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

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Abstract. Yield maps and GPS-based soil maps have been increasingly used in U.S. agriculture but little research has explored the economic relationship between mapping technologies and agricultural productivity. Research on this relationship is lacking, perhaps because maps are information inputs that do not directly enter the production function in a comparable way to conventional inputs. A stochastic frontier model was used to evaluate one potential avenue through which mapping technologies may influence productivity – technical efficiency. After controlling for farmers' potentially endogenous choice of map technologies, adoption of yield maps has a positive influence on technical efficiency, and unexpectedly, adoption of soil maps has a negative influence on technical efficiency. Given that yield maps are a basic information input, this suggests that increased availability of some information or data-type inputs, by themselves, can have 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

Adoption rates of precision agriculture technologies in U.S. row crop production have varied widely over the past two decades. Among the most widely-used precision technologies are yield monitors. Adoption rates of yield monitors on national corn land area increased from 19% in 1998 to 61% in 2010 (USDA-ERS 2017a). This upward trend is likely to continue as yield monitors are now standard on new equipment (Schimmelpfennig and Ebel 2016). In contrast, variable rate technologies (VRT) used for seeding and chemical applications have experienced slow growth – VRT was adopted on about 28% of 2010 national corn land. In between these two extremes are the adoption of GPS-based yield maps and soil maps. Similar to yield monitors, yield map adoption has increased in recent years in corn and soybean production; approximately 44% of national corn area adopted yield maps in 2010.[1] Adoption of soil maps has increased at a slower rate – approximately 31% of 2010 national corn area (Schimmelpfennig 2016).

The economic relationship between output and many types of precision agriculture technologies such as yield monitors, VRT, and GPS-based auto-guidance systems are generally straightforward – they are capital equipment used directly as inputs to crop production. These technologies can have substantial fixed costs of adoption and recurring expenses for GPS subscriptions and machinery repair, but they provide potential benefits through lower variable costs and/or higher revenues. Given these relatively direct relationships, the agricultural economics literature has made great strides in understanding the mechanisms driving variation in adoption.

What is less well understood is the economic relationship between output and GPS-based yield maps and soil maps. Research on this relationship is relatively lacking, perhaps because maps are information inputs that do not directly enter the production function in a comparable way to conventional inputs.[2] The value of a hard-copy map 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 from information inputs on larger and less tightly-held farms with non-owner operators. Maps may provide information that cannot be economically acquired through experience on very large farms; that is, maps may substitute for detailed knowledge of land characteristics and soil productivity (Deininger and Byerlee 2012). Further, the incentive structure 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). As a result, the value of information inputs like maps may vary by farm structure and may not be directly observable through reductions in per-hectare variable costs or revenue increases.

The objective of this paper is to examine one potential avenue through which yield and soil maps may influence productivity – technical efficiency. Specifically, differences in technical efficiency were evaluated between adopters and non-adopters of yield and soil maps on U.S. corn fields. Adoption was modeled as a discrete choice problem, which provided insight into the characteristics of fields, farms, and operators that may influence technology choice. After

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[1] For the context of this paper, "yield maps" refer to georeferenced yields recorded in either hard or soft copy form. While yield maps are a potential byproduct of yield monitors, not all farmers with yield monitors opt to generate yield maps (e.g., some farmers use yield monitors for "real time" data viewing only). See Schimmelpfennig (2016) for a schematic of the relationship between yield monitors and yield maps.

[2] Two notable exceptions are Schimmelpfennig and Ebel (2016) and Schimmelpfennig (2016). The former finds that a combination of yield monitors and yield maps provides cost savings to corn farmers of roughly $61.8 per hectare. These cost savings were higher than cost savings from adopting yield monitors alone or adoption of a more advanced combination of yield monitors, yield maps, and variable rate technology. Similarly, Schimmelpfennig (2016) found that GPS-based mapping systems (including yield monitors and soil/yield mapping) had a small, positive effect on both net returns and operating profits for the average-sized U.S. corn farm.

controlling for endogenous choice of both yield and soil maps, a stochastic frontier model was estimated to analyze the extent to which map adoption influences technical efficiency on U.S. corn fields. This specification also allowed investigation of linkages between map adoption, farm structure (e.g., farm size, ownership status), and technical efficiency.

