# TESTING FOR COMPLEMENTARITY: GLYPHOSATE TOLERANT SOYBEANS AND CONSERVATION TILLAGE

EDWARD D. PERRY, GIANCARLO MOSCHINI, AND DAVID A. HENNESSY

Many decisions in agriculture are made over combinations of inputs and/or practices that may form a technology system linked through complementarity. The presence of complementarity among producer decisions can have far-reaching implications for market outcomes and for the effectiveness of policies intended to influence them. Identifying complementarity relations, however, is made difficult by the presence of unobserved heterogeneity. Drawing on recent methodological advances, in this paper we develop a test for complementarity between glyphosate tolerant soybeans and conservation tillage that overcomes certain limitations of previous studies. Specifically, we develop a structural discrete choice framework of joint soybean-tillage adoption that explicitly models both complementarity and the correlation induced by unobserved heterogeneity. The model is estimated with a large unbalanced panel of farm-level choices spanning the 1998–2011 period. We find that glyphosate tolerant soybeans and conservation tillage are complementary practices. In addition, our estimation shows that farm operation scale promotes the adoption of both conservation tillage and glyphosate tolerant seed, and that all of higher fuel prices, more droughty conditions, and soil erodibility increase use of conservation tillage. We apply our results to simulate annual adoption rates for both conservation tillage and no-tillage in a scenario without glyphosate tolerant soybeans available as a choice. We find that the adoption of conservation tillage and no-tillage have been about 10% and 20% higher, respectively, due to the advent of glyphosate tolerant soybeans.

*Key words*: complementarity, conservation tillage, discrete choice models, genetically engineered crops, mixed logit, supermodularity, technology adoption, unobserved heterogeneity.

*JEL codes*: C35, D22, Q12, Q55.

Decision variables in many real-world problems are often best viewed as combined in clusters, for example, bundles of goods or sets of practices. This clustering naturally arises when the payoff associated with the level of one variable is increasing in the level of another variable; that is, when they are complements. The underlying supermodular structure of the decision makers' objective function constitutes the essence of such situations (Milgrom and Roberts 1990). Complementary choices are ubiquitous and appear in consumption problems, production contexts, dynamic choices, and organizational design (Berry et al. 2014). They are relevant in agricultural settings as well, where farmers' decisions increasingly pertain to choices of "systems" composed of alternative combinations of inputs or practices. For example, the choices of which crop to produce, what rotation to use, and type of tillage to employ are often intertwined with mechanical equipment investments and the choices of an array of chemical inputs and genetics. An accurate characterization of such choices—that is, determining whether they form a technology system linked through complementarity—is crucial for both policy analysis and the evaluation of alternative hypotheses. Indeed, many policy interventions entail spillover effects and unintended consequences, which are often the result of unaccounted-for

Edward D. Perry is a PhD candidate and GianCarlo Moschini is Professor and Pioneer Chair in Science and Technology Policy, both with the Department of Economics and the Center for Agricultural and Rural Development, Iowa State University. David A. Hennessy is Professor and the Elton R. Smith Chair in Food and Agricultural Policy, Department of Agricultural, Food, and Resource Economics, Michigan State University, and Professor of Economics, Iowa State University. The authors thank editor JunJie Wu and the journal's reviewers for their helpful comments. The support of USDA NIFA Policy Research Center Grant 11061138/2012-01764 is gratefully acknowledged. Correspondence may be sent to: moschini@iastate.edu

*Amer. J. Agr. Econ.* 98(3): 765–784; doi: 10.1093/ajae/aaw001
Published online February 17, 2016

complementarities between targeted and other variables.

An open question in agriculture that can benefit from a focus on complementarity relates to the environmental implications of genetically engineered (GE) crop varieties. Since their introduction in 1996, GE crops have been both commercially successful and controversial (Moschini 2008). Environmental concerns have ranged from the possibility that adoption of GE crops facilitates monoculture to the detriment of desirable rotations, to the incentive that herbicide tolerant crops provide for the increased use of certain herbicides, and the risk of resistance build-up among the weeds and insects targeted by GE traits. Potential environmental benefits have been posited as well, however, such as a reduction in the use of certain insecticides and a reduction in agriculture's footprint (Barrows, Sexton, and Zilberman 2014). An additional important hypothesized impact, which at present remains unresolved, is that the adoption of glyphosate tolerant (GT) crops induces the adoption of environmentally beneficial tillage methods.

Tillage is an important part of farming. It aids in seedbed preparation and has historically provided a critical means for weed control both before and after the crop has emerged (Givens et al. 2009). It has nonetheless been associated with several negative effects, including increased soil erosion (Blevins and Frye 2003), chemical runoff (Fawcett, Christensen, and Tierney 1994), and the carbon footprint of agriculture (Kern and Johnson 1993; West and Marland 2002). Conservation tillage (CT), defined as a tillage system that leaves at least 30% of crop residues on the soil surface, has long been advocated as a way to reduce these detrimental effects (Holland 2004). Even before the introduction of GT crops, the use of CT had increased significantly in the second half of the twentieth century, largely due to the adoption of chemical herbicides that allowed growers to reduce their reliance on tillage for weed control. Despite this, the chemical-induced diffusion of CT was limited by several factors. First, to be effective some herbicides need to be applied at levels that can injure the crop; for high-residual chemicals, those injuries can potentially extend to future crops. In addition, the range of weeds that a typical chemical can treat is narrow, the post-emergence application window for many chemicals is highly sensitive to the environment, and there is often antagonism between grass and broad-leaf herbicides. In this setting, the advent of GT soybeans, introduced in the United States in 1996, was a game changer. Glyphosate is an effective broad-spectrum, low-residual herbicide, and GT crops can be treated with glyphosate with little to no injury (Carpenter and Gianessi 1999).

Because the combination of glyphosate and GT crops provides such an effective and convenient post-emergent weed control strategy, it can change farmers' propensity to adopt CT. Indeed, previous evidence indicates a positive correlation between GT crops and CT: cropped acreage under "no-tillage" systems has increased considerably in the United States, Argentina, and Canada since the introduction and widespread adoption of GE varieties (Barrows, Sexton, and Zilberman 2014; Fernandez-Cornejo et al. 2014). To investigate whether these correlations indicate a complementary relationship, previous research has employed econometric models that estimate whether the adoption of GT varieties induces the adoption of CT, and also whether the adoption of CT induces the adoption of GT varieties. For cotton, Kalaitzandonakes and Suntornpithug (2003), Roberts et al. (2006), and Frisvold, Boor, and Reeves (2009) conclude in favor of complementarity, whereas Banerjee et al. (2009) fail to reject the null hypothesis that CT and GT cotton are independent. For soybeans, Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) and Fernandez-Cornejo et al. (2013) present evidence in support of a causal relationship between CT and GT soybeans, whereas the results in Fernandez-Cornejo et al. (2003) partially reject the presence of complementarities.

Overall, the evidence in favor of complementarity between GT crops and CT outweighs that against it, but data limitations and certain methodological assumptions restrict the generality of the existing findings. With respect to data, we note that, because of its nature, complementarity is best studied at the level of individual choices. Yet, three of the papers cited above (Roberts et al. 2006; Frisvold, Boor, and Reeves 2009; and Fernandez-Cornejo et al. 2013) rely on state-level data rather than farm-level choices. The three studies that do rely on farm-level data (Fernandez-Cornejo et al. 2014; Kalaitzandonakes and Suntornpithug

2003; and Banerjee et al. 2009) have access to just a single cross-section. Regarding methodology, two important features for the identification of complementarity have been neglected by previous studies. First, an appropriate test for complementarity requires a choice-set defined over all possible combinations of the available practices (Gentzkow 2007). For example, a grower facing the choice between two binary technologies would be modeled as choosing between four technology systems. When this is not true—as is the case for the bivariate probit or logit models often used in existing studies in this area—complementarity is either ruled out or inadequately characterized (Gentzkow 2007; Miravete and Pernías 2010). The second important modeling feature is allowance for the possibility that the unobserved returns are correlated across practices. This is because the clustering (or lack thereof) of the observed practices may be the result of correlated unobserved tastes, rather than complementarity. Restricting the unobserved returns across practices to be uncorrelated—as done by nearly all existing studies dealing with the complementarity between GT crops and CT—can lead to accepting complementarity when it is absent, or rejecting complementarity when it is present (Athey and Stern 1998; Cassiman and Veugelers 2006).

In this article we reconsider the problem of testing for complementarity between GT crops and conservation tillage. The novelty of our contribution relates to both the data used, which are considerably more extensive than in previous applications, and the econometric methodology that we apply, which draws on recent econometric advances. Concerning data, we use a representative farm-level dataset that spans the period 1998–2011 and contains the seed and tillage choices of 29,518 soybean growers. Because GT soybeans were commercially introduced in 1996, our data cover much of the period during which growers transitioned from conventional (CV) soybeans to GT soybeans. Moreover, while our data set is not a balanced panel, it does contain repeated observations over time for a subset of the individuals (on average, 43% of farmers sampled in any given year are resampled the next year). As a result, for many farmers we observe whether or not their tillage choice changed upon switching to GT soybeans, thus aiding in distinguishing complementarity from the correlation among unobserved returns. Regarding methodology, our empirical framework is based on a structural model with a single choice set for farmers that includes all four possible combinations of adoption decisions over GT soybeans and CT. This contrasts with previous farm-level tillage studies, where a grower is modeled as making two simultaneous, albeit distinct, adoption decisions. In such models, complementarity is not directly estimated and consequently the results can be difficult to interpret.[1] Our model also controls for the correlation induced by unobserved heterogeneity by estimating the full covariance matrix associated with the individual random effects.[2]

Our results indicate that GT soybeans and CT are indeed complementary, a conclusion supported by several robustness checks. We also use our results to investigate the counterfactual scenario in which soybean growers did not have the option of choosing GT soybeans. We find that the adoption rates for both CT and no-tillage have increased by about 10% and 20%, respectively, due to the availability of GT soybeans. One of the implications of this result is that soil erosion was potentially lowered by 27 million tons per year during the 1998–2011 period. An approximate dollar value for this reduction is $189 million per year.

The rest of this article proceeds as follows. We first develop the model to be estimated, beginning with an exposition on the challenges associated with the econometric analysis of complementarity. We then specify the model and present the econometric procedure, with an explicit discussion of the identification conditions. This is followed by a description of the data, and a presentation and discussion of the empirical results. The article concludes with a brief investigation of some counterfactual scenarios and a discussion of possible policy implications.

