TO SPRAY OR NOT TO SPRAY: THE ECONOMICS OF WEED AND INSECT MANAGEMENT UNDER EVOLVING ECOLOGICAL CONDITIONS

By

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ABSTRACT

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The protection of crops from insect pests and weeds is fundamentally a problem of ecological management. Modern pesticides used to perform such management are essential to efficient production of corn and soybean, the two most widely grown crops in the United States. What pesticides are sprayed where, when, and by whom is both shaped by and shapes ecological conditions. This dissertation consists of three essays on how American corn and soybean growers make insect and weed management decisions, and the impacts of these decisions on the environment.

The first essay measures the impact of glyphosate-resistant weeds on farmers' tillage practices using field-level data from across the United States, demonstrating how selection pressure within weed populations can limit the long-term benefits of pesticide technologies. Using a two-stage, panel data econometric model, we estimate that the spread of glyphosate-resistant weeds has led to reduction in the adoption of conservation tillage by soybean growers by as much as 8.5 percentage points. Nationally, we estimate that the reduction in conservation tillage adoption due to glyphosate-resistant weeds has increased soil erosion into water ways by over 65 million metric tons and carbon emissions due to fuel consumption by 226,000 metric tons.

The second essay measures the impact of farmers' pesticide use on butterfly abundance. By examining a full suite of pesticides in a single model, we account for substitution effects between products. We find neonicotinoids, the most widely used class of insecticides, have a

detrimental impact on butterfly populations, both in aggregate and for prominent species such as Monarchs. Overall, our results show that changes in pesticide use between 1998 and 2014 accounted for a 9% decrease in total butterfly abundance.

Finally, the third essay examines farmers' decisions to custom hire to spray insecticides rather than performing such field tasks on their own. Using a pilot choice experiment, we demonstrate how the value farmers place on timeliness when custom hiring varies according to farmer characteristics. We find risk-averse farmers are more sensitive to potential delays, while those with more developed social networks are less sensitive.

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Introduction

Pesticides use is almost ubiquitous in American row crop agriculture. Since the 1980s, over 90% of corn and soybean acres in the United States have been sprayed with one or more pesticides (Fernandez-Cornejo et al., 2014). Herbicides and insecticides, which provide protection from weed competition and insect pest damage respectively, represent the two most widely applied classes of pesticides in corn and soybeans (Fernandez-Cornejo et al., 2014). This dissertation consists of three essays on the economics of the use of these pesticides in these two crops, the most widely grown crops in the United States.

Farmers spray pesticides because they provide more value over mechanical control, cultural control, and no protection alternatives. Pesticides prevent crop loss. Without control, corn yield would be potentially reduced 50% in the United States and Canada, a production value of over $26 billion annually (Soltani et al., 2016). Global wheat yields in 2001-2003 would been potentially 30% lower without crop protection, 50% lower in corn, and 45% lower in soybeans (Oerke, 2006). And among pest control options, pesticides protect crops more reliably and at lower financial cost to farmers than other pest control alternatives (Cooper & Dobson, 2007; Swinton & Van Deynze, 2017).

While pesticides provide undeniable benefits to farmers, their use can also impose costs on the environment and to human health. The negative impacts of pesticides were brought to the forefront of public consciousness by the publication of Rachel Carson's *Silent Spring* in 1962, soon after their use became widespread (Carson, 1962). Certain pesticides have been found to alter the behavior, metabolism, and development of wildlife in detrimental ways, which in turn has led to population declines (Köhler & Triebskorn, 2013). Pesticides can also be hazardous to human health, with effects ranging from mild and short-term (e.g. headaches, dizziness) and to long-term and debilitating (e.g. asthma, cancer) (Kim et al., 2017).

Economists have long had an interest in pesticide use as a study system. Economists have contributed to important management tools, including the concept of economic density thresholds for pests after which spraying becomes profitable (e.g. Auld & Tisdell, 1987; Hueth & Regev, 1974; Marra & Carlson, 1983). Other avenues of research have examined the roles of uncertainty and farmer attitudes towards risk in driving pesticide decisions (Horowitz & Lichtenberg, 1994; Pannell, 1991) and the impacts of emerging crop protection technologies on the use of alternatives (e.g. Perry, Ciliberto, et al., 2016; Perry, Moschini, et al., 2016).

This dissertation contains three essays that contribute to the literature on the economics of pesticides by examining pest control decisions in corn and soybean fields. Each of the essays relates to either how ecological factors affect or are affected by farmers decisions, and therefore also contribute to the modeling of agriculture as a managed ecosystem (Swinton et al., 2007). The results highlighted in these analyses will help policymakers, farmers, and agribusinesses make more well-informed decisions by better projecting the environmental effects of changes in environmental conditions and technologies.

The first essay is an econometric evaluation of the effects of glyphosate-resistant weeds on the adoption of conservation tillage in soybeans. The broad-spectrum herbicide glyphosate, commonly marketed as Roundup, quickly became the most widely applied soybean pesticide following the commercial introduction of varieties with genetically engineered tolerance to the chemical (Fernandez-Cornejo et al., 2014; Perry, Ciliberto, et al., 2016; Swinton & Van Deynze, 2017). Glyphosate-tolerant soybean seed allowed farmers to more readily adopt conservation tillage practices, as the broad-spectrum weed control value of tillage diminished relative to glyphosate (Perry, Moschini, et al., 2016). Meanwhile, an overreliance on glyphosate quickly resulted in the evolution of resistance in targeted weed populations (Livingston et al., 2015). Using panel data from thousands of U.S. soybean growers over 18 years, this essay shows that glyphosate-resistant weeds have diminished the conservation benefits of a glyphosate-based weed control system by reducing the adoption of conservation tillage in soybeans by as much as 8.5 percentage points in some states.

The second essay evaluates data from over a decade of butterfly population and pesticide use tracking surveys to measure the effects of pesticide use decisions on butterfly abundance. Previous studies have found negative impacts on butterfly abundance from specific pesticides such glyphosate (Saunders et al., 2018) or neonicotinoid insecticides (Forister et al., 2016; Gilburn et al., 2015). This study is the first to empirically link butterfly abundance to regional-scale pesticide use measures that account for contemporaneous changes in pesticide technology adoption by farmers. The resulting analysis finds that changes in pesticide use between 1998 and 2014 resulted in a 9% decrease in total butterfly abundance, and a 30%, 46%, and 39% decrease in the abundances of monarchs, silver-spotted skippers, and cabbage whites respectively. The increasing use of neonicotinoid seed coatings in corn and soybeans drives this result.

Finally, the third essay presents a conceptual model of a farmer's decision to custom hire for pest control. When farmers custom hire for pest control, they expose themselves to increased risk of yield loss due to late completion of field operations (referred to as timeliness costs) relative to when they choose to provide pest control on their own. The proposed model is rooted in transaction cost theory, which posits that firms' choices between contracting out production activities or completing them on their own is driven by frictions in contracting that can prevent potentially mutually beneficial trades (Coase, 1937; Williamson, 1979). The model suggests farmer characteristics and resources such as social capital, risk aversion, and equipment capital affect their sensitivity to timeliness losses from custom hiring when considering custom pest control options. The resulting implications are illustrated empirically with a pilot choice experiment.

Tying these three essays together is a focus on socio-ecological feedbacks in agricultural systems. As farmers adopt new technologies to control weeds and pests, ecosystems respond. Weeds evolve resistance to a popular herbicide and farmers respond by returning to old technologies. Farmers adopt new insecticidal seed treatments, and butterfly populations fall as new toxins are introduced to their habitats. And the feasibility of custom pest control depends on the potential for timeliness costs, which are derived from the speed at which pest populations can damage a crop. Using economic theory and econometric modelling, this dissertation highlights how socio-ecological linkages shape farmer incentives. The findings presented therein can help guide policy attempts to align these incentives with public objectives.

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CHAPTER 1. Are Glyphosate-Resistant Weeds a Threat to Conservation Agriculture? Evidence from Tillage Practices in Soybeans

Abstract

The use of conservation tillage in American soybean production has become increasingly common since the 1950's, improving soil health, reducing soil erosion, and reducing fuel consumption. This trend has been reinforced by the availability of the general-purpose herbicide glyphosate and glyphosate-resistant seed genetics since the mid-1990's. Weeds have since evolved to resist glyphosate, reducing its effectiveness. In this paper, we provide evidence that the spread of glyphosate-resistant weeds is responsible for significant reductions in the use of conservation tillage in soybean production. To capture the effects of glyphosate-resistant weeds on tillage adoption, we estimate a probit model of tillage choice, using a large panel of field-level soybean management decisions from across the United States, spanning 1999-2016. We find that while the first two glyphosate-resistant weed species have little effect on tillage practices, by the time that eight glyphosate-resistant weed species are present, conservation tillage use falls by 5.7 percentage points and no-tillage use falls by 10.0 percentage points. Using a simple benefit transfer model to illustrate how these results can be applied, we conservatively estimate that between 2005 and 2016, farmers' tillage responses to the spread of glyphosate-resistant weeds have caused water quality and climate damages valued at nearly $390 million. This total is likely to grow as glyphosate-resistance becomes more widespread and farmers continue to turn to tillage for supplemental weed control.

Introduction

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

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

As glyphosate use became more frequent in soybeans and other crops, weeds soon evolved to resist the chemical. In 2000, a population of horseweed growing in a soybean field in Delaware became the first identified case of glyphosate-resistance in weeds (VanGessel, 2001).

As of 2017, glyphosate-resistance had been identified in 17 weed species in the United States (Heap, 2017). The rise of glyphosate-resistant weeds (GRWs) has led to a growing literature on best practices to delay and manage the onset of herbicide-resistance in weeds (Beckie, 2006; Evans et al., 2015; Bonny, 2016; Beckie and Harker, 2017). The increased use of tillage for weed control is frequently found amongst these recommendations.

A smaller literature has focused on how farmers have responded to the onset of GRWs. Livingston et al. (2015) reports the results of cross-sectional surveys of corn and soybean growers in 2010 and 2012, respectively. They find that farmers experiencing problems with GRWs frequently supplemented glyphosate-based weed control with non-glyphosate herbicides, increased their use of glyphosate, and increased the use of tillage. Wechsler et al. (2017), using farm-level cross-sectional data from corn-growing states in 2005 and 2010, find that low numbers of GRWs have a fairly small impact on corn farmers' weed control practices, costs, and yields. Perry, Ciliberto, et al. (2016) observe a sharp increase in the use of non-glyphosate herbicides in corn and soybeans from 2007 to 2011 and speculate that this increase is due to GRWs. Most recently, Lambert et al. (2017) find that weed control costs increase by $34-55/acre following the emergence of GRWs in upland cotton fields as farmers adopt labor-intensive alternatives to glyphosate.

In this paper, we contribute to 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. We do so first by developing a conceptual model of a cost-minimizing farmer who chooses among multiple herbicide and tillage options to meet predetermined weed control targets. This model indicates a non-linear response to herbicide-resistance: As more weed species develop herbicide resistance, farmers become increasingly likely to make major changes to their weed control practices. We test this model empirically with data on the field-level weed control choices of thousands of soybean farmers during 1999-2016. Our econometric results indicate that while low numbers of GRWs have little impact on tillage choices, by the time that eight GRWs are present, conservation tillage falls by 5.7 percentage points and no-till adoption falls by 10.0 percentage points. Extrapolating from literature estimates of soil erosion and carbon emissions from tillage, and their environmental costs, we estimate that the shift towards more intensive tillage practices in response to GRWs has caused water quality and climate damage worth nearly $390 million. These damages accrued from 2005-2016 and have been most acute in the southern states where GRWs are most prevalent.

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

Conceptual Model

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

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 conventional, intensive tillage. A farmer can select any combination of L alternative herbicides to supplement weed control provided by his tillage system. Let h_l denote the (non-negative) quantity of herbicide $l \in \{1, \cdots, L\}$, so that a farmer's herbicide choice set is $\boldsymbol{H} = \mathbb{R}_+^L$.[2] Together, a farmer's weed control choice set is $\{\tau^{CT}, \tau^{IT}\} \times \boldsymbol{H}$.

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

[1] Farmers and weed control experts typically utilize 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.

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

control costs for each of the two tillage systems subject to K constraints (one for each weed species):

$$\min_{\boldsymbol{h}} \boldsymbol{w} \cdot \boldsymbol{h} + c(\bar{\tau}) \qquad (1.1)$$

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

The optimality conditions for this problem are:

$$w_l = \textstyle\sum_k \lambda_k\, \partial g_k(\boldsymbol{h}, \bar{\tau})/\partial h_l \;\; \forall l \qquad (1.2)$$

$$\lambda_k[g_k(\boldsymbol{h}, \bar{\tau}) - \bar{g}] = 0 \;\forall k \qquad (1.3)$$

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

$$V(\bar{\tau}) \equiv \boldsymbol{w} \cdot \boldsymbol{h}^*(\bar{\tau}) + c(\bar{\tau}) \qquad (1.4)$$

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

$$\tau^* = \underset{\tau \in \{\tau^{CT}, \tau^{IT}\}}{\operatorname{argmin}} V(\tau) \quad (1.5)$$

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 $\widetilde{\boldsymbol{h}}^*(\bar{\tau})$ 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 $\widetilde{\boldsymbol{h}}^*(\bar{\tau}) \neq \boldsymbol{h}^*(\bar{\tau})$? 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 $\widetilde{\boldsymbol{h}}^*(\bar{\tau}) \neq \boldsymbol{h}^*(\bar{\tau})$, as $\partial^2 g_k/\partial {h_l}^2 < 0$ and therefore, by the continuity and strict monotonicity of $\partial g_k(\boldsymbol{h}, \bar{\tau})/\partial h_l$, $\boldsymbol{h}^*(\bar{\tau})$ cannot satisfy equation (1.2) 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 $\widetilde{\boldsymbol{h}}^*(\bar{\tau}) = \boldsymbol{h}^*(\bar{\tau})$, as $\partial g_k(\boldsymbol{h}, \bar{\tau})/\partial h_l$ would be multiplied by $\lambda_k = 0$ in equation (1.2) 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 resistance towards a single herbicide is likely not to influence tillage choices. As more weeds develop resistance to a herbicide, changes in herbicide use, and hence tillage practices as well, become more likely as farmers seek alternative methods to reach their weed control targets. But because some weeds may and are in fact likely to be over-controlled (i.e. the weed target constraint is non-binding) the response to herbicide resistance is inherently non-linear. If the herbicide costs associated with conservation tillage outweigh savings in tillage costs, then a farmer will switch to intensive tillage.

The Case of Glyphosate and Glyphosate-Resistant Weeds

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

In terms of our conceptual model, this implies that glyphosate has a non-zero marginal weed control effectiveness under conservation tillage ($\partial g_k(\boldsymbol{h}, \tau^{CT})/\partial h_l$) for all weeds, leading to over control (i.e. $\lambda_k = 0$) for many weeds. 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 the use of another herbicide must increase or the farmer must switch to intensive tillage in order 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, we its advantage as a broad-spectrum weed control method over intensive tillage falls as additional herbicides are necessary to maintain weed control targets. Therefore, we expect compounding pressure to utilize intensive tillage over conservation tillage as glyphosate-resistance becomes more widespread. In other words, as the number of glyphosate-resistant weeds increases, we expect both that intensive tillage becomes more common and that the rate at which it becomes more common in response to the occurrence of glyphosate-resistance to increase.

Empirical Model

To test the implications of the conceptual analysis presented above, we estimate a dynamic probit model with the tillage decision as the dependent variable. We include farm-level random effects to control for unobserved, time-invariant heterogeneity and a first-stage control function to account for potentially endogenous herbicide use. The unit of analysis, is the field-level (j) tillage decision on each farm (i) in a year (t). With y_{jit}^{CT} as an indicator for the use of conservation tillage, z_{it} as the number GRWs, y_{jit}^{NGH} as an indicator for the use of non-glyphosate herbicides, $y_{i,t-1}^{CT}$ as an indicator for the farms conservation tillage decision in the previous period, p_t^{fuel} as an index for fuel prices, $\boldsymbol{x_{it}}$ as a vector of farm-level conditioning variables, and δ_i as a time-invariant, normally-distributed, farm-level random effect to account for unobserved heterogeneity, the structural function we seek to estimate is the probability that conservation tillage is chosen:

$$\Pr\left(y_{jit}^{CT} = 1 \middle| z_{it}, y_{jit}^{NGH}, y_{i,t-1}^{CT}, \boldsymbol{p_t}, \boldsymbol{x}_{it}, t, \delta_i\right) = \Phi(\beta_0 + z_{it}\beta_1 + z_{it}^2\beta_2 + y_{jit}^{NGH}\beta_3 +$$

$$+ y_{i,t-1}^{CT}\beta_4 + p_t^{fuel}\beta_5 + \boldsymbol{x}_{it}\boldsymbol{\beta_6} + t\beta_7 + \delta_i) \quad (1.6)$$

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

In this specification, we account for a non-linear 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 that may have contributed to shifts in the use of conservation tillage over time.

Before estimating this structural function via maximum likelihood, we must first address two issues: 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, $y_{i,t-1}^{CT} = \max_j\{y_{ji,t-1}^{CT}\}$, assuming that previously used conservation tillage equipment remains available in following period. However, including the lagged dependent variable in a panel data model forces us to address the initial conditions problem (Arellano and Honore, 2001). This problem occurs when the modelled process is not observed from its beginning. Therefore, the initial condition, y_{i0}^{CT}, is likely correlated with the farm-level random effect, δ_i.

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

$$\delta_i = \alpha_0 + y_{i0}^{CT}\alpha_1 + \bar{\boldsymbol{x}}_i\boldsymbol{\alpha_2} + \boldsymbol{x}_{i0}\boldsymbol{\alpha_3} + \theta_i;\ \theta_i \sim Normal(0, \sigma_\theta^2) \qquad (1.7)$$

where $\boldsymbol{x}_{i0}$ is a vector of all initial period explanatory variables and $\bar{\boldsymbol{x}}_i$ is a vector of explanatory variables averaged across all periods (Rabe-Hesketh and Skrondal, 2013). While 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 unwieldly due to the large number of incidental parameters. Rabe-Hesketh and Skrondal (2013) show that the above constrained model performs similarly to the original Wooldridge solution. In this form, the random effect 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 $\overline{\boldsymbol{x}}_i$ to account for this potential effect. This expression can be substituted directly into the structural equation, Equation (1.6), and estimation can proceed.

The second issue relates to the use of non-glyphosate herbicides, y_{jit}^{NGH}. As herbicide use decisions are made simultaneously with tillage decisions, this variable is potentially endogenous. As our primary goal is to achieve consistent estimation of the parameters on the GRW terms of the tillage model, one could consider omitting this variable to avoid the issue of endogeneity entirely. However, the use of non-glyphosate herbicides is almost certainly correlated with GRWs, so its omission would induce omitted variable bias in the parameters of interest.

In cases like this one, 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 are included, while the "plug-in" methods generally estimate coefficients and partial effects inconsistently (Wooldridge, 2015).

A third option, which we use here, is a control function approach for binary endogenous variables in binary dependent variable models known as two-stage residual inclusion

(Wooldridge, 2014; Terza et al., 2008). This method offers computational simplicity when compared to jointly-estimated, bivariate techniques. 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 aggregate measure of the unobserved variables which induce the problem in the first place.

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

$$\Pr\left(y_{jit}^{NGH} = 1 \middle| z_{it}, y_{i,t-1}^{CT}, p_t^{GH-NGH}, \boldsymbol{x'}_{it}, t, \mu_i\right) = \Phi\left(\gamma_0 + z_{it}\gamma_1 + z_{it}^2\gamma_2 + y_{i,t-1}^{CT}\gamma_3 + p_t^{GH-NGH}\gamma_4 + \boldsymbol{x'}_{\boldsymbol{it}}\boldsymbol{\gamma}_{\boldsymbol{5}} + t\gamma_6 + \mu_i\right) \quad (1.8)$$

The price variable, p_t^{GH-NGH}, is the difference between the indexed price of glyphosate and an index of non-glyphosate herbicide prices, while $\boldsymbol{x'}_{\boldsymbol{it}}$ is a vector of farm size indicator variables, omitting the soil and drought measures included in the tillage model. The farm-level random effect, μ_i, is assumed to follow a normal distribution with zero-mean and variance σ_μ^2. To account for the joint determination between tillage and herbicide choices, we include lagged tillage choice $y_{i,t-1}^{CT}$. This first-stage model is estimated following standard maximum likelihood procedures for probit models with random effects.

To ensure identification of the second-stage tillage 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 differential between glyphosate and non-glyphosate prices, p_t^{GH-NGH}, satisfies the exclusion restriction.

To satisfy the exclusion restriction, p_t^{GH-NGH} must satisfy three conditions: (1) it must not have a direct influence on the dependent variable in the structural model, y_{jit}^{CT}; (2) it must be uncorrelated with omitted explanatory variables in the structural model; and (3) it must be strongly correlated with the potentially endogenous variable, y_{jit}^{NGH} (Terza et al., 2008). We argue these three conditions are satisfied. 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 (2016), where the premium for glyphosate-tolerant seed is assumed not to directly affect tillage decisions. The remaining two conditions are addressed in the following sections.

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

$$\Pr\left(y_{jit}^{CT} = 1 \middle| z_{it}, y_{jit}^{NGH}, y_{i,t-1}^{CT}, p_t^{fuel}, \boldsymbol{x}_{it}, t, \hat{r}_{it}, y_{i0}^{CT}, \overline{\boldsymbol{w}}_i, \boldsymbol{w}_{i0}, \theta_i\right) = \Phi(\beta'_0 + z_{it}\beta_1 + z_{it}^2\beta_2 + y_{jit}^{NGH}\beta_3 + y_{i,t-1}^{CT}\beta_4 + p_t^{fuel}\beta_5 + \boldsymbol{x}_{it}\boldsymbol{\beta_6} + t\beta_7 + \hat{r}_{jit}\beta_8 + y_{i0}^{CT}\alpha_1 + \overline{\boldsymbol{w}}_i\boldsymbol{\alpha_2} + \boldsymbol{w}_{i0}\boldsymbol{\alpha_3} + \theta_i) \quad (1.9)$$

This structural function can be estimated using standard maximum likelihood procedures for probit models with random effects.[3]

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

Data

The core of our data are field-level survey data, representative at the Crop Reporting District level, collected by the market research company Kynetec. These data contain observations on chemical and mechanical weed control practices of 22,151 farmers from 1999 through 2016 in 31 soybean-growing states[4] 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. Sample lists for each year are constructed from the previous year's list supplemented with 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 recontacted a minimum of eight times to reduce non-response error and up to 25 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.

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

The Kynetec survey data include three levels of tillage intensity: conventional, conservation, or no-till. Following Perry, Moschini, and Hennessy (2016), where a shorter

[4] 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.

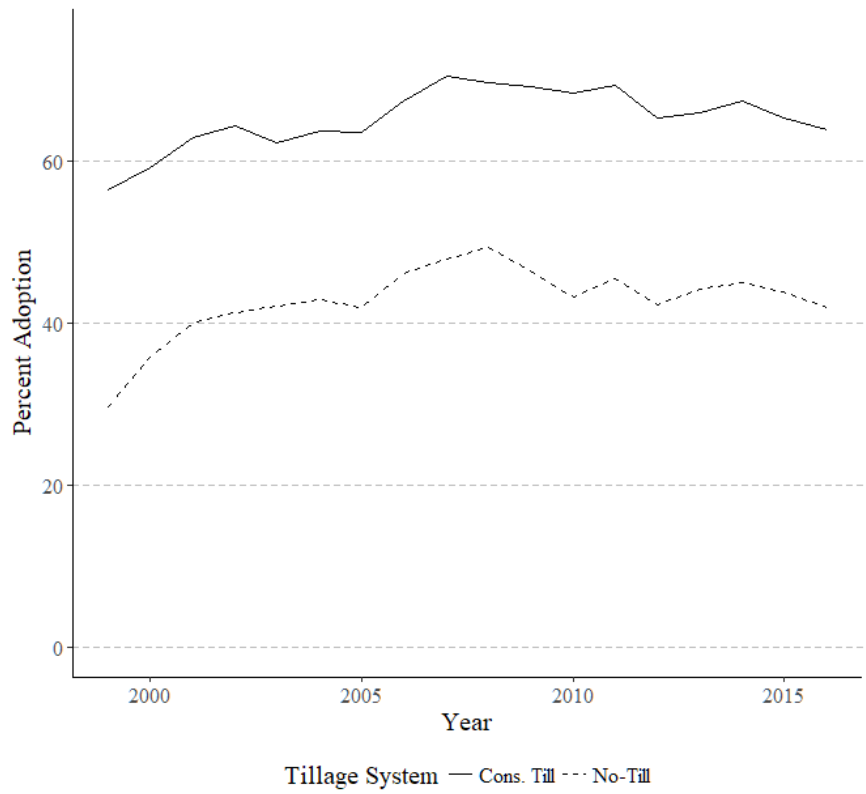

Figure 1.1. Percentage of Fields in Sample Under No-Till and Conservation Tillage Over Time. Conservation tillage includes no-till fields as well as other forms of reduced tillage.

subset of these data are used, we define two binary tillage decision variables: a conservation tillage indicator equal to one when either conservation or no-till is used, and no-till indicator equal to one when no-till is used, grouping other conservation tillage practices along with conventional tillage. Because the effect of GRWs on no-till 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 1.1.

The practice data also identify the herbicide products applied over each field in each year. We identify the active ingredients in each of these products and define a binary variable equal to one whenever the field is treated with a product containing a non-glyphosate active ingredient.

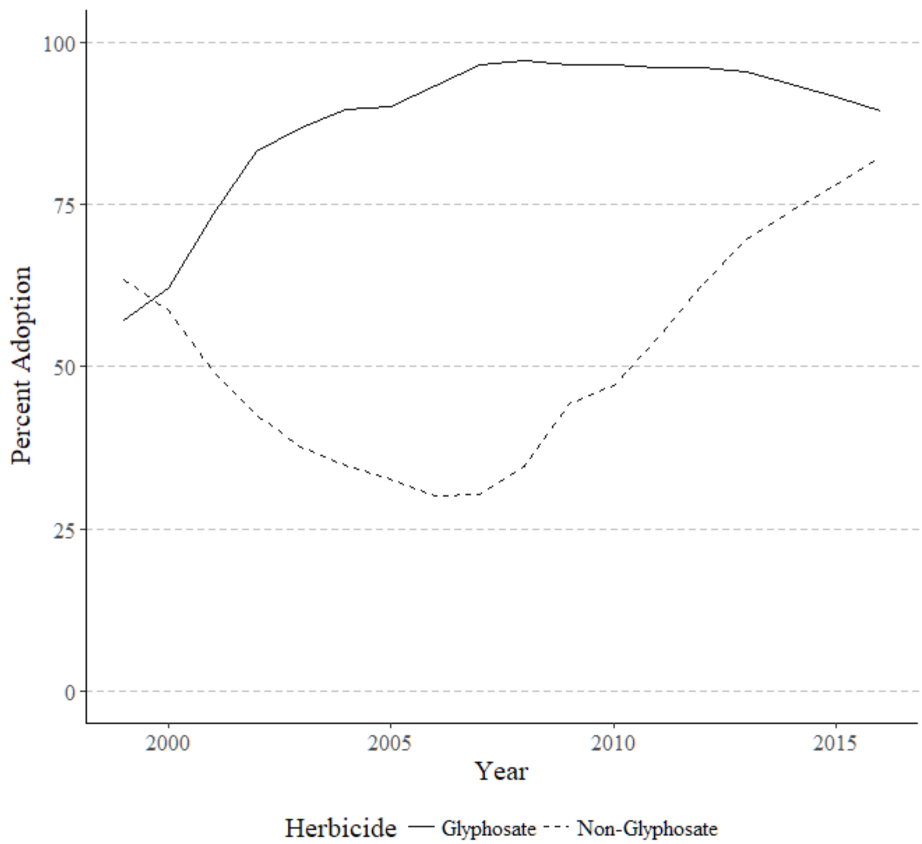

Figure 1.2. Percentage of Fields in Sample Treated with Glyphosate and Non-Glyphosate Herbicides Over Time.

The proportions of fields in the sample treated with glyphosate and non-glyphosate herbicides is presented in Figure 1.2. Early in the sample period, the use glyphosate became increasingly common, and the use of non-glyphosate products fell rapidly, likely due to the advent of glyphosate-tolerant soybean seed. Starting in 2006, this trend reversed, and non-glyphosate products were used more and more commonly. Glyphosate use reached near-saturation in the same year and continued to be used on over 90% of fields through 2016.

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 each year. Because non-glyphosate herbicides represent a basket of several related products, we

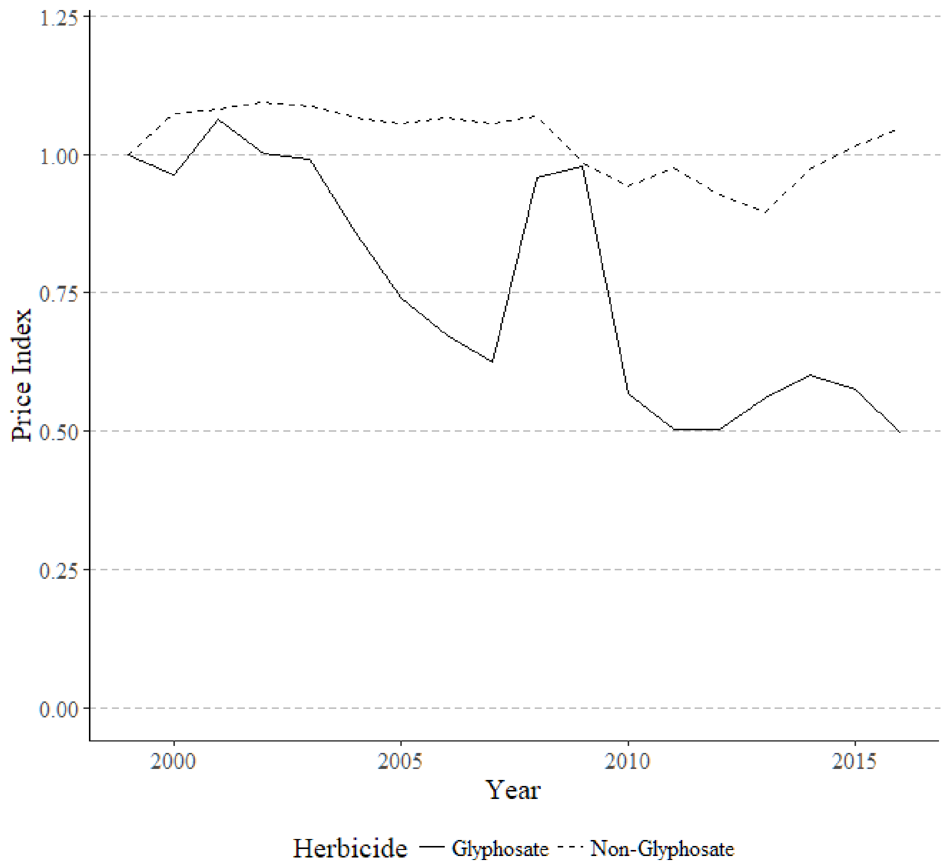

Figure 1.3. Price Indices for Glyphosate and Non-Glyphosate Herbicides Over Time. Both prices normalized to 1 in 1999.

construct a Laspeyres index 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 $p_t^{GH-NGH} = p_t^{GH} - p_t^{NGH}$. These price indices are presented in Figure 1.3.