Technical efficiency is significantly influenced by map adoption and systematically differs between adopters and non-adopters according to farm size, ownership status, and operator attributes. Specifically, yield maps have a positive effect on technical efficiency, but soil maps have an unexpected negative effect on technical efficiency. Overall, the results suggest that increased availability of information or data-type inputs, by themselves, can have indirect production effects on farmers and that these effects may differ by farm structure.

Technology Adoption, Farm Structure, and Technical Efficiency

The analysis presented here lies within the broader context of research examining the relationships between technical efficiency, technology adoption, and farm structure in the U.S. 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).

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 increase 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 estimated that gains to nitrogen productivity from adopting soil testing only 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 little focus on the linkages between data-driven inputs (e.g., yield and soil maps), farm structure, and technical efficiency. This was investigated using an econometric model and empirical specification that were sufficiently general to allow quantification of the role of data-driven input adoption on technical efficiency.

Econometric Approach and Regression Specifications

A stochastic frontier model was estimated to evaluate the relationship between map adoption, farm structure, and technical efficiency. However, yield and soil map adoption 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. Therefore, a control function approach to account for potential endogeneity (e.g., Wooldridge 2014) was used. Estimation proceeded in two steps. First, a bivariate probit model explaining adoption of both maps was estimated. Generalized residuals were 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 would 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 (v_i) minus a (non-negative) disturbance term (u_i). In this analysis, it was assumed that the random noise component is a mean-zero, independent and identically-distributed (i.i.d.) error term. The disturbance term depends on efficiency related inputs and an inefficiency term (ω_i), which was 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, total field output y_i was modeled as the following generalization of a primal stochastic frontier model (Wang 2002):

$$\ln(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(x_{ji}) + \boldsymbol{\gamma}' d_i + v_i - u_i \tag{1}$$

$$u_i = \alpha_0 + \sum_{l=1}^{m} \alpha_l z_{li} + \omega_i$$

$$v_i \sim N\left(0, \sigma_{v,i}^2\right)$$

$$\omega_i \sim N^+(0, \sigma_u^2, i)$$

Note that v_i and ω_i are assumed to be mutually independent. Following the extensive literature on frontier estimation, the productive inputs were assumed to be labor, capital, total nitrogen applied, and farm area. The Cobb-Douglas production specification in (1) was modified slightly to incorporate soil quality variables and regional indicators, denoted by d_i with regression impacts given by $\boldsymbol{\gamma}$. Note that this specification implies that $E[u_i] = \mu_i = \hat{\alpha}_0 + \sum_{l=1}^{m} \hat{\alpha}_l z_{li}$. Given the expected differences in technical efficiency on fields with differing levels of map adoption, as well as farm structure, it was assumed that z_i contains indicators for use of yield maps and GPS-based soil maps, years of operator experience with the field, and indicators for whether the field is insured, owned by the operator, or rented for free. Estimation of all coefficients in equation (1) was 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).[3] As such, both variance terms were parameterized as functions of field-level characteristics[4]:

$$\sigma_{v,i}^2 = \exp\left[\delta_{v,0} + \sum_{n=1}^{O} \delta_v h_{n,i}\right] \tag{2}$$
$$\sigma_{u,i}^2 = \exp\left[\delta_{u,0} + \sum_{p=1}^{Q} \delta_u h_{p,i}\right]$$

Given the Cobb-Douglas specification in equation (1), output-oriented technical efficiency was the preferred measure of field-level productivity. This measure quantifies how much output (kilograms

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

[4] Wang (2002) argues that u and $\sigma_{u,i}^2$ 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. Ideally, the same set of regressors would be used to parameterize $(\boldsymbol{u}, \sigma_{u,i}^2, \sigma_{v,i}^2)$; that is, set $z_l \equiv h_n \equiv h_p \ \forall\, l, n, p$. Numerical difficulties due to the nonlinear optimization in the maximum likelihood routine prevented an implementation of this most general parameterization.

