Iowa State University
Digital Repository

CARD Working Papers CARD Reports and Working Papers

4-2015

Testing for Complementarity: Glyphosate Tolerant Soybeans and Conservation Tillage

Edward D. Perry
Iowa State University, eperry@iastate.edu

GianCarlo Moschini
Iowa State University, moschini@iastate.edu

David A. Hennessy
Iowa State University, hennessy@iastate.edu

Follow this and additional works at: http://lib.dr.iastate.edu/card_workingpapers

Part of the Agricultural and Resource Economics Commons, Agricultural Economics Commons, Econometrics Commons, and the Organizational Behavior and Theory Commons

Recommended Citation

Perry, Edward D.; Moschini, GianCarlo; and Hennessy, David A., "Testing for Complementarity: Glyphosate Tolerant Soybeans and Conservation Tillage" (2015). *CARD Working Papers*. 558.
http://lib.dr.iastate.edu/card_workingpapers/558

This Article is brought to you for free and open access by the CARD Reports and Working Papers at Iowa State University Digital Repository. It has been accepted for inclusion in CARD Working Papers by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.

Testing for Complementarity: Glyphosate Tolerant Soybeans and Conservation Tillage

Abstract

Many decisions in agriculture are made over combinations of inputs and/or practices that may be complements. The presence of complementarity among producer decisions can have deep implications for market outcomes and for the effectiveness of policies intended to influence them. Identifying complementarity relations, however, is a challenging pursuit. Drawing on recent methodological advances, in this paper we propose a new test for complementarity between glyphosate tolerant soybeans and conservation tillage that overcomes limitations of previous studies. Specifically, we develop a structural discrete choice framework of joint soybean-tillage adoption that explicitly models both complementarity and unobserved heterogeneity. The model is estimated with a large dataset of farm-level choices that spans the 1998–2011 period and contains repeated observations for many of the sampled individuals. We find that glyphosate tolerant soybeans and conservation tillage are indeed complementary practices, a conclusion supported by several robustness checks. 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 also apply our results to simulate annual adoption rates for conservation tillage in a scenario without glyphosate tolerant soybeans available as a choice. We find that the adoption of conservation tillage has been about ten percent higher due to the advent of glyphosate tolerant soybeans.

Keywords

complementarity, conservation tillage, discrete choice models, genetically engineered crops, mixed multinomial logit, supermodularity, technology adoption, unobserved heterogeneity

Disciplines

Agricultural and Resource Economics | Agricultural Economics | Econometrics | Organizational Behavior and Theory

This article is available at Iowa State University Digital Repository: http://lib.dr.iastate.edu/card_workingpapers/558

Testing for Complementarity: Glyphosate Tolerant Soybeans and Conservation Tillage

Edward Perry, GianCarlo Moschini, and David A. Hennessy

Working Paper 15-WP 555
April 2015

Center for Agricultural and Rural Development
Iowa State University
Ames, Iowa 50011-1070
www.card.iastate.edu

Edward Perry is a Ph.D. candidate, Department of Economics and Center for Agricultural and Rural Development, Iowa State University. E-mail: eperry@iastate.edu.

GianCarlo Moschini is Professor and Pioneer Chair in Science and Technology Policy, Department of Economics and Center for Agricultural and Rural Development, Iowa State University, Ames, IA 50011, USA. Email: moschini@iastate.edu.

*David A. Hennessy is Professor of Economics at the Department of Economics and Center for Agricultural and Rural Development, Iowa State University. E-mail: hennessy@iastate.edu***.**

This publication is available online on the CARD website: *www.card.iastate.edu*. Permission is granted to reproduce this information with appropriate attribution to the author and the Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa 50011-1070.

Iowa State University does not discriminate on the basis of race, color, age, ethnicity, religion, national origin, pregnancy, sexual orientation, gender identity, genetic information, sex, marital status, disability, or status as a U.S. veteran. Inquiries can be directed to the Interim Assistant Director of Equal Opportunity and Compliance, 3280 Beardshear Hall, (515) 294-7612.

Testing for Complementarity: Glyphosate Tolerant Soybeans and Conservation Tillage

Edward Perry, GianCarlo Moschini and David A. Hennessy *

Abstract

Many decisions in agriculture are made over combinations of inputs and/or practices that may be complements. The presence of complementarity among producer decisions can have deep implications for market outcomes and for the effectiveness of policies intended to influence them. Identifying complementarity relations, however, is a challenging pursuit. Drawing on recent methodological advances, in this paper we propose a new test for complementarity between glyphosate tolerant soybeans and conservation tillage that overcomes limitations of previous studies. Specifically, we develop a structural discrete choice framework of joint soybean-tillage adoption that explicitly models both complementarity and unobserved heterogeneity. The model is estimated with a large dataset of farm-level choices that spans the 1998–2011 period and contains repeated observations for many of the sampled individuals. We find that glyphosate tolerant soybeans and conservation tillage are indeed complementary practices, a conclusion supported by several robustness checks. 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 also apply our results to simulate annual adoption rates for conservation tillage in a scenario without glyphosate tolerant soybeans available as a choice. We find that the adoption of conservation tillage has been about ten percent higher due to the advent of glyphosate tolerant soybeans.

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

JEL codes: C35, D22, Q12, Q55

20 April 2015

* Edward Perry is a Ph.D. candidate, GianCarlo Moschini is Professor and Pioneer Chair in Science and Technology Policy, and David A. Hennessy is Professor, all with the Department of Economics and the Center for Agricultural and Rural Development, Iowa State University, Ames, IA 50011. The authors gratefully acknowledge the support of USDA NIFA Policy Research Center Grant 11061138/2012-01764, as well as the support of a USDA NIFA National Needs Fellowship and of the Pioneer Chair in Science and Technology Policy.

Introduction

Decision variables in many real-world problems are often best viewed as combined in clusters, e.g., bundles of goods or sets of practices. This clustering naturally arises when choices complement one another, i.e., when the payoff associated with the level of one variable is increasing in the level of another variable. The underlying supermodular structure of the decisionmakers' objective function constitutes the essence of such situations (Milgrom and Robert 1990). Complementary choices are ubiquitous and appear in consumption problems, production contexts, dynamic choices, and organization design (Berry et al. 2014). They are increasingly relevant in an agricultural setting as well, where farmers' decisions often pertain to choices of "systems" that are in turn composed of alternative combinations of inputs or practices. For example, the choices of which crop to produce, what rotation to use, and the type of tillage to employ are often deeply intertwined with mechanical equipment investments and the choices of an array of chemical inputs and genetics. An accurate characterization of such choices 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 complementarities between targeted and un-targeted variables.