Glyphosate prices dropped significantly following the expiration of Monsanto's patent in 2000 while non-glyphosate prices remained steady, so p_t^{GH-NGH} is negative in all years. During 2007-2009, glyphosate prices spiked relative to non-glyphosate 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 describes farm size as one of five categories: less than 100 acres, l00-249 acres, 250-499 acres, 500-999 acres, and 1,000 acres or more. These are included as 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 state-level data on the number of reported glyphosate-resistant weed species at the beginning of the growing season, as reported by the International Survey of Herbicide Resistant Weeds (Heap, 2017).[5] The number of species resistant to glyphosate in each state in our sample in 2004, 2008, 2012, and 2016 is presented in Figure 1.4. To the best of our knowledge, the ISHRW is the best available measure for this variable, providing consistent reporting on the development of herbicide resistance by mode of action across the full timeframe and the geographic region of our panel. As the primary contributors to the ISHRW data are university extension weed scientists, we assume that these counts represent the knowledge available to a typical farmer when making tillage decisions through an extension weed control guide (e.g., Sprague and Burns, 2017).

We rely on NASS annual price indices for diesel fuel (National Agricultural Statistics Service, 2018). As conservation tillage typically requires lighter field implements and therefore less fuel, we expect its use to be more frequent when fuel prices are higher (Lal, 2004).

[5] 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/).

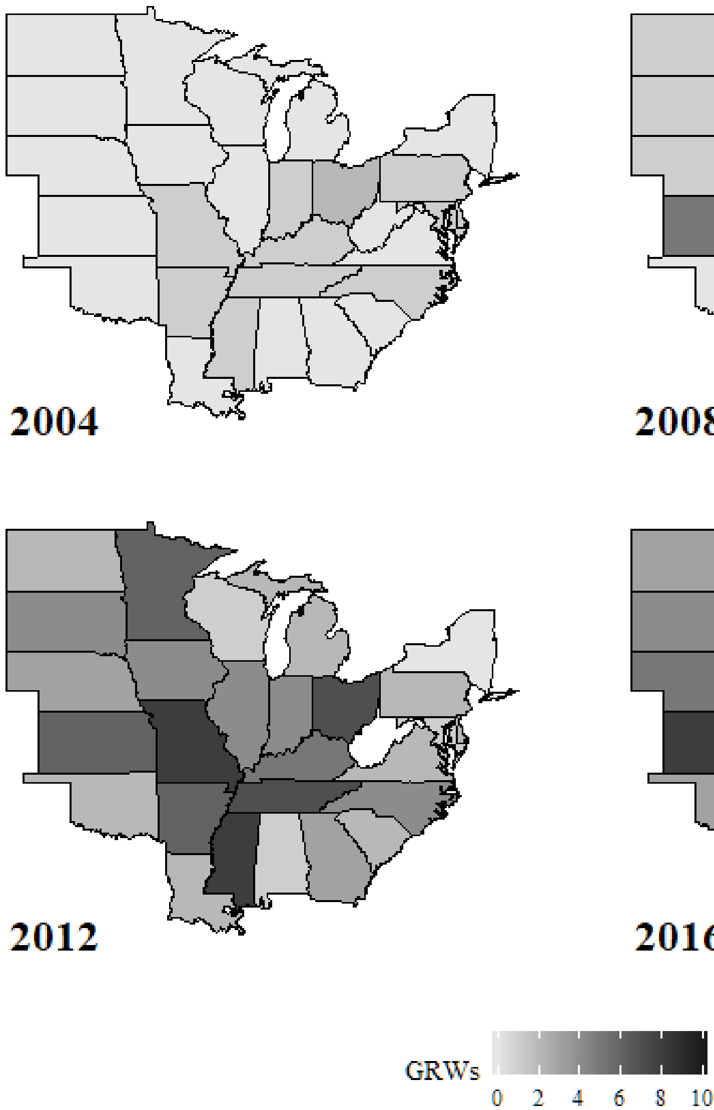

Figure 1.4. Number of Weed Species Resistant to Glyphosate (GRWs) by State. Prior to 2001, no species had been identified as glyphosate resistant at the start of the growing season.

Finally, we include a pair of variables to control for a field's soil conditions. Previous studies have shown that conservation tillage systems are more likely to be adopted on highly-erodible lands (Uri, 1999; Soule et al., 2000). Past research has also found that the use of conservation tillage (but not no-till) is more likely in years following drought conditions (Ding et al., 2009). Therefore, for each farm we include the proportion of the land in a farm's county that

Table 1.1. 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	GfK
Tillage Decision, Cons. Till	Binary indicator of use of a conservation tillage system (including no-till)	Field	GfK
Non-Glyphosate Herbicide Use	Binary indicator of use of a herbicide other than glyphosate	Field	GfK
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	GfK
Non-Glyphosate Price	Laspyres index of non-glyphosate herbicide prices, normalized to 1 in 1999	National	GfK
Fuel Price	Index of diesel fuel prices, normalized to 1 in 1999	National	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 farmland operated by farm, categorized into five bins	Farm	GfK

National Resources Inventory has classified as highly-erodible (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 (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 1.1, along with the scale at which they are measured and their original source.

Results and Discussion

In this section, we present the results of our empirical model. First, we offer a brief discussion of our first-stage models of non-glyphosate herbicide use before discussing the coefficients and goodness-of-fit for our second-stage models of tillage adoption. We present two measures of goodness-of-fit: the percentage of observations correctly predicted and pseudo-R^2 measures widely used when generalized linear mixed-effects models are reported (Nakagawa and Schielzeth, 2013). We then turn to the implications of our tillage decision models, examining predicted probabilities of conservation tillage and no-till adoption at extant GRW species counts. Finally, we use our tillage decision model for conservation tillage adoption to explore a counter-factual scenario in which no weed species adapt to resist glyphosate to get a sense of the degree of environmental damages induced by GRWs through farmers' tillage responses.

First-Stage Non-Glyphosate Herbicide Use Models

The first-stage model of non-glyphosate herbicide use is estimated twice, once with past no-till use and again with past conservation tillage use as independent variables for the estimation of control functions for corresponding second-stage models. Results from each are presented in Table 1.2. In both estimations, coefficients on both GRW terms indicate that glyphosate-resistant weed species are statistically significant and similar in scale. The negative coefficient on the linear term and positive coefficient on the quadratic term indicate that although the first GRW species to appear have relatively little impact on the use of non-glyphosate herbicides, the probability of non-glyphosate herbicide use rises faster as GRW counts reach higher levels.

Table 1.2. Results from First-Stage, Non-Glyphosate Herbicide Use Models. Models estimated separately for use with no-till and conservation tillage second-stage models. P-values in bold are less than 0.05.

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

The coefficient on the price differential between glyphosate and non-glyphosate herbicides is 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) of the exclusion restriction (Wooldridge, 2014). As the coefficient is statistically significant at even very low alpha thresholds, 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 models.

No-Till and Conservation Tillage Models

The results from the second-stage, tillage choice models are presented in Table 1.3, estimated for both no-till and conservation tillage use as the dependent variable. Both models correctly predict the tillage decision for a field about four-fifths of the time. Further, the models correctly predict tillage decisions at roughly the same rate for fields regardless of the observed outcome. This balance is important for modelling counter-factual scenarios, because if the model's accuracy depended largely on its target, then prediction would be systemically biased towards the model's naturally favored outcome.

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

Table 1.3. Results from Second-Stage, Tillage Decision Models. Models are estimated separately for no-till and conservation tillage. P-values in bold are less than 0.05.

	Dep. Var.: Tillage Decision			
	No-Till Model		Cons. Till Model	
	Est.	*p*	*Est.*	*p*
(Intercept)	-1.373	**<0.001**	-1.000	**<0.001**
GRWs	0.009	0.488	0.022	0.097
GRWs (Squared)	-0.010	**<0.001**	-0.007	**<0.001**
Non-Glyphosate Use	0.345	**0.008**	0.352	**0.003**
Non-Glyphosate Use (Residuals)	-0.137	**0.012**	-0.143	**0.004**
Fuel Price	0.074	**<0.001**	0.059	**<0.001**
Past Tillage Decision	0.637	**<0.001**	0.770	**<0.001**
Palmer's Z-Index	-0.001	0.826	-0.005	0.079
Soil Erodibility Index	0.650	**<0.001**	0.445	**<0.001**
Year Trend	0.026	**<0.001**	0.017	**<0.001**
Size (100 - 249 Acres)	0.009	0.748	0.063	**0.010**
Size (250 - 499 Acres)	0.004	0.891	0.060	**0.023**
Size (500 - 999 Acres)	-0.027	0.370	0.056	**0.041**
Size (1000 Acres or more)	-0.112	**<0.001**	-0.029	0.328
Initial Conditions Correction	Yes		Yes	
Random Effects	Farm-level		Farm-level	
Unique Farms/Observations	22,151/93,345		22,151/93,345	
Percent Correct (Dep. Var. = 1)	72.3%		82.4%	
Percent Correct (Dep. Var. = 0)	81.2%		73.1%	
Percent Correct (All Obs.)	77.6%		79.4%	
Marginal R^2	0.467		0.413	
Conditional R^2	0.707		0.625	

heterogeneity (i.e. the fixed effects) and allowing for a random intercept for each farm to account for unobserved heterogeneity improves model fit substantially.

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

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, 2016).

Previous use of conservation tillage has a statistically significant and positive effect. This indicates that some “inertia” is present for conservation tillage: farms that use conservation tillage today are more likely to use it in the future, perhaps due to increased familiarity with the system (Uri, 1999). This pattern holds when no-till is modelled separately from other conservation tillage systems.

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 (though this coefficient is only statistically significant at the 10% level), but not no-till. This pattern follows results found in the literature on tillage adoption (Ding et al., 2009). Fields in counties with more highly-erodible land are also more likely to be under conservation tillage systems. The positive time trend likely reflects the effects of payments through federal conservation programs and state-level extension efforts to promote conservation tillage adoption, as well as increased familiarity with these practices over time. Medium sized farms are slightly more likely to adopt conservation tillage than the largest (1,000 acres or more) and smallest farms (less than 100 acres), while the largest farms are slightly less likely to adopt no-till.

Effects of GRWs on Tillage Decisions

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

The predicted probabilities of adoption of conservation tillage and no-till for the observed range of GRW counts, with other variables held at their means, are presented in Figure 1.5. These curves show the negative and compounding effect of GRWs on the use of conservation tillage, consistent with the expectations of the conceptual model. Through the first two glyphosate resistant weed species, the predicted rate of no-till use remains statistically indistinguishable from the rate at zero GRWs (44% adoption). However, by the eighth GRW, the predicted rate of adoption falls by 10.0 percentage points, a 22.5% reduction among no-till users. The impact of GRWs on conservation tillage is similar, though less severe. Through the first two

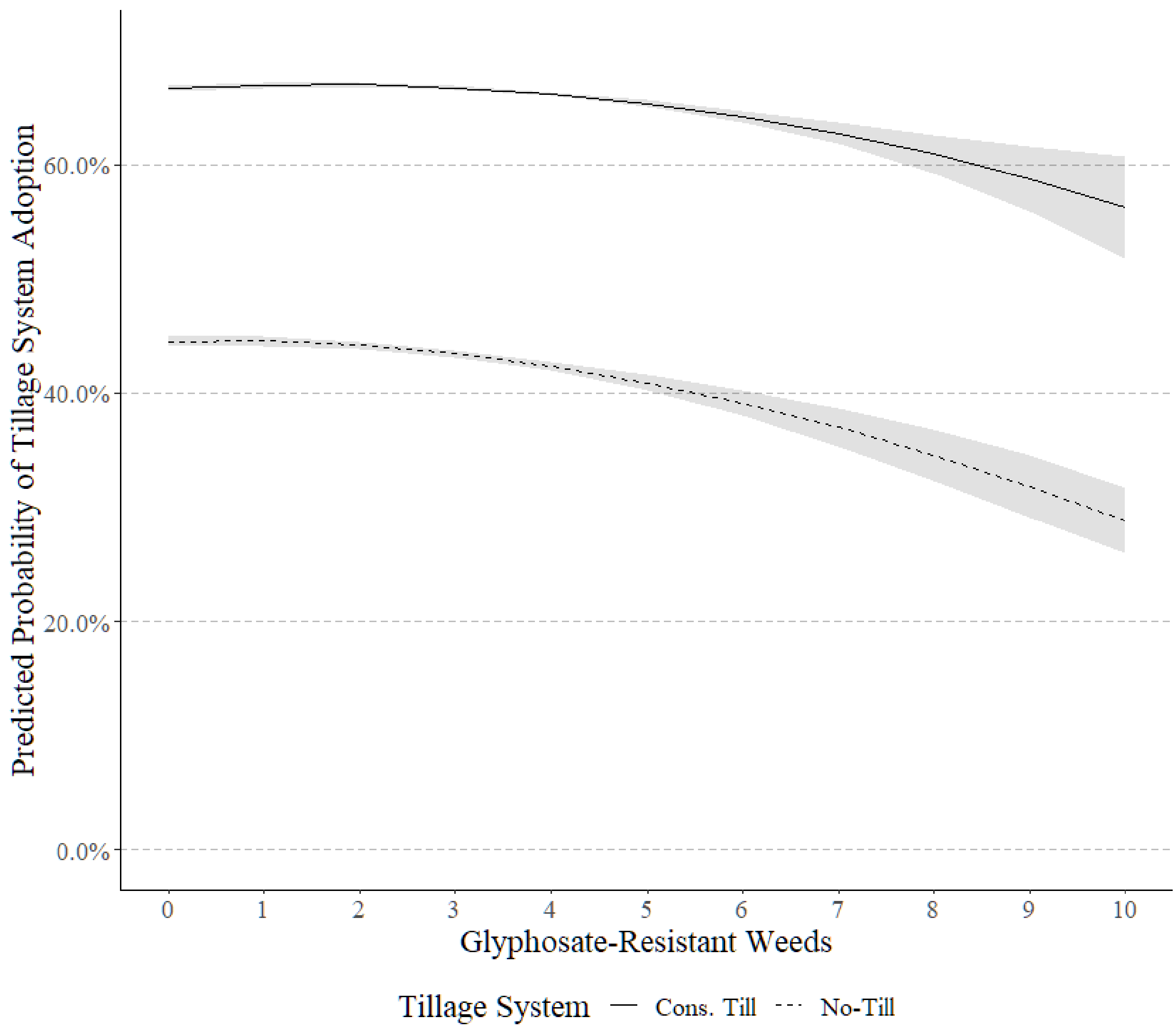

Figure 1.5. Predicted Adoption of No-Till and Conservation Tillage by the Number of Glyphosate Resistant Weeds. The shaded region indicates a 95% confidence interval, computed via the delta method.

GRWs, conservation tillage is used at rates not statistically different from zero GRWs (66.9% adoption). But by the eighth reported GRW, conservation tillage rates fall by 5.7 percentage points, an 8.6% reduction among CT users generally. The magnitude of predicted reduction in conservation tillage and no-till use due to eight identified GRWs corresponds with that of the increase in use attributed to the introduction of glyphosate-resistant soybean seeds (Perry,

Table 1.4. GRW Coefficients Under Alternative Specifications. P-values are presented in parentheses. P-values in bold are less than 0.05.

	No-Till		Cons. Till	
Alternative Specification	Linear	Quadratic	Linear	Quadratic
Machinery Price Included	0.023 (0.141)	-0.010 **(<0.001)**	0.014 (0.343)	-0.006 (<**0.001**)
Soybean Price Included	0.025 (0.088)	-0.011 **(<0.001)**	0.013 (0.339)	-0.006 (<**0.001**)
Quadratic Term Omitted	-0.051 (<**0.001**)	–	-0.030 (<**0.001**)	–

Moschini, and Hennessy, 2016). 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 negative effect of GRWs on conservation tillage and no-till adoption is robust to alternative specifications. Table 1.4 presents estimated coefficients for the linear and quadratic GRW terms for both no-till and conservation tillage models estimated with alternative covariate structures. In our first alternative specification, we include a NASS machinery price index representing price changes over time for both tillage-related implements and other machinery. Including this covariate from our analysis does not affect the direction, significance, or relative magnitude of coefficients on either the linear or quadratic GRW terms. In our next specification, we include soybean prices, measured annually at the state-level in September of the previous year from NASS. Including soybean prices does not meaningfully change our key result relative to the base model. Finally, excluding the quadratic GRW term results in a negative and statistically significant coefficient on the linear term, corroborating that GRWs have a negative effect overall on no-till and conservation tillage adoption.

To test whether including the quadratic term improves the model fit over the linear terms alone, we conduct a likelihood ratio test of the full model versus a specification where the quadratic terms for GRWs are excluded. For the no-till model the likelihood ratio is 54.886 (p-value for Chi-squared test < 0.001) and for the conservation tillage model the ratio is 23.033 (p-value < 0.001). Both models exhibit significantly better fit when the quadratic terms are included, providing further support for the non-linear tillage response to GRWs suggested by the conceptual model.

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 model given realized GRW emergence patterns (denoted Ac for "actual") and a counterfactual scenario in which no weed species evolve to resist glyphosate, all else equal (denoted Cf for "counterfactual"). The counterfactual scenario is simulated by setting $z_{it} = 0$ for all observations in a counterfactual dataset, leaving all other variables the same as observed.

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

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

$$S_t^n = \frac{\sum_{i=1}^{I_t} \sum_{j=1}^{J_{it}} P_{jit}^n A_{jit}}{\sum_{i=1}^{I_t} \sum_{j=1}^{J_{it}} A_{jit}}, n \in \{Ac, Cf\} \qquad (1.10)$$

As a display of the spatial variation in the effect of GRWs on tillage decisions over our sample period, the differences between the acre-shares under conservation tillage, $S_t^{Cf} - S_t^{Ac}$, are

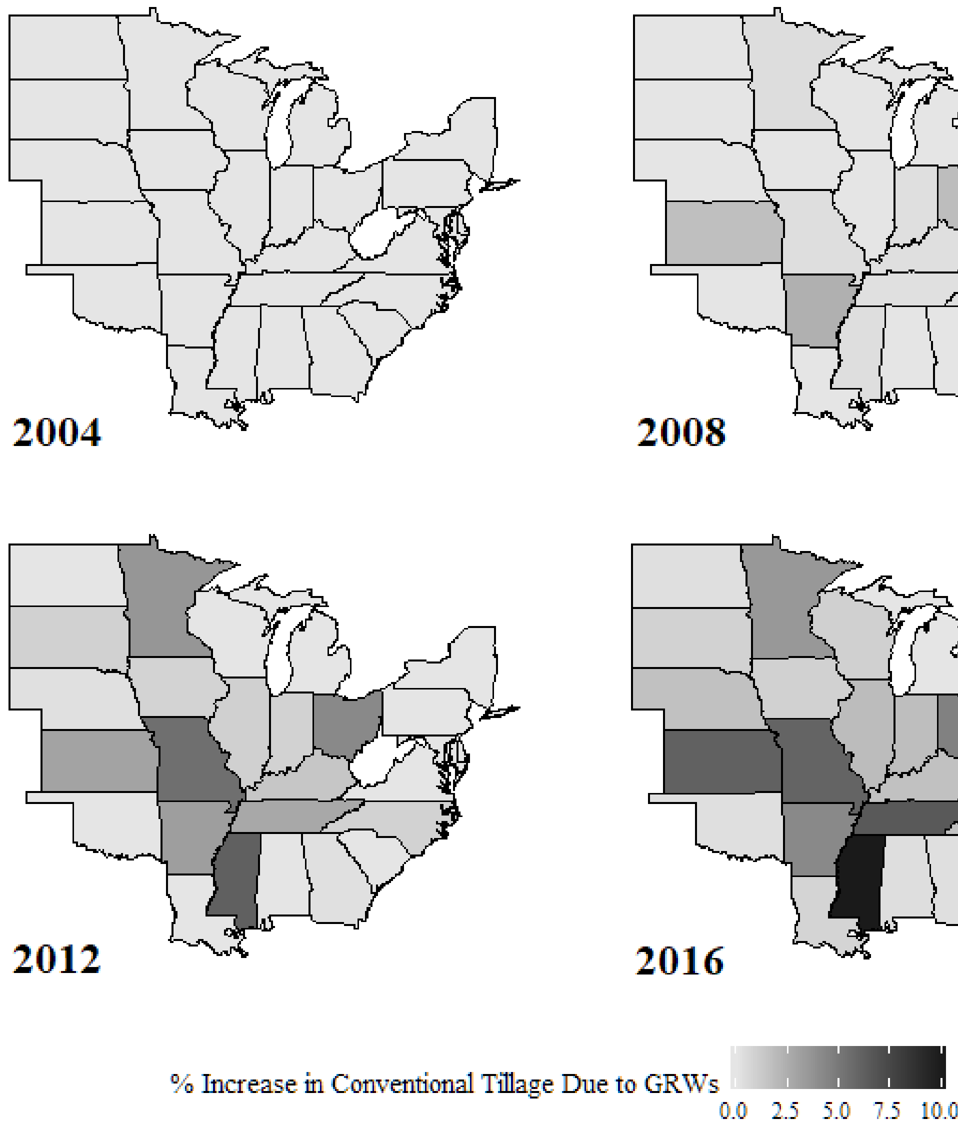

Figure 1.6. Increases in Percentage of Soybean Acres Under Conventional Tillage Attributed to GRWs.

calculated separately for each state and presented in four maps for 2004, 2008, 2012, and 2016 in Figure 1.6. On the majority of soybean acres, GRWs have had negligible impact on tillage practices, with increases in intensive 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 be used on 8.5% more soybean acres had GRWs been absent.

Environmental Damages Resulting from Farmers' Tillage Responses to GRWs

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 et al., 1999). An intuitive follow-up to the preceding analysis of farmers' tillage responses to GRWs is to estimate the resulting environmental damages from increased tillage.

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

To quantify the soil erosion impact of increased use of conventional tillage, we rely on median erosion rates for soils under conventional and conservation tillage as reported in a review of 495 studies (Montgomery, 2007). For conventional tillage, the reported median erosion rate is 1.54 mm per acre-year. For conservation tillage, the median erosion rate is 0.08 mm per acre-year. Assuming a soil density of 1,200kg/m^3, this implies a 6.8 ton/acre-year reduction in soil erosion in fields under conservation tillage 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 et al., 1999). Lal (2004) synthesizes the literature on fuel consumption required for various tillage operations, reporting the results as mean kilograms CO_2-equivalent emissions (CE) per hectare. We convert these means to metric tons CE/acre. The resulting mean increase in carbon emissions from fuel 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 (National Resource Conservation Service, 2009). For carbon emissions, we rely on the global Social Cost of Carbon (SSC), as reported by the United States Government (Interagency Working Group on Social Cost of Greenhouse Gases, 2016). This measure, widely used in policymaking prior to 2017, estimates the social costs of a metric ton of CO_2 released into the atmosphere for each year beginning in 2010. We rely on the reported average SCC estimate at a 3% discount rate, a conservative estimate. As the annual growth in this measure is almost exactly linear, we estimate the SCC for years prior to 2010 by regressing the SCC on a year trend (R^2 = 0.987). These prices are adjusted using the Consumer Price Index to reflect the real value of damages in each year, and range from $22.73 per ton CO_2 in 2000 to $37.51 in 2016.

Table 1.5. Estimated Social and Environmental Damages Resulting from Increased Use of Intensive Tillage in Response to GRWs. Prior to 2007, GRWs had yet to reach impactful levels in any state.

	Social Damages		Environmental Damages	
Year	Current Value [a] (USD)	Present Value [b] (USD 2016)	Soil Erosion [c] (Metric Tons)	Carbon Emissions [d] (Metric Tons CE)
2007	2,200,000	2,800,000	450,000	2,000
2008	5,200,000	6,500,000	1,020,000	4,000
2009	13,800,000	16,900,000	2,730,000	9,000
2010	19,200,000	23,000,000	3,730,000	13,000
2011	32,300,000	37,400,000	6,090,000	21,000
2012	41,600,000	46,800,000	7,650,000	26,000
2013	48,200,000	52,600,000	8,730,000	30,000
2014	61,600,000	65,400,000	11,000,000	38,000
2015	63,800,000	65,700,000	11,400,000	39,000
2016	72,100,000	72,100,000	12,770,000	44,000
Total	359,800,000	389,300,000	65,560,000	226,000

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

Finally, the conservation tillage acre-share differentials computed in the previous subsection are multiplied by the acres planted to soybean in each year (National Agricultural Statistics Service, 2018), providing an annual estimate of the number of acres that would be under conservation tillage in the absence of GRWs, but are instead under conventional practices. The environmental impact and social value coefficients are applied to these acres, providing an estimate for the value of damages to water quality and the climate. Annual social and environmental damages are presented in Table 1.5. Social damages are presented as lost value in current year price levels and as 2016 present value.

In total, we estimate that the net present value of water quality and climate damage from farmer's tillage responses to GRWs in U.S. soybean fields is approximately $390 million, accumulated between 2006 and 2016. This social cost has been growing, exceeding $70 million annually in the latest years 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, while the climate damage will be realized globally. If weed species continue to evolve to resist glyphosate across the country, and farmers continue increase tillage to achieve similar levels of weed control, we expect the rate at which these damages grow to accelerate. Further, this analysis only considers tillage-related water quality damages and the climate effects of increased fuel consumption so it is only a partial accounting of the full environmental damages induced by GRWs. For example, increased fuel consumption and soil disturbance under conventional tillage systems may have localized air quality impacts, while herbicide substitutes for glyphosate may have additional water quality, air quality, and human health impacts.

Conclusion

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

Our approach represents a novel direction in the herbicide resistance literature in two ways. First, we focus on how farmers have changed their management behavior in response to herbicide resistance, while other economic studies focus on how resistance has affected costs, returns, or yields (Livingston et al., 2015; Wechsler et al., 2017; Lambert et al., 2017). Second, we quantify the environmental damages from farmers' responses to herbicide resistance, which would not be possible without our focus on practices. 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 damages from these additional tools, partially accounted for in this paper, imply that weed susceptibility to herbicides is a resource that provides value to not only farmers, but the public as well.

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

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

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

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CHAPTER 2. Measuring the Effects of Pesticide Technology Change on Midwestern Butterfly Populations

Abstract

Changing pesticide use is frequently implicated as a driver of declines in butterfly abundance. Existing empirical evidence of linkages between pesticide use and butterfly abundance is limited to studies that fail to account for the full suite of pesticides used by farmers, which fail to account for the effects of substitute pesticides. In this paper, we bring together data on the use of the six principal pesticide groups on corn and soybean fields and butterfly abundance data to create a unique county-level panel dataset spanning the 60 counties in the American Midwest over 17 years. We estimate count data models of total butterfly abundance and the abundance of three important species to measure the effects of each pesticide group. We find that neonicotinoids, a group of systemic insecticides applied to corn and soybean seeds before planting, have a strong negative association with total butterfly abundance and two of our three indicator species. Further, we find a positive association between the planting *Bacillus thuringiensis* (*Bt)* traited corn seeds and butterfly abundance, though only in counties with large areas of cropland where interaction between butterflies and affected cropland is likely. We estimate that farmers' changes in pesticide use since 1998 has accounted for a 9% decrease in overall butterfly abundance in the median county in our sample, driven by a shift towards neonicotinoid seed treatments since the mid-2000s.

Introduction

Butterfly populations are in decline in the United States and globally. Total butterfly abundance in Ohio declined 33% from 1996 to 2016, a 2% decline per year (Wepprich et al., 2019). The decline observed in the American Midwest is consistent with a 35% global decline in the abundance of lepidoptera, the taxonomic order including both butterflies and moths, from 1970 to 2010 (Dirzo et al., 2014). Declines in butterfly populations also coincide with a 45% decline in insect abundance across all taxa during the same period (Dirzo et al., 2014). Despite ample evidence that butterfly populations are in decline, direct evidence pointing to specific causes remains weak (Belsky & Joshi, 2018; Braak et al., 2018; Fox, 2013).

In this research, we evaluate associations between the decline of butterfly abundance and changes in the levels and types of agricultural pesticides applied and in the American Midwest. Pesticides are agricultural chemicals applied in order to protect crops and include both insecticides which target insect pests and herbicides which target weeds. American farmers apply hundreds of millions of pounds of pesticides every year to protect their crops from pest damage and weed competition (Osteen & Fernandez-Cornejo, 2013). Since the 1980s, pesticides have been sprayed on nearly every field of the most widely grown crops in the Midwest, corn and soybeans, suggesting widespread demand for at least some crop protection (Fernandez-Cornejo et al., 2014).