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

$$E[\exp(-u_i|\,\varepsilon_i)] = \exp\left(-\mu_{*i} + \frac{1}{2}\sigma_{*i}^2\right)\frac{\Phi\left(\frac{\mu_{*i}}{\sigma_{*i}} - \sigma_{*i}\right)}{\Phi\left(\frac{\mu_{*i}}{\sigma_{*i}}\right)} \tag{3}$$

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 (Battese and Coelli 1988). 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).[5]

Data Construction and Field Characteristics

The Agricultural Resource Management Survey (ARMS) is the U.S. Department of Agriculture's (USDA) 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, as well as farms within geographical areas. 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 cropland, 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

Data from the 2010 ARMS Phase II corn survey were used, as well as 2010 Costs and Returns data, to generate national estimates of the cost of corn production. These estimates have been produced annually for major livestock and field crop enterprises since 1975. Direct costs of crop production 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.

The sample was comprised 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), the sample can be extended to represent 28.3 million hectares planted to corn. This represented approximately 79% of the 35.7 million planted corn hectares in 2010 (USDA-NASS 2017). Fields in the sample were from prime U.S. corn-growing regions, primarily from the Corn Belt, Great Lakes, Great Plains, and Prairie regions.

Compilation and Construction

Productive inputs were derived from the cost of production data associated with the ARMS Phase II survey. These inputs were assumed to be labor, capital, nitrogen, and land. Labor was calculated as the sum of paid and unpaid labor hours provided on the field. The capital variable,

[5] These intervals do not account for parameter uncertainty.

expressed in 2010 dollars per hectare, was an estimate of the cost of replacing capital consumed in annual production on the particular field, plus an annualized measure of the opportunity cost of the remaining field-level capital investment in machinery and equipment (USDA-ERS 2017c). Total nitrogen (in kilograms) was the sum of the nitrogen content of purchased commercial fertilizer and the (estimated) nitrogen content of applied manure. Land (in hectares) was the reported size of the farm. Output was calculated as the product of field size and yield (in kg/ha).

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. Prices for yield and soil maps were therefore predicted using ARMS data about field-level use of consultant services. In particular, it is observed 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) were also reported.

To obtain predicted prices for both map types, ARMS data were first pooled across 2006-2007 and 2009-2012. Fields for which no recommendation services were employed are dropped from the pooled sample. A weighted OLS regression was then performed of total technical/consultant services costs on indicators for the particular services hired and their interactions with the set of 19 states in the 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) were constructed from coefficient estimates of the state-by-year interactions.

Prices for the productive inputs were constructed from the ARMS cost of production estimates. In particular, the wage rate was calculated as the sum of the cost of paid and unpaid labor hours divided by total labor hours. The nitrogen price was calculated similarly as the sum of the costs of nitrogen from commercial fertilizer and manure divided by total kilograms of nitrogen applied. The price of land was 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, the 2010 state-level prices of diesel from the April release of NASS' Agricultural Prices survey were used.

County weather data were derived from Oregon State University's PRISM Climate Group database (Daly et al. 2008). Using daily data from annual PRISM records, cumulative season growing degree days (GDD) were constructed by summing monthly GDD for each month of the growing season (May, June, July, and August). Monthly PRISM data were 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, NCCPI values were used from the Corn and Soybeans sub-model. Apart from these, two field-level measures indicating if any part of the field contains a wetland or is highly-erodible were also included.

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 511 hectares. This is nearly four times as large as the average farm size for fields that use neither technology (153 hectares). This positive correlation between adoption of site-specific information and farm size could suggest that these technologies had the greatest returns on large operations.