[1] For example, Fernandez-Cornejo et al. (2003) found that the adoption of GT soybeans did not induce the adoption of CT, but that the adoption of CT did induce the adoption of GT soybeans. It seems difficult to provide a structural interpretation to such an asymmetric adoption interaction, and it is unclear what one ought to conclude about whether CT and GT soybeans are complementary.

[2] An example of the type of unobserved factors we have in mind is a farmer's education. If producers with more education are both more likely to use CT and adopt GT soybeans, then the unconditional correlation between CT and GT soybeans would be greater than the correlation that conditions on education.

*Modeling Complementarity*

The definition of complementarity between two activities is that the marginal return to each activity is increasing in the level of the other activity. The relevant return to focus on depends on the objective function of the decision maker. For technology adoption, it is natural to focus on the profit associated with the various potential choices. The characterization of the notion of complementarity is best expressed by the property of supermodularity of the objective function (Brynjolfsson and Milgrom 2013). Consider two technologies or practices that a producer can choose to adopt separately, together, or not at all. Let $d_j = 1$ and $d_j = 0$ denote, respectively, the adoption and non-adoption of practice $j$, for $j \in \{1, 2\}$. The profit from using any one of the four possible combinations of practices can therefore be expressed as $\tilde{\pi}(d_1, d_2)$. Practices $d_1$ and $d_2$ are said to be complementary if profits are supermodular, i.e., if

$$(1) \qquad \gamma \equiv [\tilde{\pi}(1,1) - \tilde{\pi}(1,0)] - [\tilde{\pi}(0,1) - \tilde{\pi}(0,0)] \geq 0.$$

When two practices are complementary, therefore, adoption of one while using the other has a larger effect on profits than adopting the practice in isolation. The structural representation in (1) provides the basis for testing hypotheses about complementarity. Depending on the type of data at hand, there are two ways to proceed. First, given access to firm-level profit data, $\gamma$ can be directly estimated (see Cassiman and Veugelers 2006). Often, however, data on profits (or other suitable performance measures) are not available—this is the case in our study. Alternatively, the hypothesis of equation (1) can be tested using adoption data only. The presumption is that a producer chooses the combination of practices that maximizes returns, thereby revealing information about the interaction between those practices.

Two significant challenges arise, however, in testing for complementarity with adoption data. First, the empirical framework needs to explicitly distinguish between complementarity and the correlation induced by unobserved heterogeneity. A common reduced-form approach taken by past studies, for example, has been to test for complementarity by estimating the correlation between two activities after controlling for firm characteristics (Arora and Gambardella 1990; Arora 1996; Cassiman and Veugelers 2006). The main limitation of this approach is that one can rarely control for all relevant characteristics; thus, finding a conditionally positive correlation will, at best, indicate that complementarity might be present. Alternatively, Athey and Stern (1998) outline a structural framework in which $\gamma$ can be directly estimated (while still controlling for unobserved heterogeneity). Several papers have since used such a framework to test for complementarity in different environments. For example, Miravete and Pernías (2006) use a version of the multinomial probit model to test for complementarity among production and innovation strategies, and Gentzkow (2007) uses a mixed logit model to test for complementarity between print and online newspapers. Although these two papers pursue different modeling frameworks, an essential element of both is that the choice-set includes all possible combinations of available practices.[3] This permits the sign of $\gamma$ to be directly estimated. Furthermore, both papers control for the potential correlation among the unobserved returns. Miravete and Pernías (2006) estimate the covariance between the unobserved returns to each practice. Similarly, Gentzkow (2007) allows the normally distributed error terms in his mixed logit framework to be correlated. This is in contrast to multinomial logit models, where the errors are assumed to be independently and identically distributed (IID) across alternatives.[4]

The second significant challenge to testing for complementarity with adoption data is sufficient identifying variation. The basic problem is that the observed clustering

[3] In general, if there are $n$ available practices then the choice-set would consist of $2^n$ alternatives. As Berry et al. (2014) note, the fact that the choice set grows exponentially can be a serious limitation to the types of problems that can be studied using this approach.

[4] Two related studies in the agricultural literature deserve mention. Wu and Babcock (1998) use a multinomial logit model to explore the environmental implications of three farming practices. The choice-set they specify consists of all eight possible combinations of the three practices. However, because of computational considerations, they do not allow for correlation among the unobserved returns. Moreover, the objective of their study was not to test for complementarity (e.g., they do not try to estimate $\gamma$). Dorfman (1996) uses a multinomial probit model to study two technology adoption decisions by US apple growers. He also specifies the choice-set over all combinations of decisions, and his model allows for the unobserved returns to be correlated (by estimating the covariance matrix). However, he does not attempt to identify structural complementarity.

of two practices could result either from unobserved heterogeneity or true complementarity (as defined in equation [1]). For example, observing that two practices are almost always adopted together could be entirely due to individuals simply having a high preference for both practices, rather than the presence of an interaction effect. Additional information or identifying restrictions are thus required to distinguish between these two alternative explanations. In estimating our model we draw on three sources for identification. One source is exclusion restrictions, i.e., the inclusion of variables that affect the returns to some practices but not others (Gentzkow 2007). The intuitive basis of exclusion restrictions is that changing a variable that only directly affects one practice will have no impact on the adoption of another practice unless they are interrelated.[5] A second source of identification is panel data (Gentzkow 2007). Repeated observations for an individual indicate whether (s)he, upon changing one practice, is more (less) likely to choose another practice, thereby indicating that the practices are complements (substitutes). A third source of identification, the intuition behind which is similar to the idea of exclusion restrictions, is exogenous variation in choice-sets (Nevo 2000, 529). If some growers lack access to a certain practice, for example, GT seed, then observing that they are less (more) likely to adopt another practice, for example, CT, would indicate the presence of complementarity (substitutability). We return to how identification conditions apply specifically in our setting after we have provided details on the model.

*The Model*

We implement a variant of the mixed logit model similar to Gentzkow's 2007 framework.

Let soybean growers be indexed by $i \in \{1, \ldots, N\}$, a year by $t \in \{1, \ldots, T\}$, and a field by $f \in \{1, \ldots, F_{it}\}$. The formal unit of analysis is a farm-field-year combination. On each field in a given year, a soybean grower makes a discrete choice for two practices: the type of seed to plant, denoted by $d_s$; and the type of tillage to employ, denoted by $d_\tau$. For seed, a grower may choose conventional seed ($d_s = CV$) or glyphosate tolerant seed ($d_s = GT$); for tillage, he may choose intensive tillage ($d_\tau = IT$) or conservation tillage ($d_\tau = CT$). With two practices, there are four mutually exclusive systems $(d_s, d_\tau)$:

$$(2)\qquad \Omega_0 \equiv \{(CV,\ IT), (GT,\ IT),\\ (CV,\ CT), (GT,\ CT)\}.$$

Denote the choice set for each grower in each year by $\Omega_{it}$. For the most part, $\Omega_{it} = \Omega_0$. That is, we assume that nearly all growers in all years can choose among all four systems. However, a handful of crop reporting districts (CRDs) early on in the sample have no observed GT soybean purchases.[6] For these districts-years, the presumed choice-set is: $\Omega_{it} = \{(CV, IT), (CV, CT)\}$.

Rather than directly specifying the normalized returns for each pair of choices, as done in Gentzkow (2007), in our setting it is instructive to start with the (unobserved) per-acre profit associated with system $(d_s, d_\tau)$, denoted by $\tilde{\pi}_{itf}(d_s, d_\tau)$. For each of his/her field in each time period, grower $i$ chooses system $(d_s, d_\tau)$ such that $\tilde{\pi}_{itf}(d_s, d_\tau) > \tilde{\pi}_{itf}(d'_s, d'_\tau)$, for all $(d'_s, d'_\tau) \in \Omega_{it}$ where $(d'_s, d'_\tau) \neq (d_s, d_\tau)$. For each system, the per-acre returns are specified to depend on a number of observable and unobservable variables, as follows:

$$(3)\qquad \tilde{\pi}_{itf}(CV, IT) = \tilde{\beta}_0^{CV,IT} + \beta_1 p_{CV,t} + \beta_2 r_{CV,t} + \left(\tilde{\beta}_3^{CV} + \tilde{\beta}_3^{IT}\right) Size_{it} + \tilde{\beta}_4^{IT} Fuel_t + \tilde{\beta}_5^{IT} Futures_t + \tilde{\beta}_6^{IT} EI_i + \tilde{\beta}_7^{IT} Palmer_{it} + \left(\tilde{\beta}_8^{CV} + \tilde{\beta}_8^{IT}\right) Trend_t + \tilde{\nu}_i^{CV} + \tilde{\nu}_i^{IT} + \tilde{\varepsilon}_{itf}^{CV,IT}$$

$$(4)\qquad \tilde{\pi}_{itf}(GT, IT) = \tilde{\beta}_0^{GT,IT} + \beta_1 p_{GT,t} + \beta_2 r_{GT,t} + \left(\tilde{\beta}_3^{GT} + \tilde{\beta}_3^{IT}\right) Size_{it} + \tilde{\beta}_4^{IT} Fuel_t$$

[5] Keane (1992) demonstrated via simulation that the covariance matrix of a multinomial probit model is not well identified without exclusion restrictions.