Historically farmers have always sought to control pest and weed populations, investing heavily in labor-intensive practices to provide even low levels of protection for their crops (Swinton & Van Deynze, 2017). Because crop protection is both a critical and costly component of production, farmers change their crop production practices as new technologies become available seeking improved quality of control and/or lower costs. When synthetic pesticides were first introduced, they were rapidly adopted by farmers as they provided several advantages over status quo crop protection practices (Fernandez-Cornejo et al., 2014; Osteen & Fernandez-Cornejo, 2013; Swinton & Van Deynze, 2017). Pesticide use often reduces profit risk by reducing the risk of catastrophic crop loss, making their use attractive to risk-averse farmers (Horowitz & Lichtenberg, 1994; Pannell, 1991). Pesticide-based crop protection systems are also simpler than alternative practices, which often require a combination of several methods (Bastiaans et al., 2008; Castle et al., 2009; Lechenet et al., 2017). Finally, pesticide-based systems are frequently cheaper and provide better protection than non-chemical alternatives (Osteen & Fernandez-Cornejo, 2013; Swinton & Van Deynze, 2017).

Just as the first pesticides reduced the risk, cost, and complexity of crop production, new pesticide technologies have improved on older systems. Which pesticides farmers use has changed drastically over time as farmers substitute among different products (Fernandez-Cornejo et al., 2014; Osteen & Fernandez-Cornejo, 2013; Perry et al., 2016; Perry & Moschini, 2019; Swinton & Van Deynze, 2017). The latest waves of technological change began in the mid-1990s as genetically engineered seed varieties with herbicide and insect resistant traits were introduced, followed by the introduction of insecticidal seed coatings in the mid-2000s (Douglas & Tooker, 2015; Perry et al., 2016). These technologies allowed for novel pest and weed control systems that provided protection at historically similar levels at lower costs and reduced complexity. Pesticide products associated with these systems were rapidly adopted and the use of other products fell considerably as farmers replaced older technologies (Fernandez-Cornejo et al., 2014; Perry et al., 2016; Perry & Moschini, 2019). We aim in this paper to distinguish between the effects of different pesticide groups on butterfly abundance while accounting for substitution patterns among pesticide technologies.

While pesticides provide clear benefits to farmers, their use is frequently suggested as a driver of declines in butterfly abundance (Agrawal & Inamine, 2018; Belsky & Joshi, 2018; Braak et al., 2018; Thomas, 2016). In order for pollinator populations to be affected by pesticides, they must be exposed to pesticides, either directly or through interaction with environments damaged by pesticides (Sponsler et al., 2019). Butterflies often rely on habitat in close proximity to cropland during different stages of their lifecycles, using vegetation along field edges and in hedgerows for food and shelter (Braak et al., 2018). Butterflies in such areas can potentially be exposed to pesticides by coming into contact with treated crops or plants contaminated inadvertently through spray drift or translocation via water (Braak et al., 2018; Sponsler et al., 2019). While pesticides can move through the environment, proximity of butterfly populations to treated cropland is likely to impact the effects of the pesticide use.

Pesticides represent a diverse class of agrochemicals. There are multiple mechanisms through which pesticides might affect exposed butterfly populations (Sponsler et al., 2019). Insecticides can be applied via sprayer or via chemical seed coatings that are incorporated into the crops tissue upon germination. Sprayed insecticides, used specifically for their acute toxicity to insects, pose a self-evident threat when butterflies are directly exposed to spray or residues. Residues from seed-applied neonicotinoid insecticides persist in the soil and water and can contaminate non-target plants (Douglas et al., 2015; Douglas & Tooker, 2015; Nuyttens et al., 2013). Herbicides are only applied via sprayer and even though they are not known to cause acute harm to insects, they may have indirect effects on butterfly abundance by reducing suitable habitat and forage (Belsky & Joshi, 2018; Pleasants & Oberhauser, 2013).

Empirical evidence directly linking spatial patterns of agricultural pesticide use to butterfly abundance is sparse, and past studies have examined the effects of only a single pesticide active ingredient group at a time (Braak et al., 2018). Saunders et al. (2018) find evidence of a negative association between glyphosate use and monarch abundance in areas of Illinois with heavily concentrated agriculture, though this pattern was only present from 1994 to 2003. Forister et al. (2016) find a negative association between neonicotinoid use and butterfly abundance in Northern California since neonicotinoid pesticides were first approved in 1995. Gilburn et al. (2015) find a similar negative association between neonicotinoid use and butterfly abundance in the United Kingdom.

These papers each examine the effects of a single pesticide active ingredient group (e.g. glyphosate herbicides, neonicotinoid insecticides) at a time. Therefore they cannot assess the relative impact of different pesticides. Changes in the use of specific pesticides are often associated with changes in the use of substitutes which may have their own negative (or positive) associations with butterfly abundance. As a result, the results of the aforementioned papers are of little use for assessing the net effect of contemporaneous changes in the use of multiple pesticides. Expected positive effects of reductions in single pesticides may be overstated if the substitute pesticides are more harmful.

A related branch of research assesses changes in the relative toxicity of pesticides used by farmers over time by applying active-ingredient specific measures of toxicity to insects and other taxa to pesticide application data, creating a kind of ambient toxicity measure. DiBartolomeis et al. (2019) find a 48-fold increase in the average oral insect toxicity to bees of insecticides used in the United States from 1992 to 2014, driven largely by the large increase in the use of neonicotinoids. Perry and Moschini (2019) observe a decrease in ambient insecticide toxicity to bees between 1998 and 2006, attributable to reductions in sprayed insecticide use as farmers adopted *Bt* seed varieties, though this decrease is offset by a neonicotinoid-fueled return to 1998 levels by 2012.

While studies that examine multiple classes of pesticides simultaneously better account for substitution patterns between pesticides, no such studies directly link changes in pesticide use to butterfly abundance. Past studies rely on lab-based acute toxicity measures and cannot account for sub-lethal effects such as reduced fertility, increased predation risk due to behavioral change, or reduced habitat availability (DiBartolomeis et al., 2019). Further, robust toxicity data is unavailable for butterfly species, so applying results from these studies to butterfly populations would require imputation from bee data (Braak et al., 2018).

In this research, we address shortfalls from each of these branches of research by incorporating pesticide use measures for a wide suite of pesticide classes directly into population models of butterfly abundance. By modelling butterfly populations explicitly as a function of pesticide application measures, we capture lethal, sub-lethal, and indirect effects of pesticides on abundance. Our models further allow for the assessment of the relative impact of different classes of pesticides on abundance, allowing for comparisons of impact size and direction between substitutes and across pesticide types. Finally, our models can be used to calculate the net impact of observed changes in pesticide use on butterfly abundance over time in way that accounts for patterns of substitution between pesticide products.

The remainder of this paper is organized as follows. In the next section, we present our conceptual framework, which we use to examine potential linkages between pesticide use and butterfly abundance. We then describe the data used in this research, followed by a description of the statistical methods used to measure pesticide effects on butterfly abundance. Next we present results, before providing a discussion of the findings in context of previous studies of pesticide externalities and policy.

Conceptual Framework

In this section, we present a conceptual framework integrating a model of farmer's pesticide application choices and a model of local butterfly population abundance. By examining the intersections of these two models, we identify two key implications for measuring pesticide effects on butterfly abundance which we will use to motivate the remainder of the paper.

We model farmers as profit maximizers who choose the optimal level of control for pest and weed damage, following a two-step procedure where they first determine the profit-maximizing level of damage control and then choose a combination of damage control technologies (i.e. pesticides) to achieve the optimal level of pest control at the least cost (Lichtenberg & Zilberman, 1986). The types of costs farmers consider when choosing among pesticides include labor and capital costs (Osteen & Fernandez-Cornejo, 2013; Swinton & Van Deynze, 2017), risk (Pannell, 1991), as well as complexity (Castle, Goodell, & Palumbo, 2009). Different combinations of pesticides have different cost levels for each of these types of costs, so farmers must make trade-offs when choosing between different alternatives. These trade-offs depend on characteristics at the farm (e.g. equipment availability, labor availability, acreage farmed, etc.) and regional (e.g. yield potential, pest and weed pressure, etc.) levels. As new technologies become available to a farmer and the suite of available pesticides expands, farmers will respond and adopt these new technologies if they provide sufficient damage control at lower costs.

Farmers' pesticide choices can also create external social costs (Zilberman & Millock, 1997). These social costs include acute and chronic human health effects (Brethour & Weersink, 2001), as well as damage to environmental quality through detrimental effects to non-target plants, insects, and wildlife. Not least of these are butterfly species. Butterflies are herbivores and rely on vegetation for habitat and forage. The degree to which butterfly habitat and forage range intersects with cropland and cropland-adjacent areas varies between butterfly species. Species characteristics such as migratory behavior and dietary diversity (i.e. specialist or generalist) may influence the likelihood that butterflies of that species interact with cropland.

For pesticides to influence butterfly abundance, butterflies must be exposed to pesticides in the environment, either through contact during application, consumption of toxic compounds during foraging, or destruction of potential forage or habitat. The likelihood of such exposure depends on the distance between butterfly habitat and the cropland on which farmers apply pesticides. The effect of distance on pesticide effects will depend both on the tendency of specific butterfly species to forage or inhabit in cropland or cropland-adjacent areas and on the specific pesticides used, which may have different potentials to reach butterflies and remain in the environment (Sponsler et al., 2019).

Our conceptual framework has two key implications for identifying the effects of changes in pesticide use on butterfly abundance. First, farmers substitute between pesticides as new technologies improve on older systems, providing less costly means of achieving the same goal. As a result, increases in the use of one pesticide are frequently associated with decreases in the use of others that achieve the same goal. Such displacement occurs within pesticide classes (i.e. herbicides and insecticides) rather than between. Displaced technologies may themselves influence butterfly abundance, so attempting to measure the effects of one pesticide without accounting for changes in the use of others risks biasing estimates due to omitted variables. Further, measures of the effects of one pesticide without similar measures for the effects of substitutes are of limited policy value, as the damage from one pesticide should be evaluated relative to what will replace it if the full effects of possible regulation are to be accounted for (Zilberman & Millock, 1997).

Second, the effect of a pesticide on butterfly abundance is a function of the distance between butterfly habitat and where the pesticide is applied. This implies an interaction effect between geographic proximity to cropland and cropland pesticide use mediating the effects of the pesticide on butterfly abundance. Additionally, the traits of specific butterfly species may affect the strength of this effect, as differences in foraging and migratory behavior may affect how frequently or closely butterflies interact with cropland.

Data

We bring together data from several sources to construct a unique panel dataset. The unit of observation is a county-year: the base geographic unit in the panel is a county and the base temporal unit is a year. The panel includes observations from 60 counties and 17 years (1998-2014). The annual number of monitored counties ranges from 15 to 37 based on data availability. Figure 2.1 shows the counties included in the panel and the number of years they contribute data.

Butterfly Abundance Data

For butterfly abundance, we use county-year aggregates of monitoring surveys conducted by four volunteer programs associated with the North American Butterfly Monitoring Network.

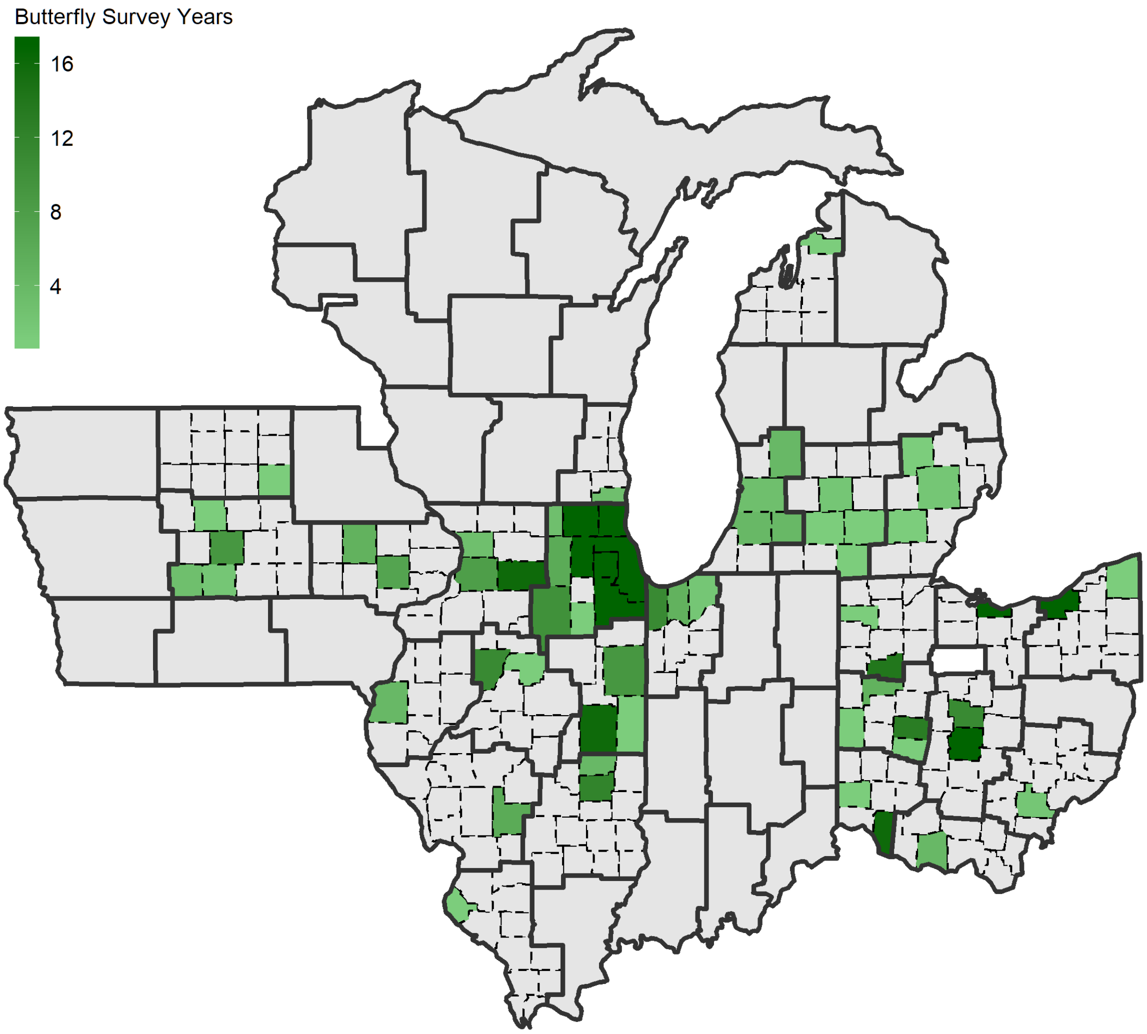

Figure 2.1. Counties Monitored in North American Butterfly Monitoring Network. Crop-reporting district (CRD) boundaries indicated in bold. County boundaries indicated by dashed lines. Grey indicates no monitoring.

Both the Illinois Butterfly Monitoring Network and the Ohio Lepidopterists provide data throughout the period of study, while the Iowa Butterfly Survey Network and Michigan Butterfly Network provide data beginning in 2006 and 2011, respectively. At approximately weekly intervals, citizen-scientist volunteers travelled along a fixed path, counting individuals by species within a 5-meter buffer of the path (Pollard & Yates, 1994). Subsets of these data have been previously analyzed to assess overall butterfly population trends in Ohio (Cayton et al., 2015; Wepprich et al., 2019) and Monarch population trends in Illinois (Saunders et al., 2016, 2018). A brief summary of Pollard survey methods is provided in Appendix B.

Counts by species and in total (across species) are summed across surveys conducted during June through August for each county-year. To better understand how pesticide effects may vary by species, we consider three specific butterfly species: monarchs (*Danaus plexippus*), silver-spotted skippers (*Epargyreus clarus*), and cabbage whites (*Pieris rapae*). These species are selected for specific examination because of they are consistently observed throughout the study region and timeframe.

These three species also exhibit distinct behavioral and lifecycle traits that allow for examination of how such traits might influence vulnerability to specific pesticides. Pollinator traits identified as particularly relevant to pesticide exposure include breadth of diet (i.e. specialist vs. generalist) and range (i.e. migratory vs. resident) (Sponsler et al., 2019). Monarchs are both migratory and host plant specialists. Silver-spotted skippers are residents to the region, host generalists, and are also known to be found feeding in soybean fields as caterpillars. Cabbage whites are residents, though invasive, host generalists, and the most frequently identified species in the data.

Table 2.1 summarizes behavioral traits for each of these three species. Table 2.2 presents the mean count per hour of sampling during four periods to illustrate changes in populations over time. In accordance with recent studies of subsets of the same survey data, we observe declines in the abundance of each of the three species-of-interest and across all species over the period of our sample (Saunders et al., 2018; Wepprich et al., 2019).

Table 2.1. Butterfly Species-of-Interest and Selected Traits.

Species	Breadth of Diet	Mobility	Other Notes
Monarch	Specialist	Migratory	
Silver-Spotted Skipper	Generalist	Non-migratory	Feeds on soybean
Cabbage White	Generalist	Non-migratory	Invasive, most common species

Table 2.2. Butterfly Species-of-Interest Mean Counts per Survey-Hour.

Species	1998-2002	2003-2007	2008-2012	2013-2014
Monarch	2.6	3.6	2.2	1.0
Silver-Spotted Skipper	1.3	1.5	1.3	0.6
Cabbage White	5.1	7.1	5.0	4.8
All Species	53.2	49.3	42.7	34.9

Pesticide Use Data

Pesticide application data was collected via paid phone interviews by Kynetec USA, Inc., a market research company. These data were collected via computer-assisted telephone interviews of soybean and corn growers. Lists of eligible growers were constructed from lists of growers who receive federal payments, membership lists of state and national growers associations, and subscription lists to agricultural periodicals. Sampling lists were constructed to ensure representativeness of applications at the level of the crop reporting district (CRD), USDA-designated groupings of counties in each state with similar geography, climate, and cropping practices. Non-respondents were recontacted at least eight times to reduce non-response error. Respondents were asked to detail their field-level pesticide, tillage, and seed choices during the previous growing season. Respondents were compensated monetarily upon survey completion, and responses were crosschecked against realistic application rates and consistency with other reported practices.

Pesticide use is measured in area-treatments for each pesticide group. Area-treatments are defined as the average number of times a pesticide within a group is applied on a field within a defined region in a season (Kniss, 2017). Area-treatment measures are preferred over volumetric measures because they account for dramatic differences in application rates and associated toxicity between different products (Kniss, 2017; Perry & Moschini, 2019). More precisely, acre-treatments are calculated for each pesticide group as the sum of soybean and corn acres treated on respondent farms within each CRD divided by the total planted acres of soybean and corn in each CRD for each year.

Farmers apply hundreds of distinct pesticide products to soybeans and corn. To simplify our analysis, we identify six groups of pesticides, divided into three classes, herbicides, sprayed insecticides, and systemic insecticides. These groups of pesticides together represent the majority and diversity of pesticide use on these crops. The first class is herbicides, represented by glyphosate, and non-glyphosate herbicides. The second class is sprayed insecticides, which is comprised of pyrethroids and organophosphates. The final class is systemic insecticides, which includes neonicotinoids and *Bt* traited seed. Average area-treatments of each pesticide on soybean and corn fields for CRDs in our sample are presented in Figure 2.2.

Glyphosate and non-glyphosate herbicides represent farmer use of herbicides. Our glyphosate variable measures all applications of herbicides containing glyphosate as an active ingredient, while non-glyphosate herbicides measures all other herbicide applications. Glyphosate is a broad-spectrum herbicide for which soybean and corn seed with genetically engineered resistance has been available since the late 1990s. Such seed increased the flexibility of glyphosate, allowing season-wide protection from any weed. Through the early period of our sample, glyphosate use rose while the use of non-glyphosate herbicides fell as farmers adopted

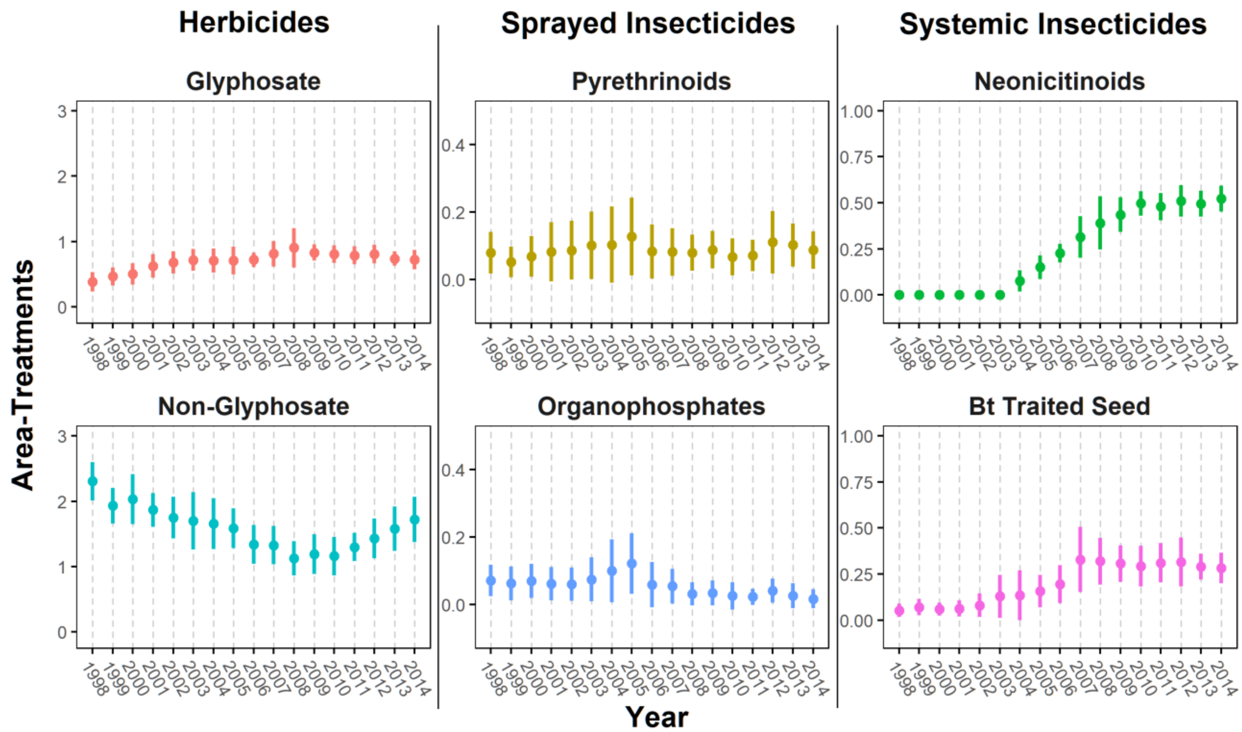

Figure 2.2. Pesticide Use in Sampled Crop-Reporting Districts. Points represent mean acre-treatments for each pesticide group for crop-reporting districts represented in each year. Vertical lines represent one standard deviation above and below the mean.

glyphosate-resistant soybean and corn seed. Since 2008, non-glyphosate herbicide use has risen, likely in response to the spread of glyphosate-resistant weeds.

Pyrethroids and organophosphates constitute the two sprayed insecticide groups as the two insecticide chemistries most frequently applied via broadcast spray. These pesticides represent the two primary sprayed insecticide groups used to control insect pests in corn and soybean (Furlan & Kreutzweiser, 2015). Organophosphate use has declined since 2005 as neonicotinoid seed treatments and *Bt* traited seed has spread, while pyrethroid use has remained steady on average.

The final two pesticide groups, neonicotinoids and *Bt* traited seed, represent the systemic insecticides available to farmers. Systemic insecticides remain present in crop tissue for several weeks post application. When pests feed on crops protected with systemic insecticides, they consume compounds toxic to insects. *Bt* traited seed is genetically modified to produce insecticidal proteins. Such seed has been available only in corn since 1996 and is targeted to European corn borer and, since 2003, corn rootworm and earworm. We observe increasing adoption over the period of our study. Neonicotinoids are most frequently applied via seed treatments in the form of an insecticidal dust coating corn or soybean seed that is taken up by plant tissue as the crop develops. When neonicotinoids are present in plant tissue, they provide protection from a broad spectrum of insect pests. Their use has grown dramatically since their introduction in 2004 in response to the appearance of soybean aphid and demand for additional systemic insecticides to supplement *Bt* traited corn, which target insects were quickly evolving to resist (Douglas & Tooker, 2015).

Land Cover Data

We measure cropland cover as the proportion of land within each county planted to soybeans and corn using the USDA Cropland Data Layer (CDL) (*USDA National Agricultural Statistics Service Cropland Data Layer*, 2019). The CDL has used satellite images to classify land cover into distinct categories at 30m x 30m resolution consistently across the region of study since 2010 with over 90% accuracy for major crops (Lark et al., 2017).

Because of inconsistent data availability from the CDL prior to 2010, we use a time-invariant measure, averaging the proportion of land under soybeans or corn for each county between 2010 and 2014. There is little interannual variability in these measures over this period (Figure 2C.1), so we use the same value for each county across years, assuming the proportion remains roughly constant through the earliest years of the panel. A similar method is used in

Saunders et al. (2018) using Illinois land cover data from the National Land Cover Database over a similar time period. To verify that interannual variability at the county level is not an artifact of the CDL data generating process, we also examine the proportion of total land area planted under soybeans or corn using NASS acreage estimates for the full sample period (Figure 2C.2), where we find a similar pattern of steady cropland cover was also present from 1998 to 2014 for the sampled counties. The cropland variable ranges from 0.00 – 0.85 with a mean of 0.44, representing a broad spectrum of agricultural intensity (Figure 2C.3).

Weather Data

Local weather patterns have been previously shown to affect butterfly distributions, abundances, and the timing of life, though the strength of such associations varies by species and land cover (Cayton et al., 2015; Diamond et al., 2014; Saunders et al., 2016, 2018; Zipkin et al., 2012). To control for potential weather effects on annual butterfly abundance, we generate county-level measures of precipitation and temperature that capture variation between years and within seasons.

Daily weather data was gathered from NASA Daymet, a 1km x 1km spatial grid of daily weather conditions using data from a network of weather stations (Thorton et al., 2018). To aggregate to the county-level, we average daily Daymet data over a 0.2 x 0.2 decimal degree (approximately 10km x 10km) rectangle centered at the centroid of each county. Temperature is measured in growing degree days (GDDs), which measures the number of degrees Celsius within a range in which butterflies can develop (11.5°C to 33°C) (Cayton et al., 2015). Precipitation is measured in millimeters. We partition each season into three intervals: early (March and April), mid (May and June), and late (July and August) season. Daily accumulation of precipitation and

GDD are summed over each interval and the resulting variables measure accumulated precipitation and GDDs for each county during each interval for each year.

Monarchs annual migration brings Midwestern populations through Texas each spring, where GDD and precipitation variation has been found to correlate with summer abundance in Illinois (Saunders et al., 2018). To account for climate factors during Monarchs spring migration, we construct annual measures by calculating average accumulated GDD between March 22 and May 2 and precipitation during February, March, and April over Texas.

Data Analysis

Count Models

We develop a Poisson regression model to estimate expected butterfly counts, for each species-of-interest and in aggregate, in each county-year. For county i located in CRD $c(i)$ in year t, we treat the observed butterfly count (y_{it}) as a Poisson random variable with covariates on the log-link scale.

$$\log(y_{it}) = \beta_0 + \beta_C \cdot crop_i + \boldsymbol{\beta_P} \cdot \boldsymbol{pest_{c(i)t}} + \boldsymbol{\beta_{PC}} \cdot \left(\boldsymbol{pest_{c(i)t}} \cdot crop_i\right) + \boldsymbol{\beta_W} \cdot \boldsymbol{weather_{it}} + \boldsymbol{\beta_i} + \boldsymbol{\beta_t} + \log(minutes_{it}) \qquad (2.1)$$

For covariates, we include the vector of weather variables ($\boldsymbol{weather_{it}}$), cropland cover ($crop_i$), the vector of CRD-level pesticide area-treatments ($\boldsymbol{pest_{c(i)t}}$), and the interactions of pesticide area-treatments and cropland cover ($\boldsymbol{pest_{c(i)t}} \cdot crop_i$). We also include vectors of fixed effects for county ($\boldsymbol{\beta_i}$) and year ($\boldsymbol{\beta_t}$) to control for unmeasured temporally invariant factors within each county and spatially invariant factors within each year (Wooldridge, 2010). Finally, we control for changes in sampling by including the summed duration in minutes of all surveys in each county-year ($minutes_{it}$) as an offset. As a result, the exponentiated dependent variable can be interpreted as the rate of butterflies counted per minute.

For the total abundance, silver-spotted skipper, and cabbage white models, we include only local weather variables. For the monarch models, we estimate an additional specification of the model including Texas spring weather variables as described in the data section to account for climatic variation along the population's spring migration route.

We include the interaction between cropland cover and pesticide area-treatments to provide a more proximate measure of pesticide applications than CRD-level pesticide area-treatments alone. Our measure of cropland cover is measured at the county level for the crops for which we have associated CRD-level pesticide application data (soybean and corn) and distinguishes between counties where soybean and corn dominate the landscape and counties where such land cover is less common. This serves as a proxy for the distance between the habitat and foraging range of the sampled butterfly populations and where pesticides are applied. Including this term identifies how the magnitude, and direction, of the pesticide-abundance relationship varies between counties where butterflies are likely to come into direct contact with fields where pesticides are applied and counties where they are not. Previous studies have made similar use of interaction terms in multiple regression models to identify complex relationships between potential drivers of butterfly abundance, including interactions between temperature and urbanization as well as between glyphosate adoption and cropland cover (Diamond et al., 2014; Saunders et al., 2018).

By including pesticide area-treatments, cropland proportion, and interaction terms, we measure the impact of agriculture on butterfly abundance in three distinct but related ways. The linear pesticide area-treatment terms capture the effects of pesticide use overall. The interaction terms capture how the effects of pesticide use change as the likelihood that butterflies come across cropland varies. Finally, the linear cropland proportion term captures how cropland affects butterfly abundance through mechanisms other than pesticide use.[1]

We obtain quasi-maximum likelihood coefficient estimates via R 3.5.1 (R Core Team, 2018). We compute standard errors for coefficients via sandwich estimators that are robust to violations of the typical assumption used in Poisson regression that the conditional mean equals the conditional variance[2] (Wooldridge, 2010). We assess model fits via McFadden's pseudo R-squared and a likelihood ratio test against the null model with only the fixed effects. We use the robust standard errors to perform z-tests ($\alpha = 0.05$) against the null hypotheses that each coefficient is equal to zero.

