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Precision Agriculture Technology Adoption and Technical Efficiency

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Abstract: We explore the relationship between precision agriculture (PA) technology adoption and technical efficiency using the 2016 USDA Agricultural Resource Management Survey (ARMS). Previous studies on the effects of PA examine technologies in isolation. However, efficiency gains from PA are likely cumulative, that is, the true impact of precision farming depends on the implementation of an overall precision strategy and integration of complementary tools. To address this gap in the literature, we perform a two-step analysis. First, we use cluster analysis to identify distinct producer groups in regards to their adoption of PA technologies. These producer groups map naturally onto the standard technology adoption curve (laggards, late majority, early majority, innovators). Second, we use stochastic frontier analysis (SFA) to estimate differences in technical efficiency between groups. We find efficiency gains associated with advanced PA adoption. Efficiency gains are largest as farms move from the late majority stage (passive data collection) to the early majority stage (use data collected to make actionable decisions) of technology adoption. Differences in efficiency across PA groups have strong implications for farm consolidation in U.S. agriculture.

Keywords: precision agriculture, technical efficiency, technology adoption

JEL Codes: Q16, Q12

Introduction

Precision agriculture (PA) uses inter- and intra-field variation to optimize input application and increase profitability. PA promises to enhance efficiency by reducing input costs without sacrificing yield, or by shifting the production frontier outward for a constant level of inputs. Technologies such as automated guidance systems, variable rate technology (VRT), and yield mapping have grown in popularity since their introduction in the 1990s, while newer technologies, including unmanned aerial vehicles (UAVs) and multi-spectral sensors, are being adopted more widely. Despite the promise of PA technology, its impact on efficiency is not well understood. Much of the research on PA adoption evaluates technologies independently without considering how producers often pool complementary tools to create overarching PA systems. Failure to examine PA collectively provides an incomplete picture regarding the benefits of PA adoption.

A growing body of research assesses the profitability of PA adoption (Miller et al., 2018; Erickson, Lowenberg-DeBoer, and Bradford, 2017; Schimmelpfennig and Ebel, 2016; Lambert, Paudel, and Larson, 2015; Shockley, Dillon, and Stombaugh, 2011; Griffin et al., 2004). Schimmelpfennig (2016) uses ARMS data to shows that PA has a small positive impact on farm net returns and operating profits, but that benefits vary by technology type. Thompson et al. (2019) find significant variation in the benefits perceived by producers from PA adoption, depending on the technology. Earlier studies link the success of PA technology to the availability of detailed intra-field information (Bullock et al., 2009; Tenkorang and Lowenberg-DeBoer, 2008; Bullock and Lowenberg-DeBoer, 2007; Bullock, Lowenberg-DeBoer, and Swinton, 2002; Bullock and Bullock, 2000). Farm information is shown to be a complementary input in the use of PA, but must first be collected and made actionable to generate benefits (Bullock et al., 1998).

Rather than examining PA technologies in isolation, more recent work examines PA technology adoption and usage in bundles. Lambert, Paudel, and Larson (2015) use principal components analysis (PCA) to identify three PA bundles among U.S. cotton farmers: (i), yield monitors and grid soil sampling, (ii), digital maps and farm data software, and (iii), aerial imagery, handheld GPS devices, soil survey maps. Extending their work, Miller et al. (2018) categorize PA technologies as: i), embodied knowledge technologies, requiring little informational input to be made useful, or ii), information intensive technologies, which generate large volumes of data requiring additional analysis to inform future production decisions. Ofori, Griffin, and Yeager (2020) show that farmers' time-to-adoption is shorter for embodied knowledge technologies than for information intensive technologies, a likely result of the "out-of-the-box" functionality afforded by tools such as GPS guidance and section control systems.

Of particular interest is the ability of adopters of different PA technology bundles to improve productivity and input efficiency. Confirming the importance of integrating complementary technologies, Schimmelpfennig and Ebel (2016) find that adopting VRT alone does not generate variable cost savings, but does if bundled with yield monitoring and soil mapping. Khanna (2001) finds that sequentially adopting soil testing and variable rate fertilizer can lead to higher nitrogen productivity than only soil testing, but that the benefits are heterogeneous.

Technical efficiency, which measures the extent to which a firm achieves its feasible production frontier for a given mix of inputs, is commonly used to measure farm productivity. It. A large body of work finds positive technical efficiency benefits associated with agricultural technology adoption (Mayen, Balagtas, and Alexander, 2010; Chen, Huffman, and Rozelle, 2009).

However, in some cases positive efficiency effects may be driven by scale economies enjoyed by larger operations (Xin et al., 2016; Mugera and Langemeier, 2011; Page, 1984).

There are two channels through which PA can impact technical efficiency based on the taxonomy proposed by Miller et al. (2018). First, embodied knowledge technologies may directly enhance input usage, e.g. GPS auto-steer reduces overlap, saving fuel, chemicals, and time in the field without sacrificing yield. Second, information intensive technologies deliver field data that influence site-specific input decisions, e.g. detailed soil nutrient maps inform precise nutrient application rates, thus lowering the operation's fertilizer costs while maintaining or even increasing output.

McFadden (2017) uses USDA Agricultural Resource Management Survey (ARMS) data to estimate the impact of yield and soil mapping on technical efficiency. He finds that the use of yield mapping increases technical efficiency while soil mapping depresses efficiency, though the net effect of adopting both remains slightly positive. One possibility for the unexpected negative association between soil mapping and efficiency is the omission of other relevant PA technologies. The way producers integrate mapping tools with complementary technologies as part of a broader PA strategy should be considered. We build on the work of McFadden (2017) by including all available PA technologies provided in the ARMS and comparing technical efficiencies across technology bundles that reflect producer adoption patterns.

