definition	Value	Source
Market parameters			
ϑ	Elasticity of substitution	0.739	The Allen-Uzawa elasticity of substitution (AES) estimate from the previous section (**Table 2.A6**).
κ_m	Herbicide share in corn production cost	Mean: κ_1 = 0.017, κ_2 = 0.019	Herbicide cost shares are approximated by multiplying the sample averages of herbicide cost share in total herbicide cost (obtained from AgroTrak) and the herbicide proportion in corn production cost from Iowa's corn budget estimates between 2010 and 2016 (available at https://www.extension.iastate.edu/agdm).
ζ	Price elasticity of corn demand	Mean = -0.53	Hochman and Zilberman (2018)
ϵ_m	Price elasticity of herbicide supply	$\epsilon_1 \in \{0.5, 1.0, 1.5\}$, $\epsilon_2 \in \{0.5, 1.0, 1.5\}$	Norton et al. (2008), Just (2006)

Table 2.A11 (cont'd)

Variable	Definition	Value	Source
Environmental parameters			
d_m	Herbicide damage prices	d_1 =4.68 for status-quo scenario, d_2 = 5.35	The unit is dollars per gallon ($/gal). Obtained from the previous section (**Table 2.A7-2.A8**).

Notes: m equals 1 for glyphosate herbicide, 2 for the composite herbicide.

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CHAPTER 3 Aligning Bt Maize Planting with Pest Incidence and Efficacy Erosion Risk Suggests the Need for Paradigm Shifts

Introduction

Corn rootworm, *Diabrotica virgifera*, is a key pest in US maize (*Zea mays L.*) production, with estimates attributing over one billion in losses annually to this pest (Metcalf 1986; Dun et al. 2010). Corn rootworm larvae feed underground, wounding or clipping entire roots; this feeding reduces the movement of water and nutrients into the plant. Severe damage can reduce grain yield by approximately 15%-18% for every root node consumed (Oleson et al. 2005; Dun et al. 2010; Tinsley et al. 2013).

In 1996, the first genetically modified maize hybrid expressing an insect-specific Bt (*Bacillus thuringiensis*) protein was introduced for control of another key maize pest, the European corn borer (*Ostrinia nubilalis* Hübner). After the success of that technology, the first rootworm-active Bt maize, expressing the Cry3Bb1 protein, was introduced in 2003. Bt maize has since become a vital tool for managing maize insects in the US Corn Belt and Canada (Head and Wald 2009). Hybrids typically incorporate several toxins that target both above-ground (caterpillars) and below-ground(rootworms) pests (Tabashnik et al. 2013). Hybrids expressing multiple rootworm-active toxins currently comprise the majority of Bt maize planted in the US (See Appendix 3.A1-3.A2 for a detailed illustration). In fact, the majority of maize acres in the US are now planted to hybrids expressing rootworm-active Bt proteins, regardless of pest presence or pressure (**Figure 3.1**).

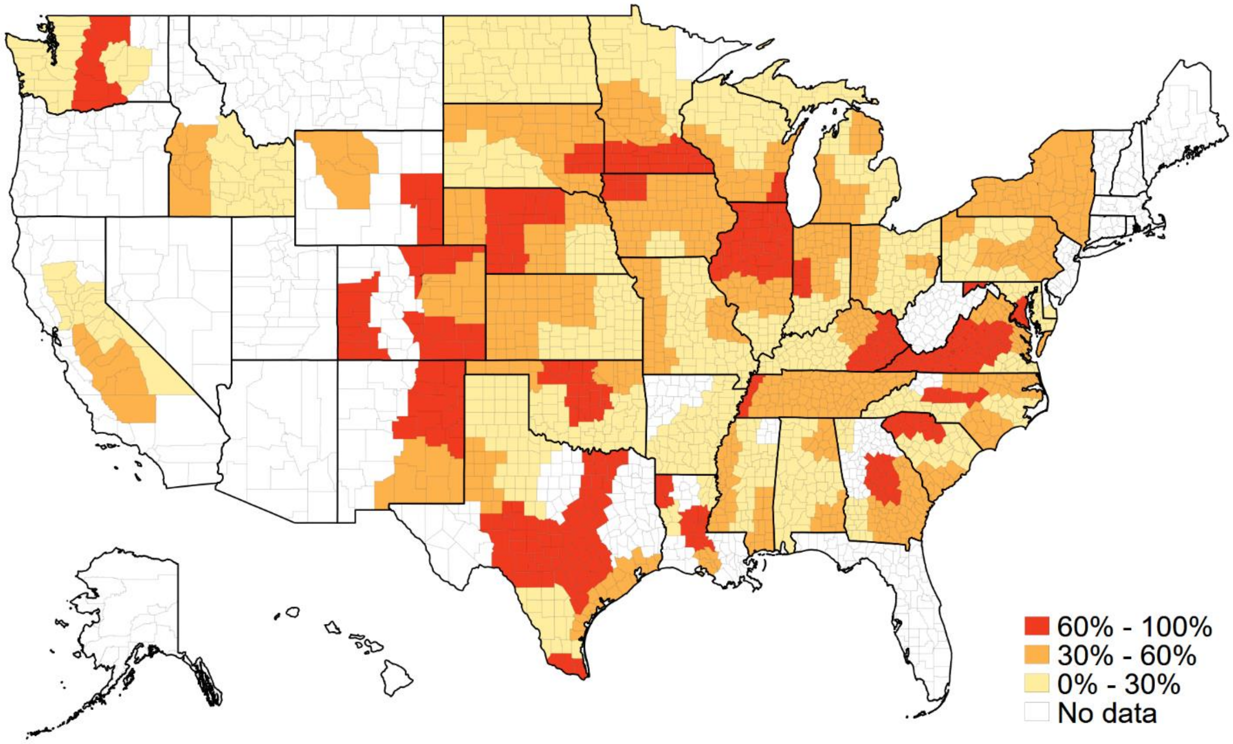

Figure 3.1 Planting percentage (%) of rootworm Bt maize in 2016, at crop reporting district level.

The Bt planting rate is calculated as the percentage of maize area that is planted to varieties containing rootworm-active Bt toxins in a crop reporting district. (Data source: TraitTrak®, GfK Kynetec.)

However, none of the currently available rootworm-active toxins are classified as high-dose toxins that kill at least 99.99% of susceptible pests in the field according to the US EPA guidelines (EPA 1998; Meihls et al. 2008; Gassman et al. 2014), and the initial resistance allele frequency is high (Onstad and Meinke 2010). High rates of Bt adoption in turn imposed high selection pressure on target insects and shifted insect populations towards reduced susceptibility and control. Numerous cases of practical field resistance to multiple Bt traits have sparked concerns that non-Bt crops are not being planted at adequate levels to delay resistance (Reviewed in

Tabashnik and Carrière 2017; Gassman et al. 2011; Tabashnik and Gould 2012; Gassman et al. 2014; Jakka et al. 2016; Taylor and Krupke 2018; Calles-Torrez et al. 2019). A paradigm shift in how current and future transgenic maize hybrids are deployed may be needed.

However, it has been difficult to assess the economic cost of reduced susceptibility of rootworms to Bt maize or Bt efficacy erosion, and in turn, place a value on preserving susceptibility for the future. We attempt to do this here, using Bt efficacy trial data on root injury collected from public universities across 10 Corn Belt states, combined with nationally representative farmer-level data on seed use. Furthermore, we examine how deploying Bt maize in the Corn Belt aligns with current pest damage and Bt efficacy erosion risk, and propose policy guidelines for sustainable use to benefit producers in the long term.

A Biologically Motivated Modeling Approach

Western corn rootworms are the most widespread rootworm species in the Corn Belt and have one generation per year. The life cycle begins the previous season, with eggs laid near the base of maize stalks and overwinter in the soil until larvae hatch in the spring (ca. late May-early June) and crawl to maize roots to feed; 5-10 days after the larvae pupate in the soil, adults emerge and mate typically near the plant where the females emerge (**Figure 3.2**). Many mated, gravid females disperse to different fields to search for optimal oviposition sites with a significant portion engaging in long-distance flight, thereby homogenizing the rootworm population at the local scale (Coats et al. 1986; Naranjo 1990; Marquardt and Krupke 2009; Martinez and Caprio 2016; St. Clair et al. 2020; St. Clair and Gassmann 2021). Therefore, larvae hatched in a given maize field come from two sources in the previous season: females emerging and mating in that same field, or migrating females from surrounding fields.

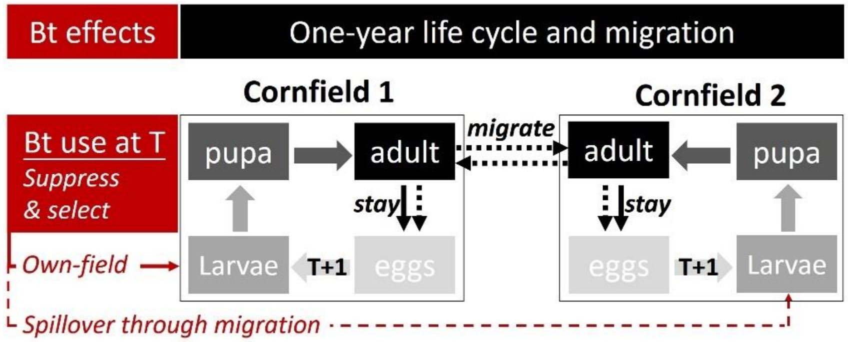

Figure 3.2 Rootworm Lifecycle, adult dispersal, and Bt effects.

Rootworm larvae are limited to feeding on maize and a few other hosts, so rotation with a non-maize crop is an effective way to control this pest (Carrière et al. 2020; St. Clair and Gassmann 2021). In some production systems, however, the opportunity for crop rotation is limited or less attractive from an economic standpoint. Such systems include livestock farms where maize is needed for animal feed, as well as production areas in the western plains where maize is intensively farmed as the main crop (Figure 3.A3 in the Appendix). Where crop rotation is not practiced, insecticides were used for many years to reduce rootworm injury (Cox et al. 2007). Since the introduction, transgenic rootworm Bt hybrids, however, have virtually replaced both liquid and granular soil insecticides as the major approach for larval damage management, with high-dose neonicotinoid seed treatments often provided in conjunction by the seed manufacturers. Besides, environmental conditions, rainfall in particular, are also important in altering rootworm densities (Tinsley et al. 2018).

Because rootworm larvae feed only on maize roots, planting Bt hybrids in a maize field will reduce root damage not only this year but in the future as the insect population drops. However, the selection pressure from using Bt this year will deplete Bt efficacy in subsequent years. As illustrated in **Figure 3.2**, a grower's Bt planting creates not only intertemporal effects on his or her field, or *own-field effects*, but also broader *spillover effects* due to the dispersal behavior of adults in the landscape, potentially resulting in areawide suppression, as well as depleting Bt efficacy across the neighborhood (Hutchison et al. 2010; Dively et al. 2018).

To quantify the economic costs of Bt efficacy erosion and determine the sustainable use of Bt hybrids, we took advantage of two unique data sources to compile a Corn Belt representative dataset spanning 2005-2016. One was the TraitTrak® survey data, which to our knowledge is the most comprehensive source of seed use data and representative at the crop reporting district (CRD) level and provides field-level information on specific seed varieties planted. This gave us a measure of the proportion of acres planted to rootworm-specific Bt hybrids in each CRD. The second source was a dataset of root injury in Bt and non-Bt trial fields, compiled from 10 public universities (North Dakota, South Dakota, Nebraska, Minnesota, Iowa, Wisconsin, Illinois, Indiana, Michigan, and Ohio) research trials across the Corn Belt. The trial fields monitor the rootworm pressure in the region (more precisely, in the preceding year, due to the one-generation-per-year lifecycle described above), and provided a measure of background rootworm pressure on unprotected (non-Bt) maize, as well as allowed for comparisons of Bt efficacy overtime throughout the region. The typical measure of rootworm pressure and associated maize root damage is the 'root injury scale' (Oleson et al. 2005). This 0-3 scale is the accepted standard for measuring rootworm larval feeding on maize roots. The score reflects the cumulative proportion of root nodes pruned to within 3.8 cm of the base of the plant. The higher the proportion of roots pruned, the lower the water and nutrients moving into the plant, and the lower the yield. For analytical convenience, we rescaled the 0 to 3 measure to 0 to 1 and use the standardized root injury scale to operationalize root injury hereafter. **Figure 3.3** shows the spatial distribution of the trial data and the background rootworm pressure from 2014 to 2016. Comparing the Eastern Corn Belt (Indiana, Ohio, and Michigan) with the Western region (remaining states) reveals a substantial difference in rootworm pressure, with most observations falling below 0.11 in the East, but a large proportion of ratings in the West greater than 0.38, which is more than one node injury.

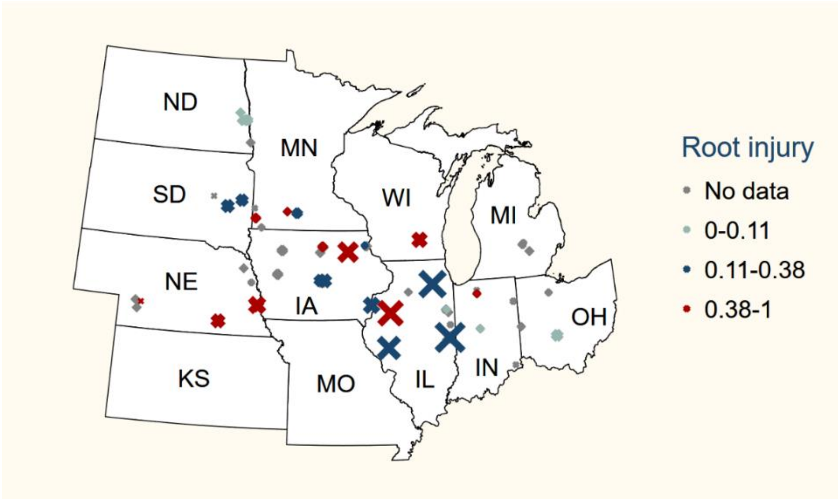

Figure 3.3 Spatial distribution of trial fields in the sample and rootworm pressure during 2014-2016.

The cross symbols represent the site locations in the sample, with a larger size indicating a greater number of observations (2005-2016 average) at the site. The colors of the symbol represent the value of the standardized root injury scale (0-1), averaged over all non-Bt observations at the location during 2014-2016, as shown on the right. The data are divided into three categories by quantile, and sites with no observations during this period are marked as gray (Data source: University research trial data.)

Our overall approach is as follows. First, we develop econometric models to estimate *own-field effects*. Because root injury in non-Bt trial fields represents rootworm pressure in the CRD in the preceding year, the relationship between non-Bt root injury and two-year lagged Bt coverage in the CRD serves as proxy measurements of how Bt use reduces rootworm pressure in the next year (future benefit); using the differences between root injury data to Bt treatment vs. control (non-Bt) maize plots, whereas the relationship between Bt efficacy and the two-year lagged Bt coverage represents how current Bt maize planting may reduce Bt maize efficacy in the subsequent year (future cost). Second, we use biological relationships (i.e. the female adult dispersal proportion) to calibrate for the *spillover effects* into the larger area. Taken together, a dynamic game of Bt planting was established to determine the sustainable use of Bt technology, which was then evaluated for the West and East to account for the regional heterogeneity in terms of rootworm pressure.

Panel (A) of **Figure 3.4** provides an overview of the temporal changes in root injury, Bt coverage (two-year lagged), and Bt efficacy during 2005-2016. A general decreasing trend in non-Bt maize root injury is observed as Bt coverage increases over time, with an exception around 2012, one of the most droughty years in the past decades. In addition, the root injury difference in Bt and non-Bt fields, or Bt efficacy, has generally decreased as well, as a result of increasing selection pressure from greater Bt coverage. A closer look at the root injury and Bt protection with respect to Bt coverage in Panel (B) suggests the future cost is greater than future benefit for a marginal increase in Bt use: the decrease in non-Bt root injury reflects the future suppression, and the larger reduction in Bt protection captures the Bt efficacy decline as Bt are more intensively used in the area.

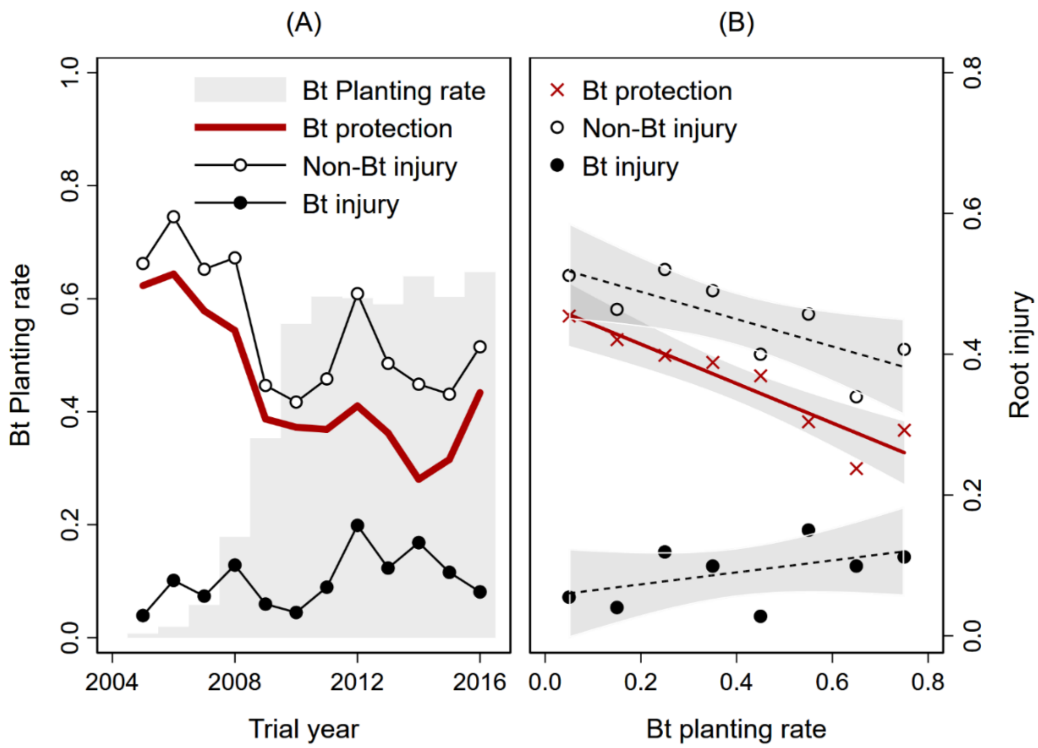

Figure 3.4 Time trends in rootworm pressure and Bt protection effect, and Bt planting rate, 2005-2016.

