Information technologies and field-level chemical use for corn production

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Information technologies and field-level chemical use for corn production[1]

Jae-hoon Sung and John A. Miranowski[2]

Abstract

We investigate the effectiveness of soil testing and pest scouting by focusing on field-level chemical use for corn production. Based on the ARMS phase II and phase III data, we estimate equations for technology adoptions and chemical use. For estimation, we incorporate nonlinear endogenous switching regression to account for the nonnegative chemical use and endogeneity problems regarding adoptions of conservation practices. We find that: 1) adopting information technologies are positively correlated with farmers' human capital, field characteristics, and corn prices. 2) the effects of information technologies on farmers' nitrogen use depends on crop rotation. To be specific, farmers who adopt soil testing and crop rotation use nitrogen less than farmers who use crop rotation but do not adopt soil testing by about 8 lb/acre, but soil testing has insignificant effects on the rate of nitrogen application by farmers who grew corn continuously. 3) farmers' management practices such as the use of manure and GM corns have significant effects on their nitrogen and herbicide use, but the directions and sizes of them depends on adoption of information technologies and previous field use.

Keywords: Information technologies, chemical use, ARMS

JEL codes: Q15, Q16

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Introduction

Production uncertainty has been recognized as a major factor in fertilizer and pesticide use (Feder 1979; Babcock 1992; Ribaudo et al. 2011). Production uncertainty includes unexpected events during the growing season as well as imperfect information regarding heterogeneous environmental conditions and chemical performance (Lichtenberg 2002). Farmers may have incentives to reduce production risk by over-applying chemical inputs.[3] In addition, some farmers may also apply chemical inputs in amounts beyond actual crop requirements based on their desired yield goal (Ribaudo et al. 2011).

Intensive use of chemicals by farmers has serious environmental and economic effects (Lambert et al. 2006; Ribaudo et al. 2011). Nutrient and pesticide runoff is one of the leading causes of impaired quality of water supplies, including drinking water (Lambert et al. 2006). The cost of removing nitrate from drinking water in the United States is estimated to be more than $4.8 billion annually, and agricultural production accounts for about 35% of that cost (Ribaudo et al. 2011).

Soil testing (e.g., soil N test, soil P test, and plant tissue test) and scouting have been shown to decrease the agricultural use of chemicals. Soil testing provides information about nutrient availability in the soil and enable farmers to apply fertilizer at rates which are closer to actual crop requirements. Scouting provides farmers with information about pest infestation, pesticide performance, and pest resistance, allowing farmers to adjust their pesticide application rates to be more consistent with an economic threshold population of pests (Miranowski, Ernst, and Cummings 1974).[4] Scouting may also decrease farmers' perceived risk by reducing uncertainty regarding pest infestation and damage. Thus, scouting could decrease risk-averse farmers' pesticide use by raising their economic threshold population (Feder 1979). For these reasons, we consider soil testing and scouting to be information technologies

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[3] Uncertainty refers to the environment in which economic decisions are made. Risk means the economically relevant implications of uncertainty (Moschini & Hennessy 2001).

[4] Miranowski, Ernst, and Cummings (1974) define "economic threshold population" as the infestation level at which the economic cost of reduced crop sales is predicted to exceed the cost of applying corrective pesticide or taking some other pest control measures. Thus, farmers will apply pesticide when the pest infestation level is higher than the economic threshold population.

However, the effectiveness of soil testing and scouting in reducing farmers' chemical use is an empirical question. The information generated by soil testing and scouting will reduce farmers' chemical use only if farmers recognize that the information is useful in increasing their profits or utility (Miranowski, Ernst, and Cummings 1974). The usefulness of information technologies thus depends on the characteristics of individual farmers, such as knowledge about crop production technology (Lichtenberg 2002). Uncontrollable market and environmental conditions, such as crop price fluctuations and severe weather events, can also alter farmers' chemical application practices (Babcock 1992). Finally, chemical application rates may also depend on a combination of information technologies and other conservation practices, rather than on information technologies alone (Wu and Babcock 1998).

In our study, we analyze the effectiveness of information technologies by focusing on field-level fertilizer and pesticide use for corn production. Corn production is selected for three reasons. First, corn is the most chemical-intensive crop (Ribaudo et al. 2011; Fernandez-Cornejo et al. 2014). Second, corn growers are least likely to adopt more efficient fertilizer management practices (Ribaudo et al. 2011). Third, recent expansion of corn acreage in the U.S. due to ethanol production raises concerns about the negative externalities of agriculture production (Secchi and Babcock 2007; Langpap and Wu 2011; Hendricks, Smith, and Sumner 2014). Specifically, the increase in demand for corn would cause farmers to cultivate even marginal land for corn production and increase continuous corn production. Cultivating marginal land, which is prone to soil erosion, is likely to increase farmers' fertilizer use and consequently the sediment load in the watershed (Secchi and Babcock 2007). Continuous corn production requires more chemical use, which could increase nutrient and pesticide loss to ground and surface water (Meehan et al. 2011; Sawyer 2015).

This study examines four research questions. First, what factors encourage farmers to use information technologies? Second, how do scouting and soil testing affect farmers' chemical input management? Third, do the effects of information technologies on farmers' input management differ between farmers using crop rotation and those engaged in continuous corn production? Fourth, how do the effects of field management practices on chemical use depend on historical land use and information technology adoptions? To answer these questions empirically, we construct equations for farmers' information technologies adoption and for their input use decisions, and estimate those equations by using nonlinear endogenous switching regression.

The next section of the article reviews relevant literature. Section 3 shows our model specification and related assumptions. Section 4 explains the implications of the variables selected and how we constructed our field-level data. Section 5 describes our results, and section 6 discusses our conclusions and policy implications. Appendix includes tables regarding summary statistics and estimation results.

Literature review

Theoretically, the effectiveness of information technologies on chemical use is unclear, and this ambiguity emphasizes the need for empirical studies. Feder (1979) finds that information regarding the degree of infestation, the amount of pest damage, and the effectiveness of pesticides would reduce chemical application only if pesticides are themselves risk-reducing. Lichtenberg (2002) explores how information provision affects farmers' chemical application rates and application efficiency. He finds that the influence of information technologies on farmers' chemical management is not deterministic, and the effect of information technologies depends on the specific relationships among production technology, chemical input, and production uncertainty. These studies use variance as the measure of risk; however, if we define risk reduction more generally, such as second order stochastic dominance, it is difficult to predict how reducing risk would affect farmers' chemical input use without distributional assumptions regarding uncertainty (Moschini and Hennessy 2001).

Empirically, the literature on soil testing suggests that it does decrease farmers' fertilizer use, but its effectiveness depends on other factors (Babcock and Blackmer 1992; Fuglie and Bosch 1995; Wu and Babcock 1998; Khanna 2001; Ribaudo et al. 2011). Fuglie and Bosch (1995) find that soil N testing is more effective in reducing nitrogen use when farmers have greater uncertainty about available nitrogen in the soil. Wu and Babcock (1998) show that soil testing reduces nitrogen use when it is used in combination with conservation tillage and crop rotation. Khanna (2001) analyzes the effects of soil testing and application technique on the productivity of nitrogen. Her results show that gains in nitrogen productivity from soil testing differ from one farmer to another. However, except for Ribaudo et al. (2011), all of these results are difficult to generalize because of their limited study area and untreated missing data.[5] Also, only Wu and Babcock (1998) deal with endogeneity problems regarding other conservation practices. Lastly, most of previous literature does not take into account nonnegative chemical use even though farmers' chemical use is always greater than zero.

Scouting has been studied as a factor in Integrated Pest Management (IPM), but few empirical studies have examined its effects on pesticide management in isolation. Carlson (1970) and Miranowski, Ernst, and Cummings (1974) construct simulation models which predict that scouting could reduce insecticide use. Mishra, Nimon, and El-Osta (2005) find positive effects of scouting on pesticide expenditure. Yee and Ferguson (1996) find scouting of cotton fields actually increases the number of pesticide treatments.

Insufficient empirical evidences for the usefulness of information technologies may be an obstacle in designing more effective chemical management. To improve the efficiency of chemical management policies, policy makers should understand the factors influencing individual farmers' responses. Our empirical study contributes to filling this gap. First, our results are based on extensive field-level data covering the 16 major corn-producing states. Second, by using weights in field-level data, our results can be generalized in a statistically reliable manner. Third, in order to control for endogenous conservation practices and guarantee nonnegative chemical use, we use exponential function and nonlinear endogenous switching regression models for estimation (Terza 2009; Wooldridge 2014). Thus, our model is more adequate in reflecting farmers' chemical use than models in previous literature. Fourth, by identifying

[5] Fuglie and Bosch (1995) and Wu and Babcock (1998) study only farmers in Nebraska, and Khanna (2001) look only at Iowa, Illinois, Indiana, and Wisconsin. Khanna (2001) employed survey data, but simply dropped missing observations based on an assumption of missing at random.

factors influencing individual farmers' chemical use and adoptions of the technologies, the results can serve as an important source of information for policy makers.

