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Are Glyphosate-Resistant Weeds a Threat to Conservation Agriculture? Evidence from Tillage Practices in Soybean

Braeden Van Deynze, Scott M. Swinton, and David A. Hennessy

Department of Agricultural, Food, and Resource Economics

Michigan State University

Contact: vandeynz@msu.edu

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Are Glyphosate-Resistant Weeds a Threat to Conservation Agriculture?

Evidence from Tillage Practices in Soybean

Abstract

The use of conservation tillage in American soybean production has become increasingly common since the 1950's, improving soil health, reducing soil erosion, and reducing fuel consumption. This trend has been reinforced by the availability of the general-purpose herbicide glyphosate and glyphosate-resistant seed genetics since the mid-1990's. However, weeds have since evolved to resist glyphosate, reducing its effectiveness. In this paper, we provide evidence that the spread of glyphosate-resistant weeds is responsible for significant reductions in the use of conservation tillage in soybean production. To capture the effects of glyphosate-resistant weeds on tillage adoption, we estimate a probit model of tillage choice, using a large panel of field-level soybean management decisions from across the United States, spanning 1999-2016. We find that while the first two glyphosate-resistant weed species have little effect on tillage practices, by the time that eight glyphosate-resistant weed species are present, conservation tillage use falls by 6.2 percentage points and no-tillage use falls by 9.2 percentage points. We conservatively estimate that the spread of glyphosate-resistant weeds has indirectly caused water quality and climate damages valued at over $470 million. This total is likely to grow as glyphosate-resistance become more widespread and farmers continue to turn to tillage for supplemental weed control.

Introduction

Since the mid-1900's, chemical herbicides have been an essential tool for weed control in the conventional production of soybeans and other U.S. field crops. Prior to the first commercial herbicides, farmers typically relied on mechanical weed control, characterized by multiple tillage passes to uproot established weeds and disrupt weed seedling emergence. While intensive tillage can provide effective weed control, it comes at a cost to the environment, leading to increased soil erosion and energy use, which can impair water quality and increase the carbon footprint of agricultural production (Uri et al., 1999). In this paper, we explore how the declining efficacy of glyphosate, the most widely used herbicide in American soybean production, has led farmers to increase the use of tillage as a weed control tool.

When first introduced, herbicides were rapidly adopted by American field crop farmers. Herbicides offered weed control as good or better than tillage at lower cost (Swinton and Van Deynze, 2017). The introduction of soybean varieties genetically engineered to resist glyphosate (and later other herbicides), has further shifted soybean weed control away from tillage (Perry et al., 2016a; Fernandez-Cornejo et al., 2012). Glyphosate is a broad-spectrum herbicide that could effectively control virtually all weeds when resistant seed varieties were first introduced. Glyphosate-tolerant crops, like Roundup Ready™ soybean, allow farmers to spray the herbicide throughout the growing season without damaging their crop. Farmers utilizing these technologies could rely exclusively on glyphosate for weed control, forgoing tillage passes and therefore providing cost savings to farmers and averting environmental damages.

As glyphosate use became more frequent in soybeans and other crops, weeds soon evolved to resist the chemical. In 2000, a population of horseweed growing in a soybean field in Delaware became the first identified case of glyphosate-resistance in weeds (VanGessel, 2001). As of 2017, glyphosate-resistance has been identified in 17 weed species in the United States (Heap, 2017). The rise of glyphosate-resistant weeds (GRWs) has led to a growing literature on best practices to delay and manage the onset of herbicide-resistance in weeds (Beckie, 2006;

Evans et al., 2015; Bonny, 2016; Beckie and Harker, 2017). The increased use of tillage for weed control is frequently found amongst these recommendations.

A smaller literature has focused on how farmers have responded to the onset of GRWs. Livingston et al. (2015) reports the results of cross-sectional surveys of corn and soybean growers in 2010 and 2012 respectively. They find that farmers experiencing problems with GRWs frequently supplemented glyphosate-based weed control with non-glyphosate herbicides, increased their use of glyphosate, and increased the use of tillage. Wechsler et al. (2017) find that low numbers of GRWs have a fairly small impact on corn farmers' weed control practices. Perry et al. (2016b) observe a sharp increase in the use of non-glyphosate herbicides in corn and soybeans from 2007 to 2011 and speculate that this increase is due to GRWs. Most recently, Lambert et al. (2017) find that weed control costs increase by $34-55/acre following the emergence of GRWs in upland cotton fields as farmers adopt labor-intensive alternatives to glyphosate.

In this paper, we contribute to this literature by providing the first estimate of the impact of GRWs on the adoption rates of conservation tillage practices in soybeans. We do so first by developing a conceptual model of a cost-minimizing farmer who chooses among multiple herbicide and tillage options to meet predetermined weed control targets. This model indicates a non-linear response to herbicide-resistance: As more weed species develop herbicide resistance, farmers become increasingly likely to make major changes to their weed control practices. We then test this model empirically with data on the field-level weed control choices of thousands of soybean farmers during 1999-2016. Our econometric results indicate that while low numbers of GRWs have little impact on tillage choices, by the time that eight GRWs are present, conservation tillage falls by 6.2% and no-till adoption falls by 9.2%. Extrapolating from literature estimates of soil erosion and carbon emissions from tillage, and their costs, we estimate that this shift towards more intensive tillage practices has caused damage to water quality and climate worth $470 million.

The rest of this paper is structured as follows: We first present a conceptual model of a cost-minimizing farmer who seeks to control several weeds with many herbicide and tillage options. We then present our empirical strategy, followed by a discussion of the data. After presenting of our econometric results, we conduct a benefit-transfer simulation to illustrate potential environmental costs. We close with a discussion of the policy implications of our findings and directions for future research.

Conceptual Model

We model a farmer's tillage decision as a two-stage cost-minimization problem, assuming a farmer has already determined optimal levels of weed control that are consistent with maximization of expected utility (Lichtenberg and Zilberman, 1986). Letting $k \in \{1, \cdots, K\}$ index different weed species, a farmer sets a weed control target for each of their soybean fields, denoted in vector form as $\bar{\boldsymbol{g}} = (\bar{g}_1, \cdots, \bar{g}_K)$. This target represents the acceptable density of each weed in the field.

A farmer can achieve these weed control targets through a combination of tillage systems and chemical herbicides. A farmer selects a single tillage system τ from the choice set $\{\tau^{CT}, \tau^{IT}\}$, where CT denotes conservation tillage systems and IT denotes conventional, intensive tillage systems. A farmer can select any combination of L alternative herbicides to supplement weed control provided by his tillage system. Let h_l denote the (non-negative) quantity of herbicide $l \in$

$\{1, \cdots, L\}$, so that a farmer's herbicide choice set is $\boldsymbol{H} = \mathbb{R}_+^L$.[1] Together, a farmer's weed control choice set is $\{\tau^{CT}, \tau^{IT}\} \times \boldsymbol{H}$.

These choices provide weed control through a "kill function" for each weed, denoted by $g_k(\boldsymbol{h}, \tau)$. We assume that for all weeds $g_k(\boldsymbol{h}, \tau)$ is twice continuously differentiable, that larger quantities of herbicide increase control at a decreasing rate ($\partial g_k / \partial h_l > 0$ and $\partial^2 g_k / \partial {h_l}^2 < 0$, $\forall k, l$), and that intensive tillage provides greater weed control than conservation tillage for any given choice of herbicides ($g_k\left(\overline{\boldsymbol{h}}, \tau^{IT}\right) > g_k\left(\overline{\boldsymbol{h}}, \tau^{CT}\right)$, $\forall k, \overline{\boldsymbol{h}} \in \boldsymbol{H}$). Notice that when weed k has adapted to resist herbicide l, $\partial g_k / \partial h_l = 0$ for all quantities of that herbicide.