Pesticide Effects by Group

To explore the effects of each pesticide group we graphically examine each group's effect on butterfly abundance as implied by our models. We do so by plotting predicted expected counts per hour over the observed ranges of each pesticide variable. To examine the differential impacts of pesticides at different levels of county cropland cover, we plot predictions calculated with the share of county land area planted to corn and soybean set at 0.15 and 0.65, representing the first and third quartiles of the variable, with all other covariates set at their means (Greene,

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[1] Note that by including the interaction term, we are including both the effects of pesticide applications per *cropped* acre at the *CRD* level ($\boldsymbol{\beta_P}$) and the effects of pesticide applications per *total* land acre at the *county* level ($\boldsymbol{\beta_{PC}}$). This is a result of simple unit analysis between the pesticide application measure where units are applications per CRD cropped acre and the cropland measure where units are county cropped acre per county land acre.

[2] Fully robust standard errors are obtained from the square-root of the diagonal of the asymptotic variance matrix estimator for $\hat{\boldsymbol{\beta}}$, given as $\left(\sum_{i=1}^{N} \widehat{\boldsymbol{A}}_i\right)^{-1}\left(\sum_{i=1}^{N} \hat{\boldsymbol{s}}_{\boldsymbol{i}}\, \hat{\boldsymbol{s}}_{\boldsymbol{i}}'\right)\left(\sum_{i=1}^{N} \widehat{\boldsymbol{A}}_i\right)^{-1}$, where $\widehat{\boldsymbol{A}}_i$ is the expected value of the Hessian of the log likelihood for observation i and $\hat{\boldsymbol{s}}_{\boldsymbol{i}}$ is the transposed gradient (i.e. the score).

2010). We include 90% confidence intervals for these predictions, computed using Delta-method standard and the asymptotic variance matrix for the estimated model parameters.

Net Pesticide Effects

To estimate for the cumulative impact of all changes in pesticides over the course the period of study, we compare predictions in expected values between two pesticide use scenarios for each county-year observation in our panel. We compute the difference between predicted population values computed using observed pesticide values ($\hat{y}_{it}$) and predictions computed using pesticide values observed for each county in 1998 ($\hat{y}_{it}^{98}$), the first year of the period of study. With $f(\cdot)$ as the exponentiated right-hand side of Equation (3.1), $\boldsymbol{x_{it}}$ as a vector of all covariates other than $\boldsymbol{pest_{it}}$, and $\widehat{\boldsymbol{\beta}}$ as the vector of estimated coefficients, these predicted values are calculated as:

$$\hat{y}_{it} = f(\boldsymbol{pest_{c(i)t}}, \boldsymbol{x_{it}};\ \widehat{\boldsymbol{\beta}});\text{ and} \qquad (3.2)$$

$$\hat{y}_{it}^{98} = f(\boldsymbol{pest_{c(i),t=1998}}, \boldsymbol{x_{it}};\ \widehat{\boldsymbol{\beta}}). \qquad (3.3)$$

This difference is divided by $\hat{y}_{it}^{98}$ to compute proportional change:

$$\frac{\hat{y}_{it} - \hat{y}_{it}^{98}}{\hat{y}_{it}^{98}}. \qquad (3.4)$$

We estimate Delta-method standard errors for both $\hat{y}_{it}$ and $\hat{y}_{it}^{98}$ using the fully robust asymptotic variance matrix. Using these standard errors, we test the hypothesis H_a: $\hat{y}_{it} < \hat{y}_{it}^{98}$ against the null of no difference using a z-test ($\alpha = 0.05$) to establish when net changes in pesticide use in county i between year t and 1998 have contributed to a statistically significant decline in butterfly abundance.

Results

Poisson model results are presented in Table 2.3. All four models represent a good fit of the data; each model has McFadden's pseudo R-squared statistics exceeding 0.80. For all four models, the addition of explicit covariates for pesticide use, cropland cover, and weather provides a significant improvement over equivalent models with only county and year fixed effects, as evidenced by likelihood ratio tests.

None of the coefficients on local seasonal precipitation and temperature are statistically significant. This result, suggesting that local weather conditions are not consistently linked to local annual abundance, is consistent with a previous analysis of a subset of these butterfly abundance data focused on Illinois monarch populations (Saunders et al., 2018). The cropland coefficient is statistically insignificant in all four models, suggesting that the row crop proportion of county land cover is not consistently associated with butterfly abundance after accounting for variation in pesticide use and other county fixed effects.

For monarch butterflies, spring GDD accumulation and precipitation in Texas is correlated with summer abundance at a statistically significant level, corroborating the findings in Sanders et al. (2018) (Table 2A.1). However, these variables only vary temporally and not over counties in each year. Because the effects of these variables are controlled for equivalently in the base model by including annual fixed effects and their inclusion does not affect the estimates for the pesticide and land cover coefficients, we use the base model to report results for Monarchs.

Our Poisson model estimates include statistically significant coefficients for at least one pesticide group for all three species-of-interest and total abundance. In the total abundance model, coefficients for all pesticide groups except for glyphosate are statistically significant,

Table 2.3. Poisson Models of Butterfly Abundance. Standard errors robust to dispersion assumptions. All models include county and year fixed effects.

Species	Variable	Estimate	Std. Error	z-score	Pr(>|z|)
Total	Intercept	-1.61	0.71	-2.25	**0.025**
	Precipitation, early	0.000083	0.00043	0.19	0.847
	Precipitation, mid	-0.00054	0.00043	-1.27	0.204
	Precipitation, late	0.000013	0.00030	0.04	0.966
	GDD, early	-0.00062	0.00092	-0.67	0.503
	GDD, mid	-0.00007	0.00067	-0.11	0.914
	GDD, late	0.00040	0.00060	0.67	0.503
	Cropland	1.60	1.15	1.39	0.163
	Glyphosate	0.39	0.27	1.46	0.144
	Non-glyphosate	-0.23	0.10	-2.25	**0.024**
	Pyrethroids	0.90	0.38	2.34	**0.019**
	Organophosphate	-2.24	0.60	-3.74	**< 0.001**
	Bt	-1.47	0.54	-2.70	**0.007**
	Neonicotinoids	-1.28	0.48	-2.68	**0.007**
	Cropland X Glyphosate	-0.16	0.86	-0.18	0.856
	Cropland X Non-glyphosate	0.73	0.35	2.09	**0.037**
	Cropland X Pyrethroids	-1.27	1.43	-0.89	0.374
	Cropland X Organophosphate	0.98	2.18	0.45	0.654
	Cropland X Bt	3.18	1.55	2.06	**0.040**
	Cropland X Neonicotinoids	-0.31	0.94	-0.33	0.744
	N	401			
	Pseudo R-squared	0.811			
	Likelihood ratio (vs. f.e.only)	139,793 (Pr(>Chi-squared) < 0.001)			
Monarch	Intercept	-1.71	1.39	-1.23	0.221
	Precipitation, early	-0.000038	0.00088	-0.04	0.965
	Precipitation, mid	0.00083	0.00075	1.10	0.270
	Precipitation, late	0.000494	0.00044	1.11	0.266
	GDD, early	0.00017	0.00186	0.09	0.928
	GDD, mid	-0.00081	0.00137	-0.59	0.553
	GDD, late	0.00074	0.00111	0.67	0.505
	Cropland	-3.80	2.10	-1.81	0.071
	Glyphosate	0.85	0.52	1.63	0.102
	Non-glyphosate	-0.32	0.20	-1.64	0.100
	Pyrethroids	0.72	1.14	0.63	0.530
	Organophosphate	-1.58	1.86	-0.85	0.397
	Bt	-2.09	0.88	-2.36	**0.018**
	Neonicotinoids	-2.09	0.87	-2.41	**0.016**
	Cropland X Glyphosate	-1.49	1.37	-1.09	0.278
	Cropland X Non-glyphosate	0.68	0.43	1.59	0.113
	Cropland X Pyrethroids	-3.86	2.30	-1.68	0.093
	Cropland X Organophosphate	2.23	3.04	0.73	0.463
	Cropland X Bt	7.14	2.10	3.40	**0.001**
	Cropland X Neonicotinoids	-2.83	1.14	-2.49	**0.013**
	N	396			
	Pseudo R-squared	0.829			
	Likelihood ratio (vs. f.e.only)	6,185 (Pr(>Chi-squared) < 0.001)			

Table 2.3 (cont.).

Species	Variable	Estimate	Std. Error	z value	Pr(>|z|)
Silver-Spotted Skipper	Intercept	-4.79	1.56	-3.08	**0.002**
	Precipitation, early	0.000102	0.00118	0.09	0.931
	Precipitation, mid	-0.00134	0.00123	-1.09	0.275
	Precipitation, late	-0.001323	0.00069	-1.93	0.054
	GDD, early	0.00230	0.00153	1.50	0.133
	GDD, mid	-0.00200	0.00129	-1.55	0.121
	GDD, late	0.00048	0.00105	0.46	0.647
	Cropland	0.59	4.23	0.14	0.889
	Glyphosate	1.42	0.65	2.19	**0.028**
	Non-glyphosate	0.95	0.28	3.45	**0.001**
	Pyrethroids	-0.18	1.02	-0.17	0.863
	Organophosphate	-5.04	1.20	-4.19	< **0.001**
	Bt	-0.98	1.48	-0.66	0.509
	Neonicotinoids	-2.82	1.45	-1.94	0.053
	Cropland X Glyphosate	-3.10	1.56	-1.98	**0.047**
	Cropland X Non-glyphosate	-1.91	0.82	-2.34	**0.019**
	Cropland X Pyrethroids	-3.22	3.28	-0.98	0.325
	Cropland X Organophosphate	7.04	3.59	1.96	0.050
	Cropland X Bt	6.08	3.56	1.71	0.088
	Cropland X Neonicotinoids	-2.71	1.95	-1.39	0.165
	N	388			
	Pseudo R-squared	0.865			
	Likelihood ratio (vs. f.e.only)	4,890 (Pr(>Chi-squared) < 0.001)			
Cabbage White	Intercept	-5.73	1.76	-3.26	**0.001**
	Precipitation, early	0.000550	0.00099	0.55	0.580
	Precipitation, mid	-0.00099	0.00079	-1.25	0.210
	Precipitation, late	0.000321	0.00060	0.53	0.593
	GDD, early	-0.00070	0.00274	-0.25	0.799
	GDD, mid	0.00220	0.00143	1.54	0.123
	GDD, late	0.00198	0.00195	1.02	0.310
	Cropland	0.10	2.65	0.04	0.970
	Glyphosate	-0.15	0.62	-0.23	0.815
	Non-glyphosate	-1.25	0.36	-3.48	**0.001**
	Pyrethroids	1.72	1.30	1.32	0.185
	Organophosphate	-4.94	2.15	-2.30	**0.021**
	Bt	-2.11	1.26	-1.67	0.094
	Neonicotinoids	-4.87	1.28	-3.80	< **0.001**
	Cropland X Glyphosate	0.41	1.95	0.21	0.835
	Cropland X Non-glyphosate	2.03	0.56	3.61	< **0.001**
	Cropland X Pyrethroids	-6.99	3.67	-1.91	0.057
	Cropland X Organophosphate	8.76	4.26	2.06	**0.040**
	Cropland X Bt	8.30	3.18	2.61	**0.009**
	Cropland X Neonicotinoids	0.21	1.44	0.15	0.882
	N	387			
	Pseudo R-squared	0.904			
	Likelihood ratio (vs. f.e.only)	21,384 (Pr(>Chi-squared) < 0.001)			

while the cropland interaction coefficient is significant and positive for non-glyphosate herbicides and *Bt* traited seed. The positive interaction terms imply that the relationship between these pest control inputs and total butterfly abundance is more positive in counties where cropland in more common. For the monarch model, neonicotinoids and *Bt* traited seed coefficients are statistically significant, both for coefficients on area-treatments and on cropland interaction terms, but neither herbicide group has a significant effect. By contrast, in the silver-spotted skipper model, both herbicide coefficients are statistically significant for both the area-treatment and cropland interaction terms. Among insecticides, only the organophosphate coefficient is statistically significant. Finally, in the cabbage white model, the non-glyphosate herbicides, organophosphate, and neonicotinoid coefficients are statistically significant, as well as the cropland interaction coefficients for non-glyphosate herbicides, organophosphate, and *Bt* seed. The effects of each pesticide group on total abundance and abundance of each species-of-interest are displayed visually in Figure 2.3.

Many pesticide effects have notable differences between counties with abundant cropland and ones without (Figure 2.3). Non-glyphosate herbicide use is negatively related to total abundance in areas with low amounts of cropland but positively related in areas with high amounts of cropland. Pyrethroids have a positive association with total abundance at low levels of cropland but display no association at higher levels. Both organophosphates and neonicotinoids have strong negative associations with total abundance at both low and high levels of cropland.

For monarchs, neonicotinoid pesticides and *Bt* traited seed, both systemic pesticides, have significant associations with abundance. Neonicotinoids have a strong negative association with monarch populations at both high and low levels of cropland. *Bt* seed adoption has a weak

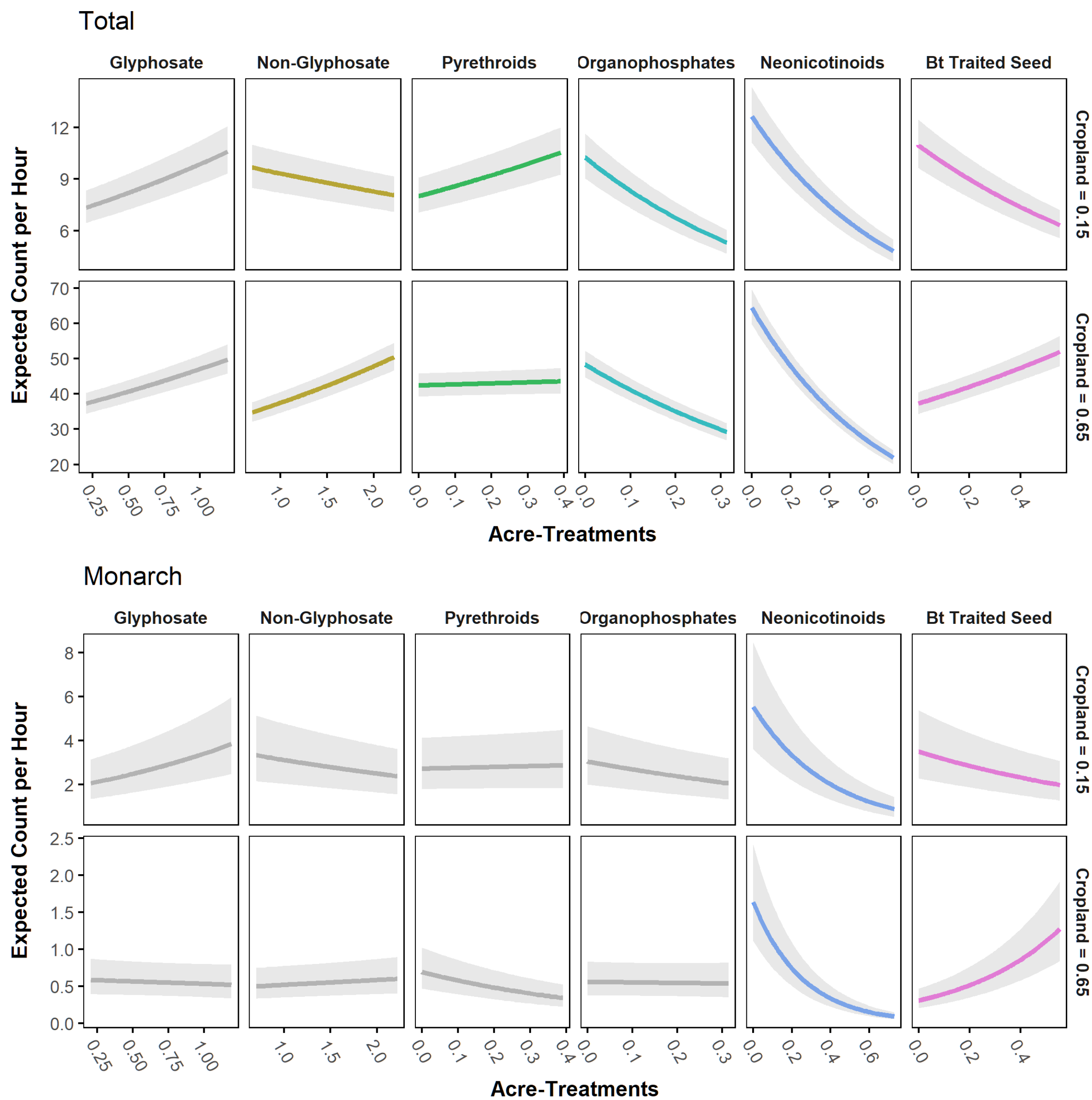
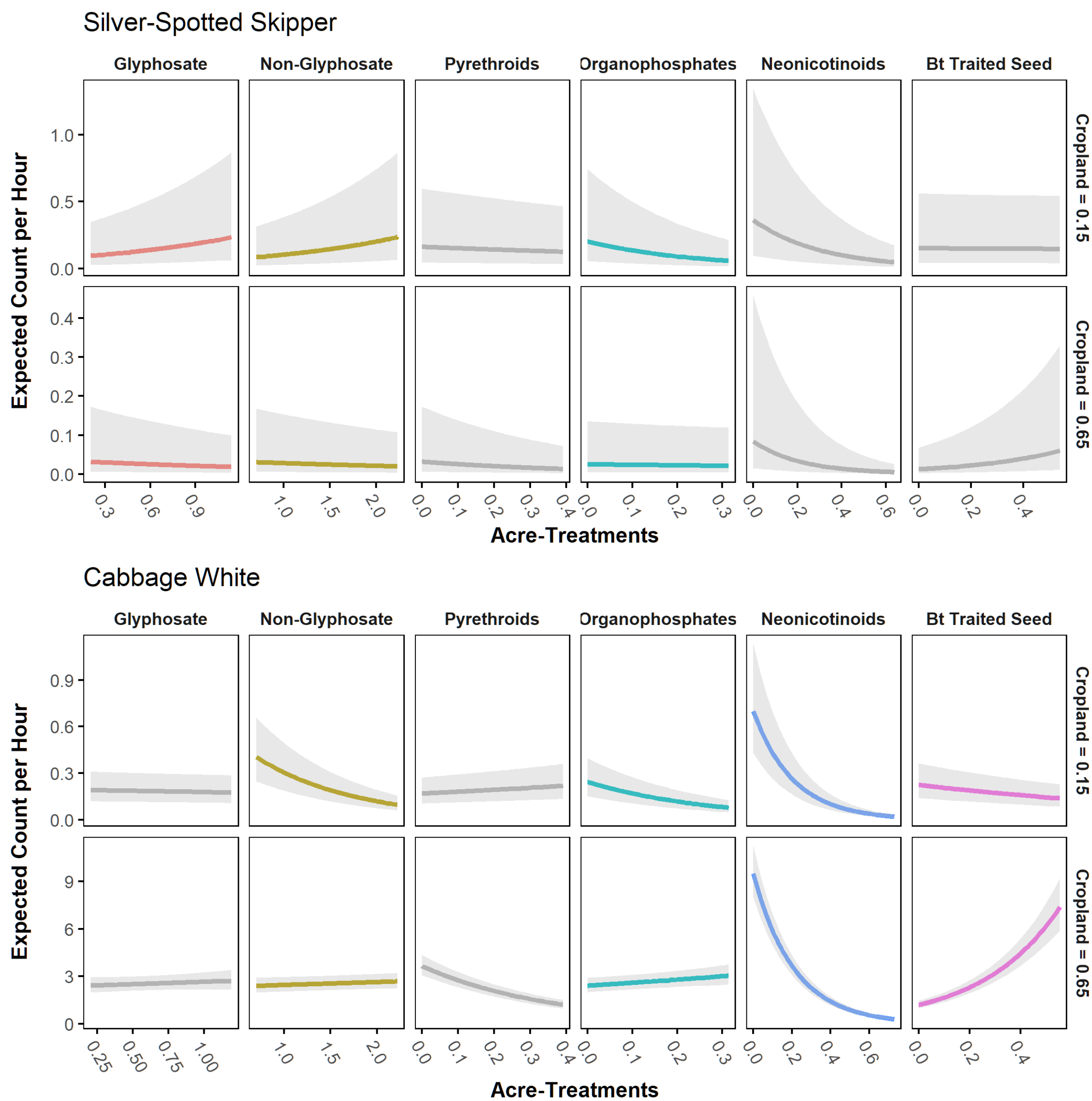


Figure 2.3. Pesticide Effects by Species and Cropland. Expected counts are predicted using Poisson abundance models with methods described in the text. Color indicates either the primary or cropland interaction coefficient is statistically significant ($\alpha = 0.05$) for the given pesticide for the Poisson abundance models.

Figure 2.3 (cont'd).



negative association with monarch populations in counties with low amounts of cropland, but a strong positive association in counties with high amounts of cropland as a result of the cropland interaction coefficients.

Silver-spotted skipper abundance is positively associated with herbicide use, both glyphosate and non-glyphosate products, at low levels of cropland, though slightly, and negatively associated with organophosphate use. We do not find these associations at higher levels of cropland, though silver-spotted skippers are rarely observed in high cropland counties. Cabbage white abundance has a strong negative association with neonicotinoid use at both high and low levels of cropland. Cabbage white abundance is also negatively associated with organophosphate, Bt seed, and non-glyphosate use at low levels of cropland. At high levels of cropland, Bt seed use is positively associated with cabbage white abundance, and the negative associations with non-glyphosate and organophosphate use is no longer detected.

To examine the net effects of substitution between pesticide technologies over time, we compare the predicted values for every observation in the panel to the predicted values for the same observations under a counterfactual pattern of pesticide use where the pesticide use variables are held constant at the levels used in that county in 1998 (Figure 2.4). The net effect of pesticides over time on the abundance of all three species-of-interest, and total abundance, has become increasingly negative over time. Net negative effects are first detected at a statistically significant level in 2003 for silver-spotted skippers, 2004 for monarchs and across all species, and in 2005 for cabbage whites. By 2014, the last year of our panel, over 75% of counties displayed statistically significantly negative net effects from pesticides on silver-spotted skipper, monarch, and total abundance, and 66% of counties display statistically significant net effects on cabbage white abundance.

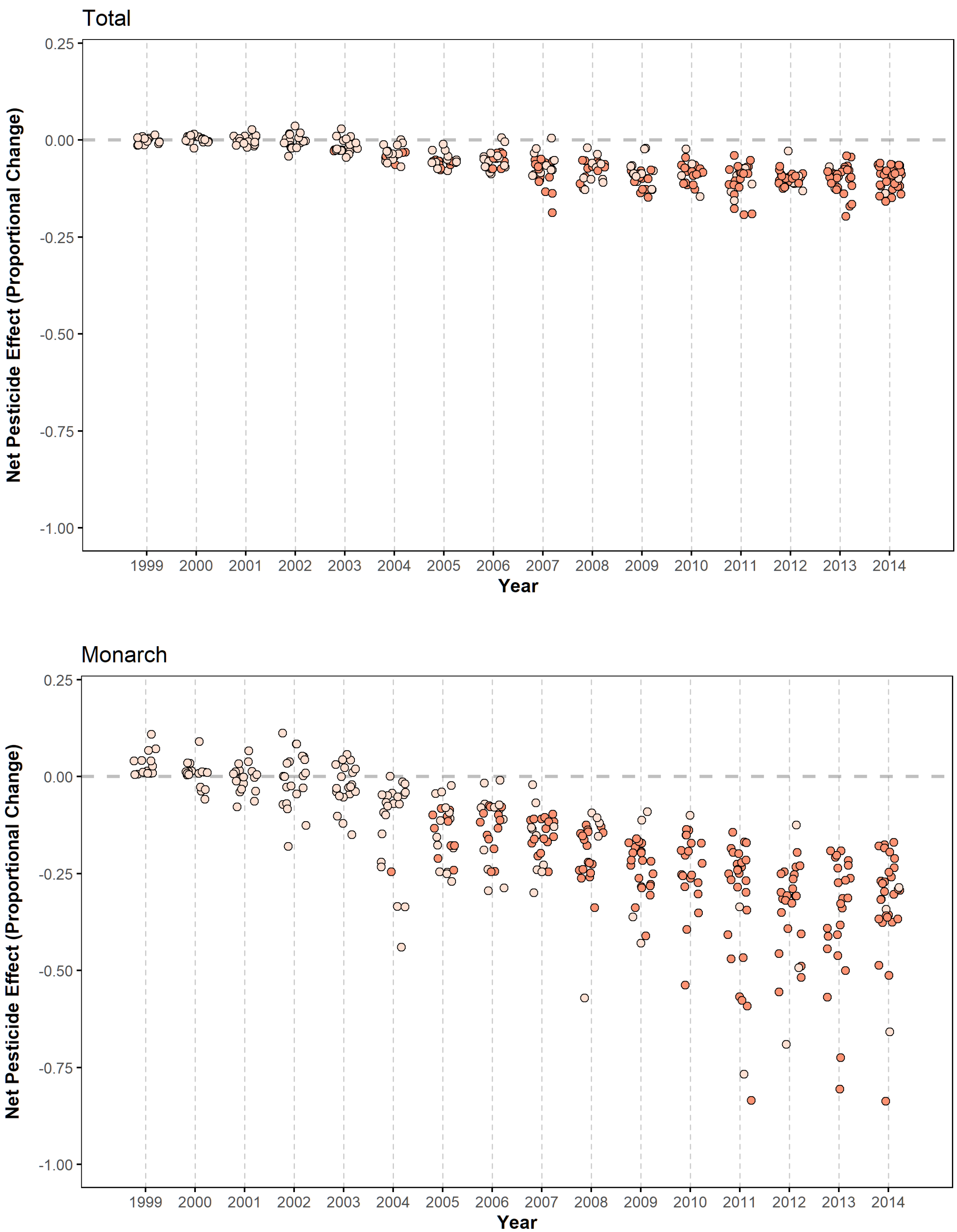
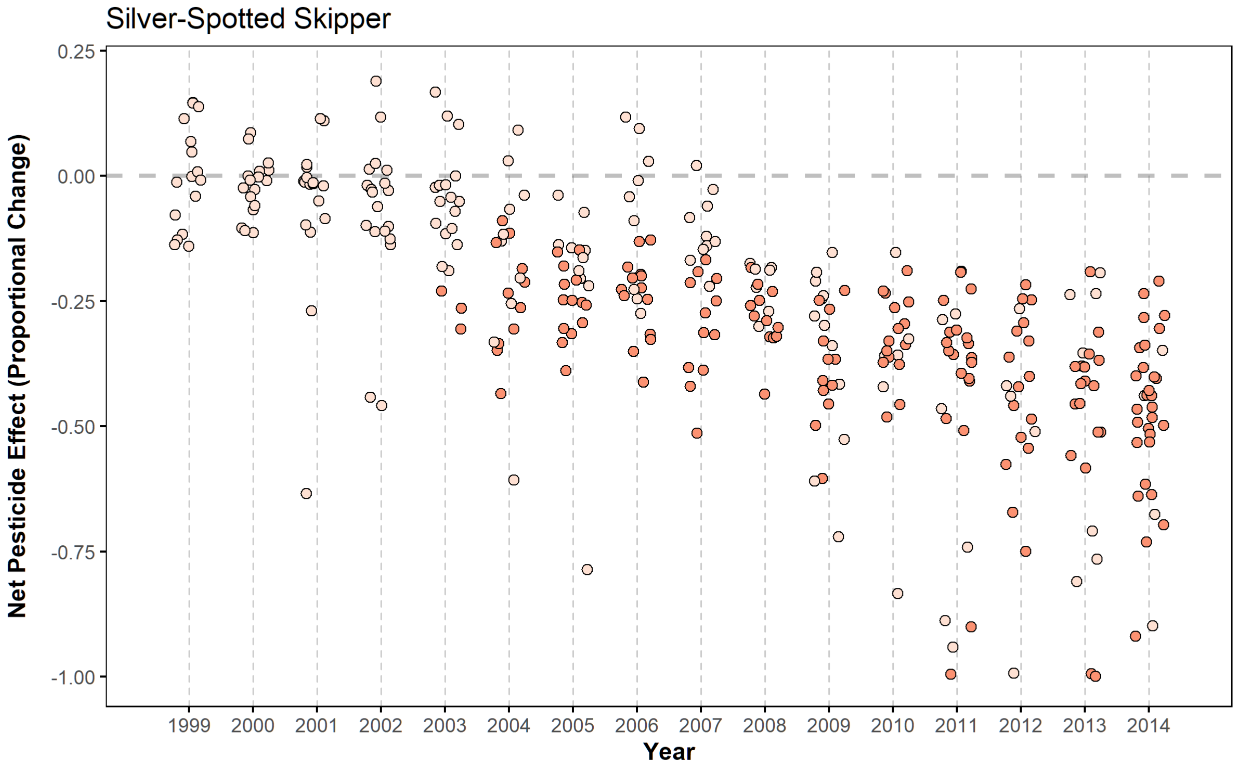
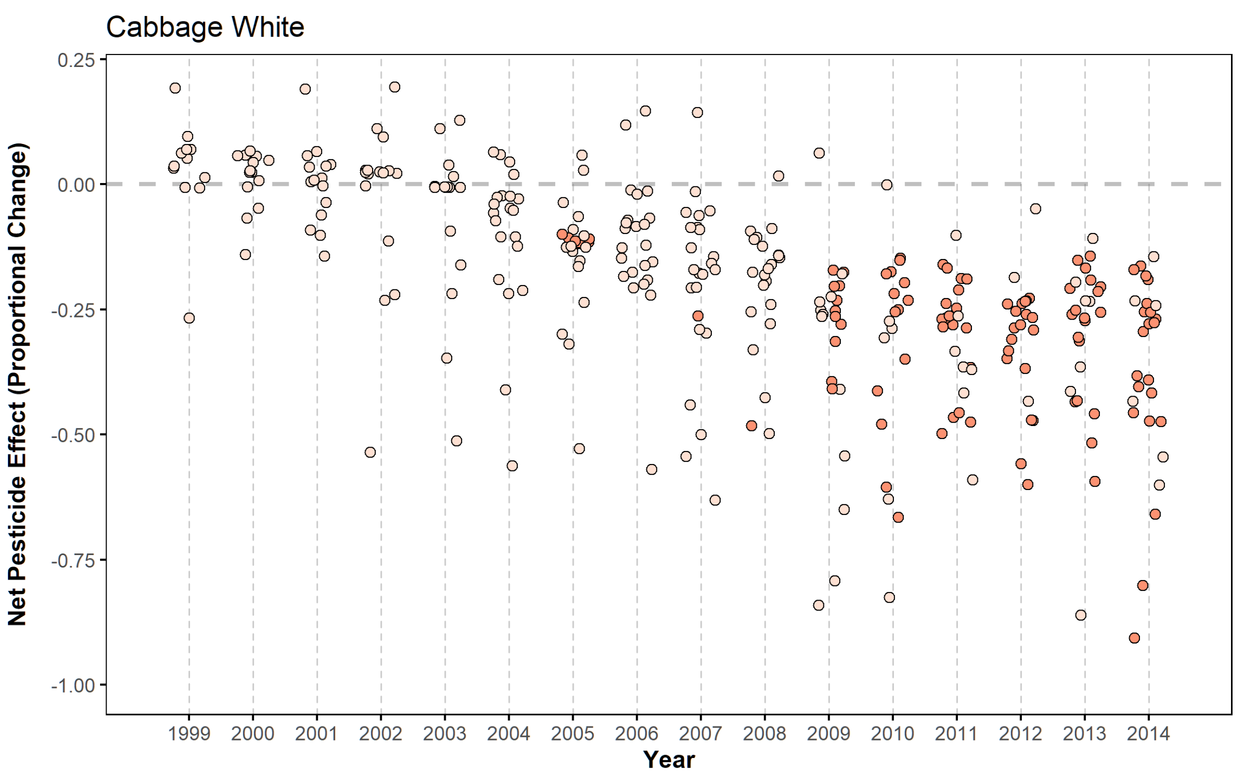


Figure 2.4. Net Pesticide Effect Since 1998 by Species. Red filled dots indicate a statistically significant difference between predicted values fitted with observed pesticide levels and pesticide levels from 1998 ($\alpha = 0.05$).