Empirical Model

To evaluate the impact of information technologies and crop rotation on farmers' input management, we employ nonlinear regression with endogenous switching (Terza 2009). This technique is chosen for two reasons. First, the extent to which adopters of information technologies would use fertilizers and pesticide without adopting these technologies cannot be observed. Second, farmers' input management decisions are voluntary. This may result in a correlation between farmers' decisions regarding adoptions of information technologies and their input use – for example, more risk-averse farmers may have a higher demand for both accurate information from the technologies and risk-reducing inputs.

Our model consists of equations for farmers' information technology adoption, crop rotation use, and chemical use. First, consider farmer *i* can choose from four management plans consisting of two practices: crop rotation and the use of information technologies. Let $\mathrm{U_{1,i}}$ represent his expected utility from adopting information technology, and $\mathrm{U_{0,i}}$ represent his expected utility from staying with traditional management. The farmer should adopt the technology if $\mathrm{U^*_{t,i}} = \mathrm{U_{1,i}} - \mathrm{U_{0,i}} > 0$. Likewise, farmer *i* knows his expected utility from using crop rotation ($\mathrm{U_{2,i}}$) and his expected utility from continuous corn production ($\mathrm{U_{3,i}}$), and he uses crop rotation if $\mathrm{U^*_{r,i}} = \mathrm{U_{2,i}} - \mathrm{U_{3,i}} > 0$. Let $I_{j,i}$ be an index representing the farmer's decisions regarding practice j for $j \in \{\text{crop rotation, information technology}\}$, then the farmer's observable choice among four management plans can be represented by

$$I_{t,i} = 1 \; and \; I_{r,i} = 1, \; if \; U^*_{t,i} > 0, U^*_{r,i} > 0;$$

$$I_{t,i} = 1 \; and \; I_{r,i} = 0, if \; U^*_{t,i} > 0, U^*_{r,i} < 0;$$

$$I_{t,i} = 0 \; and \; I_{r,i} = 1, if \; U^*_{t,i} < 0, U^*_{r,i} > 0;$$

$$I_{t,i} = 0 \; and \; I_{r,i} = 0, if \; U^*_{t,i} < 0, U^*_{r,i} < 0;$$

For estimation, we specify $U_{t,i}^{*}$ and $U_{r,i}^{*}$ as linear functions of observed explanatory variables $(Z_{t,i}, Z_{r,i})$:

$$U_{t,i}^{*} = Z_{t,i}^{'}\gamma_t + \varepsilon_{t,i}; U_{r,i}^{*} = Z_{r,i}^{'}\gamma_r + \varepsilon_{r,i} \tag{1}$$

where γ is a vector of parameters, and $\varepsilon_{t,i}$ and $\varepsilon_{r,i}$ are error terms and follow standard bivariate normal distribution.

Second, incorporating information technologies and crop rotation has an effect on farmers' chemical management. Let $Y = f(X)$ represent the relationship between farmers' input demand and a vector of explanatory variables. A farmer's input use based on decisions regarding adoption of the technologies and crop rotation would be specified as

$$\begin{aligned} Y_{tr,i} &= \exp(X_i^{'}\beta_{tr,i} + \varepsilon_{tr,i}) \ \ if \ \ I_{t,i} = 1, I_{r,i} = 1; \\ Y_{to,i} &= \exp(X_i^{'}\beta_{to,i} + \varepsilon_{to,i}) \ if \ \ I_{t,i} = 1, I_{r,i} = 0; \\ Y_{ro,i} &= \exp(X_i^{'}\beta_{ro,i} + \varepsilon_{ro,i}) \ \ if \ \ I_{t,i} = 0, I_{r,i} = 1; \\ Y_{oo,i} &= \exp(X_i^{'}\beta_{oo,i} + \varepsilon_{oo,i}) \ \ if \ \ I_{t,i} = 0, I_{r,i} = 0 \end{aligned} \tag{2}$$

where $Y_{.,i}$ is the input demand depending on farmer *i*'s decisions to use information technology and crop rotation. The exponential function is used to model the expected value of nonnegative dependent variable directly. Equation (3) represents the expected value of a farmer's input use conditional on adoption status.

$$\begin{aligned} E(Y_{tr,i} \mid I_{t,i} = 1, I_{r,i} = 1) &= \exp(X_i^{'}\beta_{tr,i})E(\exp(\varepsilon_{tr,i}) \mid I_{t,i} = 1, I_{r,i} = 1) \\ E(Y_{to,i} \mid I_{t,i} = 1, I_{r,i} = 0) &= \exp(X_i^{'}\beta_{to,i})E(\exp(\varepsilon_{to,i}) \mid I_{t,i} = 1, I_{r,i} = 0) \\ E(Y_{ro,i} \mid I_{t,i} = 0, I_{r,i} = 1) &= \exp(X_i^{'}\beta_{ro,i})E(\exp(\varepsilon_{ro,i}) \mid I_{t,i} = 0, I_{r,i} = 1) \\ E(Y_{oo,i} \mid I_{t,i} = 0, I_{r,i} = 0) &= \exp(X_i^{'}\beta_{oo,i})E(\exp(\varepsilon_{oo,i}) \mid I_{t,i} = 0, I_{r,i} = 0) \end{aligned} \tag{3}$$

If Equation (1) and Equation (2) are correlated, nonlinear least square (NLS) estimates of coefficients in Equation (2) should be biased because the last terms in Equation (3) are not one. To correct for this sample selection bias, we assume that $(\varepsilon_{t,i}, \varepsilon_{r,i}, \varepsilon_{1,i}, \varepsilon_{2,i}, \varepsilon_{3,i}, \varepsilon_{4,i})$ follows multivariate normal distribution with mean of zero and the following covariance matrix:

$$Cov(\varepsilon_{t,i},\varepsilon_{r,i},\varepsilon_{tr,i},\varepsilon_{to,i},\varepsilon_{ro,i},\varepsilon_{oo,i})=\begin{bmatrix} 1 & \rho & \sigma_{tr}^{t} & \sigma_{to}^{t} & \sigma_{ro}^{t} & \sigma_{oo}^{t} \\ \rho & 1 & \sigma_{tr}^{r} & \sigma_{to}^{r} & \sigma_{ro}^{r} & \sigma_{oo}^{r} \\ \sigma_{tr}^{t} & \sigma_{tr}^{r} & \sigma_{tr}^{2} & \sigma_{to}^{tr} & \sigma_{ro}^{tr} & \sigma_{oo}^{tr} \\ \sigma_{to}^{t} & \sigma_{to}^{r} & \sigma_{to}^{tr} & \sigma_{to}^{2} & \sigma_{ro}^{to} & \sigma_{oo}^{to} \\ \sigma_{ro}^{t} & \sigma_{ro}^{r} & \sigma_{ro}^{tr} & \sigma_{ro}^{to} & \sigma_{ro}^{2} & \sigma_{oo}^{ro} \\ \sigma_{oo}^{t} & \sigma_{oo}^{r} & \sigma_{oo}^{tr} & \sigma_{oo}^{to} & \sigma_{oo}^{ro} & \sigma_{oo}^{2} \end{bmatrix} \quad (4)$$

where $Var(\varepsilon_{m,i})=\sigma_m^2$, $Cov(\varepsilon_{m,i},\varepsilon_{n,i})=\sigma_m^n$, $Cov(\varepsilon_{t,i},\varepsilon_{m,i})=\sigma_m^t$, and $Cov(\varepsilon_{r,i},\varepsilon_{m,i})=\sigma_m^r$ for $\forall\ m,n\in(tr,to,ro,oo)$ and $m\neq n$. Based on these assumptions, the conditional expectations of $\varepsilon_{m,i}$ for $\forall\ m\in(tr,to,ro,oo)$ become