Bt planting rate variable is lagged for two years (i.e., the Bt rate value shown in 2005 is that in 2003), and is calculated as the rate of maize acres planted to rootworm Bt hybrids in the CRD. Only fields where soil insecticides or high-level seed treatments were not applied are included. States for which all fields were planted to non-Bt maize are excluded for a reasonable comparison. Bt protection is calculated as the difference in root injury between non-Bt (Non-Bt injury) and Bt fields (Bt injury). The dots in Panel (B) are fitted linearly, with 95% confidence intervals shaded in gray; Root injury variables in Panel (A) share the y-axis from Panel (B) (Data source: University trial data; TraitTrak®, GfK Kynetec.)

Own-field and Spillover Effects

Own-Field Effects: Regressions

Since reductions in maize root damage could be a result of other (i.e. abiotic) factors, such as precipitation during egg emergence, so we turn to field-level econometric models for further analysis. Moreover, given the nature of the root injury scale as cumulative proportions of roots eaten, the fractional response model is adopted (Wooldridge 2010). Therefore, the econometric model is specified as the following:

$$E\left(rw_{i,t} \middle| X\right) = \Phi\begin{pmatrix} \alpha \times bt_{i,t} + \gamma \times coverage_{d[i],t-2} + \beta \times bt_{i,t} \times coverage_{d[i],t-2} \\ +\psi_{m[i]} + \theta Z + constant \end{pmatrix} \tag{1}$$

where $E(\cdot)$ denotes the conditional expectation and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. The notation i indexes the trial field, and t denotes the trial year in which data for field i are observed (represents the rootworm pressure in the area for the preceding year $t-1$. The $m[i]$ identifies the location of the field and $d[i]$ indicates the CRD of the field. The dependent variable $rw_{i,t}$ is the standardized root injury scale ranging from 0 to 1, and the two critical explanatory variables are $bt_{i,t}$ and $coverage_{d[i],t-2}$. The variable $bt_{i,t}$ equals 1 if the field grows Bt maize hybrids, and 0 if not, and $coverage_{d[i],t-2}$ represents the area coverage of Bt, namely the ratio of maize acres that grow Bt hybrids in year $t-2$ in the CRD in which the trial field i resides (ranges from 0 to 1). While the data do not allow identification of the same field over time, the same sites can be identified, and sites are nested within CRD. Therefore, by including the site effects $\psi_{l[i]}$, we control for the site-specific unobservable confounding factors that are time-constant, such as soil properties. The vector Z is a set of confounding factors that change over time and space, including precipitation in April, May, July, and August (in 100 mm); seed treatment rate, a dummy variable assigned 1 if high level (i.e., 1.25 mg a.i.; a.i. is the abbreviation for active ingredient) treatment is applied and 0 otherwise, as 1.25 mg a.i is the only level of the neonicotinoid seed treatment that is expected to offer protection against root feeding by RW larvae (Tinsley et al. 2016, Alford and Krupke 2018). In addition, trials with soil insecticide treatment are excluded from the main analysis, as they are less representative of the situations of interest, and the protection already provided by soil insecticides may obscure the extent of realized Bt protection.

The coefficients of such models are typically interpreted through Average Partial Effects (APE), namely the partial effects averaged across all observations (Wooldridge 2010). Let parameters $a, r,$ and b denote the APEs corresponding to the coefficients $\alpha, \gamma,$ and β in eq. (1). Therefore, parameter a is the Bt protection effect absent efficacy reduction caused by historical planting, i.e., the reduction (presumably) in standardized root injury scale in Bt fields compared to non-Bt fields on average, all else being equal. The parameter r gives the historical suppression effect, i.e., the reduction in standardized root injury scale in the current fields – whether planted to Bt or non-Bt maize - when planting Bt in the previous year compared to planting non-Bt. Lastly, the parameter b captures the pest susceptibility (and control efficacy) erosion associated with historical planting, or a measure of long-term cost, which is relevant to Bt fields only ($bt = 1$), i.e., the increase in root injury for Bt fields for one percent increase in area coverage.

Table 3.1 Fractional response model results (APEs) for root damage

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
Bt treatment in the trial field (bt)	-0.43***	-0.45***	-0.39***
	(-22.39)	(-30.52)	(-16.63)
Bt planting rate ($coverage$)	-0.22***	-0.23***	-0.19***
	(-5.27)	(-4.50)	(-5.07)
Interaction term ($bt \times coverage$)	0.27***	0.28***	0.23***
	(5.29)	(5.83)	(5.96)
Precipitation, April	-0.03	-0.02	-0.02
	(-0.61)	(-0.41)	(-0.58)
Precipitation, May	-0.02	-0.04	-0.02
	(-0.40)	(-0.79)	(-0.55)
Precipitation, June	-0.05***	-0.07***	-0.05***
	(-3.44)	(-3.01)	(-3.39)
Precipitation, July	0.02	0.03	0.02
	(0.40)	(0.60)	(0.59)
Precipitation, August	-0.03	-0.05***	-0.03*
	(-1.54)	(-3.13)	(-1.78)

Table 3.2 (cont'd)

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
High-level seed treatment	-0.09***	-0.10***	-0.07***
	(-7.32)	(-12.63)	(-6.65)
Ratio of continuous maize in total crop land		-0.21	
		(-0.98)	
Soil insecticides			-0.15***
			(-10.15)
Observations	1489	1119	1891

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parentheses. Standard errors are clustered at crop reporting district (CRD) level.

The APE estimates of the main variables are presented in Column (1), **Table 3.1**: $a = -0.43$, $b = 0.27$, and $r = -0.22$. The estimates imply that if a field was planted to non-Bt maize in a year, then growing Bt hybrids in the subsequent year will reduce root injury scale value by 0.43 compared to growing non-Bt maize. Instead, if Bt hybrids were planted, then the temporal suppression will benefit both Bt and non-Bt growers by reducing root injury value by 0.22. However, for Bt fields, Bt history will also select for resistance and hence lower the Bt effect from 0.43 to (0.43 - 0.27) = 0.16. Therefore, Bt history will overall has a negative impact on Bt fields by a magnitude of -(0.27-0.22) = -0.05, but will be beneficial to non-Bt fields by a magnitude of 0.22.

For robustness purposes, we also investigated additional specifications. First, we included cropping pattern variables, namely the ratio of corn-to-corn acres to total crop acres, to capture the effect of continuous maize planting. Results in column (2) show that the effect is not statistically significant and the main variable estimates are close to those in column (1). Second, we also included the trials with soil insecticides, where the soil insecticide variable is a dummy variable with 1 indicating soil insecticide being applied in the trial. As expected, the subsample has shown a smaller magnitude for the three critical parameters. Third, while the main analysis is conducted using CRD-level Bt coverage as an approximation of the area surrounding the trial fields, we also present the results using county-level Bt coverage for robustness purposes, and the estimates in Table 3.A1 in the Appendix are very close to the main results since the Corn Belt region is typically heavily sampled (See Figure 3.A4 in the Appendix). Lastly, for comparison of the standard linear model and fractional response model, we also present the estimation results using ordinary least square estimation in Table 3.A2-3.A3 in the Appendix, which gives relatively poor estimates.

Spillover Effects: Calibrations

It should again be emphasized that, although we used area coverage in the regression, the estimates essentially measure the *own-field effects* for a cornfield, because the trial fields are representative of rootworm pressure in the area. One can think of the area as one large single cornfield. Having obtained the *own-field effects*, we can further calibrate for the *spillover effect* from adult female dispersal correspondingly. The rootworm biology implies that for a cornfield, the ratio between reduction in root damage associated with own Bt use and surrounding Bt use is simply the ratio between native population and migration population, or the ratio between native females and migrated females (assuming no difference in eggs per female). Specifically, let u be the proportion of female dispersal in typical cornfields, then the ratio between own field effect and spillover effect is given by $(1-u)/u$. Let $\tilde{b}$ and $\tilde{r}$ be the corresponding selection and suppression associated with spillover effects from 100% regional Bt coverage, then we have $\tilde{b} = bu/(1-u)$, and $\tilde{r} = ru/(1-u)$. Let P_{t-1} denote the fraction of regional Bt planting which ranges from 0 to 1, then we can add the spillover effects into the profit structure to capture the geographical externalities associated with planting Bt.

The parameter u is calibrated using previous literature. Work by Coats et al. (1986) and Naranjo (1990) suggest that 15-24% of western rootworm females engage in sustained (long-distance) flights before they are ca. 2 weeks old. In the simulation work by Martinez and Caprio (2016), a 5%-25% range is used to calibrate for female post-mating dispersal proportion. For robustness purposes, we follow Martinez and Caprio (2016) and use both the lower bound of 5% and the upper bound of 25% in the following analysis.

The Game of Bt Hybrid Planting

Maize growers acting according to pure self-interest would seek to maximize their payoffs by weighing the avoided yield loss associated with Bt hybrid against the additional cost of the Bt trait, or the seed premium, as well as any future cost. However, if growers' Bt choices are instead motivated by group interest, then growers would consider spillover effects to the local area and internalize the spatial externality costs into private payoffs. Because root protection provided by Bt is affected and will affect not only one's field but also the surrounding local area, a grower's optimal choice would depend on the average behavior of the population and therefore can be analyzed as a dynamic population game (Smith 1982; Bauch et al. 2003; Bauch and Earn 2004; Milne et al. 2015; Elokda 2021). Intuitively, very high levels of historical Bt coverage would allow non-Bt growers to "freeride" through intertemporal areawide suppression and disincentivize Bt planting, thus are difficult to maintain. Similar to this, growers in areas where Bt hybrids have never been planted are likely to find it profitable to grow Bt hybrids at full efficacy, making zero coverage unstable either. In what follows, we provide an empirical analysis of the Bt planting game to explore what differences, if any, exist between equilibrium Bt coverage driven by self-interest versus group interest.

Description of Game

Formally, assume a local area of homogeneous cornfields that are managed by a homogenous population of maize growers. In the absence of Bt toxin, the grower of field i would expect standardized root injury of v_i (i.e., background rootworm pressure), and v_i is independently drawn from a distribution $F(v)$ on the support of [0, 1]. Growers each privately know their expected root injury, but the *ex-ante* distribution $F(v)$ is identical to all fields and is common knowledge.

A grower chooses between two planting strategies - Bt hybrid or non-Bt maize - by comparing their payoffs conditional on what s/he and the population have chosen. The payoff per acre to a maize grower choosing non-Bt maize (denoted as $s_t = 0$) is

$$\pi(s_t = 0|s_{t-1}, P_{t-1}) = m \times \min\{-r \times s_{t-1} - \tilde{r} \times P_{t-1}, v_t\} \equiv m \times \min\{B, v_t\}. \quad (2)$$

where s_{t-1} and P_{t-1} represent the historical Bt choice in the same field and the historical Bt coverage in the area. The m denotes the market value of one unit reduction in standardized root injury; $m = \$\ 3 \times \kappa \times py$, where κ is the percentage of yield loss for each node of roots injured, and p is the maize price (\$/bu), The y is the yield potential (bu/acre), or the yield that could have been realized without rootworm damage. In **Figure 3.5**, we contrast the actual or realized yield and the yield potential to illustrate the yield loss attributed to rootworm damage during the 2014-2016 periods, and the figure shows that the East states generally suffer less from the pest. See Data and Variables for parameter calibrations.

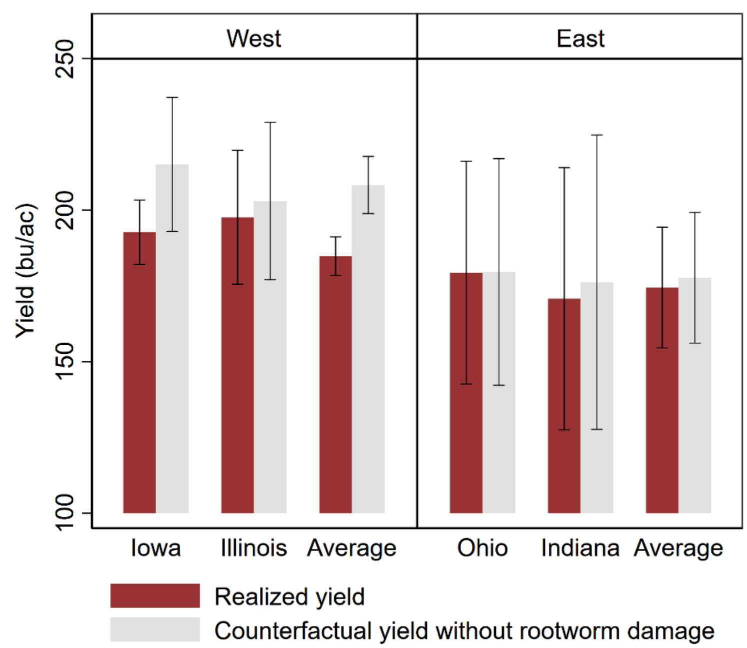

Figure 3.5 Yield loss associated with rootworm incidence, 2014-2016 average.

For each region (West and East), two representative states and the region-average are presented. The bars represent means, and the error bars represent the 95% confidence intervals.

While non-Bt growers do not bear additional seed costs, they potentially take advantage of intertemporal suppression from their fields ($r \times s_{t-1}$) and freeride on the areawide suppression ($\tilde{r} \times P_{t-1}$), and $B \equiv -r \times s_{t-1} - \tilde{r} \times P_{t-1}$ represents the potential root injury reduction. Nevertheless, when the background pest pressure v_t is very low, the actual reduction is constrained by v_t.

Bt hybrid growers control the root damage through direct Bt exposure, but the potential root injury reduction associated with the Bt trait needs to be adjusted to account for not only intertemporal suppression but also efficacy erosion effects, i.e., the potential reduction is $A \equiv -a - (b+r) \times s_{t-1} - (\tilde{b} + \tilde{r}) \times P_{t-1}$. Growing Bt hybrid also incurs additional costs. For growers acting according to self-interest, they would consider Bt seed premium (\$/acre; denoted by c), as well as the future cost to their fields expressed as $m \times (b + r)$. This future cost expression entails two implicit assumptions: one, a maize grower maximizes payoffs of the current year t and the next year $t + 1$, and no further in time; two, Bt hybrids are presumed to be planted for the next year. This would be less computationally demanding on the growers since they do not have to predict the future evolution of optimal decisions. Moreover, we would like to take a precautionary perspective because rootworm pressure involves a lot of uncertainties due to, for example, stochastic weather, so regardless of the actual choice in the future as future more information arrives, the decision-making based on the currently available information presumes the situation where growers have to rely on Bt to control the pest infestation.

We use C_{self} to denote the total cost normalized in terms of the standardized root injury scale for growers acting according to self-interest, and $C_{self} \equiv (b + r) + c/m$, i.e., they internalize only the intertemporal externality cost to their field through $b + r$. However, if growers instead are motivated by group interest and recognize the spatial (also intertemporal) externality associated with their Bt use in the local area, then their total normalized cost should include the spatial externality cost $\tilde{b}+\tilde{r}$ and is thus given by

$$C_{group} \equiv \frac{c}{m} + (b+r) + (\tilde{b}+\tilde{r}). \tag{3}$$

Therefore, the payoff to Bt growers is

$$\pi(s_t = 1 | s_{t-1}, P_{t-1}) = m \times [\min\{A, v_t\} - C], \tag{4}$$

where C is C_{self} (C_{group}) for growers motivated by self-interest (group-interest), and we refer to the corresponding equilibrium level of Bt coverage as "individual optimum" ("group optimum").

Characterization of Equilibrium

Field i's best choice is to grow Bt hybrids if and only if $\pi(s_t = 1 | s_{t-1}, P_{t-1}) \geq \pi(s_t = 0 | s_{t-1}, P_{t-1})$, or equivalently if its expected root injury v_i is such that

$$\min\{A, v_t\} \geq B + C, \tag{5}$$

that is, the actual root protection by Bt hybrids must be sufficiently high to adjust for the seed premium, the future cost, and the foregone freeride benefits. Therefore, all fields in the area have an identical threshold value of v for choosing Bt hybrids, and the probability of an arbitrary field planting Bt hybrids is

$$\begin{aligned}\Pr(s_t(v_t) = 1) = {} & \Pr(s_{t-1} = 0) \times \Pr(s_t = 1 | s_{t-1} = 0) \\ & + \Pr(s_{t-1} = 1) \times \Pr(s_t = 1 | s_{t-1} = 1).\end{aligned} \tag{6}$$

Further, the homogeneity assumption implies that the areawide Bt coverage P_t is equivalent to the probability of growing Bt hybrids in an individual field, i.e., $P_t = \Pr(s_t(v_t) = 1)$. Thus eq. (6) implies

$$\begin{aligned}P_t = {} & (1 - P_{t-1}) \times 1[-a - \tilde{b} \times P_{t-1} \geq C] \times (1 - F(C - \tilde{r}P_{t-1})) \\ & + P_{t-1} \times 1[-a - \tilde{b} \times P_{t-1} - b \geq C] \times (1 - F(C - r - \tilde{r}P_{t-1})),\end{aligned} \tag{7}$$

which can be further rewritten as

$$g(P_t) = k(P_{t-1}), \tag{8}$$

where $g(x) = x$.