Figure 2.4 (cont'd).





Changes in pesticide use between 1998 and 2014 account for a 9% decrease in total butterfly abundance in the median county. For monarchs, silver-spotted skippers, and cabbage whites, changes in pesticide use account for median decreases in abundance of 30%, 46%, and 39% respectively.

Discussion and Conclusion

Our results show that neonicotinoid insecticide use is negatively associated with butterfly abundance both across landscape configurations and across species. Neonicotinoids are negatively associated with total abundance and with the abundance of both monarchs and cabbage whites. Silver-spotted skippers show a similar pattern, but the model driving this result is estimated with statistically insignificant parameters (though coefficient on neonicotinoid use is marginally so, with $p = 0.053$). For all four models, neonicotinoids display the largest magnitude effects at both high and low cropland levels.

The finding of a negative association between butterfly abundance and neonicotinoid use is broadly consistent with previous studies. Past studies of regional-level butterfly abundance find a similar negative relationship between abundance and neonicotinoid use in California and the United Kingdom (Forister et al., 2016; Gilburn et al., 2015). These studies examined neonicotinoids but no other pesticide groups; our findings suggest that this result persists even when other pesticides are accounted for. The increase in neonicotinoid use from 2004-2014 coincides with increasingly negative net pesticide effects and largely drives this result, mirroring results in past studies which rely on bee toxicology data (DiBartolomeis et al., 2019).

The negative effect of neonicotinoids stands in stark contrast to the associations between butterfly abundance and *Bt* seed use, the other systemic pesticide option available to farmers. In all four models, *Bt* seed use is positively associated with butterfly abundance in those counties with high levels of cropland, though the parameters driving this result for silver-spotted skippers are noisily estimated. *Bt* adoption is linked to sharp reductions in the use of sprayed insecticides (Osteen & Fernandez-Cornejo, 2013; Perry & Moschini, 2019). It is possible that the positive effect we observe is an indirect effect that results from the adoption of *Bt* decreasing the frequency of application of sprayed insecticides that may be more harmful to butterflies, though one would expect including sprayed insecticide variables as covariates would control for this effect. Another possibility is that *Bt* adoption leads to changes in sprayed insecticide use beyond adjusting the frequency of spraying. One possible mechanism includes changes in the timing of sprayed insecticide application. Changes in the timing of insecticide spraying may lead to applications during periods when butterflies are less vulnerable. Future research could address this hypothesis with data on the precise timing of in-season insecticide applications.

Our results for sprayed insecticides are less conclusive. Organophosphate use is negatively associated with total butterfly abundance, though unassociated with monarch abundance. Pyrethroid use on cropland is positively associated with total abundance in less agricultural landscapes, but this pattern does not hold in more agricultural counties or for any of the three individual species-of-interest. Our findings indicate that pyrethroids are less harmful than organophosphates in all contexts we examine, and so the decreasing use of organophosphates since 2004 has been a boon to butterfly populations, offsetting some of the negative pressure from increased neonicotinoid use.

Our herbicide results suggest that herbicides have little impact on the abundance of any of the species-of-interest and an inconsistent association with total abundance. Most importantly, our results find no impact of herbicide use on monarch abundance. Previous studies have pointed to increased glyphosate use as a driver of monarch decline. Pleasants and Oberhauser (2013) find large declines in both milkweed, the plant species used as a breeding host for monarchs and a weed targeted by corn and soybean farmers, and monarchs between 1999 and 2010. Saunders et al. (2018) find a negative relationship between county-level glyphosate purchases and site-level monarch abundance, particularly in areas where agriculture is most intensive, though only prior to 2005. Our results, which account for changes in glyphosate use as well as contemporaneous changes in the use of other herbicide and pesticides, do not corroborate these past findings and show no link between monarch populations and the use of either glyphosate or non-glyphosate herbicides.

The direction and magnitude of the net pesticide effects we estimate are consistent with observed declines in the abundance of Midwestern butterfly populations reported in the literature. Total butterfly abundance in Ohio declined 33% from 1996 to 2016, and monarch and cabbage white abundance were declining during the same period (Wepprich et al., 2019). Our findings suggest that changes in pesticide use patterns, namely the widespread adoption of neonicotinoid insecticides, can account for at least part of these declines. The net pesticide effect on total butterfly abundance between 1998 and 2014 that we estimate accounts for about a third of magnitude of total decline in abundance over the same period, leaving two-thirds of the decline unexplained.

Understanding the full range of externalities associated with the full suite of pesticide technologies available to farmers is critical to understanding tradeoffs associated with their use and regulation (Zilberman & Millock, 1997). Our results suggest that the use of pesticides, notably neonicotinoids, creates a negative environmental externality by reducing butterfly abundance. By contrast, *Bt* traited seed adoption creates a positive externality through a positive association with butterfly abundance. These findings improve the understanding of the full social costs (and benefits) of pesticides and can be used in evaluating regulations and farmers' incentives.

To prevent further declines in butterfly abundance, farmers may reduce pesticide use voluntarily. Recent studies in France and the United States suggest that pesticide use could be reduced in row crop production without negatively affecting profits for the median farm in each region (Lechenet et al., 2017; Mourtzinis et al., 2019). However, these studies are based on deterministic cost models that do not account for the reductions in risk and complexity that pesticides frequently provide over alternatives. In order to overcome these barriers to reducing pesticide use, farmers may require compensation in the form of a payment-for-environmental-services program. Studies have found that farmers will enter such programs at lower payment rates when farmers believe their participation meaningfully impacts environmental outcomes (Chèze et al., 2020; Ma et al., 2012). The results of the present study can be used to improve farmer knowledge of the non-target effects of pesticide use.

Alternatively, regulatory agencies may consider imposing restrictions on pesticide use. Pesticide externalities, both in terms of butterfly losses and other environmental and health outcomes, vary widely depending on which pesticides are used, where they are used, and how they are used, creating challenges for implementing efficient externality taxes (Zilberman & Millock, 1997). As a result, pesticide regulation typically takes the form of bans on specific technologies.

There is recent precedent for regulating pesticides specifically to protect insect populations. In the European Union, neonicotinoid seed treatments have been banned since 2013 due to concerns about toxicity to pollinators (Auteri et al., 2017). A similar ban in the United

States is predicted to lead to pest management substitutions that decrease pesticide toxicity to bees by 19%, albeit with offsetting increases in toxicity to mammals, fish, and birds (Perry & Moschini, 2019). Our findings here indicate that, like bees, butterflies would benefit from reductions in neonicotinoid use. However, given that farmers would find substitute pesticides, these gains must be balanced against non-butterfly related social costs, including damage to other species and threats to human health, associated with potential substitutes.

APPENDICIES

APPENDIX A: Monarch Results with Texas Weather Controls

Table 2A.1. Poisson Models of Monarch Abundance with Spring Texas Weather Controls. Standard errors robust to dispersion assumptions. All models include county and year fixed effects.

Species	Variable	Estimate	Std. Error	z-score	Pr(>|z|)
Monarch	Intercept	-6.40	3.14	-2.04	**0.041**
	Precipitation, early	-0.000038	0.00088	-0.04	0.965
	Precipitation, mid	0.00083	0.00075	1.10	0.270
	Precipitation, late	0.000494	0.00044	1.11	0.266
	GDD, early	0.00017	0.00186	0.09	0.928
	GDD, mid	-0.00081	0.00137	-0.59	0.553
	GDD, late	0.00074	0.00111	0.67	0.505
	Precipitation, Texas Spring	-0.0221	0.00540	-4.08	**<0.001**
	GDD, Texas Spring	0.0249	0.00713	3.50	**<0.001**
	Cropland	-3.80	2.10	-1.81	0.071
	Glyphosate	0.85	0.52	1.63	0.102
	Non-glyphosate	-0.32	0.20	-1.64	0.100
	Pyrethroids	0.72	1.14	0.63	0.530
	Organophosphate	-1.58	1.86	-0.85	0.397
	Bt	-2.09	0.88	-2.36	**0.018**
	Neonicotinoids	-2.09	0.87	-2.41	**0.016**
	Cropland X Glyphosate	-1.49	1.37	-1.09	0.278
	Cropland X Non-glyphosate	0.68	0.43	1.59	0.113
	Cropland X Pyrethroids	-3.86	2.30	-1.68	0.093
	Cropland X Organophosphate	2.23	3.04	0.73	0.463
	Cropland X Bt	7.14	2.10	3.40	**0.001**
	Cropland X Neonicotinoids	-2.83	1.14	-2.49	**0.013**
	N	396			
	Pseudo R-squared	0.829			
	Likelihood ratio (vs. f.e.only)	6,185 (Pr(>Chi-squared) < 0.001)			

APPENDIX B: Pollard Survey Methods

Each butterfly monitoring network makes use of methods described in Pollard (1977). This method is briefly summarized in this appendix. Routes are designed by volunteers in coordination with network coordinators to (a) transect a variety of habitat types, (b) follow existing pathways so not to disturb habitat, (c) be easily located by other volunteers, and (d) take between 30 minutes to two hours to complete. For each route, a single volunteer walks at a consistent pace along routes (called a “run”) a minimum of six times per year during the months of June, July, and August, with additional runs during these months or others if possible. Runs are conducted between 10:00am and 3:30pm on days with (a) less than 50% cloud cover and (b) light to moderate winds. During the run, the volunteer records all individuals by species sighted within roughly 20 feet to each side of the route. Volunteers are instructed to only identify species with certainty and not to guess.

APPENDIX C: Supplemental Figures

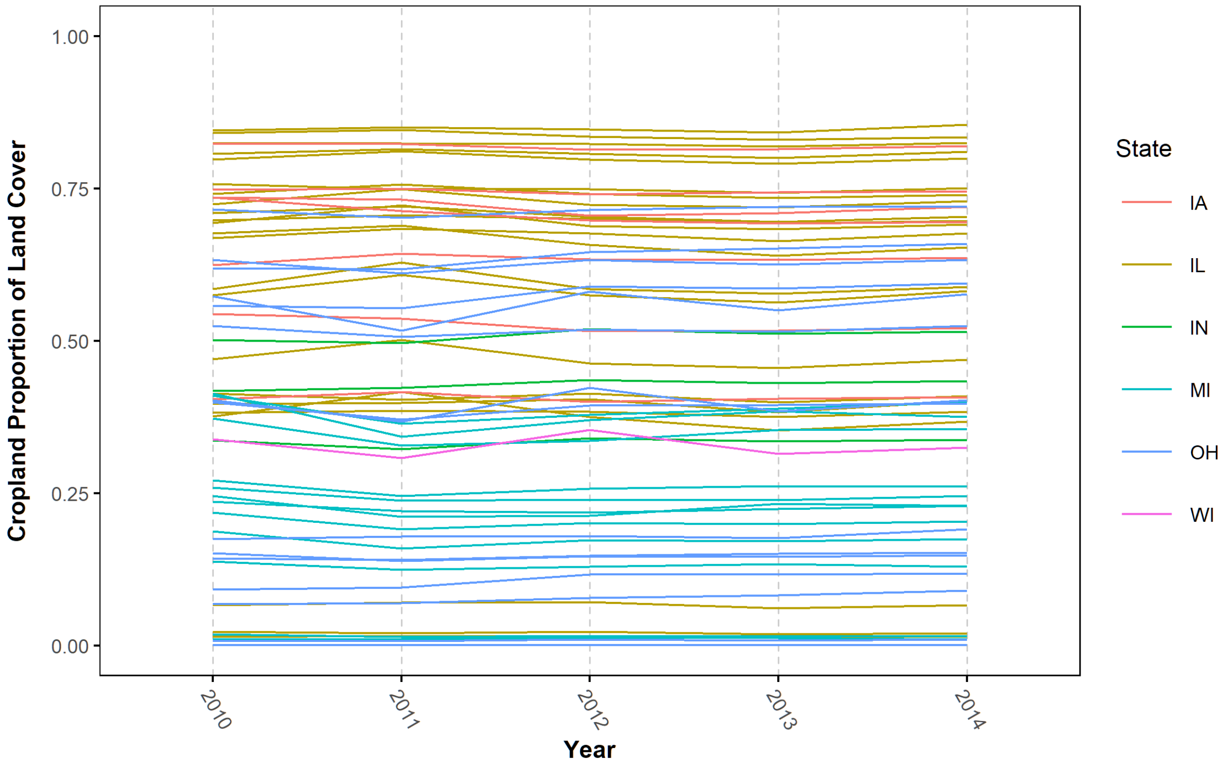


Figure 2C.1. Land Cover Patterns by County (Cropland Data Layer). Each line represents the proportion of a county in the sample classified as corn or soybean over the period with consistent Cropland Data Layer availability.

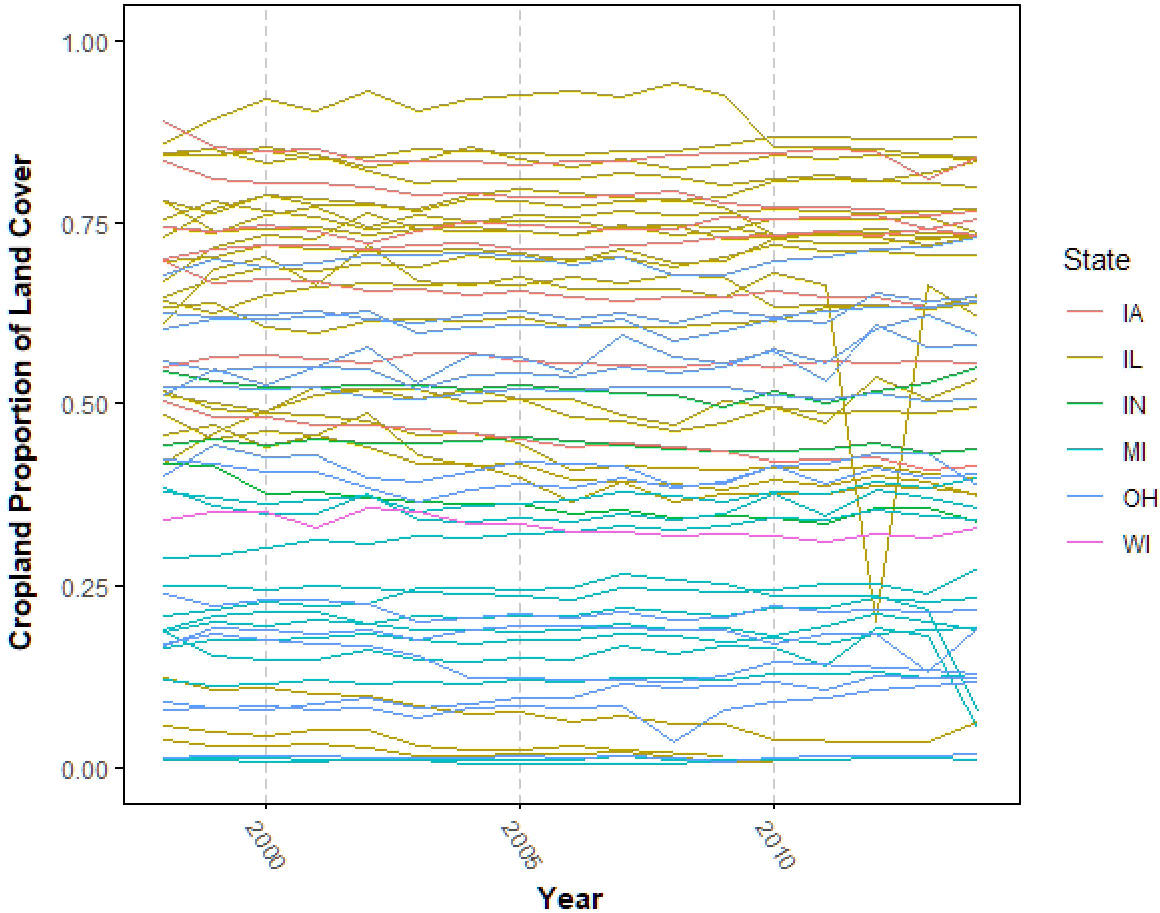


Figure 2C.2. Land Cover Patterns by County (NASS Acreage Estimates). Each line represents the proportion of a county in the sample planted with corn or soybean over the study period. Sudden drops are the result of missing values for either corn or soybean acreage in a given year.

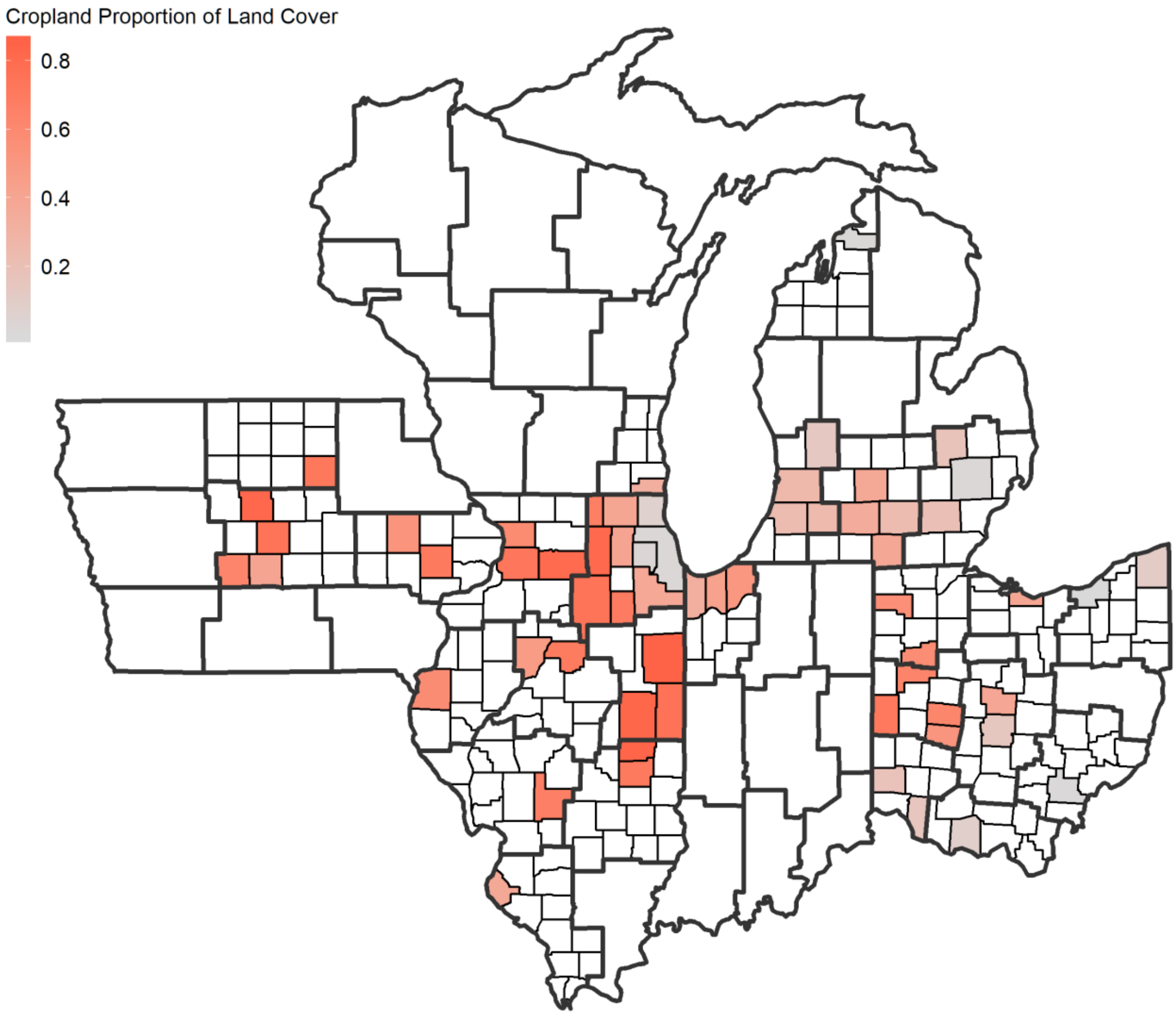


Figure 2C.3. Cropland Variable Geographic Distribution. Crop Reporting District boundaries (CRD) indicated in bold.

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CHAPTER 3. The Value of Timeliness: How Soybean Farmers Choose to Custom Hire for Pest Control

Abstract

Farmers frequently outsource machinery-intensive field operations to custom operators. In doing so, farmers expose themselves to the risk that fieldwork will not be completed in a timely manner, potentially reducing their yields and revenue. Custom hiring occurs even for activities such as pest control, where losses from late spraying can be particularly large. These potential losses, known as timeliness costs, can be exacerbated when contracting, and therefore can be considered a form of transaction costs. This paper develops a farmer choice model of custom hiring for pest control that is rooted in transaction cost theory. Hypotheses derived from this model are then illustrated through a discrete choice experiment conducted via a web survey of soybean growers in Michigan, Illinois, and Indiana. In this pilot study, farmers respond to a hypothetical pest infestation by choosing between custom operators, spraying on their own, or leaving the field to its fate. Our results imply that, among farmers who choose to spray, the mean willingness-to-pay for marginal increases in timeliness (as defined as the chance of late spraying) ranges from 37 to 52 cents per acre. We also find that farmers who are more averse to risk are more sensitive to custom operator timeliness; farmers with better developed social networks are less sensitive to risk of delay. The results of this pilot study can be used to motivate future avenues of research into the drivers of custom hire behavior in pest control and other field operations.

Introduction

Many fieldwork activities necessary to produce field crops (i.e. corn, soybean, wheat) in the Midwestern United States require large, and often expensive, agricultural machinery. While the need for such machinery is ubiquitous, the assignment of property rights over such investments often differs from operation to operation. Some farmers choose to invest in and operate such machinery themselves, while others choose to hire custom operators, who own and operate their own machinery, to complete specific machinery-intensive activities.

Custom hiring is used extensively by farmers across the Midwest, though not universally. Figure 3.1 presents trends for custom work. Between 2007 and 2012, the number of farms in Illinois, Indiana, and Michigan hiring custom for any fieldwork increased 23%, 37%, and 29% respectively (USDA NASS, 2014). Expenditures on custom work rose significantly as well during the same period, increasing by 75%, 104%, and 56% in Illinois, Indiana, and Michigan respectively (USDA NASS, 2014).

The aim of this paper is to examine why some farmers choose to custom hire while others choose ownership: a question of vertical control (Coase, 1937; Klein, 2005). Such questions are frequently studied in the context of transaction costs economics (TCE), which is focused on conditions under which vertical control of multiple stages of production is efficient relative to contracting as means of mitigating costs that emerge from conflicting incentives between contracting parties. Whether contracting or vertical control emerges as the efficient institutional arrangement is often a function of both the transaction and the potential participants in question (Williamson, 1979).

While custom hiring is widespread, the use of custom operators varies widely by production task (e.g. planting, fertilizer application, pesticide application, harvesting). Among

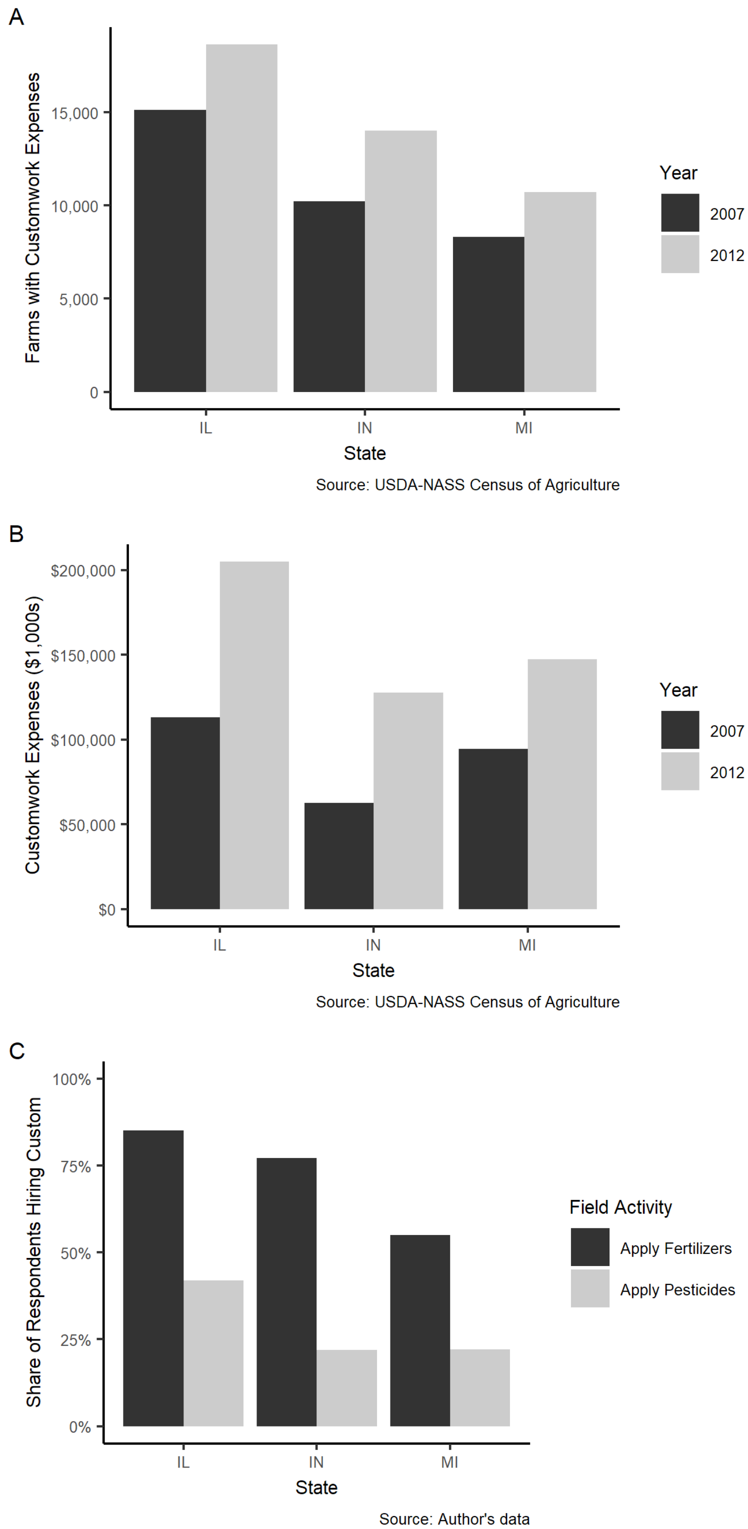


Figure 3.1. Custom Hiring Trends in Three Soybean-Growing States. Author's data collected in 2017 via a mail survey of 1,478 soybean farmers across Illinois, Indiana, and Michigan.

corn and soybean growers in Illinois, Indiana, and Michigan, custom operators are hired to apply fertilizers much more frequently than they are to apply pesticides (author's data). These tasks are distinguished by the degree to which they are vulnerable to unexpected events leading to lapses in work quality or timeliness, which in turn can lead to decreased yields and farm profitability (Allen & Lueck, 2004). The window for effective completion of many field operations (referred to as "field days") can be unexpectedly limited by adverse weather (Apland, 1993). For pest control in particular, the window for applying insecticides to is particularly stochastic, as insect pest populations, such as soybean aphid (*Aphis glycines*), can arrive unexpectedly and grow exponentially if left untreated (Johnson et al., 2009a; Ragsdale, Voegtlin, & O'Neil, 2004). Further, the degree of yield loss if pest control is not completed in a timely manner can be catastrophic, leading to potential soybean yield losses of as much as 50% (Johnson et al., 2009).

From the perspective of the farmer, choosing custom contracting over vertical control adds another layer of uncertainty, as the completion of the task is dependent on the actions of another agent under imperfect observability. Because pest control is especially vulnerable to field day stochasticity and the penalties for lapses in timeliness are so extreme, pest control is an attractive task through which to examine the decision to hire custom operators.

