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

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Conservation tillage in American soybean production has become increasingly common, improving soil health while reducing soil erosion and fuel consumption. This trend has been reinforced by the widespread adoption of glyphosate-based weed control systems. Many weed species have since evolved to resist glyphosate, reducing its effectiveness. We provide evidence that the spread of glyphosate-resistant weeds is responsible for significant reductions in the use of conservation tillage in soybean production. We estimate reduced-form and structural probit models of tillage choice, using a large panel of field-level soybean management decisions from across the United States spanning 1998–2016. We find that the first emergence of glyphosate-resistant weed species has little initial effect on tillage practices, though by the time that eight glyphosate-resistant weed species are identified, conservation tillage and no-till use fall by 3.9 percentage points and 7.6 percentage points, respectively. We further find that when ten glyphosate-resistant species are present, the predicted adoption rate of non-glyphosate herbicides rises 50 percentage points, and that the availability of non-glyphosate herbicides facilitates continued use of conservation tillage as glyphosate-resistant weeds proliferate. Using a simple benefits transfer model, we conservatively estimate that between 2008 and 2016 farmers' tillage responses to the spread of glyphosate-resistant weeds have caused water quality and climate damages via fuel emissions valued at nearly $245 million. This value does not account for climate damages due to carbon released during soil disruptions and is likely to grow as glyphosate resistance becomes more widespread and more farmers turn to tillage for supplemental weed control.

Key words: Agriculture, conservation, conservation tillage, control functions, glyphosate, herbicides, herbicide resistance, no-till, tillage, weed control.

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Since the mid-1900s, 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. Although intensive tillage can provide effective weed control, this control comes at a cost to the environment, leading to increased soil erosion and energy use, which can impair

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water quality and increase the carbon footprint of agricultural production (Uri, Atwood, and Sanabria 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 return to increased use of tillage and non-glyphosate herbicides to control weeds.

When first introduced, herbicides were rapidly adopted by American field crop farmers. Herbicides offered weed control at least as good as tillage but at lower cost (Swinton and Van Deynze 2017). The introduction of soybean varieties genetically engineered to tolerate glyphosate (and later other herbicides) has further shifted soybean weed control away from tillage (Fernandez-Cornejo et al. 2012; Perry, Moschini, and Hennessy 2016b). Glyphosate is a broad-spectrum herbicide that could effectively control almost all weeds in the early 1990s, when herbicide tolerant crop varieties were first introduced. Glyphosate-tolerant crops, like Roundup Ready™ soybeans, allow farmers to spray the herbicide throughout the growing season without damaging their crop. Farmers using these technologies could rely exclusively on glyphosate for weed control, forgoing tillage passes and therefore providing cost savings to farmers and averting environmental damages. In many instances, glyphosate also replaced herbicides with higher acute toxicity to non-target species, including humans (e.g., atrazine, a possible human carcinogen that is toxic to many fish; Ribaudo and Bouzaher 1994; Ye, Wu, and Hennessy 2021).[1]

As glyphosate use became more frequent in soybeans and other crops, weeds soon evolved to resist the chemical. In 2000, glyphosate resistance in weeds was first identified in a population of horseweed growing in a Delaware soybean field (Van Gessel 2001). Glyphosate resistance has since been identified in seventeen weed species in the United States (Heap 2020). 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 (e.g., Beckie 2006; Evans et al. 2015; Bonny 2016; Beckie and Harker 2017). The increased use of tillage for weed control is frequently found among 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 who self-report experiencing problems with GRWs supplemented glyphosate-based weed control with non-glyphosate herbicides and increased their use of both glyphosate and tillage.[2] Reporting on farm-level, repeated cross-sectional yield and weed control practice data from corn-growing states in 2005 and 2010, Wechsler, McFadden, and Smith (2017) find that low numbers of GRWs have a fairly small impact on corn farmers' weed control practices, costs, and yields. Lambert et al. (2017) use data from a 2012 survey of upland U.S. cotton farmers and find that weed control costs increase by $34–55/acre following the emergence of GRWs as farmers adopt labor-intensive alternatives to glyphosate.

These papers all rely on cross-sectional or repeated cross-sectional data that are not suitable for panel data methods that can control for unobserved heterogeneity over time at the microlevel. Perry et al. (2016a), using farmer-level panel data from corn and soybean growers across the U.S., 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. But this study neither explicitly includes data on glyphosate resistant weed prevalence nor addresses practice change beyond herbicide use. Finally, none of these previous studies on farmer response to herbicide resistance includes data beyond 2012. Since 2012, herbicide resistance weeds have become far more widespread (Heap 2020), providing an improved opportunity to observe farmer response.

In this paper, we contribute to the literature on weed management in the face of herbicide resistance by providing the first estimate of the impact of GRWs on the adoption rates of conservation tillage practices in soybeans. Like Perry et al. (2016a), we also find a sharp increase in non-glyphosate herbicide use,

[1] Although the possibility of chronic human toxicity from glyphosate is actively debated (NRC 2016), the focus of this paper is on farmer responses to glyphosate-resistant weeds.

[2] A reviewer notes other possible farmer responses to the spread of GRWs include switching to seeds with other traits, such as tolerance to glufosinate, 2,4-D, or dicamba herbicides. To date, there is little documentation of widespread adoption of such responses over our study period, and these traits are typically adopted jointly with their associated herbicides. Hence, this paper concentrates on the use of non-glyphosate herbicides broadly and tillage as responses to the spread of GRWs.

which we argue has allowed at least some farmers to continue conservation tillage practices even in the face of spreading GRWs. We reach our findings 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 nonlinear response to herbicide resistance: as more weed species develop glyphosate resistance, farmers become increasingly likely to make major changes to their weed control practices. We test this model empirically with data on the field-level weed control choices of thousands of soybean farmers during 1998–2016.

Our econometric results, which account for substitution effects between tillage and herbicides, and take advantage of panel data to control for unobserved heterogeneity, indicate that low numbers of GRWs have little impact on tillage choices. However, by the time that eight GRW species are identified at the state level, conservation tillage adoption falls by 3.9 percentage points and no-till adoption falls 7.6 percentage points. Meanwhile, our reduced-form model of herbicide use predicts that use of herbicides other than glyphosate grows 50 percentage points over the range of observed GRW species identified (zero through ten).

Extrapolating from literature estimates of soil erosion and fuel emissions from tillage, and their environmental costs, we conservatively estimate that the shift toward more intensive tillage practices in response to GRWs has caused water quality and climate damage via fuel emissions costing nearly $245 million through 2016, the final year of our panel. These damages accrued beginning in 2008 and have been most acute in the southern states, where GRWs are most prevalent. Our estimate does not account for additional damages due to carbon released from soil disruption during tillage events, which are likely considerable. These findings are of particular relevance for policymakers considering working lands programs that rely on farmers voluntarily reducing tillage, including those that provide credits in exchange for practice adoption.

The rest of this paper is structured as follows: we first present a conceptual model of a cost-minimizing farmer who seeks to control multiple weed species and is faced with a shrinking set of herbicide options to accompany tillage options. We then present our empirical strategy and follow this with a discussion of the data. After presenting our econometric results, we conduct a benefits transfer simulation to illustrate a subset of potential environmental costs. We close with discussions of the policy implications of our findings and of 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 *minimum* level of control acceptable for each weed in the field.[3]

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, and IT denotes intensive tillage (sometimes referred to as "conventional tillage"). A farmer can select any combination of L alternative herbicides to supplement weed control provided by their 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 $\boldsymbol{H} = \mathbb{R}_+^L$.[4] Together, a farmer's weed control choice set is $\{\tau^{CT}, \tau^{IT}\} \times \boldsymbol{H}$. In principle, the farmer's choice of whether to plant a herbicide-tolerant crop variety conditions the herbicide options. However, because the subset of feasible herbicide options with no herbicide-tolerant crop is subsumed by the options with herbicide-tolerant crops, this herbicide choice set implicitly embeds the choice of herbicide-tolerant crop traits.

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[3]Farmers and weed control experts typically use a *maximum* acceptable density of weeds in a field measured as individuals per area (e.g. weeds/m^2). This value is typically an "economic threshold" at which control action is cost efficient (Marra and Carlson 1983; Swinton and King 1994). In this model we instead use a functionally identical concept of minimum acceptable control.

[4]Note that farmers can combine different products via tank mixes and can broaden the set of available herbicides by planting traited seed. We envision $\boldsymbol{H}$ as a farmer's herbicide choice set accounting for all feasible tank mixes and other combinations of retail products.