Now, we characterize the equilibrium using the solution concept of *stationary equilibrium strategy*. Analogous to the commonly used Nash Equilibrium strategy where the equilibrium is a choice of strategies that tend to persist once the players are using it, the stationary equilibrium strategy tends to persist over time once it is prevalent in the population. In other words, when all individuals play such a strategy, it is the best response for every individual to not deviate from the strategy in a single period. Define P^* such that $g(P^*) = k(P^*)$, then P^* is the equilibrium coverage of the dynamic game such that if every grower in the population follows the strategy in eq. (5) where P_{t-1} is replaced with P^*, then P^* is self-sustaining. We used this solution concept for this game because it is a practical strategy to be easily followed by growers for policy purposes.

Self-interest versus Group-interest

we use the period 2014-2016, the most recent three years in our sample, to empirically evaluate P^*. The parameter calibrations are summarized in Table A4 (See Methods and Materials for details), and **Figure 3.6** illustrates the equilibrium results for the individual optimum. Panel (A) presents the empirical CDF function $F(\cdot)$, and it shows the East has much lower rootworm pressure than the West region. Panel (B) and (C) visualizes eq. (8) using the lower ($u = 0.05$) and upper ($u = 0.25$) bound of u, respectively. Panel (B) shows the sustainable level P^*_{self} is 0.64, which is very close to the status-quo (0.63), resulting from a combination of relatively small cost and high rootworm pressure. In contrast, the East has a much smaller intercept due to lower rootworm pressure and a steeper CDF function, thus a substantially lower $P^*_{self} = 0.14$. Compared to the status-quo of 0.68, the P^*_{self} is only one-fifth of it, suggesting a major overplanting behavior in the East. Figure 3.A5 in the Appendix provides an overview of data availability and background rootworm pressure for each state.

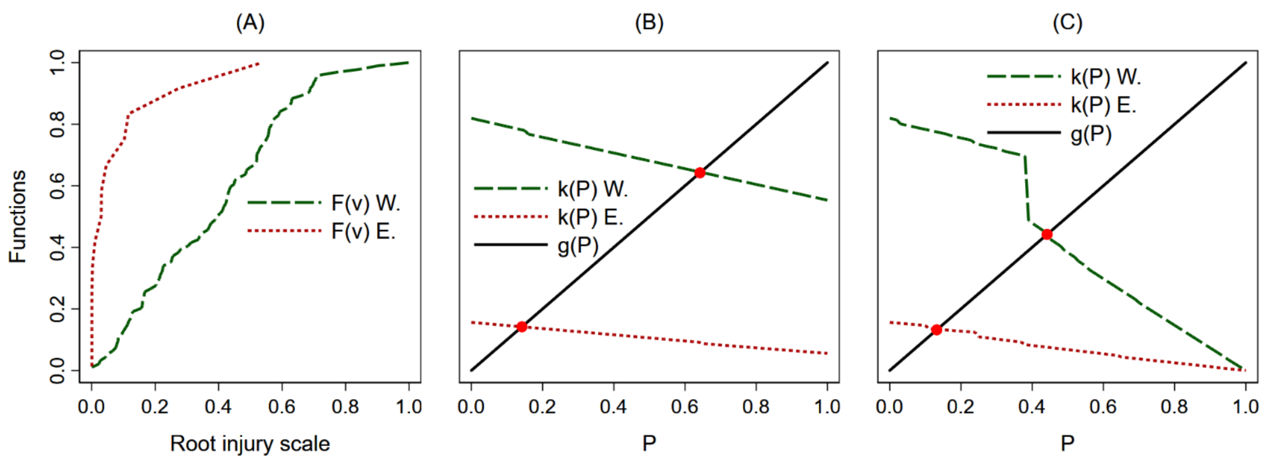

Figure 3.6 Equilibrium outcome when growers act according to group interest.

Panel (A) is the empirical cumulative distribution functions (CDF) for the West and East regions, respectively. Panel (B) and (C) are the equilibrium results under the smallest and largest spatial spillover effects within the reasonable range, where the female adult rootworms' dispersal proportion (u) is assumed to be 5% and 25%, respectively. The equilibrium points are denoted by red dots (i.e., where lines cross).

When the upper bound of spillover effects is assumed (Panel (C)), P^*_{self} in the West and the East are reduced to 0.44 and 0.13, respectively. This is because as spillover effects increase, the indicator function begins to have an impact, as illustrated by the part of the green line with a very steep slope in Panel (C). This effectively changes where the two lines intersect. Intuitively, greater spillover effects make it easier for the non-Bt benefit to exceed the Bt benefit if Bt was planted in the preceding year, thereby disincentivizing Bt planting conditional on Bt history.

The empirical difference between group optimum and individual optimum, however, is strikingly small (See Figure 3.A6 in the Appendix). Specifically, the equilibrium Bt coverage under $u = 0.05$ is 0.64 and 0.14 for the West and East, respectively, and rounds up to 0.43 and 0.13 under $u = 0.25$. That is, where individual growers act according to complete self-interest would preserve the Bt susceptibility resource to nearly the same extent as where they consider group interest. Moreover, the group optimum is usually difficult to achieve, as it requires growers to be unselfish and voluntarily act according to the group interest. In practice, the individual optimum as the second best would be a more feasible solution, as in many other environmental problems.beyond which Bt hybrids are preferred over non-Bt plants, denoted as v^*. The threshold for the individual optimum coverage P^*_{self} will depend on Bt history, i.e., whether Bt was planted in the preceding year, so a subscript is used (v_1^* for having Bt history, and v_0^* otherwise). Results in **Table 3.2** show that at $u = 5\%$, the Bt planting threshold for both regions is 0.13 and 0.35 for fields without and with Bt history, respectively. The values are very close before rounding up because the seed premium per unit market value gain (c/m) is similar in the two regions (Table 3.A2 in the Appendix), and the difference in P^* carries little weight given the size of spillover effects. However, at $u = 25\%$, the policies differentiate: while the thresholds for the East remain close to that under $u = 5\%$ due to a small change in P^*, for the West it is optimal for maize growers not to plant Bt maize at all if the field was planted to Bt maize in the preceding year. That is, at the 44% regional coverage, planting non-Bt seeds and taking advantage of the suppression benefit from own-field Bt history and spatial spillover is more profitable than planting Bt at additional cost. The status-quo ($\bar{P}$) is used as a reference, where we use the regional average of Bt planting rate between 2014-2016 as P^* (See Table 3.A4 in the Appendix), and v^* is such that $\bar{P}$ =

$100 \times (1 - F(\bar{v}))$. We lack information to recover how the threshold is affected by Bt history though, so the same threshold is used.

Table 3.2 Summary of alternative scenarios

	West			East		
	$\bar{P}$	P^*_{self}		$\bar{P}$	P^*_{self}	
Spillover effect assumption (u)		5%	25%		5%	25%
P	0.63	0.64	0.44	0.68	0.14	0.13
$\bar{v}_0$	0.26	0.13	0.16	0.00	0.13	0.14
$\bar{v}_1$	0.26	0.35	/	0.00	0.35	0.36

Discussion

Currently, resistance mitigation strategies include rotating to a non-host crop (e.g., soybeans), rotating with Bt hybrids expressing different modes of action, and supplementing (or replacing) Bt toxins with synthetic insecticides, including granular, liquid, and seed treatment insecticides. While evidence of remedial action effectiveness has been accumulating (Carrière et al. 2020), these are *post-hoc* remedial efforts and may not be viable or desirable for all producers due to agronomic and economic constraints. Data from most transgenic crops deployed over the last several decades indicate that resistance may be best viewed as an inevitable consequence of widespread use, and management should therefore focus on strategies that maximize the usable life of each approach. Lowering the selection pressure upon pest insects is the single most effective approach to delay resistance evolution (i.e., less planting of Bt hybrids) (Tabashnik and Carrière 2017; Tabashnik and Gould 2012).

However, managing resistance is a technological issue as well as a behavioral one (Hardin 1968). In essence, achieving the Bt planting level that is optimal for self-interested growers (i.e., the individual optimum) requires them to recognize the tradeoffs between current and future interests arising from intertemporal efficacy erosion and suppression; and achieving what is the best for the local group of growers or the community (i.e., the group optimum) further requires growers to internalize the spatial spillover externalities and relinquish individual freedom to plant Bt for their neighbors. The extent to which existing Bt planting levels differ from the individual- and group optimum is critical to formulating effective and efficient regulations, necessitating a data-driven approach.

Combining two sets of unique data - the trial data on Bt efficacy and rootworm pressure, as well as survey data on rootworm-specific Bt planting rates - the findings of this paper suggest that Bt use comes at a considerable long-term cost of Bt efficacy erosion, reducing Bt efficacy by more than half on average across the Corn Belt from 2005 to 2016. Although a fraction of the long-term cost is offset by the long-term benefit associated with intertemporal suppression, the net future cost is still equivalent to around a 12% Bt efficacy reduction. Because rootworm pressure and Bt efficacy in a grower's field are affected by spatial spillover, the grower's Bt choice (plant Bt or non-Bt) is also dependent on past Bt choices made by others in the local area. Therefore, we develop a dynamic game to find the individual and group optimum.

The empirical game analysis presented in this paper demonstrated that distinctions between individual and group optimum are rather trivial. In some circumstances, autonomous or voluntary collective actions are observed in managing resources within a small local group or community, which essentially utilizes the social capital or social norms (Pretty 2003; Brown 2018), but cooperatives remain uncommon and difficult to establish (Gould 2018). Therefore, the individual optimum, as the second-best option, preserves pest susceptibility almost as well as the group optimum, and it is also more feasible for policy purposes. Nevertheless, a discrepancy still exists between the actual Bt planting rate and the individual optimum. This is especially true for the Eastern Corn Belt, where the corresponding Bt rates are 68% and 13%~14% across a reasonable range of spatial spillover assumptions.

Among other things, trait bundling and a lack of information on future costs may play the most important role in causing the discrepancy. Below-ground traits have been increasingly stacked, or bundled together, with above-ground insect-resistant and herbicide-tolerant traits. As illustrated in Figure 3.A7, in recent years the majority of the rootworm-active hybrids contain multiple traits. For example, Bayer offers the SmartStax seed product, which confers multiple traits: above-ground Bt, below-ground Bt, and tolerance to glyphosate and glufosinate, and it is also the only available product that contains the rootworm Bt trait. (https://www.dekalbasgrowdeltapine.com/en-us/seed-finder/corn.html#plid=H72K0968D&territory=C6J&view=national, accessed 8 August, 2022).

Bundling is frequently found to increase purchase likelihood and consumers are likely to purchase more than they would otherwise if items were sold separately (Drumwright 1992), due to reasons such as reduced time and cognitive effort required to make purchase decisions (Harries and Blair 2006). Previous research on seed trait bundling has also suggested sub-additive pricing instead of component pricing (Shi et al. 2010). Bundling has thus been suggested as a strategy for marketing new high-tech products as it reduces perceived risk and increases the perceived benefit of the bundled new products (Sarin et al. 2003), and experimental results also provided evidence that bundling an innovation with an existing and related product increases adoption intention (Reinder et al. 2010). Because the costs and benefits of individual items are decoupled, consumers are more likely to purchase something that they don't need (Soman and Gourville 2001) – rootworm Bt trait in our case.

In addition to the trait cost obscured as a result of trait stacking, growers are likely underinformed about the cost of Bt efficacy erosion, or the future cost. Our study contributes to filling this knowledge gap, and more extension work is needed to educate growers and disseminate the information. The long-term capacity to control the pests could benefit from more informed and rational decisions.

We propose two general policy guidelines for the Bt-rootworm management problem. First, we suggest regulators focus on seed suppliers in an effort to reform how seed products are presented and marketed by breaking down the price for each trait. Individual traits are thus monetarily separated to draw farmers' attention to the individual cost of each trait, recoupling the costs and benefits of each trait. Second, collaborative efforts from academic researchers and extension workers are needed to better inform growers in order to achieve the second-best individual optimum, if not the group optimum. Furthermore, the problem and policy solution for the Western Corn Belt can take slightly different forms. The discrepancy between the individual optimum and actual Bt planting level is quite small due to high rootworm pressure in the West. This implies that a more integrated management strategy synthesizing different technologies – those expected in the coming years in particular - might be warranted. As an environmentally benign tool of insect management (Mendelsohn et al. 2003), delaying resistance and maintaining the Bt efficacy for the future, even while new tools are being developed, is in the best interests of sustainable crop production. This is especially so under the projections of a warming climate (Deutsch et al. 2018).

It is also worth emphasizing that these issues we identified and the policy guidelines we provided are not limited to this specific problem of rootworm Bt toxins; rather, they apply more broadly to managing biological commons or crop biotechnology. The RNAi technology is a closely related example. Although recently registered RNAi-expressing maize hybrids are expected to be planted in 2022, this approach will only be provided in combination with existing Bt toxins (e.g., *Cry3Bb1*), to enhance efficacy and minimize the risk of rapid resistance evolution to this novel approach (Fishilevich et al. 2016). Tabashnik and Carrière (2017) comment that “insects are remarkably adaptable and are expected to evolve resistance to any control method, including transgenic plants with combinations of protective traits as different as Bt toxins and RNAi”. This is also demonstrated by the rapid evolution of cross-resistance across the toxins deployed in stacked rootworm Bt hybrids (Zukoff et al. 2016), indicating that current pyramids are not composed of truly independent modes of action in terms of resistance management. These policy guidelines may also find a wider audience outside of the United States, particularly in countries like China that have long restricted crop biotechnology but have begun to change their stance.

Data and Variables

1. University trial data

In this study, we have collected university research trial data, which monitor the rootworm pressure in the surrounding area. The research fields are generally small (ca. less than 10 ha) in size and are designed to maximize female rootworm oviposition by planting maize following maize and planting maize late in the season compared with background plantings, this serves to attract gravid females to a comparatively late and rare source of maize pollen. These research fields, therefore, are likely to serve as a “worst-case” scenario for feeding pressure, as they effectively over-represent damage relative to typical grower practices in the region. Multiple variables were used in the analysis sourced from this dataset, including root injury scale, Bt variety planted in the trial fields, soil insecticide use, and seed treatment application in the trial.

2. TraitTrak® survey data

The TraitTrak® survey is a unique and large plot-level survey dataset that spans the period 1995 to 2016 and is nationally representative. The survey is conducted annually by Gfk Kynetec, a market research company specializing in providing agricultural data services, and has been widely used in previous studies (Shi et al. 2010; Perry et al. 2016; Lee and Moschini 2020; Ye et al. 2021). For each sampled plot, the dataset provides specific seed information planted to the plot, as well as the associated seed price and actual expenditures. This unique feature allows us to distinguish rootworm-targeting Bt hybrids from others and thus more precise identification. The Bt coverage rates at CRD and county level as well as seed premiums used in the analysis are both obtained from this dataset.

3. Complementary data sources

Aside from the two primary data sources, we also exploit information from multiple other sources. For the control variables: site-specific precipitation is obtained by averaging the precipitation at the four closest neighboring coordinates in the Parameter-elevation Regression on Independent Slopes Model (PRISM) dataset, a fine-scale weather dataset gridded at 2.5 arc-minute (4 km) resolution for the contiguous United States; the cropping pattern (continuous maize planting) variable is constructed from Cropland Data Layer (CropScape). For the parameter calibrations: maize cash price p is obtained from maize elevators, compiled to state-year level; parameter κ is drawn using results from Tinsley (2013) and is calibrated as 15%; actual yield data is obtained from National Agricultural Statistics Service (NASS).

4. Calibrations for yield potential.

The yield potential y in the absence of rootworm damage is recovered by adding back the yield loss associated with root damage. Specifically, we first calculate the average root injury for Bt and non-Bt fields for each county. Then, we obtain the county-average root damage as the weighted average of root injury, using the Bt planting rate at CRD level as the weight, and denote it as l. So the yield potential is calculated as the actual yield in the county divided by $(1 - 3 \times \kappa \times l)$.

APPENDIX

APPENDIX

Rootworms are targeted by several toxins: Cry3Bb1, registered in 2003 by Monsanto; Cry34/35Ab1, registered in 2005 by Dow AgroSciences and DuPont Pioneer; and mCry3A and eCry3.1Ab, registered in 2006 and 2014, respectively, by Syngenta. The chronological trends of adoptions of maize hybrids possessing each individual trait, as well as the stacking of the traits, is depicted in **Figure 2.A1-2.A2**.