Previous research has examined drivers of farmer choices to contract at either end of the production cycle. Some studies focus on the choice to access different marketing channels and the characteristics of contracts that govern them (Davis & Gillespie, 2007; Dorward, 2001; Franken, Pennings, & Garcia, 2009; Hobbs, 1997; Hudson & Lusk, 2004; Hueth, Ligon, Wolf, & Wu, 1999; Royer, 2011). Others focus on the control of property rights and contracting characteristics for arable land (Allen & Lueck, 1992, 1992, 1993). These studies model the choice to contract or among contracts as functions of drivers of transaction costs, or the presence of factors that mitigate them. Such studies typically find support for the hypothesis that the contracts or organizational structures that minimize transaction costs are ultimately selected, confirming the central hypothesis of transaction cost economics.

Both uncertainty and the value of the asset subject to uncertainty are cited as drivers of transaction costs, creating frictions that prevent efficient contracting (Williamson, 1979). In this paper, we examine the role of uncertainty in driving transaction costs in pest control, which we expect can explain the relatively low rate of custom hiring (i.e. contracting) for this field operation. In the following section, we build a conceptual model for custom hiring in pest control based around uncertainty and the probability a custom operator provides timely service. Beyond examining the role of uncertainty in increasing transaction costs, we also examine the role of social capital in mitigating such costs by providing information networks and reputational punishment mechanisms to distinguish between trustworthy and untrustworthy custom operators (Williamson, 1993; Wilson, 2000).

In the third section, we describe a choice experiment conducted with farmers in Michigan, Indiana, and Illinois designed to illustrate the implications of our conceptual model. In the fourth section, we describe our empirical strategy for analyzing the choice experiment data, followed by results. We close with a discussion of our findings in the context of our hypotheses and broader transaction costs literature, and implications for the future of custom hiring in pest control and other activities.

Conceptual Model

In this section, we first describe a simple choice model in which a farmer faces an acute pest infestation and chooses among three possible responses: (1) spraying with their own equipment, (2) hiring a custom operator to spray for them, or (3) not spraying at all. We then elaborate on the model with transaction costs theory and expected utility theory to motivate hypotheses as to what factors drive farmers' custom hiring decisions for pest control. These models provide insight into the tradeoffs involved in custom hiring for pest control and the characteristics of farmers who might be more likely to custom hire.

In what follows, we assume for simplicity that the farmer's pest control decision is separable from the rest of their production activities. All production costs not related to pest control are assumed to be unaffected by the farmer's pest control decisions and are therefore omitted from the analysis.

Base Model

To begin, assume a profit maximizing farmer with one field growing a generic crop. The field has yield potential of Y (assumed to be certain for simplicity) which sells at a price we set to one as the numeraire. The farmer's field is infested with a generic insect pest. If sprayed with the appropriate insecticide on time, the pest infestation does no yield damage. If the insecticide is applied late, the pest inflicts damage $d \in (0, 1]$ as a proportion of the field's yield potential Y.

The farmer chooses a response $a \in A = \{self, custom, nospray\}$, where $self$ represents the ownership option in which the farmer sprays with their own sprayer, $custom$ represents the custom hiring option, and $nospray$ represents the option to not spray at all and accept all damages. Each alternative has an associated profit π_a, where c_a is the alternative-specific cost of pest control and Y_a is yield realized when option a is selected:

$$\pi_a = Y_a - c_a \qquad (3.1)$$

For now, we assume that choosing either $self$ or $custom$ will lead to on-time treatment with certainty, and so $Y_{self} = Y_{custom} = Y$ and no damage occurs. When $nospray$ is selected yield damage is realized and no costs associated with spraying are accrued, so $\pi_{nospray} = (1 - d)Y$. For the remainder of the analysis, we will focus on differences between $self$ and $custom$, though it should be noted that for values of d close to zero and spraying costs sufficiently high, spraying will not occur, consistent with the concept of an economic damage threshold (Ragsdale et al., 2018).

It is clear in the above model that the crucial differences between spraying options is the alternative-specific cost of treatment, c_a. These costs are given as:

$$c_{self} = chem + labor + equip; \qquad (3.2)$$

$$c_{custom} = chem + fee. \qquad (3.3)$$

In Equation (3.2) and Equation (3.3), insecticides chemical costs, labelled as $chem$, are incurred under both alternatives and therefore ignored in the comparative analysis.

When $self$ is chosen, additional costs incurred include $labor$, the wages (or equivalently opportunity cost of time) of the farmer applying the chemicals, and $equip$, the cost of owning and operating the sprayer. Equipment costs embody fuel, maintenance, and depreciation, as well as any costs involved with procuring a sprayer if one is not readily available such as search costs or rent. Because the farmer’s window of time to react to the infestation is limited, these procurement costs can be prohibitively high if a farmer has not made prior arrangements via long-term rental or ownership of a sprayer. For $custom$, the only additional cost is fee, the amount paid to the operator in return for services.

This simple cost comparison leads to three proposed hypotheses:

H1: When on-farm labor is more costly, custom hiring is more likely.

H2: When a farmer owns their own sprayer, custom hiring is less likely.

H3: When a custom operator charges a higher fee, they are less likely to be hired.

Transaction and Timeliness Costs

A farmer's decision to custom hire has clear parallels to a traditional firm's choice between producing its own inputs or procuring them via contracting with another firm. Referred to as the make-or-buy decision, this topic is frequently examined in the transaction costs economics (TCE) literature (Coase, 1937; Klein, Crawford, & Alchian, 1978; Klein, 2005; Shelanski & Klein, 1995; Williamson, 1979). In the custom pest control context, the input is the application of insecticides on a specific insect-infested field. The farmer chooses between spraying with their own equipment (the vertical integration option) and hiring a custom operator (the contracting option).

The key insights of TCE are (a) that transactions require costly governance; (b) that these costs, referred to as transaction costs, vary among alternative governance structures depending upon the characteristics of the activity or asset exchanged and the identities of the trading partners; and (c) that firms will utilize governance structures that minimize such transaction costs (Shelanski & Klein, 1995). Transactions vary in many ways, but TCE studies have identified two transaction characteristics as especially important: asset specificity and uncertainty (Klein, 2005).

Asset specificity is typically defined as the degree to which investment in assets or actions are specific to the transaction and therefore cannot be recovered should the transaction fall through. Uncertainty in this case relates to the value of said assets or actions and the behavior of trading partners (Klein, 2005). Asset specificity and uncertainty can create circumstances for trading partners to act opportunistically (Klein, 2005). Governance structures (e.g. contracts, markets, or vertical integration) can mitigate the incentives to do so, though such structures often create additional administrative costs (e.g. monitoring, enforcement, etc.) (Klein, 2005).

Asset specificity can manifest itself temporally, especially for pesticide application. Once an economically significant pest infestation is recognized, there often exists a critical period during which the infestation can be treated before risking significant yield loss. The value of these losses due to late treatment are referred to as timeliness costs (Allen & Lueck, 2004). However, the exact dates during the growing season when pests will approach economically damaging levels, or whether a pest infestation will occur at all, is impossible to know *a priori* (Johnson et al., 2009). Typically, farmers must choose whether they will spray on their own or hire a custom operator before such uncertainty is resolved.

When custom hiring, a farmer forfeits control over when and where the sprayer is used, which can increase the likelihood of delays in treatment, amplifying potential timeliness costs (Allen & Lueck, 2004). A farmer who owns and operates their own sprayer can more readily apply pesticides precisely when and where they are needed once uncertainty regarding a potential pest infestation is resolved. The custom operator may have other customers with pest infestations simultaneously occurring and must choose whose field to treat first. Random occurrences that would lead to delays even if the farmer chose to spray on their own, like unexpected weather, are amplified if they chose to custom hire as they further increase the likelihood of overburdening the custom operator. Because of the high degree of uncertainty, limited optimal treatment window, and large potential yield losses surrounding pest control, timeliness costs have the potential to be sizable.

We include timeliness costs into the model by introducing uncertainty, from the perspective of the farmer, over whether pest control will be completed within the optimal window. Rather than assuming each Y_a is certain, instead now assume that each Y_a is a binary random variable with support $\{Y, (1-d)Y\}$, the full yield when spraying occurs within the optimal window and the damaged yield when late spraying occurs. Let $p_a$be the alternative-specific probability that treatment is delayed from the perspective of the farmer, so that

$$E(Y_a) = (1-p_a)Y + p_a[(1-d)Y] = (1-p_a d)Y. \qquad (3.4)$$

Assuming all other variables are known with certainty, then

$$E(\pi_a) = (1-p_a d)Y - c_a. \qquad (3.5)$$

Under assumptions of expected-profit maximization, the farmer chooses the alternative that maximizes Equation (3.5). Assume for simplicity that $p_{self} = 0$ and $p_{nospray} = 1$. For $p_{nospray}$, this assumption is trivial because there is no chance of damage avoidance if no spraying occurs, so the application is late by definition. For p_{self}, this assumption is equivalent to assuming that the spray will always occur on time if farmer is doing so themselves.[1]

The probability of on-time pest control for custom operators, p_{custom}, is more complex. From the perspective of the farmer, the probability that a custom operator sprays on time is related to the concept of trust. Bhattacharya et al. (1998) propose a formal definition of trust expressed verbally as "an expectancy of positive (or nonnegative) outcomes that one can receive based on the expected action of another party in an interaction characterized by uncertainty." In this model of trust, agents hold "conjectures" about other agents, defined as the probability from the agent's perspective that other agents will complete specific actions (Bhattacharya et al.,

[1] Equivalently, the problem be scaled so that p_{self} is the baseline probability and custom operators are compared to that baseline. Then the assumption becomes that all relevant external drivers such as weather influence p_{self} no more than they do p_{custom} so that all additional uncertainty can be attributed to the custom operator.

1998). In the above model, p_{custom} serve as conjectures in the Bhattacharya et al. sense. Bhattacharya et al. do not hypothesize as to how conjectures are formed. At this stage, we will assume simply that conjectures exist; factors supporting favorable or unfavorable conjectures will be discussed later in this section.

With timeliness costs included in the model as above, it is clear that farmers will be less likely to choose a custom operator when p_{custom} is closer to one, all else equal. Further, d, the damage suffered when spraying is late, now appears in the $E(\pi_a)$ function, Equation (3.5). Each alternative is associated with a $p_a dY$ term, which we define as "expected damage," and when timeliness costs are larger, the alternative becomes less attractive to the farmer. Timeliness costs are composed of the probability of delay, the damage from delay, and the yield potential. We propose the following hypotheses:

H4: When the the damage from delay is higher (i.e. dY is larger), custom operators are less likely to be hired.

H5: When the probability a custom operator is delayed in spraying is higher (i.e. p_{custom} is closer to one), that custom operator is less likely to be hired.

Risk Aversion

In the development of the preceding model, the farmer is assumed to be risk neutral and would be indifferent between two alternatives: an alternative with a pre-determined profit and one with multiple possible outcomes but the same profit in expectation. In this modification of the model, we allow for a more general case where farmers may be risk averse, preferring non-stochastic options to stochastic alternatives with equivalent expected profit. Rather than assuming that farmers maximize expected profit, we instead assume farmers choose the response to potential pest infestation which maximizes their expected utility, u, a function of profit conditioned by a risk attitude parameter r, where larger values indicate more aversion towards risk. Each custom operator can be thought of as a lottery, with payoffs Y and $(1-d)Y$ and conjectures about the reliability of the custom operator serving as probabilities of each outcome Not spraying and spraying on one's own are essentially degenerative lotteries. Costs c_a serve as the price of each lottery. For each alternative, the expected utility is then represented as:

$$u_a = u(Y, d, c_a, p_a; r). \qquad (3.6)$$

By including risk attitude parameter r, we allow for a variety of possible behavioral theories, including the curvature of the utility function (Von Neumann & Morgenstern, 1944), loss aversion and probability weighting schemes (Tversky & Kahneman, 1992), and models that do not rely on weighted averages of outcomes and allow uncertainty to directly affect utility (Gneezy, List, & Wu, 2006). If some farmers are more averse to risk than others, then this should be reflected in their custom hiring decisions, and farmers who are more risk averse will be less likely to select risky options. This constitutes our sixth hypothesis:

H6: More risk averse farmers (i.e. r is larger) are more sensitive to potential delays in spraying.

Conjectures and Social Capital

Because a farmer's conjecture about a custom operator is ultimately subjective, it can be viewed as a function of not just the relationship between the farmer and the operator themselves, but also other circumstances surrounding the relationship relevant to the decision in question. In this section, we draw on social capital theory to form an additional hypothesis as to what factors drive custom hiring decisions.

Social capital theory proposes that social institutions and relationships between people can be viewed as productive assets (Schmid & Robison, 1995). Personal relationships and social networks can reduce transaction costs by easing the flow of information and establishing informal punishment systems for those who violate norms (Schmid & Robison, 1995). For example, empirical research analyzing over 3,000 cropland rental contracts, both formal and informal, from Nebraska and South Dakota finds evidence supporting reputational enforcement mechanisms in which farmers with more developed social networks are more likely to participate in informal (i.e. unwritten) contracts (Allen & Lueck, 1992b).

In the context of custom pest control, a similar social capital mechanism may exist. Farmers who consistently communicate with many other farmers can both rely on other farmers for additional information about the custom operator's reliability and easily spread news of late spraying by a specific operator. Therefore, the probability that a custom operator delays pesticide application, p_{custom}, may depend on the social network of the farmer who is contracting for the work. To capture this possible effect, we present p_{custom} as a function of a farmer's social capital, represented as $social$:

$$p_{custom} = p_{custom}(social). \qquad (3.7)$$

When farmers have more social capital, they can rely on these networks to punish custom operators who provide late service by damaging their reputation among potential customers. All else equal, such punishment introduces additional costs to the operator for spraying late. Therefore, from the perspective of the farmer, any given operator is less likely to provide late service, and farmers are likely to weight probabilities of delay downward (i.e. $\frac{dp_{custom}}{dsocial} < 0$). This leads to the following proposed hypothesis:

H7: When a farmer has a more developed social network, they are less sensitive to potential delays in spraying by custom operators.

Choice Experiment and Survey

As an illustration of the implications of the custom hire model presented above (i.e. hypotheses H1-H7), we deployed a discrete choice experiment. A choice experiment allows the researcher to gather choice data on important decisions even when they occur infrequently and allows the researcher to observe the full choice set because the choice set is designed by the researcher themselves (Hensher, Rose, & Greene, 2015). We deployed the choice experiment described below as a pilot study to motivate future, in-depth analysis of the potential roles transaction cost drivers play in the decision to custom hire. While the choice experiment presented in this study does not definitively test hypotheses H1-H7, it does provide initial data on which of the hypotheses may be most promising for further analysis.

Experimental Design

In this choice experiment, farmers were asked to imagine that their largest soybean field is infested by a generic, unspecified insect pest. The characteristics described for the hypothetical pest were similar to soybean aphid, though the species was not mentioned by name. We utilized soybean as a model crop because soybean farmers are likely to have recent experiences with acute pest infestations during the spread of soybean aphid in the mid-2000's. Farmers were presented with the option of hiring one of three custom operators to spray, spraying themselves with their own equipment, or not spraying at all.

Farmers were presented with chemical spraying costs (in dollars per acre) and expected soybean price (in dollars per bushel). These attributes remained fixed for all farmers through all choice scenarios. Farmers were told that they would be responsible for chemical costs in all spraying options (as is typical in custom pesticide application contracts) and instructed to assume that all custom options are available even if those specific options are not present in their area. The soybean price and chemical cost values were selected such that spraying dominates not spraying for a profit-maximizing, risk-neutral farmer in the scenario with the lowest yields and the highest damage. The focus of this design, therefore, is on the choice of who sprays, though the option to not spray and allowing damage to occur remains.

Respondents each completed eight choice scenarios. Each scenario included a specific expected pest damage attribute, which referred to the portion of yield lost to insect damage if spraying occurs after a three-day window. This attribute is the d variable in the conceptual model.

Within each scenario, each custom operator option was presented as one of the following: an agricultural cooperative (or "co-op"), an agricultural input dealer (or "dealer"), or another farmer. These three classes of custom operators represent the most common providers of custom pest control services. All three options were presented in each choice scenario, along with a "spray myself" option, where the farmer would treat the field with their own equipment and labor, and a "do not spray" option, where the farmer would leave the field to its fate and damage would be guaranteed. Each of the custom choices had an associated custom fee, presented as a dollar per acre fee paid to the operator, and a percent chance of a three-day delay, representing the probability that the pest damage occurs due to late spraying (p_a). Fee levels were based on the range of custom spraying rates reported in extension survey reports from Ohio, Michigan, Illinois, Iowa, and Indiana. Levels for each variable included in the choice experiment are presented in Table 3.1. An example of a choice scenario as seen within the survey is presented in Figure 3.2.

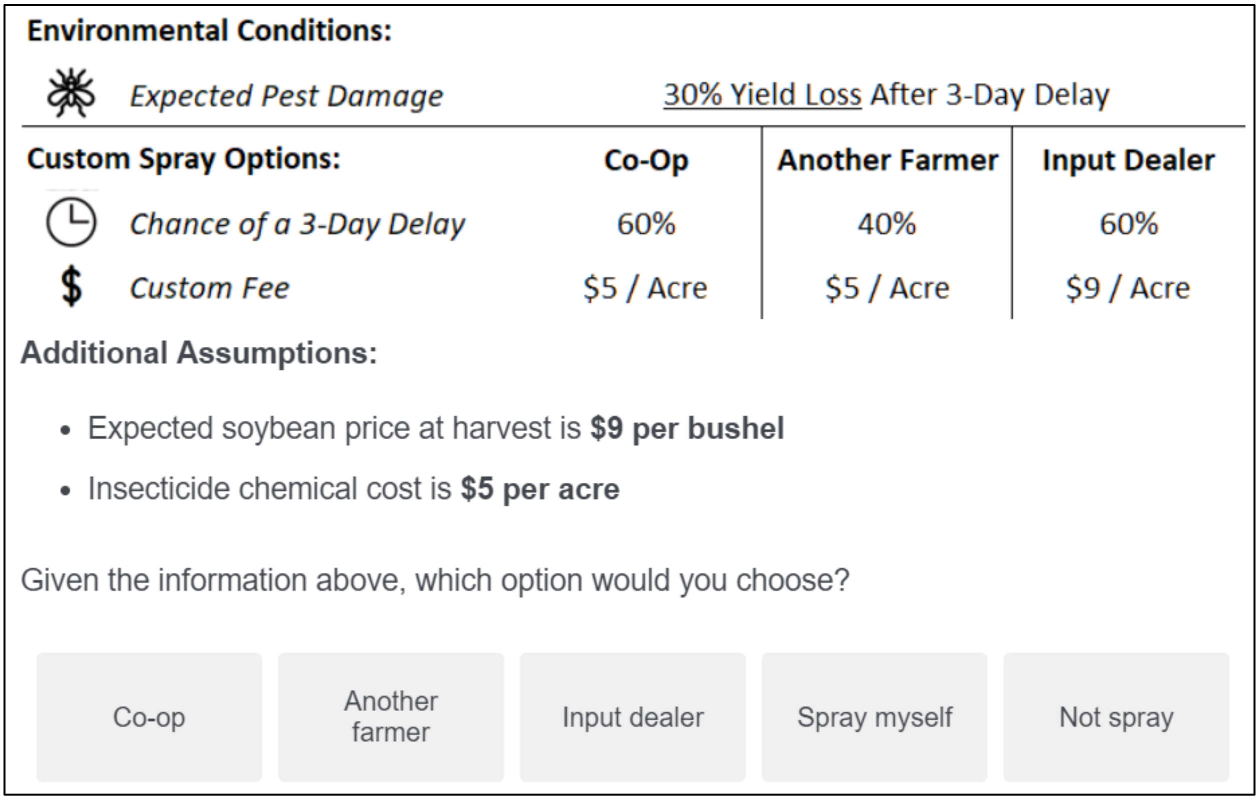


Figure 3.2. Example Choice Scenario.

Table 3.1. Levels and Descriptions of Choice Experiment Attributes.

Attribute	Description	Value(s)
Fixed		
Chemical costs	Costs of insecticides used to spray, measured in dollars per acre	\$5/ac
Soybean price	Price of soybean at harvest, measured in dollars per bushel	\$9/bu
Scenario		
Pest damage	Damage the insect pest would induce if spraying is delayed three days, measured in portion of yield potential (d)	10%, 20%, 30% (3)
Choice		
Custom fee	Fee paid to operator for services, measured in dollars per acre (fee)	\$5/ac, \$9/ac, \$13/ac (3)
Chance of delay	Probability spraying occurs three days late and pest damage occurs, measured as a percentage (p)	20%, 40%, 60% (3)
Operator identity	Identity of the custom operator	Co-op, input dealer, another farmer (3)

A 24-row fractional factorial experimental design was generated using the software package Ngene and split into three blocks of eight scenarios each. After consulting subject-matter experts during the design stage, eight choice scenarios was determined to be the maximum feasible number of scenarios per farmer. Budget considerations pre-empted pilot data collection necessary for the use of priors in the generation of designs targeting efficiency criteria (Hensher et al., 2015). Because of these constraints, the design was generated by randomly selecting 24 rows from the full factorial design.

A common critique of stated preference methods, including choice experiments, is that they are potentially prone to hypothetical bias. Hypothetical bias occurs when participants respond differently in hypothetical settings than they do when faced with actual decisions (Tonsor & Shupp, 2011). To mitigate hypothetical bias, respondents were presented with an additional page encouraging farmers to take their time and respond as if their choices would have real impacts on their farm. The language was designed to be a light version of a “cheap talk” script, a method that has been shown to reduce hypothetical bias in a variety of settings (List, 2001; Lusk, 2003; Silva, Nayga, Campbell, & Park, 2011), including online surveys (Tonsor & Shupp, 2011).

Before deployment, the survey was reviewed by 20 professionals in the agricultural community unassociated with the study, including employees of the Michigan Department of Agriculture and Rural Development, Michigan State University Extension, and the Michigan Soybean Promotion Committee, as well as active farmers. Comments from phone and email interviews with reviewers were incorporated into the survey design to improve clarity and ensure the choice experiment represented a feasible scenario.

Survey Deployment

The target population for the survey was farmers with 100 or more acres of soybeans planted in 2017 in Michigan, Indiana, and Illinois, with a focus on Michigan farmers. We employed a web survey design, utilizing both email and postal mail contacts to improve response rates (Dillman et al., 2014). Sixty-five farmers completed surveys for a total of 519 completed choice scenarios (one choice scenario was left incomplete). The survey deployment system was programmed to randomly assign a block to each respondent in a balanced manner, and so two blocks were completed 22 times while the third was completed 21 times.

Additional Survey Data

The experimental data is supplemented with additional data from the survey. Farmers were asked questions about their past spraying and custom hiring activities, their capacity to spray with on-farm equipment, and the characteristics of their farm. Farmers were also asked about their general attitudes towards trust and risk, and the number of other farmers with whom they are comfortable discussing important business matters. The full survey instrument is provided in Appendix A.

Empirical Analysis

The goal of this pilot empirical model is to examine the relevance of the proposed hypotheses H1-7 that emerge from the conceptual model by translating the conceptual model into an empirically tractable form. To do so, we estimate a series conditional logit models on the choice experiment data and accompanying survey data on respondent characteristics. First, we estimate a series of candidate models using only variables for the attributes in the choice experiment and select a preferred model based on a number of model selection criteria. We then expand on the preferred model by including farmer characteristics, allowing us to explore how preferences for custom hiring vary according to attitudes and resources.

M1: Base Model Candidates

The conditional logit model is based on the random utility model, in which the farmer is assumed to associate a level of utility with each alternative in a choice set and select the alternative that provides them with the highest utility level (McFadden, 1973). The level of utility associated with each alternative consists of both a systemic portion for which characteristics (i.e. cost, quality, etc.) are known to the econometrician and a stochastic portion accounting for characteristics unobserved by the econometrician. By estimating conditional logit models using data on observed choices, one can measure farmer preferences over, and willingness-to-pay for, and the characteristics of those alternatives.

Random utility models are typically applied in settings where the characteristics included in the systemic portion of utility are certain. More recent applications of the random utility model have considered cases where there is uncertainty over whether an alternative possesses one or more characteristics, often by including the probability that an alternative possesses a characteristic as a characteristic itself. Applications include measuring preferences for environmental quality where the outcome of a project is uncertain (Faccioli, Kuhfuss, & Czajkowski, 2019; Glenk & Colombo, 2011, 2013; Lundhede, Jacobsen, Hanley, Strange, & Thorsen, 2015; Makriyannis, Johnston, & Whelchel, 2018; Roberts, Boyer, & Lusk, 2008; Rolfe & Windle, 2015) and preferences for travel time reliability of transportation options (Hensher, Greene, & Li, 2011; B. Li & Hensher, 2017; H. Li, Tu, & Hensher, 2016; Z. Li, 2018; Z. Li &

Hensher, 2013; Z. Li, Hensher, & Rose, 2010). In these studies, the possible levels of the characteristic and the probability of the level occurring both influence how each alternative affects utility. The two are frequently interacted to capture changes in the expected value of the uncertain characteristic.

In our setting, the uncertain characteristic is whether the custom applicator arrives on time and prevents the pest from damaging the crop. This uncertainty is present only for the custom options. When a farmer chooses to spray on their own the probability of delay is assumed to be zero, and when they choose not to spray the probability is assumed to be one (i.e. damage is guaranteed), consistent with the framing in the choice experiment and the conceptual model.

In our simplest model (M1-ED, for expected damage), we assuming that farmers hold preferences over outcomes rather than probabilities and that the utility of outcomes is weighted by the probability they occur (Von Neumann & Morgenstern, 1944). In our setting, the outcome is the potential pest damage to the farmers crop, dY. This value is measured in bushels per acre and is computed for each farmer for each choice occasion as the percent of yield loss unique to the choice occasion multiplied by their expected pest-free soybean yield. The probability of this damage occurring is given by p_a for a given alternative. M1-ED can be characterized by the following (dis)utility expressions:

$$\text{M1-ED: } u_a = b_{fee} * fee_a + b_{ED} * p_a * dY + c_a \qquad (3.8)$$

The alternative-specific constants (c_a's), b_{fee}, and b_{ED}, represent coefficients to be estimated. The alternative specific constants capture the average of all unobserved sources of (dis)utility associated with each alternative (Hensher et al., 2015), including the costs $labor$ and $equip$ associated with the $self$ option and residual preference for specific custom operator options.

Note that not spraying is the base level for the alternative specific constants, the probability of delay (p_a) is zero if the farmer chooses to spray on their own, the probability that damage will occur is one if the farmer chooses not to spray at all, and $fee_a = 0$ for the non-custom alternatives.

Including the interaction between dY and p_a allows for a measure of the marginal (dis)utility for expected damages, a component of timeliness costs. This model assumes that farmers are risk neutral and that the utility effects of damage and probability of delay are inseparable. Versions have been used in settings evaluating preferences under outcome uncertainty in environmental and transportation settings (Burghart, Cameron, & Gerdes, 2007; Glenk & Colombo, 2013; Li et al., 2010; Roberts et al., 2008).

An alternative model, M1-DU (for direct utility), allows the probability of delay to affect utility both through the effect on expected damage and a direct effect on utility itself. M1-DU, known as the direct utility model, is a simple extension of M1-ED, with the additional term $b_{DU} * I_a^{custom} p_a$ added to the utility expression, where I_a^{custom} is an indicator variable equal to one for custom hiring alternatives where delay is uncertain (Glenk & Colombo, 2013). The M1-DU model is thus characterized as:

$$\text{M1-DU: } u_a = b_{fee} * fee_a + b_{ED} * p_a * dY + b_{DU} * I_a^{custom} p_a + c_a \qquad (3.9)$$

Including $I_a^{custom} p_a$ separate from the interaction of p_a with dY allows for residual preference for timeliness beyond what is measured by the interaction term. If farmers are risk neutral and weighting damage exactly according to the probability of its occurrence, then b_{DU} would be estimated at zero. A negative estimate of b_{DU} would suggest that farmers are risk-averse or otherwise have a distaste for uncertainty beyond its effects on increasing expected damage, indicating risk aversion or other behavioral distortions from simple risk-neutral weighting of outcomes. Such direct utility models have been found to outperform expected utility models in various settings, including contracts for irrigation water contingent on uncertain rainfall and emissions reduction programs (Glenk & Colombo, 2011, 2013; Rigby, Alcon, & Burton, 2010). This model also allows for an "uncertainty effect" in which farmers discount risky alternatives because of the existence of risk itself, rather than because of the effects of risk on the expected utility of alternative, a result that has been used to explain apparent violations of the internality axiom of expected utility theory (Gneezy et al., 2006).

M1-ED and M1-DU are also considered against a model specification that is linear in the choice attributes. Such a model assumes that all interaction effects are zero and farmers do not condition yield outcomes by the probability of their occurrence (Glenk & Colombo, 2013). While this is an extreme assumption, the model is retained to ensure as a test that such probability conditioning occurs. This model, M1-L, is presented below:

$$\text{M1-L: } u_a = b_{fee} * fee_a + b_L * dY + b_{DU} * I_a^{custom} p_a + c_a \qquad (3.10)$$

To select a preferred model, we use multiple criteria. Noting that M1-EU is nested in M1-DU, we test the linear restriction that $b_{DU} = 0$ in M1-DU using a likelihood ratio test to establish which of these two models is preferred. To compare M1-L to the preferred of M1-DU or M1-EU, we rely on Akaike's information criteria[2] (AIC) and the alternative Bayesian information criteria (BIC), as M1-L does not nest in either M1-DU or M1-EU (Burnham & Anderson, 2002).

[2] Hurvich and Tsai (1989) find that AIC performs poorly in small sample settings. However, the corrected criterion, AICc, introduces a bias correction term that is a function of only the number of parameters of the model and the sample size. Because these values are the same for the models compared by the AIC criterion, and therefore the rankings of AICc and AIC will be identical, we choose to rely on the simpler AIC criterion.