We now turn to the costs of weed control. Denote the per unit costs of herbicide l as w_l and the costs of tillage system τ as $c(\tau)$. These costs include labor, fuel, and chemical expenses, as well as potential capital investments for new tillage equipment if adopting a system for the first time. A farmer's objective is to minimize these costs while achieving their weed control target. To do so, the farmer first determines the herbicide combination that minimizes total weed control costs for each of the two tillage systems subject to K constraints (one for each weed species):

$$\min_{\boldsymbol{h}} \boldsymbol{w} \cdot \boldsymbol{h} + c(\bar{\tau})$$

$$s.t.\, \boldsymbol{g}(\boldsymbol{h}, \bar{\tau}) \geq \overline{\boldsymbol{g}}$$

The optimality conditions for this problem are:

$$w_l = \textstyle\sum_k \lambda_k \, \partial g_k(\boldsymbol{h}, \bar{\tau}) / \partial h_l \;\; \forall l \qquad (1)$$

[1] Note that farmers can combine different products via tank mixes. We envision $\boldsymbol{H}$ as a farmer's herbicide choice set accounting for all feasible tank mixes and other combinations of retail products.

$$\lambda_k[g_k(\boldsymbol{h},\bar{\tau}) - \bar{g}] = 0 \ \forall k \qquad (2)$$

where λ_k are Lagrange multipliers for each constraint. Call the solution to the above minimization problem $\boldsymbol{h}^*(\bar{\tau})$, and call the value function for this solution $V(\bar{\tau})$:

$$V(\bar{\tau}) \equiv \boldsymbol{w} \cdot \boldsymbol{h}^*(\bar{\tau}) + c(\bar{\tau})$$

A farmer then compares the solutions to these first-stage cost-minimization problems for each tillage type and selects the least-cost option:

$$\tau^* = \underset{\tau \in \{\tau^{CT}, \tau^{IT}\}}{\operatorname{argmin}} \{V(\tau^{CT}), V(\tau^{IT})\}$$

The full solution to a farmer's weed control problem is thus the tillage-herbicide pairing, $\left(\tau^*, \boldsymbol{h}^*(\tau^*)\right)$.

Comparative statics of herbicide resistance

Now we use an exercise in comparative statics to consider how a decrease in the effectiveness of herbicide l, $\partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$, would affect $\boldsymbol{h}^*(\bar{\tau})$. Let $\widetilde{\boldsymbol{h}}^*(\bar{\tau})$ denote the optimal herbicide choices in a scenario with $\partial \tilde{g}_k(\boldsymbol{h},\bar{\tau})/\partial h_l < \partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$, *ceteris paribus*. Under what conditions does $\widetilde{\boldsymbol{h}}^*(\bar{\tau}) \neq \boldsymbol{h}^*(\bar{\tau})$?

If the weed control constraint for weed k is binding in either scenario (hence $\lambda_k > 0$), then $\widetilde{\boldsymbol{h}}^*(\bar{\tau}) \neq \boldsymbol{h}^*(\bar{\tau})$, as $\partial^2 g_k/\partial {h_l}^2 < 0$ and therefore, by the continuity and strict monotonicity of $\partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$, $\boldsymbol{h}^*(\bar{\tau})$ cannot satisfy optimality condition (1) if $\partial \tilde{g}_k(\boldsymbol{h},\bar{\tau})/\partial h_l < \partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$.

But if the weed control constraint for weed k is non-binding in both scenarios (hence $\lambda_k = 0$), then $\widetilde{\boldsymbol{h}}^*(\bar{\tau}) = \boldsymbol{h}^*(\bar{\tau})$, as $\partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$ would be multiplied by zero in optimality condition (1) and play no role in the solution. Thus, decreasing herbicide effectiveness has no effect on herbicide or tillage choices for weeds that were "over-controlled" prior to evolving to resist the herbicide.

Further, this result implies that decreasing herbicide effectiveness *weakly increases* weed control costs for a given tillage choice, and therefore a single weed evolving to resist a single herbicide is likely not to influence tillage choices. As more weeds develop resistance to a herbicide, changes in the usage of the herbicide become more likely. But because some weeds may and are in fact likely to be over-controlled (i.e. the constraint is non-binding) the response to herbicide resistance is inherently non-linear. If the herbicide costs associated with conservation tillage outweigh savings in tillage costs, then a farmer will switch to intensive tillage.

The case of glyphosate and glyphosate-resistant weeds

Glyphosate is a broad-spectrum herbicide which, prior to the onset of resistance, is highly effective at controlling essentially all weeds. The introduction of glyphosate-resistant varieties allowed farmers to rely heavily (sometimes exclusively) on this specific herbicide for weed control in soybean at relatively low cost. Glyphosate was rapidly adopted as the use of other herbicides declined (Livingston et al., 2015). Swinton and Van Deynze (2017) attribute this trend to the cost-dominance of a glyphosate-based weed control system. When used in conjunction with glyphosate-resistant seed, pre- and post-emergent applications of glyphosate make tillage passes for weed control redundant, providing no additional weed control but incurring additional fuel, machinery, and labor costs for a farmer.

When and where weeds are susceptible to glyphosate and it is cost-competitive with alternative herbicides, our conceptual model implies that glyphosate will become prevalent as a cost-effective way to meet all of a farmer's weed control targets. We expect glyphosate to continue to be used even as glyphosate-resistance becomes more frequent, because it can still control still-susceptible weeds at a low cost. However, we expect intensive tillage and supplemental use of non-glyphosate herbicides to become more frequent, as our conceptual model implies that farmers will need to rely on more tools to attain their weed control targets. Because non-glyphosate herbicides and intensive tillage behave as substitutes in our model, with both options providing supplemental weed control when glyphosate alone does not suffice, we expect the use of non-glyphosate herbicides to be positively associated with conservation tillage.

Empirical Model

To test the implications of the conceptual model presented above, we estimate a dynamic probit model with the tillage decision as the dependent variable. We include farm-level random effects and a first-stage control function to account for endogenous herbicide use. The unit of analysis, is the field-level (j) tillage decision on each farm (i) in a year (t). With y_{jit}^{CT} as an indicator for the use of conservation tillage, z_{it} as the number GRWs, y_{jit}^{NGH} as an indicator for the use of non-glyphosate herbicides, m_{it} as an indicator for conservation tillage machinery stock, $\boldsymbol{p}_t$ as a vector of input prices, $\boldsymbol{x_{it}}$ as a vector of farm-level conditioning variables, and d_i as a time-invariant, normally-distributed, farm-level random effect to account for unobserved heterogeneity, the core structural function we seek to estimate is the probability that conservation tillage is chosen:

$$\Pr\left(y_{jit}^{CT} = 1 \middle| z_{it}, y_{jit}^{NGH}, s_{it}, \boldsymbol{p_t}, \boldsymbol{x}_{it}, t, d_i\right)$$
$$= \Phi(\beta_0 + z_{it}\beta_1 + z_{it}^2\beta_2 + y_{jit}^{NGH}\beta_3 + p_t^m m_{it}\beta_4 + m_{it}\beta_5 + \boldsymbol{p}_t\boldsymbol{\beta_6} + \boldsymbol{x}_{it}\boldsymbol{\beta_7} + t\beta_8$$
$$+ d_i)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

In this specification, we account for a non-linear response to additional reported GRWs, suggested by our conceptual model, by including the variable in quadratic form. The input price vector, $\boldsymbol{p_t}$, include price indices for glyphosate, non-glyphosate herbicides, fuel, and agricultural machinery. As machinery prices, p_t^m, are particularly relevant if the farm does not yet own the necessary equipment, we include an interaction term between this variable and the equipment stock. Because certain farm-level variables, $\boldsymbol{x_{it}}$, are likely to affect tillage choices, we include measures of farm size (for scale economies in use of tillage equipment), soil quality (which affects tillage difficulty and soil water retention), and drought incidence (as tillage tends to reduce water retention). We include a time trend t to capture the effects of other unobserved time-varying factors that may have contributed to shifts in the use of conservation tillage over time.

Before estimating this structural function via maximum likelihood, we must first address two issues: missing data on each farm's equipment portfolio and endogeneity of non-glyphosate herbicide use.

Because the equipment stock, m_{it}, is not directly observed, we proxy for it using evidence that the farmer had previous access to conservation tillage equipment. Formally speaking, we use as a proxy the maximum of the farmer's lagged tillage decisions, $y_{i,t-1}^{CT} = \max_j\{y_{ji,t-1}^{CT}\}$, assuming that previously used conservation tillage equipment remains available in following period. However, including the lagged dependent variable in a panel data model forces us to address the initial conditions problem (Arellano and Honore, 2001). This problem occurs when the modelled process is not observed from its beginning. Therefore, the initial condition, y_{i0}^{CT}, is likely correlated with the farm-level random effect, d_i.