The empirical identification and modelling of complementarity/substitutability, however, faces several challenges. One of these relates to data availability. Because of its nature, complementarity is best studied at the level of individual choices, rather than with aggregate data. Representative samples of individual data are not common, and when available may still be limited as to what information is included. Furthermore, reliable inference about complementarity requires a structural model, as reduced-form models produce, at best, correlation measures that are often unsatisfactory, especially as the basis for counterfactual policy analyses (Nevo and Whinston 2010). Identification of the desired structural model, however, can be problematic because of the presence of unobserved heterogeneity, particularly when the information provided by individual-level data is limited. Consequently, much recent work has been devoted to advancing the econometric modelling of complementary choices (see, for example, Athey and Stern 1998).

In this paper, we consider the problem of testing for complementarity in the context of two important agricultural practices. More specifically, we propose a framework that draws on recent econometric advances and apply it to the question of whether the adoption of glyphosate tolerant crops and conservation tillage are complementary. This is an important question that has attracted considerable attention, but on which, to date, there is no conclusive evidence. The novelty of our contribution relates to both the data used, which is considerably more extensive than in previous applications, and to the econometric methodology that we apply, which permits us to overcome some limitations of previous studies.

Since their commercial introduction in 1996, genetically engineered (GE) crop varieties have been both successful and controversial (Moschini 2008). A particularly contentious debate relates to the environmental impacts of the adoption of GE crops (Barrows, Sexton, and Zilberman 2014). Concerns about negative consequences have ranged from the possibility that the adoption of GE crops facilitate 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. But positive environmental impacts have also been posited, an important being that the adoption of glyphosate tolerant (GT) crops induces the adoption of environmentally beneficial tillage methods.

Tillage has historically been an essential part of the farming process. It aids in seedbed preparation and provides an effective means for weed control both before and after the crop has emerged (Givens et al. 2009). But tillage has also been associated with several negative effects, which include 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 less than 30% of crop residues on the soil surface, has long been advocated as a way to reduce these detrimental effects (Holland 2004). Anecdotal evidence suggests that GT crops and CT are complementary. Because GT crops can tolerate applications of glyphosate, tillage is no longer as necessary for post-emergent weed control. Thus, growers who may not find it profitable to adopt CT with conventional crop varieties may find it profitable when used with GT varieties, i.e., as a system. Indeed, cropped acres under 'no-tillage' systems have increased considerably in the United States, Argentina, and Canada since the introduction and widespread adoption of GE varieties (Barrows, Sexton, and Zilberman 2014).

Whereas a positive correlation between GT crops and CT is well established, conclusions about a causal relationship are more problematic. For example, Fernandez-Cornejo et al. (2003) found that farmers who adopted GT soybeans were no more likely to adopt a no-tillage system (though farmers who adopted no-till were more likely to adopt GT soybeans). Conversely, Roberts et al. (2006)

found that the likelihood of adopting CT is greater when more land is planted to GT cotton. Several other studies have examined the issue with mixed results (Banerjee et al. 2009; Fernandez-Cornejo et al. 2013; Frisvold, Boor, and Reeves 2009; Kalaitzandonakes and Suntornpithug 2003). Overall, the evidence leans in favor of a complementary relationship, but some important limitations of previous studies prevent a conclusive assessment. First, the tillage data used in past studies has been limited in both detail and scope. Of the papers cited above, three rely on state-level data (rather than individual choices), and the three studies that rely on farm-level data have access to a single cross-section. Second, the empirical frameworks used by previous studies lack certain key features that have recently been documented by a separate body of literature as essential for the identification of complementarity between two practices or goods. For example, to test for whether two activities complement, the choice-set should include all four possible combinations of those two activities (Gentzkow 2007). When this is not true—as is the case for bivariate probit or logit models—identification of complementarity is tenuous, or just not possible (Miravate and Pernías 2010). Furthermore, when using individual data, it is increasingly recognized that a proper accounting for unobserved heterogeneity is essential. Neglecting this feature can lead to the acceptance of complementarity when it does not exist, or to its rejection when it does (Athey and Stern 1998; Cassiman and Veuglers 2006).

The structural model that we propose and estimate permits a direct test for the hypothesis that CT and GT soybeans complement, while controlling for unobserved heterogeneity. Specifically, we model soybean growers as choosing, for each field, one of the four following tillage-soybean systems: (i) intensive tillage (IT) and conventional (CV) soybeans, (ii) IT and GT soybeans, (iii) CT and CV soybeans, or (iv) CT and GT soybeans. Growers are assumed to choose the system with the maximum per acre return, where returns are modeled as depending on both observable and unobservable characteristics, the latter potentially being correlated across practices. We apply the model to a new and extensive farm-level dataset for the period 1998–2011. One unique feature of this dataset is that it contains repeated observations for a subset of the sampled individuals. 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 that the adoption rate for CT has been increased by about 10% as a result of the availability of GT soybeans.

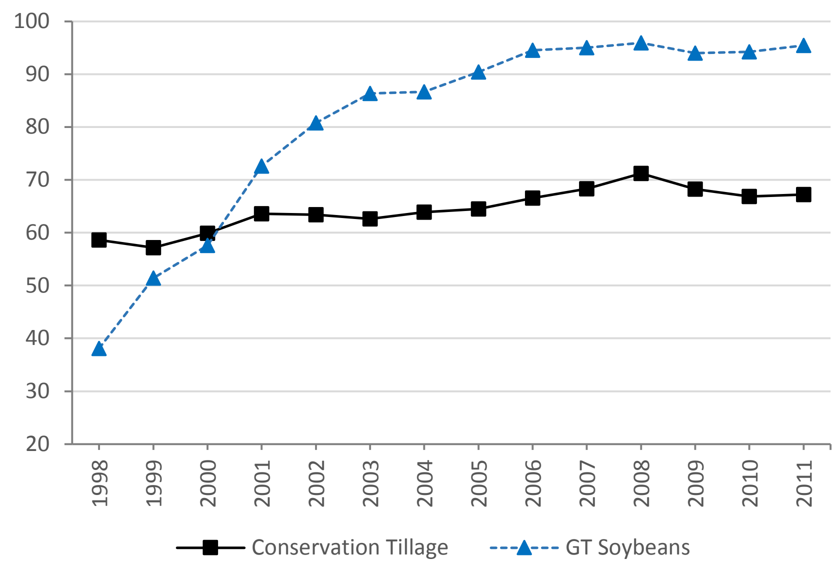
The rest of this paper proceeds as follows. We first review the conventional wisdom and empirical evidence on the relationship between seed choice and tillage practices. Next, we provide a short review of the relevant methodological literature. Based on that, we then develop the model to be estimated, and present the econometric procedure that we employ. This is followed by a description of the data, and a presentation and discussion of the empirical results. The paper concludes with a brief investigation of some counterfactual scenarios and a discussion of possible policy implications.