M2: Preference Heterogeneity by Farmer Characteristics

To examine how farmer sensitivity to delay varies across farmers and to illustrate hypotheses related to farmer characteristics, we expand on the base model selected from M1-ED, M1-DU, and M1-L by introducing variables that characterize the farmer. These variables can be interacted with characteristics of the alternatives (i.e. dY, p_a) so that the resulting coefficients (i.e. b_{ED}, b_{DU}, b_L, the alternative specific constants) can vary by the characteristics of the farmer respondent. We build this model from the model that emerges from the model selection process and label the resulting model with interactions M2. We select characteristics relevant to our conceptual model and hypotheses, dividing characteristics into two classes: characteristics that affect utility under custom options and characteristics that affect utility when the farmer chooses to spray on their own.

For custom option characteristics, we include "Number of Close Farmers" as a proxy of social capital to illustrate H7. This variable measures the number of other farmers, excluding those associated with the respondent's operation, who the farmer feels "close enough to discuss important business problems with." As an illustration of H6, that more risk averse farmers are wary of custom hiring, we include "Risk Score," the farmer's self-rating on a four-point scale where one is defined as "fully prepared to take risks" and four is defined as "unwilling to take risks." Similar versions of this question have been shown to have strong predictive validity for risky behavior and responses are simpler to collect in a survey setting than alternative measures of risk attitudes (Beauchamp, Cesarini, & Johannesson, 2017). To examine how farms of different sizes respond differently to uncertainty, we include "Acres Planted," which measures the total acres the farmer planted in 2018 of soybeans or any other crop. We interact each selected farmer characteristic with dY, p_a, and their interaction (for a three-way interaction) to examine the effects of each characteristic on farmer preferences for timeliness in custom hiring.

For characteristics relevant when the farmer sprays on their own, we include variables that proxy for costs incurred when that alternative is selected. “Farm Income Share,” measured as a proportion of total income, proxies for the opportunity cost of labor, with a higher proportion of income from off-farm sources assumed to indicate a higher opportunity cost of on-farm labor. This variable allows us to illustrate H3: that higher labor costs lead to more frequent custom hiring. This variable is interacted with the alternative specific constant for “Spray Myself,” c_{self} to capture variation in preferences for spraying using one’s own labor.

To aid in interpretation in the coefficients for these interactions, we center each non-binary characteristic at zero by subtracting the sample mean. Therefore, the resulting coefficients can be interpreted as piecewise utility changes resulting from a unit change from the mean.

Choices by Sprayer Ownership

To illustrate H2, that farmers with their own equipment are more likely to choose to spray on their own, we compare the frequency that “Spray myself” was selected among alternatives between respondents who report owning or leasing a self-propelled sprayer, those who own a tractor-pulled sprayer, and those who do not own a sprayer at all. Self-propelled sprayers are specialized equipment that can apply chemicals over larger areas more quickly, and at lower equipment and labor costs, than tractor-pulled sprayers. While this method cannot distinguish between equipment and labor cost savings resulting from sprayer ownership, it provides an equipment gradient over which we can examine differences in the likelihood that custom hiring is selected.

Results

In this section, we first discuss summary statistics for selected farmer characteristics and the raw choice shares from the survey data. We then present results for the M1 models and the results of the model selection process before proceeding to M2, the selected model with farmer characteristic interactions. Finally, we present willingness-to-pay measures for reductions in the p_a variable, which we define as willingness to pay for timeliness, and demonstrate the effects of farmer characteristics for these findings.

Summary Statistics

Most of the responding farmers report possessing both the equipment and certification to perform the tasks on their own. Seventy-five percent of respondents are certified to spray restricted use pesticides and 69 percent own or lease their own sprayer (Table 3.2). Insecticides are used infrequently among the respondents. The median respondent sprayed insecticides twice in the past ten seasons (mean 3.4) and twice on soybeans specifically (mean 2.7) (Table 3.3). When spraying does occur, custom spraying is not uncommon; 32 percent of respondents typically hire custom when spraying is needed.

Respondents routinely hire custom operators. The median respondent hired a custom operator for any field operation in five of the past ten seasons (mean 5.5), and specifically for spraying pesticides in one of those seasons (mean 2.6) (Table 3.3). Seventy-four percent of respondents reported custom hiring for at least one field operation in at least one of the past ten seasons.

Table 3.2. Summary of Categorical Survey Variables.

Variable	Description	Category	N [a]	% of Sample [b]
Who sprays	Who sprays insecticides in a typical year	Custom applicator	21	32%
		Employee (family excluded)	2	3%
		Family member	5	8%
		Primary operator (myself)	34	52%
		Other	3	5%
Certification	Whether anyone who works on the farm is certified to spray restricted use insecticides	No	16	25%
		Yes	49	75%
Sprayer ownership	Whether the farm owns a sprayer	No	20	31%
		Yes	45	69%
Farm revenue	Gross farm income in 2017	Less than $150,000	8	12%
		$150,000 - $349,999	25	39%
		$350,000 - $999,999	16	25%
		$1,000,000 - $4,999,999	8	12%
		More than $5,000,000	1	2%
		No Response	7	11%
Gender	Farmer's gender	Female	5	8%
		Male	56	86%
		No Response	4	6%
Education	Farmer's level of education	High school graduate	15	23%
		Some college	12	19%
		2-year degree	14	22%
		4-year degree	18	28%
		Professional degree	5	8%
		No Response	1	2%
Household income	Farmer's household income in 2017	Less than $20,000	4	6%
		$20,000 - $39,999	2	3%
		$40,000 - $59,999	7	11%
		$60,000 - $79,999	6	9%
		$80,000 - $99,999	10	15%
		More than $100,000	26	40%
		No Response	10	15%
State	Farmer's state of residence	IL	10	15%
		IN	22	34%
		MI	33	51%

[a] Number of responses to each item, accounting for item non-response. Total number of responses is 65.

[b] Percentages may not add to 100% due to rounding.

Table 3.3. Summary of Numeric Survey Variables.

Variable	Description	Min.	25th-Perc.	Med.	75th-Perc.	Max.	Mean	Std. Dev.	N [a]
Past custom	Years in the last ten when custom work was used	0	0.5	5	10	10	5.5	4.3	63
Past custom, spray	Years in the last ten when custom spraying was used	0	0	1	3.5	10	2.6	3.3	63
Past spray	Years in the last ten when any insecticides were used	0	1	2	5	10	3.4	3.1	63
Past spray, soybeans	Years in the last ten when insecticides were used on soybeans	0	1	2	3	10	2.7	2.6	59
Age	Age in years	27	54	59	66	80	58		
Close farmers	Not including those who work on your operation, about how many other farmers would you say you feel close enough to discuss important business problems with?	0	2	3	5	15	4.2	3.0	61
Risk score	Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (Fully prepared to take risks = 1; Unwilling to take risks = 4)	1	2	2	3	4	2.3	0.8	64
Expected yield	Expected yield, in bushels per acre, of largest soybean field	35	53	57	65	81	58	9.3	64
Farming income	Percent of farmer's household income from agriculture	0	25	52	95	100	58	34.5	62
Planted acres	Total planted acres in 2017	150	409	697	1251	3700	997	804	64

[a] Number of responses to each item, accounting for item non-response. Total number of responses is 65.

Table 3.4. Response Shares to the Choice Experiment.

Alternative	N	% of Responses [a]
Co-op	79	15.2%
Input dealer	127	24.5%
Farmer	59	11.4%
Myself	236	45.5%
None	18	3.5%

[a] Percentages may not add to 100% due to rounding.

Most respondents consult with a small circle of other farmers on important issues, though some have larger networks. The median respondent is close enough with three other farmers to discuss important business issues (mean 4.2) and a quarter of respondents are close enough to five or more other farmers to have such discussions (Table 3.3). Farmers on average expressed a slight preference for risk-taking behavior, with a mean risk score of 2.3 (Table 3.3).

Finally, we report the unconditional rates at which each of the alternatives was selected in the choice experiment (Table 3.4). Respondents chose to spray with their own equipment most frequently (45.5% of choice occasions). Among custom options, input dealers are selected most frequently (24.5%), followed by co-ops (15.2%), and other farmers (11.4%). Not spraying is selected rarely (3.5%).

While we do not claim that our sample is representative of the population, we present a brief comparison of the demographic statistics of our sample relative to equivalent measures reported by the USDA for the sampled population (Appendix B).

Model Selection and M1 Results

Results for M1-ED, M1-DU, and M1-L are presented in Table 3.5. In the first stage of model selection, we perform a likelihood ratio test of a single linear restriction between M1-DU

Table 3.5. Results of M1 Conditional Logit Models.

	M1-EU		M1-DU		M1-L	
Variable	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**
Fee, fee ($/Acre)	-0.10***	0.023	-0.11***	0.023	-0.11***	0.023
Delay Probability, $I_a^{custom}p_a$			-2.6***	0.47	-3.6***	0.47
Damage, dY (bu/acre)					-0.037**	0.017
Expected Damage, $p_a dY$	-0.19***	0.028	-0.088**	0.017		
ASC - Farmer	0.081**	0.35	2.3***	0.37	3.3***	0.37
ASC - Co-op	1.1***	0.33	2.8***	0.38	3.8***	0.38
ASC - Dealer	1.5***	0.34	3.1***	0.37	4.1***	0.37
ASC - Self	0.52	0.37	1.5***	0.32	2.1***	0.32
Log Likelihood	-661.5		-651.6		-652.5	
AIC	1335.1		1317.1		1319.1	
BIC	1360.5		1346.8		1348.7	
Choice Occasions	511		511		511	
Respondents	64		64		64	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

and M1-ED, $b_{DU} = 0$. The likelihood ratio test statistic is 19.24, which is larger than the chi-squared critical value at the 5% level with one degree of freedom (3.84). Therefore, we reject the null hypothesis that the restriction holds and proceed with M1-DU as the preferred model over M1-EU.

We then compare M1-DU to M1-L by their AIC and BIC, where lower values indicate the preferred model. For both AIC and BIC, M1-DU is preferred over M1-L, though by two units or less in both cases, indicating that both models perform about the same by these metrics. Because M1-DU both performs marginally better by both model selection criteria and is consistent with the conceptual model, we proceed with M1-DU as the preferred model.

All coefficients for the preferred model are statistically significant at the 5% level or better. The coefficient for fee, b_{fee}, is negative, suggesting that farmers custom hire less when options are more expensive. The coefficient for expected damage, b_{ED}, is also negative, indicating that farmers lose utility as the expected timeliness costs associated with the alternative

Table 3.6. Results of M2-DU, the Preferred Conditional Logit Model with Interactions for Farmer Characteristics.

	M2-DU	
Variable	**Coef.**	**S.E.**
Fee, fee (\$/Acre)	-0.12***	0.025
Delay Probability, $I_a^{custom} p_a$	-3.6***	0.74
x Close Farmers (Count)	0.39***	0.15
x Risk Score (1-4, 4 is risk averse)	-0.016	0.48
x Acres Planted	-0.00021	0.00091
Expected Damage, $p_a dY$	-0.15***	0.053
x Close Farmers	-0.024**	0.011
x Risk Score	-0.073**	0.034
x Acres Planted	-0.00031***	0.000072
ASC - Farmer	3.9***	0.69
ASC - Co-op	4.4***	0.70
ASC - Dealer	4.8***	0.70
ASC - Self	2.6***	0.66
x Farm Income Share (proportion)	0.0066*	0.0036
Log Likelihood	-527.9	
AIC	1,083.7	
BIC	1,141.9	
Choice Occasions	471	
Respondents	59	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

increases. The negative estimate for coefficient b_{DU} indicates that farmers have a distaste for increased probability of delay separate from the effects of p_a on their potential yields. The alternative specific constants are all positive, indicating residual preference for all spraying options over not spraying at all.

M2-DU Results with Farmer Characteristics

Results for M2-DU, the preferred model M1-DU with farmer characteristics, are presented in Table 3.6. The core results for coefficients estimated without farmer characteristics remain consistent with M1-DU, including the rankings of the alternative specific constants.

The coefficient for “Close Farmers” interacted with the probability of delay is positive and statistically significant, indicating that farmers who are close to more farmers are less sensitive to the probability a custom operator sprays late. On the other hand, the coefficient for “Close Farmers” interacted with expected damage is negative, indicating that farmers with broader social networks are more sensitive to increases in expected damage.

The coefficients for the remaining two characteristics interacted with timeliness cost variables, “Risk Score” and “Acres Planted,” are statistically insignificant when interacted with the probability of delay, but negative and statistically significant when interacted with expected damage. The coefficient for the variable “Farm Income Share” interacted with the alternative specific constant for spraying on one’s own is statistically significant and positive, though only at the 10% level, indicating that farmers who receive a larger share of their household income from agriculture are more likely to choose to spray on their own.

Choices by Sprayer Ownership

Among the 20 respondents who do not own or lease a sprayer, none chose to spray on their own in any choice occasion. Among the 24 respondents who own or lease self-propelled sprayers and the 21 who own or lease a tractor-pulled sprayer, spraying on one’s own was selected in 76 percent and 54 percent of choice occasions. These results suggest that respondents who own more specialized spraying equipment are less likely to custom hire for pest control.

Willingness-to-Pay for Timely Spraying

We now consider farmers willingness-to-pay (WTP) for reductions in a custom operator’s probability of delay, conditional on choosing to spray. Using the estimated coefficients from M2-DU, WTP for reductions in the probability of delay at a given damage rate is calculated as

$$\frac{b_{ED} d\bar{Y} + b_{DU}}{b_{fee} * 100}. \qquad (3.11)$$

In this expression, $\bar{Y}$ is the mean expected soybean yield for respondents (58.1 bushels per acre). Because all characteristics interacted with the probability of delay were centered at zero prior to estimation, and therefore have means of zero, their effects are omitted from this calculation. We divide by 100 to give a measure of WTP measured in dollars per percent change in probability of delay per acre, rather than dollars per probability unit (i.e. on the $[0, 1]$ scale). We find that, on average, farmers are willing to pay $0.37 per acre for a one percent reduction in the probability of delay when the potential damage rate (d) is 10% of yield, $0.45 per acre when the potential damage rate is 20%, and $0.52 per acre when the potential damage is 30%. These WTP for a marginal change in the probability of delay represent 2.7 percent, 3.2 percent, and 3.7 percent of median custom pest control costs per acre as presented in the choice experiment ($9 per acre in custom fees and $5 per acre in chemical costs).

To show how farmer characteristics affect WTP to avoid delay, we illustrate WTP for each respondent in the sample according to farm size (Figure 3.3A), the number of close farmers (Figure 3.3B), and risk score (Figure 3.3C). Respondent-level WTP is calculated by adding the statistically significant interaction coefficients, multiplied by associated characteristics and potential damage levels, to the numerator of Equation (3.11) (Hensher et al., 2015; Rigby et al., 2010). The potential damage rate d is set at each of the three levels included in the choice experiment to further demonstrate the impact of increasing damage on WTP to avoid delay.

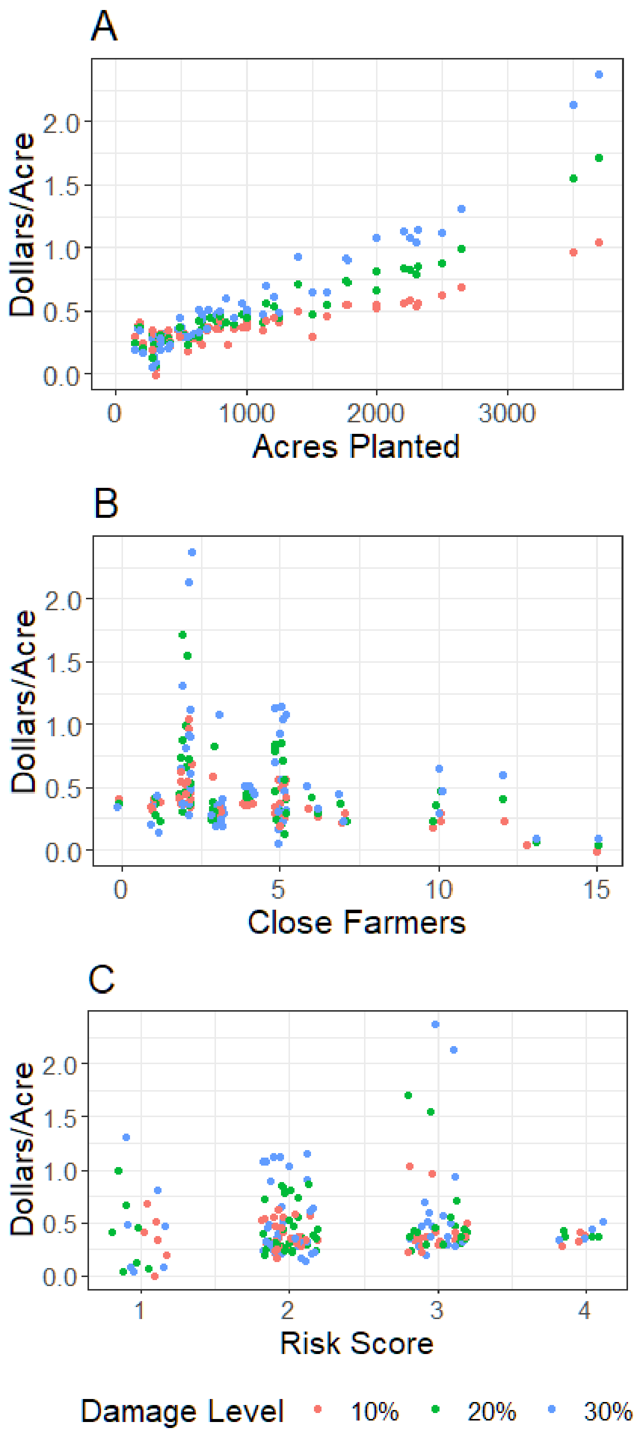


Figure 3.3. Willingness-to-Pay (WTP) for Reductions in the Probability of Delay. WTP is calculated for each respondent at each damage level and presented by (A) acres planted, (B) close farmers, and (C) risk score. Random displacement on the horizontal axis has been added to distinguish between overlapping points.

Discussion

In this section, we discuss how the results of our pilot study relate to the hypotheses derived from the conceptual model, with particular focus on the roles of timeliness costs, risk attitudes, and social capital in shaping farmers' custom hiring decisions. Table 3.7 reports our assessments of support from the pilot study for each hypothesis.

As predicted by H3, higher custom fees reduce custom hire use. However, we find only weak evidence that farmers with higher opportunity costs of labor, as measured by the proportion of household income derived from agriculture, are more likely to custom hire, as predicted by H1. On the other hand, farmers who possess more specialized equipment (i.e. self-propelled sprayers) are less likely to custom hire, a result that provides some support for H2, that sprayer ownership decreases custom use. These results support the implication of the conceptual model that farmers are more likely to custom hire when performing a task on their own is more expensive. Future research should explore whether labor or equipment costs are more important in driving this outcome, which in turn would allow for better predictions of how changes in labor and equipment markets might affect custom hiring demand.

The next hypotheses, H4 and H5, relate to how uncertainty and timeliness costs affect decisions to custom hire. Our results illustrate how farmers are less likely to choose to custom hire when expected damage is higher, supporting H4. Note that both increases in the probability of delay and the increase in the absolute level of damage can drive this effect, so this result also provides weak evidence for H5.

By interpreting b_{DU} we can disentangle (dis)taste for uncertainty from their (dis)taste for pest damage and address H5 separately from H4. Changes in p_a can affect utility levels through two mechanisms: a direct effect and an indirect effect through increasing expected damage. We

Table 3.7. Hypotheses, Relevant Parameters, and Determination of Support.

	Hypothesis	Relevant Evidence	Support?
H1	When on-farm labor is more costly, custom hiring is more likely.	M2-DU: ASC – Self x Farm Income Share	✓
H2	When a farmer owns their own sprayer, custom hiring is less likely.	Results by sprayer ownership	✓
H3	When a custom operator charges a higher fee, they are less likely to be hired.	M1-DU/M2-DU: Fee	✓
H4	When the scale of the damage from delay is higher (i.e. dY is larger), custom operators are less likely to be hired.	M1-DU/M2-DU: Expected Damage	✓
H5	When the probability a custom operator is delayed in spraying is higher (i.e. p_{custom} is closer to one), that custom operator is less likely to be hired.	M1-DU/M2-DU: Delay Probability	✓
H6	More risk averse farmers (i.e. r is larger) are more sensitive to potential delays in spraying.	M2-DU: Delay Probability x Risk Score, Expected Damage x Risk Score	✓
H7	When a farmer has a more developed social network, they are less sensitive to potential delays in spraying by custom operators.	M2-DU: Delay Probability x Close Farmers, Expected Damage x Close Farmers	✓

interpret b_{DU} as the direct utility effect of p_a and $b_{ED}dY$ as the expected damage effect. Even for the farmers with the maximum potential damage (81 bushels per acre pest-free yield and 30% pest damage), the direct utility effect from p_a is roughly equal to the utility effect through expected damage from increasing expected damage (-3.6 utility units per additional percent probability of delay for both effects).

The fact that a direct effect of p_a exists also provides potential evidence that farmers do not respond to potential delays in custom hiring in a risk-neutral way under the traditional expected utility model. While the negative estimates for coefficient b_{DU} provide evidence of possible risk aversion among farmers in the context of custom hiring, this finding does not address how individual differences in risk attitudes affect decisions, the question at the core of H6. We use the interaction coefficients from M2-DU to address this hypothesis. Our findings suggest more risk averse farmers are more sensitive to the probability of delay, but only through its effect on expected damage. If the direct effect of p_a represents risk averse attitudes in the traditional expected utility model sense, we would expect more risk averse farmers to have larger marginal disutility from p_a alone. Our findings do not support this conclusion, so the direct utility effect of p_a can be viewed as potential evidence that alternative models of risk attitudes such as prospect theory (Tversky & Kahneman, 1992) or direct uncertainty effects (Gneezy et al., 2006) may be more relevant in custom hiring scenarios. Future research should directly address alternative models of risk preferences when assessing drivers of custom hiring behavior among growers.

We address H7 by examining the coefficients for interaction terms including the “Close Farmers” variable. Our results indicate that farmers with broader social networks are less sensitive to increases in the probability of delay in support of our hypothesis. While the coefficient for the interaction of “Close Farmers” with expected damage is negative, the coefficient for the interaction with delay probability is large enough to counteract this negative effect. We interpret the coefficient for “Close Farmers” interacted with delay probability as a mitigating effect of social capital on the marginal disutility of p_a. At the median potential yield damage (i.e. median pest-free yield expectation Y of 57 bushels per acre multiplied by the median pest damage rate d of 20%), the mitigating effect of social capital exceeds the negative impact on the marginal utility from expected damage. This comparison suggests that social capital ultimately has a mitigating effect on the marginal disutility from the probability of delay for the majority of farmers. In Figure 3.3, panel B, there is a clear downward correlation between respondent WTP for reductions in the probability of delay and the number of farmers the respondent is close with, further supporting H7. Therefore, our results on the whole provide some support for H7.

That farmers with more close relationships with other farmers are more likely to custom hire is in line with past findings that U.S. farmers rely on informal social mechanisms to facilitate transactions that may otherwise not occur (Allen & Lueck, 1992b, 2004; Wilson, 2000). While previous findings regarding the role of social capital in facilitating agricultural contracting focus on land, our results provide some evidence that such mechanisms persist and in non-land contexts. Future research should seek to measure the relationships and social networks of both custom operators and the farmers who hire them in order to further explore how social capital might support custom hiring markets.

We also include “Acres Planted” as a possible farmer characteristic influencing sensitivity to timeliness costs, finding that farmers who farm more land are more sensitive to expected damage. However, “Acres Planted” does not influence sensitivity to delay probability separate from its impact on sensitivity to expected damage. There are multiple conflicting theoretical expectations as to the direction of the effect of farm size on sensitivity to uncertainty when custom hiring. Larger farms represent more possible revenue for a custom operator, who are often paid by the acre. If a custom operator sprays late, a farmer can withhold future business and the custom operator would lose out on more revenue if that farm is large. Therefore, we might expect larger farms to underweight probabilities of delay in a similar way that those with more social capital do, suggesting a positive expectation for this coefficient. On the other hand, a larger farm requires more time to complete field operations. This might lead to increased sensitivity to the probability of delay, because if delays were to occur, then custom operators would struggle more to catch up. Our null finding does not rule out either possibility. If both mechanisms mutually exist, their effects could counteract each other. Future research might examine the connection between farm size, transaction costs, and custom hiring decisions more closely.

A common critique of stated preference studies, including choice experiments, is that they do not pass a "scope test" in that results are not sensitive to the scope or magnitude of the good in question (Arrow et al., 1993; Lew & Wallmo, 2011). Our finding that larger farms are more sensitive to greater damage is evidence that farmers are sensitive to scope.

The alternative specific constants (c_a's) in M1-DU indicate a distinct ranking among alternative providers of custom services (Table 3.5). The alternative specific constant is largest for input dealers, followed by co-op providers, and then other farmers. All three custom alternatives have larger constants than the constant for the alternative in which farmers spray on their own, indicating that farmers would prefer to have a custom operator spray if there were no custom fees and timely service were guaranteed.

Input dealers, and co-ops as well, often offer additional services beyond custom spraying. These include agricultural inputs like fertilizers, seed, and pesticides and other custom services such as the application of fertilizers or harvest. These additional services may provide a possible explanation for respondents' preference for custom spraying from input dealers and co-ops over similar service from other farmers. Farmer customers of input dealers and co-ops can purchase other goods and services from these custom operators when hiring for custom spraying services (or vice versa), reducing search costs. Another possible explanation for the ordering of preferences between custom service providers is that other farmers have their own fields which may require treatment during the same critical window as their customers. Custom operators who manage their own farms have a clear incentive to prioritize their own fields over their customers', which may explain the preference among respondents for non-farmer providers of custom spraying.

Conclusion

This paper provides a model for how farmers choose between custom hiring and spraying themselves when their fields are threatened by insect pests and examines this model empirically with data from a discrete choice experiment. Although the sample size is not large enough for extrapolation to a farmer population, the results illustrate how timeliness can be an important driver in these decisions, as evidenced by strong marginal disutility from increased probabilities of delay even beyond the effects such increased probability of delay on increased probability of pest damage.

Previous research has examined the related "lease-own" decision for agricultural equipment in non-stochastic environments (Ford & Musser, 1994). However, to our knowledge no previous study has empirically tested transaction cost theories for their ability to explain the common phenomenon of custom hiring in agriculture. This paper begins to fill that gap by proposing a theoretical model of custom pest control hiring decisions and providing results from a pilot study to examine the empirical basis for hypotheses regarding the drivers of the custom hiring decision.

Using a discrete choice model of custom hiring in a pest control setting, we illustrate how uncertainty over the reliability of custom operators can create timeliness costs, a specific type of transaction cost that is especially relevant in agricultural contexts (Allen & Lueck, 2004). While previous studies have identified timeliness costs in custom hiring through case study methods

(Allen & Lueck, 2004), we provide indicative evidence that timeliness costs can drive farmers away from custom hiring and towards ownership of equipment. Further, we illustrate that risk-averse farmers might be more sensitive to these costs. Finally, we illustrate that farmers who are more integrated into the agricultural community (i.e. who have more close friends who farm) are less sensitive to timeliness costs.

Understanding which farmers opt to custom hire, and which custom operators they choose when multiple providers are available, can assist in identifying regions where demand for custom services may be high. Pest pressure dynamics, weather patterns, pesticide spraying regulations, and road infrastructure are all regional factors that can affect the ability of firms to provide timely services. For regions threatened by pests that affect many nearby fields concurrently, many farmers are likely to need to apply insecticides at the same time. In such setting, farmers are likely to find custom pest control unattractive, as custom operators will be harder pressed to provide timely services to many farmers concurrently. Areas with highly variable weather are more likely to have unexpected delays in spraying for a given field, which might create backups in a custom operator's schedule. Problems created by weather will be exacerbated in states with stricter restrictions on weather conditions suitable for pesticide applications or regions where road conditions make moving between fields more difficult.

Theoretical models and empirical approaches building on this first attempt to characterize the drivers of custom hiring can be applied to scenarios where farmers custom hire for services other than pest control, such as harvest or fertilizer application. These field operations are subject to other forms of ecological uncertainty which may induce timeliness costs in unique ways. Farms across the country make decisions regarding custom hiring every year for a variety of field operations, providing a rich context to test transaction cost theories and examine what conditions lead to various distributions of property rights between farms and the operators they employ. Such studies would provide additional insight into how farmers view timeliness and other transaction costs in the context of different field operations, providing valuable information for custom operators while also building on the broader transaction costs economics literature.

APPENDICIES

Appendix A: Online Survey Instrument

The following pages contain images of the survey instrument. The survey was administered on via respondents' web browsers and contained conditional logic leading to multiple versions. Notes have been added to explain where reactive elements exist and to clarify structure. Choice experiment blocks were removed for brevity. Unless otherwise noted, each panel represents a separate page of the survey instrument.

MICHIGAN STATE UNIVERSITY

Questionnaire Intro

Claus Isenberg (CC BY-NC-SA 2.0)

THANK YOU for your participation in the this survey! In this short web questionnaire, we will ask about your **pest control** and **custom hiring** practices in **soybeans**.

Your answers will help researchers understand what you and other farmers value when considering who you turn to for help in your fields. This knowledge will help businesses and extension better serve the needs of **your operation**.

Remember that your answers to this survey will remain anonymous, and that there are no right or wrong answers. **Your opinions matter!** You can skip any questions, but we certainly hope you complete the entire survey. If you have any questions or issues, feel free to reach out to **Braeden Van Deynze**, Graduate Research Assistant, at vandeynz@msu.edu.

We expect this questionnaire will take **no more than 20 minutes** to complete. At the end you will have a chance to request a summary of the results, once they have been analyzed. When you are ready to begin, please press the button below!

Figure 3B.1. Screenshots of Online Survey Instrument.

On your farm, who is typically responsible for applying insecticides on **soybean** fields?

- ○ Primary operator (Myself)
- ○ Family member
- ○ Employee (Family excluded)
- ○ Commercial or custom applicator (A person who provides both labor and machinery for spraying at a set rate)
- ○ ______ Other (Please specify)

For the following questions, please consider only **foliar insecticide treatments** in response to insect populations found in your fields. Please exclude preventative treatments done before insects have been found.

