Yield Maps, Soil Maps, and Technical Efficiency:
Evidence from U.S. Corn Fields

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Abstract

Adoption of precision agriculture technologies in the U.S. has had varying impacts over the past two decades. Yield maps, and to a lesser extent, soil maps produced using global positioning have been increasingly used on U.S. corn fields since 2005. However, little research has been done on the mechanisms by which mapping technologies, in isolation, can lead to improved input productivity, technical efficiency, or profitability on U.S. farms. As such, we estimate a stochastic production frontier that permits us to analyze the extent to which maps and related technologies influence technical efficiency on U.S. corn fields. After controlling for farmers' potentially endogenous choice of map technologies, we find that technical efficiency is significantly influenced by map adoption and the structure of field ownership. Given that maps are a basic information input, this suggests that increased availability of information or data-type inputs, by themselves, can provide indirect production benefits to farmers.

Keywords: Technical efficiency, yield maps, GPS-based soil maps, precision agriculture, stochastic frontier, control functions

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Introduction

Precision agriculture technologies have had highly-varying adoption rates and impacts on U.S. row crop production over the past two decades. Among the most widely-used precision technologies are yield monitors, with adoption rates on national corn acreage increasing from 19% in 1998 to 61% in 2010. Yield maps have had similar, though not as pronounced, adoption trends on corn and soybean acres over this period (USDA-ERS, 2017a). This set of complementary technologies has proven to be among the most commercially advantageous, saving corn farmers roughly $25/ac (Schimmelpfennig and Ebel, 2016).

In contrast, variable rate technologies (VRT) used for seeding and chemical applications have experienced somewhat sluggish growth, though they increase corn farm profitability by 1.1% (Schimmelpfennig, 2016), and increase savings associated with yield monitoring and soil mapping (Schimmelpfennig and Ebel, 2016). If relevant site-specific information were available freely, variable-rate nitrogen applications could be more profitable for corn farms (Bullock et al., 2009). This mixed evidence underscores substantial heterogeneity in both the revenue and cost advantages of sequentially- or simultaneously-adopted precision farming equipment.

Despite this mixed evidence, the economic relationships between output and yield monitors, VRT equipment, and global position systems (GPS)-based auto-guidance systems are generally straightforward: these are capital equipment used directly as inputs to crop production. As such, these technologies can have substantial fixed costs of adoption, with the potential for reducing variable costs or increasing revenues. For example, operation of a yield monitor from a tractor cab requires a network of several sensors that collect data from the combine's grain elevator (Darr, 2017). Conditional on recurring expenses for GPS subscriptions and machinery repair, adoption involves an up-front purchase of software and other equipment.

The economic relationships underpinning adoption and use of GPS-based yield maps and soil maps are less clear and have been less explored, perhaps because they are information inputs that do not directly enter the production function in a way comparable to conventional inputs (e.g., capital, labor, seeds, chemicals, tillage, and growing conditions). The value of a printed map in hard copy may be low if farmers prefer spatial analyses from experts, computer software, or a combination of sources (Griffin et al., 2008). More broadly, there may be little or no gain from GPS-based mapping on small family-held farms operated by owners with decades of experience farming the same or similar plots.

However, there could be substantial gains to these information sources on larger and less tightly-held farms with non-owner operators. This could occur because maps provide information that cannot be economically acquired through experience on very large farms, i.e., maps substitute for detailed knowledge of land characteristics and soil productivity (Deininger and Byerlee, 2012). Further, the incentive structures on large farms may systematically differ from those on small farms in such a way that adoption is more likely (Allen and Lueck, 1998; Sumner, 2014). In sum, the value of data-type inputs like maps may not directly manifest as reductions in per-acre variable costs or revenue increases.

The objective of this paper is to examine potential differences in technical efficiency on U.S. corn fields between adopters and non-adopters of GPS-based yield and soil maps. Adoption is modeled as a discrete choice problem, offering insights into the characteristics of fields, farms, and operators that influence technology choice. After controlling for endogenous choice of both technologies, we show that technical efficiency systematically differs between adopters and non-adopters according to farm size, ownership status, and operator attributes, as well as management practices and other exogenous inputs. We estimate a stochastic frontier model (Aigner et al., 1977;

Wang, 2002) using a benchmark Cobb-Douglas production function. We account for endogeneity of yield and soil map adoption in the stochastic frontier using a control function method (Wooldridge, 2014).

Technology Adoption, Farm Structure, and Technical Efficiency

Our analysis is set within the broader context of research examining the relationships between technical efficiency, technology adoption, and farm structure. Some of the earliest work in this literature focuses on the linkages between farm size and farm productivity, with a sharp dichotomy between agriculture in developed countries and developing countries (Deininger and Byerlee, 2012). Many studies report a significant inverse relationship between farm size and partial crop productivity (e.g., output per unit of land area) in developing world agriculture. For example, using a panel of plot-level data in 2010-2011 for rural Rwanda, Ali and Deininger (2015) find that doubling planted land area results in a 38-48% decrease in crop value per hectare.

The mechanisms giving rise to this inverse relationship in developing country agriculture are not well understood and so continue to be explored. Differences in wages between the agriculture sector and non-agriculture sector may be the result of limited labor mobility or other labor market imperfections that cause larger farms to be less productive per unit of land (Ali and Deininger, 2015). Institutional features and national policies that divert resources away from large farms to small farms may also play a substantial role (Adamopoulos and Restuccia, 2014). Although Foster and Rosenzweig (2011) find that larger farms in rural India have higher per-acre profitability and a greater (but diminishing) return to acquiring land, their analysis implies that removing barriers to land amalgamation could improve agricultural efficiency.

In contrast, the direct relationship in developed countries between farm size and productivity or efficiency, especially in the U.S. and Europe, is relatively better understood. Larger operations, in principle, can exploit scale economies in costs or production to obtain higher profits, facilitated by managerial ability and technology or practice adoption, among other factors. For example, a farm with more able operators who can more efficiently combine productive inputs to generate higher profits may also be more successful at increasing its operational size. Large farms may also have lower unit prices of inputs because bulk purchases enable lower unit costs of processing and shipping (MacDonald et al., 2013). The extent to which technology and practice adoption impact farm productivity or efficiency, however, depends crucially on the type of agricultural production. Regarding this relationship, there are important distinctions between livestock operations and crop farms (MacDonald et al., 2010).

Certain livestock operations have been able to substantially increase in size because of decreased exposure to stochastic environmental conditions (e.g., extreme heat, intense rainfall, drought, and freezes). Livestock farms with enclosed animal housing allow for more monitoring and control of inputs, which permits "factory-style" production with the potential for scale economies. A large amount of empirical evidence confirms that commercial dairy farms tend to be technically efficient and experience small-to-moderate scale economies (e.g., Mosheim and Lovell, 2009; Mayen et al., 2010; Dong et al., 2016; Latruffe et al., 2017). The evidence is mixed for U.S. hog farms and U.S. broiler operations. MacDonald and Wong (2011) find modest scale economies in broiler growing, with no distinguishable effect of sub-therapeutic antibiotics on output. In contrast, Key and McBride (2014) find that hog farms using sub-therapeutic antibiotics have higher productivity than non-adopters, with evidence of mildly-decreasing economies of scale. This suggests there could be potentially important interactions between technology and practice adoption and technical efficiency, which could also be important for crop production.

In a meta-analysis of agricultural technical efficiency, Bravo-Ureta et al. (2007) find that rice, corn, and other grain farms have lower levels of mean technical efficiency, on average, than dairy, cattle, and non-grain crop farms. At the same time, it is well-documented that field crop production generally experiences non-increasing returns to scale. However, the development and diffusion of new technologies and management practices can have major effects on both efficiency and scale of crop production. The latter effect could be somewhat nuanced. For example, widespread adoption could extend the range of output over which crop farms realize constant returns. Labor-saving innovations, like conservation tillage and herbicide-tolerant and insect-resistant seeds, are two prominent examples of technologies that contribute to increased farm size (MacDonald et al., 2010). On the other hand, certain technologies that provide data for management decisions and recommendations, like yield maps and soil maps, could help reduce diseconomies of scale. This could be true because they provide non-owner operators and hired managers with information that substitutes for detailed local knowledge of land characteristics, soil characteristics, and areas of high pest pressure.

These information technologies, and precision agriculture equipment more broadly, may operate more directly on production by increasing input productivity, output productivity, or technical efficiency. Khanna (2001) used data from a mail survey of cash grain farms in Iowa, Illinois, Indiana, and Wisconsin to examine the factors influencing adoption of soil tests and variable rate fertilizer equipment. She estimates that gains to nitrogen productivity from only adopting soil testing were 6-7%, while additional gains from adopting variable rate technologies for fertilizer applications were 18-33%, depending on soil quality. Although yields are a partial measure of productivity, Schimmelpfennig and Ebel (2011) found that adopters of GPS mapping had significantly higher yields on corn fields in 2001 and 2005 and soybean fields in 2002 and 2006 than non-adopters.

Despite considerable research concerning the effects of precision agriculture on input costs and farm profitability, there has been much less focus on the linkages between data-driven inputs (e.g., yield and soil maps), farm structure, and technical efficiency. We take up this line of inquiry by estimating a two-step econometric model detailed in the next two sections. The econometric model and empirical specification are sufficiently general to allow us to quantify the role of data-driven input adoption on technical efficiency.

Motivating Structural Model

We develop a structural model of technology adoption that motivates our empirical analysis. We assume that U.S. corn farmers operate in perfectly-competitive markets. As in prior work (e.g., Pope and Just, 2003; Isik and Khanna, 2003), we assume that farmers can vary the amount of certain inputs (e.g., labor and fertilizer) in the short-term, but that other inputs (e.g., land or capital) can only be changed in the long-run. These are referred to as variable inputs and fixed inputs.

We assume farmers' productive input choices are driven by the desire to maximize profits. Technology adoption decisions, on the other hand, are driven by both monetary and non-monetary factors. Non-monetary costs and benefits may reflect, among other things, farmers' eagerness to try new technologies or their perceptions that precision agriculture technologies could be relatively more sustainable. These factors may also be influenced by farmers' risk aversion.