$$\begin{aligned}
E(\exp(\varepsilon_{tr,i})\mid I_{t,i}=1,I_{r,i}=1)&=\exp(\frac{\sigma_{tr}^2}{2})\frac{\Phi_2(Z_{t,i}\gamma_t+\sigma_{tr}^t,Z_{r,i}\gamma_r+\sigma_{tr}^r,\rho)}{\Phi_2(Z_{t,i}\gamma_t,Z_{r,i}\gamma_r,\rho)}\\
E(\exp(\varepsilon_{to,i})\mid I_{t,i}=1,I_{r,i}=0)&=\exp(\frac{\sigma_{to}^2}{2})\frac{\Phi_2(Z_{t,i}\gamma_t+\sigma_{to}^t,-Z_{r,i}\gamma_r-\sigma_{to}^r,-\rho)}{\Phi_2(Z_{t,i}\gamma_t,-Z_{r,i}\gamma_r,-\rho)}\\
E(\exp(\varepsilon_{ro,i})\mid I_{t,i}=0,I_{r,i}=1)&=\exp(\frac{\sigma_{ro}^2}{2})\frac{\Phi_2(-Z_{t,i}\gamma_t-\sigma_{ro}^t,Z_{r,i}\gamma_r+\sigma_{ro}^r,-\rho)}{\Phi_2(-Z_{t,i}\gamma_t,Z_{r,i}\gamma_r,-\rho)}\\
E(\exp(\varepsilon_{oo,i})\mid I_{t,i}=0,I_{r,i}=0)&=\exp(\frac{\sigma_{00}^2}{2})\frac{\Phi_2(-Z_{t,i}\gamma_t-\sigma_{oo}^t,-Z_{r,i}\gamma_r-\sigma_{oo}^r,\rho)}{\Phi_2(-Z_{t,i}\gamma_t,-Z_{r,i}\gamma_r,\rho)}
\end{aligned} \quad (5)$$

where Φ_2 is a cumulative density function of the standard bivariate normal distribution (see Appendix). As a result, the following equations are estimated separately:

$$\begin{aligned}
Y_{tr,i}&=\exp(X_i^{'}\beta_{tr}+\frac{\sigma_{tr}^2}{2})\frac{\Phi_2(Z_{t,i}\gamma_t+\sigma_{tr}^t,Z_{r,i}\gamma_r+\sigma_{tr}^r,\rho)}{\Phi_2(Z_{t,i}\gamma_t,Z_{r,i}\gamma_r,\rho)}+\xi_{tr,i}\ if\ I_{t,i}=1,I_{r,i}=1\\
Y_{to,i}&=\exp(X_i^{'}\beta_{to}+\frac{\sigma_{to}^2}{2})\frac{\Phi_2(Z_{t,i}\gamma_t+\sigma_{to}^t,-Z_{r,i}\gamma_r-\sigma_{to}^r,-\rho)}{\Phi_2(Z_{t,i}\gamma_t,-Z_{r,i}\gamma_r,-\rho)}+\xi_{to,i}\ if\ I_{t,i}=1,I_{r,i}=0\\
Y_{ro,i}&=\exp(X_i^{'}\beta_{ro}+\frac{\sigma_{ro}^2}{2})\frac{\Phi_2(-Z_{t,i}\gamma_t-\sigma_{ro}^t,Z_{r,i}\gamma_r+\sigma_{ro}^r,-\rho)}{\Phi_2(-Z_{t,i}\gamma_t,Z_{r,i}\gamma_r,-\rho)}+\xi_{ro,i}\ if\ I_{t,i}=0,I_{r,i}=1\\
Y_{oo,i}&=\exp(X_i^{'}\beta_{oo}+\frac{\sigma_{00}^2}{2})\frac{\Phi_2(-Z_{t,i}\gamma_t-\sigma_{oo}^t,-Z_{r,i}\gamma_r-\sigma_{oo}^r,\rho)}{\Phi_2(-Z_{t,i}\gamma_t,-Z_{r,i}\gamma_r,\rho)}+\xi_{oo,i}\ if\ I_{t,i}=0,I_{r,i}=0
\end{aligned} \quad (6)$$

where $\xi_{m,i}=Y_{m,i}-E(Y_{m,i})$ for $\forall\ m\in(tr,to,ro,oo)$.

The above approach can be used to examine the effects of information technologies on farmers' chemical input application. We separately calculate the effects of information technologies on famers using crop rotation and farmers growing corn continuously. To be specific, for a farmer with characteristics *(X, Z)*, we calculate the effects of information technology adoption on chemical use of crop rotation users as the difference between two equations in Equation (7).

$$
\begin{aligned}
E(Y_{tr,i} \mid I_{ti}=1, I_{ri}=1) &= \exp(X_i^{'}\beta_{tr} + \frac{\sigma_{tr}^2}{2}) \frac{\Phi_2(Z_{t,i}\hat{\gamma}_t + \sigma_{tr}^t, Z_{r,i}\hat{\gamma}_r + \sigma_{tr}^r, \rho)}{\Phi_2(Z_{t,i}\hat{\gamma}_t, Z_{r,i}\hat{\gamma}_r, \rho)} \\
E(Y_{ro,i} \mid I_{ti}=0, I_{ri}=1) &= \exp(X_i^{'}\beta_{ro} + \frac{\sigma_{ro}^2}{2}) \frac{\Phi_2(-Z_{t,i}\hat{\gamma}_t - \sigma_{ro}^t, Z_{r,i}\hat{\gamma}_r + \sigma_{ro}^r, -\rho)}{\Phi_2(-Z_{t,i}\hat{\gamma}_t, Z_{r,i}\hat{\gamma}_r, -\rho)}
\end{aligned} \tag{7}
$$

Also, the effects of information technologies on chemical use of farmers growing corn continuously can be calculated by the difference between two equations in Equation (8).

$$
\begin{aligned}
E(Y_{to,i} \mid I_{ti}=1, I_{ri}=0) &= \exp(X_i^{'}\beta_{to} + \frac{\sigma_{to}^2}{2}) \frac{\Phi_2(Z_{t,i}\hat{\gamma}_t + \sigma_{to}^t, -Z_{r,i}\hat{\gamma}_r - \sigma_{to}^r, -\rho)}{\Phi_2(Z_{t,i}\hat{\gamma}_t, -Z_{r,i}\hat{\gamma}_r, -\rho)} \\
E(Y_{oo,i} \mid I_{ti}=0, I_{ri}=0) &= \exp(X_i^{'}\beta_{oo} + \frac{\sigma_{oo}^2}{2}) \frac{\Phi_2(-Z_{t,i}\hat{\gamma}_t - \sigma_{oo}^t, -Z_{r,i}\hat{\gamma}_r - \sigma_{oo}^r, \rho)}{\Phi_2(-Z_{t,i}\hat{\gamma}_t, -Z_{r,i}\hat{\gamma}_r, \rho)}
\end{aligned} \tag{8}
$$

Estimation

Terza (2009) and Wooldridge (2010, pp 724~748; 2014) suggest a two-step method to estimate a nonlinear endogenous switching regression model. The first step is to estimate Equation (1) by using a bivariate probit model to get consistent estimates of γ_t, γ_r, and ρ. Second, we use Poisson quasi-maximum likelihood estimator (QMLE) to estimate Equation (6). The advantage of Poisson QMLE is that consistency of the estimator does not depend on the distributional assumption when conditional expectations in Equation (5) and the probit model regarding technology adoption and crop rotation are correctly specified (Wooldridge 2010, pp 724~748).

Two issues must be addressed in the above estimations: potential endogenous variables and inconsistent variance estimates. First, some explanatory variables related to farm management practices in

Equation (2) could be endogenous, such as crop insurance, conservation tillage, and genetically modified (GM) seeds adoption. To address these endogenous variables, we use the control function approach as specified in Terza, Basu, and Rathouz (2008) and Wooldridge (2014). This method assumes that proposed control functions act as a kind of sufficient statistic for capturing endogeneity (Wooldridge 2014). Thus, by inserting control functions in the second stage estimation, we alleviate the endogeneity problem.

Wooldridge (2014) suggests using generalized errors as control functions. To be specific, when the endogenous variable (y_2) is discrete, we assume that y_2 follows a probit model and the control function is $\mathrm{e}_2 = \mathrm{y}_2\lambda(Z\delta) - (1-\mathrm{y}_2)\lambda(-\mathrm{Z}\delta)$ where Z is the vector of explanatory variable for y_2, δ is a vector of parameters, and $\lambda(.)$ is the inverse Mills ratio. To apply control function, we have to impose at least one exclusion restriction on Z. That is, in addition to X, Z has to include at least one variable which is not included in X and satisfies properties of instrument variables (IV) (Terza, Basu, and Rathouz 2008; Wooldridge 2014).[6] Lastly, based on the coefficients of generalized errors, we do a simple test of endogeneity.

The second issue is that variance estimates from the two-step method are not consistent because it does not take into account the variation of first-step estimates. We also have to account for the sampling design of our field-level data. To correct for standard errors, we apply design-based variance estimation. That is, based on probability weights, we generate 1,000 random bootstrap samples, and then estimate Equation (6) 1,000 times (Goodwin & Mishra 2005).[7] The USDA provides replicate weights for Delete-a-Group Jackknife estimators. However, the number of replicate weights have been changed from 15 to 30 after 2008. Also, Goodwin, Mishra, and Ortalo-Magné (2003) suggest that a jackknife procedure may not be valid when only a subset of the data are used.