Background

Prior to the introduction of herbicides, the primary method for weed control in soybeans was tillage. In the 1960s, growers transitioned to using newly developed, pre-emergence herbicides as part of their weed control plan. Mechanical cultivation, however, remained an important tool for post-emergent weed control. It wasn't until the 1980s, with the introduction of several post-emergence herbicides, that farmers could rely almost entirely on chemicals for weed management. By 1994, 72% of soybean acres were treated with post-emergence herbicides (Carpenter and Gianessi 1999). With this trend came a considerable increase in the use of CT (Blevins and Frye 1993; Fernandez-Cornejo et al. 2013; Givens et al. 2009). However, although post-emergence herbicides had become an integral part of many farms' practices (and contributed to the use of CT), some limitations continued to apply. For example, in order to be effective, some of these herbicides may need to be applied at levels that can injure the crop. Moreover, some pre-emergence herbicides have high residual activity, which can have negative effects on future crops. In addition, the range of weeds that each can treat is typically narrow, making the mixing and application aspects complex and often costly. The advent of genetically modified 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 Gianassi 1999). The use of glyphosate with GT soybeans thus provided a very effective and convenient post-emergent weed control strategy, and arguably served to intensify the complementarities that had already existed between post-emergence herbicides (with CV soybeans) and CT.

Several surveys report correlations suggestive of a complementary relationship between GT crops and CT. For example, a 1997 USDA survey found that 60% of GT soybean acres used CT, whereas just 40% of conventional (CV) soybeans used CT (Fernandez-Cornejo and Caswell 2006). A 2006 USDA survey found an even wider gap: soybean growers reported using CT on 86% of GT acres versus 36% for CV acres (Fernandez-Cornejo et al. 2014). In a 2005 survey of 1,195 growers in six states, Givens et al. (2009) found that for those who had previously used IT, 23% switched to CT upon switching to GT soybeans, whereas for those who had already used CT, only 5% switched to IT. The data we use for our empirical analysis indicate similar associations.[1] We find that the correlation coefficient between GT soybeans and CT is 0.125 and is significant at a 1% level. Moreover, about 67% of acres planted to GT soybeans use CT whereas about 50% of acres planted to CV soybeans use CT. Changes over time also show a positive correlation. Figure 1 contains U.S. annual adoption rates for GT soybeans and CT from 1998–2011. 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.

Figure 1. Conservation Tillage and GT Adoption Rates for U.S. Soybeans (percent of acres)



Moving beyond the analysis of basic correlations, previous research has sought to identify a complementary relationship between CT and GT varieties by looking at: (i) whether the adoption of GT varieties induces the adoption of CT; and, (ii) whether the adoption of CT induces the adoption of GT varieties. These studies have focused on cotton and soybeans, where weed control is critical for yields. For cotton, four studies have tested for a positive interaction between GT cotton and CT.

[1] We provide more details about our data in the "Data" section below.

Three have concluded in favor of complementarity, whereas one has not. Roberts et al. (2006) estimated a simultaneous logit model using annual Tennessee cotton data from 1997 to 2004 and found that a 1% increase in the probability of adopting conservation tillage is associated with a 1.74% increase in GT cotton acres. They also found that a 1% increase in the probability of using GT varieties led to a 0.24% increase in the adoption of conservation tillage. Frisvold, Boor, and Reeves (2009) estimated a similar simultaneous logit model using state-level data from 16 states for the period 1997–2002. They too found that higher rates of GT cotton adoption led to higher adoption rates for conservation tillage and vice versa. Kalaiztandonakes and Suntornpithug (2003) developed a simultaneous adoption model for CT, GT cotton, Bt cotton, and stacked trait cotton. Growers were modelled as choosing the share of land to allocate to each technology, where that choice could depend on the chosen shares for all other technologies. The model was estimated with farm-level data from a 1999 survey of 620 cotton growers. They found that the share of land allocated to CT was significantly and positively impacted by the share of land allocated to GT cotton. Banerjee et al. (2009) estimated a simultaneous binomial logit model using a 2003 Agricultural Resource Management Survey (ARMS) of 1,253 cotton growers. Contrary to previous studies, they failed to reject the null hypothesis that CT and GT cotton are independent. They found that the impact of CT adoption on GT cotton adoption was not significant at a 10% level of significance and vice versa. They posited that one potential spurious reason for their findings is that herbicide tolerance is often bundled with the best yielding varieties and thus many of the farmers that adopted GT varieties may not have done so for the trait.

For soybeans, three studies have presented evidence on a causal relationship between CT and GT soybeans, with one partially rejecting the presence of complementarities. Two of these studies are based on a 1997 nationwide ARMS survey of individual soybean growers. Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) estimated a binomial probit model for GT soybeans using 1,444 survey respondents. They assumed that the type of tillage employed was exogenous to the soybean choice. The relationship between tillage and GT soybeans was thus modelled by including a dummy variable that indicated whether intensive tillage was used. Consistent with expectations, they found that intensive tillage reduced the likelihood of adopting GT soybeans. Fernandez-Cornejo et al. (2003) built on Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) by allowing the type of tillage used to be endogenous. Using a simultaneous bivariate probit model (and the same survey data), they found that the use of no-till increased the likelihood of using GT soybeans but that the use of

GT soybeans did not increase the likelihood of using no-till. They noted that one potential reason for not finding evidence of the latter could be that the adoption rate for GT soybeans was still relatively low in 1997. More recently, Fernandez-Cornejo et al. (2013) considered the relationship between herbicide use, conservation tillage, and GT soybeans. They used state-level panel data from 12 major soybean producing states for the period 1996–2006 to estimate two regressions with conservation tillage adoption rates and herbicide use as the dependent variables. Based on Granger Causality Tests, they treated state-level GT soybean adoption rates as exogenous. They found that higher rates of GT soybean adoption were associated with higher rates of conservation tillage adoption and lower levels of herbicide use.

Our study differs from previous work in several significant ways. First, we have access to an extensive and representative farm-level dataset on tillage and seed choices that spans the period 1998–2011 and contains the choices of 29,518 soybean growers. Because GT soybeans were commercially introduced in 1996, our data covers much of the period during which growers transitioned from CV soybeans to GT soybeans. Moreover, whereas our dataset 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 re-sampled the next year. Thus, for many farmers we observe whether or not their tillage choice changed upon switching to GT soybeans. Econometrically, we exploit this information by incorporating individual random effects. Second, our empirical framework specifies a single choice set for each farmer that consists of the four possible combinations of adoption decisions of GT soybeans and CT. As we show below, this allows us to explicitly estimate complementarity. This is in contrast with previous farm-level tillage studies, where a grower is modelled as making two simultaneous, albeit distinct, adoption decisions. In these models, complementarity is not directly estimated and consequently the results can be difficult to interpret.[2]

Our study also controls for the correlation induced by unobserved heterogeneity, an important feature of the data generating process that has hitherto been ignored. Neglecting this feature can incorrectly lead to the conclusion of complementarity when it does not exist and vice versa. For

[2] 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.

example, if producers with greater 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. The bivariate logit and probit models used by previous studies in this area do not allow for the unobserved returns for tillage and seed practices to be correlated. As a result, part of what could be driving their results is a set of factors unrelated to a synergistic effect between GT crops and CT. The framework that we utilize allows for unobserved factors that affect GT crops and CT to be correlated. This reduces the likelihood of accepting complementarity when it does not exist, or rejecting it when it does. Given the importance of these issues, the next section discusses in more detail some of the challenges associated with the econometric identification of complementarity.