The purpose of this study is twofold. First, we use cluster analysis to group producers based on their adoption of PA technology. Second, we use stochastic frontier analysis (SFA) to compare technical efficiency scores across PA bundle adopters. We use the 2016 ARMS, which provides detailed field-level information on management practices and resource use for a representative sample of corn producers. Though both topics have been approached separately elsewhere in the production literature—Lambert, Paudel, and Larson (2015), Schimmelpfennig and Ebel (2016), and Miller et al. (2018) in the case of PA bundling, and McFadden (2017) in the case of PA and technical efficiency—the two have yet to be examined jointly.

We contribute to the existing literature on PA adoption and technical efficiency by evaluating the impact of PA as practiced by U.S. farmers. Ignoring PA bundling fails to capture the cumulative impact of PA on efficiency. In the following sections, we provide an overview of the 2016 ARMS dataset, describe our methodological approach, summarize our results, and discuss their implications.

USDA Agricultural Resource Management Survey (ARMS) Data

The Agricultural Resource Management Survey (ARMS) is a comprehensive, multi-phase survey conducted yearly by the USDA National Agricultural Statistical Service (NASS) and USDA Economic Research Service (ERS). ARMS employs a stratified sampling design and assigns sampling weights (expansion factors) to participating farms to create a nationally representative sample.[1] The first phase of the survey identifies qualifying farms that produce the specified commodity. USDA targets a different commodity each year on a rotating basis, typically every five to six years. Phase II documents management practices such as seed, nutrient and chemical application, labor and machinery usage, and technology adoption for a single field within the respondent's operation. Output (bushels) produced from the field is also recorded, allowing researchers to tie production outcomes to managerial decisions. The Phase III questionnaire catalogues farm-level and operator characteristics such as demographics, farm size, and ownership structure.[2] Nearly two-thirds (65%) of Phase II respondents also completed the Phase III survey.

[1] Sampling weights represent the inverse of the probability of selection based on NASS's sampling design.
[2] Access to ARMS farm- and field-level data is strictly restricted to protect personally identifiable information.

Phase II of the 2016 corn survey provides much greater detail on PA technology adoption than the 2010 survey, which was the last iteration of ARMS for corn. It includes questions about the use of yield monitors, GPS mapping, automated guidance systems, and variable rate technology (VRT). Producers are also asked what types of farm data they collect from the field, the tools used to store and analyze data, and whether a technical consultant is employed to help interpret data. These questions allow us to observe how farmers combine "hard" PA tools (equipment and machinery) with "soft" PA tools (software, GPS maps, ag-tech services).

Summary statistics for variables relevant to this study are displayed in Table 1. Means are expanded to represent all corn fields in the U.S. using NASS-provided expansion weights. Our sample consists of 1,594 farms that completed the Phase II questionnaire, of which 1,038 also completed Phase III.[3] Observed fields are expanded to represent over 75 million corn acres nationwide, equivalent to approximately 80 percent of 2016's planted corn acreage. Adoption rates for PA technologies are slightly higher than previous estimates from ARMS, indicating modest growth in ag-tech usage (Schimmelpfennig, 2016; Schimmelpfennig and Ebel, 2016).

Sixty-six percent of corn farms collect at least one type of farm data. Yield monitors are the most popular data collection tool at 55% of corn farms, up from 48% in 2010. However, only 32% of farms use yield monitor data to generate GPS yield maps, indicating a disconnect between data collection and usage for decision making on some farms. GPS guidance is the second most commonly used "hard" PA technology. Use of guidance systems grew from 29% in 2010 to 42% in 2016. VRT for seeding, fertilizer, or pesticides was used on 26% of corn farms in 2016 compared to 19% in 2010. PA technology adoption paths are conditional, however. For example, 57% of

[3] We restrict our sample to those growing corn conventionally and reporting positive production inputs, i.e. non-zero values for nitrogen, pesticide, capital, and labor. Inclusion of zeros for inputs is shown to significantly bias output elasticities downward in Cobb-Douglas production frontier estimation (Battese, 1997).

farms using variable rate fertilizer collect soil core tests vs. 20% of farms overall. Although soil core sampling is considered an "entry-level" PA practice, it has a lower adoption rate than yield monitors or GPS guidance, technologies that often come standard with new equipment.

Advanced data collection technologies such as drones, crop sensors, and soil sensors show low rates of adoption—likely due to the novelty of these products at the time of the survey. However, farms already using well-established PA technologies (yield monitors, GPS guidance, and VRT) are more likely to use advanced data collection practices. About half of producers collecting some type of farm data (31% overall) share their data with an outside service provider or extension agent. One-third of producers access farm data on a personal computer while 14% access their data on a mobile device. The least popular form of data access is through an ag-tech company website such as Bayer's Climate FieldView or John Deere's Operations Center at eight percent of farms. This is not surprising since ag-tech software platforms were still relatively new in 2016.

Cluster Analysis

Table 1 indicates moderate growth in the adoption of traditional PA technologies among corn producers but low diffusion of advanced data collection and analysis tools.[4] Adoption of PA is sequential; producers adopt technologies piece-meal and evaluate their effectiveness before adding complementary tools (Lambert, Paudel, and Larson, 2015; Schimmelpfennig and Ebel, 2016; Miller et al., 2017). Though ARMS data is cross-sectional, preventing us from analyzing a farm's technological progression over time, we can assess farms' state of PA adoption at a given time.