One approach to address this issue in non-linear models is to explicitly model the distribution of the random effect conditional on the initial condition and the other explanatory variables (Wooldridge, 2005). While this method can take several forms, we follow a specification for the random effect that has been shown to produce unbiased estimates for parameters:

$$d_i = \alpha_0 + \alpha_1 y_{i0}^{CT} + \boldsymbol{\alpha_2}\bar{\boldsymbol{w}}_i + \boldsymbol{\alpha_3}\boldsymbol{w}_{i0} + a_i;\ a_i \sim Normal(0, \sigma_a^2)$$

where $\boldsymbol{w}_{i0}$ is a vector of all initial period explanatory variables and $\bar{\boldsymbol{w}}_i$ is a vector of explanatory variables averaged across all periods (Rabe-Hesketh and Skrondal, 2013). While Wooldridge (2005) originally suggests including all explanatory variables from all time periods in this auxiliary model, doing so results in a model that is often computationally unwieldly due to the large number of incidental parameters. Rabe-Hesketh and Skrondal (2013) show that the above constrained model performs similarly to the original Wooldridge solution. In this form, the random effect d_i is constrained to depend on $\boldsymbol{w}_{it}$ in the same fashion for $t > 0$. But because the presence of any non-zero parameters in the tillage model implies that y_{i0}^{CT} is directly dependent on $\boldsymbol{w}_{i0}$, we include $\boldsymbol{w}_{i0}$ separately from $\bar{\boldsymbol{w}}_i$ to account for this effect. This expression can be substituted into the structural equation and estimation can proceed.

The second issue relates to the use of non-glyphosate herbicides, y_{2it}, which is very likely to be endogenous to the tillage decision. As our primary goal is to achieve consistent estimation of the parameters on the GRW terms, one could consider omitting this variable to avoid the issue of endogeneity entirely. However, the use of non-glyphosate herbicides is almost certainly correlated with GRWs, so its omission will induce omitted variable bias in the parameters of interest.

To address this problem, we use a control function approach for binary endogenous variables in binary dependent variable models (Wooldridge, 2014; Terza et al., 2008). Prior to estimating the structural function, we estimate a first-stage reduced form model for the distribution of the endogenous variable, calculate generalized residuals of this model, and include these residuals, denoted as $\hat{r}_{jit}$ in the structural model as an explanatory variable. The idea is that the residuals serve as a sufficient statistic for the degree of endogeneity in the explanatory variable. The unobserved variables that are the source of the endogeneity, for example unobserved latent weed pressure, are captured in the error term of the first-stage model. By including the residuals of the first-stage model in the second-stage, structural model, we essentially control for endogeneity by including an imperfect but sufficient aggregate measure of the unobserved variables which induce the problem in the first place.

The reduced form model we estimate for the first-stage model of non-glyphosate herbicide use is:

$$\Pr\left(y_{jit}^{NGH} = 1 \middle| z_{it}, y_{i,t-1}^{CT}, p_t^{GH-NGH}, \boldsymbol{x'}_{it}, t, b_i\right)$$
$$= \Phi\left(\gamma_0 + z_{it}\gamma_1 + z_{it}^2\gamma_2 +, y_{i,t-1}^{CT}\gamma_3 + p_t^{GH-NGH}\gamma_4 + \boldsymbol{x'_{it}\gamma_5} + t\gamma_6 + b_i\right)$$

The price variable, p_t^{GH-NGH}, is the difference between the indexed price of glyphosate and an index of non-glyphosate herbicide prices, while $\boldsymbol{x'_{it}}$ is farm size dummies, omitting the soil and drought measures included in the tillage model. The farm-level random effect, b_i, is assumed to follow a normal distribution with zero-mean and variance σ_b^2. To account for the possible joint-determination between tillage and herbicide choices, we include lagged tillage choice $y_{i,t-1}^{CT}$, to avoid a recursive loop of endogeneity. Previous research has observed that the first adoption of new tillage systems often requires expensive equipment investments, creating an inertia of sorts in tillage decisions (Krause and Black, 1995). This first-stage model is estimated following standard maximum likelihood procedures for probit models with random effects.

To ensure identification of the second-stage, tillage choice model, at least one exclusion restriction is required so that the first-stage residuals have variation that is not entirely determined by variables already in the model (Wooldridge, 2014). We therefore exclude herbicide prices (both glyphosate and non-glyphosate) from the structural function, leaving $\boldsymbol{p}_t^-$ as a vector of fuel and machinery prices. This restriction assumes that herbicide prices drive variation in tillage decisions only through their effect on herbicide choices.

With residuals from the first-stage model and the auxiliary model for d_i in hand, the structural function we ultimately estimate is:

$$\begin{aligned}\Pr\left(y_{jit}^{CT} = 1 \middle| z_{it}, y_{jit}^{NGH}, y_{i,t-1}^{CT}, \boldsymbol{p}_t^-, \boldsymbol{x}_{it}, t, \hat{r}_{it}, y_{i0}^{CT}, \overline{\boldsymbol{w}}_i, \boldsymbol{w}_{i0}, a_i\right) \\ = \Phi(\beta'_0 + z_{it}\beta_1 + z_{it}^2\beta_2 + y_{jit}^{NGH}\beta_3 + p_t^m y_{i,t-1}^{CT}\beta_4 + y_{i,t-1}^{CT}\beta_5 + \boldsymbol{p}_t^-\boldsymbol{\beta_6} + \boldsymbol{x}_{it}\boldsymbol{\beta_7} \\ + t\beta_8 + \hat{r}_{it}\beta_9 + \alpha_1 y_{i0}^{CT} + \boldsymbol{\alpha_2}\overline{\boldsymbol{w}}_i + \boldsymbol{\alpha_3}\boldsymbol{w}_{i0} + a_i)\end{aligned}$$

This structural function can be estimated using standard maximum likelihood procedures for probit models with random effects.[2]

Data

The core of our data are field-level survey data, representative at the Crop Reporting District level, collected by the market research company GfK. These data contain observations on chemical and mechanical weed control practices of 22,151 farmers from 1999 through 2016 in 31 soybean-growing states across the United States, for a total of 93,345 field-level

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[2] We specifically use a Laplace approximation of the likelihood function. Estimation is performed using the R package "lme4".

observations. Importantly, many farms provide data for multiple fields per year and responses in multiple years, giving the data a panel structure necessary to estimate the proceeding empirical model. Tillage decisions, non-glyphosate herbicide use, herbicide prices, and farm size variables are all sourced from this dataset.

The GfK survey data include three levels of tillage intensity: conventional, conservation, or no-till. Following Perry et al. (2016a), where the same data is used, we define two binary tillage decision variables: a conservation tillage indicator equal to one when either conservation or no-till is used, and no-till indicator equal to one when no-till is used, grouping other conservation tillage practices along with conventional tillage. Because the effect of GRWs on no-till practice use is of particular interest, we estimate our empirical model twice, once with each of our two definitions of tillage practices as the dependent variable. The proportion of fields in the sample classified at no-till and conservation tillage is presented in Figure 1.

The GfK data also identify the herbicide products applied over each field in each year. We identify the active ingredients in each of these products and define a binary variable equal to one whenever the field is treated with a product containing a non-glyphosate active ingredient. The proportions of fields in the sample treated with glyphosate and non-glyphosate herbicides is presented in Figure 2. Early in the sample period, the use glyphosate became increasingly common, and the use of non-glyphosate products fell rapidly, likely due to the advent of glyphosate-tolerant soybean seed. Starting in 2006, this trend reversed, and non-glyphosate products were used more and more commonly. Glyphosate use reached near-saturation in the same year, and continued to be used on over 90% of fields through 2016 (though noticeably less in later years).

We use the GfK data to compute price indices for both glyphosate and non-glyphosate herbicides. For glyphosate prices, we calculate the mean price paid in dollars per pound each year. For non-glyphosate herbicides, we construct a Laspeyres index of all non-glyphosate herbicide products used throughout the sample period, with the mean dollar per pound and volume shares from across the full sample used as the base. These indices are scaled so that both equal one in 1999, the first year of our sample. These input price indices enter the empirical model as relative prices, and are therefore differenced as $p_t^{GH-NGH} = p_t^{GH} - p_t^{NGH}$. These price indices are present in Figure 3. Because glyphosate prices dropped significantly following the expiration of Monsanto's patent in 2000 while non-glyphosate prices remained steady, p_t^{GH-NGH} is negative in all years.