As such, the farmer's objective is to maximize expected utility from a convex combination of profits and net non-monetary benefits:

$$(1) \qquad \max_{x_v \in R^+, T_1 \in \{0,1\}, T_2 \in \{0,1\}} \mathrm{E}[U] = \mathrm{E}\left\{u\left[PY - p_f x_f - p_v x_v - p_1 T_1 - p_2 T_2\right] + (1-u)\left[d_{nm} T_1 + e_{nm} T_2\right]\right\}$$
$$s.t.\ Y = a x_f^b x_v^c d^{T_1} e^{T_2} \exp(\varepsilon),$$

where $u \in (0,1]$ is a weight reflecting the importance of profits relative to net non-monetary benefits, P is the output price, p_v is the price of variable input x_v, p_f is the price of fixed input x_f, p_1 is the price paid for precision agriculture technology T_1, p_2 is the price paid for precision agriculture technology T_2, and Y is output (total bushels of corn). The production function for Y is assumed to have a Cobb-Douglas representation.

There are several positive parameters in the model. The parameter a captures the impact of exogenous field-level factors, such as soil productivity, that can positively impact production. The parameters b, c, d, and e capture the productivity of variable input use, fixed input use, and the precision agriculture technologies. The parameters d_{nm} and e_{nm} capture the non-monetary benefits associated with the use of the precision agriculture technologies, net of (un-modeled) non-monetary costs. We explicitly assume there is a source of uncertainty, denoted by the random variable, ε. Without loss of generality, we normalize the utility function by u and define $w \equiv (1-u)/u \in [0,\infty)$.

Assuming that $\mathrm{E}\left[\exp(\varepsilon)\right] = 1$, the first order condition for variable input use is:

(2) $$\frac{d\,\mathrm{E}[\pi]}{dx_v} = \frac{cPax_f^b x_v^c d^{T_1} e^{T_2}}{x_v} - p_v = 0 .$$

Solving equation (2) for the optimal level of x_v implies that:

(3) $$x_v^* = \left(ax_f^b d^{T_1} e^{T_2} c \frac{P}{p_v} \right)^{\frac{1}{1-c}} .$$

Substituting equation (3) back into equation (1) demonstrates that the expected utility maximization problem can be expressed as follows.[1]

[1] All intermediate derivations are contained in the appendix.

(4)

$$\max_{T_1,T_2} \mathrm{E}\left[U\right] =$$

$$Pax_f^b\left[\left(ax_f^b d^{T_1} e^{T_2} c\frac{P}{p_v}\right)^{\frac{1}{1-c}}\right]^c d^{T_1} e^{T_2} - p_f x_f - p_v\left(ax_f^b d^{T_1} e^{T_2} c\frac{P}{p_v}\right)^{\frac{1}{1-c}} + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2$$

$$= \left(Px_f^b d^{T_1} e^{T_2}\left(\frac{c}{p_v}\right)^c\right)^{\frac{1}{1-c}}\left(1-c\right) - p_f x_f + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2.$$

Therefore, a farmer uses precision agriculture technology T_1 if:

(5)

$$\mathrm{E}\left[U \mid T_1 = 1\right] - \mathrm{E}\left[U \mid T_1 = 0\right] \geq 0$$

$$\Rightarrow \frac{1}{1-c}\ln\left(P\right) + \frac{1}{1-c}\ln\left(a\right) + \frac{b}{1-c}\ln\left(x_f\right) + \frac{\ln\left(e\right)}{1-c}T_2 + \frac{c}{1-c}\ln\left(c\right) - \frac{c}{1-c}\ln\left(p_v\right) + \ln\left(1-c\right) + \ln\left(d^{\frac{1}{1-c}} - 1\right)$$

$$\geq \ln\left(p_1 - wd_{nm}\right).$$

We model a such that $a \equiv a_0 \prod_{i=1}^{N} A_i^{a_i}$, where a_0 is a constant, A_i are exogenous variables, and a_i are productivity parameters. Equation (5) is restricted to positive values by exponentiating $\left(p_1 - wd_{nm}\right)$. We express wd_{nm} as a linear combination of variables correlated with the farmer's net non-monetary benefits of adopting T_1. Thus, it is profit-maximizing for a farmer to use technology T_1 if:

(6) $$cons_1 + \sum_{i=1}^{N}\beta_{A_i}\ln\left(A_i\right) + \beta_P\ln\left(P\right) - \beta_v\ln\left(p_v\right) + \beta_f\ln\left(x_f\right) + \beta_2 T_2 + \boldsymbol{\beta}_{\mathbf{nm}}^{\mathbf{1}}{}'\mathbf{x}_{\mathbf{nm}} - p_1 \geq 0,$$

where $cons_1 \equiv \frac{1}{1-c}\ln\left(a_0\right) + \ln\left(1-c\right) + \frac{c}{1-c}\ln\left(c\right) + \ln\left(d\right)$, $\beta_{A_i} \equiv \frac{a_i}{1-c}$, $\beta_P \equiv \frac{1}{1-c}$, $\beta_v \equiv \frac{c}{1-c}$, $\beta_f \equiv \frac{b}{1-c}$, $\beta_2 \equiv \frac{\ln\left(e\right)}{1-c}$, $\boldsymbol{\beta}_{\mathbf{nm}}^{\mathbf{1}}$ is a vector of parameters, and $\mathbf{x}_{\mathbf{nm}}$ is a vector of variables that are highly correlated with non-monetary factors influencing the technology adoption decision.

Similarly, it is profit-maximizing for a farmer to use technology T_2 if:

$$(7) \qquad cons_2 + \sum_{i=1}^{N} \beta_{A_i} \ln\left(A_i\right) + \beta_P \ln\left(P\right) - \beta_v \ln\left(p_v\right) + \beta_f \ln\left(x_f\right) + \beta_1 T_1 + \boldsymbol{\beta}_{\mathbf{nm}}^{2}{}' \mathbf{x}_{\mathbf{nm}} - p_2 \geq 0,$$

where $cons_2 \equiv \frac{1}{1-c}\ln\left(a_0\right) + \ln\left(1-c\right) + \frac{c}{1-c}\ln\left(c\right) + \frac{1}{1-c}\ln\left(e^{\frac{1}{1-c}} - 1\right)$, $\beta_1 \equiv \frac{\ln\left(d\right)}{1-c}$, and $\boldsymbol{\beta}_{\mathbf{nm}}^{2}$ is a vector of parameters.

The results of the theoretical model suggest that there are cross-equation parameter restrictions across the production function ($\ln\left(Y\right) = \ln\left(a_0\right) + \sum_{i=1}^{N} a_i \ln\left(A_i\right) + b\ln\left(x_f\right) + c\ln\left(x_v\right)$ $+T_1\ln\left(d\right) + T_2\ln\left(e\right) + \varepsilon$), equation (6), and equation (7). As such, estimating these equations simultaneously could improve efficiency and facilitate model identification. However, as an intermediate step, we estimate a two-step, control-function-based stochastic frontier model (described below). Since variable input use decisions are made before yields are realized, we consider them to be exogenous variables in this analysis.

Econometric Approach and Regression Specifications

We estimate a two-step, control-function model to account for potential endogeneity of yield map and soil maps within the stochastic frontier framework. These are potentially endogenous because they are choice variables that could be correlated with the operator's unobserved managerial ability or human capital, unobserved pest pressure, or other unobservable factors directly correlated with output. We use control functions (e.g., Wooldridge, 2014) to account for this potential endogeneity. In particular, we first estimate a bivariate probit model explaining field use of both maps. Generalized residuals are estimated as equation-level scores (first derivatives of the bivariate normal log-likelihood) and then linearly appended in the stochastic frontier regression. If endogeneity is a substantial concern, estimated coefficients on the generalized residuals will be statistically significant (Wooldridge, 2014).

Stochastic frontier analyses have been widely used to study technical efficiency, input productivity, and scale economies in the production economics literature (Kumbhakar and Lovell, 2003). In this approach, output is related to inputs through a conventional production function, plus a composed error term. This error term can be decomposed as a random noise component minus a non-negative disturbance due to inefficiency. In this analysis, we assume that the random noise component is a mean-zero, independent and identically-distributed (i.i.d.) error term. The inefficiency is assumed to follow a truncated normal distribution with truncation point at zero.

For field *i* with productive input x_i and efficiency-related inputs z_i, we model total field output y_i as the following generalization of a primal stochastic frontier model (Wang, 2002):

$$
\begin{aligned}
&\ln\left(y_i\right) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln\left(x_{ji}\right) + \gamma' d_i + v_i - u_i \\
&u_i = \alpha_o + \sum_{l=1}^{m} \alpha_l z_{li} + \omega_i \\
&v_i \sim N\left(0, \sigma_{v,i}^2\right) \\
&\omega_i \sim N^+\left(0, \sigma_{u,i}^2\right).
\end{aligned}
\tag{8}
$$

Note that v_i and ω_i are assumed to be mutually independent. Following the extensive literature on frontier estimation, we assume that the productive inputs are labor, capital, total nitrogen applied, and farm acreage. The Cobb-Douglas production specification in (8) is modified slightly to incorporate soil quality variables and regional indicators, denoted by d_i with regression impacts given by γ. Note that this specification implies that $E\left[u_i\right] = \mu_i = \hat{\alpha}_0 + \sum_{l=1}^{m} \hat{\alpha}_l z_{li}$. Given the expected differences in technical efficiency on fields with differing levels of map adoption, as well as farm structure, we assume that z_i contains indicators for use of yield maps and GPS-based soil maps, indicators for whether the field is insured, owned by the operator, or rented for free, and years of operator experience with the field. Estimation of all coefficients in equation (8) is performed via maximum likelihood.

Un-modeled heteroscedasticity in stochastic frontier models has potentially more severe consequences than those of linear models. Although estimated regression coefficients (excluding the intercept) remain unbiased in the presence of heteroscedasticity in v_i, technical efficiency estimates will be biased. Ignored heteroscedasticity in the inefficiency term generates bias in both the frontier and efficiency estimates (Kumbhakar and Lovell, 2003).[2] As such, we parameterize both variance terms as functions of field-level characteristics:

$$\begin{aligned} \sigma_{v,i}^2 &= \exp\left[\delta_{v,0} + \sum_{n=1}^{O} \delta_v h_{ni}\right] \\ \sigma_{\mathrm{u},i}^2 &= \exp\left[\delta_{\mathrm{u},0} + \sum_{p=1}^{Q} \delta_u h_{pi}\right]. \end{aligned} \tag{9}$$

Wang (2002) argues that u and $\sigma_{\mathrm{u},i}^2$ should be specified using the same set of regressors since it permits non-monotonic (and less *ad hoc*) relationships between inefficiency and its potential influences. We would ideally use the same set of regressors to parameterize $\left(u, \sigma_{u,i}^2, \sigma_{v,i}^2\right)$; that is, set $z_l \equiv h_n \equiv h_p \quad \forall\, l, n, p$. Numerical difficulties due to the nonlinear optimization in the maximum likelihood routine prevent us from implementing this most general parameterization.