[6] CRDs are regions—each representing a collection of counties—used by the USDA for statistical reporting of certain data. It is also the finest level at which our seed and tillage data are representative.

$$+\tilde{\beta}_5^{IT} Futures_t + \tilde{\beta}_6^{IT} EI_i$$
$$+\tilde{\beta}_7^{IT} Palmer_{it}$$
$$+\left(\tilde{\beta}_8^{GT} + \tilde{\beta}_8^{IT}\right) Trend_t + \tilde{\nu}_i^{GT} + \tilde{\nu}_i^{IT}$$
$$+\tilde{\varepsilon}_{itf}^{GT,IT}$$

$$(5)\quad \tilde{\pi}_{itf}(CV, CT)$$
$$= \tilde{\beta}_0^{CV,CT} + \beta_1 p_{CV,t} + \beta_2 r_{CV,t}$$
$$+\left(\tilde{\beta}_3^{CV} + \tilde{\beta}_3^{CT}\right) Size_{it} + \tilde{\beta}_4^{CT} Fuel_t$$
$$+\tilde{\beta}_5^{CT} Futures_t + \tilde{\beta}_6^{CT} EI_i$$
$$+\tilde{\beta}_7^{CT} Palmer_{it} + \left(\tilde{\beta}_8^{CV} + \tilde{\beta}_8^{CT}\right) Trend_t$$
$$+\tilde{\nu}_i^{CV} + \tilde{\nu}_i^{CT} + \tilde{\varepsilon}_{itf}^{CV,CT}$$

$$(6)\quad \tilde{\pi}_{itf}(GT, CT)$$
$$= \tilde{\beta}_0^{GT,CT} + \beta_1 p_{GT,t} + \beta_2 r_{GT,t}$$
$$+\left(\tilde{\beta}_3^{GT} + \tilde{\beta}_3^{CT}\right) Size_{it} + \tilde{\beta}_4^{CT} Fuel_t$$
$$+\tilde{\beta}_5^{CT} Futures_t + \tilde{\beta}_6^{CT} EI_i$$
$$+\tilde{\beta}_7^{CT} Palmer_{it} + \left(\tilde{\beta}_8^{GT} + \tilde{\beta}_8^{CT}\right) Trend_t$$
$$+\tilde{\nu}_i^{GT} + \tilde{\nu}_i^{CT} + \tilde{\varepsilon}_{itf}^{GT,CT}.$$

In these equations, $p_{CV,t}$ and $p_{GT,t}$ represent the year $t$ seed prices for CV and GT soybeans, respectively. Similarly, $r_{CV,t}$ and $r_{GT,t}$ denote the prices of herbicides used on these two types of varieties. $Size_{it}$ is a dummy variable indicating whether the grower grew more than 500 acres in soybeans. $Fuel_t$ is a price index for diesel fuel, $Futures_t$ is the average soybean futures price in January for the next November contract, $EI_i$ is an index that measures soil erodibility, $Palmer_{it}$ is a drought severity index, and $Trend_t$ is a time trend.[7] The $\nu_i$ terms are time-invariant, practice-specific normally distributed unobservables. They represent individual characteristics we do not observe, such as education, which may affect the returns to the different practices. As we discuss further below, we allow for the $\nu_i$ to be correlated across systems. The terms $\tilde{\varepsilon}_{itf}^{d_s,d_\tau}$ are system-specific IID type I extreme value errors.[8] Their inclusion captures the fact that growers with the same characteristics and the same environment may still choose a different system.

The remaining symbols in equations (3)–(6) are parameters to be estimated. The intercepts $\tilde{\beta}_0^{d_s,d_\tau}$ are alternative-specific constants that capture the mean unobserved returns to each system. The superscripts of the other parameters indicate whether, and how, the associated variables are presumed to have a practice-specific effect. For example, we assume that $EI_i$, which is invariant across systems, will differ in its impact on profits depending on the type of tillage used. If this were not the case, that is, if the effect of $EI_i$ was the same across systems, then it would have no effect on the grower's choices (the term would drop out upon differencing the equations). This highlights the additional fact that not all of the parameters in equations (3)–(6) are identified. Only parameters that contribute to differences in per acre returns are estimable (Train 2009).

To clarify which parameters are identified, as well as how the model nests a test for complementarity, we normalize returns relative to a base system, which is taken to be the $(CV, IT)$ system. Defining $\pi_{itf}(d_s, d_\tau) \equiv \tilde{\pi}_{itf}(d_s, d_\tau) - \tilde{\pi}_{itf}(CV, IT)$, normalized returns can then be written as follows:

$$(7)\quad \pi_{itf}(CV, IT) = 0$$

$$(8)\quad \pi_{itf}(GT, IT) = \beta_0^{GT} + \beta_1(p_{GT,t} - p_{CV,t})$$
$$+ \beta_2(r_{GT,t} - r_{CV,t}) + \beta_3^{GT} Size_{it}$$
$$+ \beta_8^{GT} Trend + \nu_i^{GT} + \varepsilon_{itf}^{GT}$$

$$(9)\quad \pi_{itf}(CV, CT) = \beta_0^{CT} + \beta_3^{CT} Size_{it}$$
$$+ \beta_4^{CT} Fuel_t + \beta_5^{CT} Futures_t + \beta_6^{CT} EI_i$$
$$+ \beta_7^{CT} Palmer_{it} + \beta_8^{CT} Trend_t$$
$$+ \nu_i^{CT} + \varepsilon_{itf}^{CT}$$

$$(10)\quad \pi_{itf}(GT, CT) = \pi_{itf}(GT, IT)$$
$$+ \pi_{itf}(CV, CT) + \gamma + \varepsilon_{itf}^{\gamma}$$

[7] Further details on and summary statistics for each of these variables are provided in the Data section below.

[8] Per standard practice, the variance of the extreme value distribution is normalized to $\pi^2/6$. Thus, the model coefficients are identified relative to the unobserved scale parameter (see, e.g., Kurkalova, Kling, and Zhao 2006).

where, for each system, the parameters' superscript now denotes the practice that is different relative to the base system $(CV, IT)$ (e.g., $\beta_0^{GT} \equiv \tilde{\beta}_0^{GT,IT} - \tilde{\beta}_0^{CV,IT}$). Furthermore:

$$\text{(11)} \quad \gamma \equiv \left(\tilde{\beta}_0^{GT,CT} - \tilde{\beta}_0^{GT,IT}\right) - \left(\tilde{\beta}_0^{GT,IT} - \tilde{\beta}_0^{CV,IT}\right)$$

$$\text{(12)} \quad \varepsilon_{itf}^{\gamma} \equiv \left(\tilde{\varepsilon}_{itf}^{GT,CT} - \tilde{\varepsilon}_{itf}^{GT,IT}\right) - \left(\tilde{\varepsilon}_{itf}^{CV,CT} - \tilde{\varepsilon}_{itf}^{CV,IT}\right).$$

Hence, the sum $\gamma + \varepsilon_{itf}^{\gamma}$ captures whether GT soybeans and CT are complementary. To see this, note that, in terms of the un-normalized returns, we have:

$$\text{(13)} \quad \gamma + \varepsilon_{itf}^{\gamma} = \left(\tilde{\pi}_{itf}(GT, CT) - \tilde{\pi}_{itf}(GT, IT)\right) - \left(\tilde{\pi}_{itf}(CV, CT) - \tilde{\pi}_{itf}(CV, IT)\right).$$

Equation (13) revisits the relation in equation (1), which determines whether the two choices of interest are complementary. However, this relation is now adjusted for the presence of unobserved heterogeneity; complementarity can vary over the population through $\varepsilon_{itf}^{\gamma}$. Because $E[\varepsilon_{itf}^{\gamma}] = 0$, it follows that $\gamma$ is best interpreted as a measure of *mean* complementarity in the population. If our estimate for $\gamma$ is statistically significantly greater (less) than zero, then GT soybeans and CT are, on average, complements (substitutes). Note also that, in this framework, $\gamma$ does not vary on the basis of the observable characteristics. This is a consequence of our assumption that the observable variables have practice-specific effects rather than system-specific effects. This assumption is primarily rooted in our goal of obtaining a straightforward test for complementarity, as encapsulated by $\gamma$. In this regard we follow Miravete and Pernías (2006), Gentzkow (2007), and Kretschmer, Miravete, and Pernías (2012), who also specify the observable variables as having practice-specific effects rather than system-specific effects.[9]

To control for the correlation induced by unobserved heterogeneity, we allow for $\nu_i^{GT}$ and $\nu_i^{CT}$ to be correlated. Specifically, we assume that $(\nu_i^{GT}, \nu_i^{CT}) \sim N(0, \Sigma)$, where

$$\text{(14)} \quad \Sigma = \begin{pmatrix} \sigma_{GT}^2 & \sigma_{GT,CT} \\ \sigma_{GT,CT} & \sigma_{CT}^2 \end{pmatrix}.$$

By estimating $\sigma_{GT,CT}$, we control for unobserved factors that contribute simultaneously to the returns of $\pi_{itf}^{GT,IT}$ and $\pi_{itf}^{CV,CT}$. For example, if $\nu_i^{CT}$ is large (small) whenever $\nu_i^{GT}$ is large then these two terms will be positively (negatively) correlated. Without controlling for such correlation, estimates of $\gamma$ would be biased upward (downward). Some of the specific kinds of unobserved variables that we have in mind include the grower's education, attitude towards new technologies, and degree of risk aversion. For example, better educated individuals may face lower adoption costs and so may be more likely to use both GT soybeans and CT. Similarly, individuals that are generally more open to new technologies (so-called early adopters) may be more likely to use both GT soybeans and CT. If a person is very risk averse, on the other hand, the opposite may hold true: GT soybeans may be viewed as less risky than CV soybeans, whereas CT may be viewed as more risky than IT, leading to a negative correlation between the unobserved returns.

Because we have differenced out the returns to the $(CV, IT)$ system, the model as written in equations (7)–(10) makes explicit which parameters are identified. The parameters on variables that enter all of the equations are identified relative to the $(CV, IT)$ system. For example, the sign of the estimate for $\beta_1^{GT}$ will indicate whether a large farm is more likely to adopt GT soybeans *relative to* CV soybeans. The parameters on the alternative-specific variables, such as prices, indicate how changes in the differences of those variables affect returns. For example, $\beta_1$ is the effect of a change in the price of GT seed relative to the price of CV seed.

### *Identification*

The model as presented is formally identified: there are more moments than parameters. However, as noted previously, the precise identification of the parameters, in particular the complementarity and covariance parameters, requires additional sources of variation and information that go beyond the basic formal requirements. The issue is

[9] See Athey and Stern (1998) for a more detailed discussion of these issues.

that the patterns of adoption generated by a model with positively correlated unobserved returns ($\sigma_{GT,CT}$ is high) and practices that are substitutes ($\gamma < 0$) can be very similar to the adoption patterns generated by a model with negatively correlated unobserved returns ($\sigma_{GT,CT}$ is low) and practices that are complements ($\gamma > 0$). Thus, to distinguish between correlated tastes and complementarity requires some form of variation in the data that would occur because of only one of these effects, while holding the other constant.[10]

As noted earlier, one source of identification is exclusion restrictions. To illustrate the role of these identifying restrictions in the context of the model just presented, suppose that the price of GT soybean seeds relative to that of CV soybeans directly affects the seed choice but not the tillage choice (i.e., the relative seed price is an excluded variable). Further, suppose that there is a shock to this relative price, for example it decreases. Then some producers will switch from CV soybeans to GT soybeans. If GT soybeans and CT are independent, then there should be no change in the adoption of CT since the seed price does not directly affect it. If they complement, however, then we would also observe an increase in the use of CT. Some of the producers that previously chose CV soybeans with IT would switch to using GT soybeans with CT. Intuitively, the switch to GT soybeans (based on the price change) would shift up the return to CT, thus also leading to its adoption.