These choices provide weed control through a "kill function" for each weed species, 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 $\left(g_k\left(\bar{\boldsymbol{h}},\tau^{IT}\right) > g_k\left(\bar{\boldsymbol{h}},\tau^{CT}\right),\ \forall k,\bar{\boldsymbol{h}} \in \boldsymbol{H}\right)$. Notice that when weed k has adapted to completely resist herbicide l (or if the herbicide was never lethal for that weed), then $\partial g_k/\partial h_l = 0$ 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 targets. 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):

$$(1)\quad \min_{\boldsymbol{h}} \boldsymbol{w}\cdot\boldsymbol{h} + c(\bar{\tau})\, s.t. \boldsymbol{g}(\boldsymbol{h},\bar{\tau}) \geq \bar{\boldsymbol{g}}$$

The optimality conditions for this problem are:

$$(2)\quad w_l = \sum\nolimits_k \lambda_k \partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l\ \forall l \in \{1,\cdots,L\}$$

$$(3)\quad \lambda_k[g_k(\boldsymbol{h},\bar{\tau}) - \bar{g}] = 0\ \forall k \in \{1,\cdots,K\}$$

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 $V(\bar{\tau})$:

$$(4)\quad V(\bar{\tau}) \equiv \boldsymbol{w}\cdot\boldsymbol{h}^*(\bar{\tau}) + c(\bar{\tau})$$

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

$$(5)\quad \tau^* = \underset{\tau \in \{\tau^{CT},\tau^{IT}\}}{\operatorname{argmin}} V(\tau)$$

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 a given herbicide l against a given target weed k, represented by a decrease in $\partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$, would affect $\boldsymbol{h}^*(\bar{\tau})$. Let $\tilde{\boldsymbol{h}}^*(\bar{\tau})$ denote the optimal herbicide choices in a scenario with a different, separate kill function denoted $\tilde{g}_k(\boldsymbol{h},\tau)$, where weed k has evolved genetic resistance to herbicide l. That is, we assume that $\partial \tilde{g}_k(\boldsymbol{h},\bar{\tau})/\partial h_l < \partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$, *ceteris paribus*. Under what conditions does $\tilde{\boldsymbol{h}}^*(\bar{\tau}) \neq \boldsymbol{h}^*(\bar{\tau})$? That is, under what conditions does the optimal herbicide regime for a given tillage system differ when one herbicide becomes less effective against a given target weed?

If the weed control constraint for weed k is binding under either kill function (hence $\lambda_k > 0$), then $\tilde{\boldsymbol{h}}^*(\bar{\tau}) \neq \boldsymbol{h}^*(\bar{\tau})$, 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 equation (2) 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 $\lambda_k = 0$ in both pre-resistance and post-resistance weed control cost minimization problems), then $\tilde{\boldsymbol{h}}^*(\bar{\tau}) = \boldsymbol{h}^*(\bar{\tau})$, as $\partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$ would be multiplied by $\lambda_k = 0$ in equation (2) and play no role in the solution. Thus, decreasing herbicide effectiveness from $\partial g_k(\boldsymbol{h},\bar{\tau})/\partial h_l$ to $\partial \tilde{g}_k(\boldsymbol{h},\bar{\tau})/\partial h_l$ 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 partial or even complete resistance toward a single herbicide does not necessarily influence tillage choices. As more weeds develop resistance to a herbicide, changes in herbicide use and tillage practices become more likely as farmers seek alternative methods to reach their weed control targets. But because some weeds are likely to be overcontrolled (i.e., the weed target constraint is non-binding), the response to herbicide resistance is inherently non-linear. As more weeds develop herbicide resistance, equation (2) implies three potential responses: (a) increase in the rate of herbicide h_l, (b) replacement or supplementation of initially optimal herbicide h_l, with another herbicide with efficacy against the resistant weed(s), and (c) change in tillage practice, τ. This last response is triggered when the rising cost of control with herbicides under conservation tillage begins to outweigh the savings in tillage costs, inducing the cost-minimizing farmer to switch to intensive tillage.

The Case of Glyphosate and Glyphosate-Resistant Weeds

Glyphosate is a broad-spectrum herbicide that, in the absence of genetic resistance, is highly effective at controlling essentially all weeds. The introduction of glyphosate-tolerant crop varieties allowed farmers to rely heavily (sometimes exclusively) on this specific herbicide for weed control in soybeans throughout the growing season at a relatively low cost. As glyphosate use ramped up, the use of other herbicides declined (Livingston et al. 2015). Swinton and Van Deynze (2017) attribute this trend to the cost dominance of glyphosate-based weed control. When used in conjunction with glyphosate-tolerant crops, pre- and post-emergent applications of glyphosate make tillage passes for weed control redundant as it provides little to no additional weed control but incurs additional fuel, machinery, and labor costs for a farmer.

In terms of our conceptual model, the pre-resistance, broad-spectrum effectiveness of glyphosate used alongside conservation tillage is represented by non-zero marginal weed control effectiveness under conservation tillage $\partial g_k\left(\boldsymbol{h},\tau^{CT}\right)/\partial h_l > 0$) for all weeds. Because glyphosate provides effective control for all weeds, it is unlikely that the effective control constraint, equation (3), is binding for each, leading to over control (i.e., $\lambda_k = 0$). When a weed develops resistance to glyphosate, the marginal weed control effectiveness of glyphosate falls. If this weed is not sufficiently controlled by other methods under lower glyphosate resistance (i.e., $\lambda_k > 0$), then either glyphosate use must rise or some other herbicide must be added, or else the farmer must switch to intensive tillage to continue to meet their weed control targets. For a single weed, this can be achieved by adopting a specialized herbicide. However, as more weeds evolve to resist glyphosate, its advantage as a broad-spectrum weed control method over intensive tillage falls because additional herbicides become necessary to achieve weed control targets. Therefore, we expect increasing pressure to use intensive tillage over conservation tillage as glyphosate-resistant weeds become more widespread. In other words, as glyphosate-resistant weeds proliferate, we expect both that intensive tillage becomes more common and that the rate at which it becomes more common will increase.

Empirical Model

To test for the implications of the conceptual analysis, we estimate a series of dynamic probit models with the tillage decision as the dependent variable. Our primary objective is to estimate the impact of increasing glyphosate resistance among weeds on τ^* from equation (5), the optimal tillage choice. We do so by developing a model of the probability that $\tau^* = \tau^{CT}$ conditional on glyphosate resistance, where glyphosate resistance among weeds is measured as a count variable representing the number of weeds a farmer expects to exhibit glyphosate resistance, z_{it}. We use a two-pronged empirical approach, estimating both a reduced-form tillage model and a structural model using a first-stage control function to account for potentially endogenous herbicide use. The former allows us to estimate the total effect of GRWs on tillage decisions. The latter allows us to examine the direct effect of GRWs on the adoption of conservation tillage while also conditioning on related herbicide decisions, which we expect to be affected by the onset of GRWs, allowing us to test whether farmers first supplement glyphosate with non-glyphosate chemical control, thereby allowing continued use of conservation tillage in the presence of GRWs.

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 of GRWs, y_{jit}^{NGH} as an indicator for the use of non-glyphosate herbicides, $y_{i,t-1}^{CT}$ as an indicator for the farm's conservation tillage decision in the previous period, $\boldsymbol{p_t}$ as a vector of indices for prices relevant to the tillage decision (specifically, fuel prices p_t^{FUEL}, soybean prices p_t^{BEANS}, herbicide prices represented as the price premium on glyphosate over a bundle of alternatives p_t^{GH-NGH}), and $\boldsymbol{x_{it}}$ as a vector of farm-level conditioning variables, the structural function we seek to estimate is the probability that conservation tillage is chosen:

$$\begin{aligned}(6)\quad &\Pr\left(y_{jit}^{CT}=1|z_{it},y_{jit}^{NGH},y_{i,t-1}^{CT},\boldsymbol{p_t},\boldsymbol{x}_{it},t,\delta_i\right)\\ &=\Phi(\beta_0+z_{it}\beta_1+z_{it}^2\beta_2+y_{jit}^{NGH}\beta_3+\\ &+y_{i,t-1}^{CT}\beta_4+\boldsymbol{p_t\beta_5}+\boldsymbol{x}_{it}\boldsymbol{\beta_6}+t\beta_7+\delta_i+\varepsilon_{jit}),\end{aligned}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. To account for the multilevel nature of our data, δ_i is a normally distributed farm-level random effect with zero-mean and variance σ_δ^2, and ε_{jit} is a normally distributed error term with zero-mean and variance σ_ε^2.

In this specification, we account for a nonlinear response to additional GRWs suggested by our conceptual model by including the variable z_{it} in quadratic form. As controls we include variables $\boldsymbol{x_{it}}$, including measures of farm size (for scale economies in use of tillage equipment), soil erodibility (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 consistent across observations that may have contributed to shifts in the use of conservation tillage over time. We call the function represented in equation (6) the structural tillage function.

Before estimating this structural function via maximum likelihood, we must first address two issues: the initial conditions problem induced by including a lagged dependent variable and the potential endogeneity of non-glyphosate herbicide use.

Adopting conservation tillage requires significant farmer investment in both learning new skills and acquiring new equipment (Krause and Black 1995; Uri 1999). Farmers who have made these investments in previous seasons face lower costs associated with conservation tillage. To account for this effect, we use the farmer's lagged tillage decision across all observed fields, $y_{i,t-1}^{CT}=\max_j\left\{y_{ji,t-1}^{CT}\right\}$, assuming that previously used conservation tillage equipment remains available in the following period. However, including the lagged dependent variable in a panel data model forces us to address the initial conditions problem (Arellano and Honoré 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, δ_i.