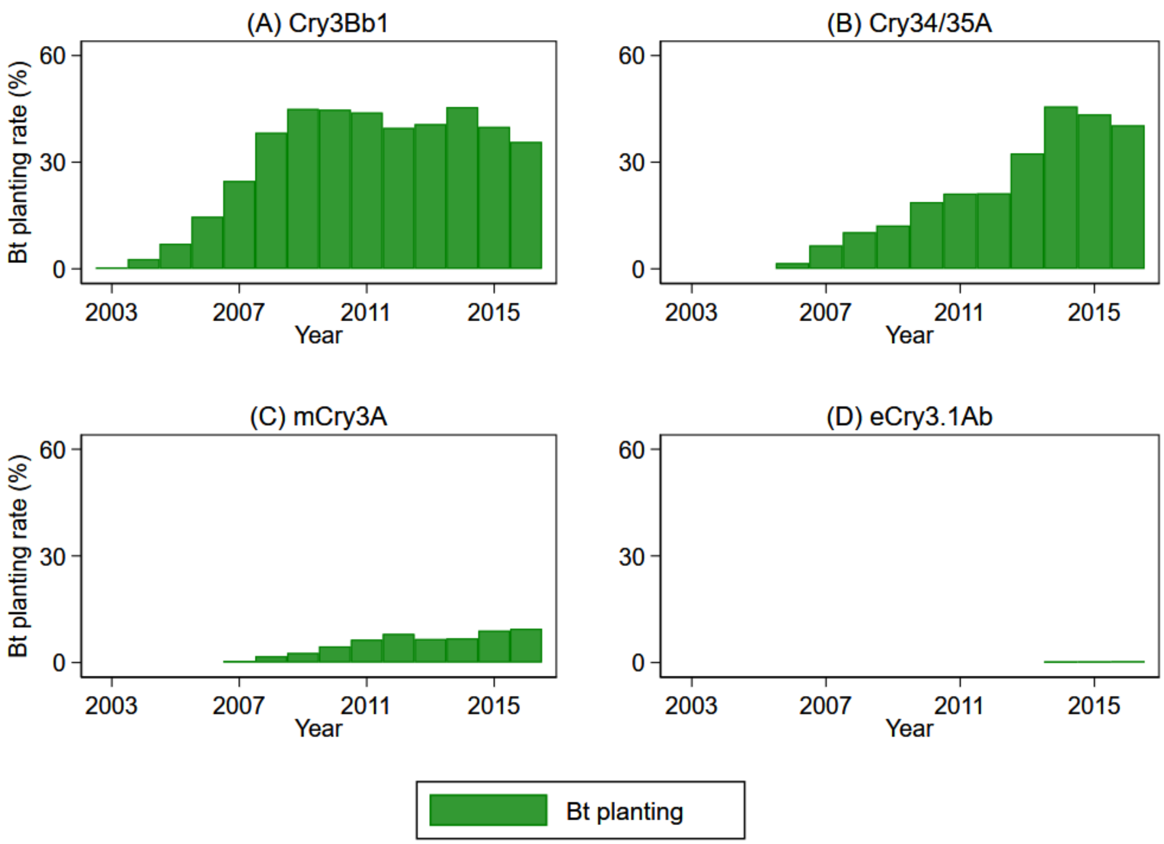

Figure 3.A1 Time trends of Rootworm Bt trait adoptions in the sample, 2003-2016.

The Bt planting rate is calculated as the percentage of maize area that plants varieties containing each Bt toxin (Data source: TraitTrak®, Kynetec.)

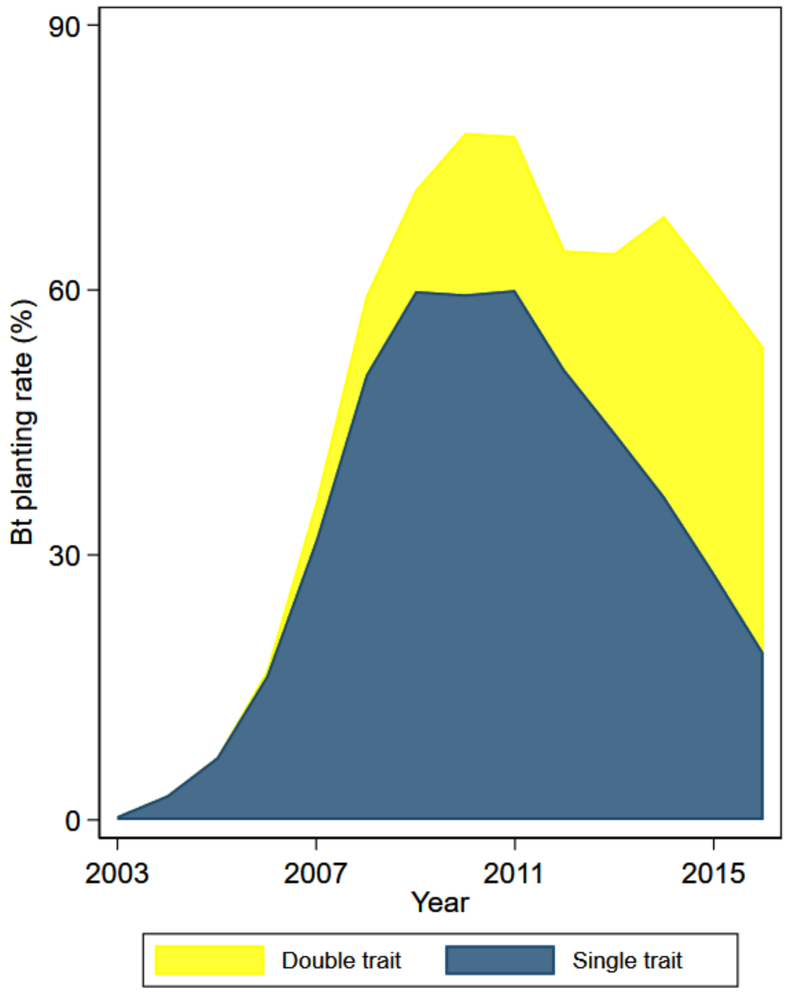

Figure 3.A2 Time trends of single- and double-trait adoptions in the sample, 2003-2016.

The Bt planting rate is calculated as the percentage of maize area that plants varieties containing one and two Bt toxins, respectively (Data source: TraitTrak®, Kynetec.)

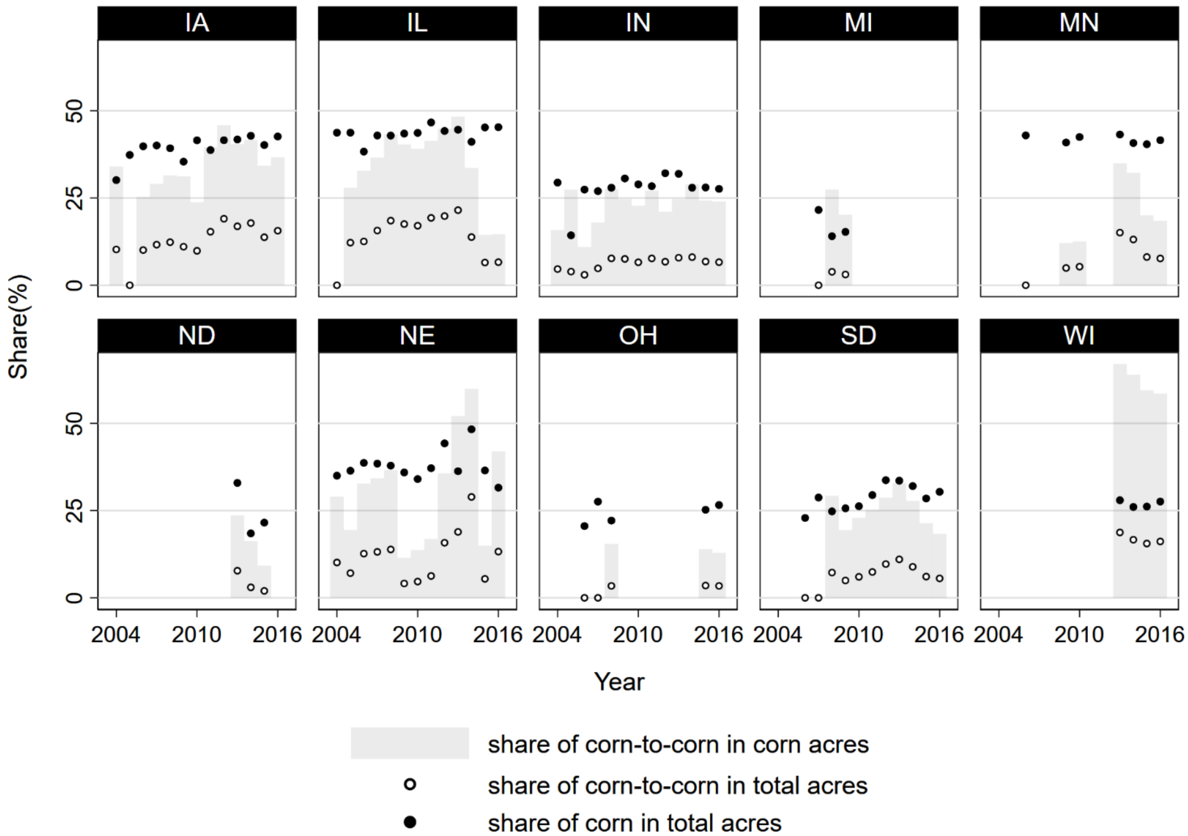

Figure 3.A3 State-specific time trends in maize cropping patterns, 2000-2016.

(Data source: Cropland Data Layer, NASS.)

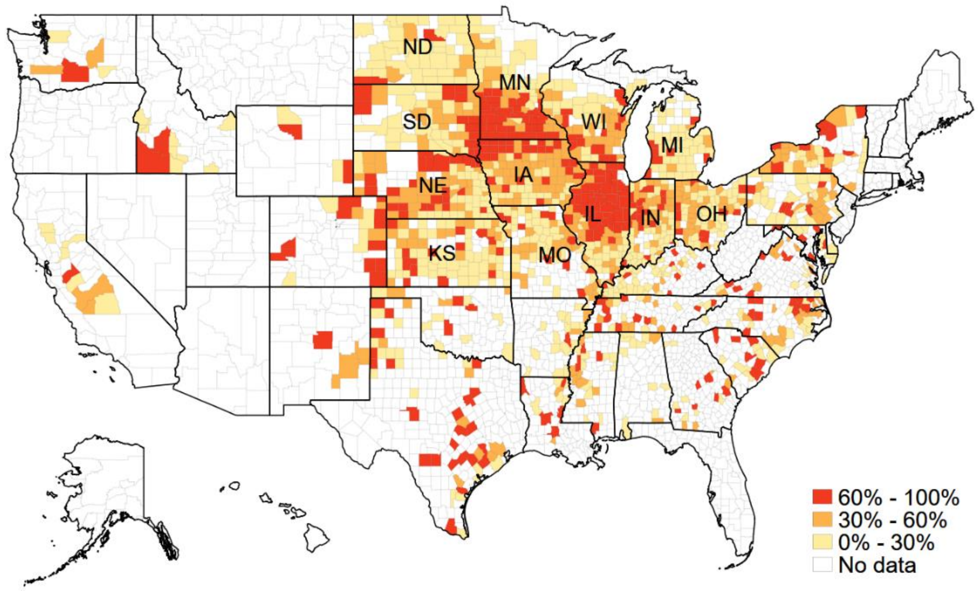

Figure 3.A4 Planting percentage (%) of rootworm Bt maize in 2016, at the county level.

The Bt planting rate is calculated as the percentage of maize area that plants varieties containing rootworm-active Bt toxins. (Data source: TraitTrak®, Kynetec.)

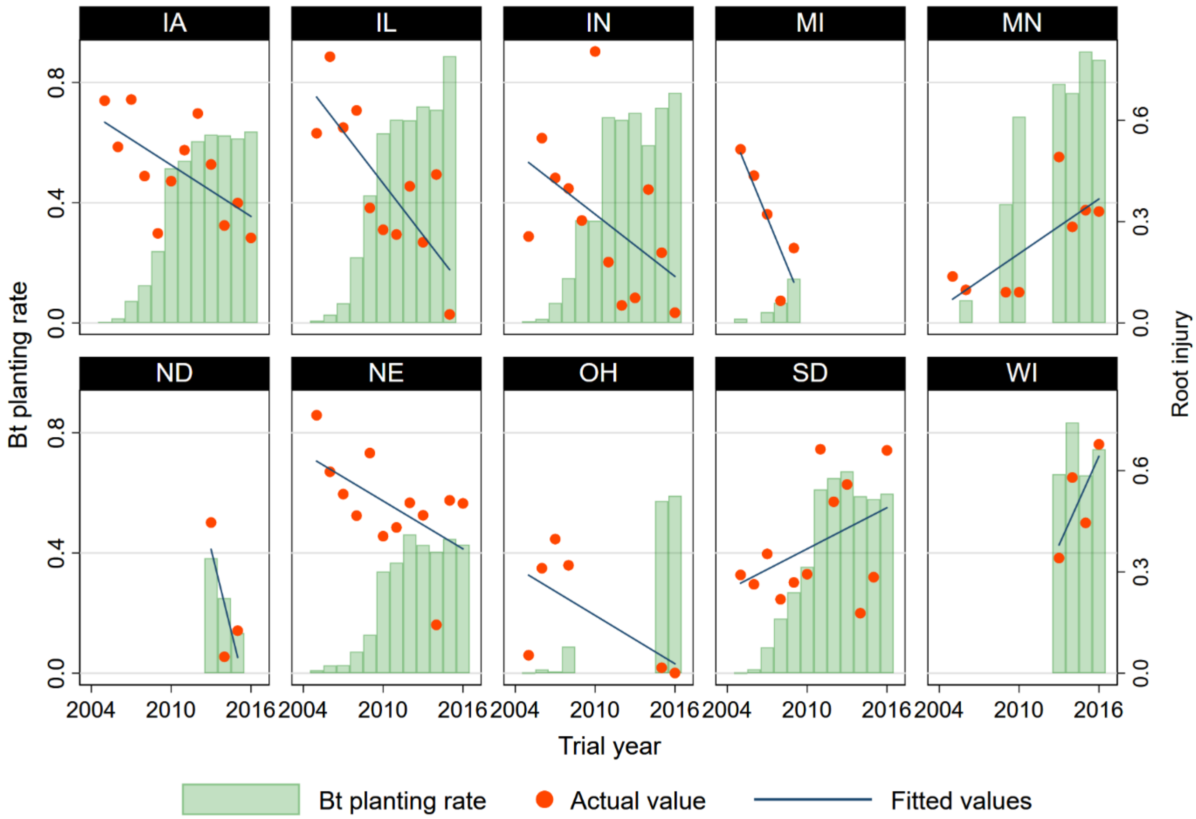

Figure 3.A5 State-specific time trends of background (non-Bt trial fields) rootworm pressure and Bt planting rate, 2005-2016.

Bt planting rate variable is lagged for two years, i.e., the Bt rate value shown in 2005 is that in 2003, and is calculated as the rate of maize acres planted to rootworm Bt hybrids in the CRD. Only fields where soil insecticides or high-level seed treatments were not applied are included. (Data source: Trial data; TraitTrak®, Kynetec)

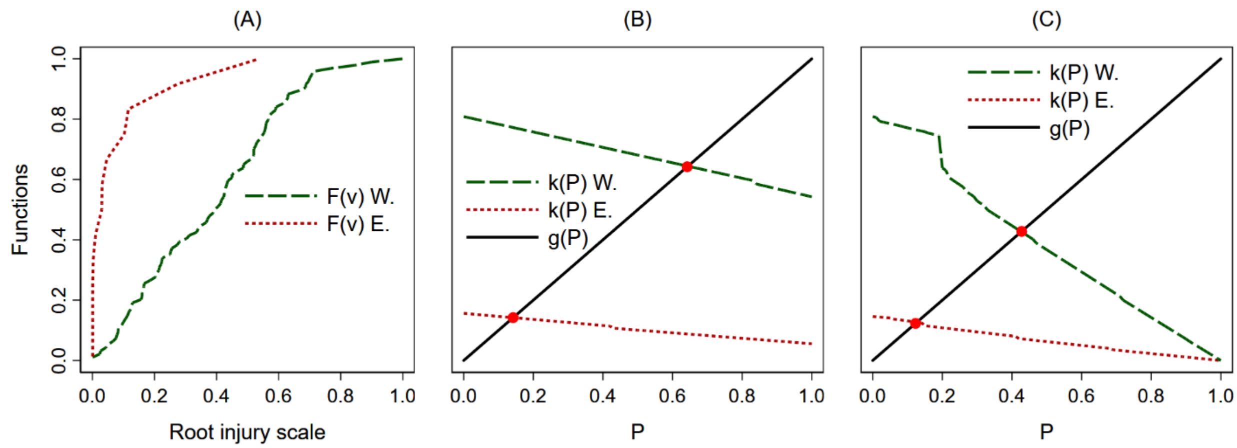

Figure 3.A6 Equilibrium outcome when growers act according to group interest.

Panel (A) is the empirical cumulative distribution functions (CDF) for the West and East regions, respectively. Panel (B) and (C) are the equilibrium results under the smallest and largest spatial spillover effects within the reasonable range, where the female adult rootworms' dispersal proportion (u) is assumed to be 5% and 25%, respectively. The equilibrium points are denoted by red dots (i.e., where lines cross).