The variables that fulfill the exclusion restrictions in our model are those that affect the seed choice – that is, variables in equation (8) – but not the tillage choice (equation [9]), and vice versa. The specific variables that we assume directly affect the seed choice but not the tillage choice include the difference in seed prices ($p_{GT,t} - p_{CV,t}$) and the difference in herbicide prices ($r_{GT,t} - r_{CV,t}$) (i.e., these variables enter the second equation but not the third). Differences in relative seed prices should have no effect on the relative return to the different tillage operations. With regard to herbicide prices, previous studies by Bull et al. (1992), Fawcett, Christensen, and Tierney (1994), and Fuglie (1999) do not find a significant difference in pesticide use between CT and IT systems; thus we assume it does not directly affect the tillage choice.[11]

The variables assumed to directly affect the tillage choice but not the seed choice include $Fuel_t$, $Futures_t$, $EI_i$, and $Palmer_{it}$. The variable $Fuel_t$ is included to capture the argument that CT generally requires less fuel (Triplett and Dick 2008). For a given tillage method, however, there will be little difference in fuel usage for different seed types. Similarly, the $EI_i$ only enters the tillage equation because the degree of erodibility will not have a differential effect on the seed choice (holding the tillage-type constant). The same argument applies for $Palmer_{it}$, which is included because CT leaves more ground cover in place and may be chosen to conserve moisture in dry years. Finally, $Futures_t$ is included to capture changes in relative returns due to yield differences between the tillage options. Previous research has generally indicated that there is no significant yield difference between GT and CV soybeans (Qaim 2009). Rather, the primary reason farmers prefer GT soybeans is because they provide easier weed control and a reduction in management time (Qaim 2009).

The contribution of panel data to identification occurs through the estimation of the distribution of the time-invariant random effects. Intuitively, if the adoption of GT soybeans and CT are correlated because of a high covariance parameter $\sigma_{GT,CT}$ (rather than complementarity), then the adoption of GT soybeans and CT for a given individual would be uncorrelated over time. Individuals may have a high propensity to use both, but conditional on changing one practice, they would be no more (or less) likely to use another. On the other hand, if we observe across time periods that whenever a given individual adopts GT soybeans, he or she is more likely to adopt CT, then this would imply the presence of synergies. Regarding choice-set variation, as noted previously, early on in our sample we do not observe any purchases of GT varieties in certain crop reporting districts (CRDs). We interpret this to mean that they were not available as an

[10] For a more comprehensive discussion of these issues, see Gentzkow (2007).

[11] As part of robustness checks reported later, we do allow for herbicide prices to differ in their impact by the type of tillage employed. We find that it does not affect our complementarity result.

option, and thus we exclude them from the choice-sets of individuals within that region.[12]

### Estimation

The model is estimated by the method of simulated maximum likelihood (SML) (Train 2009). To simplify the notation, let $j$ denote system $(d_s, d_\tau)$, that is, $j \in \Omega_{it}$. Furthermore, rewrite equations (7)–(10) as:

$$(15) \quad \pi^j_{itf} = x^j_{itf}\beta^j + \nu^j_i + \varepsilon^j_{itf}$$

where $x^j_{itf}$ is the vector of explanatory variables pertaining to system $j$, and $\beta^j$ is the associated parameter vector (note that $\pi^{CV,IT}_{itf} = 0$, as above). Let $\theta$ denote the vector of all parameters to be estimated (this includes the vector of all $\beta$ parameters, which implicitly also define the complementarity parameter $\gamma$, as well as the parameters of the covariance matrix $\Sigma$). Then, for a *given* realization $\nu^j_i$, the probability of choosing system $j$ is provided by the standard logit expression:

$$(16) \quad L^j_{itf}(\nu;\theta) = \frac{e^{x^j_{itf}\beta^j + \nu^j_i}}{\sum_{k\in\Omega_{it}} e^{x^k_{itf}\beta^k + \nu^k_i}}.$$

Let $j_{itf} \in \Omega_{it}$ denote the actual system choice of grower $i$ for field $f$ in year $t$, and define $\zeta_i \equiv \{j_{itf}\}$ as the set of all actual choices in the sample for grower $i$. Given $\nu^j_i$, the probability of $\zeta_i$ is given by the product of the corresponding logits:

$$(17) \quad L_{\zeta_i}(\nu;\theta) = \prod_{j\in\zeta_i} L^j_{itf}(\nu;\theta).$$

The unconditional probability is given by the integral over all $\nu$ that generate $\zeta_i$:

$$(18) \quad P_{\zeta_i} = \int L_{\zeta_i}(\nu;\theta) f(\nu) d\nu.$$

Since $P_{\zeta_i}$ is an integral it can be estimated via simulation. For each individual, multiple draws of the $\nu_{ij}$ are taken, $L_{\zeta_i}$ is computed, and then averaged. Specifically, let $R$ denote the number of draws of $\nu^j_i$ for each individual. Then $P_{\zeta_i}$ is approximately given by:

$$(19) \quad P_{\zeta_i} \approx \frac{1}{R}\sum_{r=1}^{R} L_{\zeta_i}(\nu_r;\theta).$$

The SML estimator is therefore given by:

$$(20) \quad \hat{\theta} = \arg\max_{\theta} \sum_i \left[\ln \frac{1}{R}\sum_{r=1}^{R} L_{\zeta_i}(\nu_r;\theta)\right].$$

The statistical package that we use is the Stata user-written mixlogit package developed by Hole (2007) (for further details see also Cameron and Trivedi (2010), 523). In simulating the likelihood function, we use 250 Halton draws, which is well above the minimum recommendation of 100 (Hensher, Rose, and Greene 2005, 616).[13] It is also important to re-emphasize that the estimated parameters, $\hat{\theta}$, are identified relative to the unobserved variation of the IID extreme value unobservables, which are implicitly normalized prior to estimation (see earlier footnote 8). Thus, for example, instead of estimating the complementarity parameter $\gamma$, the model actually estimates $\gamma/\varphi$ (where $\varphi$ is the unobserved scale parameter for the extreme value type I distribution). For simplicity, and slightly abusing notation, we continue to use the same parameter symbols (e.g., $\gamma$) for the remainder of the paper.

### Data

The model is estimated with farm-level seed and tillage data from the survey company GfK.[14] These data, which are designed to be representative at the CRD level, span 1998–2011 and include about 4,982 farmers per year (each farmer can have multiple fields). As noted above, about 43% of growers sampled in any given year are also sampled the next year. In total, our sample contains 82,056 farm-field-year observations across

[12] Because only a small number of CRDs do not have observed GT seed purchases (early on in our sample), this type of identification plays a small role in our analysis.

[13] Train (2000) demonstrated that the SML estimates for a mixed logit model using 100 Halton draws outperform the SML estimates using 1,000 random draws. The practical benefit of this is that estimation time is decreased by a factor of ten while simultaneously increasing accuracy. For a further discussion of Halton sequences, see Train (2009).

[14] Specifically, we use data from GfK's AgroTrak® and Soybean TraitTrak™. See the company's website (http://www.gfk.com/us) for a brief description of these proprietary data products.

**Table 1. Distribution of Tillage and Seed Systems (% of observations)**

| System | 1998–2001 | 2002–2006 | 2007–2011 | 1998–2011 |
|---|---|---|---|---|
| (CV,IT) | 20.73 | 6.34 | 2.26 | 10.18 |
| (GT,IT) | 21.53 | 30.41 | 29.38 | 27 |
| (CV,CT) | 20.3 | 6.63 | 3.01 | 10.35 |
| (GT,CT) | 37.44 | 56.61 | 65.34 | 52.47 |
| Observations | 28,701 | 29,240 | 24,115 | 82,056 |

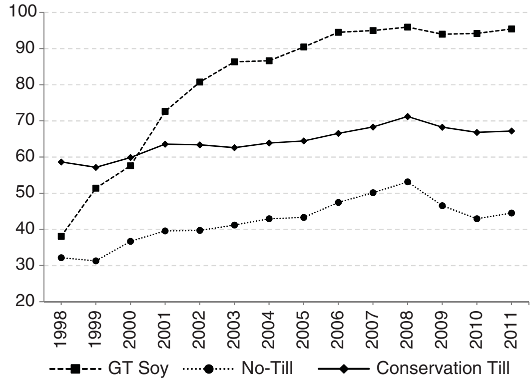


**Figure 1. Conservation tillage and GT adoption rates for US soybeans (percent of acres)**

235 CRDs in 31 states (with the largest soybean states being the most heavily represented). Among the variables previously defined, those that come from the GfK data include tillage and seed choices (i.e., the endogenous variables), seed and herbicide prices, and the variable for farm size. With respect to the tillage choice, in our data each plot is identified as using one of three following alternatives: "Intensive Tillage," "Conservation Tillage," or "No-Till." For our baseline specification, we treat intensive tillage as a distinct category, and combine the plots identified as "Conservation Tillage" and "No-Till" into the model's CT category. However, we also consider an alternative aggregation procedure where the model's CT category is associated only with the plots classified as "No-Till" (NT) in the data set and combine the remaining two classifications into the model's IT category. Where applicable, we make explicit which definition is being used.

The shares for each seed-tillage system are provided in table 1, where the distribution of system choices over time is disaggregated into three subperiods. From 1998 to 2001, CV soybeans still accounted for about 40% of the observations, but from 2002 to 2006 they only made up about 13%, and for the final subperiod just over 5%. Overall, systems with GT soybeans accounted for about 80% of all observations, whereas systems with CT accounted for about 62% of all observations.

Table 1 also shows that about 67% of acres planted to GT soybeans use CT whereas about 50% of acres planted to CV soybeans use CT. This is generally consistent with previous work based on different data sources (e.g., Fernandez-Cornejo et al. (2014)). The correlation coefficient between GT soybeans and CT is 0.125 and is significant at a 1% level. Changes over time also show a positive correlation. Figure 1 contains US annual adoption rates for GT soybeans, CT, and NT from 1998 to 2011. GT soybean adoption increased from just under 40% of acres in 1998 to about 95% of acres in 2011. Over the same period, CT increased from just under 60% of acres in 1998 to nearly 70% of acres in 2011. NT increased even more, from 32% in 1998 to 45% in 2011 (and a peak of 53% in 2008).