[6] We apply this restriction only when we estimate equations regarding adoptions of technologies and crop rotation for the two-step procedures. However, when we estimate results in Table 3, 4, and 5, we exclude unreasonable variables in X. For example, we exclude total GDD, HDD, and precipitation during the growing season when we analyze adoptions of crop rotation because crop rotation is determined before planting.

[7] The crucial assumption of this approach is that the sampling scheme of the data and population of samples are constant from 2001 to 2010.

Data and Model Specification

The data for this study come from the USDA's Agricultural Resource Management Survey (ARMS) Phase II and Phase III in 2001, 2005 and 2010. The ARMS Phase II data contain field-level information on production practices. The ARMS Phase III data include financial information related to farm operation and socioeconomic characteristics of farmers. The ARMS data have two useful attributes. First, we can link production practices of farmers and their individual characteristics by merging the ARMS Phase II and Phase III data. Second, the ARMS data include the weights accounting for sampling design. Our results and inferences can thus be generalized in a statistically reliable manner by using these weights (Dubman 2000).

We select 3,180 fields for corn grain and corn silage harvested in 16 states in 2001, 2005, and 2010.[8] We exclude fields for organic corn and fields operated by the retired farmers, and only include fields operated by mainstream farms (Goodwin and Mishra 2005). Table 1 and 2 show the summary statics of variables and their definitions. About 70% of farmers adopted scouting or crop rotation, but only 27% were using soil testing for nitrogen application. In the case of chemical application, more than 72% of farmers applied nitrogen or herbicide for corn production. Only about 17% of farmers applied insecticide for corn production, and the quantity of insecticide applied and its variation are smaller than herbicide and nitrogen application rates.

Adopting Information Technologies and Crop Rotation

We assume that adopting information technologies and crop rotation depends on farm or farmer characteristics, management practices, input and output prices, and environmental conditions. Corn fields are defined as being in crop rotation if corn was not planted on the fields during the previous season.

Characteristics of operators or their farms include years of farming experience and education levels, field ownership, and farm size. Years of farming experience, education levels are used as proxies of available human capital (Khanna 2001). Education levels have been proven to have a positive effect on

[8] The states included in this study are Colorado, Illinois, Iowa, Indiana, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, Pennsylvania, South Dakota, Texas, and Wisconsin.

adoption of information technologies (Fuglie and Bosch 1995; Yee and Ferguson 1996; Wu and Babcock 1998). In this paper, we add a dummy variable having a value of one when the farmer graduated from college. However, the effect of years of farming experience on adoption of new technologies and practices will vary among farmers and technologies. To be specific, as farmers' experience accumulates, they have more knowledge and information about current management practices. More experience may make risk-averse farmers reluctant to adopt new practices and technologies. On the other hand, accumulated knowledge about a given field could reduce uncertainty regarding the adoption of unfamiliar practices or technologies. Farm size would have positive effects on adoption of information technologies since large farms are able to spread both the cost and the risk of adopting the technologies across more acreage (Gould, Saupe, and Klemme 1989; Wu and Babcock 1998). We use total acreage as the measure of farm size. Lastly, farmers may have more incentives to adopt information technologies for their rented fields because they will have less information about the fields such as historical land use and pest infestation levels than the landowner (Wu and Babcock 1998). We include a dummy with a value one for rented fields.

Second, irrigation status, manure use (tied to animal production), and fall application of nitrogen are included as variables that represent specific management practices, and we expect that they have positive effects on adoption of information technologies. The potential payoffs of information technologies would be greater for irrigated farms because such farms use chemical inputs more intensively. In addition, only high yields of irrigated fields may be able to support the cost of adopting information technologies. Irrigation would also motivate farmers to use continuous corn production because irrigation would make continuous corn production more profitable than crop rotation (Wu and Babcock 1999).[9] We include dummy variables for manure use and nitrogen application during the previous fall in equations for soil testing and crop rotation. Since manure use and fall application of nitrogen would increase a farmer's uncertainty about the availability of nitrogen in the soil, farmers who use manure or apply nitrogen during

[9] Irrigated corn yield is higher than dryland corn yield, and irrigation could compensate for the corn yield-loss resulting from continuous corn production. However, if we consider the risk of production such as pesticide resistance and soil erosion, continuous, corn production would be less profitable than crop rotation in the long term.

the fall are more likely to adopt soil testing during the spring. In addition, if manure application is related to farms' livestock production, manure use would be positively correlated with continuous corn production because livestock production increases on-farm demand for corn as livestock feed.

Third, state-level relative prices of corn to soybeans and multistate-level nitrogen prices are included to control for market conditions. Chicago Board of Trade (CBOT) futures prices are used for corn and soybeans, and these prices are adjusted to take into account regional differences in farm-gate prices (Barr et al. 2011). A high relative price of corn to soybeans would give farmers an incentive to grow more corn. Nitrogen prices would be negatively correlated with continuous corn production.[10] Also, high prices for nitrogen would motivate farmers to use soil testing so as to apply nitrogen more efficiently.

Chemical use[11]

We include farmers' management practices as control variables for their chemical use: conservation tillage, manure use, irrigation, chemical application timing, and GM corn adoption.[12] First, conservation tillage systems are likely to reduce fertilizer use and soil erosion by increasing soil quality (Lambert et al. 2006). However, the relationship between conservation tillage and pesticide use is an empirical question because it depends on the conservation tillage system employed and given environmental conditions such as soil type and pest infestation levels during the previous years (Fernandez-Cornejo et al. 2012). Second, since manure is an important source of nitrogen, using manure would reduce commercial fertilizer application rates. Third, since irrigated fields are more productive than non-irrigated fields, irrigated farms would have more incentive to apply more chemical to maximize corn yields than non-irrigated farms

[10] The comparative advantage of using information technologies would depend on its cost and the price of the chemical in question. When applying more nutrients and pesticides is cheaper than using information technologies, farmers are unlikely to adopt information technologies. However, many of the observations in the ARMS data reported zero cost or did not report the cost of adopting information technologies. Indirectly, nitrogen prices would be one way to control for economic returns of soil testing. However, equations for pesticide usage do not take into account market conditions, which is one of the limitations of this study.
[11] We use the sum of quantities of active ingredients in pesticides. However, the sum of active ingredients may not be appropriate since it does not take into account heterogeneity among active ingredients (Fernandez-Cornejo and Jans 1995).
[12] In this study, variables for manure use and application timing are used only in equations for fertilizer use, and variables for GM seeds are used only for pesticide use. Conservation tillage includes mulch-till, ridge-till, and no-till practices.

generally. Lastly, farmers applying nitrogen in the fall would apply more nitrogen in order to compensate for nitrogen loss during the winter.

The adoption of biotechnologies has serious implications for farmers' pesticide use.[13] Herbicide tolerant (HT) corn encourages farmers to use more glyphosate, which is less toxic but more efficient than traditional herbicides such as Atrazine (Fernandez-Cornejo et al. 2014). Insect resistant (Bt) corn seeds are a substitute for insecticides because they contain a gene producing a protein toxic to targeted insects such as corn rootworm and the European corn borer.

As government policies, we include federal crop insurance to measure the effects of income stabilizing policies on field-level chemical input use. We use a dummy having one if a corn field was covered by federal crop insurance. The moral hazard effects of crop insurance on farmers' chemical use are controversial. At the field level, reducing production risk may encourage farmers to use a lower amount of risk-reducing inputs in their corn fields, even though they increase the acreage allocated to corn. However, if banks offer more attractive loans to insured farmers (e.g., lower interest rates), farmer may choose to invest more money in chemical inputs to achieve the maximum corn yield (Weber, Nigel, and O'Donoghue 2015).

Environmental Variables

We include the number of heavy rainfalls during the early spring, from March to May, in the equation for farmer decisions regarding crop rotation, soil testing adoptions, and nitrogen use. Since high soil moisture hinders corn root development, farmers would be reluctant to grow corn when soil moisture in their fields is high. The number of heavy rainfalls during the early spring is also used to control for the nitrogen loss caused by rainfalls before planting or during the planting season.[14] The total growing degree days (GDD)

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[13] In the category of GM seeds, we include HT corn seeds and Bt corn seeds. However, this classification does not account for the effects of GM corn stacked traits such as Bt and HT and GM corn stacked Bt traits, and may make the effect of GM seeds on farmers' pesticide use statistically insignificant by aggregating or averaging the various effects of GM seeds.