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

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
Map Adoption					
Yield Maps	Percent in (0,1)	0	0	100	100
GPS Soil Maps	Percent in (0,1)	0	100	0	100
Yields and Productive Inputs					
Yield	kg/ha	9,164	9,353	10,483	10,859
Labor Hours	Hours	57	74	83	77
Farm Hectares	Hectares	153	277	493	511
Nitrogen Applications	kg/ha	151	165	166	182
Capital	Dollars	3633	5773	6841	6110
Prices					
Corn Price	Dollars/kg	0.208	0.205	0.206	0.207
Labor Price	Dollars/hr	20.94	21.1	21.3	20.7
Land Price	Dollars/ha	12,681	20,027	26,473	27,248
Nitrogen Price	Dollars/kg	0.86	0.86	0.86	0.84
Field and Operator Structure					
Area Owned	Percent in (0,1)	0.52	0.48	0.37	0.35
Area Rented for Fixed Cash Payment	Percent in (0,1)	0.33	0.38	0.38	0.52
Area Rented for Flexible Cash Payment	Percent in (0,1)	0.01	0.03	0.01	0.05
Area Rented for Share of Crop	Percent in (0,1)	0.12	0.11	0.23	0.08
Area Rented for Cash and Share of Crop	Percent in (0,1)	0.004	0	0	0
Area 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 Region					
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

a Means were expanded to the population of 2010 U.S. corn fields using a NASS-provided base weight.

Average per-hectare nitrogen applications also varied substantially with adoption of these technologies, ranging from 151 kilograms/hectare (kg/ha) among non-adopting fields to 182 kg/ha on fields with both technologies. This variation may reflect some degree of farmers' self-selection into map use. For example, those with historically high input use may have more incentive to acquire information that could improve input use efficiency. In terms of the empirical specification, the association between nitrogen applications and map adoption provides additional support for inclusion of soil quality and regional indicator variables.

Labor hours and capital use, however, had less straightforward associations with adoption. Fields with mapped yields but not GPS-mapped soils used the highest quantities of labor and capital, though fields with both map types employed 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.[6] Given the relationship between map adoption patterns and input use, it is not surprising average yields were higher on fields with both technologies (10,859 kg/ha) than on fields using neither (9,164 kg/ha).

Interestingly, no significant differences in average wage rates or nitrogen prices were observed across the four adoption cases. Regardless of technology, the mean price of labor was $21/hour and the mean price of nitrogen was $0.86/kg. One reason 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 of manure are difficult to accurately impute. However, fields using both technologies were, on average, more than twice as valuable ($27,248/ha) as fields using neither type of map ($12,681/ha). Although non-owner operators could potentially use map output to help negotiate rental contract terms, this trend more likely reflects scenarios in which maps were more actively used in conjunction with careful input monitoring on high-value cropland.

There were also interesting trends pertaining to adoption and structural aspects of the corn field or operator. Roughly 52% of non-adopting fields were owned by the operator. This ownership percentage declines to just 35% on fields employing both types of maps. On these fields, roughly 52% were rented for cash with a fixed cash payment. A much smaller percentage of fields were 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 were 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 were insured, while 72% of fields without maps were insured. Since the former set of fields had relatively higher land values (in terms of per-hectare rental rates), higher rates of insurance uptake were expected.

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 was 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 hectares by state across the four map adoption scenarios.[7] 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. However, operations in Corn Belt states (Iowa, Illinois, Indiana, and Ohio) adopted these technologies at somewhat higher rates. Similarly, among the set of fields adopting both types of maps, average yields were highest (in excess of 9,416 kg/ha) in Corn Belt and upper Midwest states. However, this region was also highly productive without use of either type of map.

The weighted means (Table 1) and spatial tends (Figures 1 and 2) confirm the hypotheses detailed earlier. Mapped fields were higher-yielding, insured at higher rates, and were relatively higher-value. These fields were located on generally larger farms with non-owner operators that had one-to-two years less experience with the field than on fields for which neither map technology was used. Regression results (next section) give further support for these trends.

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

[7] These figures are intended to illustrate trends over broad geographical regions. They are not necessarily 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.