Finally, the GfK dataset describes farm size as one of five categories: less than 100 acres, l00-249 acres, 250-499 acres, 500-999 acres, and 1,000 acres or more. These are included as dummy variables in the empirical model, with less than 100 acres as the baseline.

We supplement the GfK field-level data with state-level data on the number of reported glyphosate-resistant weed species at the beginning of the growing season, as reported by the International Survey of Herbicide Resistant Weeds (Heap, 2017).[3] The number of species resistant to glyphosate in each state in our sample in 2004, 2008, 2012, and 2016 is presented in Figure 4. To the best of our knowledge, the ISHRW is the best available measure for this variable, providing consistent reporting on the development of herbicide resistance by mode of action across the full timeframe and the geographic region of our panel. As the primary contributors to the ISHRW data are university extension weed scientists, we assume that these

[3] These data were provided to us through personal communication with Ian Heap, via email, as a custom report on herbicide-resistance in the United States generated from the ISHRW database. These data are consistently updated and can be viewed publicly on the ISHRW website.

counts represent the knowledge available to a typical farmer when making tillage decisions through an extension weed control guide (e.g., Sprague and Burns, 2017).

For fuel and farm machinery prices, we rely on NASS annual price indices for diesel fuel and farm implements, including planters and tillage equipment (National Agricultural Statistics Service, 2018). As conservation tillage typically requires lighter field implements and therefore less fuel, we expect its use to be more frequent when fuel prices are higher (Lal, 2004). As first adoption of conservation tillage can require a costly equipment investment (Krause and Black, 1995), we include machinery prices interacted with a dummy variable indicating whether a farm used conservation tillage on any of its fields in the previous season.

Finally, we include a pair of variables to control for a field's soil conditions. Previous studies have shown that conservation tillage systems are more likely to be adopted on highly-erodible lands (Uri, 1999; Soule et al., 2000). Past research has also found that the use of conservation tillage (but not no-till) is more likely in years following drought conditions (Ding et al., 2009). Therefore, for each farm we include the proportion of the land in a farm's county that National Resources Inventory has classified as highly-erodible (National Resource Conservation Service, 2018). We also include the Palmer's Z-index of a farm's climate division in the September of the prior year, where a more negative Z-index score indicates drier conditions (National Environmental Satellite, Data, and Information Service, 2018).

Results

In this section, we present the results of our empirical model. First, we discuss the coefficients and goodness-of-fit for our structural models of tillage adoption, after a brief discussion of our first-stage models of non-glyphosate herbicide use. We present multiple measures of goodness-of-fit: the percentage of observations correctly predicted and pseudo-R^2

measures widely used when generalized linear mixed-effects models are reported (Nakagawa and Schielzeth, 2013). We then turn to the implications of our tillage decision models, examining predicted probabilities of conservation tillage and no-till adoption at extant GRW species counts. Finally, we use our tillage decision model for conservation tillage adoption to explore a counter-factual scenario in which no weed species adapt to resist glyphosate to get a sense at the degree of environmental damages induced by GRWs through farmers' tillage responses.

First-stage non-glyphosate herbicide use models

The first-stage model of non-glyphosate herbicide use is estimated twice, once with past no-till use and once with past conservation tillage use as independent variables for the estimation of control functions for corresponding second-stage models. Results from each are presented in Table 1. In both estimations, coefficients on both GRW terms indicate that glyphosate-resistant weed species are statistically significant and similar in scale. The negative coefficient on the linear term and positive coefficient on the quadratic term indicate that although the first GRW species to appear have relatively little impact on the use of non-glyphosate herbicides, the probability of non-glyphosate herbicide use rises faster as GRW counts reach higher levels.

The coefficient on the price differential between glyphosate and non-glyphosate herbicides is positive and statistically significant for both models, indicating that this variable is an eligible candidate for an exclusion restriction (Wooldridge, 2014). As expected, in years when glyphosate is expensive relative to alternatives, non-glyphosate herbicides are more likely to be used.

No-till and conservation tillage models

The results from the second-stage, tillage choice models are presented in Table 2, estimated for both no-till and conservation tillage use as the dependent variable. Both models correctly predict the tillage decision for a field about 80% of the time. Perhaps more importantly, the models correctly predict tillage decisions at roughly the same rate for fields regardless of the observed outcome. This balance is important for modelling counter-factual scenarios, because if the model's accuracy depended largely on its target, then prediction would be systemically biased towards the model's naturally favored outcome.

Both models explain the majority of the variance in tillage adoption outcomes, as measured by the pseudo-R^2 metrics proposed for generalized linear mixed-effect models by Nakagawa and Schielzeth (2013). Marginal R^2 measures the variance explained by fixed factors alone (i.e. the observed independent variables), while conditional R^2 measures the variance explained by the full model, including random effects. These measures are preferred to alternatives such as the commonly used McFadden's pseudo-R^2 because (a) they can be interpreted on the same unit-scale as the usual R^2 commonly reported for ordinary least-square models, and (b) they separately identify the contributions of fixed and random effects. For both models, around two thirds of the total explained variance is accounted for via the observed heterogeneity (i.e. the fixed effects), and allowing for a random intercept for each farm to account for unobserved heterogeneity improves model fit substantially.

The statistical significance of the residuals from the first-stage, non-glyphosate herbicide use models in both second-stage models allows us to reject a null hypothesis that non-glyphosate use is exogenous to tillage decisions (Wooldridge, 2014). The use of non-glyphosate herbicides is positively associated with the use of conservation tillage and no-till practices, as the coefficients on this term are positive and statistically significant in both models. When farmers move away from intensive conventional tillage practices, they give up a weed control tool and must supplement lost weed control through other means. As glyphosate is used on nearly all fields in our sample regardless of tillage system, this means supplementing with non-glyphosate herbicides.

Both fuel price and machinery price have statistically significant coefficients of the expected signs in both models. The positive coefficients on fuel price likely stem from the fact that conservation tillage systems require less fuel than conventional tillage, and are therefore more likely to be selected when fuel is costly (Lal, 2004). This is consistent with recent studies of tillage adoption (Perry et al., 2016a). More expensive machinery leads to less frequent conservation tillage use, due to the investment cost of the equipment (Krause and Black, 1995). This explanation is further supported by the positive and statistically significant coefficient on the interaction term between past tillage decisions (equal to one when a farm has been observed using no-till or conservation tillage in the previous period) and machinery price. When a farm has used no-till in the past, the coefficient on machinery price is reduced by two fifths; when a farm has used conservation tillage in the past, the coefficient is nearly zero.

Previous use of conservation tillage has a statistically significant and positive effect. This indicates that some unexplained “inertia” is present for conservation tillage: farms that use conservation tillage today are more likely to use it in the future, perhaps due to increased familiarity with the system (Uri, 1999). However, this pattern does not hold when no-till is modelled separately from other conservation tillage systems, suggesting that the primary avenue through which previous no-till decisions impact current ones is through changes to a farm’s equipment portfolio.

The remaining coefficients follow their expected signs. Fields experiencing recent drought (represented with negative Palmer's Z-index values) are more frequently under conservation tillage, but not no-till. This pattern follows results found in previous studies (Ding et al., 2009). Fields in counties with more highly-erodible land are also more likely to be under conservation tillage systems. The positive time trend likely reflects the effects of payments through federal conservation programs and state-level extension efforts to promote conservation tillage adoption, as well as increased familiarity with these practices over time. Medium sized farms are slightly more likely to adopt conservation tillage than the largest (1,000 acres or more) and smallest farms (less than 100 acres), while the largest farms are slightly less likely to adopt no-till.

Effects of GRWs on tillage decisions

The primary focus of this paper is the effects of glyphosate-resistant weeds on farmers' tillage practices. In models for both conservation tillage and no-till, the coefficient on the linear term for GRWs is positive but statistically insignificant and the coefficient on the quadratic term is negative and statistically significant. This indicates that GRWs have a negative effect on conservation tillage use, and the emergence of additional GRWs has increasing impact.