[14] The number of heavy rainfalls means the number of rainy days with totals above 25.4 mm (Grossman, Knight, and Karl 2012)

and total precipitation during the growing season are included to take into account weather effects on crop choices, information technologies adoptions, and chemical use (Snyder 1985). Since farmers decide crop rotation before planting, we include the average values of total GDD and precipitation during the growing season over previous 20 years as farmers' expected weather conditions during the growing season. The daily Parameter-elevation Regression on Independent Slope Model (PRISM) data are used for weather variables. For soil quality and land characteristics, we include the county-level National Commodity Crop Productivity Index (NCCPI) – Corn and soybeans in all equations to control for time-invariant soil productivity. Soil variables are based on the Soil Survey Geographic database (SSURGO).

Endogenous Variables

Among the explanatory variables in equations for chemical application, we assume that conservation tillage, GM seed adoptions and crop insurance purchases are endogenous (Wu and Babcock 1998; Fernandez-Cornejo and Wechsler 2012; Fernandez-Cornejo et al. 2012). Farmers' choices of GM seeds and tillage systems would be correlated with input use because of their chemical management skills and uncontrolled variables such as historical pest infestation levels. To control for these unobserved factors in adopting GM seeds, we use the multi-state GM seed prices as instrument variables of GM seeds. To be specific, we calculate the average values of ratios between field-level total cost per unit of purchased GM seeds and that of conventional corn varieties over multiple states.[15]

Conservation tillage systems are considered as an adaptation strategy for abnormally dry conditions because it increases soil moisture (Ding, Schoengold, and Tadesse 2009). We use dry weather conditions, available water capacity (AWS), and depth to water table, saturated hydraulic conductivity (Ksat) as the

[15] Since, in our data set, few observations have information about the cost of Bt corn resistant to corn rootworm, we use total cost of GM Bt variety for insect resistance to the European corn borer (Bt-ECB) and GM herbicide resistant seed variety. Also, we separate the 16 states into four regions based on USDA farm production regions. Region 1 (Corn Belt) is Iowa, Illinois, Indiana, Missouri, and Ohio. Region 2 (lake states) is Michigan, Minnesota, and Wisconsin. Region 3 (Northern Plain areas) is Colorado, Kansas, Nebraska, North Dakota, and South Dakota. Region 4 is Kentucky, Pennsylvania, and Texas.

IVs for adoption of conservation tillage. As a measure of dry weather conditions, we construct the drought index based on Yu and Babcock (2010).

In addition, we use off-farm work hours per week of an operator and his or her spouse as the IV for adoption of conservation tillage systems and GM seeds. Since conservation tillage systems and GM seeds could lower labor requirements for chemical management, a high degree of commitment to off-farm work would increase farmers' incentive to adopt conservation tillage systems and GM seeds (Gould, Saupe, and Klemme 1989).

Crop insurance demand would be affected by farmers' attitude toward the risk and asymmetric information (Just, Calvin, and Quiggin 1999). More risk-averse farmers are likely to choose higher coverage, and their attitude toward risk would be one factor affecting input use. As IVs for corn insurance, we use farm debt (Ifft, Kuethe, Morehart 2015). To be specific, farms having a higher debt are more likely to be subject to borrower-imposed insurance purchases.

Results

Decisions on adoption of information technologies and crop rotation

Table 3, 4, and 5 include the results regarding farmers' decisions on adoption of information technologies and crop rotation. To begin with, the results show that field characteristics have significant effects on farmers' cropping patterns and adoption of information technologies. From the results, we know that farmers are more likely to be used for information technologies when their fields are irrigated, due to the fact that irrigated fields reap a higher potential payoff from information technologies than non-irrigated fields by using chemical more efficiently. In addition, the results show that irrigation has positive effect on crop rotation, supporting our hypothesis that continuous corn production is more profitable for irrigated fields than crop rotation.

The results regarding soil testing and pest scouting imply that farmers' knowledge or ability regarding chemical management have a significant effect on adoption of information technologies. To be specific, education levels and years of farming experience, proxy variables for human capital of farmers, have opposite effects on adoption of information technologies: farmers who graduated from college are more likely to adopt information technologies, as we hypothesized in previous section. However, as the number of years a farmer has operated the field increases, the likelihood of adopting information technologies decreases. This may reflect the fact that farmers do not want to change their practices and adopt new technologies as they become more familiar with current or conventional practices.

The results indicate that farmers are more likely to adopt pest scouting and crop rotation for their rented fields, but the effects of field ownership on facilitating weed scouting are insignificant. As we hypothesized, lack of information regarding pests, such as the history of pest infestation and the emergence of pest resistance in rented fields, makes farmers more likely to adopt insect scouting and crop rotation. In addition, from the results, we know that only farmers' decisions on insect scouting adoption is significantly affected by their farm size.

Adopting crop rotation is significantly affected by corn prices. The result shows that, as the relative price of corn increases, the likelihood of crop rotation decreases significantly. Also, the large effects of output prices would show that farmers' responses to output prices are much responsive.[16] However, increases in nitrogen price do not have significant effects on the likelihood of crop rotation.[17]

Lastly, the results indicate that farmers are more likely to produce corn continuously when they produce corn silage. If farmers grow corn silage for their livestock, they have the higher likelihood of using continuous corn production to meet their feed requirements.

Decision on chemical application

[16] This result coincides with the findings in Hendricks, Smith, and Sumner (2014). They estimate farmers' short-term and long-term acreage elasticity to corn price. They find that the short-term acreage elasticity to corn price is larger than the long-term acreage elasticity to corn price

[17] There are two possible reasons for this unexpected result. First, the price of nitrogen has a smaller effect on farmers' annual return than corn prices. Thus, if corn prices and nitrogen prices move in opposite directions simultaneously, farmers would choose continuous corn production even though nitrogen prices drop. Second, nitrogen prices would be endogenous (Hendricks, Smith, and Sumner 2014) – that is, for major corn producing states, the price of fertilizer would increase as acres allocated to corn increase.

Table 6 shows the results regarding farmers' nitrogen application based on soil testing adoption and previous field use. To begin with, the results regarding the timing of nitrogen application and manure use support our hypothesis in the previous section, but the significance of these variables depends on farmers' previous land use and adoption of soil testing. To be specific, the results show that manure applications reduce nitrogen applications, except for farmers using soil testing and growing corn continuously. In addition, nitrogen application during the previous fall increases nitrogen application rates of farmers who did not use soil testing by 13~15%, but the effects of fall nitrogen applications are not significant for soil testing adopters. This result would show that soil testing result in similar nitrogen application rates regardless of the timing of nitrogen applications by providing farmers with more accurate information about soil nutrient conditions. In addition, the results show that irrigation increases nitrogen application rates by 44%~83%. The explanation for this is straightforward since the marginal productivity of nitrogen use are larger for irrigated farmers than non-irrigated farmers.

The results regarding pesticide application are given in Table 7 and 8. As shown, fewer explanatory variables are statistically significant compared to results regarding nitrogen applications. First, the effects of management practices are worth noting. The use of herbicide tolerant GM seeds has positive effects on the rate of herbicide application by weed scouting adopters. The results show that the use of herbicide tolerant GM seeds increases the herbicide use of weed scouting adopters by 38 to 128%, reflecting the fact that herbicide tolerant GM seeds induce farmers to use more glyphosate.

In the case of weather conditions, the results show that total GDD and precipitation during the growing seasons have positive effects on herbicide use generally. These results may be due to the fact that good weather conditions such as enough GDD and precipitation also positively affect weed infestation levels.

Also, the effects of crop insurance on farmers' chemical application rates are insignificant for most groups. These results show that the intensive margin effects of crop insurance on farmers' chemical use are ignorable, and that crop insurance would alter farmers' chemical use by changing farmers' land allocation (Wu 1999; Mishra, Nimon, and El-Osta 2005).

Lastly, in Table 6-8, there is evidence that self-selection occurred in the adoption of information technologies and crop rotation. To be specific, the coefficients of σ_{ro}^{r} are significant at 1% level in all equations for chemical use. Also, σ_{ro}^{t} and σ_{tr}^{t} are significant in equations for nitrogen use and herbicide use. These results suggest that, prior to adopting crop rotation or weed scouting, chemical use of farmers who adopt these practices are different from chemical use of non-adopters on average.