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

Variable	Unit	No Yield Maps, GPS Soil Maps	Yield Maps, No GPS Soil Maps	Yield and GPS Soil Maps
Yields and Productive Inputs				
Yield	kg/ha	188	1,319**	1,632**
Labor Hours	Hours	17	26***	20***
Farm Hectares	Hectares	123**	340***	358***
Nitrogen Applications	kg/ha	15*	15**	30***
Capital	Dollars	2140***	3208***	2477***
Prices				
Corn Price	Dollars/kg	-0.003*	-0.002**	-0.001
Labor Price	Dollars/hr	0.19	0.38	-0.20
Land Price	Dollars/ha	7,346***	13,793***	14,569***
Nitrogen Price	Dollars/kg	0	0	-0.02
Field and Operator Structure				
Area Owned	Percent in (0,1)	-0.04	-0.15***	-0.17***
Area Rented for Fixed Cash Payment	Percent in (0,1)	0.05	0.05	0.19***
Area Rented for Flexible Cash Payment	Percent in (0,1)	0.02	0	0.03
Area Rented for Share of Crop	Percent in (0,1)	-0.02	0.11***	-0.04
Area Rented for Cash and Share of Crop	Percent in (0,1)	-	-	-
Area 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 Region				
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***

a Differences in means estimated using the delete-a-group jackknife procedure. Significance is denoted as *** p<0.01, ** p<0.05 and * p<0.10.

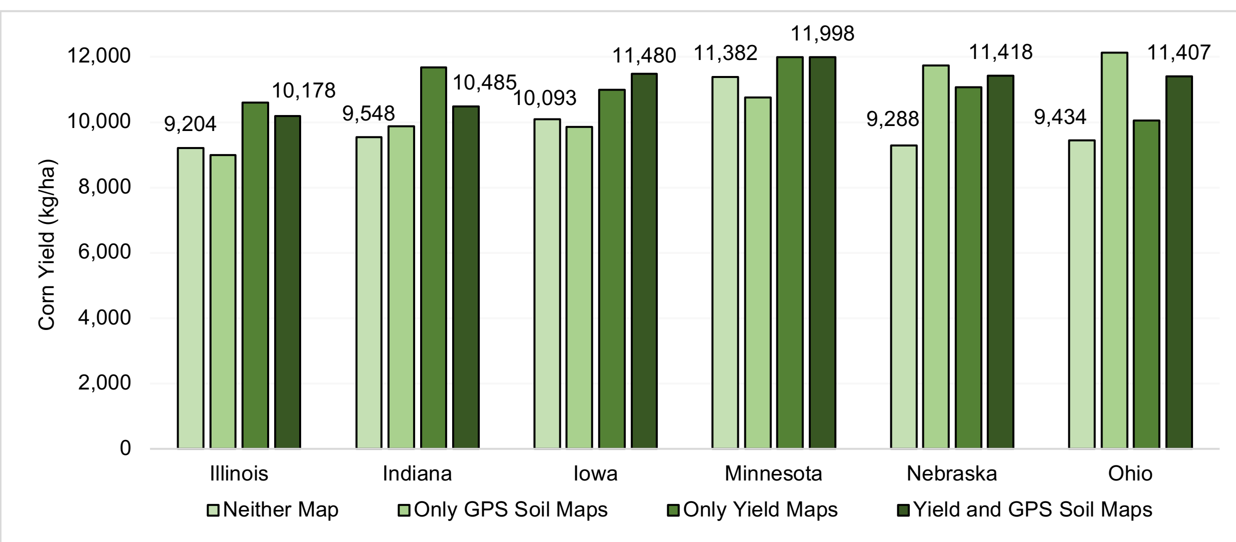

Fig. 1 Average Corn Yields on Fields with Yield Maps and GPS-based Soil Maps, 2010