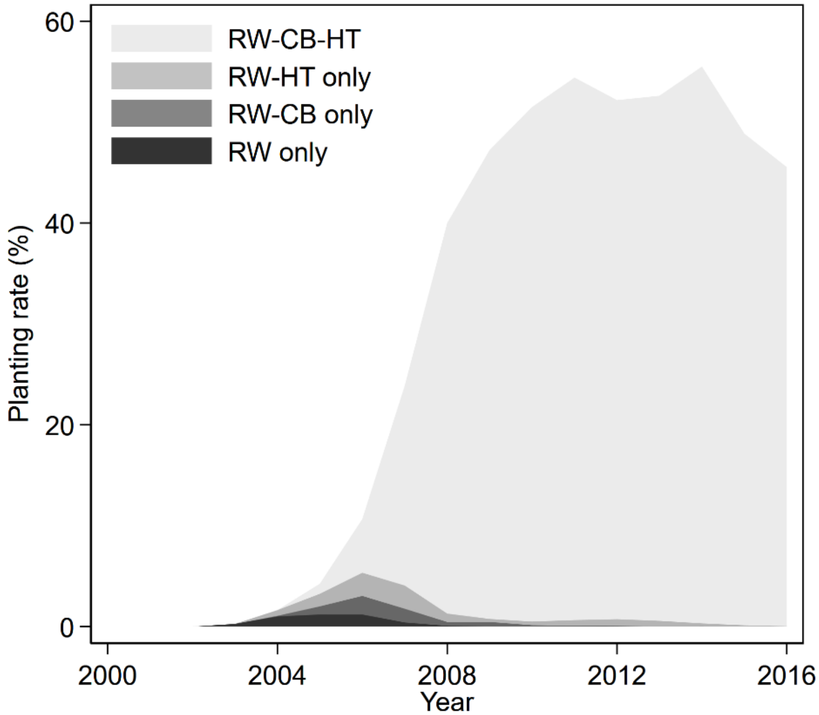

Figure 3.A7 Rootworm Bt trait stacking increases over time.

“RW”, “CB”, and “HT” are abbreviations for traits protecting against below-ground pests, above-ground pests, and herbicides. Planting rates are calculated as the percentage of maize acres planted to each hybrid at the national level. (Data source: TraitTrak Kynetec.)

Table 3.A1 Fractional response model results (APEs) for root damage, using county-level Bt planting rate

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
Bt treatment in the trial field (bt)	-0.42***	-0.44***	-0.37***
	(-20.43)	(-24.83)	(-15.28)
Bt planting rate ($coverage$)	-0.17***	-0.21***	-0.15***
	(-4.32)	(-3.99)	(-4.27)
Interaction term ($bt \times coverage$)	0.22***	0.23***	0.19***
	(5.26)	(5.85)	(5.77)
Precipitation, April	-0.02	-0.02	-0.02
	(-0.54)	(-0.39)	(-0.53)
Precipitation, May	-0.02	-0.04	-0.03
	(-0.56)	(-0.90)	(-0.68)
Precipitation, June	-0.06***	-0.07***	-0.05***
	(-3.75)	(-3.27)	(-3.77)
Precipitation, July	0.02	0.03	0.03
	(0.59)	(0.66)	(0.76)
Precipitation, August	-0.03	-0.06***	-0.03*
	(-1.61)	(-3.44)	(-1.85)

Table 3.A1 (cont'd)

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
High-level seed treatment	-0.08^{***}	-0.10^{***}	-0.07^{***}
	(-6.41)	(-9.64)	(-5.89)
Ratio of continuous maize in total crop land		-0.26	
		(-1.21)	
Soil insecticides			-0.15^{***}
			(-10.32)
Observations	1466	1117	1868

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parentheses. Standard errors are clustered at crop reporting district (CRD) level.

Table 3.A2 Linear regression results for root damage, using CRD-level Bt planting rate

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
Bt treatment in the trial field (bt)	-0.44***	-1.75***	-0.41***
	(-12.14)	(-23.64)	(-10.14)
Bt planting rate ($coverage$)	-0.28***	-0.93***	-0.29***
	(-4.85)	(-4.52)	(-4.97)
Interaction term ($bt \times coverage$)	0.25***	1.10***	0.27***
	(4.40)	(6.12)	(4.52)
Precipitation, April	-0.03	-0.09	-0.03
	(-0.51)	(-0.41)	(-0.60)
Precipitation, May	-0.02	-0.16	-0.02
	(-0.47)	(-0.80)	(-0.61)
Precipitation, June	-0.05***	-0.26***	-0.05***
	(-2.95)	(-2.98)	(-3.14)
Precipitation, July	0.02	0.11	0.02
	(0.45)	(0.60)	(0.62)
Precipitation, August	-0.03	-0.20***	-0.03**
	(-1.47)	(-3.02)	(-2.05)

Table 3.A2 (cont'd)

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
High-level seed treatment	-0.10***	-0.47***	-0.09***
	(-4.26)	(-9.70)	(-3.51)
Ratio of continuous maize in total crop land		-0.83	
		(-0.97)	
Soil insecticides			-0.12***
			(-3.67)
Observations	1489	1119	1891

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parentheses. Standard errors are clustered at crop reporting district (CRD) level.

Table 3.A3 Linear regression results for root damage, using county-level Bt planting rate

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
Bt treatment in the trial field (bt)	-0.43***	-1.70***	-0.39***
	(-10.96)	(-19.16)	(-8.15)
Bt planting rate ($coverage$)	-0.21***	-0.82***	-0.22***
	(-3.28)	(-3.99)	(-3.02)
Interaction term ($bt \times coverage$)	0.20***	0.91***	0.20***
	(3.73)	(5.93)	(2.90)
Precipitation, April	-0.02	-0.08	-0.02
	(-0.47)	(-0.39)	(-0.55)
Precipitation, May	-0.03	-0.17	-0.03
	(-0.62)	(-0.90)	(-0.78)
Precipitation, June	-0.06***	-0.27***	-0.06***
	(-3.12)	(-3.22)	(-3.34)
Precipitation, July	0.02	0.12	0.03
	(0.64)	(0.66)	(0.82)
Precipitation, August	-0.03	-0.22***	-0.03**
	(-1.50)	(-3.33)	(-2.16)

Table 3.A3 (cont'd)

	Root injury (rw)		
	Model (1)	Model (2)	Model (3)
High-level seed treatment	-0.09***	-0.45***	-0.08***
	(-3.98)	(-7.70)	(-3.29)
Ratio of continuous maize in total crop land		-1.02	
		(-1.20)	
Soil insecticides			-0.12***
			(-3.75)
Observations	1466	1117	1868

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parentheses. Standard errors are clustered at crop reporting district (CRD) level.

Table 3.A4 Parameter calibration results.

Region	*c*	*m*	*p*	*y*	*c/m*	*Bt planting rate*
West	25.39	330.01	3.46	213.41	0.08	0.63
East	26.83	302.56	3.71	183.46	0.09	0.68

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CHAPTER 4 Climate Adaptation Value of Drought-tolerant Technology in a Crop Insurance Context

Introduction

As atmospheric carbon dioxide continues to rise at a rate of 2 to 2.5 ppm per year, global warming is predicted to continue. While most research on agricultural production has concentrated on temperatures (Schlenker and Roberts 2009; Tack et al. 2015; Kawasaki and Uchida 2016; Gammans et al. 2017; Miller et al. 2021), the drought aspect of climate change has received greater attention (Mazdiyasni and AghaKouchak 2015; Lesk et al. 2016; Kuwayama 2018; Yu et al. 2022). The past decade has seen an increase in the frequency and severity of drought occurrences – the catastrophic drought that swept across much of the Western corn production states in 2021 is expected to last into 2022 growing seasons and result in another record-dry year since 2012, not long ago. Economically, Drought has been the most expensive cause of crop insurance claims in the United States, accounting for roughly half of all indemnity payments (Wallander et al. 2017; Perry et al. 2020).

Adaptation measures such as altering planting dates, double cropping, and conservation agriculture have contributed to the resilience of agricultural production systems to climate change (Kawasaki 2019; Cui 2020; Cui and Xie 2022; Chen and Gong 2022; Gammans et al. 2019). The new advent of drought-tolerant (DT) seed technology appears to be bringing new adaptation opportunities. Despite its relatively short history, drought-tolerant corn, which was released in 2012 and has been widely available since 2013, has shown a comparable adoption velocity as its famous forerunner, insect-resistant Bt maize (Figure 4.A1 in the Appendix). Field trials with DT hybrids in the Corn Belt region have revealed yield increases in the face of water stress (Mounce et al. 2016; Gaffney et al. 2015; Nemali et al. 2015).

Nonetheless, questions remain about the climate adaptation value of DT technology in large-scale corn production, specifically in terms of three areas: one, numerous laboratory and empirical studies have suggested yield penalties associated with higher drought tolerance due to resource constraints (Lybbert and Bell 2010; Tollefson 2011; Zhao et al. 2015; Lobell et al. 2020; Yu et al. 2021); two, the adaptive value of this technology, namely whether the marginal benefit increases with increased environmental stress (Lobell 2014b); three, in practical settings, DT varieties may perform differently than in laboratory settings due to environmental heterogeneity and behavioral differences associated with the planting DT corn, such as increased seeding rate (Lobell et al. 2014a). A strand of literature has discussed whether these technological advances actually led to increased drought sensitivity, in trade-off to continued rises in mean yield, and readers are referred to Goodwin and Piggott (2020) for a detailed discussion.

The empirical adaptation value of DT will have important implications for the federal crop insurance program (FCIP), whose premiums are mandated to be actuarially fair. A good example is the Biotech Endorsement (BE) program, which was implemented across the Corn Belt from 2009 to 2012 and gave an actuarially accurate discount to account for the lower yield risk of selected corn hybrids (Goodwin and Piggott 2020). If the insurance premium fails to reflect the risk reductions associated with DT, adoption of DT hybrids will likely be disincentivized, compromising corn growers' long-term ability to adapt to drought (Annan and Schlenker 2015; Miao 2020). Furthermore, because DT research and development involves significant upfront fixed costs, often supported by both private and public research funding (Lybbert and Carter 2015), a lack of market demand will prevent future investments and advances, particularly from the private sector.

To address the central question of DT benefits on county-level yield in commercial corn production, we employ primarily a large and unique panel dataset on seed use. Two issues are important to discuss and clarify at this time. The first issue that immediately emerges in this setting is whether high-DT counties systematically differ from low-DT counties and confounds the yield impact. On the demand side, counties with better corn yield potential and/or greater drought risk are expected to profit more, making DT technology more likely to be adopted. On the supply side, the drought-prone corn-producing areas are prioritized in developing and marketing DT seeds; indeed, the majority of field trials in the United States are undertaken in the drought-prone Western Corn Belt (Gaffney et al. 2015; McFadden et al. 2019). As a result, as illustrated in **Figure 4.1**, higher DT adoption rates are found in the Western Corn Belt, particularly Nebraska, Kansas, and Colorado. Interestingly, Panel (A) in Figure 4.A2 shows that during the DT-available years in our sample (2013-2016), DT was almost always stacked with 1st GE seeds (defined as seeds containing insect-resistant Bt or herbicide-resistant traits), which were already ubiquitous by 2012 (the primary reason that BE program ended in 2012, see Goodwin and Piggott 2020); yet Figure 4.A3 shows that 1st GE-DT stacking seeds cost less than 1st GE only seeds, despite a higher retail price. These observations suggest that during the first few years of DT marketing (2013-2016), seed companies and/or retailers had a lot of promotions (free units and discounts) on 1st GE-DT stacked seeds to help expand the DT market, and as a result, DT came at a low or no cost for corn growers during this period, and changes in DT planting were more likely supply-driven. Second, as previously mentioned, our analysis intends to capture differences in behavioral reactions to DT planting in evaluating the empirical value of DT rather than excluding them. Planting density changes are one example (see Panel (B) in Figure 4.A3). That is, we are interested in how the use of DT has affected corn production when these resultant responsive behaviors are taken together, rather than a purely technical and agronomic relationship.

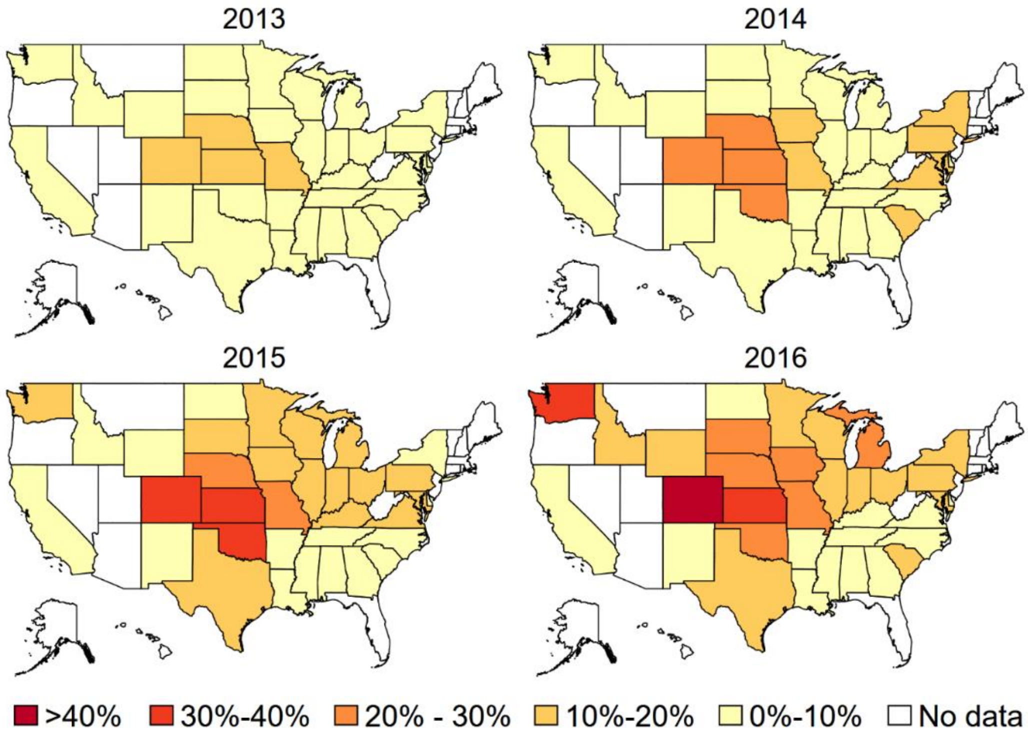

Figure 4.1 Geographical distribution of DT planting (%) during 2013-2016, at the state level. Measured as the percentage of corn acres (%) that were planted to DT-containing hybrids. The state-level statistics have the highest confidence in the Corn Belt, since it is the most heavily sampled, whereas states like Oklahoma and Texas are only lightly sampled and thus less representative at the state level. (Date source: TraitTrak®, GfK Kynetec.)

The remainder of the article is structured as follows. We first outline the biology underpinning existing drought-tolerance technologies to set the stage for DT suspicions. Then we empirically characterize the DT technology from several perspectives. This is followed by a simulation of the DT value in the crop insurance context. The last section concludes and discusses the implications.

Background on Drought-tolerance Biotechnology

Despite long-standing efforts in human history to select improved varieties against environmental stress (Yu and Babcock 2010), this new wave of drought-tolerant corn seeds features biotechnology advances since the 2000s. Tools like marker-assisted selection allow for better identification of genes associated with drought tolerance to be introduced into DNA molecules for analysis. Syngenta, the agri-tech giant, was the first to release such hybrids under the name Agrisure Artesian® in 2011, using the molecular breeding process. This was soon followed by the launch of another conventionally bred brand, Dupont Pioneer's Optimum AQUAmax®. Monsanto, on the other hand, used genetic engineering in partnership with BASF to develop the only commercially marketed GE seeds, known as the Genuity DroughtGard®. The GE hybrids were first launched in 2012, although they were not widely available until 2013. The plant expresses the cold-shock protein B (cspB) to regulate biological functions as a gene from the soil bacterium *Bacillus subtilis* was inserted into it. According to Figure 4.A4 in the Appendix, the market share of GE DT has been increasing since its debut but traditionally bred DT, particularly Dupont cultivars, still dominates the DT market as of 2016.

However, technological challenges remain. Unlike traits that target biotic pressures like insects and weeds, which might be pinned down to a single gene, tolerance to abiotic stresses such as drought often involves several physiological processes and a larger set of genes. However, only a few genes can be manipulated at the same time using existing genetic engineering techniques. Conventional breeding transfers genes at a comparatively lower cost, but transferring the desired gene to the plant may cause other nearby genes to be transferred as well, causing unexpected effects. This is commonly referred to as “yield drag”. Furthermore, genetic approaches – whether genetic engineering or conventional breeding – suffer from what is known as pleiotropy in genetics. That is, a gene and its products often have multiple and sometimes unpredictable effects on a plant. Consequently, any genetic alterations related to drought tolerance are likely to have unanticipated negative consequences.

The two most frequently discussed limitations of DT hybrids concern the lowest and highest extremes of the drought severity continuum. That is, whether yield gains under water-limited situations come at the expense of reduced yield under normal or ample water conditions; and whether crops are protected from severe or extreme droughts (Chang et al. 2013). Some studies have documented no statistically significant differences in yields between DT and non-DT seeds - and sometimes even higher yields from DT hybrids - under high-yielding conditions, which is somewhat counter to expectations (Gaffney et al. 2015; Adee et al. 2016; Zhao et al. 2018; Nemali et al. 2015). Gaffney et al. (2005), for example, found an average yield gain of 1.9 percent under favorable conditions, and a yield advantage of 6.5 percent under water-limited conditions. Syngenta's on-farm testing further reveals that a significant yield boost is retained even in the lowest-yielding environment of less than 50 bu/acre.

Several factors might explain this. Before being selected for commercialization, conventionally bred hybrids are often tested for years in field trials and evaluated in terms of yield penalties (Heffner et al. 2009; Gaffney et al. 2015). For the genetically engineered products, drought-specific gene switches (“promoters”) were being used to control the timing and intensity of engineered genes’ expression, so that the genes are effective primarily under drought conditions, rather than turned on all the time – including under normal conditions to cause negative growth effects (Gurian-Sherman 2012). Seed producers are also likely to cross-select high-performing elite lines or cross drought-tolerant genes into elite commercial varieties which increase overall yield.