With regard to the remaining variables, the *EI* data were obtained from the National Resources Inventory (a survey conducted by the National Resources Conservation Service), soybean futures were obtained at www.quandl.com, diesel fuel prices were obtained from Quick Stats at the USDA-NASS website, and the Palmer Z-Index was obtained from www.ncdc.noaa.gov. Below we provide additional details, as well as a discussion of their expected effects, for each of the regressors. Table 2 provides a summary of their distributions.

*Farm Size* is a dummy variable that indicates whether a grower planted more than 500 acres in soybeans. The arbitrary cut-off of 500 acres was a natural choice given the available data, in which each farm is classified into one of five categories: (i) <100 soybean acres, (ii) 100–249 acres, (iii) 250–499 acres, (iv) 500–999 acres, and (v) 1,000 or more acres.[15] We include *Farm Size* for both the seed and tillage choices to control for scale effects. Past studies have noted that the use of CT, in particular no-tillage, can require large fixed costs in the form of better adapted machinery (Knowler and Bradshaw 2007).

[15] For robustness checks we also estimate the model with the *Size* variable cutoffs set at 250 and 1,000 acres. Overall, the results remained unchanged.

**Table 2. Regressor Summary Statistics**

| Variable | Mean | S.D. | Min | 0.25 | Median | 0.75 | Max |
|---|---|---|---|---|---|---|---|
| *Size (>500 acres)* | 0.33 | 0.47 | 0 | 0 | 0 | 1 | 1 |
| *Futures ($/bu)* | 7.3 | 2.78 | 4.48 | 5.2 | 6.37 | 9.6 | 13.13 |
| *Fuel Price Index* | 49.96 | 24.33 | 19.6 | 29 | 43.8 | 65.4 | 91.2 |
| *Erodiblity Index* | 8.36 | 9.49 | 0.29 | 2.67 | 5.2 | 11.32 | 192.07 |
| *Palmer's Z-Index* | 0.29 | 2.47 | −4.93 | −1.46 | −0.11 | 1.48 | 11.84 |
| *Seed Price ($/50lb bag)* | 8.98 | 1.92 | 6.34 | 7.46 | 8.67 | 9.84 | 12.41 |
| *Herbicide Price Index* | −0.28 | 0.2 | −0.65 | −0.42 | −0.26 | −0.1 | 0 |

Given this, we expect that larger farms will be more likely to adopt CT. With regard to the seed choice, we have no strong prior expectations. Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) find that larger farms are more likely to adopt GT soybeans, whereas Fernandez-Cornejo et al. (2003) find no size effect. The latter argue that since the adoption of GT soybeans does not require significant fixed costs, there should not be significant differences in adoption between large and small farms.

*Futures* is the Chicago Mercantile Exchange mean soybean futures price in the month of January for the same year November contract. It is included as a proxy for the output price that is expected by producers. We use January because that is a common time at which practice decisions are made, and we use November because it is the closest month after harvest. We include it as an explanatory variable for the tillage choice because there might be yield differences between IT and CT. Previous studies, however, are inconclusive on the effect of output prices on CT (Knowler and Bradshaw 2007).

*Fuel Price* is an annual index for diesel fuel prices (as noted above, it is obtained from USDA-NASS). We use the mean index from September to May as this is the period during which most tillage decisions are made. The index is included to control for potential differences in fuel usage between CT and IT operations. From 1998 to 2011, real fuel prices rose significantly and thus could explain some of the variation in tillage trends. Since CT tends to use less fuel, our expectation is that higher prices will increase the likelihood of using CT.

*EI* is a county-specific, time-invariant index of soil erodibility due to water events. It measures a soil's potential to erode. A higher index indicates that greater investment is required to maintain the sustainability of the soil under intensive cultivation. The National Resources Inventory considers scores of 8 or above to indicate highly erodible land. The *EI* is included for a couple of reasons. First, the 1985 Farm Bill requires a producer that grows crops on highly erodible land to meet certain minimum conservation requirements (Stubbs 2012) in order to be eligible for some government payments. An acceptable way to comply is to use CT. Second, a grower may be more likely to use CT on highly erodible land in order to preserve the soil's productivity into the future (Soule, Tegene, and Wiebe 2000). Given these two rationales, as well as previous findings, we expect that the *EI* will have a positive sign; that is, a grower will be more likely to use CT on more erodible land.

*Palmer's Z* is the mean Palmer's Z-Index for the month of September in the prior year (this variable is at the climate-division level; see Xu et al. (2013) for more details). This index indicates how dry a locality is relative to normal conditions. Negative values indicate drier conditions, whereas positive values indicate wetter conditions. We include Palmer's Z-Index because the presence of drought may increase the likelihood of adopting CT. For instance, Ding, Schoengold, and Tadesse (2009) find that drought is associated with a greater likelihood of using no-till and other CT practices.

The *Seed Price* term ($p_{GT,t} - p_{CV,t}$) is the difference between mean annual US GT and CV soybean seed prices ($/50 lb bag). In our data we observe the transaction prices for each individual, but we do not observe the price for the type of seed they did not buy (e.g., if a grower purchased CV seeds, we do not know the price they would have paid for GT seeds). Thus, as a proxy for that price, we average over all individuals within a given year. We aggregate to the national level because, beyond 2003, there are very few observations for CV seed purchases. As a result, averaging at a finer level would

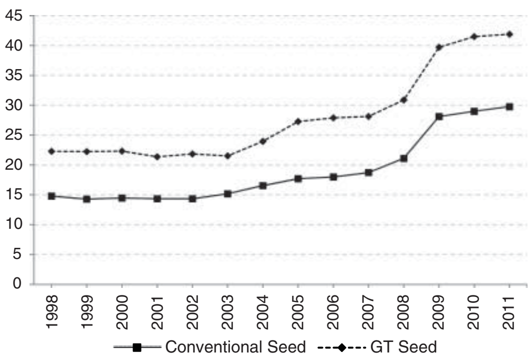


**Figure 2. US soybean seed prices, 1998–2011 ($/50lb)**

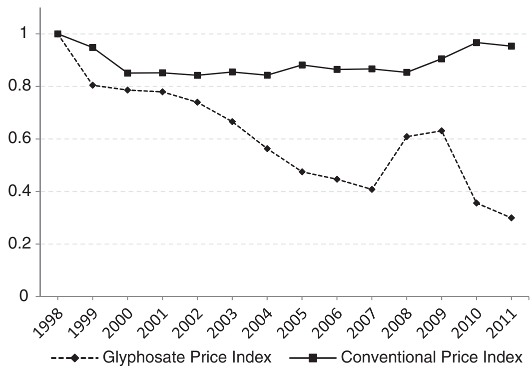


**Figure 3. US soybean herbicide prices, 1998–2011**

introduce considerable sampling variation. Figure 2 presents GT and CV seed prices from 1998 to 2011.

Prior to 2009 there was comparatively little movement in both relative prices and overall prices. The increase in soybean output prices in 2008 led to a significant rise in seed prices in 2009. In terms of expectations, the higher the price of GT seed relative to CV seed, the smaller the return for GT seeds. Thus, a negative sign is expected. It is worth noting, however, that previous studies have found a positive sign for seed price (see, e.g., Fernandez-Cornejo, Klotz-Ingram, and Jans 2002). This is likely because of the rapid diffusion of GT soybeans that coincided with a slight increase in relative prices; we control for this process with a time-trend.

The *Herbicide Price* term $(r_{GT,t} - r_{CV,t})$ is the difference between the annual US price indices for glyphosate and for a group of seven post-emergence conventional herbicides. Our assumption is that the glyphosate price is the main herbicide price a grower looks at when considering the adoption of GT soybeans. For CV soybeans, the matter is less straightforward. As noted earlier, many of the herbicides used on CV soybeans are only effective against specific weed species. In addition, only some of these herbicides can be applied post-emergence. We chose to use only the prices from post-emergence herbicides because they are what primarily differentiate CV soybeans from GT soybeans.[16] In terms of calculation, glyphosate prices are annual volume-weighted averages in dollars per pound. The price for CV soybeans is a Laspeyres Index: each year, the index is a weighted average of the ratio of current prices to base prices. For the base, we use the mean prices and shares of the seven herbicides for the entire 1998–2011 period, and the resulting index is rescaled to equal 1 for the year 1998. Figure 3 presents these indices for the 1998–2011 period. For comparison, both the glyphosate and CV herbicide prices are normalized to equal 1 in 1998. The price of glyphosate has fallen considerably and almost uniformly since 1998. This is primarily due to the expiration of Monsanto's patent in 2000. The exception to the trend decline occurred during 2008–2009, when prices rose significantly. During 2008–2009, commodity prices, and in turn land used for cropping, were very high. This, combined with a growing demand for GT corn, led to shortages in glyphosate and an associated price increase.

The time *Trend* variable is included to capture the impact of other factors that contributed to the diffusion of GT soybeans and CT. This was particularly important for GT soybeans, as adoption rose from 38% to 86% over the period 1998–2003. This adoption pattern was driven by a variety of factors that are not captured by our model. We expect that the adoption of GT soybeans will be positively associated with this trend variable. For CT, we have no strong prior expectations.

## *Empirical Results*

Table 3 contains our baseline specification. Overall, the results are consistent with expectations. The alternative-specific constant for GT seed varieties is positive and significant.

[16] The seven herbicides we include are Raptor®, Flexstar® 1.88L, Fusion®, FirstRate®, Select® 2 EC, Cobra®, and Pursuit® 2 EC. We selected these herbicides because they were the most frequently used post-emergence herbicides applied on CV soybeans.