One approach to addressing 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). Although this method can take several forms, we follow a specification for the random effect that has been shown to produce unbiased estimates for parameters:

$$(7)\quad \delta_i=\alpha_0+y_{i0}^{CT}\alpha_1+\bar{\boldsymbol{x}}_i\boldsymbol{\alpha_2}+\boldsymbol{x}_{i0}\boldsymbol{\alpha_3}+\theta_i;\ \theta_i \sim Normal\left(0,\sigma_\theta^2\right);$$

where $\boldsymbol{x}_{i0}$ is a vector of all initial period explanatory variables (including z_{it}, z_{it}^2, and $\boldsymbol{p_t}$) and $\bar{\boldsymbol{x}}_i$ is a vector of all explanatory variables averaged across all available periods (Rabe-Hesketh and Skrondal 2013), including GRW numbers. Although Wooldridge (2005) suggests including all explanatory variables from all time periods in this auxiliary model, doing so results in a model that is often computationally unwieldy 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 δ_i is constrained to depend on $\boldsymbol{x}_{it}$ 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 $\boldsymbol{x}_{i0}$, we include $\boldsymbol{x}_{i0}$ separately from $\bar{\boldsymbol{x}}_i$ to account for this potential effect. This expression can be substituted directly into the structural equation, equation (6), and estimation can proceed as usual.

The second issue relates to the use of non-glyphosate herbicides, y_{jit}^{NGH}. As herbicide use decisions may be made simultaneously with tillage decisions, this variable is potentially endogenous. Our primary goal is to achieve consistent estimation of the parameters on the GRW terms of the tillage model rather than the partial effect of non-glyphosate herbicides on tillage. With that in mind, we consider two approaches. First, we omit the non-glyphosate herbicide variable to estimate a reduced form model of the probability of conservation tillage adoption unconditional on herbicide choices:

$$\begin{aligned}(8)\quad &\Pr\left(y_{jit}^{CT}=1|z_{it},y_{i,t-1}^{CT},\boldsymbol{p_t},\boldsymbol{x}_{it},t,\delta_i\right)\\ &=\Phi(\beta'_0+z_{it}\beta'_1+z_{it}^2\beta'_2+y_{i,t-1}^{CT}\beta'_4\\ &+\boldsymbol{p_t}\boldsymbol{\beta'_5}+\boldsymbol{x}_{it}\boldsymbol{\beta'_6}+t\beta'_7+\delta_i+\varepsilon_{jit}).\end{aligned}$$

In this formulation, we essentially treat non-glyphosate herbicide use as unobserved, assuming that it is part of the error term ε_{jit} and independent of the observed explanatory variables. If this assumption is violated, such a model is still useful in that the estimates of GRW parameters will now include both any direct effect of GRWs on tillage decisions and any indirect effect the GRW variable might have via its effect on non-glyphosate herbicide use.

However, we also seek to test the implication from our conceptual model that GRWs will affect tillage choices through their effect on the suite of necessary herbicides to achieve acceptable levels of weed control. We expect that when non-glyphosate herbicides are used as a first response to GRWs, conservation tillage is more likely to be used even in the presence of GRWs. Therefore, we also present an extended model that accounts for the expected endogeneity of non-glyphosate herbicide use through a first-stage model that produces a control function (Wooldridge 2014; Wooldridge 2015).

In cases like this, where both the dependent variable and potentially endogenous variable are discrete, straight-forward approaches like two-stage least squares are unavailable (Wooldridge 2015). Alternatives in this setting include bivariate probit models jointly estimated with maximum likelihood and "plug-in" methods where the fitted values for a first-stage model of the potentially endogenous variable are directly included in the structural model (Wooldridge 2015). The bivariate probit approach is computationally complex, especially when random intercepts and lagged dependent variables are included, whereas "plug-in" methods generally estimate coefficients and partial effects inconsistently (Wooldridge 2015).

In the present setting we use a third option: a control function approach for binary endogenous variables in binary dependent variable models known as two-stage residual inclusion (Terza, Basu, and Rathouz 2008 Wooldridge 2014). This method offers computational simplicity when compared to jointly estimated, bivariate techniques, particularly in cases where lags are included for the dependent variables. Prior to estimating the tillage model, 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 aggregated measure of the unobserved variables that induce the problem in the first place.

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

$$\begin{aligned}(9)\quad &\Pr\left(y_{jit}^{NGH}=1|\boldsymbol{x'}_{it},\mu_i\right)\\ &=\Phi\left(\boldsymbol{x'_{it}}\boldsymbol{\gamma}+\mu_i+\rho_{jit}\right).\end{aligned}$$

The vector $\boldsymbol{x'_{it}}$ represents all explanatory variables from equation (6), including the additional initial condition correction variables constructed in equation (7), whereas a farm-level random effect, μ_i, is assumed to follow a normal distribution with zero-mean and variance σ_μ^2, whereas ρ_{jit} is a normally distributed error term with zero-mean and variance σ_ρ^2.

We estimate the first-stage model of non-glyphosate herbicide use following standard maximum likelihood procedures for probit models with random effects. The model is estimated twice, once with lagged no-till use and again with lagged conservation tillage use as independent variables to estimate control functions for corresponding second-stage models.

To ensure identification of the second-stage tillage model, at least one exclusion restriction is required so that the first-stage residuals have independent variation that is not entirely determined by variables already in the model

(Wooldridge 2014). We argue that the indexed price premium between glyphosate and non-glyphosate prices, p_t^{GH-NGH}, satisfies the exclusion restriction.

To satisfy the exclusion restriction, p_t^{GH-NGH} must meet three conditions: it must (*a*) not have a direct influence on the dependent variable in the structural model, y_{jit}^{CT}; (*b*) be uncorrelated with omitted explanatory variables in the structural model; and (*c*) be strongly correlated with the potentially endogenous variable, y_{jit}^{NGH} (Terza, Basu, and Rathouz 2008). We argue that these three conditions are met. First, we assume that these prices only affect farmers' tillage choices via their effects on the herbicides required for each alternative system, thereby satisfying condition (1). A similar assumption is maintained in Perry, Moschini, and Hennessy (2016b), where the premium for glyphosate-tolerant seed is assumed not to directly affect tillage decisions. The remaining two conditions are addressed as the paper proceeds.

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

$$(10)\quad \Pr\left(y_{jit}^{CT}=1|z_{it},y_{jit}^{NGH},y_{i,t-1}^{CT},\boldsymbol{p_t^{till}},\boldsymbol{x}_{it},t,\hat{r}_{it},y_{i0}^{CT},\bar{\boldsymbol{x}}_i,\boldsymbol{x}_{i0},\theta_i\right) = \Phi\left(\beta_0+z_{it}\beta_1+z_{it}^2\beta_2+y_{jit}^{NGH}\beta_3+y_{i,t-1}^{CT}\beta_4+\boldsymbol{p_t^{till}\beta_5}+\boldsymbol{x}_{it}\boldsymbol{\beta_6}+t\beta_7+\hat{r}_{jit}\beta_8+y_{i0}^{CT}\alpha_1+\bar{\boldsymbol{x}}_i\boldsymbol{\alpha_2}+\boldsymbol{x}_{i0}\boldsymbol{\alpha_3}+\theta_i\right),$$

where $\boldsymbol{p_t^{till}}$ is the full vector of prices omitting p_t^{GH-NGH} in accordance with the exclusion restriction. This structural function can be estimated using standard maximum likelihood procedures for probit models with random effects.[5] Note that in the structural form, the GRW variable can affect tillage decisions both directly through the effects estimated in Equation (10) (β_1 and β_2) and indirectly through the effect on non-glyphosate herbicide use estimated in equation (9) (γ_1 and γ_2, through β_3), whereas in the reduced-form the total of both these effects is accounted for with β'_1 and β'_2. In both models, the effects of GRWs can also compound across periods in both formulations through β_4 and β'_4, the parameters on the lagged tillage decision. These will serve as our primary parameters of interest.

In sum, we estimate each of equations (8)–(10) twice, once for the use of all forms of conservation tillage as the dependent variable and again for the specific use of no-till, for a total of six models.

For the two-stage residual inclusion method to fully account for the endogeneity we expect with regards to the consistent estimation of the y_{jit}^{NGH} parameter in equation (6), we must also assume that ρ_{jit} in equation (9) and ε_{jit} from equation (6) are independent conditional on the explanatory variables, and that μ_i and θ_i are independent conditional on the explanatory variables as well (Wooldridge 2014). These are strong assumptions, and they would fail to hold if remaining unexplained factors at the farm or field level jointly influence both the tillage and herbicide use decisions. The strength of this assumption is one limitation of our analysis, although we contend that the inclusion of initial conditions correction variables and $y_{i,t-1}^{CT}$ in $\boldsymbol{x'_{it}}$, the explanatory variables for non-glyphosate herbicide use in equation (9) largely accounts for potentially correlated errors and farm-level random effects across equations in a similar way as their inclusion accounts for unobserved effects that may jointly influence $y_{i,t-1}^{CT}$ and δ_i as shown in equation (7).

We present and interpret the reduced-form estimates of the tillage model in equation (8) on their own and in comparison to the two-stage, structural model. The reduced-form results represent robust estimates of the full effect of GRWs on tillage choice. The structural model results allow GRWs to affect tillage choice through two paths: their direct impact on tillage holding herbicide choice constant and their effect on herbicide choices that themselves impact tillage, and we expect that the sum of these two effects in the structural model to match the total effect estimated from the reduced form. However,

[5]Specifically, we use a Laplace approximation of the likelihood function. Estimation is performed using the R package *lme4* (Bates et al. 2015).

we note that the structural estimates are less robust to distributional assumptions on the error terms and farm-level random effects.