[4] Trends in adoption of advanced data intensive PA such as remote sensing and ag-tech software are harder to identify at the national-level. Most of the ARMS literature on PA adoption focuses on well-established technologies (yield monitoring, GPS guidance, soil sampling, and VRT).

We apply agglomerative hierarchical cluster analysis (HCA) to observations based on the PA variables shown in Table 1.[5] Ward's linkages method is used to join clusters that minimize total within-cluster variance.[6] An important consideration in multivariate analysis is determining the optimal number of clusters (PA groups). We retain four clusters based on the scree plot in Figure 1, which shows a distinct "elbow point" in total within-cluster sum of squares at the fourth cluster (Ketchen and Shook, 1996).[7] Four clusters balances the desire to minimize cluster variance with the need to group farms parsimoniously. Inspection of the clustering dendrogram confirms this choice (see Figure A1 in the supplementary appendix).

Table 2 displays summary statistics for PA, production, and demographic variables by cluster assignment. A noticeable pattern emerges with respect to PA adoption across groups; clusters correspond to stages in the technology adoption curve (Rogers, 1962). A complete lack of PA adoption characterizes the 305 farms in cluster 1. Given that yield monitoring technology—considered the "gateway" PA device—has been commercially available since the early 1990s and often comes standard with new combine harvesters, this group can be safely described as "laggards" with respect to PA. Note that while farms in cluster 1 are 29% of our sample, they expand to represent over 35% of U.S. corn farms based on NASS-provided expansion weights, making laggards the largest segment of the PA technology adoption curve.

Farms in the "late majority" stage (cluster 2) collect farm data and have high rates of yield monitoring (68%), but are unlikely to produce yield maps. Rates of adoption for most other PA

[5] For comparison, a principal components analysis (PCA) was performed to group technologies, rather than farms, based on latent relationships in adoption patterns. PCA produces groups of technologies that are generally consistent with the results of our cluster analysis.
[6] Ward's linkage was chosen based on its superior ability to group non-adopters. The Gower dissimilarity method was applied to accommodate binary data. Cluster results are robust to different distance methods. Cluster analysis was performed using the Cluster package in R.
[7] The heuristic "elbow method" chooses the optimal number of clusters via visual inspection of the scree plot. Clusters are retained up to the point at which the last substantial drop in total within-cluster sum of squares occurs.

technologies are similarly low among this group, with the exception of GPS guidance, soil core sampling, accessing data on a desktop computer, and data sharing which are moderately common. The late majority cohort is most recognizable for adopting PA passively, e.g., upgrading to a yield monitor equipped combine but failing to fully utilize the technology.

Cluster 3 groups farms in the "early majority" stage of the PA technology adoption curve. These farms are distinct from late majority farms in both their propensity to use a yield monitor and to create GPS yield maps, suggesting the transition from late to early majority depends on the farm's ability to make data actionable. Other notable differences include significantly higher rates of variable rate seeding and fertilizer application, GPS guidance, and accessing farm data through computers, mobile devices, and ag-tech company websites.

"Innovators" or "early adopters" are the least common, representing 14% of all U.S. corn farms. These farms have the highest rates of adoption for all forms of PA. In addition to the classic PA technologies, innovators are likely to use soil core data, GPS soil mapping, VRT, farm data software, and share their data with service providers. Advanced data collection technologies such as soil and crop sensors and drones are relatively common among this group. For example, nearly one in five early adopters collect aerial imagery via drone or satellite vs. four percent of all corn producers.

While farms are more concentrated in less advanced PA adoption groups, the diffusion of innovation in PA is more evenly distributed in terms of acres operated. Figure 2 shows that farms in mature stages of the adoption curve represent fewer farms, but are responsible for a greater share of corn acreage and production. Laggards, for example, are the largest group by number of farms, but represent only 21% of corn acres planted in 2016. Conversely, the innovator group has the fewest number of farms, but contributes nearly one fourth of all corn production. This is because farms classified as PA innovators are over five times the size of laggard farms on average—implying significant economies of scale associated with PA.

In addition to size, corn farms at different stages of the PA technology adoption curve have starkly different production and demographic characteristics. Input application rates are significantly higher among farms with high rates of PA adoption. They are also younger, more educated, and more likely to rent farmland. Differences in corn yields across cluster groups suggests that farms actively using PA are more productive. The largest productivity benefit appears to take place between the late and early majority stage where corn yields increase by 10%. In the following section, we use stochastic frontier analysis to formally test for differences in efficiency between PA groups.

Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) has been used throughout the agricultural production literature to estimate farm technical efficiency (Kumbhakar and Lovell, 2000). In the SFA framework, output is a function of both a deterministic component (production frontier) and a composed error, which is the sum of a stochastic residual and a non-negative inefficiency term. Deviations from the production frontier result from random noise (e.g. production shocks) and systematic factors that depress input productivity. We adapt the approach taken by Reifschneider and Stevenson (1991), Caudill and Ford (1993), and Caudill, Ford and Gropper (1995) (referred to as the RSCFG model) as follows:

$$\ln y_i = \ln \boldsymbol{x}_i' \boldsymbol{\beta} + v_i - u_i \tag{1}$$

$$v_i \sim N(0, \sigma_{vi}^2)$$

$$u_i \sim N^+(0, \sigma_{ui}^2)$$

$$cov(v_i, u_i) = 0,$$

where y_i is output (total corn bushels) produced by field i. The vector $\boldsymbol{x}_i$ contains inputs that shape the production frontier including nitrogen fertilizer, pesticides, capital value, labor hours, total farm acres, corn production practice (irrigated vs. non-irrigated), and regional dummy variables to control for agro-climatic conditions that may shift the production frontier for a given mix of inputs. We assume a standard Cobb-Douglas functional form for the production frontier.