Econometrics of Complementarity

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 $j = 1, 2$. 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 (Athey and Stern 1998)

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

That is, two practices are complementary if the adoption of one while using the other has a larger effect on profits than adopting the practice in isolation. This structural representation constitutes the essence of complementarity and provides the vehicle for testing hypotheses about it. Depending on the type of data at hand, there are two main ways to proceed. If one has access to firm-level profit data, then γ can be directly estimated via OLS (see Cassiman and Veugelers 2006). Often, however, a researcher does not have access to profits (or other suitable performance measures). Indeed, this is typically the case for studies dealing with agricultural practices and technology adoption. Alternatively, one can test the hypothesis of equation (1) by 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.

There are, however, two significant challenges to testing for complementarity with adoption data: first, whichever empirical framework is used, it needs to explicitly model both complementarity and unobserved heterogeneity at the same time; second, there needs to be sufficient identifying variation. A 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) proposed a structural framework in which γ could 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) used a version of the multinomial probit model to test for complementarity among production and innovation strategies, and Gentkow (2007) used a mixed logit model to test for complementarity between print and online newspapers.

The (different) frameworks used by Miravete and Pernías (2006) and Gentkow (2007) share two essential characteristics. First, the choice-set of each individual includes all possible combinations of available practices. For example, in an agricultural context, if there are three binary practices to choose from, then the choice set would consist of all eight possible combinations.[3] By specifying the choice set in this way, the model can be parameterized in such a way that γ is directly estimated. The second essential characteristic of these papers is that they control for unobserved heterogeneity. Miravete and Pernías (2006), for example, 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. Similar to Gentzkow's (2007) framework, for our empirical analysis we develop a variant of the mixed logit model that allows the normally distributed error terms to be correlated across the seed and tillage choices. 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. As noted earlier, individuals with greater education 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

[3] More generally, 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.

(so-called early adopters) may likewise 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, and this would manifest as a negative correlation between the unobserved returns.

The second significant challenge to testing for complementarity with adoption data is that there needs to be sufficient identifying variation. The main source of such identification comes from exclusion restrictions, i.e., the inclusion of variables that affect the returns to some practices but not others (Gentzkow 2007). Such variables are essential for disentangling the effects of complementarity from unobserved heterogeneity.[4] To illustrate, suppose that the price of GT soybean seeds relative to the price 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 find it in their interest to switch from CV soybeans to GT soybeans. If GT soybeans and CT are independent, then there should be no change to the adoption of CT since the seed price does not directly affect it. If they are complements, 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. In our analysis, some of the variables that fulfil the exclusion restriction are seed prices (excluded from the tillage choice) and the degree of soil erodibility (excluded from the seed choice). Below we discuss the excluded variables in more detail.

Exclusion restrictions are not the only source of identification. If one has repeated observations for a given individual, this can also aid in separating complementarity from unobserved heterogeneity (Gentzkow 2007). Indeed, as noted above, we have repeated observations for many of the individuals in our data. This can help with identification in the following way. Suppose we observe an individual in two time periods, and that in the second period that individual switches from CV soybeans to GT soybeans. If upon switching to GT soybeans that individual also switches from IT to CT, then this would signal that GT soybeans and CT are complements (controlling for all relevant time series variables). A third source of identification, which is in fact similar to the concept of exclusion restrictions, is exogenous variation in choice-sets (Nevo 2000, p. 529). If GT

[4] In an influential paper, Keane (1992) demonstrated via simulation that the covariance matrix of a multinomial probit model is not well-identified without exclusion restrictions.

soybeans are not available in certain regions of the country, then by comparing the adoption rate of CT in these regions to CT adoption rates in regions with GT soybeans, we can more accurately identify whether complementarities exist. Indeed, early on in our sample, we do not observe any purchases of GT varieties in certain crop reporting districts (CRDs). [5] We interpret this to mean that they were not available as an option, and thus exclude them from the choice-sets of individuals within that region.[6]

Finally, we note two other empirical studies in the agricultural adoption literature that have used a joint adoption framework. Wu and Babcock (1998) use a multinomial logit model to explore the economic and environmental implications of three different farming practices. The choice-set they specify consists of all eight possible combinations of those three practices, thus in theory allowing them to explicitly estimate complementarity. However, because of computational considerations, they do not allow for unobserved heterogeneity. Moreover, the objective of their study was not to test for complementarity (and so they do not try to estimate γ). Dorfman (1996) uses a multinomial probit model to study two technology adoption decisions by U.S. apple growers. Like Wu and Babcock (1998), he specifies the choice-set over all combinations of decisions (in his case, four), but he also allows for unobserved heterogeneity by estimating the variance covariance matrix. However, he does not attempt to identify structural complementarity.

The Model

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

Let soybean growers be indexed by $i \in \{1,...,N\}$, a year by $t \in \{1,...,T\}$, and a field by $f \in \{1,...,F_{it}\}$. 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: (i) the type of seed to plant, denoted by d_s; and (ii) the type of tillage to employ, denoted by d_τ. 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

[5] A crop reporting district (CRD) is a spatial delimiter used by the USDA (it is a collection of counties). It is also the finest level at which our seed and tillage data are representative.

[6] 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.

$(d_\tau = IT)$ or conservation tillage $(d_\tau = CT)$. Define a system as a combination of practices. With two practices, there are four mutually exclusive systems

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

Denote the choice set for each grower in each year by Ω_{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, as noted above, a handful of CRDs early on in the sample have no observed GT soybean purchases. For these districts-years the presumed choice-set is: $\Omega_{it} = \{(CV, IT), (CV, CT)\}$.

Rather than specifying the normalized returns for each pair of choices, as in Getzkow (2007), it is instructive to start with the (unobserved) per-acre profit associated with system (d_s, d_τ), 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_τ) 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, per-acre returns are specified to depend on a number of observable and unobservable variables, as follows.