Data

The core of our data are field-level survey data, representative at the Crop Reporting District level, purchased from the market research company Kynetec in the fall of 2017. These data contain observations on chemical and mechanical weed control practices of 22,151 farmers from 1998 through 2016 in thirty-one soybean-growing states[6] across the United States with more intensive sampling in regions where soybeans are more widely grown, for a total of 93,345 field-level observations (not including fields observed in 1998, which form the initial condition, or $t = 0$, for our panel). Sample lists for each year are constructed from the previous year's list and supplemented with federal subsidy payment recipient lists from the United States Department of Agriculture, agricultural publication subscription lists, and the membership lists of state and regional agricultural associations. Survey data were collected via computer assisted telephone interviews. Non-respondents were re-contacted a minimum of eight times to reduce non-response error and up to twenty-five times in areas where response rates were low. Respondents were compensated monetarily upon completion of the interview. All interviews were recorded for verification purposes, and data was crosschecked against established ranges for prices, application rates, and consistency with other reported practices.

The raw data are structured as application-level units, with chemical, seed, tillage, and application area information provided. Field-level observations are constructed by aggregating application observations which share distinct application area for each uniquely identified respondent within in each year. Many farms provide data for multiple fields per year and responses in multiple years, giving the data an unbalanced panel structure and allowing us to estimate the preceding empirical model. Tillage decisions, non-glyphosate herbicide use, herbicide prices, and farm size variables are all sourced from this dataset. Note that because farmers sometimes come and go from the panel, the lagged tillage variable and initial conditions variables are relative to the most recent available year and the first year the farmer appears in the sample, respectively.

The Kynetec survey data include three levels of tillage intensity: conventional, conservation, and no-till. Following Perry, Moschini, and Hennessy (2016b), where a shorter duration subset of these data is used, we define two distinct but related binary tillage decision variables: a conservation tillage indicator equal to one whenever either conservation or no-till is used, and a no-till indicator equal to one whenever no-till is used, grouping other conservation tillage practices along with conventional tillage. Because the effect of GRWs on no-till 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 as no-till and conservation tillage is presented in figure 1.

The data on farming practices 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-

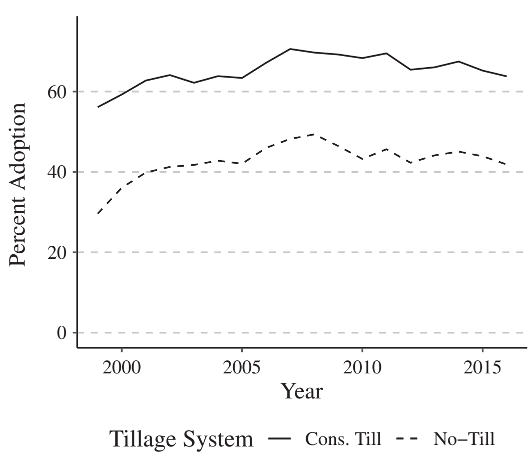

Figure 1. Percentage of fields in sample under no-till and conservation tillage over time

Note: Conservation tillage includes no-till fields as well as other forms of reduced tillage.

[6]The states sampled are Alabama, Arkansas, Delaware, Florida, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Michigan, Minnesota, Mississippi, Missouri, Nebraska, New Jersey, New York, North Carolina, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Virginia, West Virginia, and Wisconsin.

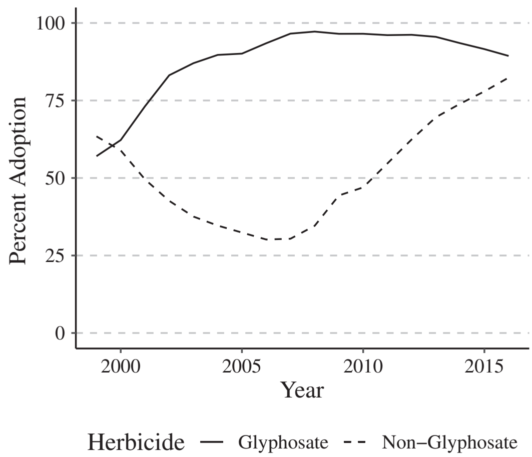

Figure 2. Percentage of fields in sample treated with glyphosate and non-glyphosate herbicides over time

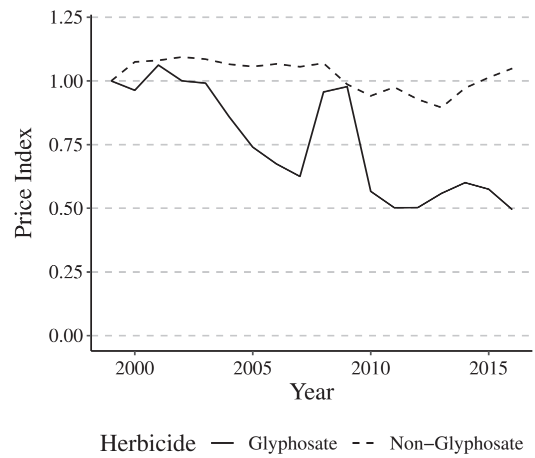

Figure 3. Price indices for glyphosate and non-glyphosate herbicides over time

Note: Both prices normalized to 1 in 1999.

glyphosate active ingredient.[7] 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 of 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 commonly. Glyphosate use reached near saturation in the same year and continued to be used on over 90% of fields through 2016.

We use the practice 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 of active ingredient each year. Because non-glyphosate herbicides represent a basket of several related products, we construct Laspeyres indices of prices and quantities for 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 $p_t^{GH-NGH} = p_t^{GH} - p_t^{NGH}$, or the glyphosate price premium. These price indices are presented in figure 3.

Glyphosate prices dropped significantly following the expiration of Monsanto's patent in 2000, whereas non-glyphosate prices remained steady, so the price premium p_t^{GH-NGH} is negative in all years. During 2007–2009, glyphosate prices spiked relative to non-glyphosate prices when a global production slump, resulting from a shortage of the input phosphate rock (Alewell et al. 2020), coincided with rising demand due to higher crop prices. Because p_t^{GH-NGH} is driven primarily by patent law and global demand trends, we argue that this variable is uncorrelated with omitted variables in the structural function and therefore satisfies condition (2) of the exclusion restriction. We address condition (3) in the results section that follows.

The field-level practice dataset categorizes farm size into five classes based on soybean acres operated: less than 100 acres, 100–249 acres, 250–499 acres, 500–999 acres, and 1,000 acres or more. These are included as a series of binary variables in the empirical model, with the less than 100 acres category excluded as the baseline.

We supplement the field-level practice data with annual 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

[7]The five most common non-glyphosate herbicide active ingredients that appear in our sample are, in order, atrazine, acetochlor, metolachlor-S, 2,4-D, and mesotrione.

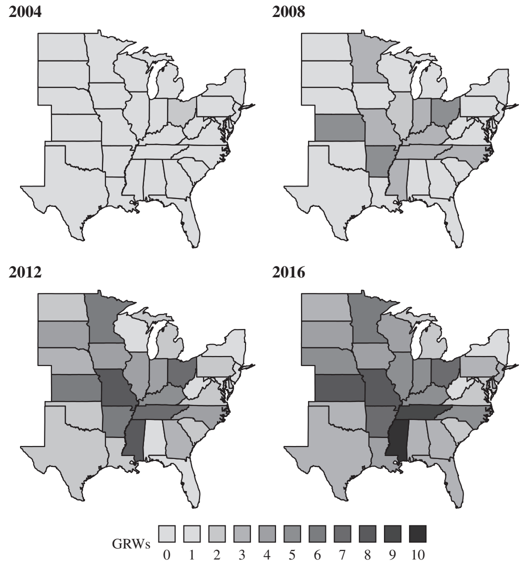

Figure 4. Number of glyphosate-resistant weeds species (GRWs) by state for selected years

Notes: States presented are states represented in the analyzed data. Underlying data presented in Supplementary table S1.1.

Herbicide Resistant Weeds (ISHRW) (Heap 2020).[8] The number of species resistant to glyphosate in each state in our sample in selected years is presented graphically in figure 4, demonstrating the rapid spread of GRWs throughout the study region over the panel period.

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 who confirm reports from farmers with laboratory dose–response experiments, the data represent species confirmed to demonstrate herbicide resistance. We assume that these counts represent the knowledge available to a typical farmer when making tillage decisions through an extension weed control guide (e.g., Sprague and Burns 2018).

[8]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 (http://www.weedscience.org/).

Though the ISHRW measure is an imperfect measure of the spread of GRWs, it is particularly useful in the present setting. Glyphosate resistance can vary both in (*a*) the degree of resistance and (*b*) the speed it spread throughout a regional or local weed population, and the ISHRW data can distinguish neither of these specific trends. However, the ISHRW variable remains a useful proxy for the spread of GRWs for two reasons. First, it is available consistently over time across a broad geographic region, allowing its use throughout the full period and region of our farmer panel. Second, it closely tracks with other potential measures of the spread of GRWs, including infested acres data available over only the last seven years of our nineteen-year panel (Supplementary Material 1, figure S1.1). Although the ISHRW measure does not allow for nuanced examination of response to incremental resistance or precise knowledge of the species resistant to glyphosate on a given field, it still holds valuable information on the likelihood a farmer expects to experience resistance in each year and how that likelihood varies across the wide geographic range of our panel.