Given the Cobb-Douglas specification in equation (8), output-oriented technical efficiency is our preferred measure of field-level productivity. This measure quantifies how much output

[2] The magnitudes of potential biases resulting from ignored heteroscedasticity must ultimately be empirically determined. As a specification check, we report parameter estimates and marginal effects under the assumption that the noise and inefficiency terms are homoscedastic.

(bushels of corn) is lost due to an inefficient combination of inputs. Under the heteroscedasticity assumption, the output-oriented technical efficiency index is (Battese and Coelli, 1988):

$$E\left[\exp\left(-u_i \mid \varepsilon_i\right)\right] = \exp\left(-\mu_{*i} + \frac{1}{2}\sigma_{*i}^2\right)\frac{\Phi\left(\frac{\mu_{*i}}{\sigma_{*i}} - \sigma_{*i}\right)}{\Phi\left(\frac{\mu_{*i}}{\sigma_{*i}}\right)}, \tag{10}$$

where $\mu_{*i} = \frac{\sigma_{v,i}^2\mu_i + \sigma_{u,i}^2\varepsilon_i}{\sigma_{v,i}^2 + \sigma_{u,i}^2}$, $\sigma_{*i}^2 = \frac{\sigma_{v,i}^2\sigma_{u,i}^2}{\sigma_{v,i}^2 + \sigma_{u,i}^2}$, and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. One attractive feature of this index is that values lie in $[0,1]$. Confidence intervals can then be constructed using standard formulas (e.g., Kumbhakar et al., 2015), although these intervals do not account for parameter uncertainty.

Input-oriented technical inefficiency, in contrast, quantifies by how much inputs can be reduced without resulting in output loss, i.e., $\min\left\{\theta : y \le f\left(\theta x\right)\right\}$, where $f\left(\cdot\right)$ is a neoclassical, single-output production function and θ is a real-valued scalar (Kumbhakar and Lovell, 2003). Output-oriented measures appear more commonly in the literature, though input-oriented measures are suitable if inputs (rather than output) are considered endogenous. Only in special cases (e.g., constant-returns-to-scale production) will these two measures coincide. Using standard formulas, we consider input-oriented technical efficiency as a robustness check to our preferred output-oriented efficiency estimates.[3]

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[3] Assuming a Cobb-Douglas production function with input elasticities β_j, as in equation (8), and $\theta = \exp(-\lambda)$, it can be shown that $\hat{\lambda} = E\left(u_i \mid \varepsilon_i\right) / \sum_{j=1}^{k}\hat{\beta}_j$. Note that $E\left(u_i \mid \varepsilon_i\right) = \frac{\sigma_{*i}\phi\left(\mu_{*i} / \sigma_{*i}\right)}{\Phi\left(\mu_{*i} / \sigma_{*i}\right)} + \mu_{*i}$, where μ_{*i} and σ_{*i} are given by the formulas immediately below equation (10), and $\phi\left(\cdot\right)$ is the probability density function of the standard normal distribution (Jondrow et al., 1982; Kumbhakar et a., 2015).

Data Construction and Field Characteristics

The U.S. Department of Agriculture's (USDA) Agricultural Resource Management Survey (ARMS) is a primary source of information about resource use, production practices, and financial characteristics of U.S. farms. It is a cross-sectional, multi-phase survey. More specifically, it has a stratified, dual-frame, probability-weighted sampling design. The sampling strata have sampling weights that are recalibrated after survey implementation to create population estimates based on useable observations. The survey approach collects information based on a list of farms (e.g., list frame), as well as farms within geographical areas (e.g., area frame). This increases survey comprehensiveness, as well as complexity (USDA-ERS, 2017b).

After an initial selection procedure to screen operations outside of the survey's scope, the surveys are administered in two phases. Phase II of the survey is enumerated and gathers field-level information about input use, practice adoption, and other management practices. Commodity versions of the Phase II survey are administered approximately once every five years. The Phase III survey is administered by mail each year on a larger and diverse national sample of crop and livestock operations. Although there are multiple versions of the Phase III survey, the core version elicits data on acreages, commodity marketing and income, operating and capital expenditures, assets and debts, and other farm and household financial information (USDA-ERS, 2017b).

Production Costs and Returns Data

We use data from the 2010 ARMS Phase II corn survey, as well as 2010 Costs and Returns data used to generate national cost of corn production estimates. These cost estimates have been produced annually for major livestock and field crop enterprises since 1975, though the methodology was revised in 1995 to incorporate recommendations from the American Agricultural Economic Association's Task Force on Commodity Costs and Returns. Each year, preliminary cost of production estimates are released the first week of May, with final estimates released during the first week of October. Forecasts for major field crops are released and updated mid-June through mid-December of each year (USDA-ERS, 2017c).

The cost of production accounts includes direct costs incurred for crop production. These costs are decomposed into cash and non-cash expenditures. Cash expenditures are realized when inputs are purchased or rented, whereas non-cash expenditures accrue to inputs that are owned by the operation. Marketing and storage costs are excluded. Generally, there are four methods used to estimate commodity costs: direct costing, input quantity valuation, indirect costing, and whole-farm expense allocation. The extent to which these four methods are used for certain costs depends largely on whether item-specific expenses can be directly reported by the respondent in the ARMS survey. For example, the direct costing approach is used for commercial fertilizers and chemicals, while unpaid labor hours are estimated using a method that incorporates off-farm wage estimates. The capital variable used in this analysis is an estimate of the cost of replacing capital consumed in annual production on the field, plus an annualized measure of the opportunity cost of the remaining field-level capital investment in machinery and equipment (USDA-ERS, 2017c).

After dropping fields with missing information and merging with soil, weather, and climate datasets, we have a sample of 1,793 conventional (e.g., non-organic) corn fields in 2010. Using a calibrated base weight provided by the National Agricultural Statistics Service (NASS), our sample can be extended to represent 70 million acres planted to corn. This represents approximately 79% of the 88.2 million planted corn acres in 2010 (USDA-NASS, 2017). Fields in our sample are from prime U.S. corn-growing regions, primarily from the Corn Belt, Great Lakes, Great Plains, and Prairie regions.

Compilation and Construction

Productive inputs are derived from the cost of production estimates associated with the ARMS Phase II survey. These inputs are assumed to be labor, capital, nitrogen, and land. Labor is calculated as the sum of paid and unpaid labor hours provided on the field. The capital variable, expressed in 2010 dollars per acre, is a general measure of the cost of replacing capital used to produce corn on the particular field. Total nitrogen (in pounds) is the sum of the nitrogen content of purchased commercial fertilizer and the (estimated) nitrogen content of applied manure. Land (in acres) is the reported size of the farm. Output (in bushels) is calculated as the product of the field's size and yield (in bushels/acre).

Although ARMS Phase II has detailed information about management practices related to crop rotations, pesticide and fertilizer use, irrigation, and field operations, less detailed information is collected on machinery and equipment prices. We therefore predict prices for yield and soil maps using ARMS data about field-level use of consultant services. In particular, we observe whether technical or consultant services were hired to make recommendations about fertilizers, soil or tissue sampling, pest management, irrigation, and other decisions, including development and/or interpretation of yield maps or remote sensing maps. Total cost of these services (in aggregate) are also reported.

To obtain predicted prices for both map types, we first pool ARMS data across 2006-2007 and 2009-2012. Fields for which no recommendation services were employed are dropped from the pooled sample. We next perform a weighted OLS regression of total technical/consultant services costs on indicators for the particular services hired and their interactions with the set of 19 states in our sample, in addition to a full set of state and year fixed effects. State-level yield and soil map prices (or, more accurately, controls for prices) are constructed from coefficient estimates of the state-by-year interactions.

Prices for the productive inputs are constructed from the ARMS cost of production estimates. In particular, the wage rate is calculated as the sum of the cost of paid and unpaid labor hours divided by total labor hours. The nitrogen price is calculated similarly as the sum of the costs of nitrogen from commercial fertilizer and manure divided by total pounds of nitrogen applied. The price of land is calculated as its opportunity cost, as measured by cash rental rates on farmland producing corn in the same local area. To proxy for fuel costs, we use the 2010 state-level price of diesel from the April release of NASS' Agricultural Prices survey.

County weather data are derived from Oregon State University's PRISM Climate Group database (Daly et al., 2008). Using daily data from annual PRISM records, we construct cumulative season growing degree days (GDD) by summing monthly GDD for each month of the growing season (May, June, July, and August). Monthly PRISM data are also used to construct precipitation measures, again by summing over each month in the growing season.

County averages of soil characteristics from the Natural Resource Conservation Service's (NRCS) Soil Survey Geographic Database (SSURGO) were used to control for soil productivity. The National Commodity Crop Productivity Index (NCCPI) is an index developed by NRCS that captures a soil's inherent capacity to grow certain field crops (Dobos et al., 2012). The index lies in [0,1] and aggregates certain physical and chemical properties of soil (e.g., type, depth to water table, available water capacity, saturated hydraulic conductivity, and other characteristics) and weather attributes (e.g., frost-free days). In the econometric analysis, we use NCCPI values from the Corn and Soybeans sub-model. Apart from these county variables, we also include two field-level measures indicating if any part of the field contains a wetland or is highly-erodible.

Empirical Trends and Regression Results

Table 1 contains weighted means of variables either used directly in the econometric analysis or used to create variables that enter the analysis. Several interesting trends emerge pertaining to technology adoption and productive inputs. Corn fields for which both yields and soils were mapped are on farms with an average size of 1,262 acres. This is nearly four times as large as the average farm size for fields that use neither technology (378 acres). This positive correlation between adoption of site-specific information and farm size could suggest that these technologies have the greatest returns on large operations. Average per-acre nitrogen applications also vary substantially with adoption of these technologies, ranging from 135 pounds/acre (lb./ac) among non-adopting fields to 162 lb./ac on fields with both technologies.