Nevertheless, the field-trial evidence is overall divided and inconclusive (Lindsey and Thomison 2016). In addition, the ability of laboratory evidence to be precisely replicated in large-scale commercial production is limited in this case for primarily two reasons. First, the complexity of real-world droughts – in terms of timing, duration, and intensity – as well as environmental heterogeneity, particularly soil quality, are beyond the capabilities of controlled experiments. Given that the majority of the trials in producing the hybrids were conducted in the Western Corn Belt, this is predicted to result in variability between the Eastern and Western Corn Belt regions. Second, as discussed in previous sections, the application of DT may trigger behavioral responses in linked input decisions and farm management practices.

Conditional Mean Analysis of Yield Risk

Data and Variables

An initial investigation of the DT protection against adverse environmental stresses can be garnered from a simple conditional mean analysis of yield risk; specifically, we examine the yield risk responses to environmental stresses in relation to DT planting. Following previous studies (Goodwin and Piggott 2020; Perry et al. 2020), downward yield risk associated with drought can be operationalized using the loss-cost ratio (LCR, in %), namely the drought-related indemnified amount divided by total liability aggregated at the county level. The data are obtained from the Cause of Loss and Summary of Business databases maintained by the USDA Risk Management Agency, which provide the cause-specific claims information and total liabilities by crop annually at the county level. The DT planting rate (DT, in %) is constructed from a large field-level survey data called TraitTrak®. It is provided by GfK Kynetec, a market research company specializing in the collection of agriculture-related survey data, and is available from 1995 to 2016. The Gfk data products have been used in a number of studies, and previous work has verified the validity of the data (Perry et al. 2016; Ye et al. 2021). The field-level data are aggregated into the crop reporting district (CRD) level, at which the survey data are representative.

The Drought Severity and Coverage Index (DSCI) given by Drought Monitor is used to assess water stress or drought severity. The U.S. Drought Monitor is a collaborative effort by several organizations and is frequently used by federal agencies in the United States (Kuwayama et al. 2018). The index, which ranges from 0 (no drought) to 500 (severe drought), is a measure that takes into account both spatial coverage and drought severity. More information can be found at: https://droughtmonitor.unl.edu/data/docs/DSCI_fact_sheet.pdf. Since 2001, daily data have been available nationally, and we averaged them from June to August to create the drought variable $DSCI$. In comparison to previous studies' typical measures of water condition, such as precipitation, the Palmer Z index, and vapor pressure deficit, this index is a comprehensive "stress" measure that takes into account multiple dimensions of drought, such as precipitation, the USDA/NASS Topsoil Moisture, the Keetch-Byram Drought Index (KBDI), NOAA/NESDIS satellite Vegetation Health Indices, actual local observations, and experts' judgment[4]. The temperature data comes from the Parameter-elevation Regression on Independent Slopes Model (PRISM) dataset, which is a fine-scale weather dataset for the contiguous United States gridded at 2.5 arc-minute (4 km) resolution. At the county level, two temperature variables are created: stress degree days (SDD) and growing

[4] Please see https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx.

degree days (GDD) for temperatures above 29°C and within 10°C-29°C, respectively, and are averaged across the corn growing season from April to September (Schlenker and Roberts 2009; Perry et al. 2020).

Descriptive Evidence

Our study area is the Corn Belt of the United States. We include only counties with observations from 2001 to 2016 in the sample to create a balanced panel, yielding 758 counties and 105 CRDs annually. The sample includes 355 counties in the Eastern Corn Belt and 403 counties in the Western Corn Belt, with 347 counties located west of the 100th meridian, i.e. in the rainfed area (Table 4.A1). **Figure 4.2** depicts the temporal variations in environmental stress and yield risk. It demonstrates that yield risk moves in lockstep with water and heat stress, which often change direction concurrently. In 2012, an extreme drought episode hit the U.S., causing a significant increase in both water and heat stress, accompanied by the worst drought-related yield risk between 2001 and 2016.

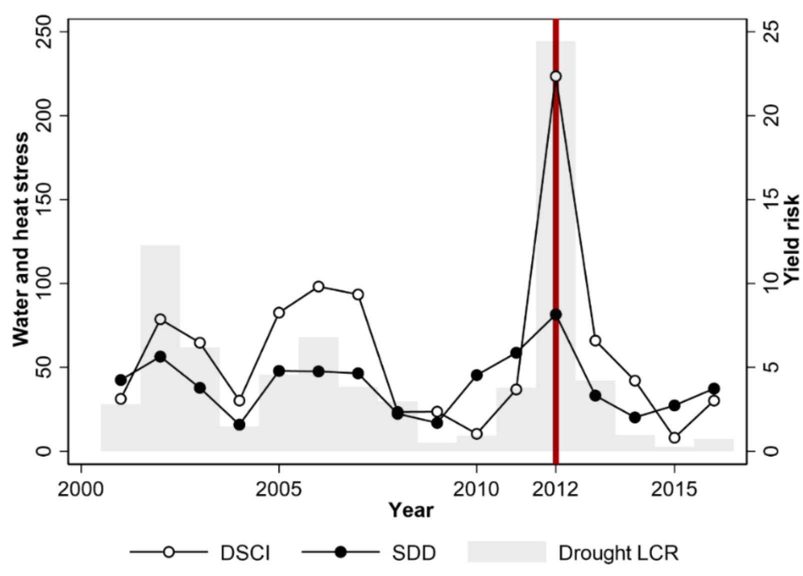

Figure 4.2 Time trends of water stress, heat stress, and yield risk, 2001-2016.

Water and heat stress is measured by the June-August average of Drought Severity and Coverage Index (DSCI) and April-September aggregated stress degree days (SDD), and yield risk is measured by the drought-related loss-cost ratio (Drought LCR, in %). (Date source: U.S. Drought Monitor; PRISM; and TraitTrak®, GfK Kynetec.)

As an intuitive comparison, we divide the counties into two subsamples based on whether they grow DT hybrid, for the Western and Eastern Corn Belt respectively. In **Figure 4.3**, the yield risk variable LCR is transformed using the inverse standard normal cumulative distribution function and is linearly fitted to drought measure $DSCI$ for both DT and non-DT subsamples. Several things are shown in the top Western Corn Belt panel: one, in the absence of drought (the left-end at zero), yield risks in DT and non-DT subsamples are very close; two, the disparities between the red and blue lines, or DT benefits, grow larger as drought exposure increases – indicating climate adaptation values. Furthermore, drought exposure in the DT subsample spans the entire range of $DSCI$. The DT counties in the Eastern Corn Belt, on the other hand, have experienced drought levels no higher than 152. As a result, the linear fits of the DT and non-DT subsamples are less comparable for the region. The greater densities at lower drought levels for the non-DT subsample in the bottom panel also show that the Eastern was less affected by drought than the Western Corn Belt.

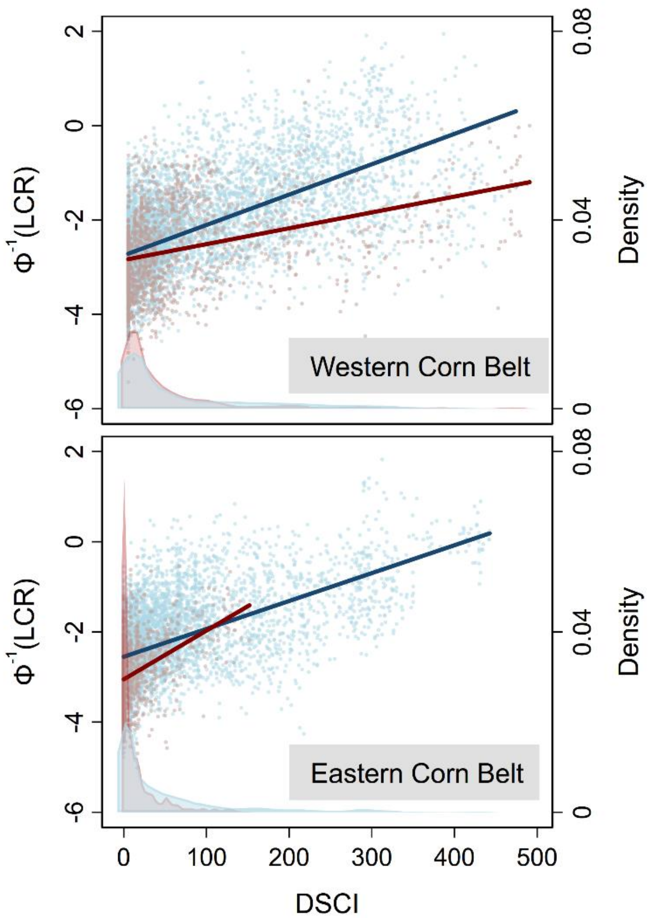

Figure 4.3 Comparison between DT and non-DT subsamples, in Western (top panel) and Eastern (bottom panel) Corn Belt.

The dots represent the observations in the sample, where the inverse normal of yield risk (LCR) is fitted linearly to the drought measure ($DSCI$). The shaded areas show the kernel densities of $DSCI$. The DT and non-DT subsamples are represented by red and blue colors, respectively. Note that DT observations are present only during 2013-2016, while the non-DT subsample covers the year 2012, resulting in greater densities at higher drought levels. The mean DT planting rate of the DT subsample is 17% and 9% for the Western and Eastern panel, respectively. (Data source: USDA Risk Management Agency; U.S. Drought Monitor; and TraitTrak®, GfK Kynetec.

Model Specifications

While **Figure 4.3** depicts these relationships intuitively, it should be interpreted with caution because other factors may influence both DT planting and yield outcomes. Therefore, a regression analysis is warranted to provide a conclusive characterization. Given its proportional nature, the yield risk factors are best modeled as a fractional response, as illustrated in **Figure 4.3** (Papke and Wooldridge 1996). The fractional response model is specified as follows:

$$E\left(y_{i,t}\middle|\boldsymbol{x_{i,t}}\right) = \Phi\left(\begin{matrix} \alpha DT_{r[i],t} + \beta_1 DSCI_{i,t} + \beta_2 SDD_{i,t} \\ +\gamma_1 DT_{r[i],t} \times DSCI_{i,t} + \gamma_2 DT_{r[i],t} \times SDD_{i,t} + \theta GDD_{it} \end{matrix}\right) \tag{1}$$

where the conditional mean of yield risk $y_{i,t}$ (i for county and t for year) is specified as a probit function, and $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. The explanatory variables are defined as above. We also included year-fixed effects δ_t to eliminate year-specific unobservable factors affecting yield risk, such as other unobserved climatic factors. The year-fixed effects are preferred over time trends because yield risk, unlike yield, fluctuates in nature. In order to control for county-specific unobserved heterogeneity, the correlated random effect (CRE) approach is applied (Papke and Wooldridge 2008). Specifically, rewrite the above equation so that the unobserved county effect enters additively, as follows:

$$E\left(y_{i,t}\middle|\boldsymbol{x_{i,t}}, c_i\right) = \Phi\left(\boldsymbol{x_{i,t}}\boldsymbol{\pi} + c_i\right). \tag{2}$$

As commented in Papke and Wooldridge (2008), although alternative functional forms such as logistic function in place of the standard normal CDF are possible, the probit function has computational advantages when the time-constant unobserved effect is involved. A conditional normality assumption is further imposed:

$$c_i = \vartheta + \overline{\boldsymbol{x}}_{\boldsymbol{i}}\boldsymbol{\delta} + a_i \tag{3}$$

$$a_i|\boldsymbol{x_i} \sim Normal\ (0, \sigma^2), \tag{4}$$

where $\boldsymbol{x_i} \equiv (\boldsymbol{x_{i,1}}, \boldsymbol{x_{i,2}}, \dots, \boldsymbol{x_{i,T}})$, and $\overline{\boldsymbol{x}}_{\boldsymbol{i}} \equiv T^{-1} \sum_{t=1}^{T} \boldsymbol{x_{i,t}}$ is time-averages for time-varying covariates. Following that, the conditional mean can be expressed as

$$E\left(y_{i,t} \middle| \boldsymbol{x_{i,t}}, c_i\right) = \Phi\left(\vartheta_a + \boldsymbol{x_{i,t}} \boldsymbol{\pi_a} + \overline{\boldsymbol{x}}_{\boldsymbol{i}} \boldsymbol{\delta_a}\right), \tag{5}$$

where the subscripts denote the corresponding original parameters rescaled by $(1 + \sigma^2)^{-1/2}$, for example, $\boldsymbol{\pi_a} = (1 + \sigma^2)^{-1/2} \boldsymbol{\pi}$. So the consistent estimates for average partial effects (APEs) can be obtained by differentiating the following equation with respect to the covariate of interest:

$$N^{-1} \sum_{i=1}^{N} \Phi\left(\hat{\vartheta}_a + \boldsymbol{x_{i,t}} \widehat{\boldsymbol{\pi}}_{\boldsymbol{a}} + \overline{\boldsymbol{x}}_{\boldsymbol{i}} \widehat{\boldsymbol{\delta}}_{\boldsymbol{a}}\right), \tag{6}$$

where $\hat{\vartheta}_a$, $\widehat{\boldsymbol{\pi}}_{\boldsymbol{a}}$, and $\widehat{\boldsymbol{\delta}}_{\boldsymbol{a}}$ denote consistent estimates of parameters. For example, the APE estimates for $\boldsymbol{x_{i,t}}$ are given by

$$(NT)^{-1} \sum_{t=1}^{T} \sum_{i=1}^{N} \widehat{\boldsymbol{\pi}}_{\boldsymbol{a}} \Phi\left(\hat{\vartheta}_a + \boldsymbol{x_{i,t}} \widehat{\boldsymbol{\pi}}_{\boldsymbol{a}} + \overline{\boldsymbol{x}}_{\boldsymbol{i}} \widehat{\boldsymbol{\delta}}_{\boldsymbol{a}}\right). \tag{7}$$

Estimation Results

We first present the APE estimates for the entire Corn Belt in **Table 4.1**. Column (1) in **Table 4.1** displays the average partial effects (APEs) estimates for eq. (5). As expected, the results suggest that greater drought and more extreme heat exposure increase yield risk significantly, whereas more growing degree days have no statistically significant effect. Specifically, holding everything else constant, increasing DSCI by 100 raises yield risk by around 1.8 percent, and an increase of SDD by 10 increases yield risk by about 1 percent. The SDD impact is qualitatively consistent with the temperature-drought LCR findings in Perry et al. (2020), but the magnitude is less, likely most likely because the DSCI is a more comprehensive measure of drought and hence better able to distinguish between direct heat stress and indirect heat effect through water stress (Lobell et al. 2013).

Table 4.1 Fractional response model estimation results (APEs), the Corn Belt.

	Corn Belt counties			Corn Belt counties, rainfed only		
	Main specification	No CRE	Stacking controlled	Main specification	No CRE	Stacking controlled
	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.049	0.018	0.045	0.006	-0.003	0.008
	(1.01)	(0.30)	(0.91)	(0.13)	(-0.05)	(0.16)
$DSCI$	0.018***	0.022***	0.019***	0.015***	0.024***	0.016***
	(8.16)	(5.98)	(8.67)	(7.01)	(8.90)	(7.06)
$DT \times DSCI$	-0.036**	-0.059**	-0.037**	-0.005	-0.066***	-0.006
	(-2.15)	(-2.36)	(-2.29)	(-0.28)	(-2.64)	(-0.30)
SDD	0.001***	0.000***	0.001***	0.001***	0.001***	0.001***
	(8.06)	(3.31)	(7.95)	(8.12)	(4.07)	(7.90)
$DT \times SDD$	0.001	-0.000	0.001	0.001	-0.000	0.001
	(1.10)	(-0.63)	(1.38)	(1.37)	(-0.17)	(1.54)
GDD	-0.000	-0.000**	0.000	-0.000	-0.000***	-0.000
	(-0.10)	(-2.41)	(0.03)	(-0.58)	(-3.14)	(-0.33)
$GE1$			0.047***			0.033**
			(2.80)			(1.99)
Observations	12128	12128	12128	11232	11232	11232
Pseudo R^2	0.24	0.22	0.25	0.25	0.24	0.25

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year-fixed effects are included. County-level unobserved heterogeneity is controlled except in columns (2) and (4). Standard errors are clustered at the CRD level. In regressions, $DSCI$, DT, and $GE1$ are rescaled by 1/100 for better presentation.

In terms of DT impacts, the yield risk difference attributable to DT in the absence of drought (i.e., DSCI=0) is not statistically different from zero, conditional on the controlled variables and unobserved effects. However, the marginal risk reduction by DT increases with drought level, which provides evidence of the adaptive value of the technology. At the 2012 mean drought level (i.e., $DSCI$ = 224), a 10% increase in DT planting reduces LCR by 0.8%. For comparison, we also present results without controlling for the county-level unobservable heterogeneity in column (2), which shows qualitatively the same but quantitatively very different outcomes. This demonstrates the necessity of applying the CRE approach. Despite that the specification in column (1) presumably accounts for the most of confounding factors, we included additional control factors for trait stacking, namely the planting rate of 1st GE seeds (defined as seeds containing insect-resistant Bt or herbicide-resistant traits, $GE1$ in %), in column (3). The results closely match the main specification in (1), confirming that controls in (1) are adequate.

However, when we restrict the sample to rainfed Corn Belt counties, the DT effects are found to be weak. The interaction effects are not statistically significant at the 10% level, whether investigated using the main or additionally controlled specifications. One possible explanation is that noise from the Eastern Corn Belt is given more weight in the smaller rainfed sample. Therefore, we further examine by region, in **Table 4.2**. The Western Corn Belt states are North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, and Missouri, and the Eastern states are Illinois, Indiana, Michigan, Ohio, Wisconsin, and Kentucky. Column (1) shows that the effects of environmental stress, namely drought and extreme heat, are very close to those shown in **Table**

4.1. Moreover, the $DT \times DSCI$ term more than doubled, rising from -0.036 to -0.079. These results are consistent across specifications (columns (2)), and similar results are also found when only rainfed areas are considered (columns (3)-(4)). For the Eastern Corn Belt, however, the APEs for the interaction terms are significantly positive (columns (5)-(6)). This appears odd at first view, but it becomes less so if one considers the modern breeding selection process. While the Western Corn Belt benefits from the DT hybrids that have been tailor-made to the western cornfields after years of field trials, these currently marketed hybrids may not be agronomically as suitable for cornfields in the east.