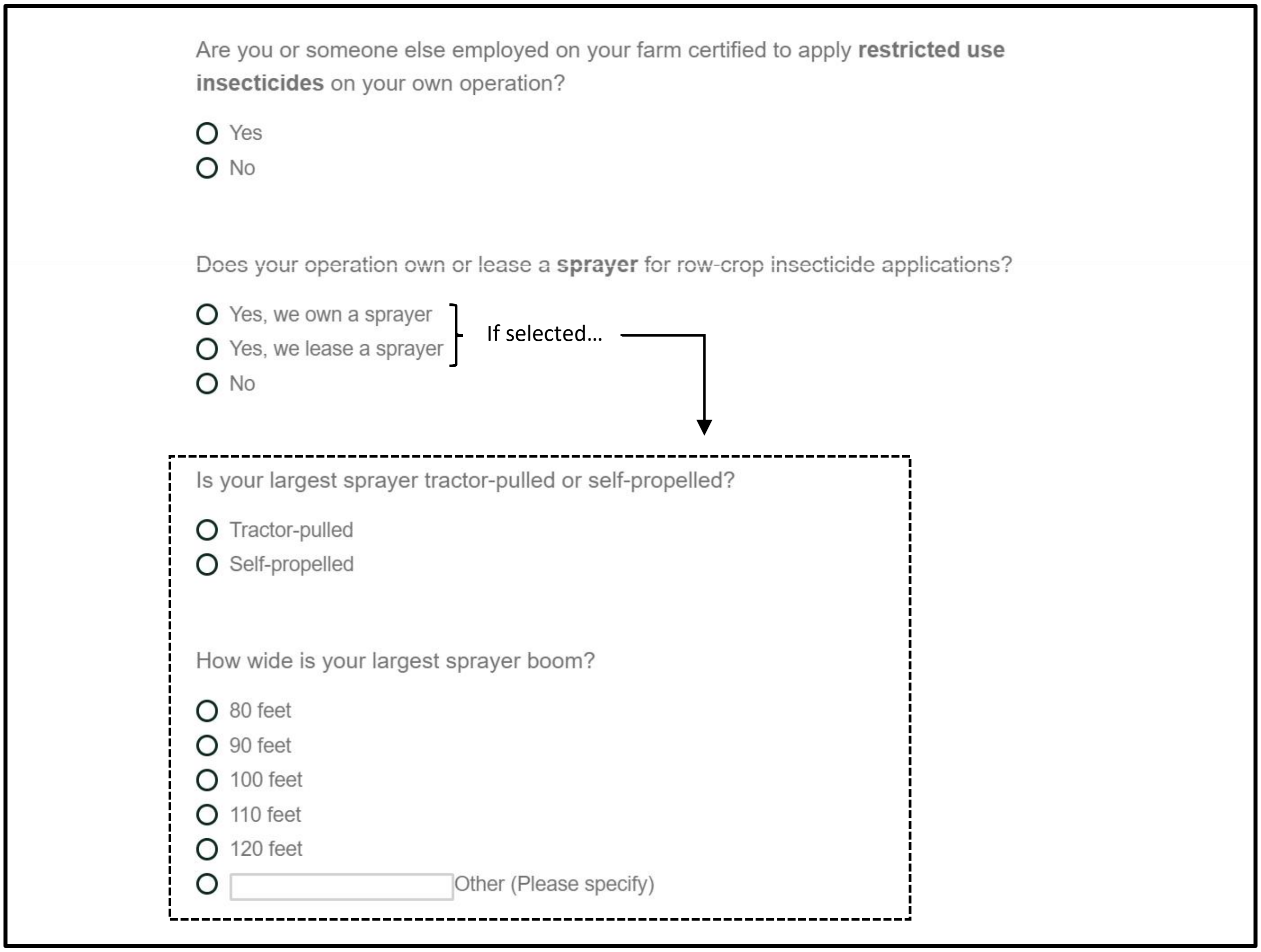
Out of the past ten seasons, how many seasons did your operation apply at least one **foliar insecticide treatment** on any field of **any crop**?

	0	1	2	3	4	5	6	7	8	9	10
Number of Seasons											

Out of the past ten seasons, how many seasons did your operation apply at least one **foliar insecticide treatment** on any of your **soybean** fields?

	0	1	2	3	4	5	6	7	8	9	10
Number of Seasons											

Figure 3B.1 (cont'd).



Are you or someone else employed on your farm certified to apply **restricted use insecticides** on your own operation?

- Yes
- No

Does your operation own or lease a **sprayer** for row-crop insecticide applications?

- Yes, we own a sprayer
- Yes, we lease a sprayer
- No

If selected…

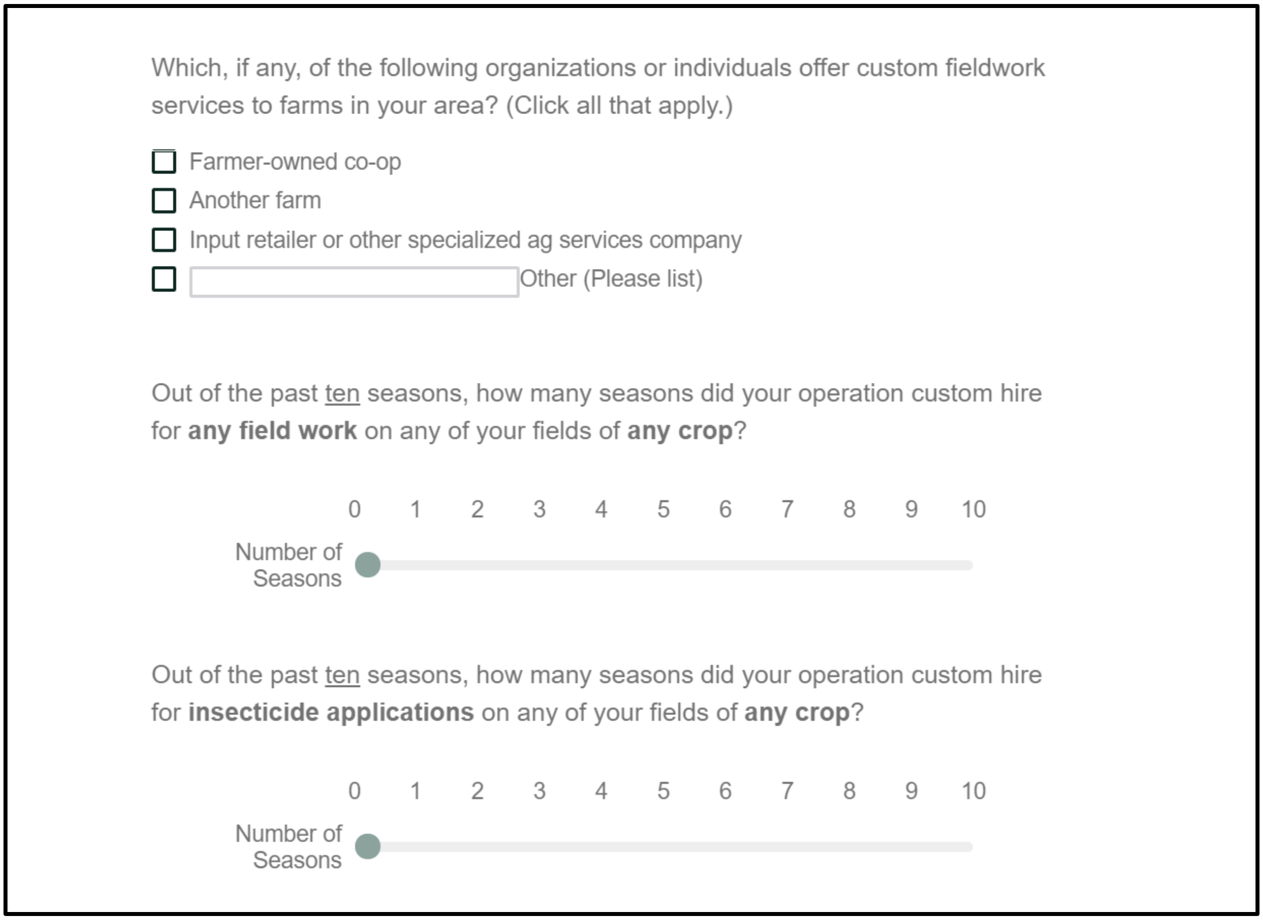
Is your largest sprayer tractor-pulled or self-propelled?

- Tractor-pulled
- Self-propelled

How wide is your largest sprayer boom?

- 80 feet
- 90 feet
- 100 feet
- 110 feet
- 120 feet
- Other (Please specify)

Figure 3B.1 (cont'd).



Which, if any, of the following organizations or individuals offer custom fieldwork services to farms in your area? (Click all that apply.)

- ☐ Farmer-owned co-op
- ☐ Another farm
- ☐ Input retailer or other specialized ag services company
- ☐ ________ Other (Please list)

Out of the past ten seasons, how many seasons did your operation custom hire for **any field work** on any of your fields of **any crop**?

0 1 2 3 4 5 6 7 8 9 10

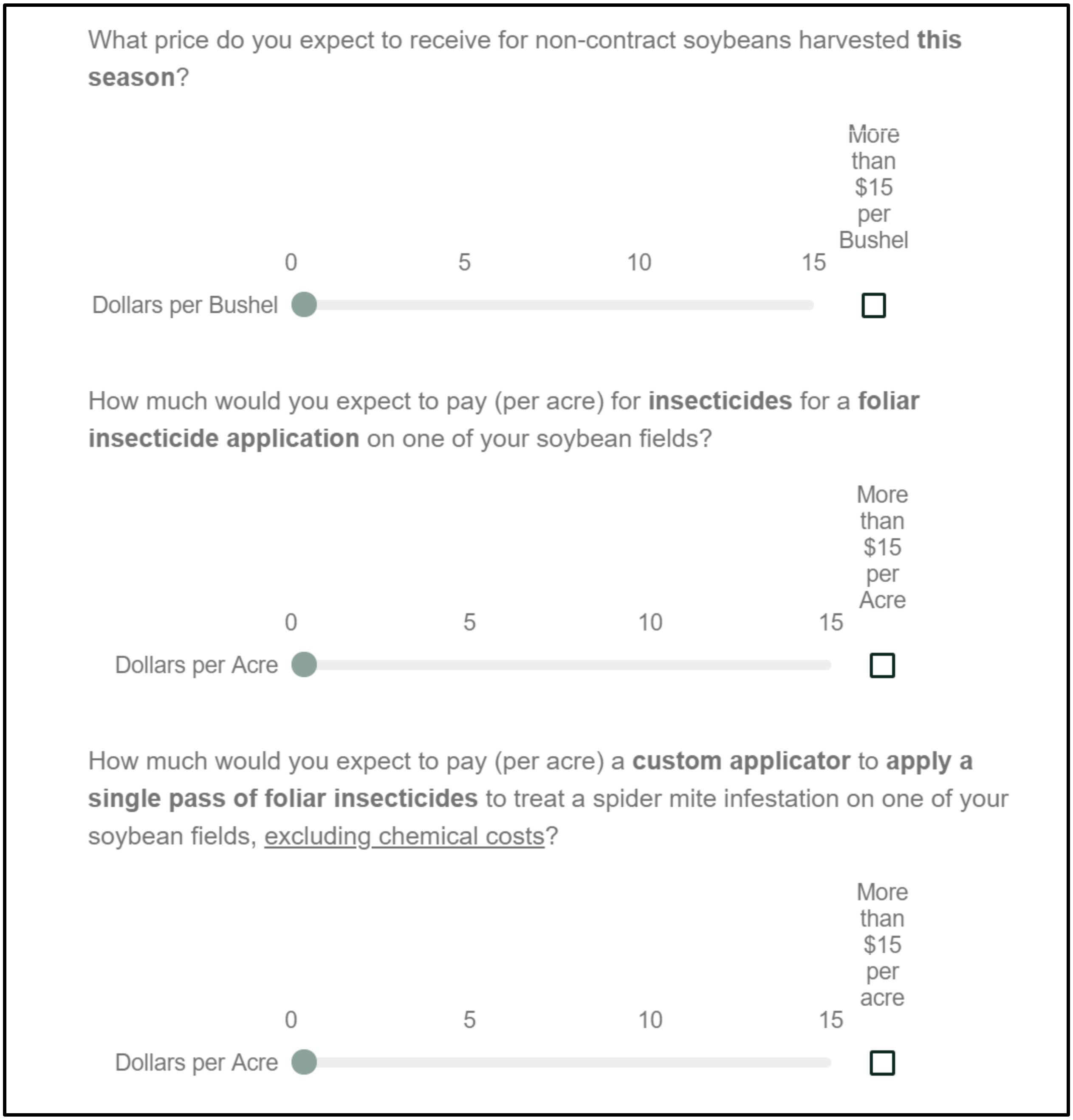
Number of Seasons

Out of the past ten seasons, how many seasons did your operation custom hire for **insecticide applications** on any of your fields of **any crop**?

0 1 2 3 4 5 6 7 8 9 10

Number of Seasons

Figure 3B.1 (cont'd).



What price do you expect to receive for non-contract soybeans harvested **this season**?

0 5 10 15 More than $15 per Bushel

Dollars per Bushel

How much would you expect to pay (per acre) for **insecticides** for a **foliar insecticide application** on one of your soybean fields?

0 5 10 15 More than $15 per Acre

Dollars per Acre

How much would you expect to pay (per acre) a **custom applicator** to **apply a single pass of foliar insecticides** to treat a spider mite infestation on one of your soybean fields, excluding chemical costs?

0 5 10 15 More than $15 per acre

Dollars per Acre

Figure 3B.1 (cont'd).

In the next eight questions, we will ask you about how you would choose to manage a new, invasive insect pest in soybean. Many farmers choose to custom hire for pest control, while others spray themselves. The purpose of this section is to measure the value farmers like yourself place on *timeliness* and *reliability* in custom hiring decisions for pest control.

Please consider the **largest field you operate**. Imagine you have planted this field to **soybeans** for the **2019 growing season**, and that the crop is progressing normally with typical weather and weed pressure, no diseases or early-season pests, and average yields expected.

Imagine also that a **new** invasive insect pest has been identified in your area. The pest infests and damages soybeans during flowering and pod-setting. Fortunately, this pest can be treated with common insecticides. If sprayed soon after the pest is first detected, yield loss can be avoided. But delayed spraying rapidly leads to reduced yield. **Imagine that this pest has been found in your field.**

For each choice, we will present you with a scenario providing information on:

- Expected yield loss if spraying is delayed
- Three options for custom spraying

You will then be asked how you would choose to treat the pest. Here is an example scenario:

[PAGE CONTINUES]

Figure 3B.1 (cont'd).

[CONTINUED FROM PREVIOUS PAGE]

EXAMPLE CHOICE

Environmental Conditions:

Expected Pest Damage	20% Yield Loss After 3-Day Delay

Custom Spray Options:	**Co-Op**	**Another Farmer**	**Input Dealer**
Chance of a 3-Day Delay	40%	20%	60%
Custom Fee	$7 / Acre	$9 / Acre	$5 / Acre

Given the information above, which option would you choose?

Co-op | Another farmer | Input dealer | Spray myself | Not spray

Some explanations:

Co-Op refers to a farmer-owned organization which provides inputs and specialty equipment services.
Another Farmer refers to a neighbor or farmer in the region who provides specialty equipment services in addition to managing their own land.
Input Dealer refers to a privately held company which provides inputs and specialty equpment services.
Chance of a 3-Day Delay refers to the chance that it takes 3 days or more to get to your field, after accounting for weather, the applicator's equipment, and the number of other customers the applicator has lined up.
Custom Fee refers to how much the option costs per acre.

Please assume also that:

- Expected soybean price at harvest is **$9 per bushel**
- Insecticide chemical cost is **$5 per acre**
- You provide chemicals for all spraying options, whether you spray yourself or custom hire
- All custom spray options are available, even if they are not currently available in your area

Note that none of the eight situations are the same, so please consider each situation independently.

Figure 3B.1 (cont'd).

In answering these questions, it can be tempting to make a choice without paying close attention to the costs and the situation. We ask that you think carefully about whether you **really would** go through with your selected spraying option in each situation. Please read each scenario carefully and seriously consider how each option would impact your farm, given your resources, experience, and time.

When you are ready to begin, please press the "→" button below.

[FOLLOWED BY 8 CHOICE EXPERIMENT QUESTIONS]

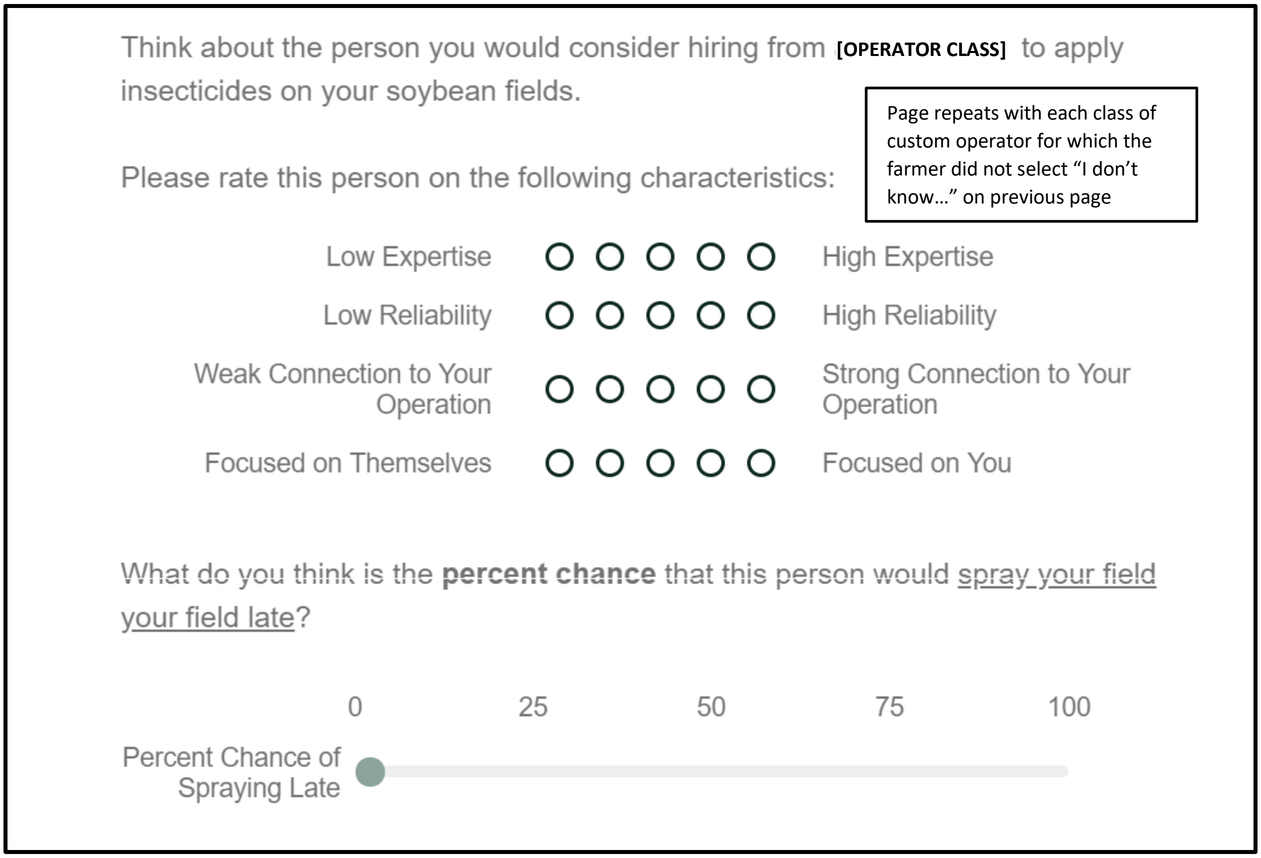
Thank you! We now have a handful of questions about **trust**.

When answering the previous questions, you may have thought of specific people or organizations. In the following question, please consider the specific person you would consider hiring from each of the custom operator categories.

Please rate the **trustworthiness** of each person on the following scale:

	Very untrustworthy	Fairly untrustworthy	Fairly trustworthy	Very trustworthy	I don't know anyone who fits this description
Co-op	○	○	○	○	○
Another farmer	○	○	○	○	○
Input dealer	○	○	○	○	○

Figure 3B.1 (cont'd).


Think about the person you would consider hiring from **[OPERATOR CLASS]** to apply insecticides on your soybean fields.

Page repeats with each class of custom operator for which the farmer did not select "I don't know…" on previous page

Please rate this person on the following characteristics:

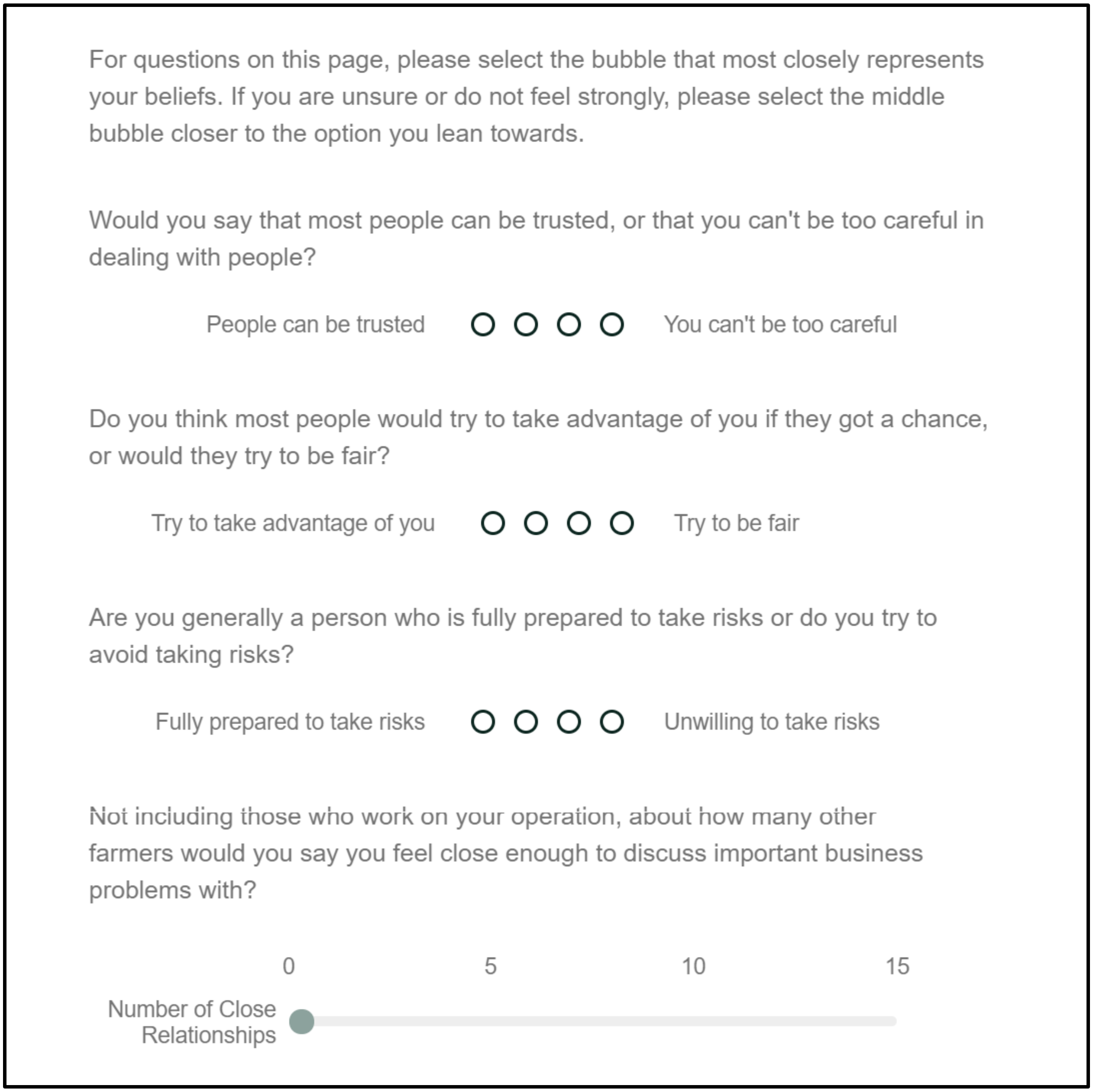
Low Expertise	O	O	O	O	O	High Expertise
Low Reliability	O	O	O	O	O	High Reliability
Weak Connection to Your Operation	O	O	O	O	O	Strong Connection to Your Operation
Focused on Themselves	O	O	O	O	O	Focused on You

What do you think is the **percent chance** that this person would spray your field your field late?

0 25 50 75 100

Percent Chance of Spraying Late

Figure 3B.1 (cont'd).



For questions on this page, please select the bubble that most closely represents your beliefs. If you are unsure or do not feel strongly, please select the middle bubble closer to the option you lean towards.

Would you say that most people can be trusted, or that you can't be too careful in dealing with people?

People can be trusted ○ ○ ○ ○ You can't be too careful

Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?

Try to take advantage of you ○ ○ ○ ○ Try to be fair

Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

Fully prepared to take risks ○ ○ ○ ○ Unwilling to take risks

Not including those who work on your operation, about how many other farmers would you say you feel close enough to discuss important business problems with?

0 5 10 15

Number of Close Relationships

Figure 3B.1 (cont'd).

Thank you! To wrap up, we have some quick questions about yourself and your farm.

Think of your **largest field** on which you regularly plant **soybeans**. How many **acres** is this field?

	0	50	100	150	200	More than 200 Acres
Acres						☐

What would **soybean yield** would you typically expect on this field?

	0	25	50	75	100
Bushels per Acre					

How many acres did your farm plant of the following crops in 2018?

Field Corn

Soybean

Wheat

Other Crops

How many people does your your farm employ in 2018, including family members?

	0	5	10	15	20
Number of Employees					

What was your farm's gross farm income in 2017?

- Less than $150,000
- $150,000 - $349,999
- $350,000 - $999,999
- $1,000,000 - $4,999,999
- More than $5,000,000

Figure 3B.1 (cont'd).

What is your gender?

Male | Female

- ○ Male
- ○ Female

What is your age?

0 25 50 75 100

Years Old

How many years have you worked in agriculture?

0 25 50 75 100

Years Working in Agriculture

What is the highest level of education you have completed?

- ○ Less than high school
- ○ High school graduate
- ○ Some college
- ○ 2 year degree
- ○ 4 year degree
- ○ Professional degree
- ○ Doctorate

What was your total household income in 2017, including net farm income, salary, wages, and investment income?

- ○ Less than $20,000
- ○ $20,000 - $39,999
- ○ $40,000 - $59,999
- ○ $60,000 - $79,999
- ○ $80,000 - $99,999
- ○ More than $100,000

What portion of your household income came from farming in 2017?

0 25 50 75 100

Percent of Income

Figure 3B.1 (cont'd).

Appendix B: Survey Deployment and Sample Representativeness

In this appendix, we assess the representativeness of the sample relative to the target population.

Emails were purchased from the agricultural marketing data company FarmMarketID for 9,290 Illinois farmers, 4,847 Indiana farmers, and 1,895 Michigan farmers, representing all available records with valid emails and 100 or more planted acres of soybeans in 2017. Farmers were emailed three times over the course of a week in August and September of 2018. Emails included a link to an online survey hosted by Qualtrics. To further encourage response, a single letter was mailed to all Michigan farmers and 1,234 of the Indiana farmers directing farmers to visit the online survey.

Of the 16,032 email addresses contacted, 388 were immediately returned as undeliverable due to spam blocking software on the receiving end. These returned emails only represent addresses employing spam blocking software that reports failure of delivery to the sender. We suspect that many more farmers' email systems blocked all the email contacts without reporting the failure of delivery or filed the email contacts directly to farmers' spam or junk folders where they were unlikely to be read. This hypothesis is supported by considerably larger response rates in Michigan and Illinois where an additional mail contact was employed.

Choice experiments targeting farmers are frequently limited by small sample sizes (Chèze, David, & Martinet, 2020), including the one presented in this paper. The challenge of obtaining large farmer samples for choice experiment surveys is made more difficult by declining trends in farmer response rates (Johansson, Effland, & Coble, 2017). Further, farmers are often sensitive about discussing pesticide applications due to public concerns over their public environmental and health effects (Chèze et al., 2020).

Direct data on the population of farmers with 100 or more acres of soybeans planted is not publicly available to the best of our knowledge, so we compare demographic characteristics of our sample to results from the 2017 Census of Agriculture over each state, which includes farms smaller than 100 acres and farms that do not grow soybeans (USDA National Agricultural Statistics Service, 2019). Michigan farmers, and to a lesser extent Indiana farmers, are overrepresented in the sample relative to the population of soybean farmers in the three states (51% of the sample versus 23% of total farms of 100 acres or more for Michigan, 34% of the sample versus 28% of total farms of 100 acres or more for Indiana). This is likely the result of issues with email delivery, as Michigan and a subset of Indiana farmers received additional mail invitations to participate in the survey. As a result, the following results should be interpreted as representing mainly the preferences of Michigan and Indiana growers.

The mean expected yield for respondents' largest soybean fields was 58.1 bushels per acre. This value is considerably higher than the mean yields reported by the Census of Agriculture for Michigan (42 bushels per acre) and Indiana (53 bushels per acre), suggesting that respondents are either more productive than the population or hold optimistic expectations. Our sampling frame was limited to farms of over 100 planted acres of soybeans while the Census of Agriculture reports yields for all growers of soybeans, including the smallest farms which typically do not operate at a commercial scale and therefore often have lower yields. Such smaller farms make up a large portion of the total population targeted by the Census of Agriculture, which may also explain the discrepancy between the mean yield reported by respondents and the mean yield reported by the Census.

Respondents reported planting between 150 and 3,700 total acres across all crops, with a mean of 997 acres planted and median of 697 acres planted. The median planted acres for respondents is considerably higher than the median planted acres for all growers with over 100 acres reported by the Census of Agriculture, which lies in the 220-259 acres range for all three states. The average age of respondents was 58, which is slightly older than the average age reported in the Census of Agriculture for farmers in Michigan and Indiana (56.6 and 55.5 respectively), but roughly equal to the average age of farmers in Illinois (58). Overall, our sample represents larger and more productive farms than those in the population.

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