The predicted probabilities of adoption of conservation tillage and no-till for a range of GRW counts, with other variables held at their means, are presented in Figure 5. These curves show the negative and non-linear effect of GRWs on the use of conservation tillage, consistent with the expectations of the conceptual model. Through the first two glyphosate resistant weed species, the predicted rate of no-till use remains statistically indistinguishable from the rate at zero GRWs (44% adoption). However, by the eighth GRW, the predicted rate of adoption falls by 9.2 percentage points, a 21% reduction among no-till users. The impact of GRWs on conservation tillage is similar, though less severe. Through the first two GRWs, conservation tillage is used at rates not statistically different from zero GRWs (66.9% adoption). But by the eighth reported GRW, conservation tillage rates fall by 6.2 percentage points, a 9.3% reduction among CT users generally. The magnitude of predicted reduction in conservation tillage and no-till use due to eight identified GRWs corresponds with that of the increase in use attributed to the introduction of glyphosate-resistant soybean seeds (Perry et al., 2016a). In effect, the advent of GRWs is undoing the stimulus to adoption of conservation tillage that was prompted by the introduction of glyphosate tolerant crop varieties.

Simulation of GRW proliferation on tillage use

To demonstrate the impact GRWs have had on farmers' tillage decisions over time and space, we compute the shares of acres under conservation tillage predicted by the model given realized GRW emergence patterns (denoted Ac for "actual") and a counterfactual scenario in which no weed species evolve to resist glyphosate, all else equal (denoted Cf for "counterfactual"). The counterfactual scenario is simulated by setting $z_{it} = 0$ for all observations in a counterfactual dataset, leaving all other variables the same as observed.

We first simulate farmers' field-level tillage decisions in the counterfactual scenario, giving us for each field in the sample P_{jit}^{Cf}, the counterfactual predicted probability of conservation tillage use on field j, operated by farmer i, in year t. We then simulate the same predicted probabilities of conservation tillage use under realized GRW emergence patterns (i.e. the original data), denoted for each field as P_{jit}^{Ac}.

The shares of soybean acres in each year under conservation tillage in both scenarios (S_t^{Ac} and S_t^{Cf}) are calculated by summing the predicted probabilities weighted by the number of acres each field represents in the population of soybean acres in a given year, denoted A_{jit}:

$$S_t^n = \frac{\sum_{i=1}^{I_t} \sum_{j=1}^{J_{it}} P_{jit}^n A_{jit}}{\sum_{i=1}^{I_t} \sum_{j=1}^{J_{it}} A_{jit}}, n \in \{Ac, Cf\}$$

As a display of the spatial variation in the effect of GRWs on tillage decisions over our sample period, the differences between the acre-shares under conservation tillage, $S_t^{Cf} - S_t^{Ac}$, are calculated separately for each state and presented in four maps for 2004, 2008, 2012, and 2016 in Figure 6. On the majority of soybean acres, GRWs have had negligible impact on tillage practices, with increases in intensive tillage adoption less than 5%. However, the impact of GRWs on tillage decisions is particularly noticeable where GRWs are most prevalent: southern states such as Mississippi, Missouri, Arkansas, and Tennessee where glyphosate is commonly used as the primary weed control tool on glyphosate-resistant cotton in addition to soybeans and corn. In Mississippi in 2016 for example, intensive tillage would be used on 8.5% fewer soybean acres had GRWs been absent.

Environmental Damages via Farmers' Tillage Response to GRWs

The use of conservation tillage systems is known to reduce soil erosion and carbon emissions, which can impair water quality and contribute to global climate change respectively (Uri et al., 1999). An intuitive follow-up to the proceeding analysis of farmers' tillage responses to GRWs is to estimate the resulting environmental damages from increased tillage.

We develop rough estimates of the social costs of increased intensive tillage use on two environmental outcomes, soil erosion and carbon emissions from fuel, by drawing upon values from the literature, applying a simple benefit transfer model to monetize social costs (Wilson and Hoehn, 2006). Tillage practices have wide-ranging impacts on the environment (Uri et al., 1999), and a full accounting of these impacts is outside the scope of the present study. However, this exercise suggests that the spread of GRWs is a problem not just for farmers, but for society. Our general approach follows the methods presented in Perry et al. (2016a).

To quantify the soil erosion impact of increased use of conventional tillage, we rely on median erosion rates for soils under conventional and conservation tillage as reported in a review of 495 studies (Montgomery, 2007). For conventional tillage, the reported median erosion rate is 1.54 mm per acre-year. For conservation tillage, the median erosion rate is 0.08 mm per acre-year. Assuming a soil density of 1,200kg/m^3, this implies a 6.8 ton/acre-year reduction in soil erosion in fields under conservation tillage (Montgomery, 2007).

Conventional tillage leads to increases in carbon emissions over conservation tillage both through increased fuel consumption and by reducing the capacity of the soil to retain carbon. However, given that the potential carbon sequestration ability of soil is highly variable and dependent on the sustained practice of conservation tillage over time, we choose to focus on carbon emissions from fuel consumption (Uri et al., 1999). Lal (2004) synthesizes the literature on fuel consumption required for various tillage operations, reporting the results as mean kilograms CO_2-equivalent emissions (CE) per hectare. We convert these means to metric tons CE/acre. The resulting increase in carbon emissions when switching from conservation to conventional tillage is 0.0234 metric tons CE/acre.

To monetize the effects these environmental impacts, we use prices previously used by federal policymakers for benefit-cost analysis. The National Resource Conservation Service estimates the costs of increased soil erosion at $4.93 per ton in water quality damage (National

Resource Conservation Service, 2009). For carbon emissions, we rely on the global Social Cost of Carbon (SSC), as reported by the United States Government (Interagency Working Group on Social Cost of Greenhouse Gases, 2016). This measure, widely used in policymaking prior to 2017, estimates the social costs of a metric ton of CO_2 released into the atmosphere for each year beginning in 2010. We rely on the reported average SCC estimate at a 3% discount rate, a conservative estimate. As the annual growth in this measure is almost exactly linear, we estimate the SCC for years prior to 2010 by regressing the SCC on a year trend (R^2 = 0.987). These prices are adjusted using the Consumer Price Index to reflect the real value of damages in each year.

Finally, the conservation tillage acre-share differentials computed in the previous subsection are multiplied by the acres planted to soybean in each year (National Agricultural Statistics Service, 2018), providing an annual estimate of the number of acres that would be under conservation tillage in the absence of GRWs, but are instead under conventional practices. The environmental impact and social value coefficients are applied to these acres, providing an estimate for the value of damages to water quality and the climate. Annual social and environmental damages are presented in Table 3. Social damages are presented as lost value in current year price levels and as 2016 present value ($PV_t = CV_t/(1+r)^{t-T}; r = 0.03; T = 2016$).

In total, we estimate the net present value of water quality and climate damage from farmer's tillage responses to GRWs is approximately $470 million. This social cost has been growing by over $70 million annually in recent years. Water quality damage will be greatest in regions where GRWs are most prevalent, while the climate damage will be realized globally. If weed species continue to adapt to resist glyphosate across the country, and farmers continue increase tillage to achieve similar levels of weed control, we expect the rate at which these damages grow to accelerate.

Discussion and Conclusion

Herbicide resistant weeds, and GRWs in particular, have become a widespread issue for farmers across the United States. This paper contributes to the literature on herbicide resistant weeds by providing new and robust evidence that farmers respond to the decreasing effectiveness of glyphosate by increasing tillage intensity. We do so by observing the field-level weed control decisions of thousands of soybean farmers across the country during the period that GRWs first emerged and subsequently spread. We find evidence that farmers' tillage responses to GRWs follow a non-linear pattern. Our empirical model further allows us to estimate the marginal, causal effects of additional GRWs on the use of alternative tillage systems. We use these estimates to provide a rough calculation of the scale of social damages that GRWs have caused by increasing tillage in soybean fields.

Our approach represents a novel direction in the herbicide resistance literature in two ways. First, we focus on how farmers have changed their management behavior in response to herbicide resistance, while other economic studies focus on how resistance has affected costs, returns, or yields (Livingston et al., 2015; Wechsler et al., 2017; Lambert et al., 2017). Second, we quantify the environmental damages from farmers' responses to herbicide resistance, which would not be possible without our focus on practices.

While this paper focuses on tillage practices, too little is known about how herbicide resistance affects the use of other weed control tools available to farmers. Future research should explore which non-glyphosate herbicides farmers are choosing to combat GRWs, which seed traits farmers select, and what those choices imply for environmental quality.