Labor hours and capital use, however, have less straightforward associations with adoption. Fields with mapped yields but not GPS-mapped soils use the highest quantities of labor and capital, though fields with both map types employ labor and capital in amounts roughly equal to those used on fields with only GPS soil maps, on average. This suggests that complementarities between mapping technologies could result in very modest labor and capital savings.[4] Given the relationship between map adoption patterns and input use, it is not surprising that average yields are higher on fields with both technologies (173 bu/ac) than on fields using neither (146 bu/ac).

Interestingly, we observe no significant differences in average wage rates or nitrogen prices across the four adoption cases. Regardless of technology, the mean price of labor is $21/hour and the mean price of nitrogen is $0.39/lb. One reason for this trend could be that operators exhibit little impact on prices paid for both hired labor and chemical inputs. Both prices likely reflect some degree of measurement error, especially since wage costs for unpaid labor and the nitrogen content

[4] The extent to which adoption of site-specific information can increase productivity of certain conventional inputs is currently being explored in robustness analysis.

of manure are difficult to accurately impute. However, fields using both technologies are, on average, more than twice as valuable ($11,027/ac) as fields using neither type of map ($5,132/ac). Although non-owner operators could potentially use map output to help negotiate higher rental contract terms, this trend more likely reflects scenarios in which maps are more actively used in conjunction with careful input monitoring on high-value cropland.

There are also interesting trends pertaining to adoption and structural aspects of the corn field or operator. Roughly 52% of non-adopting fields are owned by the operator. This ownership percentage declines to just 35% on fields employing both types of maps. On these fields, roughly 52% are rented for cash with a fixed cash payment. A much smaller percentage of fields are rented for cash with a flexible-cash payment, combination of cash and share of the crop, or rented for free. As expected, mean years of experience operating fields for which both maps are adopted (19.5 years) are lower than those for fields without adoption (22.1 years). This likely reflects an experience effect rather than an age effect, given that the literature has not found a significant relationship between operator's age and adoption (Schimmelpfennig and Ebel, 2016). Last, approximately 93% of fields with both maps are insured, while 72% of fields without maps are insured. Since the former set of fields have relatively higher land values (in terms of per-acre rental rates), we would expect higher rates of insurance uptake.

Table 2 provides difference-in-means tests across the four technology adoption cases using an adjusted Wald test that accounts for the ARMS survey design. The reference group for comparison is the set of fields without either map. Thus, estimates of significant differences in means, relative to fields with no maps, are reported for the fields adopting soil maps but not yield maps, yield maps but not soil maps, and both maps. These means tests provide evidence of significant interactions between productive inputs, prices, and structure variables across adoption decisions.

Figures 1 and 2 plot average yields and percentages of planted corn acres by state across the four map adoption scenarios.[5] The figures confirm many of the trends from Table 1 while providing insight to regional patterns of adoption. In 2010, corn was still largely produced on fields adopting neither yield maps nor soil maps. Operations in Corn Belt states (Iowa, Illinois, Indiana, and Ohio), however, adopt these technologies at somewhat higher rates. Similarly, among the set of fields adopting both types of maps, average yields are highest (in excess of 150 bu/ac) in Corn Belt and upper Midwest states. However, this region is also highly productive without use of either type of map.

The weighted means appearing in Table 1 and spatial tends from Figures 1 and 2 generally confirm the hypotheses detailed earlier. Mapped fields are higher-yielding, insured at higher rates, and are relatively higher-value. These fields are located on generally larger farms with non-owner operators that have one-to-two years less experience with the field than on fields for which neither map technology is used. Regression results presented in the next section, however, provide more rigorous evidence of trends.

Determinants of Map Adoption

Table 3 presents estimated coefficients from the bivariate probit regression. Although many of the estimated coefficients for input and output prices have the expected sign, most of them are insignificant in both equations. For example, the corn price, diesel price, wage rates, and land rental rates are all positively associated with adoption of both yield and soil maps, though large,

[5] These figures are intended to illustrate trends over broad geographical regions. We do not claim that they are statistically representative by state. Although only Illinois, Indiana, Iowa, Minnesota, Nebraska, and Ohio are depicted in Figure 2, the 19-state sample used in the empirical analysis also includes Colorado, Georgia, Kansas, Kentucky, Michigan, Missouri, New York, North Carolina, North Dakota, Pennsylvania, South Dakota, Texas, and Wisconsin.

jackknifed standard errors suggest that these prices have no meaningful impact. However, the cost of capital has a small but positive coefficient in the first equation, indicating that yield maps tend to be adopted on fields with more intensive capital use. That this capital variable is insignificant in the soil map equation could be due to the fact that its adoption hinges more on less capital-intensive decision factors (including soil data available online or from an extension agent). The regression-based controls for the price of yield maps are insignificant in both equations, though its coefficient has the expected sign in the first equation. However, the controls for GPS-based soil map prices are significant at the 10% level or better in both equations. Higher soil map prices are associated with less adoption of these maps, as well as less adoption of yield maps, which could be somewhat indicative of complementarities between the two technologies.

In the yield maps equation, we also find evidence of significant impacts of inherent soil productivity and field ownership. Operators who own the field are less likely to adopt yield maps. Gains to using yield maps could be lower to owners because their substantial local knowledge of the field renders them less useful. Alternatively, mapping or other site-specific information could be more important for renters if contract terms necessitate careful input monitoring.

The soil, weather, and years of experience variables are generally insignificant in the regression equations. One important exception, though, pertains to soil productivity captured by the NCCPI regressor: yield maps tend to be adopted on fields that are more suitable for growing corn and soybeans. However, the correlation between the equations is 0.80 and significant at the 1% level. This suggests that adoption of both maps are correlated management decisions.

Stochastic Frontier and Efficiency Estimates

Prior to estimation of the stochastic production frontier, we first undertake tests of: 1) skewness in the residuals from ordinary least squares (OLS) estimation, and 2). the presence of inefficiency (e.g., $u_i = \sigma_{u,i}^2 = 0$). Regardless of functional form, if the stochastic frontier model is a suitable representation of U.S. corn production, then OLS residuals should be negatively-skewed because $\varepsilon_i \equiv (v_i - u_i)$, with v_i distributed symmetrically (i.i.d. normal) and $u_i \geq 0$. Both the D'Agostino et al. (1990) and Coelli (1995) tests reject the null hypothesis of zero skewness in the residuals at the 5% significance level.[6] This weakly suggests the presence of an asymmetric error and supports our choice of stochastic frontier estimation.

Similarly, if there is no inefficiency in the model, then $u_i = \sigma_{u,i}^2 = 0$. This is straightforward to test using the likelihood ratio test (LRT) statistic, $-2\left[L(H_0) - L(H_A)\right]$, where $L(H_0)$ and $L(H_A)$ are the likelihoods under the OLS (restricted) and stochastic frontier (unrestricted) models, respectively. For each of the specifications discussed below, the LRT tests reject the null hypothesis of no inefficiency at the 1% significance level, again validating our choice of implementing the stochastic frontier approach.[7]

Table 4 contains coefficient estimates from the second-stage stochastic frontier analysis. Since the nature of the heteroscedasticity is unknown, we begin by estimating a full specification that includes a set of variables hypothesized to influence the variance of both the noise and inefficiency terms (model 1). We next drop a subset of regressors that do not significantly influence either variance term (model 2). To investigate the extent to which ignored heteroscedasticity could bias parameter estimates, we compare our results to those under an assumption of homoscedasticity of both error terms (model 3).

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[6] The D'Agostino et al. (1990) skewness test of normality is rejected at $\alpha = 0.015$. The Coelli (1995) test statistic, which has an asymptotic standard normal distribution is -2.43, larger than the standard normal critical value of 1.96 at $\alpha = 0.05$.

[7] The LRT test statistics are 120.7, 104.5, and 59.0 for specifications (1), (2), and (3) in Table 4. The test statistic has a mixture of chi-squared distributions, with corresponding critical values of 25.5 and 22.5 at $\alpha = 0.01$ with 12 and 10 degrees of freedom, respectively (Kodde and Palm, 1986).

The elasticities associated with labor hours, nitrogen applications, and capital equipment are all statistically significant at the 1% level and have the expected sign and magnitude across the three specifications. We find that nitrogen applications and capital have the largest elasticities, implying that a 1% increase in either input increases field output by 0.39-0.41%. Given the nature of the random field selection in the survey process, it is not of major concern that the farm size variable is insignificant. This could reflect that, even among large farms, output from a randomly-selected field in a given year could be low due to poor weather conditions or high pest pressure during the growing season. Estimates of the productive inputs sum to 0.88-0.89, and a joint test of significance confirms modestly decreasing returns to scale, consistent with most empirical crop production studies (e.g., MacDonald et al., 2010, 2013).

We find mixed evidence on the relationship between soil quality, regional indicators, and field output. The soil productivity index for growing corn and soybeans (NCCPI) is insignificant, as is the indicator for whether the field contains any NRCS-designated highly erodible land. Both variables tend to have high explanatory power for U.S. corn production during this time, similar to the results from other studies (e.g., Wechsler et al., 2017). The standard errors of these regressors could be inflated due to collinearity with indicators for the Heartland region and Northern Crescent region (Heimlich, 2000). These regions include the traditional Corn Belt and several upper Midwest states, where there is a high concentration of corn-soybean farms and high-value cropland on productive soils.

Median efficiency, as given by the 50th percentile of the empirical distribution of the output-oriented efficiency index contained in equation (10), is 80-81%. This is somewhat low for U.S. field crops, though well within the range of U.S. agriculture more broadly. Our estimates compare favorably to mean technical efficiency estimates from stochastic frontier studies using cross-sectional data (75.2%), with a Cobb-Douglas functional form (76.3%), on a sample of North American farms (78.7%), or producing corn (74.5%) (Bravo-Ureta et al., 2007). The 95% confidence intervals for mean efficiency are generally [0.50, 0.97], again confirmed by other findings in the literature.[8]

The empirical distributions of the technical efficiency estimates are negatively-skewed, as implied by the underlying stochastic frontier framework, though quite similar across three specifications (Figure 3). The most general model, specification (1), has relatively more density on [0.60, 0.80], while the homoscedastic model, specification (3) places somewhat more density on the far right side of the distribution. This general agreement among the three specifications provides suggestive evidence that the output-oriented technical efficiency estimates are not being severely biased by ignoring heteroscedasticity or omitting map variables from influencing the variance of the statistical noise.