(3) $$\begin{aligned}\tilde{\pi}_{itf}(CV, IT) = {} & \tilde{\beta}_0^{CV,IT} + \beta_1 p_{CV,t} + \beta_2 r_{CV,t} + (\tilde{\beta}_3^{CV} + \tilde{\beta}_3^{IT}) Size_{it} + \tilde{\beta}_4^{IT} Fuel_t \\ & + \tilde{\beta}_5^{IT} Futures_t + \tilde{\beta}_6^{IT} EI_i + \tilde{\beta}_7^{IT} Palmer_{it} + \tilde{v}_i^{CV} + \tilde{v}_i^{IT} + \tilde{\varepsilon}_{itf}^{CV,IT}\end{aligned}$$

(4) $$\begin{aligned}\tilde{\pi}_{itf}(GT, IT) = {} & \tilde{\beta}_0^{GT,IT} + \beta_1 p_{GT,t} + \beta_2 r_{GT,t} + (\tilde{\beta}_3^{GT} + \tilde{\beta}_3^{IT}) Size_{it} + \tilde{\beta}_4^{IT} Fuel_t \\ & + \tilde{\beta}_5^{IT} Futures_t + \tilde{\beta}_6^{IT} EI_i + \tilde{\beta}_7^{IT} Palmer_{it} + \beta_8^{GT} Trend_t + \tilde{v}_i^{GT} + \tilde{v}_i^{IT} + \tilde{\varepsilon}_{itf}^{GT,IT}\end{aligned}$$

(5) $$\begin{aligned}\tilde{\pi}_{itf}(CV, CT) = {} & \tilde{\beta}_0^{CV,CT} + \beta_1 p_{CV,t} + \beta_2 r_{CV,t} + (\tilde{\beta}_3^{CV} + \tilde{\beta}_3^{CT}) Size_{it} + \tilde{\beta}_4^{CT} Fuel_t \\ & + \tilde{\beta}_5^{CT} Futures_t + \tilde{\beta}_6^{CT} EI_i + \tilde{\beta}_7^{CT} Palmer_{it} + \tilde{v}_i^{CV} + \tilde{v}_i^{CT} + \tilde{\varepsilon}_{itf}^{CV,CT}\end{aligned}$$

(6) $$\begin{aligned}\tilde{\pi}_{itf}(GT, CT) = {} & \tilde{\beta}_0^{GT,CT} + \beta_1 p_{GT,t} + \beta_2 r_{GT,t} + (\tilde{\beta}_3^{GT} + \tilde{\beta}_3^{CT}) Size_{it} + \tilde{\beta}_4^{CT} Fuel_t \\ & + \tilde{\beta}_5^{CT} Futures_t + \tilde{\beta}_6^{CT} EI_i + \tilde{\beta}_7^{CT} Palmer_{it} + \beta_8^{GT} Trend_t + \tilde{v}_i^{GT} + \tilde{v}_i^{CT} + \tilde{\varepsilon}_{itf}^{GT,CT}\end{aligned}$$

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 that indicates whether the farmer grew more than 500 acres of soybeans. $Fuel_t$ is the price of fuel, $Futures_t$ is the soybeans futures price, 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 ν_i terms are time-invariant, practice-specific normally distributed unobservables. They represent individual characteristics that 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 ν_i to be correlated across systems. The terms $\tilde{\varepsilon}_{itf}^{d_s,d_\tau}$ are system-specific IID type I extreme value errors. They rationalize the fact that growers with the same characteristics and the same environment may still choose a different system.

The remaining terms 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, i.e., 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 obtain an estimable model suitable to test the complementarity hypothesis, 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) $$\pi_{itf}(CV, IT) = 0$$

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

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

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

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

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:

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

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

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:

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

Equation (13) re-states the relation in equation (1), that determines whether the two choices of interest are complementary. But this relation here is adjusted for the presence of unobserved heterogeneity, so that complementarity can vary over the population through $\varepsilon_{itf}^{\gamma}$. Because $E[\varepsilon_{itf}^{\gamma}] = 0$, it follows that γ is best interpreted as a measure of *mean* complementarity in the population. If our estimate for γ is statistically significantly greater (less) than zero, then GT soybeans and CT are complements (substitutes). Note that, in this framework, γ 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 γ. 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.[8]

In this model unobserved heterogeneity is captured by the random variables ν_i^{GT} and ν_i^{CT}. Specifically, we assume that $(\nu_i^{GT}, \nu_i^{CT}) \sim N(0, \Sigma)$, where

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

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

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 whenever ν_i^{GT} is large, ν_i^{CT} is also large (small), then these two terms will be positively (negatively) correlated; without controlling for such correlation, our estimate for γ would be biased upward (downward).

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 β_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, β_1 is the effect of a change in the price of GT seed relative to the price of CV seed.

As discussed previously, the main source of identification for γ are exclusion restrictions. These are variables that affect the seed choice – i.e., variables in the 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 $(p_{GT,t} - p_{CV,t})$, the difference in herbicide prices $(r_{GT,t} - r_{CV,t})$, and $Trend_t$ (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 et al. (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.[9] We include $Trend_t$ for the seed choice because of the rapid diffusion of GT seed varieties, which we are unable to fully capture with the variables we observe. In contrast, in our base specification, we assume there is no significant underlying trend for the tillage choice (post-emergence herbicides, for instance, had already been available for many years).[10]

[9] As part of robustness checks reported later, we do allow for herbicide prices to directly affect the tillage choice. We find that it does not affect our complementarity result.

[10] A specification that includes a trend for the tillage choice as well, used in the robustness checks, shows that this does not alter our result about complementarity.

The variables that we assume 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 fact that CT generally requires less fuel (Triplett and Dick 2008). For a given tillage method, however, there will be little difference in the 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 yield differences between the tillage options. Previous research has generally indicated that the 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).

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_τ), that is, $j \in \Omega_{it}$. Furthermore, rewrite equations (7)-(10) as:

$$\text{(15)} \qquad \pi_{itf}^{j} = x_{itf}^{j}\beta^{j} + \nu_i^{j} + \varepsilon_{itf}^{j}.$$

where x_{itf}^{j} is the vector of explanatory variables pertaining to system j, and β^j is the associated parameter vector (note that $\pi_{itf}^{CV,IT} = 0$, as above). Let θ denote the vector of all parameters to be estimated (this includes the vector of all β parameters, which implicitly also define the complementarity parameter γ, as well as the parameters of the covariance matrix Σ). Then, for a *given* realization ν_i^j, the probability of choosing system j is provided by the standard logit expression

$$\text{(16)} \qquad L_{itf}^{j}(\nu;\theta) = \frac{e^{x_{itf}^{j}\beta^{j} + \nu_i^{j}}}{\sum_{k \in \Omega_{it}} e^{x_{itf}^{k}\beta^{k} + \nu_i^{k}}}.$$

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 v_i^j, the probability of ζ_i is given by the product of the corresponding logits:

(17) $$L_{\zeta_i}(v;\theta) = \prod_{j \in \zeta_i}^{F_T} \frac{e^{x_{itf}^j \beta^j + v_i^j}}{\left(\sum_{k \in \Omega_{it}} e^{x_{itf}^k \beta^k + v_i^k} \right)}$$

The unconditional probability is given by the integral over all v that generate ζ_i

(18) $$P_{\zeta_i} = \int L_{\zeta_i}(v;\theta) f(v) dv$$

Since P_{ζ_i} is an integral it can be estimated via simulation. For each individual, multiple draws of the v_{ij} are taken, L_{ζ_i} is computed, and then averaged. Specifically, let R denote the number of draws of v_i^j for each individual. Then P_{ζ_i} is approximately given by

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

The SML estimator is therefore given by

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

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, p. 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, p. 616).[11]

[11] 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).