Table 9 shows the effects of information technologies based on farmers' historical land use. The results show that only soil testing has a statistically significant effect on farmers' chemical use.[18] Farmers who grow corn after another crop and adopt soil testing use less nitrogen than farmers who use crop rotation but do not adopt soil testing by about 8 lb/acre, or about 7% of average nitrogen use (see Table 1). However, soil testing has no effect on the rate of nitrogen application by farmers who grew corn continuously. One explanation for this result is that the available carryover soil nutrient after growing soybeans or another crop would be more uncertain than that in the soil after growing corn continuously (Fuglie and Bosch 1995; Wu and Babcock 1999). Thus, soil testing may decrease farmers' nitrogen application by reducing this uncertainty and related risks.

Conclusions

Information technologies can reduce production uncertainty resulting from lack of information about farms' pest management and decrease farmers' chemical application rates. However, although measuring the effectiveness of information technologies is an empirical problem, few studies have analyzed the effects of information technologies on farmers' chemical management. In our study, we investigate the effectiveness of soil testing and pest scouting by focusing on field-level chemical use for corn production. First, we find that information technologies adoption depends on the benefit and cost of adopting new

[18] In the case of insecticide and herbicide, the effects of insect scouting are extremely low and have extremely large variance. These unexpected results may stem from the large proportion of farmers who did not apply insecticides.

technology. For example, rented fields (which have larger production uncertainty than own fields), and irrigated fields (which have a higher potential payoff of adopting the technologies) higher likelihood of adopting information technologies. The factors which reduce time cost of adopting technologies (such as farmers' human capital) are positively correlated with the adoption of information technologies.

Second, after controlling for bias resulting from unobserved heterogeneity of fields or operators and the non-negativity of farmers' chemical use, we find that the effects of information technologies depend on historical land use. Farmers who adopt soil testing and crop rotation apply less nitrogen than farmers who use crop rotation but do not adopt soil testing by about 8 lb/acre. However, soil testing has no effects on nitrogen use of farmers who grow corn continuously, and the effects of pest scouting on pesticide use are insignificant.

Third, the effects of farmers' field management practices on their chemical use depend on information technology adoption. The results show that fall nitrogen application increases nitrogen use of farmers who do not adopt soil testing. Also, HT corn seeds have positive effects only on weed scouting adopters. However, the results also show that the effects of irrigation and manure use are robust to information technologies adoption and historical land use.

This study also has several limitations. First, we do not control for heterogeneous features of active ingredients in pesticide. For future study, by using quality-adjusted pesticide quantities as our dependent variables, we may overcome this limitation (Fernandez-Cornejo and Jans, 1995). Second, the poor estimates regarding insecticide use would show that unobserved variables such as farmers' yield goal, pest infestation levels, field-level soil conditions, and pest resistance would be more important to explain insecticide use. Third, we do not control for the effects of the cost of scouting and the effects of GM corns stacked traits.

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Appendix

For any $m \in (tr, to, ro, oo)$, we know that

$$(\varepsilon_{m,i}, \varepsilon_{t,i}, \varepsilon_{r,i}) \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_m^2 & \sigma_m^t & \sigma_m^r \\ \sigma_m^t & 1 & \rho \\ \sigma_m^r & \rho & 1 \end{pmatrix}\right)$$

Then, the conditional distribution of $\epsilon_{m,i}$ becomes

$$(\varepsilon_{m,i} \mid \varepsilon_{t,i}, \varepsilon_{r,i}) \sim N\left(\mu_m, \sigma_{c,m}^2\right)$$

$$\text{where } \mu_m = \frac{1}{1-\rho^2}(\sigma_m^t(\varepsilon_{t,i} - \rho\varepsilon_{r,i}) + \sigma_m^r(\varepsilon_{r,i} - \rho\varepsilon_{t,i}))$$

$$\sigma_{c,m}^2 = \sigma_m^2 - \begin{pmatrix} \sigma_m^t & \sigma_m^r \end{pmatrix} \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}^{-1} \begin{pmatrix} \sigma_m^t \\ \sigma_m^r \end{pmatrix}$$

$$= \sigma_m^2 - \frac{(\sigma_m^t)^2 + (\sigma_m^r)^2 - 2\rho\sigma_m^t\sigma_m^t}{1-\rho^2}$$

Based on this, we can calculate $E(\exp(\epsilon_{m,i})|\epsilon_{t,i}, \epsilon_{r,i})$ as

$$E(\exp\left(\epsilon_{m,i}\right) \mid \epsilon_{t,i}, \epsilon_{r,i}) = \int_{-\infty}^{\infty} \frac{\exp\left(\epsilon_{m,i}\right)}{\sqrt{2\pi}\sigma_{c,m}} \exp(-\frac{\left(\epsilon_{m,i} - \mu_m\right)^2}{2\sigma_{c,m}^2}) d\epsilon_{m,i}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_{c,m}} \exp(-\frac{\left(\epsilon_{m,i} - (\mu_m + \sigma_{c,m}^2)\right)^2}{2\sigma_{c,m}^2}) d\epsilon_{m,i} \exp\left(\mu_m + \frac{\sigma_{c,m}^2}{2}\right)$$

$$= \exp\left(\mu_m + \frac{\sigma_{c,m}^2}{2}\right)$$

For simplicity, let's assume $m = tr$, The expected value of $y_{tr,i}$ becomes

$$E(y_{tr,i} \mid X_i, \varepsilon_{t,i}, \varepsilon_{r,i}) = \exp(X_i\beta_{tr} + \frac{\sigma_{c,tr}^2}{2})\exp(\mu_{tr})$$

$$E(y_{tr,i} \mid X_i) = E_\varepsilon[E(y_{tr,i} \mid X_i, \varepsilon_{t,i}, \varepsilon_{r,i})]$$

$$= \frac{\exp(X_i\beta_{tr} + \frac{\sigma_{c,tr}^2}{2})}{\Phi_2(Z_{ti}\gamma_t, Z_{ri}\gamma_r, \rho)} \int_{-Z_{ti}\gamma_t}^{\infty} \int_{-Z_{ri}\gamma_r}^{\infty} \frac{E(\exp(\mu_{tr}))}{2\pi\sqrt{1-\rho^2}} \exp(-\frac{(\varepsilon_{t,i}^2 - 2\rho\varepsilon_{t,i}\varepsilon_{r,i} + \varepsilon_{r,i}^2)}{2(1-\rho^2)}) d\varepsilon_{t,i} d\varepsilon_{r,i}$$

The integral terms can be rewritten as

$$\exp(-\frac{(-2\sigma_{tr}^t\varepsilon_{t,i} + 2\sigma_{tr}^t\rho\varepsilon_{r,i} - 2\sigma_{tr}^t\varepsilon_{r,i} + 2\sigma_{tr}^t\rho\varepsilon_{t,i} + \varepsilon_{t,i}^2 - 2\rho\varepsilon_{t,i}\varepsilon_{r,i} + \varepsilon_{r,i}^2)}{2(1-\rho^2)})$$

$$= \exp(-\frac{(\varepsilon_{t,i} - \sigma_{tr}^t)^2 + (\varepsilon_{r,i} - \sigma_{tr}^r)^2 - 2\rho(\varepsilon_{r,i} - \sigma_{tr}^r)(\varepsilon_{t,i} - \sigma_{tr}^t)}{2(1-\rho^2)}) \exp(-\frac{-(\sigma_{tr}^r)^2 - (\sigma_{tr}^t)^2 + 2\rho\sigma_{tr}^r\sigma_{tr}^t}{2(1-\rho^2)})$$

As a result, the final equation for the expected value of $y_{tr,i}$ is as follows:

$$E(y_{tr,i} \mid X_i) = \exp(X_i\beta_{tr} + \frac{\sigma_{c,tr}^2}{2} + \frac{(\sigma_{tr}^r)^2 + (\sigma_{tr}^t)^2 - 2\rho\sigma_{tr}^r\sigma_{tr}^t}{2(1-\rho^2)}) \frac{\Phi_2(\sigma_{tr}^t + Z_{t,i}\gamma_t, \sigma_{tr}^r + Z_{r,i}\gamma_r, \rho)}{\Phi_2(Z_{t,i}\gamma_t, Z_{r,i}\gamma_r, \rho)}$$

$$= \exp(X_i\beta_{tr} + \frac{\sigma_{tr}^2}{2}) \frac{\Phi_2(\sigma_{tr}^t + Z_{t,i}\gamma_t, \sigma_{tr}^r + Z_{r,i}\gamma_r, \rho)}{\Phi_2(Z_{t,i}\gamma_t, Z_{r,i}\gamma_r, \rho)}$$

Table 1. Summary statics: Dependent variables, prices, policies, and farm characteristics