Productive inputs were selected following related literature using ARMS data (McFadden, 2017; Schimmelpfennig, 2016). Nitrogen fertilizer used is the sum of chemical nitrogen and the nitrogen content of manure applied to the field. Pesticide usage is the total pounds of active ingredients from herbicides, insecticides, and fungicides applied to the field. Capital value is the total recovery cost of machinery and equipment required to produce corn on the field. Field labor is measured by the total hours of labor (both paid and un-paid) employed. For regional dummy variables, we use the seven farm resource regions designated by USDA Economic Research Service (ERS) (Heimlich, 2000).

The stochastic error v_i is mean-zero normally distributed while u_i is non-negative and follows a half-normal distribution. Both v_i and u_i have field-dependent variance structures. Assuming heteroscedasticity in both error terms addresses two issues. One, if ignored, heteroscedasticity can produce biased and inconsistent estimates of the SFA parameters, and two, by parameterizing the variance of u_i, we can model the determinants of technical efficiency (Kumbhakar and Lovell, 2000; Wang and Schmidt, 2002).

$$\sigma_{vi}^2 = \exp(\boldsymbol{z}_i'\boldsymbol{\Theta}_v + \boldsymbol{d}_i'\boldsymbol{\Omega}_v) \tag{2}$$

$$\sigma_{ui}^2 = \exp(\boldsymbol{z}_i'\boldsymbol{\Theta}_u + \boldsymbol{d}_i'\boldsymbol{\Omega}_u).$$

The vector $\boldsymbol{z}_i$ includes farm and operator characteristics that influence the efficiency such as operator experience, education, and land tenure. Measures of PA technology adoption make up the vector $\boldsymbol{d}_i$.

Inefficiency can be modeled in the stochastic frontier framework in one of several ways depending on the assumed distribution of u_i. If u_i follows a truncated-normal distribution, variables that affect inefficiency can shift its pre-truncated mean ($E(u_i) = g(\boldsymbol{z}_i)$), scale its variance ($\sigma_{ui}^2 = f(\boldsymbol{z}_i)$), or both. However, this is computationally demanding and the log-likelihood function is unlikely to converge for a large number of determinants, as is true in our case (Kumbhakar et al., 2017). Moreover, the choice of which variables to include in the conditional mean and variance models can become arbitrary. We opt for the more parsimonious dual-heteroscedasticity model used elsewhere in the production literature (Mayen et al., 2010; Hadri, Guermat, and Whittaker, 2003; Hadri, 1999).

Given the parameterization above, the composed error term has the following distribution:

$$f(\varepsilon_i) = \frac{2}{\sigma_i}\phi\left(\frac{\varepsilon_i}{\sigma_i}\right)\left[1 - \Phi\left(\frac{\varepsilon_i\lambda_i}{\sigma_i}\right)\right] \tag{3}$$

where $\sigma_i^2 = \sigma_{vi}^2 + \sigma_{ui}^2$, $\lambda_i = \frac{\sigma_{ui}}{\sigma_{vi}}$, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal PDF and CDF, respectively. Based on (3), the log-likelihood function to be maximized is:

$$\ln L\left(\boldsymbol{\beta}, \boldsymbol{\Theta}_v, \boldsymbol{\Theta}_u, \boldsymbol{\Omega}_v, \boldsymbol{\Omega}_u, \sigma_i, \lambda_i\right) = n\ln\sqrt{2/\pi} - n\ln\sigma_i - \frac{1}{2\sigma_i^2}\sum_{i=1}^{n}\varepsilon_i^2 \tag{4}$$

$$+\sum_{i=1}^{n}\ln\left[1 - \Phi\left(\frac{\varepsilon_i\lambda_i}{\sigma_i}\right)\right].$$

We obtain estimates of individual inefficiency scores conditional on the composed error term according to Jondrow et al. (1982).

$$E[u_i|\varepsilon_i] = \hat{\mu}_{*i} + \frac{\hat{\sigma}_{*i}\phi\left(-{}^{\hat{\mu}_{*i}}/_{\hat{\sigma}_{*i}}\right)}{1-\Phi\left(-{}^{\hat{\mu}_{*i}}/_{\hat{\sigma}_{*i}}\right)}, \tag{5}$$

where $\hat{\mu}_{*i} = \frac{\varepsilon_i \hat{\sigma}_{ui}^2}{\hat{\sigma}_{vi}^2 + \hat{\sigma}_{ui}^2}$ and $\hat{\sigma}_{*i} = \sqrt{\frac{\hat{\sigma}_{vi}^2 \hat{\sigma}_{ui}^2}{\hat{\sigma}_{vi}^2 + \hat{\sigma}_{ui}^2}}$. Output-oriented technical efficiency is computed as the ratio of observed output to potential output, accounting for random noise. It measures the degree to which a farm achieves its production potential with a given level of inputs.

$$TE_i = \frac{y_i}{\exp(\ln \boldsymbol{x}_i' \boldsymbol{\beta} + v_i)} \tag{6}$$

$$= \frac{\exp(\ln \boldsymbol{x}_i' \boldsymbol{\beta} + v_i - u_i)}{\exp(\ln \boldsymbol{x}_i' \boldsymbol{\beta} + v_i)}$$

$$\exp(-u_i).$$

To estimate (6) empirically, we use the conditional expectation proposed by Battese and Coelli (1988).