**Table 3. Simulated Maximum Likelihood Results**

| Parameter (variable) | Coefficient | Standard Error |
|---|---|---|
| GT adoption | | |
| $\beta_0^{GT}$(*constant*) | 1.5973*** | (0.2060) |
| $\beta_1$(*Seed Price*) | −0.3262*** | (0.0249) |
| $\beta_2$(*Herbicide Price*) | −0.9837*** | (0.1565) |
| $\beta_3^{GT}$(*Size*) | 0.1192*** | (0.0418) |
| $\beta_8^{GT}$(*Trend*) | 0.4420*** | (0.0098) |
| CT adoption | | |
| $\beta_0^{CT}$(*Constant*) | −0.5710*** | (0.1317) |
| $\beta_3^{CT}$(*Size*) | 0.2850*** | (0.0556) |
| $\beta_4^{CT}$(*Fuel*) | 0.0069*** | (0.0021) |
| $\beta_5^{CT}$(*Futures*) | −0.0255** | (0.0124) |
| $\beta_6^{CT}$(*Erodibility*) | 0.0786*** | (0.0117) |
| $\beta_7^{CT}$(*Palmer*) | −0.0237** | (0.0097) |
| $\beta_8^{CT}$(*Trend*) | 0.0436*** | (0.0093) |
| Other parameters | | |
| $\gamma$ | 0.4609*** | (0.0405) |
| $\sigma_{GT}^2$ | 2.2200*** | (0.1097) |
| $\sigma_{CT}^2$ | 3.9186*** | (0.2225) |
| $\sigma_{GT,CT}$ | 0.3094*** | (0.0846) |

*Notes:* Number of observations = 82,056. Standard errors are clustered at the CRD level. Except for the covariance parameters, the coefficients are identified relative to $\phi$, the scale parameter for $\varepsilon_{itf}^{j}$. The covariance parameters are identified relative to $\phi^2$.
***Significant at the 1% level.
**Significant at the 5% level.

Conversely, the constant for CT is negative and significant. This is unsurprising given that a large number of farms continued to adopt IT despite the presence of synergies between GT soybeans and CT (as indicated by the result for $\gamma$). Higher prices for GT seed (relative to CV seeds) and glyphosate (relative to substitute herbicides) are associated with a lower likelihood of using GT soybeans. Larger farms are more likely to use both GT soybeans and CT. Also, the relative size of the parameter for CT is significantly larger, suggesting that farm size plays a larger role for the tillage decision. The linear time trend is significant and positive for both GT soybeans and CT, though significantly larger for GT soybeans, as would be expected. Among the variables exclusive to the tillage decisions, there are some interesting results. Higher soybean futures prices are associated with a lower likelihood of using CT, though the effect is only significant at 5%. This suggests that there may be a small perceived yield-loss associated with the use of CT. For some soils the formal agronomy literature provides evidence to support this perception (Triplett and Dick 2008). Higher fuel prices, on the other hand, significantly increase the likelihood of using CT. We also find that more drought-like conditions, as captured by Palmer's Z-Index, increase the likelihood of using CT, corroborating the finding by Ding, Schoengold, and Tadesse (2009). Finally, a higher *EI* is also found to be associated with a significantly higher probability of CT use.

For the unobservables, we find significant evidence of unobserved variation in preferences for both GT soybeans and CT. The unobserved variance for CT is particularly large, suggesting that a variety of omitted individual characteristics are important for determining the best tillage practice. This seems intuitive given the relatively large adoption rates for both CT and IT throughout the sample period. Unobserved variation in tastes is also important for the seed choice, though relatively less so. This is probably a reflection of the fact that later on GT soybeans are adopted by nearly everyone, and thus a relatively smaller variance can rationalize the small share of farms that still use CV soybeans. The covariance across the errors is also significant. The implied correlation is about 0.105. Thus, farmers who have a strong preference for GT soybeans (i.e., a large $\nu_i^{GT}$) are more likely to have a strong preference for CT (i.e., a large $\nu_i^{CT}$) and vice versa. Finally, the estimate for complementarity, $\gamma$, is highly significant and positive, indicating that GT soybeans and CT are indeed complementary practices.

What is the economic significance, to the farmer, of the estimated complementarity effect? One measure is provided by a grower's willingness to pay (WTP) for it. In a standard discrete choice random utility model, the WTP for an attribute is given by the ratio of that attribute's coefficient to the absolute value of the coefficient for the price variable (note that the ratio of the two estimated coefficients will be independent of the unidentified scaling parameter). In our model, the objective function is profit per acre. As a result, the estimated coefficient for the seed price represents the number of soybean bags planted per acre (relative to the unidentified scaling parameter). Dividing an attribute's coefficient by the absolute value of the coefficient for seed price thus gives the WTP per bag of soybeans for that attribute. For $\gamma$, this implies a WTP of about \$1.41 per bag of soybean seeds. Given that a typical density for soybeans is 1.2 bags/acre,

**Table 4. Average Elasticities**

| | GT(%) | CT(%) |
|---|---|---|
| *Seed Price* | $-1.14^{D}$ | $-0.08^{I}$ |
| *Herbicide Price* | $-0.11^{D}$ | $-0.01^{I}$ |
| *Soy Futures* | $-0.002^{I}$ | $-0.04^{D}$ |
| *Fuel Price* | $0.002^{I}$ | $0.07^{D}$ |
| *Palmer Z* | $-0.0004^{I}$ | $-0.01^{D}$ |
| *Erodibility Index* | $0.01^{I}$ | $0.10^{D}$ |

*Notes:* The reported effects are elasticities, i.e., the % change in the probability of adopting GT (CT) given a 1% change in the respective variable. See text for additional discussion.
$^{D}$ = Direct Effect; $^{I}$ = Indirect Effect.

the WTP of a typical farmer for the synergies provided by complementarity between GT seeds and CT is $1.69/acre.

Because the coefficients are identified relative to the scale parameter $\phi$, only their sign is directly interpretable. To get a better idea of the importance of each of the variables, we simulate the change in the adoption of GT soybeans and CT in response to a change in the value of each of the exogenous variables. This exercise also serves to highlight the role of complementarity for the impacts of each of the independent variables. Table 4 contains the average marginal effects (AMEs) for GT and CT adoption with respect to each of the regressors. The AME of a variable is the average change in the probability of adopting a practice, e.g., GT soybeans or CT, in response to a change in that variable. With the exception of *Size*, we compute elasticities. As an example, to calculate the effect of a change in the *EI* on GT soybean adoption, we first simulate and compute for each individual:

$$(21) \qquad \psi_{itf}^{GT,EI} \equiv \frac{\Delta \Pr(GT)}{\Delta EI} \frac{EI}{\Pr(GT)}$$

where $\psi_{itf}^{GT,EI}$ denotes the elasticity of the probability of GT soybean adoption with respect to the *EI*. The result reported in table 4 is the average of these elasticities over all individuals, time periods, and fields. The superscripts "I" and "D" indicate whether the impact of the variable on the practice is indirect or direct, respectively.

Overall, the results indicate that the seed price plays the largest role among the variables. For example, a 1% increase in the price of GT soybeans relative to that of CV soybeans results in a slightly-more-than 1% direct decrease in the probability of adopting GT soybeans. Through the complementarity effect, it also indirectly decreases the probability of adopting CT by 0.08%. The impacts of the other continuous variables can be interpreted in a similar manner. Because the variable *Size* is binary, an elasticity cannot be computed; instead, we compute the percent difference in the probability of adopting a practice between growers with more than 500 soybean acres and growers with less than 500 soybean acres. Note also that the impacts for *Size* are made up of both direct and indirect effects. The simulation indicates that a farm with 500 or more soybean acres is 6.9% more likely to adopt CT and 2.1% more likely to adopt GT soybeans.

**Table 5. Alternative Estimates for Complementarity**

| Alternative Specifications | $\gamma$ Coefficient | Standard Error |
|---|---|---|
| Include *Herbicide Price* in CT variables | 0.4143*** | (0.0395) |
| No correlation: $\sigma_{GT,CT} = 0$ | 0.5849*** | (0.0322) |
| Ignore panel aspect of data | 1.3610** | (0.6699) |
| Basic logit | 0.5473*** | (0.0333) |
| Restrict sample to Central Corn Belt only[a] | 0.3039*** | (0.0519) |
| No-till or till for tillage choice[b] | 0.6514*** | (0.0414) |

*Notes:* [a]Includes Iowa, Illinois, and Indiana, for which there are 26,304 observations in all.
[b]This variation specifies the tillage choice as being between no-till or a positive amount of tillage (rather than between conservation tillage and intensive tillage).
***Significant at the 1% level.
**Significant at the 5% level.

*Complementarity under Alternative Specifications.* Certain variations on our specification, such as allowing herbicide prices to directly impact the relative profitability of CT, are also plausible, which may be important for the complementarity finding. In addition to testing for robustness across these alternatives, this section serves to highlight the role of certain assumptions, such as admitting non-zero correlation between the unobserved returns, for the estimate of $\gamma$. Table 5 contains estimates of $\gamma$ for several different specifications. Allowing for the Herbicide Price variable to directly impact the tillage choice reduces the coefficient somewhat but does not alter the finding of complementarity.

The next specification demonstrates the effect of not allowing unobserved tastes to be correlated (i.e., $\sigma_{GT,CT} = 0$). In this case the estimate for $\gamma$ increases as it captures some of the effect that is actually the result of correlated tastes. We also estimate the model when ignoring the fact that some individuals have repeated observations (i.e., we assume that the $\nu$ terms are IID across fields and time for the same individual). This substantially increases both the estimate and the standard error for $\gamma$, which suggests that when using the mixed logit model, it is important to utilize the panel aspect of the data. The "Basic Logit" specification not only ignores the panel aspect of the data but also does not allow for unobserved heterogeneity (i.e., the $\nu$ terms are set to 0). In this case, the estimate for $\gamma$ is actually closer to the original model than the estimate that ignored the panel aspect of the data.

We also estimated the model with data from the Central Corn Belt (CCB) only (the states we include are IA, IL, and IN). These three states account for nearly 35% of US soybean land alone. Our result for $\gamma$ in this case is less than before. However, since $\gamma$ is estimated on a different sample, it is not directly comparable to the estimate obtained from our baseline specification. Because the parameters are identified relative to the scale parameter, a different value could indicate that complementarity between GT soybeans and CT is less in this region, but it could alternatively indicate that the IID portion of unobserved variation is larger in the CCB (relative to the rest of the country).