Variable	Mean	Standard deviation	Definition
			Chemical use
Nlb	113.88	75.32	Nitrogen application rate (lb/acre)
Aiqty_her	1.82	1.43	Herbicide application rate (lb AI/acre)[1]
Aiqty_ins	0.08	0.32	Insecticide application rate (lb AI /acre)
			Technology and crop rotation selection
Soil_n_test	0.27	0.49	Soil testing adopted in field (1=yes, 0=no)
Scout_w	0.72	0.45	Scouting for weed adopted in field (1=yes, 0=no)
Scout_ins	0.68	0.47	Scouting for insect adopted in field (1=yes, 0=no)
Rotation	0.73	0.44	Corn alternated with other crops
			Prices and farmer characteristics
P_{corn}	0.44	0.04	Corn price/soybean price
$P_{nitrogen}$	0.39	0.06	Nitrogen price ($/lb)
P_{HT}	1.20	0.07	Total cost of HT corn seeds/ total cost of conventional seeds ($/approximately 80,000 Kernel Bag)
P_{Bt}	1.34	0.16	Total cost of Bt corn seeds/ total cost of conventional seeds ($/approximately 80,000 Kernel Bag)
Off-work	382.48	798.6	Off-work hours per year (operator and operators' spouse)
Debt	311.30	634.66	Farm debt (1,000$)
Tenure	28.30	12.69	Number of years farmer has operated the field
Legal	0.77	0.42	Sole or family farm (1=yes, 0=no)
College	0.21	0.41	Farm operator graduated college (1=yes, 0=no)
Ownership	0.55	0.50	Field owned by farm operator (1=yes, 0=no)
Total_land	1348.69	2059.19	Total land operated during the survey year (1,000 acres)
			Public programs
Insurance	0.71	0.46	Fields covered by federal crop insurance (1=yes, 0=no)

Note: 1. We use the sum of active ingredients in herbicides and insecticides as dependent variables for pesticide use.

Table 2. Summary statistics: Practices and environmental variables

Variable	Mean	Standard deviation	Definition
Practices			
Tillage	0.46	0.50	Conservation tillage adopted in field (1=yes, 0=no)
Manure	0.29	0.45	Manure applied in field (1=yes, 0=no)
Irrigation	0.10	0.29	Field irrigated (1=yes, 0=no)
GM_{HT}	0.29	0.45	Herbicide tolerant GM seeds used (1=yes, 0=no)
GM_{Bt}	0.39	0.49	Insect resistant GM seeds used (1=yes, 0=no)
Fall_app	0.22	0.41	Nitrogen applied during the previous fall (1=yes, 0=no)
Silage	0.14	0.35	Field used for silage production (1=yes, 0=no)
Environmental conditions			
NCCPI	0.48	0.21	NCCPI-Corn and Soybeans
AWS	0.09	0.05	Hydraulic conductivity (m/second)
Ksat	6.10	8.16	Available water capacity (in./in.)
Depth	29.43	21.42	Depth to water table (cm)
GDD	1958.72	319.87	Growing degree days during growing seasons
Precipitation	524.76	180.59	Total precipitation days during growing seasons
H_rain_early	0.83	0.96	Number of heavy rainfalls during March and May
Ave_GDD	1902.58	274.08	Average of GDD over previous 20 years
Ave_Pre	461.10	81.04	Average of Total precipitation over previous 20 years
Drought	0.33	0.11	Average values of drought index in Yu and Babcock (2010)
Number of observations			3180

Table 3. Estimates regarding soil testing and crop rotation

	Soil testing		Crop rotation	
	Estimates	(S.E)	Estimates	(S.E)
P_{corn}	-3.798	(1.438)***	-7.189	(1.397)***
$P_{nitrogen}$	1.532	(0.549)***	-0.149	(0.548)
Silage	-0.084	(0.093)	-0.452	(0.086)***
College	0.199	(0.066)***	0.043	(0.071)
Tenure	-0.004	(0.002)*	0.002	(0.002)
Total_land	0.024	(0.018)	-0.013	(0.020)
Ownership	0.045	(0.056)	-0.193	(0.053)***
Irrigation	1.028	(0.106)***	-0.895	(0.121)***
Fall_app	0.114	(0.067)*	0.186	(0.068)***
Manure	-0.024	(0.077)	-0.385	(0.066)***
NCCPI	-0.305	(0.181)*	0.507	(0.184)***
H_rain_early	-0.019	(0.032)	-0.135	(0.033)***
GDD	-0.000	(0.000)	0.001	(0.000)***
Precipitation	-0.001	(0.001)**	-0.000	(0.001)
Constant	0.829	(0.650)	2.956	(0.693) ***
ρ	-		0.042	(0.043)
Year dummies	Yes		Yes	
# of Convergence	1000			
# of Observations	3178			
Wald Statistic	383.99***			
McFaddens' Pseudo R-squared	0.115			

Note: a significant at 1% level. b significant at 5% level. c significant at 1% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,100 bootstrap runs. For crop rotation, the average values of growing degree days (GDD) and total precipitation during the growing season over the previous 20 years.

Table 4. Estimates regarding weed scouting and crop rotation

	Insect scouting		Crop rotation	
	Estimates	(S.E)	Estimates	(S.E)
P_{corn}	-0.676	(1.395)	-7.353	(1.403)***
Silage	0.034	(0.085)	-0.457	(0.086)***
College	0.259	(0.072)***	0.048	(0.071)
Tenure	-0.008	(0.002)**	0.002	(0.002)
Total_land	0.095	(0.059)	-0.014	(0.020)
Ownership	-0.007	(0.055)	-0.200	(0.053)***
Irrigation	0.422	(0.132)***	-0.897	(0.121)***
NCCPI	0.292	(0.164)*	0.477	(0.182)***
GDD	0.001	(0.000)***	0.001	(0.000)***
Precipitation	0.000	(0.001)	-0.001	(0.001)
$P_{nitrogen}$	-		-0.066	(0.547)
Fall_app	-		0.219	(0.069)***
Manure	-		-0.369	(0.066)***
Heavy rainfall	-		-0.133	(0.033)***
Constant	-2.790	(0.871)***	2.986	(0.684)***
ρ	-		-0.190	(0.037)***
Year dummies	Yes		Yes	
# of Convergence	1000			
# of Observations	3178			
Wald Statistics	507.48***			
McFaddens' Pseudo R-squared	0.102			

Note: a significant at 1% level. b significant at 5% level. c significant at 1% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,100 bootstrap runs. For crop rotation, the average values of growing degree days (GDD), extreme heat degree days (HDD), and total precipitation during the growing season over the previous 20 years.

Table 5. Estimates regarding insect scouting and crop rotation

	Weed scouting		Crop rotation	
	Estimates	(S.E)	Estimates	(S.E)
P_{corn}	1.858	(1.430)	-7.324	(1.405)***
Silage	0.119	(0.084)	-0.455	(0.086)***
College	0.314	(0.078)***	0.046	(0.071)
Tenure	-0.005	(0.002)**	0.001	(0.002)
Total_land	0.139	(0.030)***	-0.015	(0.020)
Ownership	-0.145	(0.054)***	-0.200	(0.053)***
Irrigation	0.655	(0.151)***	-0.895	(0.121)***
NCCPI	0.270	(0.165)	0.490	(0.182)***
GDD	0.000	(0.000)***	0.001	(0.000)***
Precipitation	0.000	(0.001)	-0.000	(0.001)
$P_{nitrogen}$	-		-0.071	(0.547)
Fall_app	-		0.209	(0.069)***
Manure	-		-0.376	(0.066)***
Heavy rainfall	-		-0.136	(0.033)***
Constant	-2.291	(0.678)***	2.990	(0.684)***
ρ	-		-0.156	(0.044)***
Year dummies	Yes		Yes	
# of Convergence			1000	
# of Observations			3178	
Wald Statistics			715.33***	
McFaddens' Pseudo R-squared			0.138	

Note: a significant at 1% level. b significant at 5% level. c significant at 1% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,100 bootstrap runs. For crop rotation, the average values of growing degree days (GDD), extreme heat degree days (HDD), and total precipitation during the growing season over the previous 20 years.