$$\widehat{TE}_i = E[\exp(-u_i)|\varepsilon_i] \tag{7}$$

$$= \frac{1-\Phi\left(\hat{\sigma}_{*i} - {}^{\hat{\mu}_{*i}}/_{\hat{\sigma}_{*i}}\right)}{1-\Phi\left(-{}^{\hat{\mu}_{*i}}/_{\hat{\sigma}_{*i}}\right)} \exp\left(-\hat{\mu}_{*i} + {}^{1}/_{2}\,\hat{\sigma}_{*i}^2\right).$$

Note that by our specification in (2), the expected value of inefficiency is proportional to σ_{ui}^2, so we can express the un-conditional expectation of u_i as a function of $\boldsymbol{z}_i$ and $\boldsymbol{d}_i$ (Kumbhakar et al., 2017).

$$E[u_i|\boldsymbol{z}_i, \boldsymbol{d}_i] = \sqrt{{}^{2}/_{\pi}}\,\hat{\sigma}_{ui} = \sqrt{{}^{2}/_{\pi}}\,\exp\left[{}^{1}/_{2}\left(\boldsymbol{z}_i'\widehat{\boldsymbol{\Theta}}_u + \boldsymbol{d}_i'\widehat{\boldsymbol{\Omega}}_u\right)\right]. \tag{8}$$

The average marginal effects of demographic and PA adoption variables on un-conditional u_i are shown below.

$$\frac{\partial E[u_i|\boldsymbol{z}_i,\boldsymbol{d}_i]}{\partial z_k} = \sqrt{1/_{2\pi}}\,\widehat{\Theta}_{uk}\sum_{i=1}^{n}\hat{\sigma}_{ui} \tag{9}$$

$$\frac{\partial E[u_i|\boldsymbol{z}_i,\boldsymbol{d}_i]}{\partial d_k} = \sqrt{1/_{2\pi}}\,\widehat{\Omega}_{uk}\sum_{i=1}^{n}\hat{\sigma}_{ui}.$$

Note that the coefficients in $\widehat{\boldsymbol{\Theta}}_u$ and $\widehat{\boldsymbol{\Omega}}_u$ and their associated marginal effects will share the same sign, but differ in magnitude depending on the sample average of $\hat{\sigma}_{ui}$.

We estimate the above likelihood function with STATA's FRONTIER command, which accommodates the dual heteroscedasticity approach and NASS-provided sampling weights. All standard errors are computed using the standard delete-a-group jackknife procedure with 30 replicates. See Dubman (2000) for a detailed explanation of the ARMS variance estimation procedure.

Results

Before estimating the stochastic frontier model described above, we estimate an initial Cobb-Douglas production function via ordinary least squares (OLS) and test for negative skewness in the residual error, i.e. $u_i > 0$. See the appendix for Cobb-Douglas regression results and a visual of the error distribution. The error skewness parameter of -0.65 fails both the Coelli (1995) and D'Agostino, Belanger, and D'Agostino (1990) tests of zero skewness at the 0.01 level, providing evidence for the presence of inefficiency.

We then estimate a stochastic frontier model explaining inefficiency and error variance with individual PA technologies (results shown in Table A2 of the supplemental appendix). Out of 18 PA technologies and data practices, 12 enter the inefficiency variance model negatively, implying a generally positive relationship between PA adoption and efficiency. However, none of their associated coefficients are statistically significant at the 0.10 level. Moreover, explaining efficiency using discrete, un-grouped variables fails to capture the sequential nature of PA adoption. Farms at different stages of the PA adoption curve, and that share similar technology bundles, may have differences in technical efficiency that go un-detected by this specification.

We instead use dummy variables for PA groups as assigned by our hierarchical cluster analysis, allowing us to estimate the cumulative impact of PA on inefficiency. The laggard group—those with no adoption of any PA technologies—forms the baseline for interpreting the coefficients associated with the late majority, early majority, and innovators dummy variables. As is clear from Table 2, farms at different stages of PA adoption vary across several dimensions. To control for confounding factors that affect inefficiency and PA usage, we include several farm and operator characteristics related to operator ability and technology adoption. These comprise the operator's years of experience farming, farming experience squared, operator educational attainment (college and up), whether the observed field is rented (cash rent or crop share), and the operator's ownership share in the farm enterprise. We present the results of this approach in Table 3.

The sum of estimated output elasticities in Table 3 indicates slightly decreasing returns-to-scale in the production frontier. A joint Wald test for constant returns-to-scale is rejected at the 0.10 level. Coefficients on logged inputs take the expected sign and size with the exception of total farm size, which is small in magnitude and statistically insignificant. Irrigated corn fields produce an average of eight percent less output than dryland corn fields, though the difference is not significant at conventional levels. Capital and applied nitrogen having the largest impact on production with output elasticities of 0.33 and 0.30, respectively. Regional differences in corn production are apparent from Table 3. All regions in the sample have lower average production levels relative to the Heartland (i.e. Corn Belt).