The final specification changes the way the tillage choice is structured. Instead of specifying the tillage choice for the farmer as being between CT and IT, we instead specify it as being between no-tillage (NT) and tillage (i.e., some positive level of tillage). We expect the complementarities between NT and GT soybean to be even stronger than between CT and GT. Intuitively, the improved efficiency and convenience of weed control offered by GT varieties will be especially beneficial when making the leap to a NT system. This is weakly confirmed by the correlation coefficient between GT soybeans and NT, which is slightly larger at 0.139 (compared to 0.125). The estimate for $\gamma$ presented in table 4 indicates that NT and GT soybeans are complementary, and the magnitude of $\gamma$ is indeed larger than it was for the CT specification. As was noted for the case of the CCB specification, the estimates for complementarity are not directly comparable. Nonetheless, the fact that the estimates of the parameters for the GT variables – the constant, the seed price, and the herbicide price – remain essentially unchanged relative to the base specification, suggests that the larger estimate for $\gamma$ is in fact the result of stronger complementarity, rather than smaller variation in the IID portion of unobserved tastes.

*Conservation tillage without GT varieties.* A natural question that arises from our model is what CT adoption rates would have been if GT soybeans were never introduced into the market. To answer this question, we calculate the following: (i) the annual predicted CT adoption rates using the estimates from table 3 (i.e., the predicted rates based on having GT soybeans as part of the choice-set); and (ii) the annual predicted CT adoption rates after removing GT soybeans from the choice-set for all individuals (also using the parameter estimates from table 3). To arrive at the first set of adoption rates, we first compute for each farm-field-year combination the vector of predicted probabilities of choosing systems with CT (which requires simulation). Specifically,

$$(22) \quad \hat{L}^j_{itf}(\hat{\theta}) = \frac{1}{R}\sum_{r=1}^{R} \frac{e^{x^j_{itf}\hat{\beta}^j + \nu^j_{i,r}}}{\sum_{k\in\Omega_{it}} e^{x^k_{itf}\hat{\beta}^k + \nu^k_{i,r}}}, \quad j \in \{(CV, CT), (GT, CT)\}.$$

The predicted probability for choosing CT is then given by: $\hat{L}^{CT}_{itf} = \hat{L}^{CV,CT}_{ift} + \hat{L}^{GT,CT}_{ift}$. To move from this expression to annual adoption rates, we use a variable in our dataset that consists of the number of acres that each farm-field-year represents in the population for that year. Denote this quantity by $A_{ift}$. The predicted share of CT acres in year $t$ is then given by

$$(23) \quad \hat{S}^{CT}_t = \frac{\sum_{i=1}^{N}\sum_{f=1}^{F_{it}} A_{ift}\hat{L}^{CT}_{ift}}{\sum_{i=1}^{N}\sum_{f=1}^{F_{it}} A_{ift}}.$$

To compute the predicted annual shares for CT when GT soybeans are not available, we follow essentially the same steps, except that the predicted probability of using CT now just consists of a singleton,

**Table 6. Tillage Predicted Adoption Rates (percent of acres)**

| | Conservation Till Predicted Rates | | | No-Till Predicted Rates | | |
|---|---|---|---|---|---|---|
| | With GT | Without GT | Difference | With GT | Without GT | Difference |
| 1998 | 53.9 | 50.6 | 3.3 | 31.0 | 27.0 | 4.0 |
| 1999 | 55.9 | 52.1 | 3.8 | 32.8 | 28.2 | 4.6 |
| 2000 | 57.6 | 53.3 | 4.2 | 35.8 | 30.5 | 5.4 |
| 2001 | 59.6 | 54.6 | 5.0 | 38.4 | 32.0 | 6.4 |
| 2002 | 59.9 | 54.7 | 5.3 | 38.6 | 31.8 | 6.8 |
| 2003 | 62.1 | 56.3 | 5.9 | 40.6 | 33.0 | 7.6 |
| 2004 | 62.0 | 56.0 | 6.0 | 40.4 | 32.6 | 7.7 |
| 2005 | 64.8 | 59.1 | 5.8 | 45.2 | 37.3 | 7.9 |
| 2006 | 66.6 | 60.7 | 5.9 | 48.0 | 39.8 | 8.2 |
| 2007 | 66.7 | 60.6 | 6.1 | 47.6 | 39.1 | 8.5 |
| 2008 | 68.7 | 62.7 | 6.0 | 48.8 | 40.2 | 8.6 |
| 2009 | 66.7 | 60.5 | 6.1 | 45.6 | 37.2 | 8.4 |
| 2010 | 68.7 | 62.6 | 6.1 | 48.1 | 39.4 | 8.7 |
| 2011 | 69.4 | 63.3 | 6.2 | 49.4 | 40.5 | 8.9 |

denoted by $\tilde{L}_{ift}^{CV,CT}$ (i.e., the only choice being made concerns which tillage practice to use). We calculate this probability according to

$$(24)\quad \tilde{L}_{itf}^{CV,CT} = \frac{1}{R}\sum_{r=1}^{R} \frac{e^{x_{itf}^{CV,CT}\hat{\beta}^{CV,CT}+\nu_{i,r}^{CV,CT}}}{\left(1+e^{x_{itf}^{CV,CT}\hat{\beta}^{CV,CT}+\nu_{i,r}^{CV,CT}}\right)}.$$

Note that, as compared with (22), the denominator inside of the summation in (24) does not include the terms for GT choices. The predicted adoption rates for CT when GT soybeans are not available can then be computed as in (23), but with $\tilde{L}_{ift}^{CV,CT}$ replacing $\hat{L}_{itf}^{CT}$. Table 6 contains these predicted adoption rates for each year of the 1998–2011 period. In 1998 the adoption rate for CT is 3.3 percentage points less in a world without GT soybeans as an option. This difference increases steadily up until 2003, at which point it begins to level off and approach 6 percentage points (or about 10% of the no-GT soybean scenario). This is a reflection of the diffusion of GT soybeans, which also began to level off in 2003. Note also that the predicted rate for CT increases considerably over the period, by about 10 percentage points, even when GT soybeans are not available. The implication of our model is that such an increase would have been driven mainly by steadily rising fuel prices, an overall increase in farm size, and other unknown factors captured by the trend variable. The simulation is also performed for NT. In this case the gains from complementarity are even greater. In 1998, the difference is about 4 percentage points more when GT soybeans are available, and by 2011 the difference is 9 percentage points or a bit over 20% relative to the scenario without GT soybeans.[17]

*An application to soil erosion.* Conservation tillage or no tillage are not necessarily desirable, per se. Rather, interest in these practices is motivated by the fact that they affect a variety of environmentally-relevant outcomes. Exploring all such implications is beyond the scope of this paper. As suggested by a reviewer, however, it may be desirable to provide an illustration of one such impact. To do so, we compute the implied impact of GT soybeans, through their impact on CT adoption, on soil erosion. We base our computation on Montgomery (2007, 13270), which compiles and presents results from 1,673 measurements of erosion rates under different settings.[18] The median erosion rate

[17] Whereas in the text we have presented a constructive procedure to compute predicted adoption rates if GT soybeans were not available, we note that one could obtain the same results by considering the counterfactual in which CT and GT soybeans are independent. That is, the simulated adoption rates in table 6 are identical to those one would obtain by putting $\gamma = 0$ while maintaining the full choice set. The intuition for the equivalence is that when the seed and tillage practices are entirely independent, then each is chosen separately without regard to the other.

[18] We alternatively considered computing implied soil loss using the Universal Soil Loss Equation (USLE), a widely used model for this purpose. However, use of this model requires detailed information (e.g., slope length and slope steepness) that are not available to us. Moreover, there are acknowledged problems with estimating soil loss based on the USLE (Trimble and Crosson 2000; Montgomery 2007).

from these measurements under conventional agriculture is about 1.5 mm/year, which is roughly 20 times the median erosion rate of 0.08 mm/year for conservation agriculture. The difference of ≈1.4 mm/year is equivalent to ≈6.8 tons/acre per year (assuming a soil bulk density of 1,200 kg/m$^3$). Using the percent differentials for CT from table 6, and total annual US acres planted to soybeans (source: Quick Stats at the USDA-NASS website), this implies a mean reduction in soil loss of 27 million tons per year. For context, estimated total soil erosion for US cropland in 2007—assuming a mean erosion rate of 0.95 mm/year (Montgomery 2007, 13271) and given a total US cropland of 408 million acres (USDA-ERS)—can be estimated at about was 1.9 billion tons. To assess the monetary value of these savings in soil erosion we use the USDA/NRCS estimated benefits of $4.93 per ton in water quality improvements and $1.93 per ton in saved fertilizer (USDA 2009). Thus, the value of the benefits associated with the implied soil savings is $189 million per year.

## Conclusion

Complementarity is arguably a common feature among many of the inputs and practices chosen by agricultural producers. A possible instance of complementary in agriculture that has attracted considerable interest concerns the interaction between herbicide tolerant crops and conservation tillage practices. In this paper we have developed a new discrete choice model of joint practice adoption in which soybean producers choose among four tillage-soybean systems, and use it to investigate the existence and significance of complementarity between GT soybeans and CT practices. Our model explicitly incorporates both unobserved heterogeneity and complementarity, thus allowing for a direct test of whether GT soybeans and CT are complements. Using a large unbalanced panel dataset on individual farmers' choices spanning the period 1998–2011, we find that GT soybeans and CT are indeed complementary practices. This finding is robust to multiple specifications. Moreover, by ignoring unobserved heterogeneity, the degree of complementarity is overestimated. We further find that GT soybeans and no-till are likely stronger complements than GT soybeans and CT. In addition to the complementarity findings, our results indicate that highly erodible land, drought-like conditions, and higher fuel prices increase the likelihood of choosing CT. We also simulate annual adoption rates for CT and NT in a world without GT soybeans. The simulations indicate that CT adoption and NT adoption have been about 10% larger (or 6 percentage points) and 20% larger (9 percentage points), respectively, than what they would have been as a result of the availability of GT soybeans (holding total acreage fixed).

Whereas the framework of analysis that we propose and illustrate in this article has broader methodological applicability to many issues in the economics of agricultural production, some policy implications follow immediately from our finding that GT soybeans and CT are complements. When complementarities are present, policy shocks that directly affect one activity will also indirectly affect complementary activities and will do so in the same direction. In recent years, for example, glyphosate weed resistance has become increasingly problematic in certain parts of the world (Powles 2008). As a result, there has been an initiative to slow that resistance in order to preserve the viability of glyphosate. Because GT soybeans and CT complement one another, such efforts also indirectly preserve the use of CT systems. A similar type of reasoning can be applied to the recent de-regulation of other herbicide tolerant crops (e.g., Dicamba resistant crops). To the extent that these crops also promote the use of CT, then their overall benefits are potentially under-estimated.