Although evidence of decreasing returns to scale suggests there will be discrepancies between the input- and output-oriented measures of technical efficiency, these discrepancies are minor. On average, the input-oriented measure indicates that U.S. corn farms are 12-14% less efficient than the productivity levels implied by the output-oriented measure. There are also only minor differences in the empirical distribution of the input-oriented efficiency estimates across the three specifications (Figure 4). Relative to the most general heteroskedastic model, the distribution of the reduced heteroskedastic model (specification 2) is less dispersed and produces slightly higher estimates of technical efficiency. The homoscedastic model also provides several efficiency estimates that are relatively high (including outliers), though with a much greater spread in the

[8] Note that the 95% confidence intervals are generally too narrow because they do not incorporate parameter uncertainty. However, estimation uncertainty can be easily incorporated, for example, by bootstrapping the confidence intervals.

empirical distribution of the efficiency estimates. Thus, we find that controlling for certain observation-specific determinants of corn production variability reduces the overall spread in the distribution of the efficiency estimates.

Many of the regressors in our parameterization of the mean inefficiency term and variance terms are significant at the 10% level or lower. This provides some statistical validation of our empirical specifications, though the coefficients cannot be directly interpreted due to the non-linear and non-monotonic relationships between the regressors and the mean and variance terms. Importantly, coefficients on the generalized residuals for adoption of yield maps and soil maps are individually significant at the 1% levels in the first two specifications, with the exception of the coefficient on the generalized residual for soil maps in the equation for $\sigma_{v,i}^2$ in specification (1). Nonetheless, this implies that endogeneity of map adoption decisions in the stochastic frontier model is of concern and that not accounting for this endogeneity could have biased associated parameter estimates. This statistical evidences validates our use of the two-step control function procedure.

The Impacts of Yield Maps, Soil Maps, and Farm Structure on Technical Inefficiency

Adoption of yield maps was associated with a 1.60-1.82% reduction in technical efficiency on U.S. corn fields in 2010 (Table 5). Although small, these impacts are statistically significant at $\alpha = 0.10$ or lower (depending on the specification) and are commensurate with the magnitudes of impacts of other precision agriculture technologies on profitability and variable corn production costs (Schimmelpfennig and Ebel, 2016; Schimmelpfennig, 2016). In contrast, corn fields on which soil properties were mapped had 1.55-1.64% *increases* in inefficiency. There are several likely causes of this counterintuitive relationship, including selection bias and omitted variables bias not corrected by the generalized residuals.[9] However, there has been a net beneficial effect: adoption of both maps is associated with a 0.04-0.18% reduction in efficiency.

Adoption of yield maps has had a similar, but small, effect on reducing the variability of corn production due to inefficiency. Excluding the point estimate from the general heteroscedastic specification (model 1), the variance of the inefficiency term is 0.55-0.78 lower on fields whose yields have been mapped. Similar to its counterintuitive impact on mean inefficiency, soil map adoption is associated with an *increase* in the variance of inefficiency by 0.46-0.70.[10] As with the marginal effects of mean inefficiency, joint adoption of both maps has had a positive impact on corn production by lowering the variance associated with inefficiency, if only slightly.

Two other regressors of interest, the operator's years of experience with the field and whether or not the field is owned, tend to have small but intuitive marginal effects on technical inefficiency. Although insignificant in the first two specifications, in the homoscedastic model, corn fields that are owned by the operator have inefficiencies with somewhat lower means and variances (0.07% and 0.03% lower, respectively). An additional year of operating the field is associated with a reduction in mean inefficiency by 0.33-0.36% and a reduction in the variance of inefficiency by 0.16-17% (for specifications 1 and 2). The incongruities in the effects of these two regressors across the specifications could be because specification (3) also includes an indicator

[9] In particular, fields that require soil properties to be mapped using GPS technologies may be influenced by other un-modeled attributes causing them to be less efficient. Moreover, collinearity between yield maps, soil maps, and other un-modeled precision agriculture technologies (e.g., VRT and guidance systems) could result in omitted variables bias. This explanation is unlikely given the relatively low correlations in our data among the different combinations of technologies.

[10] Even though the yield map and soil map regressors do not directly enter the heteroscedasticity functions in specifications (2) and (3), they still indirectly impact both variance terms. This is because they directly enter $E\left[u_i\right]$, which in turn impacts $\sigma^2_{\mathrm{u},i}$.

for whether or not the field is rented free-of-charge and does not include re-scaled versions of the 'years operating the field' variable.[11]

Market Implications of Map Adoption and Data Inputs

U.S. crop production has experienced substantial structural change in the past three decades. During this time, production and acreage have shifted from mid-size farms to generally larger farms. Between 1982 and 2007, median farm size on U.S. cropland almost doubled from 589 acres to 1,105 acres. Larger farms have higher average rates of return on equity, a result of using labor and capital more intensively (MacDonald et al., 2013). During the past twenty years, crop farms in prime corn-growing regions have relied more extensively on corn-soybean rotations, concomitant with the use of genetically engineered (GE) herbicide-tolerant corn and soybean seeds. Use of these GE technologies tends to simplify farmers' pest management decisions and reduce labor time, potentially further reinforcing labor and capital productivity and possibly that of other inputs.

Most recently, there has been increasing public and private interest in the profitable use of large datasets (e.g., "big data") to increase the value of U.S. agricultural production. This increasing interest has, in part, been the result of rising broadband connectivity in rural areas, development and successful release of intuitive and easy-to-use smartphone applications, and broader trends toward automation and digitization of paper records. One current impediment to research on the economics of large datasets and their implementation in U.S. agriculture is a lack of access to farms' otherwise private information on management decisions and practice adoption.

[11] For specifications (1) and (2), the non-linear optimization did not converge due to scaling issues. For these specifications, we re-scaled the 'years operating field' regressor by dividing by 10. Specifications (1) and (2) with the rent-free indicator variable did not converge, so this variable was excluded from both models.

In the absence of comprehensive data on how operators have begun to use and interact with "big data" and analytics-based inputs, we can gain insight from unexplored avenues by which information inputs may provide value to farmers. That is, we may be able to infer how farmers might use (and derive value from) data on growing conditions from their smartphones, for example, by analyzing previous impacts of map use. Our analysis suggests that farmers who make use of yield maps (though not GPS-based soil maps) are more technically efficient than farmers who do not use such maps. This is similar to past findings that farms using mapping technologies have higher net returns and operating profits (Schimmelpfennig, 2016) and, more broadly, that information inputs provide value in production of certain field crops (e.g., Roberts et al., 2009). Generally, successful incorporation of relevant field-level data can increase efficiency and profitability of U.S. corn farms.

Conclusion

The goal of this research has been to analyze possible differences in technical efficiency on U.S. corn fields between adopters and non-adopters of GPS-based yield and soil maps. We model adoption using a bivariate probit model, which provides insights into the characteristics of fields, farms, and operators that influence mapping decisions. After having controlled for endogenous choice of both maps, we find that technical efficiency is significantly influenced by use of yield maps, soil maps, field ownership status, and other structural characteristics. These impacts are estimated using a generalized heteroscedastic stochastic frontier method (Wang, 2002) with a benchmark Cobb-Douglas production function. Further, we find evidence of endogenous yield and soil map adoption using estimated coefficients from first-step generalized residuals (Wooldridge, 2014).

Adjusted tests of differences in means suggest several interesting trends across map adoption scenarios. Mapped fields are higher-yielding, insured at higher rates, and are relatively higher value. These fields tend to be located on generally larger farms with non-owner operators that have one-to-two years less experience with the field than on fields for which neither map technology is used. Although map adoption rates are lower relative to other technologies released in the last two decades (e.g., herbicide-tolerant corn seeds or insect-resistant corn seeds), adoption is higher in certain regions of the U.S., including Iowa, Illinois, Indiana, and Ohio.

There are three potential caveats to our findings. First, we do not observe field-level prices for yield maps or soil maps, which could contribute to measurement error in these variables. Nationally-representative data on mapping prices paid by farmers are not generally available, though external data on custom rates could be used to internally verify our regression-based approach to controlling for prices. Second, we do not currently account for adoption of variable-rate technologies or guidance systems in the first or second stage of our regressions. Given the complementarities between different components of precision agriculture equipment (e.g., Khanna, 2001; Schimmelpfennig and Ebel, 2016; Schimmelpfennig, 2016), omitted variables bias could occur if map adoption decisions depend on joint use with these other technologies. Third, we assume that productive inputs in the stochastic frontier are exogenously determined. Recent parametric methods have been developed to correct endogeneity bias in stochastic frontiers (e.g., Shee and Stefanou, 2015; Amsler et al., 2016), though some techniques are not fully general and rely on strong assumptions about the way in which productive inputs are correlated with either the noise term or inefficiency term.