We rely on NASS annual price indices for diesel fuel (US Department of Agriculture, National Agricultural Statistics Service 2018). As conservation tillage typically requires lighter field implements, or in the case of no-till no field passes at all, and therefore less fuel, we expect its use to be more frequent when fuel prices are higher (Lal 2004). We also rely on NASS soybean prices, measured annually at the state level in September of the previous year.

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, Tegene, and Wiebe 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, Schoengold, and Tadesse 2009). Therefore, for each farm we include the proportion of the land in the farm's county classified as highly erodible (US Department of Agriculture, National Resource Conservation Service 2018). We also include the Palmer's Z-index as a measure of moisture conditions. This value is measured at the climate division level in the September of the prior year, where a more negative Z-index score indicates drier conditions

Table 1. Descriptions of Variables Included in Empirical Model

Variable	Description	Geographic scale	Source
Tillage decision, no-till	Binary indicator of use of a no-till system	Field	Kynetec
Tillage decision, conservation till	Binary indicator of use of a conservation tillage system (including no-till)	Field	Kynetec
Non-glyphosate herbicide use	Binary indicator of use of a herbicide other than glyphosate	Field	Kynetec
GRWs	Count of glyphosate resistant weeds at the start of the year	State	ISHRW
Glyphosate price	Average price of glyphosate in dollars per gallon, normalized to 1 in 1999	National	Kynetec
Non-glyphosate price	Laspeyres index of non-glyphosate herbicide prices, normalized to 1 in 1999	National	Kynetec
Fuel price	Index of diesel fuel prices, normalized to 1 in 1999	National	NASS
Soybean price	Index of soybean prices in Sept. of the previous year, normalized to 1 in 1999	State	NASS
Palmer's Z-Index	Index of anomalous moisture conditions, where negative values indicate drier conditions than usual, measured in September of the prior year	Climate division	NOAA
Soil Erodibility Index	Proportion of farmland classified as highly erodible	County	NRCS
Farm size	Acres of soybeans operated by farm, categorized into five bins	Farm	Kynetec

(US Department of Commerce, National Environmental Satellite, Data, and Information Service 2018).

In all, we bring together variables from several sources measured at disparate geographic scales. Brief descriptions of each of the variables ultimately included in the empirical model are presented in table 1, along with the scale at which they are measured and their original source. Summary statistics for each variable are available in Supplementary Material 2 (tables S2.1 and S2.2).

Results and Discussion

Our empirical results reveal that rising numbers of GRWs cause soybean farmers to shift toward non-glyphosate herbicides and—even after accounting for that change—toward less use of conservation tillage practices. Based on these results, we estimate the degree to which rising numbers of GRW species have depressed the probability of farmers adopting conservation tillage and no-till farming. Finally, so as to get a sense of the degree of environmental damages induced by GRWs through farmers' tillage responses, we apply our tillage decision model to simulate a counterfactual scenario in which no weed species adapt to resist glyphosate, enabling an estimate of environmental damages induced by GRWs through farmers' tillage responses.

Reduced Form Tillage Models

Coefficient estimates from reduced form tillage decision probit models, for both no-till and all forms of conservation tillage as the dependent variable, are presented in table 2. The coefficients on the linear GRW term are statistically insignificant, whereas the quadratic terms are negative and statistically significant for both models. These results support the primary conclusion of our conceptual model: that decreasing effectiveness of glyphosate is associated with increased pressure to adopt more intensive mechanical weed control, and this pressure is weak at low numbers of GRW species but grows stronger as additional species are identified as GRWs.

In the reduced form, the glyphosate price premium term is positive and statistically significant in both models, suggesting that in years where glyphosate is more expensive relative to non-glyphosate herbicides, reduced tillage is more common. We interpret this result as a preference for specialized non-glyphosate herbicides under such conditions,

Table 2. Results from Reduced Form, Tillage Decision Probit Models

Variable	No-till (reduced form)	Conservation tillage (reduced form)
GRWs	0.000242 (0.0136)	0.00238 (0.0132)
GRWs (squared)	−0.00668*** (0.00149)	−0.00362** (0.00147)
Glyphosate price premium	0.193*** (0.0550)	0.141*** (0.0543)
Fuel price	0.0840*** (0.0122)	0.0606*** (0.0120)
Soybean price	−0.0544** (0.0228)	−0.00193 (0.0225)
Past no-till/conservation tillage use	0.607*** (0.0133)	0.742*** (0.0130)
Palmer's Z-Index	−0.000978 (0.00293)	−0.00538* (0.00285)
Soil Erodibility Index	0.522*** (0.0389)	0.384*** (0.0354)
Soybean acres (100–249 acres)	0.0263 (0.0230)	0.0616*** (0.0218)
Soybean acres (250–499 acres)	0.0351 (0.0244)	0.0730*** (0.0229)
Soybean acres (500–999 acres)	0.0190 (0.0250)	0.0804*** (0.0234)
Soybean acres (1000 acres or more)	−0.00125	0.0119 (0.0252)
Year trend	0.0359*** (0.00333)	0.0254*** (0.00323)
Random effects	Farm level	Farm level
Initial conditions correction[a]	Yes	Yes
Observations	93,345	93,345
Unique farms	22,151	22,151
% Correct (dep. var. = 1)	72.4%	82.2%
% Correct (dep. var. = 0)	81.1%	75.1%
% Correct (all obs.)	77.2%	80.1%
Marginal R-squared	0.395	0.362
Conditional R-squared	0.630	0.565

Note: Standard errors in parentheses.
*p < 0.1,
**p < 0.05,
***p < 0.01.
[a]Includes initial period value and cross-period means for explanatory variables, and initial period value of dependent variable.

crowding out the need for the broad-spectrum effectiveness of glyphosate or intensive tillage. Fuel price has a statistically significant coefficient of the expected sign 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; Perry, Moschini, and Hennessy 2016b). Soybean prices are negatively associated with no-till adoption but not with conservation tillage adoption, a result consistent with farmer perceptions of yield drag associated with no-till (Reimer, Weinkauf, and Prokopy 2012). Use of no-till or conservation tillage in previous seasons is positively associated with use in future seasons, indicating that some inertia is present. This may be in part due to machinery investments for switching to alternative practices (Krause and Black 1995) or perhaps increased familiarity with the system (Uri 1999).

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, although this parameter is only statistically significant at the 10% level. We also find that fields in counties with more highly erodible land are more likely to be under conservation tillage systems. These patterns are consistent with results found in the literature on tillage adoption (Ding, Schoengold, and Tadesse 2009). The positive time trend may reflect the effects of federal conservation incentives 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), but size has no effect on no-till specifically.

Both the no-till and the conservation tillage models correctly predict the tillage decision for a field about four-fifths of the time. Further, the two models show balanced predictive power, correctly predicting tillage decisions at roughly the same rate whether the observed outcome was adoption or non-adoption. Both models explain the majority of the variance in tillage adoption outcomes, as measured by the pseudo-R^2 metrics proposed for

Table 3. Results from First-Stage Non-Glyphosate Herbicide Use Probit Models

	Non-glyphosate use (reduced form)	Non-glyphosate use (reduced form)
GRWs	0.142*** (0.0127)	0.143*** (0.0127)
GRWs (squared)	0.0146*** (0.00148)	0.0145*** (0.00147)
Glyphosate price premium	0.122** (0.0506)	0.122** (0.0506)
Fuel price	−0.277*** (0.0123)	−0.277*** (0.0123)
Soybean price	−0.0271 (0.0228)	−0.0269 (0.0228)
Past no-till use	0.0210 (0.0138)	—
Past conservation tillage use	—	0.00816 (0.0138)
Palmer's Z-Index	−0.0361*** (0.00287)	−0.0361*** (0.00287)
Soil Erodibility Index	0.0201 (0.0255)	0.0228 (0.0254)
Soybean acres (100–249 acres)	0.0691*** (0.0186)	0.0693*** (0.0186)
Soybean acres (250–499 acres)	0.0541*** (0.0187)	0.0545*** (0.0187)
Soybean acres (500–999 acres)	0.0576*** (0.0190)	0.0580*** (0.0189)
Soybean acres (1000 acres or more)	0.0613*** (0.0201)	0.0613*** (0.0201)
Year trend	0.0321*** (0.00293)	0.0321*** (0.00293)
Random effects	Farm level	Farm level
Initial conditions correction[a]	Yes	Yes
Observations	93,345	93,345
Unique farms	22,151	22,151
% Correct (dep. var. = 1)	83.7%	83.7%
% Correct (dep. var. = 0)	82.5%	82.5%
% Correct (all obs.)	83.1%	83.1%

Note: Standard errors, computed via the delta-method and accounting for the variance of the first-stage estimator, in parentheses.
*$p < 0.1$
**$p < 0.05$,
***$p < 0.01$.
[a]Includes initial period value and cross-period means for explanatory variables, and initial period value of dependent variable.

generalized linear mixed-effect models by Nakagawa and Schielzeth (2013). Marginal R^2 measures the variance explained by the observed independent variables, whereas 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 they can (*a*) be interpreted on the same unit scale as the usual R^2 commonly reported for ordinary least-square models, and (*b*) 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 variables, and allowing a random intercept for each farm to account for unobserved heterogeneity improves model fit substantially.