Data

The model is estimated with farm-level seed and tillage data from the survey company GfK.[12] 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 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 the tillage and seed choices (i.e., the endogenous variables), seed and herbicide prices, and the variable for farm size. The shares for each seed-tillage system are provided in Table 1, where we illustrate the distribution of system choices over time by disaggregating the shares into three sub-periods. 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 sub-period just over 5%. Overall, systems with GT soybeans account for about 80% of all observations, whereas systems with CT account for about 62% of all observations.

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

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, fuel prices were obtained from Quick Stats at the USDA-NASS

[12] 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 products.

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 distribution.

Farm Size is a dummy variable that indicates whether a grower planted more than 500 acres in soybeans. 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). Thus, 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-Corenjo et al. (2002) find that larger farms are more likely to adopt GT soybeans, whereas Fernandez-Cornejo et al. (2003) do not. 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 a November contract. It is included as a proxy for the expected output price perceived 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 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 the potential of a soil 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. As noted above, the 1985 farm bill requires a producer that grows crops on highly erodible land to meet certain minimum conservation requirements (Stubbs 2012). 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 productivity of the soil 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 (i.e., a grower will be more likely to use CT on more erodible land).

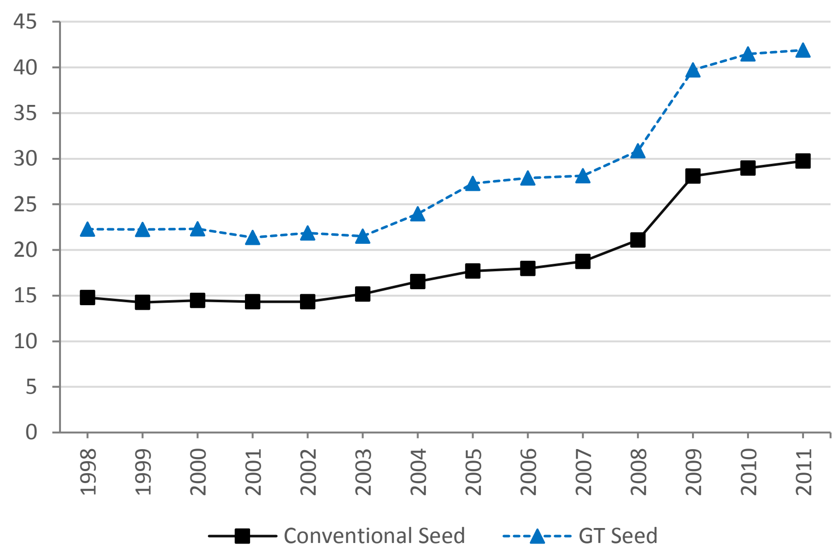
Table 2. Regressor Summary Statistics

Variable	Mean	S.D.	Min	0.25	Median	0.75	Max
Seed Price	8.98	1.92	6.34	7.46	8.67	9.84	12.41
Herbicide Price	-0.28	0.2	-0.65	-0.42	-0.26	-0.1	0
Fuel Price	54.55	23.97	25.89	33.44	52.72	72.78	99.33
Futures	7.3	2.78	4.48	5.2	6.37	9.6	13.13
Palmer Drought Index	0.29	2.47	-4.93	-1.46	-0.11	1.48	11.84
Erodiblity Index	8.36	9.49	0.29	2.67	5.2	11.32	192.07
Size	0.33	0.47	0	0	0	1	1

Palmer's Z is the mean Palmer Z-Index for the month of September in the prior year (it is CRD-year specific). This index indicates how dry a locality is relative to long-term conditions. Negative values indicate drier conditions, whereas positive values indicate wetter conditions. We include Palmer's Z index because the presence of long-term 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 U.S. 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 introduce considerable sampling variation. Figure 2 presents GT and CV seed prices from 1998 to 2011.

Figure 2. U.S. Soybean Seed Prices: 1998-2011 ($/50lb)



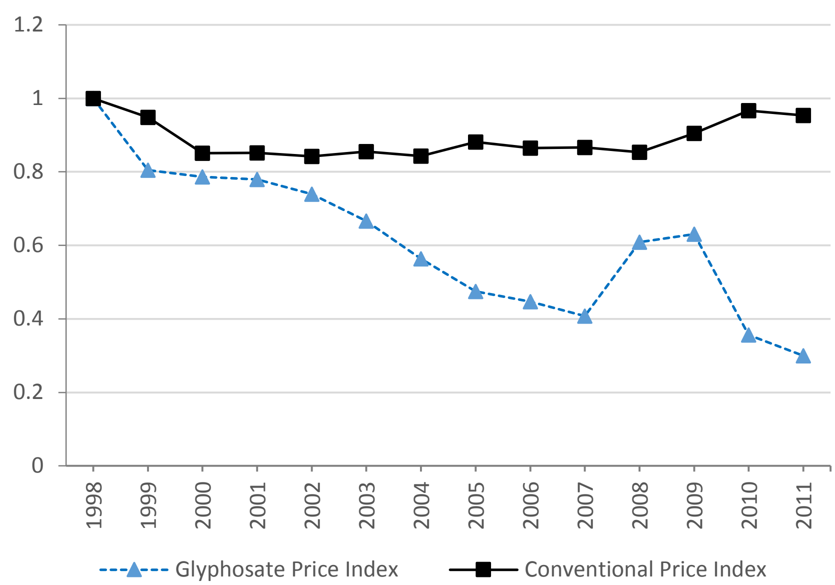
Prior to 2009 there was relatively little movement in both relative prices and overall prices. The increase in soybean output prices in 2008 led to a significant rise in seed prices in 2009. In terms of expectations, the higher the price of GT seed relative to CV seed, the smaller the return for GT seeds.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

The *Herbicide Price* term $(r_{GT,t} - r_{CV,t})$ is the difference between 1998 chained annual U.S. indices for glyphosate and a group of seven post-emergence conventional herbicides.[13] 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,

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

many of the herbicides used on CV soybeans are only effective against specific weed species. As well, 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. In terms of calculation, glyphosate prices are annual 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 mean prices and shares for the entire 1998–2011 period, and the resulting index is re-scaled 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 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 this period, commodity prices, and in turn land use, were very high. This, combined with a growing demand for GT corn, led to shortages in glyphosate and an associated price increase.