Concerning future research, an important question that remains unanswered relates to the effect of herbicide tolerant crops on herbicide use. Our framework could potentially be extended to look at this question by also incorporating the choice of how much herbicide to use. More generally, our framework could be used to consider relationships between a multitude of other agricultural choices, such as crop-rotation, farm size, row-spacing, and the type of machinery to purchase. For example, economies of scope at the farm level, rooted in the possible submodularity of a farm's cost structure (and so supermodularity of profits), represent an important possible application of our framework of analysis. Given the concerns associated with crop specialization and monoculture practices, especially *vis-à-vis* sustainability considerations, a deeper understanding of the complementarity relations that promote or hinder such trends would be valuable.

## References


Arora, A. 1996. Testing for Complementarities in Reduced-Form Regressions: A Note. *Economics Letters* 50 (1): 51–55.

Arora, A., and A. Gambardella. 1990. Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology. *Journal of Industrial Economics* 38 (3): 361–79.

Athey, S., and S. Stern. 1998. An Empirical Framework for Testing Theories about Complementarity in Organizational Design. Working Paper w6600. National Bureau of Economic Research.

Banerjee, S., S. W. Martin, R. K. Roberts, J. A. Larson, R. J. Hogan Jr., J. L. Johnson, and J. M. Reeves. 2009. Adoption of Conservation-Tillage Practices and Herbicide-Resistant Seed in Cotton Production. *AgBioForum* 12 (3–4): 258–68.

Barrows, G., S. Sexton, and D. Zilberman. 2014. Agricultural Biotechnology: The Promise and Prospects of Genetically Modified Crops. *Journal of Economic Perspectives* 28 (1): 99–119.

Berry, S., A. Khwaja, V. Kumar, A. Musalem, K. Wilbur, G. Allenby, B. Anand, P. Chintagunta, et al. 2014. Structural Models of Complementary Choices. *Marketing Letters* 25 (3): 245–56.

Blevins, R. L., and W. W. Frye. 1993. Conservation Tillage: An Ecological Approach to Soil Management. *Advances in Agronomy* 51: 33–78.

Brynjolfsson, E., and P. Milgrom. 2013. Complementarity in Organizations. In *The Handbook of Organizational Economics*, ed. R. Gibbons and J. Roberts, 11–55. Princeton, NJ: Princeton University Press.

Bull, L., H. Delve, C. Sandretto, and B. Lindamood. 1993. Analysis of Pesticide Use by Tillage System in 1990, 1991, and 1992 Corn and Soybeans. Agricultural Resource Situation and Outlook Report 32, Washington DC: Economic Research Service, U.S. Department of Agriculture, October.

Cameron, A. C., and P. K. Trivedi. 2010. *Microeconometrics Using Stata, Revised Edition*. College Station, TX: Stata Press.

Carpenter, J., and L. Gianessi. 1999. Herbicide Tolerant Soybeans: Why Growers are Adopting Roundup Ready Varieties. *AgBioForum* 2 (2): 65–72.

Cassiman, B., and R. Veugelers. 2006. In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science* 52 (1): 68–82.

Ding, Y., K. Schoengold, and T. Tadesse. 2009. The Impact of Weather Extremes on Agricultural Production Methods: Does Drought Increase Adoption of Conservation Tillage Practices? *Journal of Agricultural and Resource Economics* 34 (3): 395–411.

Dorfman, J. H. 1996. Modeling Multiple Adoption Decisions in a Joint Framework. *American Journal of Agricultural Economics* 78 (3): 547–57.

Fawcett, R. S., B. R. Christensen, and D. P. Tierney. 1994. The Impact of Conservation Tillage on Pesticide Runoff Into Surface Water: A Review and Analysis. *Journal of Soil and Water Conservation* 49 (2): 126–35.

Fernandez-Cornejo, J., C. Hallahan, R. Nehring, and S. Wechsler. 2013. Conservation Tillage, Herbicide Use, and Genetically Engineered Crops in the United States: The Case of Soybeans. *AgBioForum* 15 (3): 231–41.

Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans. 2002. Farm-level Effects of Adopting Herbicide-Tolerant Soybeans in the USA. *Journal of Agricultural and Applied Economics* 34 (1): 149–64.

Fernandez-Cornejo, J., C. Klotz-Ingram, R. Heimlich, M. Soule, W. McBride, and S. Jans. 2003. Economic and Environmental Impacts of Herbicide Tolerant and Insect Resistant Crops in the United States. In *The Economic and Environmental Impacts of Agbiotech,* ed. Nicholas G. Kalaitzandonakes, 63–88. New York: Springer.

Fernandez-Cornejo, J., S. J. Wechsler, M. Livingston, and L. Mitchell. 2014. Genetically Engineered Crops in the United States. Economic Research Report ERR-162 February 2014. Washington, DC: USDA ERS.

Frisvold, G., A. Boor, and J. Reeves. 2009. Simultaneous Diffusion of Herbicide Resistant Cotton and Conservation Tillage. *AgBioForum* 12 (3–4): 249–57.

Fuglie, K. O. 1999. Conservation Tillage and Pesticide Use in the Cornbelt. *Journal of*

*Agricultural and Applied Economics* 31 (1): 133–47.
Gentzkow, M. 2007. Valuing New Goods in a Model with Complementarity: Online Newspapers. *American Economic Review* 97 (3): 713–44.
Givens, W. A., D. R. Shaw, G. R. Kruger, W. G. Johnson, S. C. Weller, B. G. Young, R. G. Wilson, M. D. K. Owen, and D. Jordan. 2009. Survey of Tillage Trends Following the Adoption of Glyphosate-Resistant Crops. *Weed Technology* 23 (1): 150–55.
Hensher, D. A., J. M. Rose, and W. H. Greene. 2005. *Applied Choice Analysis: A Primer*. Cambridge: Cambridge University Press.
Hole, A. R. 2007. Estimating Mixed Logit Models Using Maximum Simulated Likelihood. *Stata Journal* 7 (3): 388–401.
Holland, J. M. 2004. The Environmental Consequences of Adopting Conservation Tillage in Europe: Reviewing the Evidence. *Agriculture, Ecosystems and Environment* 103 (1): 1–25.
Kalaitzandonakes, N., and P. Suntornpithug. 2003. Adoption of Cotton Biotechnology in the United States: Implications for Impact Assessment. In *The Economic and Environmental Impacts of Agbiotech: A Global Perspective*, ed. N. Kalaitzandonakes, 103–18. New York: Kleuwer Academic.
Keane, M. P. 1992. A Note on Identification in the Multinomial Probit Model. *Journal of Business and Economic Statistics* 10 (2): 193–200.
Kern, J. S., and M. G. Johnson. 1993. Conservation Tillage Impacts on National Soil and Atmospheric Carbon Levels. *Soil Science Society of America Journal* 57 (1): 200–210.
Knowler, D., and B. Bradshaw. 2007. Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research. *Food Policy* 32 (1): 25–48.
Kretschmer, T., E. J. Miravete, and J.C. Pernías. 2012. Competitive Pressure and the Adoption of Complementary Innovations. *American Economic Review* 102 (4): 1540–70.
Kurkalova, L., C. Kling, and J. Zhao. 2006. Green Subsidies in Agriculture: Estimating the Adoption Costs of Conservation Tillage from Observed Behavior. *Canadian Journal of Agricultural Economics* 54: 247–67.
Milgrom, P., and J. Roberts. 1990. The Economics of Modern Manufacturing: Technology, Strategy, and Organization. *American Economic Review* 80 (3): 511–28.
Miravete, E. J., and J. C. Pernías. 2006. Innovation Complementarity and Scale of Production. *Journal of Industrial Economics* 54 (1): 1–29.
———. 2010. Testing for Complementarity when Strategies are Dichotomous. *Economics Letters* 106 (1): 28–31.
Montgomery, D. R. 2007. Soil Erosion and Agricultural Sustainability. *Proceedings of the National Academy of Sciences* 104 (33): 13268–272.
Moschini, G. 2008. Biotechnology and the Development of Food Markets: Retrospect and Prospects. *European Review of Agricultural Economics* 35 (3): 331–55.
Nevo, A. 2000. A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand. *Journal of Economics & Management Strategy* 9 (4): 513–48.
Powles, S. B. 2008. Evolved Glyphosate-Resistant Weeds Around the World: Lessons to Be Learnt. *Pest Management Science* 64 (4): 360–65.
Qaim, M. 2009. The Economics of Genetically Modified Crops. *Annual Review of Resource Economics* 1 (1): 665–94.
Roberts, R. K., B. C. English, Q. Gao, and J. A. Larson. 2006. Simultaneous Adoption of Herbicide-Resistant and Conservation Tillage Cotton Technologies. *Journal of Agricultural and Applied Economics* 38: 629–43.
Soule, M. J., A. Tegene, and K. D. Wiebe 2000. Land Tenure and the Adoption of Conservation Practices. *American Journal of Agricultural Economics* 82 (4): 993–1005.
Stubbs, M. 2012. Conservation Compliance and US Farm Policy. Report R4259, Congressional Research Service.
Train, K. 2000. Halton Sequences for Mixed Logit. Working Paper E00-278, Department of Economics, University of California, Berkeley.
———. 2009. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.
Trimble, S. W., and P. Crosson. 2000. US Soil Erosion Rates—Myth and Reality. *Science* 289 (5477): 248.
Triplett, G. B., and W. A. Dick. 2008. No-Tillage Crop Production: A Revolution

in Agriculture! *Agronomy Journal* Supplement 100 (3): S-153.

USDA. 2009. Interim Final Benefit-Cost Analysis for the Environmental Quality Incentives Program (EQIP). Report by the National Resource Conservation Service, United States Department of Agriculture, January 9.

West, T. O., and G. Marland. 2002. A Synthesis of Carbon Sequestration, Carbon Emissions, and Net Carbon Flux in Agriculture: Comparing Tillage Practices in the United States. *Agriculture, Ecosystems and Environment* 91 (1): 217–32.

Wu, J., and B. A. Babcock. 1998. The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications. *American Journal of Agricultural Economics* 80 (3): 494–511.

Xu, Z., D. A. Hennessy, K. Sardana, and G. Moschini. The Realized Yield Effect of Genetically Engineered Crops: U.S. Maize and Soybean. *Crop Science* 53 (2013): 735–45.