Meanwhile, agrochemical companies have responded to GRWs by developing new seed technologies resistant to other herbicides (Mortensen et al., 2012; Green, 2014; Bonny, 2016). Farmers remain optimistic that agrochemical companies will develop new solutions that will maintain the simplicity of glyphosate-based weed management (Dentzman and Jussaume, 2017). However, public weed scientists have questioned whether this path forward is sustainable, as weeds will continue to evolve resistance to more and more biochemical modes of action (Duke, 2011; Mortensen et al., 2012). Davis and Frisvold (2017) suggest that the current dominant weed control regime, based on specific herbicides paired with resistant seed, may come to an end within the foreseeable future if action is not taken.

Fortunately, numerous solutions have been proposed to alleviate the threat posed by GRWs and weed resistance to other herbicides. Mortensen et al. (2012) call for increased public investment in research and promotion of integrated weed management systems, which rely on a more diverse suite of weed management practices in order to delay the onset of resistance of any specific method. A recent simulation study suggests that this approach can be profit-maximizing for farmers with longer time horizons (Frisvold et al., 2017). Davis and Frisvold (2017) suggest adapting current federal subsidies of crop insurance and other conservation programs such as the Environmental Quality Incentive Program to create incentives for the adoption of integrated weed management and other resistance management strategies. Ervin and Frisvold (2016), noting the common pool resource nature of herbicide resistance, envision community-based approaches for encouraging resistance management, modelled after drainage districts and insect eradication programs. Further research into policies to delay the onset of resistance is needed. Such studies should consider not only the private benefits to farmers from the delayed onset of resistance, but also the public damages to the environment that could result if resistance management is ignored.

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Figures and Tables

Table 1: Results from first-stage, non-glyphosate herbicide use models, estimated separately for use with no-till and conservation tillage second-stage models.

	Dep. Var.: Non-Glyphosate Herbicide Use			
	No-Till Model		Cons. Till Model	
	Est.	*p*	*Est.*	*p*
(Intercept)	-0.782	**<.001**	-0.781	**<.001**
GRWs	-0.043	**<.001**	-0.042	**<.001**
GRWs (squared)	0.026	**<.001**	0.026	**<.001**
Glyphosate Price Difference	0.433	**<.001**	0.434	**<.001**
Past Tillage Decision	0.033	**.017**	0.018	.197
Year Trend	0.040	**<.001**	0.040	**<.001**
Size (100 - 249 Acres)	0.322	**<.001**	0.323	**<.001**
Size (250 - 499 Acres)	0.516	**<.001**	0.517	**<.001**
Size (500 - 999 Acres)	0.636	**<.001**	0.637	**<.001**
Size (1000 Acres or more)	0.737	**<.001**	0.738	**<.001**
Random Effects	Farm-level		Farm-level	
Unique Farms	22,151		22,151	
Observations	93,345		93,345	
Percent Correct (Dep. Var. = 1)	63.1%		62.9%	
Percent Correct (Dep. Var. = 0)	56.3%		56.4%	
Percent Correct	59.6%		59.6%	
Marginal R^2	0.119		0.119	
Conditional R^2	0.579		0.579	

Table 2: Results from second-stage, tillage decision models, estimated separately for no-till and conservation tillage (no-till included).

	Dep. Var.: Tillage Decision			
	No-Till Model		Cons. Till Model	
	Est.	*p*	*Est.*	*p*
(Intercept)	0.562	**<.001**	0.191	.184
GRWs	0.023	.141	0.014	.343
GRWs (Squared)	-0.010	**<.001**	-0.006	**<.001**
Non-Glyphosate Use	0.385	**.003**	0.362	**.002**
Non-Glyphosate Use (Residuals)	-0.149	**.007**	-0.147	**.003**
Fuel Price	0.090	**<.001**	0.062	**<.001**
Machine Price	-1.107	**<.001**	-0.328	**.012**
Machine Price * Past Tillage Decision	0.392	**<.001**	0.363	**<.001**
Past Tillage Decision	0.029	.597	0.207	**<.001**
Palmer's Z-Index	-0.001	.711	-0.006	**.037**
Soil Erodibility Index	0.614	**<.001**	0.405	**<.001**
Year Trend	0.092	**<.001**	0.027	**.001**
Size (100 - 249 Acres)	0.009	.720	0.061	**.012**
Size (250 - 499 Acres)	0.008	.782	0.060	**.021**
Size (500 - 999 Acres)	-0.010	.751	0.068	**.012**
Size (1000 Acres or more)	-0.079	**.017**	-0.015	.610
Initial Conditions Correction	Yes		Yes	
Random Effects	Farm-level		Farm-level	
Unique Farms	22,151		22,151	
Observations	93,345		93,345	
Percent Correct (Dep. Var. = 1)	72.4%		82.3%	
Percent Correct (Dep. Var. = 0)	81.2%		74.7%	
Percent Correct (All Obs.)	77.3%		80.0%	
Marginal R^2	0.471		0.420	
Conditional R^2	0.705		0.626	

Table 3: Estimated social and environmental damages resulting from increased use of intensive tillage in response to GRWs. Prior to 2005, GRWs had yet to reach impactful levels in any state.

	Social Damages		Environmental Damages	
Year	Current Value [a] (USD)	Present Value [b] (USD 2016)	Soil Erosion [c] (Metric Tons)	Carbon Emissions [d] (Metric Tons CE)
2005	400,000	600,000	90,000	<1,000
2006	1,300,000	1,800,000	280,000	1,000
2007	4,500,000	5,800,000	920,000	3,000
2008	9,600,000	12,200,000	1,910,000	7,000
2009	19,700,000	24,200,000	3,910,000	13,000
2010	26,400,000	31,600,000	5,130,000	18,000
2011	40,100,000	46,500,000	7,580,000	26,000
2012	51,100,000	57,500,000	9,390,000	32,000
2013	57,700,000	63,100,000	10,460,000	36,000
2014	70,400,000	74,700,000	12,560,000	43,000
2015	73,200,000	75,400,000	13,090,000	45,000
2016	80,100,000	80,100,000	14,180,000	49,000
Total	434,600,000	473,500,000	79,510,000	273,000

[a] Soil erosion priced at $4.93/ton in 2009 dollars, adjusted to current year prices with CPI (National Resource Conservation Service, 2009); carbon emissions priced following Social Cost of Carbon at 3% discount rate (Interagency Working Group on Social Cost of Greenhouse Gases, 2016).
[b] Computed with a 3% annual discount rate.
[c] Assuming a 6.8 ton/acre reduction in soil erosion from conservation tillage use (Montgomery, 2007).
[d] Accounts only for reduced fuel consumption; assuming a 0.0234 tons/acre reduction in emissions from conservation tillage use (Lal, 2004).

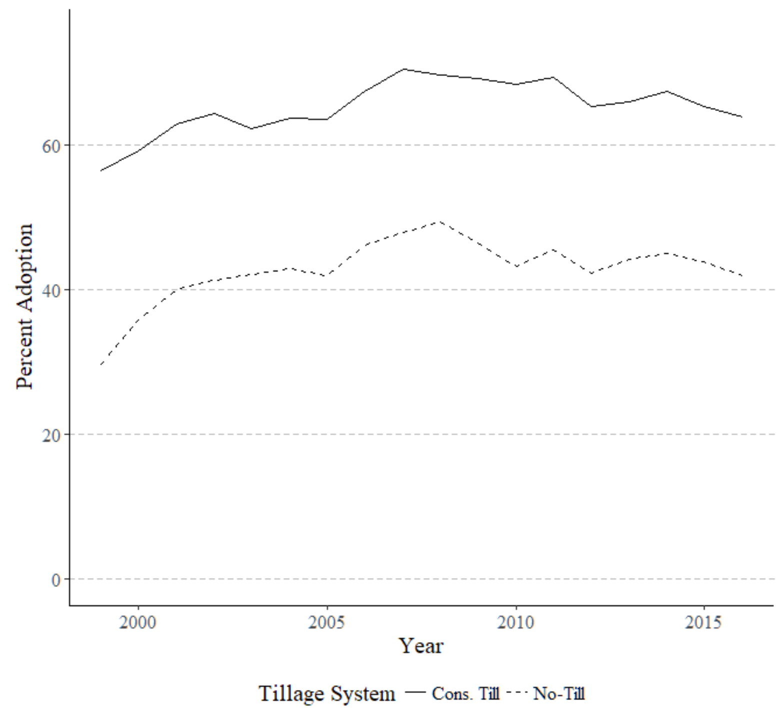

Figure 1: Percentage of fields in sample under no-till and conservation tillage (including no-till) over time.