Figure 3. U.S. Soybean Herbicide Indices: 1998-2011



The time *Trend* variable is included to capture the impact of other factors that contributed to the rapid diffusion of GT soybeans: over our sample period 1998–2003, the adoption rate for GT soybeans rose from 38% to 86%. This adoption pattern, part of the success that genetically modified varieties enjoyed in the United States, was driven by a variety factors, some of which are not explicitly modelled here. We expect that the adoption of GT soybeans will be positively associated with this trend variable.

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. 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 γ). 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 bigger role for the tillage decision. The linear time trend is highly significant and positive, 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 long-term drought-like conditions, as captured by the Palmer 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.

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, which suggests that there are a variety of individual characteristics that we do not measure that 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 low number of farms that still use CV soybeans. The covariance across the errors is also significant, though not very large in magnitude. The implied correlation is about 0.084. Thus, farmers who have a strong preference for GT soybeans (i.e., a large ν_i^{GT}) are slightly more likely to have a strong

Table 3. Simulated Maximum Likelihood Results

Variables	Coefficient	Standard Error
GT Variables		
Constant	1.5741***	(0.10865)
Seed Price	-0.3271***	(0.01480)
Herbicide Price	-0.9733***	(0.14272)
Size	0.1184***	(0.02992)
Trend	0.4427***	(0.00717)
CT Variables		
Constant	-0.6857***	(0.05129)
Size	0.2861***	(0.03090)
Futures	-0.0195**	(0.00817)
Fuel Price	0.0126***	(0.00100)
Palmer Drought Index	-0.0193***	(0.00447)
Erodibility Index	0.0787***	(0.00430)
σ_{GT}^2	2.2195***	(0.08785)
σ_{CT}^2	3.8990***	(0.10413)
$\sigma_{GT,CT}$	0.2476***	(0.06388)
γ	0.5106***	(0.02948)

Notes: based on 82,056 observations.
***Significant at the 1% level.
**Significant at the 5% level.

preference for CT (i.e., a large ν_i^{CT}) and vice versa. Finally, the estimate for complementarity, γ , is highly significant and positive, indicating that GT soybeans and CT are indeed complementary. This finding was robust to a variety of specifications.

Complementarity Under Alternative Specifications

As previously noted, there are certain variations on our specification, such as the inclusion of a time trend for CT, which may be important for the complementarity finding. This section also serves to highlight the role of certain assumptions, such as admitting non-zero correlation between the unobserved returns, for our estimate of γ. Table 4 contains estimates of γ for several different specifications. The inclusion of a linear trend for tillage choice does not significantly alter the result for complementarity. The same is true if we include the *Herbicide Price* variable for the tillage choice.

Table 4. Alternative Estimates for Complementarity

Alternative Specifications	γ Coefficient	Standard Error
Include *Trend* in CT Variables	0.4625***	(0.02954)
Include *Herbicide Price* in CT Variables	0.4961***	(0.03249)
No Correlation: $\sigma_{GT,CT} = 0$	0.6080***	(0.02123)
Ignore Panel Aspect of Data	1.3616***	(0.26258)
Basic Logit	0.5628***	(0.01877)
Restrict Sample to Central Corn Belt Only[1]	0.3182***	(0.04832)
No-Till or Till for Tillage Choice[2]	0.7039***	(0.03546)

***Significant at the 1% percent level.
[1]Includes Iowa, Illinois, and Indiana. There is a total of 26,304 observations.
[2]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).

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 γ 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 ν terms are IID across fields and time for the same individual). This substantially increases our estimate for γ, 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 ν terms are set to 0). In this case, the estimate for γ 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 alone account for nearly 35% of U.S. soybean land.

Our result for γ in this case is less than before. However, since γ is estimated on a different sample, it is not directly comparable to the estimate obtained from our baseline specification. This is because estimated parameters in any Logit model are only identified relative to the unobserved variance of the IID extreme value terms. Hence, a different value here 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 between CT and IT, we instead specify it as between no-tillage (NT) and tillage (i.e., some positive level of tillage). There is reason to think that the complementarities between NT and GT soybean are 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 an 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 γ presented in Table 4 indicates that NT and GT soybeans are complementary, and the magnitude of γ is indeed larger than it was for the CT specification. As was noted for the case for the CCB specification, the estimates for complementarity are not directly comparable. Nonetheless, there is reason to believe that the larger estimate for γ is in fact the result of stronger complementarity, rather than smaller variation in the IID portion of unobserved tastes. This is based on 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.

While the estimates for γ are informative on their own, we cannot meaningfully interpret their magnitude. We can, however, look at what our results imply for the predicted probabilities. Thus, the next section considers a counterfactual in which GT soybeans are not available as an option.

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 based on model (10) (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. 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. As above, this requires simulation. Specifically,

$$\hat{L}_{itf}^{j}(\hat{\theta}) = \frac{1}{R}\sum_{r=1}^{R} \frac{e^{x_{itf}^{j}\hat{\beta}^{j}+v_{i,r}^{j}}}{\sum_{k\in\Omega_{it}} e^{x_{itf}^{k}\hat{\beta}^{k}+v_{i,r}^{k}}};\ j \in \{(CV,CT),(GT,CT)\}. \tag{21}$$

Note that this is computed using the parameters presented in Table 3 (i.e., $\hat{\theta}$). As well, the computations are based on the choice-set used to estimate the model, Ω_{it}. The predicted probability for choosing CT is given by: $\hat{L}_{itf}^{CT} = \hat{L}_{ift}^{CV,CT} + \hat{L}_{ift}^{GT,CT}$. 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

$$\hat{S}_{t}^{CT} = \frac{\sum_{i=1}^{I_t}\sum_{f=1}^{F_{it}} A_{ift}\hat{L}_{ift}^{CT}}{\sum_{i=1}^{I_t}\sum_{f=1}^{F_{it}} A_{ift}}. \tag{22}$$

To compute the predicted annual shares for CT when GT soybeans are not available, we follow essentially the same steps as before with the exception of one important detail. The predicted probability of using CT when GT soybeans are not available now just consists of a singleton, denoted by $\breve{L}_{ift}^{CV,CT}$ (i.e., the only choice being made is the tillage practice to use). We calculate this according to

$$\breve{L}_{itf}^{CV,CT} = \frac{1}{R}\sum_{r=1}^{R} \frac{e^{x_{itf}^{CV,CT}\hat{\beta}^{CV,CT}+v_{i,r}^{CV,CT}}}{\left(1+e^{x_{itf}^{CV,CT}\hat{\beta}^{CV,CT}+v_{i,r}^{CV,CT}}\right)} \tag{23}$$

The difference between (23) and (21) is the denominator inside of the summation, which in equation (23) does not include the terms for the GT choices. Denote the annual predicted adoption rates for CT when GT soybeans are not available as $\breve{S}_{t}^{CT}$ (which are computed in the same way as before). Table 4 contains the predicted adoption rates from 1998 to 2011. In 1998 the adoption rate for CT is 3.67% 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 7 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 and an overall increase in farm size.