The estimated output-oriented technical efficiency index has a mean of 0.81 and a median of 0.83. This is generally consistent with estimates found elsewhere in the productivity literature (Bravo-Ureta, 2007) and very similar to those estimated using ARMS data (McFadden, 2017). The average inefficiency score (u_i) of 0.23 implies that, for the average farm in our sample, total corn production could increase by 23% without altering inputs. Mean standard deviations of the random noise and inefficiency terms are 0.38 and 0.30, respectively. Systematic inefficiency is responsible for close to 40% of total error variance on average. Concurrently, we perform a likelihood-ratio test of the null hypothesis that $\sigma_{ui}^2 = 0$, i.e. that no inefficiency is present and the OLS estimator is sufficient (Coelli, 1995). We compute a traditional likelihood ratio test statistic, $LR = -2[L(H_0) - L(H_a)]$, where $L(H_0)$ is the log-likelihood from the OLS model assuming $\sigma_u^2 = 0$ and $L(H_a)$ is the log-likelihood from the stochastic frontier model allowing for a positive σ_u^2. The test statistic of 35.59 rejects the null hypothesis at the 0.01 level.

Table 3 reports the estimated coefficients for the σ_{vi}^2 and σ_{ui}^2 parameterization shown in equations (2). In general, farm characteristics and PA adoption do not have a significant impact on random error variance. Cash rented or crop-share fields have significantly lower error variance. However, a test that the determinants of σ_{vi}^2 are jointly zero cannot be rejected, supporting homoscedasticity in the random error.

Conversely, the variance of inefficiency—and consequently, its mean—is significantly related to PA adoption. The coefficient for the late majority group (those that collect farm data passively) is -0.63 and statistically insignificant. The effect grows in magnitude and significance for more advanced PA groups. Relative to non-adopters, log variance of inefficiency falls by 1.13 for the early majority group (farms with high rates of yield mapping and GPS guidance) and by 1.40 for innovators (advanced PA adopters); both effects are significant at the 0.05 level. While the coefficient on the innovators group is 24% larger than that of the early majority group, a T-test cannot reject the hypothesis that their true values are equal. Farm and operator characteristics generally take the expected sign with respect to inefficiency, but lack statistical significance in most cases. Only the positive effect of renting the field enters the inefficiency model significantly at the 0.10 level. While these coefficients are useful in determining the directions of the effects of our variables of interest, they are not directly interpretable.

Table 4 reports the average marginal effects of each regressor on (un-conditional) mean inefficiency. Marginal effects are calculated according to the formulas shown in equation (9) and standard errors are constructed using the delete-a-group jackknife procedure.[8] All marginal effects are statistically significant at the 0.01 level. The non-linear effect of farming experience suggests that operators early and late in their careers are the least inefficient. An additional year of farming experience changes inefficiency by 0.005 – $0.0001 exper^2$, which is positive until about 36 years and becomes negative thereafter. Although this result appears counterintuitive at first glance, it may reflect farm succession patterns. For example, it may be an indication that young farmers initially benefit from human capital and expertise bestowed by the prior generation, but then experience a period of deteriorating efficiency when operating independently before they gain enough experience of their own. Efficiency gains achieved later in their careers are inherited by the next generation, repeating the cycle.

The average marginal effect of a college education on inefficiency is -0.01, which translates to a four percent reduction in inefficiency over farms with non-college educated operators. College may be a proxy for superior farming ability where efficient producers are more likely to have

[8] Specifically, sample average marginal effects are calculated for the full sample and each of 30 replicate samples with adjusted replicate weights provided by USDA NASS. For each variable, the squared differences between replicate sample marginal effects and the full sample marginal effect are summed to produce the standard error.

higher educational attainment. Rented fields have inefficiency scores that are 0.09 (46%) higher than owned fields—possibly the result of shorter land tenure. Inefficiency is negatively related to the operator's ownership share in the farm, though the effect is small in magnitude.

Table 4 shows a clear pattern of improved efficiency (reduced inefficiency) as farms advance through the PA technology adoption curve. Marginal effects represent mean differences in inefficiency scores between laggards (non-adopters) and farms with more sophisticated PA adoption bundles, conditional on relevant farm characteristics. Inefficiency is 0.07 lower for the late majority group than laggards. The difference grows to 0.13 for early majority farms and 0.16 for the most innovative farms. Put another way, innovators are able to achieve 16% more output (corn bushels) than laggards with the same amount of inputs. To interpret these effects in context, we report mean technical efficiency and inefficiency by PA adoption group in Table 5 (see equations (5) and (7)).

As expected, laggards have the lowest levels of technical efficiency and highest levels of inefficiency and efficiency rises at each stage of the PA adoption curve. Differences in mean inefficiency scores shown in Table 6 are largely consistent with average marginal effects.[9] The marginal effect of -0.07 for late majority farms translates to a 26% reduction in inefficiency associated with adoption of the most basic PA technology package. Farms in the early majority stage of PA adoption are 46% less inefficient than laggards while innovators are 57% less inefficient. Comparing mean levels of technical efficiency across PA groups shows that late majority farms are four percent more efficient, early majority farms are 10% more efficient, and innovators are 12% more efficient than laggards. Our results show that efficiency gains are the largest between the late and early majority stages.

[9] Note that marginal effects are conditional on farm and operator characteristics while Table 6 reports un-conditional means. The slight differences observed between marginal effects and mean comparisons is attributable to this.

We graph the distributions of technical efficiency and inefficiency by technology adoption stage in Figure 3. Figure 3a shows a clear rightward shift in the distributions of technical efficiency for the early majority and innovator groups with high concentrations of farms at high levels of efficiency. This pattern is mirrored for inefficiency in Figure 3b. Inefficiency scores are centered at the lower tail of the distribution for early majority and innovators. The spread of these distributions also vary by group. The boxplots in Figure 4 show that, not only the median, but the variability of efficiency and inefficiency are significantly improved as farms move further up the PA adoption curve. It is worth noting that the relationship between inefficiency variance and group assignment is agnostic from equation (2). The fact that inefficiency variance grows (and variance of technical efficiency shrinks) in relation to advancing stages in PA adoption is an empirical result and not imposed a priori.