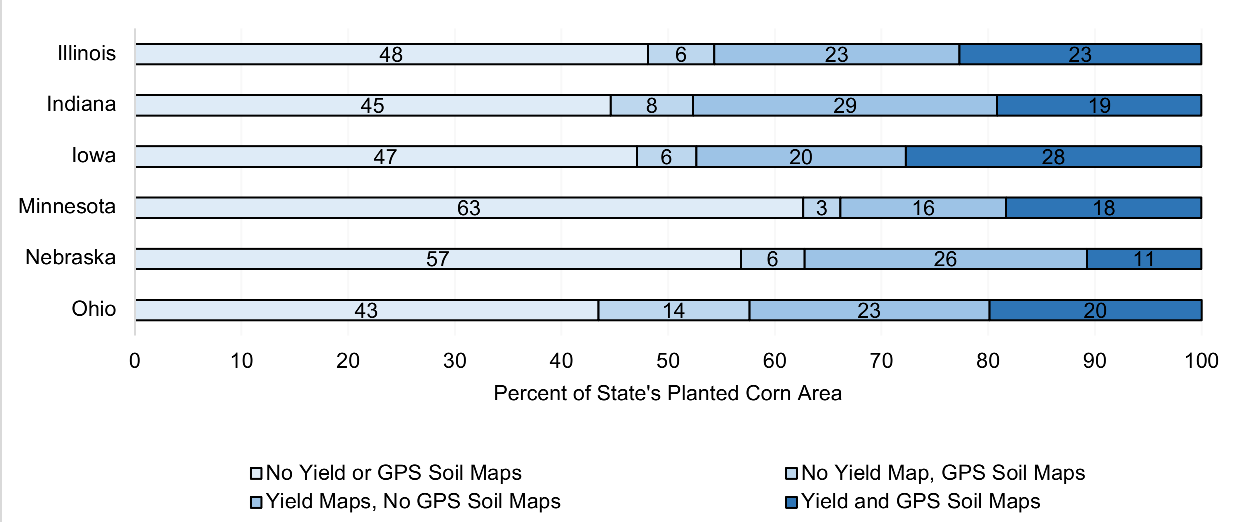

Fig. 2 Percentage of Planted Corn Area with Yield Maps and GPS-based Soil Maps, 2010

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 were insignificant in both equations. For example, the corn price, diesel price, wage rates, and land rental rates were all positively associated with adoption of both yield and soil maps, though large, jackknifed standard errors suggest that these prices had no meaningful impact. However, the cost of capital had a small but positive coefficient in the first equation, indicating that yield maps were adopted on fields with more intensive capital use. Insignificance of the capital variable 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 were insignificant in both equations, though its coefficient had the expected sign in the yield map equation. However, the controls for GPS-based soil map prices were significant at the 10% level or better in both equations. Higher soil map prices were associated with less adoption of these maps, as well as less adoption of yield maps, which could be indicative of complementarities between the two technologies.

In the yield map equation, significant impacts of inherent soil productivity and field ownership were found. Operators who own the field were 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 were generally insignificant in the regression equations. One important exception pertains to soil productivity captured by the NCCPI value – yield maps were adopted on fields that were more suitable for growing corn and soybeans. Finally, the correlation between the equations was 0.80 and significant at the 1% level, suggesting that adoption of both maps were correlated management decisions.

Stochastic Frontier and Efficiency Estimates

Table 4 contains coefficient estimates from the (second-stage) stochastic frontier analysis. Since the nature of the heteroscedasticity is unknown, a full specification that includes a set of variables hypothesized to influence the variance of both the noise and inefficiency terms was first estimated (model 1). A subset of regressors that did not significantly influence either variance term was then dropped (model 2). To investigate the extent to which ignored heteroscedasticity could bias parameter estimates, the results were compared to those under an assumption of homoscedasticity of both error terms (model 3).

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

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[b]	-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

a Estimates were expanded to the population of 2010 U.S. corn fields using a base weight. Standard errors were computed using the delete-a-group jackknife. Significance is ***p<0.01, **p<0.05, and *p<0.10.

b The 'years operating field' variable was divided by 10.

The elasticities associated with labor hours, nitrogen applications, and capital equipment were all statistically significant at the 1% level and had the expected sign and magnitude across the three specifications. Nitrogen applications and capital had 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 was 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 summed to 0.88-0.89, and a joint test of significance confirmed modest decreasing returns to scale, consistent with most empirical crop production studies (e.g., MacDonald et al. 2010, 2013).

Evidence on the relationship between soil quality, regional indicators, and field output was mixed. The soil productivity index for growing corn and soybeans (NCCPI) was insignificant, as was the indicator for whether the field contains any NRCS-designated highly erodible land. The standard errors of these regressors could have been inflated due to collinearity with indicators for the Heartland region and Northern Crescent region (Heimlich 2000). These regions included 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 (3), was 80-81%. This is somewhat low for U.S. field crops, though well within the range of U.S. agriculture more broadly. The 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 were approximately [0.50, 0.97], again consistent with the literature.