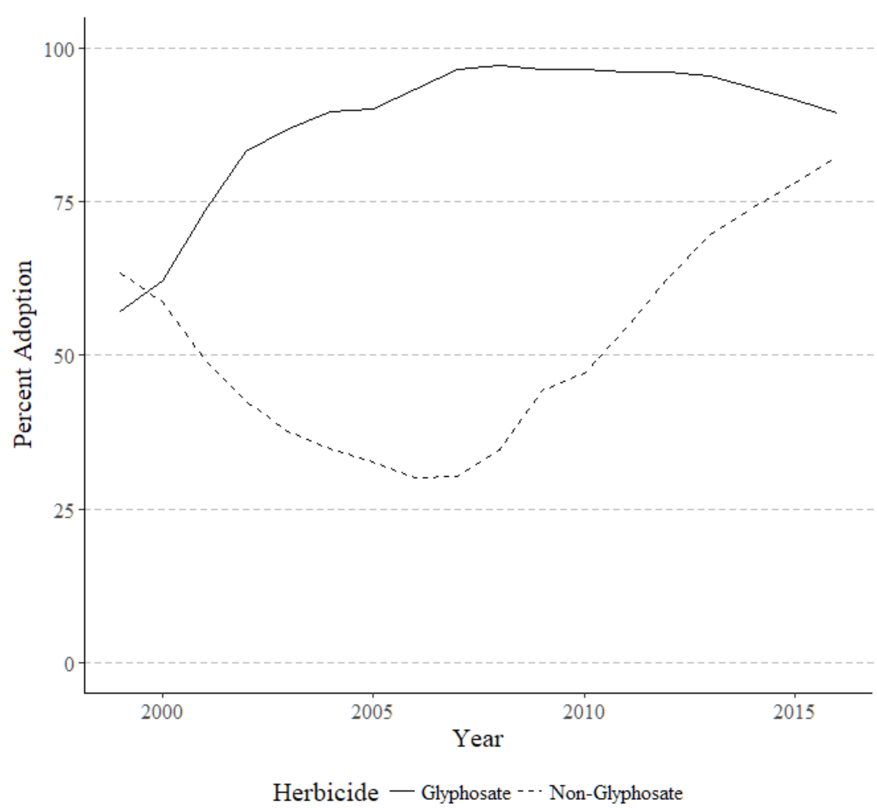

Figure 2: Percentage of fields in sample treated with glyphosate and non-glyphosate herbicides over time.

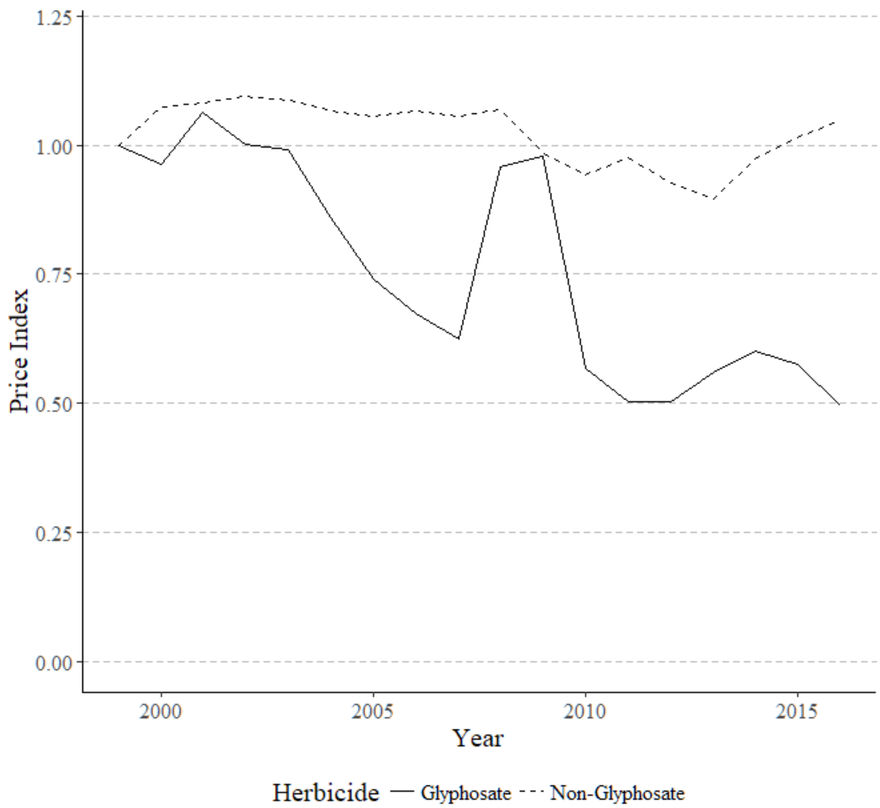

Figure 3: Price indices for glyphosate-based and non-glyphosate based herbicides over time.

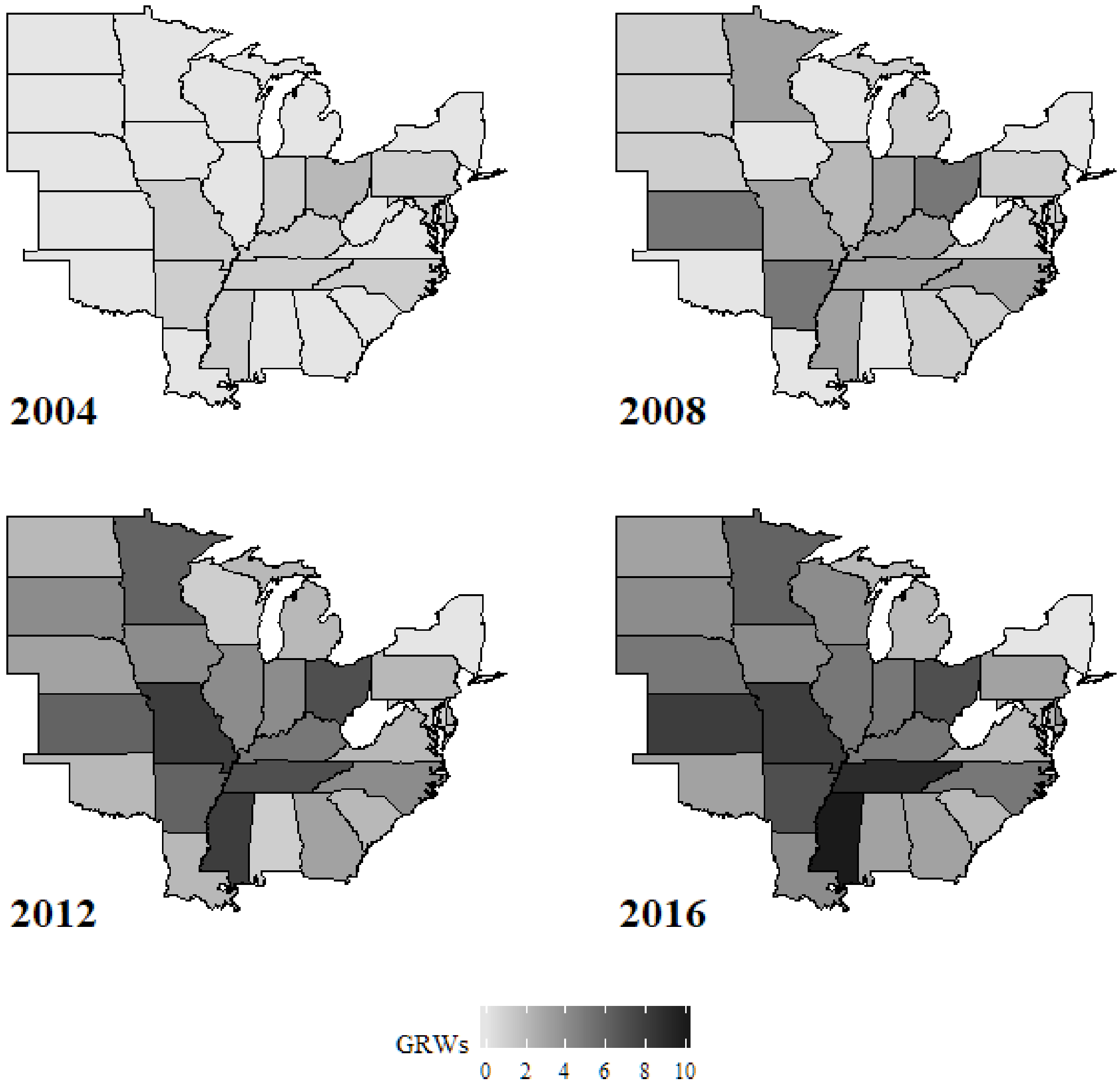

Figure 4: Number of weed species resistant to glyphosate (GRWs) at the start of the growing season by state in 2004, 2008, 2012, and 2016. Prior to 2001, no species had been identified as glyphosate resistant at the start of the growing season.