We consider several specification robustness checks in the supplemental appendix. These include a test for omitted variable bias resulting from scale economies in the inefficiency and random noise parameterization and a check for heterogeneous production frontiers á la Mayen et al. (2010). Our main findings are largely robust to these tests.

Discussion

Our results show meaningful increases in average technical efficiency between farms at latter stages of the PA technology adoption curve. Moreover, the degree of variation in inefficiency is reduced as farms combine additional PA technologies. Going from the laggard stage with no adoption to the early majority stage—where some data is collected and yield monitors are often used—is associated with modest improvements in technical efficiency. The largest improvement in efficiency is observed between the late and early majority stages. Mean efficiency rises by 5% while mean inefficiency falls by 25% between these stages (see Table 5).

The primary distinction between farms in the late and early majority groups is that of passive and active farm data usage—particularly the conversion of yield monitor data into GPS yield maps. Rates of VRT and accessing data on a computer and sharing farm data show moderate growth between these stages. This pattern supports earlier observations that reliable information is a necessary input in successful PA implementation (Bullock et al., 2009). It also implies that "embodied knowledge" technologies such as GPS guidance—adoption of which rises substantially between the late and early majority stages—can improve the efficiency of inputs, most likely through the elimination of overlap or convenience (Thompson et al., 2019; Miller et al., 2018). Another notable distinction is the relatively low rates of soil core testing among farms in the early majority group. Considering that over half of early majority farms use some form of VRT compared to just 17% of late majority farms, it is likely that variable rate application prescriptions are being informed by GPS yield map data.

We observe small marginal improvements in efficiency (two percent increase in mean technical efficiency, 11% decrease in mean inefficiency) for farms that advance to the innovators group, which is recognizable for its high rates of data collection, mapping, VRT, and data analysis via computers, mobile devices, and ag-tech software platforms. Unlike early majority farms, nearly all innovators perform soil core testing and GPS soil mapping. The combination of data collection and analysis with hard PA technologies such as variable rate applicators may explain the incremental improvements in efficiency at the innovators stage. Large advances have taken place in the ag-tech marketplace in recent years. Investment in the ag-tech sector grew by 43% between 2017 and 2018 to nearly $17 billion. Of this, about $7 billion was invested in "upstream" startups providing data and technology services to the farm (AgFunder, 2019). Our results confirm that integrating these novel technologies with well-established PA systems can lead to improved resource allocations, but that the incremental benefits are relatively small.

However, while innovators make up only 14% of corn farms, they are responsible for 24% of all U.S. corn acreage due to their large average size. Small marginal improvements in efficiency may warrant investment in advanced PA and farm data technologies if aggregated over a large scale. The potential for scale economies in PA has strong implications for farm consolidation. Investment in PA may be cost-prohibitive for small farms—who forfeit the potential improvements in productivity—while large operations are simultaneously more likely to adopt novel PA systems and to enjoy the associated efficiency benefits. Though consolidation in row-crop agriculture has occurred steadily over the previous three decades, wide spread use of PA among large operations could accelerate this trend, particularly in the presence of low operating margins (MacDonald, Hoppe, and Newton, 2018).

Our results also highlight the value of integrating data into the PA system. Farm data satisfies the definition of a factor of production in the sense that a given level and proportion of hard inputs become more productive if informative field data can be acquired (Berczi, 1981). The strong association we find between technical efficiency and active use of yield monitor data supports this claim. However, the degree to which PA data and information impact output will vary by data source, the associated collection costs, and the farmer's ability to make the data actionable.

Several papers attempt to quantify the productive value of information and data in agriculture. Muller (1974) estimates the effect of information on technical efficiency in California dairy farms directly by including proxies of information availability as output elasticity augmenters. Shapiro and Muller (1977), studying Tanzanian cotton farms, find that operators with superior production knowledge and those that seek out agricultural information are more technically efficient than their less informed competitors. Chavas and Pope (1984) argue that the value of data and information to production depends on how it influences decision making under uncertainty. Although we do not capture these nuances in the PA data-decision making process in this paper, we do regard them as topics to be addressed in future work.

Conclusions

Precision agriculture (PA) has received a great deal of attention in recent years as a means of improving agronomic outcomes while conserving inputs. Much of the literature evaluates the impact of individual PA technologies on profitability. However, the diffusion of PA follows a sequential pattern where producers incrementally stack complementary technologies. In this paper, we assess the ability of PA to improve output-oriented technical efficiency using previously unanalyzed data from the 2016 ARMS survey based on observed adoption paths.

We first sort farms into groups according to their level and mix of PA technology adoption using hierarchical clustering. We identify four distinct groups representing stages of the standard technology adoption curve: laggards/non-adopters, late majority, early majority, and innovators/early adopters. The distribution of farms across groups suggests that the PA technology adoption curve is skewed, that is, the diffusion of innovation in ag-tech is occuring relatively slowly among farm operators, in contrast to recent findings (Lowenberg-DeBoer and Erickson, 2019). Markedly, farms chategorized as laggards—those that have not adopted any form of PA technology—represent over one third of U.S. corn farms and are the single largest producer group identified, though they are responsible for the least amount of acreage. To date, this study is the first to categorize U.S. farms into stages of the technology adoption curve based on their bundling of multiple PA technolgies. The apparent need to bundle multiple technologies to fully capture PA efficiency gains could help explain why PA technology has not been adopted more widely and rapidly among corn farm operators.