First-Stage Non-Glyphosate Herbicide Use Models

We present reduced form estimates for our models of non-glyphosate herbicide use in table 3. The estimates with no-till and conservation tillage lags, and associated initial condition corrections, are nearly identical but separately estimated for use as first-stage models in the structural tillage model estimates in the following section.

GRWs have positive and statistically significant coefficients for both the linear and quadratic terms, suggesting a strong association between the adoption of additional herbicides and the development of glyphosate resistance among additional species. Unlike the effect observed in the tillage models, this effect is immediate in that an increase in the probability of non-glyphosate use is detected even when only a single species with glyphosate resistance is identified within the state.

The coefficient estimates on the price differential between glyphosate and non-glyphosate herbicides are positive and statistically significant for both models. As expected, in years when glyphosate is expensive relative to alternatives, non-glyphosate herbicides are more likely to be used. The statistical significance of this coefficient has been proposed as a test of condition (3) for the exclusion restriction (Wooldridge 2014). Given that the coefficient is statistically significant, we conclude that this condition is met, and therefore all three conditions for the exclusion restriction are met and the price differential serves as a valid candidate for exclusion in the second-stage, structural models presented in the following subsection.

The coefficients on past no-till or conservation tillage use are statistically insignificant in both cases, and therefore we fail to reject the null hypothesis that previous tillage choices have no influence on current herbicide decisions. Wetter conditions, indicated by a positive Palmer's Z-index, are associated with less frequent non-glyphosate herbicide use, possibly because of reduced days with conditions suitable for spraying. Soil erodibility has an insignificant coefficient estimate, whereas larger and mid-sized farms are more likely to use non-glyphosate herbicides than those that grow the least acres of soybeans. Finally, the year trend is positive and statistically significant, suggesting a gradual return to these herbicides unexplained by other factors. Regarding model fit, the non-glyphosate models show similar in-sample predictive performance as the reduced form tillage models, correctly identifying the adoption of non-glyphosate herbicides for approximately four-fifths of observations.

Structural Tillage Models

In table 4, we present structural tillage model coefficients from second-stage estimates that incorporate information on non-glyphosate herbicide use and residuals from first-stage models presented in the preceding subsection. For both conservation tillage and no-till, the results are broadly similar to the reduced form estimates in terms of parameter signs and statistical significance. In particular, the signs and statistical significance of the GRW parameters remain the same as in the reduced form, further supporting the implications of our conceptual model.

The statistical significance of the residuals from the first-stage, non-glyphosate herbicide use models in the conservation tillage second-stage model allows us to reject the null hypothesis that non-glyphosate use is exogenous to these decisions (Wooldridge 2014). The use of non-glyphosate herbicides is positively associated with the use of conservation

Table 4. Results from Structural (Second-Stage) Tillage Decision Probit Models

	No-till (structural model)	Conservation tillage (structural model)
GRWs	0.0163 (0.0143)	0.00337 (0.0140)
GRWs (squared)	−0.00715*** (0.00154)	−0.00486*** (0.00158)
Non-glyphosate use	−0.0396 (0.157)	0.298* (0.153)
Non-glyphosate use (residuals)	0.0247 (0.0646)	−0.116* (0.0626)
Fuel price	0.0762*** (0.0145)	0.0719*** (0.0144)
Soybean price	−0.0418* (0.0226)	0.00864 (0.0224)
Past no-till/conservation tillage use	0.610*** (0.0133)	0.743*** (0.0130)
Palmer's Z-Index	−0.000739 (0.00313)	−0.00297 (0.00304)
Soil Erodibility Index	0.527*** (0.0389)	0.390*** (0.0355)
Soybean acres (100–249 acres)	0.0202 (0.0231)	0.0510** (0.0219)
Soybean acres (250–499 acres)	0.0217 (0.0245)	0.0562** (0.0231)
Soybean acres (500–999 acres)	0.00134 (0.0252)	0.0595** (0.0237)
Soybean acres (1000 acres or more)	−0.0690** (0.0273)	−0.0130 (0.0255)
Year trend	0.0247*** (0.00295)	0.0160*** (0.00290)
Random effects	Farm level	Farm level
Initial conditions correction[a]	Yes	Yes
Observations	93,345	93,345
Unique farms	22,151	22,151
% Correct (dep. var. = 1)	72.4%	82.2%
% Correct (dep. var. = 0)	81.1%	75.1%
% Correct (all obs.)	77.3%	80.1%
Marginal R-squared	0.397	0.363
Conditional R-squared	0.630	0.565

Note: Standard errors, computed via the delta-method and accounting for the variance of the first-stage estimator, in parentheses.
*p < 0.1,
**p < 0.05,
***p < 0.01.
[a]Includes initial period value and cross-period means for explanatory variables, and initial period value of dependent variable.

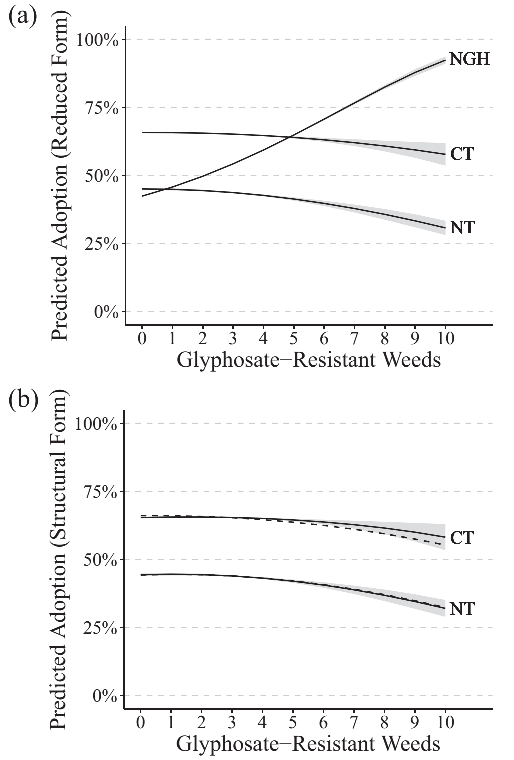

Figure 5. Mean predicted adoption of no-till (NT), conservation tillage (CT) and non-glyphosate herbicides (NG) by the number of glyphosate resistant weed species from (A) reduced-form estimates and (B) structural estimates

Notes: The shaded region indicates a 95% confidence interval, computed via the delta method. Dashed line in (B) shows direct effect predictions from structural model, excluding indirect effect from updated herbicide response. Non-glyphosate herbicide predictions are based on the model using no-till lags; results using estimates from the conservation tillage lag model are nearly identical and therefore omitted for clarity.

tillage. When farmers use conservation tillage practices, they give up a broad-spectrum 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 or reverting intensive tillage. The positive relationship between non-glyphosate herbicides and no-till suggests that as farmers turn to non-glyphosate herbicides to combat GRWs, they face reduced pressure to supplement their weed control with intensive tillage.

However, the same cannot be said for no-till, where neither non-glyphosate use nor the first-stage residual coefficients are statistically significant. This result suggests that even as farmers adopt non-glyphosate herbicides to adapt to GRWs, doing so does not delay the switch from no-till to more intensive tillage practices. Note that because in our definition of no-till alternatives includes all forms of tillage, much of this initial switch away from no-till may be to reduced tillage methods such as chisel plowing or field cultivation rather than intensive methods such as disc or rotary tillage.

Effects of GRWs on Tillage and Herbicide Decisions

In both the reduced-form and structural models for both conservation tillage and no-till, the coefficient on the squared number of GRWs is negative and statistically significant. This key result indicates that GRWs have a negative effect on conservation tillage use, and the emergence of additional GRWs has increasing impact. The predicted effects of GRWs on tillage and non-glyphosate herbicide use are shown in figure 5, both using reduced-form and, for tillage methods, structural estimates that separate direct GRW effects on tillage from indirect GRW effects through the impact of non-glyphosate herbicide use on the tillage decision.

Both the reduced-form and structural curves show the increasingly negative impact of GRWs on the use of conservation tillage practices, especially no-till, while holding constant at their means all variables other than GRWs (and non-glyphosate herbicides in figure 5B). An inverse response is observed in the first stage, reduced form non-glyphosate herbicide use model, where GRWs have a positive association with non-glyphosate use over the entire observed range of GRW counts, rising from 42.4% adoption when no GRWs have been identified to as high as 92.4% adoption when ten GRWs have been identified (figure 5A). The predicted adoption probabilities across the full observed range of GRWs are nearly identical in both the reduced-form (figure 5A) and structural form estimates when both the direct and indirect effects are included (figure 5B). We therefore interpret the curves computed from the structural model for both no-till and conservation tillage (figure 5B), noting that the implications from the robust reduced-form estimates are identical.