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Figure 1. Average Corn Yields on Fields with Yield Maps and GPS-based Soil Maps, 2010

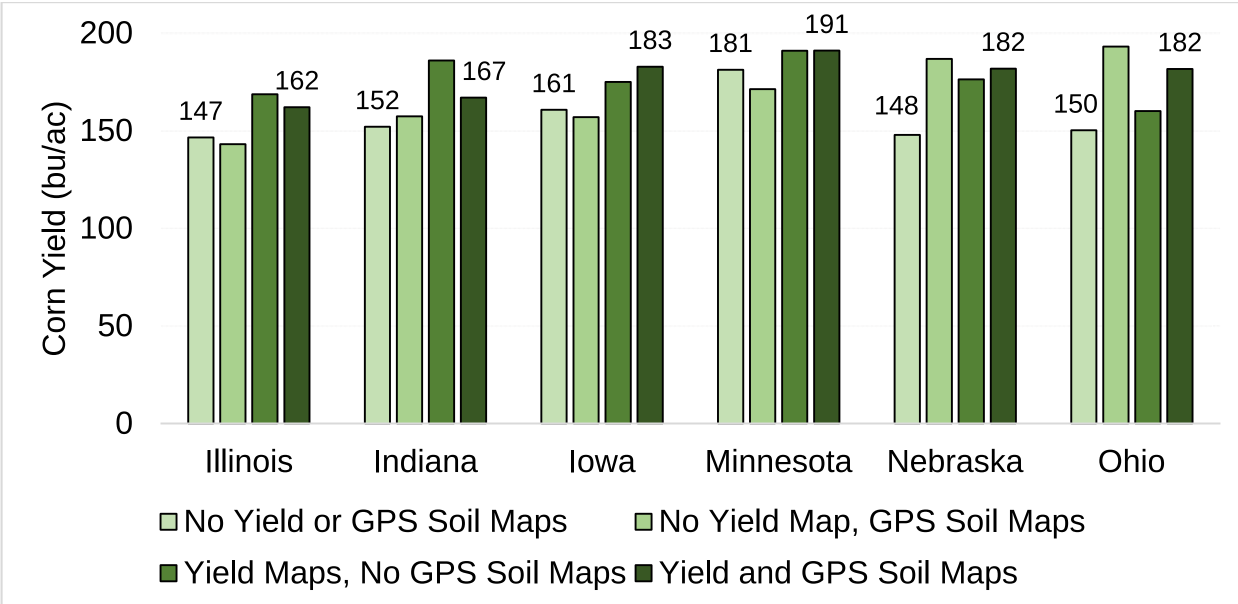

Figure 2. Percentage of Planted Corn Acres with Yield Maps and GPS-based Soil Maps, 2010