The empirical distributions of the technical efficiency estimates were negatively-skewed, as implied by the underlying stochastic frontier framework, though quite similar across three specifications (Figure 3). The most general model, specification (1), had relatively more density on [0.60, 0.80], while the homoscedastic model, specification (3) placed 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 were not being severely biased by ignoring heteroscedasticity or omitting map variables from the variance of the statistical noise.

Table 4. Stochastic Frontier Estimates[a]

	(1)	(2)	(3)
Input, Soil, and Region Characteristics Estimates, $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$			
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, $\hat{\boldsymbol{\alpha}}$			
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, $\hat{\boldsymbol{\delta}}_{\boldsymbol{u}}$			
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, $\hat{\boldsymbol{\delta}}_{\boldsymbol{v}}$			
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

a To ease computational burden, 'years operating field' were divided by 10 in specifications (1) and (2). The null hypothesis of constant returns to scale was tested 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.

Many of the regressors in the parameterization of the mean inefficiency term and variance terms were significant at the 10% level or lower. This provides some statistical validation of the 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 were 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 was of concern and that not accounting for this endogeneity could have biased associated parameter estimates; this statistical evidence validated the use of the two-step control function procedure.

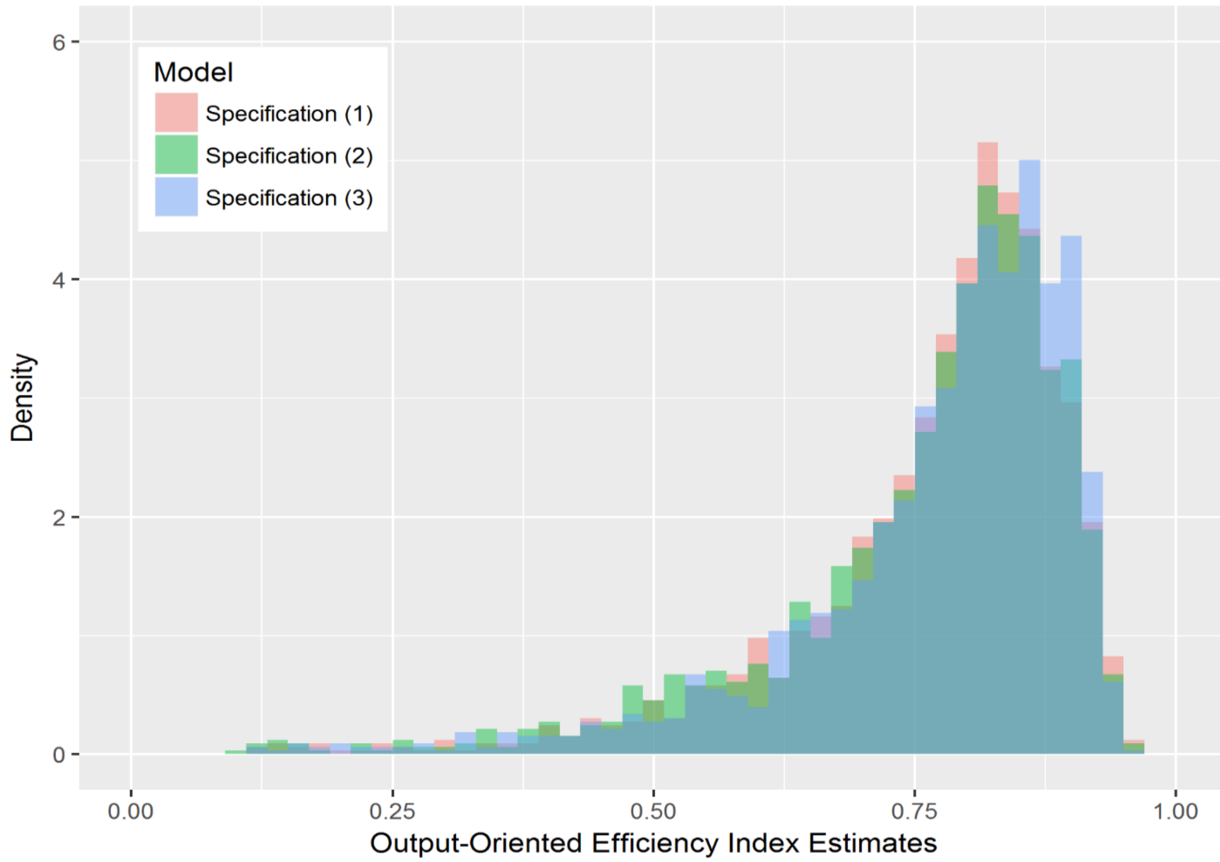

Fig. 3 Output-oriented Efficiency Index Estimates

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 inefficiency 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 consistent 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.[8] However, there has been a net beneficial effect: adoption of both maps was associated with a 0.04-0.18% reduction in inefficiency.

Adoption of yield maps 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 was 0.55-0.78 lower on fields whose yields had been mapped. Similar to its counterintuitive impact on mean inefficiency, soil map adoption was associated with an increase in the variance of inefficiency by 0.46-0.70.[9] As with the marginal effects of mean inefficiency, joint adoption of both maps had a positive impact on corn production by lowering the variance associated with inefficiency, if only slightly.

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[8] 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., variable rate technologies and guidance systems) could result in omitted variables bias. This explanation is unlikely given the relatively low correlations in the data among the different combinations of technologies.

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

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

	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, $\sigma_{u,i}^2$				
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

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