These findings confirm the expectations from the conceptual model that redundancies in weed control will cause small numbers of GRWs to have negligible effect as farmers rely on non-glyphosate herbicides to control the initial onset of GRWs before turning to mechanical methods. We find that through the first two glyphosate resistant weed species, the predicted rate of no-till use remains statistically indistinguishable from the rate at zero GRWs (44.4% adoption). However, by the eighth GRW, the predicted rate of no-till adoption falls by 7.6 percentage points, a 17.1% 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 adopted at rates not statistically different from when zero GRWs are identified (65.4% adoption). But by the eighth reported GRW, conservation tillage adoption rates fall by 3.9 percentage points, a 5.9% reduction. The predicted reduction in conservation tillage use is 6.7 percentage points if the indirect effect from increased adoption of non-glyphosate herbicides under high numbers of GRWs is not accounted for, demonstrating the importance of additional chemical weed control options in delaying the return to intensive tillage.

In effect, the advent of GRWs is undoing the stimulus to adopt conservation tillage that was prompted by the introduction of glyphosate-tolerant crop varieties. The reduction in conservation tillage and no-till use at eight identified GRWs corresponds with over half that of the increase in use attributed to the introduction of glyphosate-resistant soybean seeds (Perry, Moschini, and Hennessy 2016b).

Tillage Results under Alternative Assumptions

We examine the robustness of our results by considering a set of models estimated under alternative assumptions. Our primary focus in this exercise is the stability of the GRW parameters and the resulting predicted value curves. The full results for each of the alternative specifications discussed in this section are available in Supplementary Material 3.

Overall, the negative effect of GRWs on conservation tillage and no-till adoption is quite robust to alternative specifications. When we loosen the functional restriction imposed by the quadratic form by treating each number of GRW species as an indicator variable, the same response of initial inaction followed by a shift toward more intensive tillage is observed. (Supplementary table S3.2 and Supplementary figure S3.2). Table 5 presents estimated coefficients for the linear and quadratic GRW terms for both no-till and conservation tillage structural models estimated with an additional eight alternative covariate structures or subsamples of the panel. In all cases, the first-stage herbicide choice models were re-estimated with the same covariate or sample modifications, and then new residuals were computed for use as the control function in the second-stage, structural tillage models.

In the first alternative specification shown in table 5, we exclude the quadratic GRW term; the resulting linear coefficient estimate is negative and statistically significant, corroborating that GRWs have a negative effect overall on no-till and conservation tillage adoption. In our second specification, we estimate the model with state-level fixed effects as a vector of indicator variables to account for possible time-invariant state-level unobserved effects that may be correlated with the GRW variable; the resulting GRW estimates are nearly identical in magnitude, sign, and statistical significance. Next, we estimate both the first- and second-stage models using a linear probability model, ignoring the binary nature of our dependent variables and loosening the accompanying structural assumptions on the error terms. Doing so results in qualitatively identically conclusions.

We examine the effects of including potentially endogenous herbicide choices in our structural model with three more alternative specifications, presented in the fourth through sixth rows of table 5. First, we estimate the full structural model where instead of considering non-glyphosate use as our herbicide variable, we consider the use of any *glyphosate* herbicide, using the same glyphosate price premium variable as our exclusion restriction. For these specifications, the quadratic GRW parameter for the no-till model remains almost the same, whereas for the conservation tillage model the parameter shrinks towards zero but remains negative. We estimate the structural model without accounting for the potential endogeneity of herbicide choices by excluding the control function residuals, for both non-glyphosate and glyphosate as our herbicide choice variable. Highlighting the importance

Table 5. GRW Parameters under Alternative Specifications

Alternative specification	Linear (no-till)	Quadratic (no-till)	Linear (cons. till)	Quadratic (cons. till)
Drop quadratic term	−0.0408*** (0.0107)	—	−0.0337*** (0.0103)	—
Add state fixed effects	−0.00466 (0.0144)	−0.00565*** (0.00155)	−0.00353 (0.0139)	−0.00401*** (0.00154)
Linear probability model	0.00206 (0.00280)	−0.00183*** (0.000320)	0.00103 (0.00281)	−0.000964*** (0.000321)
Glyphosate herbicide choice for first-stage model	0.0172 (0.0134)	−0.00531*** (0.00152)	0.0152 (0.0130)	−0.0028* (0.00151)
No control function	0.0144 (0.0134)	−0.00732*** (0.00148)	0.0125 (0.0130)	−0.00411*** (0.00147)
No control function + glyphosate first-stage	0.0179 (0.0134)	−0.00603*** (0.00149)	0.0154 (0.0130)	−0.00307** (0.00147)
Delete gaps in panel (N = 12,253)	0.0470 (0.0687)	−0.00413 (0.00813)	0.0767 (0.0653)	−0.00789 (0.00781)
Single field only + no gaps (N = 11,997)	0.0360 (0.0699)	−0.00338 (0.00836)	0.0730 (0.0664)	−0.00737 (0.00806)

Note: Standard errors in parentheses. Coefficients are comparable to those in table 4.
*p < 0.1,
**p < 0.05,
***p < 0.01.

of accounting for potential endogeneity of the herbicide choice, we find in both cases that the quadratic GRW term shrinks toward zero relative to when the control function residuals are included, although the estimates remain near both the structural and reduced-form counterparts.

Finally, we test the impact of treating our unbalanced panel of farmers as balanced with estimates summarized in the final two rows of table 5. First, we estimate the full models on the subsample that includes only farmers who report in consecutive years, dropping farmers who have gaps in their participation in the panel, to account for the impact of including farmers who come and go. Second, we further reduce this subsample to include only farmers who report a single field in all years they participate in the sample, to account for potential issues related to the pooling of lagged dependent variables when multiple fields are reported in the preceding year. In both cases, the estimated coefficients and the GRW curves themselves are remarkably stable, although the standard errors on the models estimated on the subsamples are considerably larger as the sample size is reduced by an order of magnitude (87% reduction, from 93,345 to roughly 12,000).

Simulation of GRW Effects on Tillage Use

To demonstrate the impact that GRWs have had on farmers' tillage decisions over time and space, we compute the shares of acres under conservation tillage predicted by the preferred structural 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 the GRW variable $z_{it} = 0$ 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 explicitly update both non-glyphosate herbicide use and lagged tillage decisions as predicted probabilities from the first-stage herbicide use and previous period tillage models so that the simulation conforms

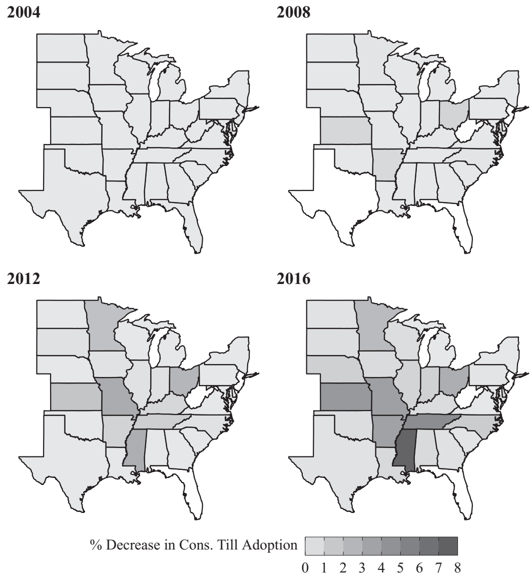

Figure 6. Decrease in percentage of soybean acres under conservation tillage attributed to GRWs

Note: White fill indicates no farms are sampled in that state in the presented year.

to the structure of our empirical model.[9] 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}:

$$(11) \quad S_t^n = \frac{\sum_{i=1}^{I_t}\sum_{j=1}^{J_{it}} P_{jit}^n A_{jit}}{\sum_{i=1}^{I_t}\sum_{j=1}^{J_{it}} A_{jit}}, n \in \{Ac, Cf\}.$$

As a display of the spatial variation in the effect of GRWs on tillage decisions over our sample period, the decrease in the acre shares under conservation tillage, $S_t^{Cf} - S_t^{Ac}$, are calculated separately for each state and presented for selected years in figure 6. On the majority of soybean acres, GRWs have had negligible impact on tillage practices, with decreases in conservation tillage adoption of 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, conservation tillage would have been used on 7.5% more soybean acres if GRWs had been absent.

Estimates of the number of soybean acres under conservation tillage in both scenarios are presented in table 6. Nationally, around 1.35 million fewer soybean acres were under conservation tillage in 2016 than would have been if glyphosate resistant weeds had been absent, representing 1.6% of all planted acres in that year. Across all years in our sample, 5.9 million more acres are predicted to be under conservation tillage in the scenario with no GRWs, a sum about equivalent to the total annual planted soybean acres in Missouri or Indiana in recent years.