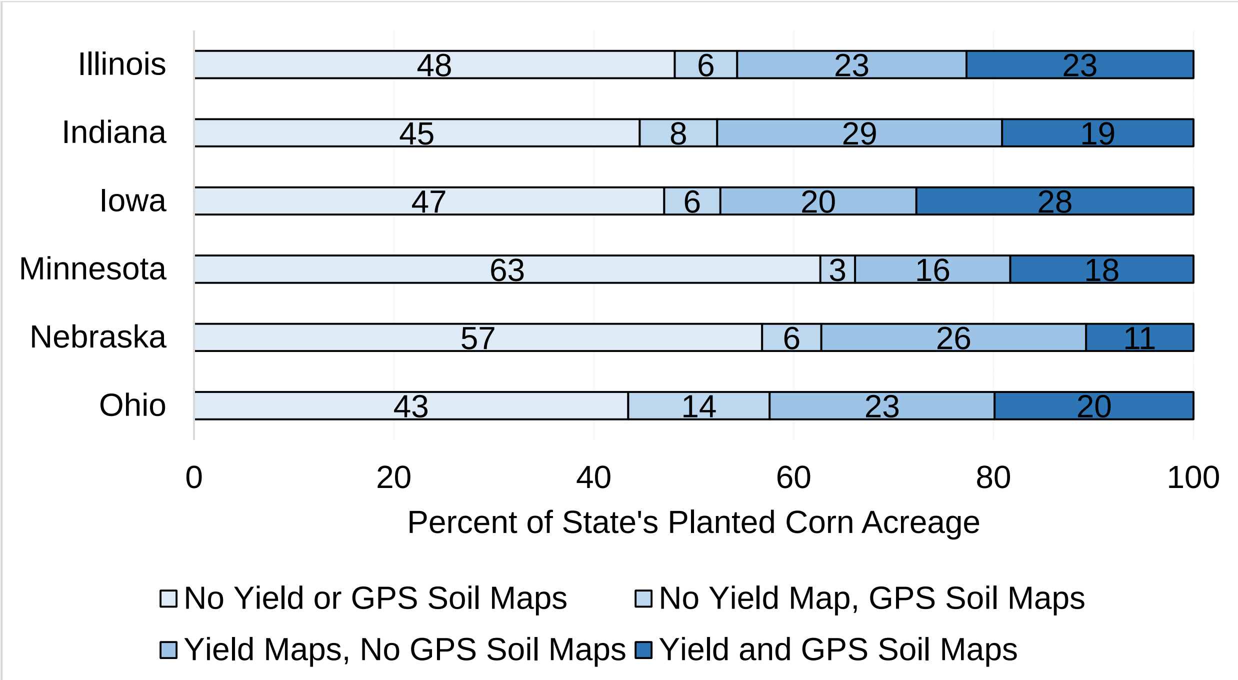

Figure 3. Output-Oriented Efficiency Index Estimates

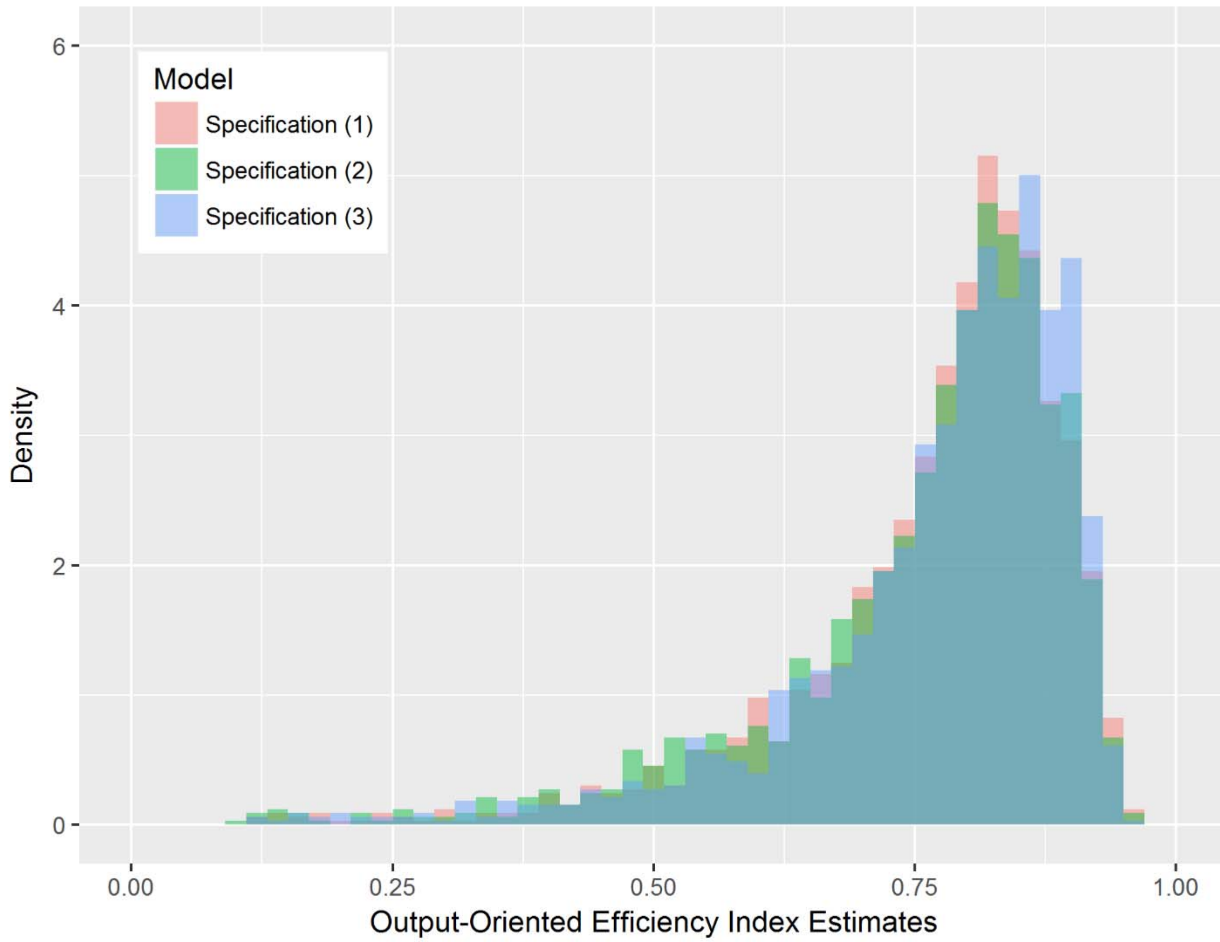

Figure 4. Relative Input-Oriented Inefficiency Index Estimates

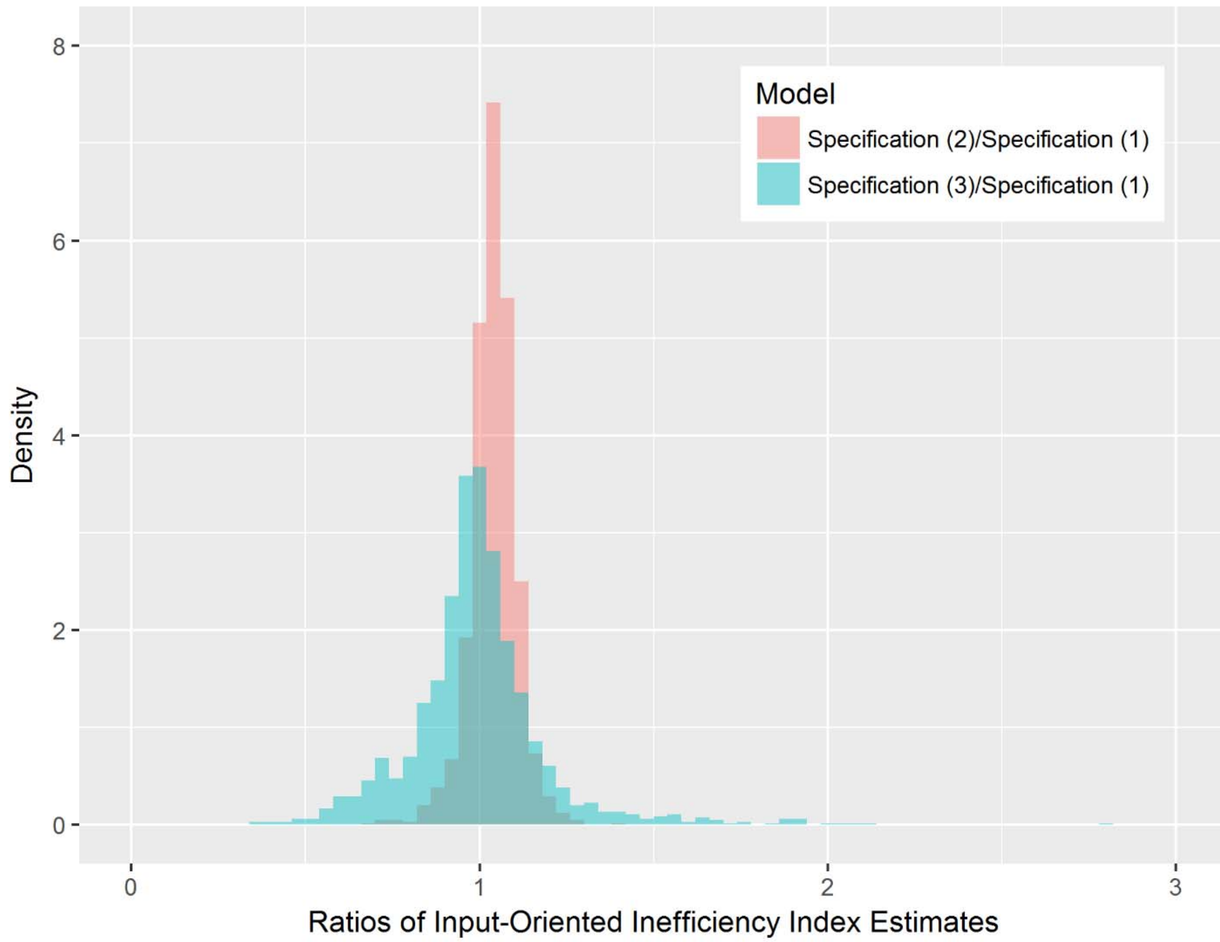

Table 1. Select Weighted Means by Map Technology Adoption Decision, 2010

Variable	Unit	No Yield or GPS Soil Maps	No Yield Maps, GPS Soil Maps	Yield Maps, No GPS Soil Maps	Yield and GPS Soil Maps
Yields and Productive Inputs					
Yield	Bushels/acre	146	149	167	173
Labor Hours	Hours	57	74	83	77
Farm Acres	Acres	378	683	1217	1262
Nitrogen Applications	lb/acre	135	147	148	162
Capital	Dollars	3633	5773	6841	6110
Prices					
Corn Price	Dollars/bushel	5.28	5.22	5.23	5.26
Labor Price	Dollars/hr	20.94	21.1	21.3	20.7
Land Price	Dollars/acre	5131.62	8104.88	10713.51	11027.43
Nitrogen Price	Dollars/pound	0.39	0.39	0.39	0.38
Field and Operator Structure					
Acres Owned	Percent in (0,1)	0.52	0.48	0.37	0.35
Acres Rented for Fixed Cash Payment	Percent in (0,1)	0.33	0.38	0.38	0.52
Acres Rented for Flexible Cash Payment	Percent in (0,1)	0.01	0.03	0.01	0.05
Acres Rented for Share of Crop	Percent in (0,1)	0.12	0.11	0.23	0.08
Acres Rented for Cash and Share of Crop	Percent in (0,1)	0.004	0	0	0
Acres Rented for Free	Percent in (0,1)	0.01	0	0	0
Operator Experience with Field	Years	22.08	20.55	19.09	19.50
Insurance	Percent in (0,1)	0.72	0.77	0.89	0.93
Field Characteristics and Geographic Location					
NCCPI, Corn and Soybeans	Index in (0,1)	0.57	0.60	0.63	0.65
Indicator for Highly Erodible Land	Percent in (0,1)	0.12	0.18	0.12	0.10
Indicator for Wetland	Percent in (0,1)	0.02	0.01	0.04	0.02
Heartland Region	Percent in (0,1)	0.49	0.60	0.69	0.82
North Crescent Region	Percent in (0,1)	0.29	0.08	0.13	0.09

Note: Means have been expanded to the population of 2010 U.S. corn fields using a NASS-provided base weight.

Table 2. Difference in Weighted Means Across Adoption Decisions, Relative to Fields with No Maps

Variable	**Unit**	**No Yield Maps, GPS Soil Maps**	**Yield Maps, No GPS Soil Maps**	**Yield and GPS Soil Maps**
Yields and Productive Inputs				
Yield	Bushels/acre	3	21^{**}	26^{**}
Labor Hours	Hours	17	26^{***}	20^{***}
Farm Acres	Acres	305^{**}	839^{***}	884^{***}
Nitrogen Applications	lb/acre	13^{*}	13^{**}	27^{***}
Capital	Dollars	2140^{***}	3208^{***}	2477^{***}
Prices				
Corn Price	Dollars/bushel	-0.07^{*}	-0.05^{**}	-0.03
Labor Price	Dollars/hr	0.19	0.38	-0.20
Land Price	Dollars/acre	2973^{***}	5582^{***}	5896^{***}
Nitrogen Price	Dollars/pound	0	0	-0.01
Field and Operator Structure				
Acres Owned	Percent in (0,1)	-0.04	-0.15^{***}	-0.17^{***}
Acres Rented for Fixed Cash Payment	Percent in (0,1)	0.05	0.05	0.19^{***}
Acres Rented for Flexible Cash Payment	Percent in (0,1)	0.02	0	0.03
Acres Rented for Share of Crop	Percent in (0,1)	-0.02	0.11^{***}	-0.04
Acres Rented for Cash and Share of Crop	Percent in (0,1)	-	-	-
Acres Rented for Free	Percent in (0,1)	-	-	-
Operator Experience with Field	Years	-1.53	-2.99^{***}	-2.58
Insurance	Percent in (0,1)	0.04	0.17^{***}	0.21^{***}
Field Characteristics and Geographic Location				
NCCPI, Corn and Soybeans	Index in (0,1)	0.02	0.06^{***}	0.08^{***}
Indicator for Highly Erodible Land	Percent in (0,1)	0.06	-0.01	-0.02
Indicator for Wetland	Percent in (0,1)	-0.01	0.02	0
Heartland Region	Percent in (0,1)	0.11	0.20^{***}	0.32^{***}
North Crescent Region	Percent in (0,1)	-0.21^{***}	-0.16^{***}	-0.20^{***}

Note: Differences in means estimated using the delete-a-group jackknife procedure. Significance is denoted as *** $p<0.01$, ** $p<0.05$ and * $p<0.1$.

Table 3. First-Stage Bivariate Probit Estimates of Yield Map and Soil Map Adoption

Variable	Yield Map Equation	GPS Soil Map Equation
Prices		
Corn price	0.38	0.06
Nitrogen price	-3.31	-1.74
Labor price	0.014	-0.003
Land rental rate	0.00002	0.0002
Capital costs	0.00003*	-0.000009
Diesel price	1.22	0.47
Control for yield map price	-0.02	0.01
Control for soil map price	-0.04*	-0.05**
Structure		
Field is owned	-0.27**	-0.12
Years operating field	-0.003	-0.000007
Soil and Weather Conditions		
NCCPI, corn and soybeans	0.93*	0.54
Field contains highly-erodible land	-0.09	0.06
Field contains wetland	-0.16	0.18
Cumulative season GDD	-0.0004	0.0003
Cumulating season precipitation	-0.0005	-0.006
Correlation of errors across equations	0.80***	
Number of observations	1,640	1,640

Note: Estimates have been expanded to the population of 2010 U.S. corn fields using a NASS-provided base weight. Standard errors are computed using the delete-a-group jackknife procedure. The 'years operating field' variable has been divided by 10. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.

Table 4. Stochastic Frontier Estimates

	(1)	(2)	(3)
Input, Soil, and Region Characteristics Estimates, $\hat{\beta}$ and $\hat{\gamma}$			
Log(Farm Size)	0.01	0.01	0.01
Log(Labor Hours)	0.08^{***}	0.08^{***}	0.07^{***}
Log (Total N Applied)	0.38^{***}	0.38^{***}	0.39^{***}
Log(Capital)	0.41^{***}	0.41^{***}	0.41^{***}
NCCPI, Corn and Soybeans	0.11	0.09	0.11
Highly Erodible Land	-0.06	-0.05	-0.05
Field Contains Wetland	0.09	0.10	0.14^{**}
Heartland Region	0.14^{***}	0.14^{***}	0.15^{***}
Northern Crescent Region	0.10^{**}	0.09^{**}	0.10^{**}
Constant	1.86^{***}	1.96^{***}	1.87^{***}
Mean Inefficiency Estimates, $\widehat{\alpha}$			
Yield Map Adoption	-12.55^{***}	-13.91^{***}	-16.52^{*}
Soil Map Adoption	10.77^{***}	11.34^{***}	14.79^{*}
Own Field	-0.12	-0.11	-0.70^{*}
Rent Field for Free			1.44^{*}
Years Operating Field	-0.14^{**}	-0.15^{**}	-0.08
Field is Insured	-2.37^{**}	-2.25^{**}	-0.49
Generalized Residual, Yield Maps	3.98^{***}	4.34^{***}	4.85^{**}
Generalized Residual, Soil Maps	-3.54^{***}	-3.65^{***}	-5.04^{*}
Constant	0.84^{***}	0.89^{***}	-0.33
Inefficiency Variance Estimates, $\widehat{\delta_u}$			
Own Field	-0.45^{***}	-0.44^{***}	
Years Operating Field	0.09^{**}	0.08^{*}	
Field is Insured	1.54^{***}	1.40^{***}	
Constant	-1.57^{***}	-1.38^{***}	-0.29
Noise Variance Estimates, $\widehat{\delta_v}$			
Yield Map Adoption	-0.91		
Soil Map Adoption	-0.46		
Own Field	0.42^{***}	0.51^{***}	
Years Operating Field	-0.04	-0.01	
Field is Insured	-0.04	-0.11	
Generalized Residual, Yield Maps	0.43^{***}		
Generalized Residual, Soil Maps	0.41		
Constant	-1.90^{***}	-2.28^{***}	-2.05^{***}
Noise Variance, $\hat{\sigma}_v^2$			0.75^{*}
Inefficiency Variance, $\hat{\sigma}_u^2$			0.13^{***}
Returns to Scale	0.89^{***}	0.88^{***}	0.88^{***}
Median Efficiency	0.80	0.80	0.81
Efficiency, 95% Confidence Interval (Means)	[0.50, 0.97]	[0.50, 0.96]	[0.50, 0.97]
Log-likelihood	-970.0	-978.1	-1000.8
N	1,639	1,639	1,639

Note: To ease computational burden, we divide the 'years operating field' by 10 in specifications (1) and (2). We test the null hypothesis of constant returns to scale using a two-sided Wald test. Models (1) and (2) did not converge using the 'rent field for free variable.' Significance is denoted as ***p<0.01, **p<0.05 and *p<0.10.