Table 4.2 Fractional response model estimation results (APEs), Western and Eastern Corn Belt

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	Western Corn Belt		Western Corn Belt, rain-fed only		Eastern Corn Belt	
	Main specification	Stacking controlled	Main specification	Stacking controlled	Main specification	Stacking controlled
DT	0.062	0.018	-0.003	-0.040	-0.113	-0.113
	(0.85)	(0.26)	(-0.05)	(-0.58)	(-1.25)	(-1.27)
$DSCI$	0.019***	0.021***	0.016***	0.017***	0.011***	0.011***
	(4.66)	(5.36)	(3.97)	(4.28)	(3.56)	(3.53)
$DT \times DSCI$	-0.079***	-0.080***	-0.081***	-0.079***	0.311***	0.311***
	(-3.08)	(-3.40)	(-2.97)	(-3.06)	(3.54)	(3.56)
SDD	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***
	(7.40)	(7.41)	(7.31)	(7.14)	(7.23)	(7.22)
$DT \times SDD$	0.001	0.001*	0.002**	0.002***	-0.002	-0.002
	(1.42)	(1.79)	(2.50)	(2.92)	(-0.61)	(-0.62)
GDD	0.000**	0.000***	0.000	0.000*	-0.000	-0.000
	(2.20)	(2.59)	(1.26)	(1.91)	(-1.11)	(-1.08)

Table 4.2 (cont'd)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$GE1$		0.089***		0.090***		-0.001
		(3.41)		(3.55)		(-0.07)
Observations	6448	6448	5552	5552	5680	5680
Pseudo R^2	0.26	0.27	0.28	0.28	0.25	0.25

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year-fixed effects are included, and county-level unobserved heterogeneity is controlled. Standard errors are clustered at the CRD level. In regressions, $DSCI$, DT, and $GE1$ are rescaled by 1/100 for better presentation.

Yield Quantile Analysis

The analysis in the previous section reveals that the DT benefit to yield is related to the stress environment, with greater protection seen under less favorable conditions on average. For a richer characterization of DT technology across the entire distribution of stress conditions, from the least to the most favorable environments, quantile analysis is employed. In particular, a yield quantile analysis provides a complete picture of how the DT protection changes across the yield distribution, which we view as a result of variations in stress environments when conditioned on county-level unobserved effects and time trends. More importantly, the yield risk analysis presented above suggests regional heterogeneity, i.e., only the Western Corn Belt benefits from the currently available DT hybrids. Therefore, we will restrict our attention to the Western Corn Belt, and further focus on the rainfed counties where irrigations are unlikely, and thus comprise a more relevant market for DT hybrids.

Model Specifications

The quantile regression method developed by Koenker and Bassett (1978) generalizes the median regression and applies asymmetric weighting across quantiles (Koenker and Hallock 2001). Given the panel data structure of our sample, the quantile of yield conditional on covariates and unobserved county heterogeneity is given by

$$Q_{y_{i,t}}\left(\tau \middle| \boldsymbol{x_{i,t}}, c_i\right) = \boldsymbol{x_{i,t}}\boldsymbol{\pi}(\boldsymbol{\tau}) + c(\tau)_i, \tag{8}$$

where $y_{i,t}$ denotes yield in county i and year t, the covariate vector $\boldsymbol{x}$ consists of DT planting rate variable, as well as state-specific cubic time trends. Take the DT variable for an example, the coefficient estimate gives the marginal effects of DT on the τ-th conditional yield quantile. The term $c(\tau)_i$, like the conditional mean analysis, represents the time-invariant county heterogeneity at τ-th quantile. Given the large number of fixed effects, the usual fixed effects model is subject to the incidental parameters problem and thus not suitable for the quantile regression (Lancaster 2000). While methodological progress in this area has been emerging in recent years (Kato et al. 2012; Machado et al. 2019), they are either computationally difficult to implement, or the consistency of the estimators requires a large number of periods relative to the cross-sectional units. For example, the quantiles via moments estimator proposed by Machado et al. (2019) will be biased for fixed T, and the confidence intervals will have poor coverage where n/T is above 10. Therefore, given the relatively large cross-sectional units (347 counties) and short timespan (2001-2016), we again adopted the Correlated Random Effects (CRE) technique to account for the unobserved heterogeneity, as we did in the preceding sections for the fractional response model (Abrevaya and Dahl 2008).

Estimation Results

Quantile estimates are depicted in **Figure 4.4**. The first thing to notice is that the DT coefficients remain statistically positive across all quantiles from 1^{st} to 99^{th}, even at the highest-yielding end. This adds to the evidence against the yield penalty hypothesis, namely that there are no statistically significant negative effects on yield in favorable conditions, but rather a positive - albeit minor - benefit is retained. Second, the coefficient generally increases going from higher to lower quantiles, or from favorable to unfavorable environments, confirming again the adaptive values of DT technology. The findings generally agree with Syngenta's on-farm strip trial data from 2012, which tested yield changes between DT and non-DT maize hybrids from low- to high-yielding environments and found a generally decreasing difference as the yield environment becomes higher.

Under the lowest-yielding environment, i.e., at the 1st quantile, a 10% increase in DT planting rate in a county increases yield by 17 bu/acre.

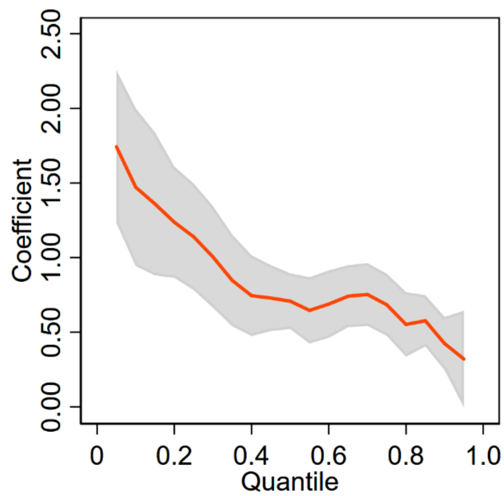

Figure 4.4 Coefficient estimates of DT planting rate (%) variable, the 1st to 99th quantiles. The red line represents point estimates of quantile regression, and the shaded areas represent the 95% confidence interval. Standard errors are obtained by bootstrapping.

To further understand the results, we illustrate the changes in cumulative density function (CDF) and probability density function (PDF) that corresponds to a 10% increase in DT planting rate from the status-quo, in **Figure 4.5**. We chose 10% because it is neither too tiny to notice the effect nor too large to be improper given that the coefficient estimates are in the marginal sense. Nevertheless, in the Appendix (Figure 4.A5-4.A6) we provide additional figures for larger DT changes. The CDF shifts rightward uniformly across the distribution in response to positive coefficients, with the largest shift occurring around the 20th percentile. The changes in the yield distribution imply an increase in mean yield as well as a decrease in yield risk as measured by variance. Specifically, probability densities are lower for yields below around 120 bu/acre and higher for yields greater than it. Lastly, as a robustness check, we also provide estimations that control for 1st

GE stacking, as shown in Figure 4.A7 in the Appendix. Similar to the conditional mean analysis results, the DT coefficient estimates are quite close across the alternative specifications.

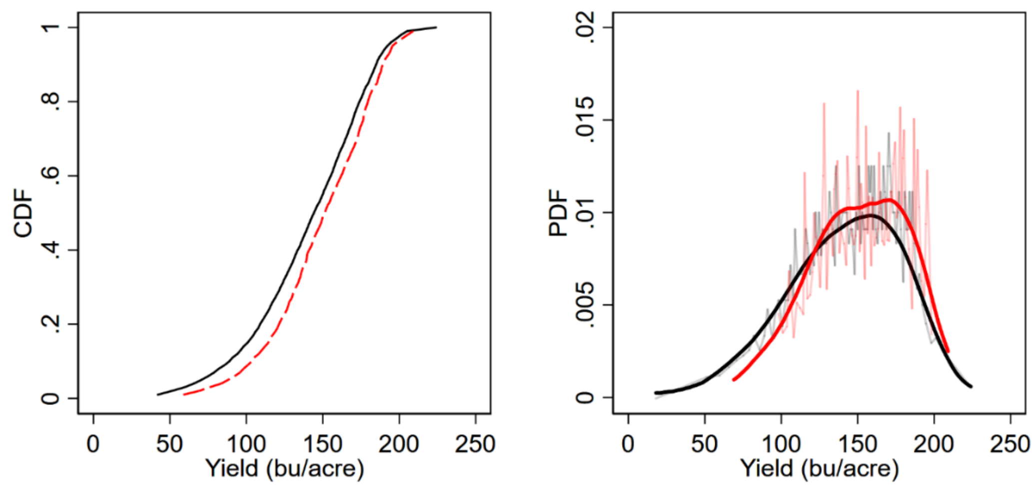

Figure 4.5 Shifts in CDF (left) and PDF (right) under 10% increase in DT planting rate.

The black lines are the empirical CDF and PDF in the sample, and the red lines are the estimates under a 10% increase in DT planting rate. PDF is approximated as CDF(x_2)-CDF(x_1)/(x_2-x_1) where x_1 and x_2 are such that CDF(x_2)-CDF(x_1) is 0.01. For example, at the median, x_2 is the yield at the 50th quantile, and x_1 is the yield at the 49th quantile. The approximations (the light black and red lines in the right panel) are then fitted using kernel density estimation to obtain smooth PDF functions for illustration purposes in the right panel.

Implications for Crop Insurance Policy

The multiple analyses in previous sections have provided ample evidence on yield protection by drought-tolerance technologies from various perspectives. Following that, we examine the value of DT in the context of crop insurance by simulating how increased DT planting rates alter actuarially fair premiums. In the United States, there are two types of insurance plans: revenue protection and yield protection. Yield-protection policies cover yield risks by guaranteeing a base yield depending on the farmer-chosen coverage level and average production history (APH). Revenue-protection policies, on the other hand, protect against price-based losses as well. As price protection is not expected from biotechnologies (Goodwin and Piggott 2020) and to focus on the yield protection aspect, we will restrict our examination of crop insurance implications to yield insurance policies.

Let $y \in [0, \infty)$ denote a random yield with cumulative distribution function $F(y)$, and mean value $\bar{y} = E(y)$. Suppose a representative farmer chooses a coverage level $\varphi \in \{0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.90\}$, then a yield level of $\varphi\bar{y}$ is guaranteed. That is, the paid indemnity amount will be $\varphi\bar{y} - y$ when realized yield y is smaller than the yield guarantee $\varphi\bar{y}$, and 0 when the actual yield reaches $\varphi\bar{y}$. The indemnity r can be expressed as

$$r = \max\{\varphi\bar{y} - y, 0\}, \tag{9}$$

and the actuarially fair premium $\bar{r}$ at coverage level φ is

$$\bar{r} = \int_0^{\infty} \max\{\varphi\bar{y} - y, 0\}\, dF(y) = \int_0^{\varphi\bar{y}} (\varphi\bar{y} - y)\, dF(y), \tag{10}$$

which can be rewritten as

$$\bar{r} = \int_0^{\varphi\bar{y}} F(y)\, dy \tag{11}$$

using integration by parts. Graphically, the actuarially fair premium is the area below the CDF $F(y)$ from 0 to $\varphi\bar{y}$. Now we introduce DT technology into yield distribution, i.e., condition yield distribution on DT as $F(y|DT)$ to reflect the distribution-wise effect of DT. Therefore, the effect of DT on actuarially fair premium $\bar{r}$ can be decomposed as

$$\frac{d\bar{r}}{dDT} = \varphi F(\varphi\bar{y}) \frac{\partial E(y|DT)}{\partial DT} + \int_0^{\varphi E(y|DT)} \frac{\partial F(y|DT)}{\partial DT}\, dy. \tag{12}$$

DT appears to have two effects on actuarially fair premium or expected indemnity payment. The positive first term reflects the DT effects through increasing mean yield. At a higher DT planting rate, the APH is expected to increase and result in a greater yield guarantee. Consequently, given the same realized yield, it becomes easier to trigger indemnity payment. The second term represents the effects of shifting distribution while maintaining the same yield guarantee. The status-quo yield distribution is first-order dominated by that under increasing DT, as seen in **Figure 4.4**, hence the second term is negatively signed. As a result, whether the actuarially fair premium increases or decreases with increased DT planting depends on the relative magnitude of the two effects. Besides, as coverage level φ goes up, the first term of the DT effect will be smaller because the yield guarantee effect is attenuated, while the second term will increase again because of first-order dominance, so whether the DT effect is stronger for greater coverage cannot be predetermined either.

Therefore, we use the distributions retrieved in **Figure 4.4** for the two scenarios to simulate the actuarially fair premium changes under a 10% DT increase. **Table 4.3** shows the simulation results. We found only a minor increase in mean yield, 138 bu/acre under the status-quo versus 140 bu/acre under the 10% DT increase. So, at the highest available coverage level of 0.9, the difference in yield guarantee is less than 2 bu/acre, and it is only 1 bu/acre at the lowest coverage level – too tiny to be impactful. The comparison between rows 1 and 2 in **Table 4.3** clearly shows that distribution-shifting, or risk reduction, has a substantially greater empirical effect than higher yield guarantee, resulting in large decreases in actuarially fair premium ranging from 36.92 percent to 63.47 percent. The reduction percentage generally increases as the coverage level decreases, and the average reduction across all levels is 46.21%. The premium simulation results provide justifications for insurance policies to offer premium discounts to DT growers.

Table 4.3 Simulation results for actuarially fair premium under status-quo and a 10% DT increase

Coverage level ($\boldsymbol{\varphi}$)	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
Premium, status-quo ($\bar{r}^0$)	1.00	1.24	1.72	2.33	3.18	4.11	5.54	7.11	9.27
Premium, 10% increase in DT ($\bar{r}^1$)	0.36	0.54	0.81	1.24	1.64	2.28	3.16	4.23	5.85
Reduction percentage (%)	63.47	56.60	52.96	46.84	48.50	44.45	43.00	40.44	36.92
Yield guarantee, status-quo	69.04	75.95	82.85	89.75	96.66	103.56	110.47	117.37	124.27
Yield guarantee, 10% increase in DT	70.09	77.10	84.10	91.11	98.12	105.13	112.14	119.15	126.16

Concluding Remarks

Advances in seed biotechnology have been accompanied by continuous debates about its yield contributions. While some studies have suggested corn yield improvements associated with genetic technology (Xu et al. 2013), a more recent study argued that yield contributions associated with genetic improvements are relatively small (13%) when compared to climate factors (48%) and agronomic improvements (39%) (Rizzo et al. 2022). However, data in the study was collected from fields that were irrigated and in favorable environments. In other words, the findings were more applicable to yield potential under optimal conditions, whereas the emphasis of seed biotechnology has been on crop protection in unfavorable conditions. This is especially true for drought-tolerant technology, which was designed in the first place for water-stressed environments. Using data from a cross-section of counties from 2001 to 2016, our analysis demonstrates that DT technology has only a marginal yield improvement in good circumstances, but the protection value in adverse conditions is substantial and more important. While the technology does not offer much in terms of increasing yield potential, its main worth comes in stabilizing yield, which is equally critical from an economic standpoint.

Will drought-tolerance technology usher in a new era of climate-resilient agriculture? This article is the first to empirically and thoroughly investigate the yield protection of drought-tolerant technology in commercial corn production in the U.S. Corn Belt. Employing both conditional mean analysis of drought-related yield risk and yield quantile analysis, our findings would characterize the technology as follows. First and foremost, there is regional heterogeneity. The DT hybrids marketed between 2013 and 2016 have benefited corn growers in the Western Corn Belt more than the Eastern Corn Belt, most likely due to seed companies emphasizing the west region in developing hybrids. As part of the modern breeding selection process, the selected hybrids are suitable to the local growing conditions, but not necessarily elsewhere. Underlying the research and marketing strategy is the differential market needs, given that the Western Corn Belt is more prone to drought and frequently experiences more severe drought occurrences.

Focusing on the rainfed Western Corn Belt, we found no evidence of yield penalty; in fact, a small yield gain is obtained even in the highest-yielding environment. This feature is crucial because this lends confidence to the corn growers to employ DT as a preventative risk management tool when the seed cost is no longer as negligible as it was in the early years of commercialization.

While the DT advantages arguably involve stochasticity, depending on the random environment, this feature will make the learning and technology diffusion process easier than previously believed (Lybbert and Bell 2010). Furthermore, yield protection from DT is generally enhanced where the environment is more stressful. As Lobell (2014) emphasizes, not every agricultural innovation has adaptation benefits in the sense that yield gain is stronger under higher degrees of stress and thus more beneficial in the future climate. Our findings indicate that the DT innovation qualifies as a climate adaptation technology, capable of providing greater benefits in a more stressful climate. The adaptation values of DT hybrids can be evaluated in a crop insurance context. Simulation analysis reveals a significant decrease in actuarially fair premium for increased DT planting, emphasizing the need for a discount scheme similar to the Biotech Endorsement program introduced between 2009 and 2012. Inadequate insurance policy pricing will prevent maize growers from taking adaption actions to use such technologies, and more research is required in this regard.