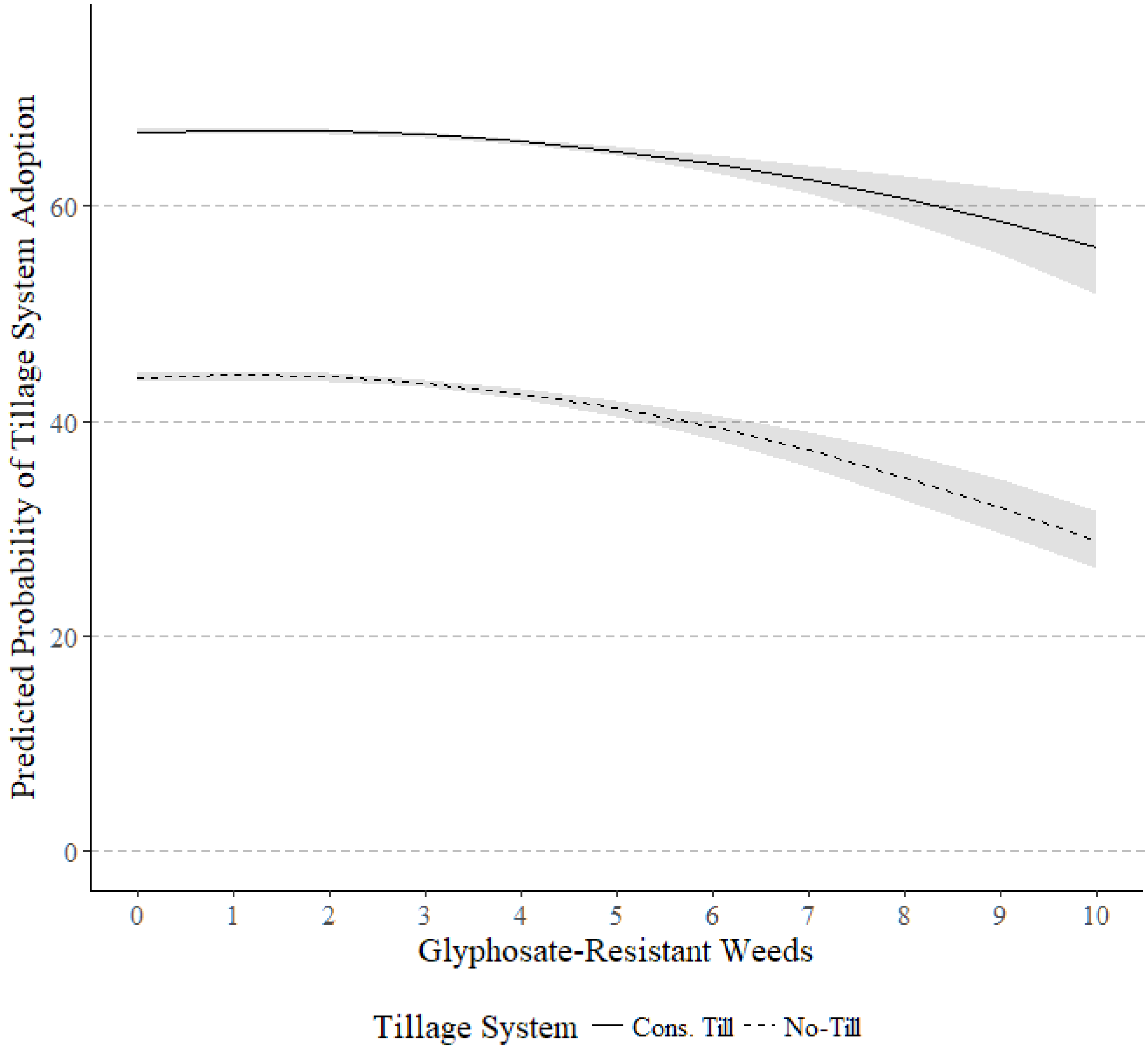

Figure 5: Predicted adoption of no-till alone and conservation tillage (including no-till) by the number of glyphosate resistant weeds identified in a farm's state. The shaded region indicates a 95% confidence interval, computed via the delta method.

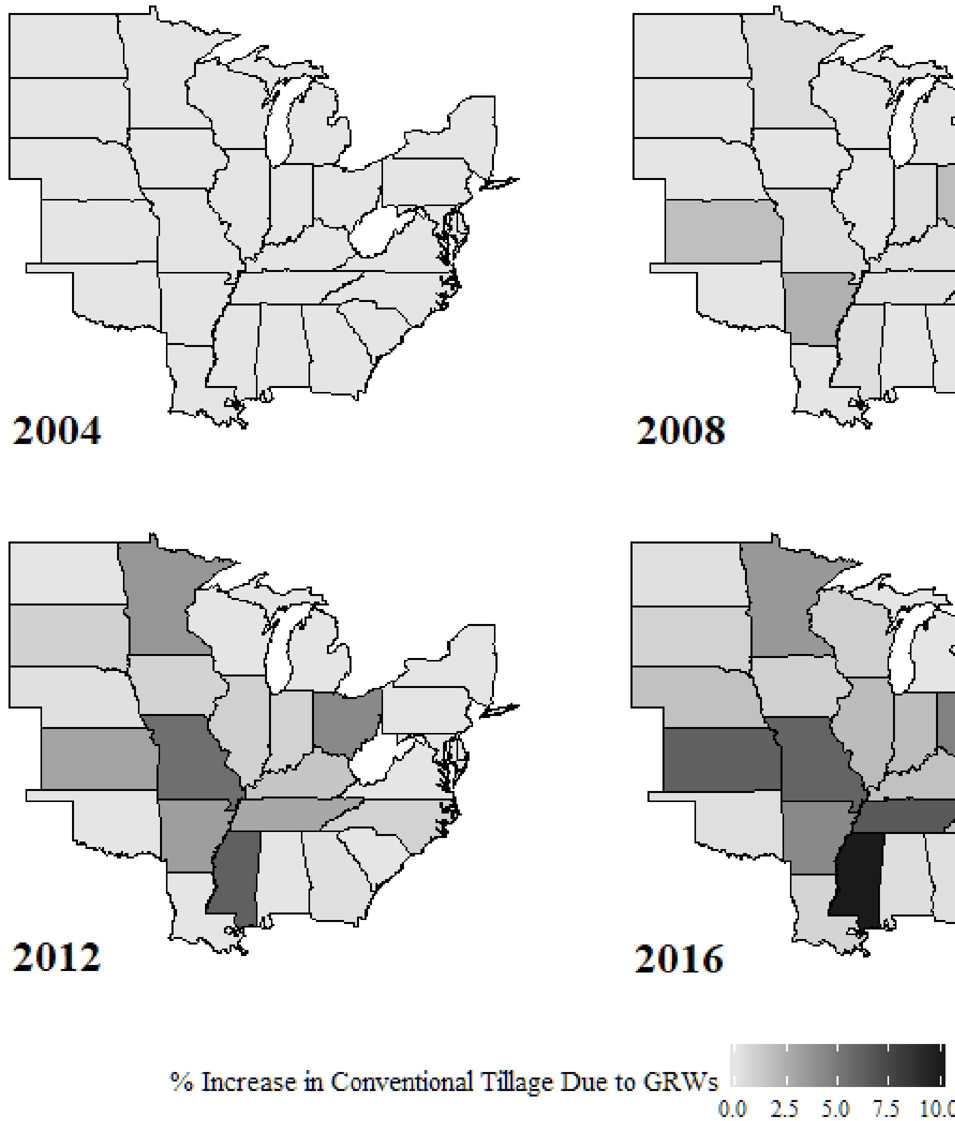

Figure 6: Increases in percentage of soybean acres by state under conventional tillage attributed to GRWs in 2004, 2008, 2012, and 2016.