Table 5. Average Marginal Effects on Mean and Variance of Inefficiency

	Yield Map Adoption	Soil Map Adoption	Own Field	Years Operating Field
Mean Inefficiency, $E[u_i]$				
General Heteroscedasticity Model (1)	-1.60*	1.56**	0.001	-0.36***
Reduced Heteroscedasticity Model (2)	-1.82**	1.64***	0.001	-0.33**
Homoscedasticity Model (3)	-1.73**	1.55*	-0.07***	-0.0009
Variance of Inefficiency, $\sigma^2_{u,i}$				
General Heteroscedasticity Model (1)	-0.43	0.46*	0.004	-0.17***
Reduced Heteroscedasticity Model (2)	-0.55*	0.53**	0.004	-0.16**
Homoscedasticity Model (3)	-0.78**	0.70**	-0.03**	-0.0004

Note: Marginal effects are calculated using standard formulas (e.g., Kumbhakar et al., 2015) and then averaged across the 1,639 field observations. Standard errors are calculated as the standard deviation of the average marginal effects across $B = 1{,}000$ bootstrapped samples. Each of the 1,000 datasets are sampled randomly with replacement. Significance is denoted as $^{***}p<0.01$, $^{**}p<0.05$, and $^{*}p<0.10$.

Appendix

Let the expected utility maximization problem for a representative farmer be:

$$\text{(A.11)}\quad \max_{x_v \in R^+, T_1 \in \{0,1\}, T_2 \in \{0,1\}} \mathrm{E}\left[U\right] = \mathrm{E}\left[u\left[PY - p_f x_f - p_v x_v - p_1 T_1 - p_2 T_2\right] + \left(1-u\right)\left[d_{nm} T_1 + e_{nm} T_2\right]\right]$$
$$s.t.\ Y = a x_f^b x_v^c d^{T_1} e^{T_2} \exp\left(\varepsilon\right),$$

where T_1 and T_2 are binary choices.

Assuming that $\mathrm{E}\left[\exp\left(\varepsilon\right)\right] = 1$, the first order condition for variable input use is:

$$\text{(A.12)}\qquad \frac{d\,\mathrm{E}\left[\pi\right]}{dx_v} = \frac{cPax_f^b x_v^c d^{T_1} e^{T_2}}{x_v} - p_v = 0.$$

Solving equation (A.12) for *x* implies that:

$$\text{(A.13)}\qquad x^* = \left(ax_f^b d^{T_1} e^{T_2} c \frac{P}{p_v}\right)^{\frac{1}{1-c}}.$$

Substituting equation (A.13) into the production function, we have:

$$\text{(A.14)}\qquad Y^* = \left[ax_f^b d^{T_1} e^{T_2} \left(c\frac{P}{p_v}\right)^c\right]^{\frac{1}{1-c}} \exp(\varepsilon).$$

Substituting equations (A.13) and (A.14) into the expected utility function implies that the maximization problem can be expressed as:

(A.15)

$$\max_{T_1, T_2} \mathrm{E}\left[U\right] =$$

$$P\left[ax_f^b d^{T_1} e^{T_2}\left(c\frac{P}{p_v}\right)^c\right]^{\frac{1}{1-c}} - p_f x_f - p_v\left(ax_f^b d^{T_1} e^{T_2} c\frac{P}{p_v}\right)^{\frac{1}{1-c}} + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2$$

$$= \left(ax_f^b d^{T_1} e^{T_2}\right)^{\frac{1}{1-c}}\left(\left(P^{\frac{1-c}{1-c}} P^{\frac{c}{1-c}}\right)\left(c^{\frac{c}{1-c}} p_v^{\frac{c}{c-1}}\right) - \left(p_v^{\frac{c-1}{c-1}} p_v^{\frac{1}{c-1}}\right)\left(cP\right)^{\frac{1}{1-c}}\right) - p_f x_f + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2$$

$$=\left(ax_f^b d^{T_1} e^{T_2}\right)^{\frac{1}{1-c}}\left(P^{\frac{1}{1-c}} c^{\frac{c}{1-c}} p_v^{\frac{c}{c-1}} - p_v^{\frac{c}{c-1}} c^{\frac{1}{1-c}} P^{\frac{1}{1-c}}\right) - p_f x_f + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2$$

$$=\left(Pp_v^{-c} ax_f^b d^{T_1} e^{T_2}\right)^{\frac{1}{1-c}}\left(c^{\frac{c}{1-c}} - c^{\frac{c}{1-c}} c^{\frac{1-c}{1-c}}\right) - p_f x_f + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2$$

$$=\left(Pax_f^b d^{T_1} e^{T_2}\left(\frac{c}{p_V}\right)^c\right)^{\frac{1}{1-c}}(1-c) - p_f x_f + \left(wd_{nm} - p_1\right)T_1 + \left(we_{nm} - p_2\right)T_2.$$

Therefore, a farmer uses precision agriculture technology T_1 if:

(A.16)

$$\mathrm{E}\left[U \mid T_1 = 1\right] - \mathrm{E}\left[U \mid T_1 = 0\right] \geq 0$$

$$\Leftrightarrow \left[\left(Pax_f^b d e^{T_2}\left(\frac{c}{p_v}\right)^c\right)^{\frac{1}{1-c}}(1-c) - p_f x_f + \left(wd_{nm} - p_1\right) + \left(we_{nm} - p_2\right)T_2\right]$$

$$-\left[\left(Pax_f^b e^{T_2}\left(\frac{c}{p_v}\right)^c\right)^{\frac{1}{1-c}}(1-c) - p_f x_f + \left(we_{nm} - p_2\right)T_2\right] \geq 0$$

$$\Rightarrow \frac{1}{1-c}\ln\left(Pax_f^b e^{T_2}\left(\frac{c}{p_v}\right)^c\right) + \ln(1-c) + \ln\left(d^{\frac{1}{1-c}} - 1\right) \geq \ln\left(p_1 - wd_{nm}\right)$$

$$\Leftrightarrow \frac{1}{1-c}\ln(P) + \frac{1}{1-c}\ln(a) + \frac{b}{1-c}\ln\left(x_f\right) + \frac{\ln(e)}{1-c}T_2 + \frac{c}{1-c}\ln(c) - \frac{c}{1-c}\ln\left(p_v\right) + \ln(1-c) + \ln\left(d^{\frac{1}{1-c}} - 1\right) - \ln\left(p_1 - wd_{nm}\right) \geq 0.$$

We choose to model a such that $a \equiv a_0 \prod_{i=1}^{N} A_i^{a_i}$, where a_0 is a constant, a_i are parameters, and A_i are exogenous variables. Therefore, equation (A.16) can be reparametrized as:

(A.17) $$cons_1 + \sum_{i=1}^{N} \beta_{A_i} \ln\left(A_i\right) + \beta_P \ln(P) - \beta_v \ln\left(p_v\right) + \beta_f \ln\left(x_f\right) + \beta_2 T_2 - \ln\left(p_1 - wd_{nm}\right) \geq 0,$$

where $cons_1 \equiv \frac{1}{1-c}\ln\left(a_0\right) + \ln(1-c) + \frac{c}{1-c}\ln(c) + \frac{1}{1-c}\ln\left(d^{\frac{1}{1-c}} - 1\right)$, $\beta_{A_i} \equiv \frac{a_i}{1-c}$, $\beta_P \equiv \frac{1}{1-c}$,

$\beta_v \equiv \frac{c}{1-c}$, $\beta_f \equiv \frac{b}{1-c}$, and $\beta_2 \equiv \frac{\ln(e)}{1-c}$.

Similarly, the condition for the use of precision agriculture technology T_2 can be expressed as:

(A.18) $$cons_2 + \sum_{i=1}^{N} \beta_{A_i} \ln\left(A_i\right) + \beta_P \ln\left(P\right) - \beta_v \ln\left(p_v\right) + \beta_f \ln\left(x_f\right) + \beta_2 T_2 - \ln\left(p_2 - we_{nm}\right) \geq 0,$$

where $cons_2 \equiv \frac{1}{1-c}\ln\left(a_0\right) + \ln\left(1-c\right) + \frac{c}{1-c}\ln\left(c\right) + \frac{1}{1-c}\ln\left(e^{\frac{1}{1-c}} - 1\right)$ and $\beta_1 \equiv \frac{\ln\left(d\right)}{1-c}$.

We restrict equations (A.17) and (A.18) to positive values by exponentiating $\left(p_2 - we_{nm}\right)$ and $\left(p_1 - wd_{nm}\right)$. We express wd_{nm} and we_{nm} as linear combinations of variables correlated with the farmer's non-monetary factors associated with adopting the precision agriculture technology. Thus, the conditions for adoption are:

(A.19) $$cons_1 + \sum_{i=1}^{N} \beta_{A_i} \ln\left(A_i\right) + \beta_P \ln\left(P\right) - \beta_v \ln\left(p_v\right) + \beta_f \ln\left(x_f\right) + \beta_2 T_{22} + \boldsymbol{\beta}_{\mathbf{nm}}^{\mathbf{1}}{}'\mathbf{x}_{\mathbf{nm}} - p_1 \geq 0,$$

and,

(A.20) $$cons_2 + \sum_{i=1}^{N} \beta_{A_i} \ln\left(A_i\right) + \beta_P \ln\left(P\right) - \beta_v \ln\left(p_v\right) + \beta_f \ln\left(x_f\right) + \beta_1 T_{11} + \boldsymbol{\beta}_{\mathbf{nm}}^{2}{}'\mathbf{x}_{\mathbf{nm}} - p_2 \geq 0,$$

where $\boldsymbol{\beta}_{\mathbf{nm}}^{\mathbf{1}}$ and $\boldsymbol{\beta}_{\mathbf{nm}}^{2}$ are vectors of parameters, and $\mathbf{x}_{\mathbf{nm}}$ is a vector of variables that are highly correlated with non-monetary factors influencing technology adoption decisions.