Environmental Damages Resulting from Farmers' Tillage Responses to GRWs

Relative to conventional tillage, the use of conservation tillage systems is known to reduce soil erosion and carbon emissions, two types of agricultural pollution that impair water quality and contribute to global climate change respectively (Uri, Atwood, and Sanabria 1999). Using simple benefits transfer techniques, we develop rough, conservative estimates of the social costs of decreased conservation tillage on two environmental outcomes: soil erosion and carbon emissions due to fuel combustion. Our approach, which follows the methods presented in Perry, Moschini, and Hennessy (2016b), draws values from the literature and applies a simple benefit transfer model to monetize social costs (Wilson and Hoehn 2006). Tillage practices have wide-ranging impacts on the environment (Uri, Atwood, and Sanabria 1999), and a full accounting of these impacts is outside the scope of the present study. Further, both glyphosate and non-glyphosate herbicides also have potential human health and environmental impacts of public concern not accounted for here. However, this exercise demonstrates

[9]That is, $\hat{\Pr}\left(y_{jit-1}^{CT}=1\right)$ and $\hat{\Pr}\left(y_{jit}^{NGH}=1\right)$ are used in place of y_{jit-1}^{CT} and y_{jit}^{NGH} to account for dynamic tillage and indirect herbicide effects on current year tillage decisions, respectively.

that the spread of GRWs is a problem not just for farmers but for the public through increases in environmental externalities.

To quantify the soil erosion impact of decreased use of conservation 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 per year. For conservation tillage, the median erosion rate is 0.08 mm per acre per year. Assuming a soil density of 1,200 kg/m^3, this implies a 6.8 ton/acre-year reduction in soil erosion in fields under conservation tillage when compared to a conventional tillage baseline (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 only on carbon emissions from fuel consumption (Uri, Atwood, and Sanabria 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 mean increase in carbon emissions from fuel

Table 6. Predicted Soybean Acreage under Conservation Tillage

	Predicted conservation tillage adoption (acres)			
	Total acres	No GRWs	Actual GRWs	Difference
2008	74,339,000	51,007,000	50,955,000	−52,000
2009	76,232,000	51,839,000	51,634,000	−205,000
2010	76,477,000	52,170,000	51,904,000	−267,000
2011	73,655,000	50,763,000	50,242,000	−520,000
2012	76,010,000	52,524,000	51,891,000	−632,000
2013	76,113,000	51,502,000	50,744,000	−759,000
2014	82,425,000	57,100,000	56,079,000	−1,022,000
2015	81,574,000	54,585,000	53,439,000	−1,146,000
2016	82,543,000	55,113,000	53,760,000	−1,353,000

Note: Total acreage based on reports from the National Agricultural Statistics Service (2018).

Table 7. Estimated Social and Environmental Damages Resulting from Increased Use of Intensive Tillage in Response to GRWs

	Environmental damages		Social costs	
	Soil erosion[a] (metric tons)	Carbon emissions[b] (metric tons CE)	Current value[c] (USD)	Present value[d] (USD 2016)
2008	350,000	1,000	1,900,000	2,400,000
2009	1,390,000	5,000	7,500,000	9,200,000
2010	1,810,000	6,000	9,900,000	11,900,000
2011	3,540,000	12,000	19,900,000	23,000,000
2012	4,300,000	15,000	24,700,000	27,800,000
2013	5,160,000	18,000	30,100,000	32,900,000
2014	6,950,000	24,000	41,100,000	43,600,000
2015	7,790,000	27,000	46,000,000	47,400,000
2016	9,200,000	32,000	54,700,000	54,700,000
Total	39,270,000	135,000	229,800,000	244,500,000

Note: Prior to 2008, GRWs had yet to reach impactful levels in any state.
[a]Assuming a 6.8 ton/acre reduction in soil erosion from conservation tillage use (Montgomery 2007).
[b]Accounts only for reduced fuel consumption; assuming a 0.0234 tons/acre reduction in emissions from conservation tillage use (Lal 2004).
[c]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 of $125 (Carleton and Greenstone 2021).
[d]Computed with a 3% annual discount rate.

consumption when switching from conservation to conventional tillage is 0.0234 metric tons CE/acre.

To monetize the effects of 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 (US Department of Agriculture, National Resource Conservation Service 2009). For carbon emissions from fuel, we rely on the global Social Cost of Carbon (SSC), using an updated version of the cost reported by the United States Government (Carleton and Greenstone 2021). This most recent work, a variation of which is widely expected to be used in federal policymaking in coming years, estimates the social costs of a metric ton of CO_2 released into the atmosphere at $125. The environmental damage and social cost coefficients are applied to the difference in conservation tillage acres between scenarios, providing an estimate for the value of damages to water quality and the climate. Annual environmental damages and associated social costs are presented in table 7. Social damages are presented as lost value in current year price levels and as present values measured in 2016 dollars.

We estimate that the cumulative net present value of water quality and climate damage from farmer's tillage operation fuel consumption responses to GRWs in U.S. soybean fields during 2008–2016 is approximately $244.5 million. This social cost has been growing annually, exceeding $54 million in 2016, the last year of our panel. Water quality damage will be greatest in regions where GRWs are most prevalent, such as the southern region of the Mississippi Basin, whereas the climate damage will be realized globally. Note that these social cost estimates omit the lost value of any long-term yield gains from no-till (Deines, Wang, and Lobell 2019; Cusser et al. 2020), as well as the lost value of carbon sequestration in untilled soil and any change in human health and environmental costs from increased use of non-glyphosate herbicides. If weed species continue to evolve to resist glyphosate across the country, and farmers continue increasing tillage to achieve similar levels of weed control, we expect the rate at which the damages modeled here and other possible damage occur to grow further.

Conclusion

Herbicide resistant weeds in general, and glyphosate resistant weeds in particular, have become a widespread problem for farmers across the United States. This paper provides new and robust evidence that farmers respond to the decreasing effectiveness of glyphosate not only by increasing use of non-glyphosate herbicides (Perry et al. 2016a) but also 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 in the aggregate, as GRW numbers grow, farmers are turning to more intensive tillage at an increasing rate. Predictions from our statistical model indicate that additional GRWs have resulted in the reduced adoption of no-till and conservation tillage on tens of thousands of acres of soybean since 2008. We use these predictions to provide a conservative calculation that the cumulative social value of environmental damages that GRWs have caused through increased tillage in soybean fields at nearly $245 million in 2016 dollars.

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 and highlight the ways that these responses represent a potential threat to environmental quality. Other economic studies focus on how resistance has affected costs, returns, or yields (Livingston et al. 2015; Lambert et al. 2017; Wechsler, McFadden, and Smith 2017). Although these studies discuss or account for practice adaptation, it is not the focus of their analysis. Second, we quantify the environmental damages from farmers' responses to herbicide resistance, which would not be possible without our focus on practices. In doing so, we provide evidence of an evolving technological landscape for farmers, where the efficacy of a ubiquitous weed control tool is waning, and additional tools are needed for supplemental control. The environmental costs linked to use of these additional tools, which are partially accounted for here, imply that weed susceptibility to herbicides is a resource that provides value not only to farmers but to the public as well.

Although this paper focuses on tillage practices, it also finds that farmers have markedly increased and diversified herbicide use in response to the proliferation of glyphosate-resistant weeds. Future research should explore how the spread of GRWs affect that non-glyphosate herbicides farmers choose beyond the binary adoption decision between exclusive and non-exclusive glyphosate use modelled here and what those choices imply for environmental quality.

Resistance in weeds to non-glyphosate herbicides, in addition to glyphosate, may be among the other factors contributing to shifting herbicide choices across all crops. Parallel rising herbicide use trends in rice and wheat, for which glyphosate-tolerant seeds do not exist, suggest the spread of other herbicide resistant weeds may drive changes in weed control practices in other crops (Kniss 2017). Our empirical results find that spreading GRWs are indeed a significant driver in both tillage decisions and herbicide choices, at least in soybeans, when accounting for other observed and unobserved factors. The spread of GRWs, and weeds resistant to other active ingredients, likely affect weed control choices in other crops besides soybeans as well.

Future studies on the effects of GRWs and herbicide resistant weeds more generally would benefit from the availability of data on the presence of these biotypes at a finer grain scale than the state-level variables we use. As farmers turn to additional herbicides to combat GRWs, efforts should be made to track the emergence of resistance in conjunction with farmer's practice and product choices across major crops. Gathering information on these two sets of variables jointly would allow examinations of more nuanced responses to herbicide resistance, including own- and cross-resistance elasticities across herbicide modes of action (i.e. the effect of resistance to one herbicide on the use of another herbicide).

Meanwhile, agrochemical companies have responded to GRWs by developing new crop seed genetics 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), and indeed a revival of interest in pesticide research has led to recent mode-of-action discoveries (Kahlau et al. 2020). However, university weed scientists have questioned whether this path forward is sustainable, as weeds will continue to evolve resistance to still-effective 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 herbicide-tolerant crops, may come to an end within the foreseeable future if action is not taken.

Numerous possible 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, Bagavathiannan, and Norsworthy 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 societal value of delaying environmental damage to the wider public.

Finally, our findings demonstrate a close link between tillage practices and farmers weed control needs. Researchers frequently suggest policymakers consider models and policies related to tillage practices and soil carbon sequestration that account for the costs farmers incur when changing practices (Murray 2015; Stevens 2018). The increasing prevalence of herbicide resistant weeds will increase costs for programs seeking to encourage voluntary adoption of conservation tillage and no-till practices, as decreasing effectiveness of herbicides represents an increase in the relative weed control value of tillage. Therefore, both researchers and policymakers are encouraged to consider farmers' present and future weed control needs when considering models and programs related to tillage practices.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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