Table 6. Estimates regarding nitrogen use

	TR		TO		RO		OO	
Insurance	-0.642	(0.306)**	-0.763	(0.549)	0.191	(0.167)	-0.053	(0.348)
Tillage	-0.573	(0.327)*	1.049	(0.676)	-0.253	(0.169)	0.767	(0.375)**
P_{corn}	0.957	(2.527)	-9.108	(3.708)***	3.954	(1.298)***	-3.082	(2.237)
$P_{nitrogen}$	0.670	(1.045)	0.230	(1.238)	-0.481	(0.635)	-0.820	(0.530)
Irrigation	0.442	(0.173)**	0.831	(0.308)***	0.772	(0.136)***	0.460	(0.191)**
Silage	-0.061	(0.187)	0.082	(0.252)	-0.223	(0.095)**	-0.223	(0.109)**
Fall_app	0.075	(0.058)	0.189	(0.150)	0.134	(0.032)***	0.123	(0.070)*
Manure	-0.515	(0.135)***	-0.103	(0.223)	-0.169	(0.065)***	-0.630	(0.094)***
NCCPI	0.020	(0.158)	0.583	(0.358)	-0.056	(0.112)	0.609	(0.203)***
H_rain_Early	-0.005	(0.035)	-0.076	(0.065)	-0.011	(0.019)	-0.012	(0.030)
Constant	5.052	(1.131)***	7.925	(1.834)***	3.604	(0.595)***	6.314	(1.130)***
$gr_{premium}$	0.486	(0.179)***	0.471	(0.332)	-0.080	(0.096)	0.107	(0.184)
$gr_{contill}$	-0.179	(0.306)	-0.654	(0.401)	0.176	(0.102)*	-0.449	(0.228)**
σ_m^t	-0.088	(0.141)	0.100	(0.224)	0.302	(0.099)***	0.299	(0.329)
σ_m^r	-0.411	(0.224)*	-0.331	(0.315)	-0.546	(0.132)***	0.096	(0.137)
Year dummies	Yes		Yes		Yes		Yes	
# of observations	547		231		1768		632	
# of convergence	951		951		951		947	
Wald Statistic	45.41***		38.66***		130.38***		130.62***	
R-squared	0.151		0.202		0.258		0.266	

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,100 bootstrap runs. "TR" is farmers adopting soil testing and growing corn after other crops. "TO" is farmers who adopt soil testing but grow corn continuously. "RO" is farmers who grow corn after other crops but do not use soil testing. "OO" is farmers who grow corn continuously and do not adopt soil testing for corn production. gr_x is the generalize errors related to variable x, σ_m^t, m $\in$ (TR, TO, RO, OO) is the covariance between soil testing and nitrogen application, and σ_m^t is the covariance between growing corn after other crops and nitrogen application. R-squared means the squared correlation coefficient between actual nitrogen application rates and predicted nitrogen application rates (Wooldridge 2010, pp 731~732).

Table 7. Estimates regarding herbicide use

	TR		TO		RO		OO	
GM_{HT}	0.383	(0.232)*	1.280	(0.500)**	-0.448	(0.617)	-0.153	(0.898)
Insurance	0.113	(0.229)	0.590	(0.341)*	-1.256	(0.418)***	0.441	(0.445)
Tillage	0.144	(0.228)	0.313	(0.484)	0.174	(0.365)	-0.951	(0.854)
P_{corn}	3.275	(1.442)**	5.230	(2.017)***	4.017	(2.567)	2.550	(4.140)
Irrigation	0.002	(0.151)	0.167	(0.212)	0.255	(0.308)	-0.171	(0.438)
Silage	0.144	(0.117)	0.341	(0.144)**	-0.059	(0.165)	-0.390	(0.281)
GDD	0.000	(0.000)***	0.001	(0.000)***	0.000	(0.000)**	0.001	(0.000)***
Precipitation	0.001	(0.000)**	0.001	(0.001)	-0.001	(0.001)	0.003	(0.002)**
NCCPI	-0.263	(0.147)*	-0.519	(0.247)**	-0.023	(0.306)	-0.193	(0.454)
Constant	-1.241	(0.825)	-3.865	(1.027)***	0.314	(1.388)	-1.370	(2.298)
gr_{GM_hi}	-0.218	(0.140)	-0.832	(0.306)***	0.264	(0.380)	0.313	(0.526)
$gr_{insurance}$	-0.046	(0.134)	-0.261	(0.204)	0.829	(0.249)***	-0.300	(0.268)
$gr_{contill}$	-0.014	(0.139)	-0.271	(0.289)	-0.054	(0.228)	0.691	(0.521)
σ_m^t	-0.373	(0.167)**	0.503	(1.668)	-0.331	(0.255)	-0.036	(0.474)
σ_m^r	-0.314	(0.174)*	-0.031	(0.198)	-0.899	(0.236)***	0.700	(0.413)*
Year dummies	Yes		Yes		Yes		Yes	
# of observations	1,643		628		671		234	
# of convergence	1000		1000		1000		1000	
Wald Statistic	69.42***		49.11***		39.00***		54.49***	
R-squared	0.116		0.025		0.149		0.197	

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,100 bootstrap runs. "TR" is farmers who adopt weed scouting and grow corn after other crops. "TO" is farmers who adopt weed scouting but grow corn continuously. "RO" is farmers who grow corn after other crops but do not use weed scouting. "OO" is farmers grow corn continuously and do not adopt weed scouting for corn production. gr_x is the generalize errors related to variable x, σ_m^t , m $\in$ $(\mathrm{TR}, \mathrm{TO}, \mathrm{RO}, \mathrm{OO})$ is the covariance between weed scouting and herbicide application, and σ_m^t is the covariance between corn growing after other crops and herbicide applications. R-squared means the squared correlation coefficient between actual herbicide application rates and predicted herbicide application rates (Wooldridge 2010, pp 731~732).

<Table 8> Estimates regarding insecticide use

	TR		TO		RO		OO	
GM_{Bt}	-1.567	(2.209)	-2.881	(2.654)	1.422	(4.110)	7.946	(5.024)
Premium	2.406	(1.151)**	2.200	(1.678)	2.263	(1.967)	-1.170	(1.880)
Tillage	-2.573	(1.536)*	1.780	(1.865)	-3.547	(2.023)*	-0.713	(2.640)
P_{corn}	20.376	(12.067)*	-13.895	(10.812)	57.042	(18.344)***	21.748	(15.479)
Irrigation	-0.235	(1.194)	-1.163	(0.913)	1.149	(2.546)	-0.081	(1.110)
Silage	-0.470	(1.064)	-0.410	(0.548)	1.225	(0.756)	0.987	(0.705)
GDD	0.002	(0.001)***	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Precipitation	-0.003	(0.002)	-0.006	(0.003)**	0.005	(0.005)	0.002	(0.005)
NCCPI	0.638	(1.074)	2.503	(1.248)**	-2.039	(1.525)	1.631	(1.701)
Constant	-16.865	(6.222)***	7.299	(6.378)	-29.700	(8.972)***	-15.067	(8.410)*
gr_{GM_ins}	0.626	(1.353)	1.446	(1.652)	-1.116	(2.416)	-5.073	(2.937)*
$gr_{insurance}$	-1.745	(0.655)***	-1.200	(1.015)	-1.155	(1.167)	0.754	(1.083)
$gr_{contill}$	1.414	(0.944)	-0.836	(1.120)	2.159	(1.185)*	0.894	(1.671)
σ_m^t	1.205	(1.729)	-0.168	(2.129)	0.880	(1.267)	0.842	(1.137)
σ_m^r	-0.106	(2.233)	1.957	(0.713)***	-2.286	(0.939)**	-2.290	(2.010)
Year dummies	Yes		Yes		Yes		Yes	
# of observations	1,562		604		752		258	
# of convergence	997		990		988		965	
Wald Statistic	79.19***		85.72***		86.15***		65.35***	
R-squared	0.058		0.069		0.035		0.052	

Note: *** significant at 1% level. ** significant at 5% level. * significant at 10% level. ( ) standard errors of estimates. Estimates and their standard errors are from about 1,000 bootstrap runs. "TR" is farmers who adopt insect scouting and grow corn after other crops. "TO" is farmers who adopt insect scouting but grow corn continuously. "RO" is farmers who grow corn after other crops but do not use weed scouting. "OO" is farmers who grow corn continuously and do not adopt insect scouting for corn production. gr_x is the generalize errors related to variable x, σ_m^t, m $\in$ $(\mathrm{TR}, \mathrm{TO}, \mathrm{RO}, \mathrm{OO})$ is the covariance between insect scouting and insecticide application, and σ_m^t is the covariance between corn growing after other crops and insecticide applications. R-squared means the squared correlation coefficient between actual insecticide application rates and predicted insecticide application rates (Wooldridge 2010, pp 731~732).

<Table 9> The effects of information technologies on chemical use

	Nitrogen (lb/acre)	Herbicide (lb AI /acre)	Insecticide (lb AI /acre)
Corn after other crops	-8.392**	-0.017	1.611
	(.368)	(0.089)	(-)
Continuous corn	-1.656	-0.079	-0.066
	(11.240)	(0.168)	(-)

Note: *** significant at 1% level. ** significant at 5% level. * significant at 1% level. ( ) standard errors of estimates. Standard errors are from about 1,000 bootstrap runs. (-) means that the variances of estimates are unreasonably large because of outliers in each iteration make.