Table 5. CT Predicted Adoption Rates (percent of acres)

Year	With GT Option	Without GT Option	Difference
1998	55.26	51.65	3.61
1999	56.55	52.38	4.17
2000	58.58	53.91	4.67
2001	59.22	53.69	5.53
2002	59.19	53.31	5.88
2003	61.47	54.92	6.55
2004	61.93	55.29	6.64
2005	65.07	58.67	6.40
2006	65.68	59.10	6.58
2007	66.96	60.18	6.78
2008	68.95	62.29	6.66
2009	64.28	57.35	6.93
2010	67.86	61.00	6.86
2011	69.91	63.10	6.81

Notes: based on the parameter estimates from Table 3.

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. 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 in a world without GT soybeans. The simulations indicate that CT adoption has been about 10% larger (or 7 percentage points) than what it would have been as a result of the availability of GT soybeans.

Whereas the framework of analysis that we propose and illustrate in this paper has broader methodological applicability to many issues in the economics of agricultural production, there are also some immediate policy implications that follow from our finding that GT soybeans and CT are complements. The basic intuition is that, when complementarities are present, policy shocks that directly affect one activity will also indirectly affect complementary activities. In recent years, for example, glyphosate weed resistance has become increasingly problematic in certain parts of the country (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 true 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, represent an obvious application of our framework of analysis. Given the concerns associated with the 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 extremely valuable. Whether or not these avenues of inquiry are viable depends mainly on data availability. As the promises of "big data" gradually come to fruition in agricultural settings, some of the aforementioned applications might be feasible.

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. *The Journal of Industrial Economics*, 361-379.

Athey, S., and S. Stern. 1998. An Empirical Framework for Testing Theories About Complementarity in Organizational Design (No. 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), 258-268.

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

Berry, S., A. Khwaja, V. Kumar, A. Musalem, K. Wilbur, G. Allenby, B. Anand, P. Chintagunta, M. Hanemann, P. Jeziorski and A. Mele. 2014. Structural Models of Complementary Choices. *Marketing Letters,* 25: 245-256.

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

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*. Economic Research Service, U.S. Department of Agriculture, Washington DC, October 1993.

Cameron, A. C., and P. K. Trivedi. 2010. *Microeconometrics Using Stata, Revised Edtion*. Stata Press.

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.

Carpenter, J., and L. Gianessi. 1999. Herbicide Tolerant Soybeans: Why Growers are Adopting Roundup Ready Varieties. *AgBioForum*, 2(2), 65-72. Available on the World Wide Web: http://www.agbioforum.org.

Ding, Y., K. Schoengold, & 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*, 395-411.

Dorfman, J. H. 1996. Modeling Multiple Adoption Decisions in a Joint Framework. *American Journal of Agricultural Economics*, 78(3), 547-557.

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), 126-135.

Fernandez-Cornejo, J., and M. Caswell. 2006. *The First Decade of Genetically Engineered Crops in the United States* (Economic Information Bulletin EIB-11). Washington, DC: USDA ERS.

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): 231-241.

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), 149-164.

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* (pp. 63-88). Springer US.

Fernandez-Cornejo, J., Wechsler, S.J., Livingston, M., L. Mitchell. 2014. *Genetically Engineered Crops in the United States*. Economic Research Report No. (ERR-162) 60 pp., 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), 249-257.

Fuglie, K.O. 1999. Conservation Tillage and Pesticide Use in the Cornbelt. *Journal of Agricultural and Applied Economics*, 31(1), 133-147.

Gentzkow, M. 2007. Valuing New Goods in a Model with Complementarity: Online Newspapers. *American Economic Review*, 97(3), 713-744.

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), 150-155.

Hensher, D. A., J. M. Rose, and W. H. Greene. 2005. *Applied Choice Analysis: a Primer*. 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 & Environment*, 103(1), 1-25.

Kalaitzandonakes, N., and P. Suntornpithug. 2003. Adoption of Cotton Biotechnology in the United States: Implications for Impact Assessment. In N. Kalaitzandonakes (Ed.), *The Economic and Environmental Impacts of Agbiotech: A Global Perspective* (pp. 103-118). New York: Kleuwer Academic.

Keane, M. P. 1992. A Note on Identification in the Multinomial Probit Model. *Journal of Business & 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.

Milgrom, P., and J. Roberts 1990. The Economics of Modern Manufacturing: Technology, Strategy, and Organization. *The American Economic Review*, 80(3), 511-528.

Miravete, E. J., and J. C. Pernías. 2006. Innovation Complementarity and Scale of Production. *The Journal of Industrial Economics*, 54(1), 1-29.

Miravete, E. J., and J. C. Pernías. 2010. Testing for Complementarity When Strategies are Dichotomous. *Economics Letters*, 106(1), 28-31.

Moschini, G. 2008. Biotechnology and the Development of Food Markets: Retrospect and Prospects. *European Review of Agricultural Economics*, 35(3), 331-355.

Nevo, A. 2000. A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand. *Journal of Economics & Management Strategy*, 9(4), 513-548.

Nevo, A., and M. D. Whinston. 2010. Taking the Dogma Out of Econometrics: Structural Modeling and Credible Inference. *The Journal of Economic Perspectives*, 24(2), 69-81.

Powles, S. B. 2008. Evolved Glyphosate-Resistant Weeds Around the World: Lessons to be Learnt. *Pest Management Science*, 64(4), 360-365.

Qaim, M. 2009. The Economics of Genetically Modified Crops. *Annual Review of Resource Economics*, 1(1), 665-694.

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, 629-643.

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 U.S. Farm Policy. *R4259, Congressional Research Service.*

Train, K. 2000. Halton Sequences for Mixed Logit. Working Paper No. E00-278, Department of Economics, University of California, Berkeley.

Train, K. E. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press.

Triplett, G. B., and W. A. Dick. 2008. No-Tillage Crop Production: A Revolution in Agriculture! *Agronomy Journal*, 100(Supplement 3), S-153.

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 & Environment*, 91(1), 217-232.

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.