APPENDIX

APPENDIX

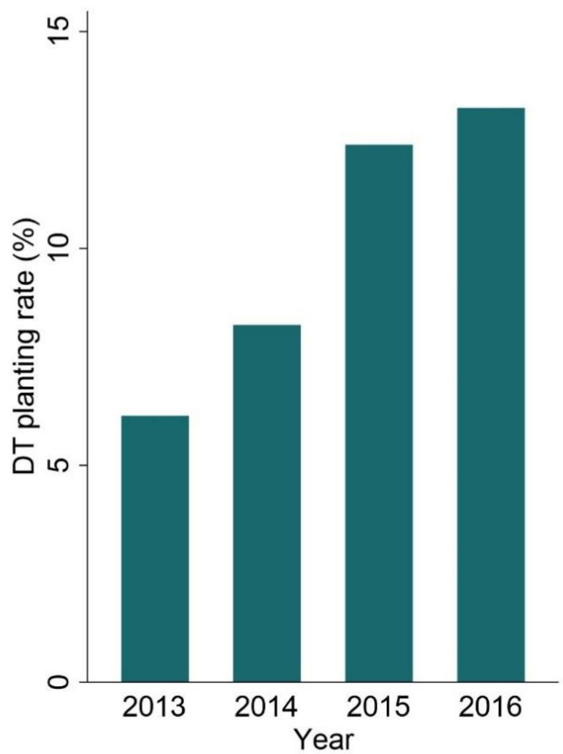

Figure 4.A1 Time trend of DT planting rate (%) during 2013-2016, at the national level.

Measured as the percentage of corn acres (%) that are planted to DT-containing hybrids. (Data source: TraitTrak®, Kynetec.)

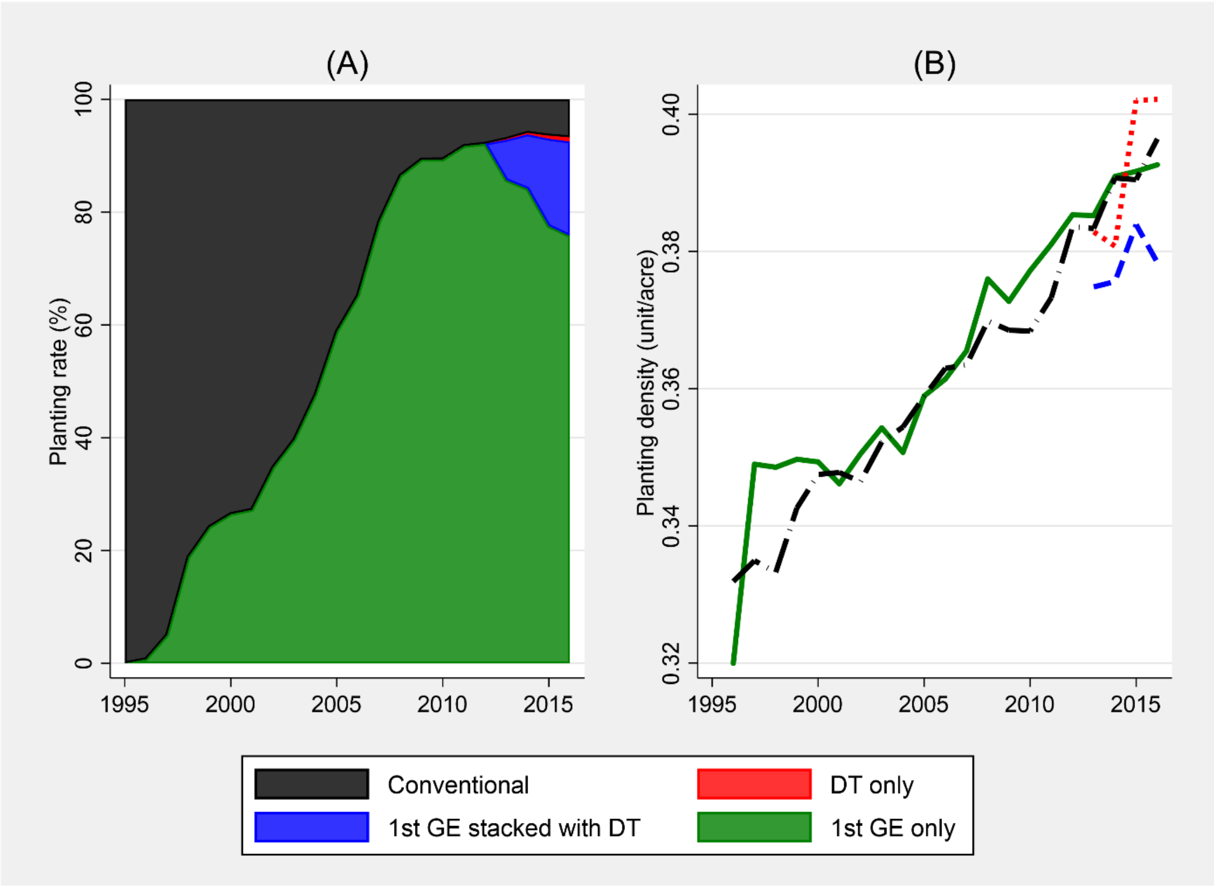

Figure 4.A2 Time trend of corn planting rate and density by seed varieties, 1995-2016.

Panel: (A) Planting rate, measured as the percentage of corn acres (%) that plant respective variety. (B) Planting density, measured as the seed units per acre of corn planting. Seeds are classified into four categories: (1) DT only, containing only DT, namely no insect-resistant Bt or herbicide-resistant (HT) traits; (2) 1st GE only, namely first-generation GE that contains Bt or HT, but no DT embedded; (3) 1st GE stacked with DT, containing DT and 1st GE (Bt/HT); and (4) conventional seed, not containing Bt, HT, or DT. (Data source: TraitTrak®, Kynetec.)

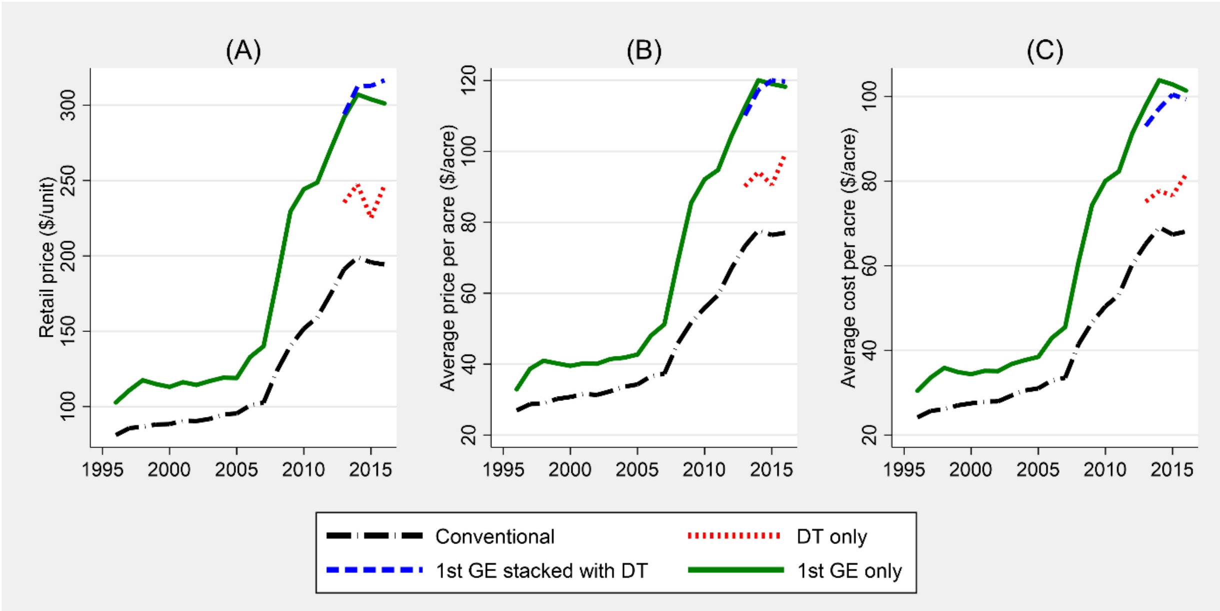

Figure 4.A3 Time trend of seed prices by seed varieties, 1996-2016.

Panel: (A) Retail price ($/unit). (B) Average price per acre ($/acre). (C) Average seed cost per acre ($/acre), net of discounts, and free units. Seeds are classified into four categories: (1) DT only, containing only DT, namely no Bt or HT; (2) 1st GE only, namely first-generation GE that contains Bt or HT, but no DT embedded; (3) 1st GE stacked with DT, containing DT and 1st GE (Bt/HT); and (4) conventional seed, not containing Bt, HT, or DT. (Data source: TraitTrak®, Kynetec.).

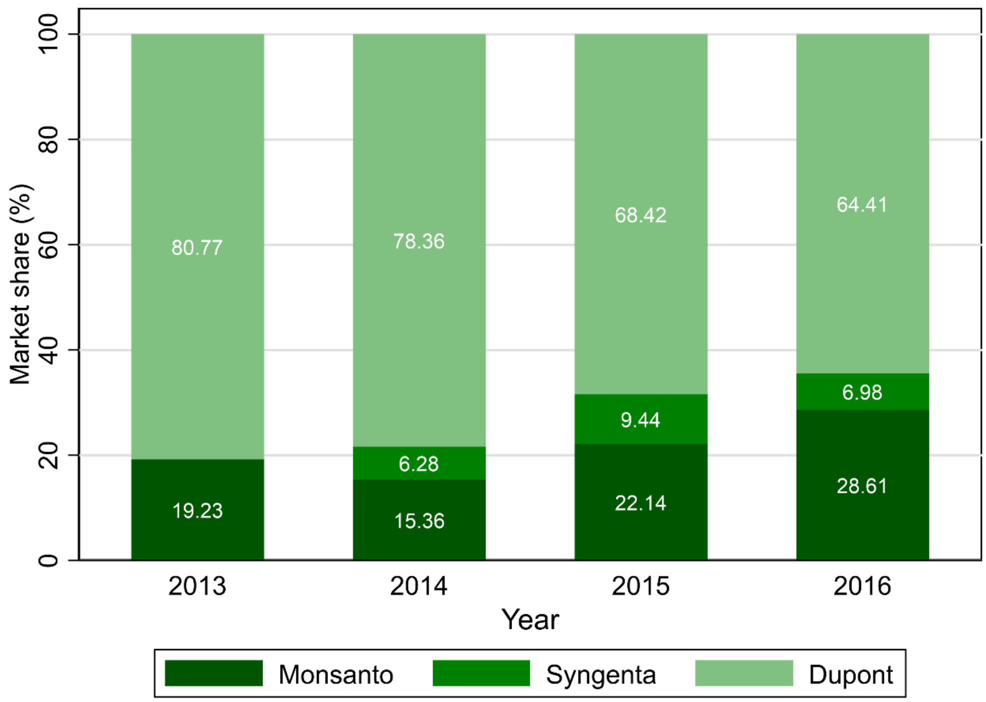

Figure 4.A4 Market shares (%) of top three companies providing drought-tolerant corn varieties, 2013-2016.

Market share is measured as the company share of drought-tolerant corn acreage. (Data source: TraitTrak®, Kynetec.)

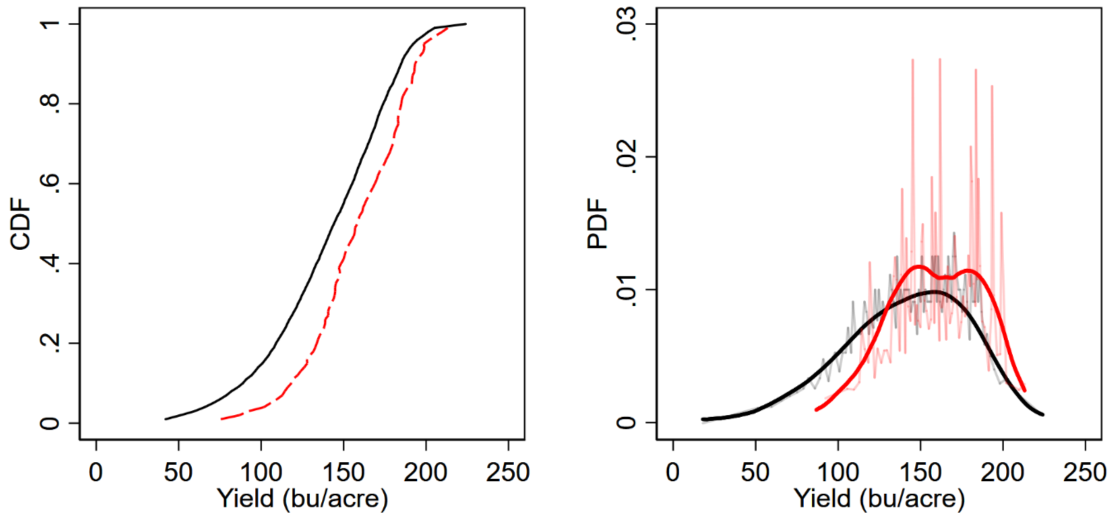

Figure 4.A5 Shifts in CDF (left) and PDF (right) under 20% increase in DT planting rate.

The black lines are the empirical CDF and PDF in the sample, and the red lines are the estimates under a 20% increase in DT planting rate. PDF is approximated as CDF(x_2)-CDF(x_1)/(x_2-x_1) where x_1 and x_2 are such that CDF(x_2)-CDF(x_1) is 0.01. For example, at the median, x_2 is the yield at the 50th quantile, and x_1 is the yield at the 49th quantile. The approximations (the light black and red lines in the right panel) are then fitted using kernel density estimation to obtain smooth PDF functions for illustration purposes in the right panel.

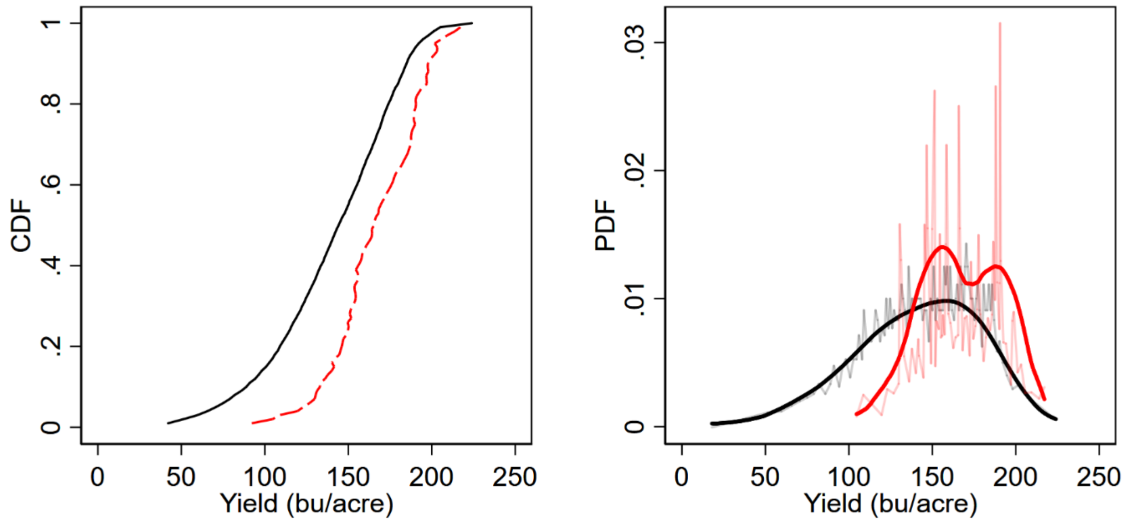

Figure 4.A6 Shifts in CDF (left) and PDF (right) under 30% increase in DT planting rate.

The black lines are the empirical CDF and PDF in the sample, and the red lines are the estimates under a 30% increase in DT planting rate. PDF is approximated as CDF(x_2)-CDF(x_1)/(x_2-x_1) where x_1 and x_2 are such that CDF(x_2)-CDF(x_1) is 0.01. For example, at the median, x_2 is the yield at the 50th quantile, and x_1 is the yield at the 49th quantile. The approximations (the light black and red lines in the right panel) are then fitted using kernel density estimation to obtain smooth PDF functions for illustration purposes in the right panel.

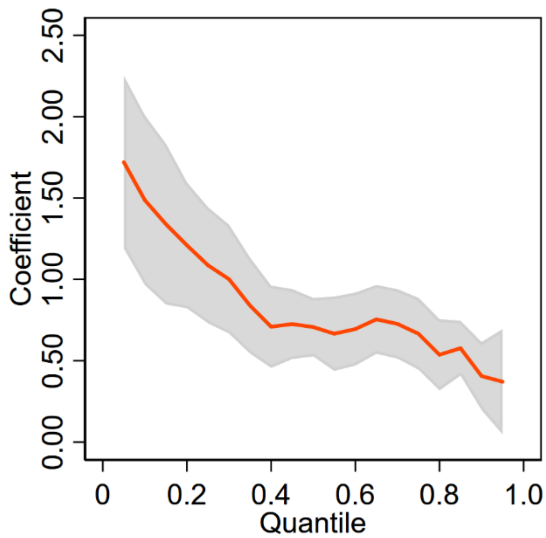

Figure 4.A7 Coefficient estimates of DT planting rate (%) variable with 1st GE stacking controlled, the 1st to 99th quantiles.

The red line represents point estimates of quantile regression, and the shaded areas represent the 95% confidence interval. Standard errors are obtained by bootstrapping.

Table 4.A1 Sample decomposition

	The Corn Belt		
	East	West	Total
Non-rainfed	0	56	56
Rainfed	355	347	702
Total	355	403	758

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