Two other regressors of interest, the operator's years of experience with the field and whether or not the field was owned, had small but intuitive marginal effects on technical inefficiency. Although insignificant in the first two specifications, in the homoscedastic model, corn fields that were owned by the operator had somewhat lower mean inefficiencies and lower variances (0.07% and 0.03% lower, respectively). An additional year of operating the field was 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 differences in the effects of these two regressors across the specifications could be because specification (3) also included an indicator for whether or not the field was rented free-of-charge and did not include re-scaled versions of the 'years operating the field' variable.[10]

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 hectares have shifted from mid-size farms to generally larger farms. Between 1982 and 2007, median farm size on U.S. cropland almost doubled from 239 hectares to 447 hectares. 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 (Coble et al 2016). 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.

In the absence of comprehensive data on how operators have begun to use and interact with "big data" and analytics-based inputs, insights can be gained from unexplored avenues by which information inputs may provide value to farmers. That is, it may be possible 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. The analysis suggests that farmers who

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

made use of yield maps (though not GPS-based soil maps) were more technically efficient than farmers who did not use such maps. This is similar to past findings that farms using mapping technologies had 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 was to analyze possible differences in technical efficiency on U.S. corn fields between adopters and non-adopters of GPS-based yield and soil maps. Adoption was modeled using a bivariate probit regression, which provided insights into the characteristics of fields, farms, and operators that influence mapping decisions. After controlling for endogenous choice of both maps, technical efficiency was found to be significantly influenced by use of yield maps (positively), use of soil maps (negatively), field ownership status (positively), and other structural characteristics. These impacts were estimated using a generalized heteroscedastic stochastic frontier method (Wang 2002) with a benchmark Cobb-Douglas production function. Further, results from the first-step generalized residuals provided evidence of endogenous yield and soil map adoption (Wooldridge 2014).

Adjusted tests of differences in means suggested several interesting trends across map adoption scenarios. Mapped fields were higher-yielding, insured at higher rates, and were relatively higher valued. These fields were located on generally larger farms with non-owner operators that had one-to-two years less experience with the field than on fields for which neither map technology was used. Although map adoption rates were 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 four caveats to the findings presented here. First, field-level prices for yield maps or soil maps were unobserved, 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 the regression-based approach to controlling for prices. Second, adoption of variable-rate technologies or guidance systems in the first or second stage of the regressions were not modeled. 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, productive inputs in the stochastic frontier were assumed to be 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. Fourth, a bivariate probit regression was used to model the joint adoption of yield and soil maps. Apart from the stringent assumptions necessary to justify application of the bivariate probit model, map use could be modeled as a continuous, dynamic problem rather than a discrete, one-shot decision.

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