We then perform a stochastic frontier analysis (SFA) allowing PA technology group membership to explain the variance and mean of farm inefficiency along with other relevant farm and operator characteristics. We show that individual PA technologies are generally positively associated with efficiency but the relationships are not statistically conclusive and effects vary by technology type, supporting to the need to evaluate technology bundles. We find meaningful efficiency benefits associated with advanced PA adoption groups as identified in our cluster analysis. These benefits grow as farmers stack complementary technologies, e.g. soil mapping and variable rate fertilizer applications. Differences in efficiency are the largest between the late and early majority groups—characterized by the transition from passive to active yield monitor data collection. We find positive but diminishing efficiency returns beyond this stage.

Farms classified as innovators have high rates of adoption for classic PA technologies as well as novel data-intensive technologies. These farms are 12% more technically efficient than laggards, but only two percent more efficient than early majority farms. The observed diminishing efficiency returns may only warrant the marginal investment if experienced on a large scale. Though innovators represent the smallest share of producers (14%), they operate almost one quarter of U.S corn acreage. These differences in efficiency attributed to higher-order PA technology bundling could be a key factor in accelerating future U.S. farm consolidation.

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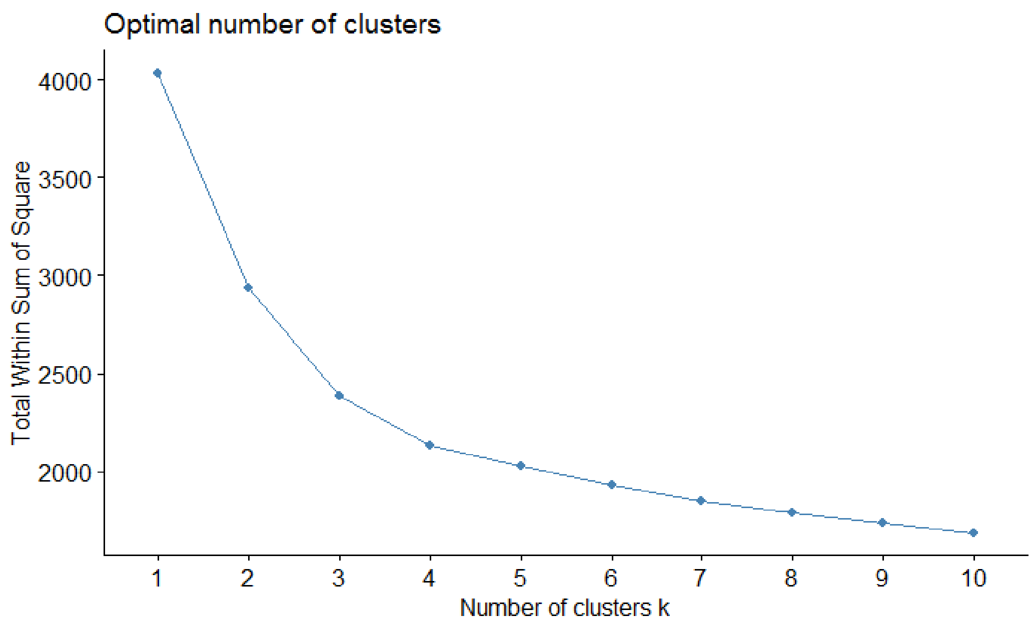

Figure 1. Cluster Analysis Scree Plot

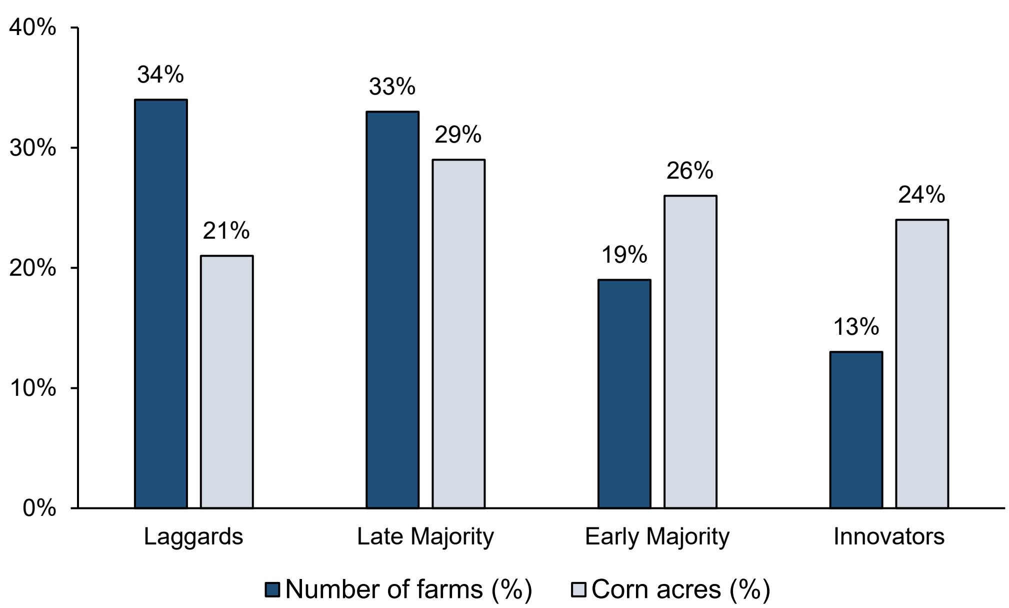

Figure 2. PA Adoption Group Distribution

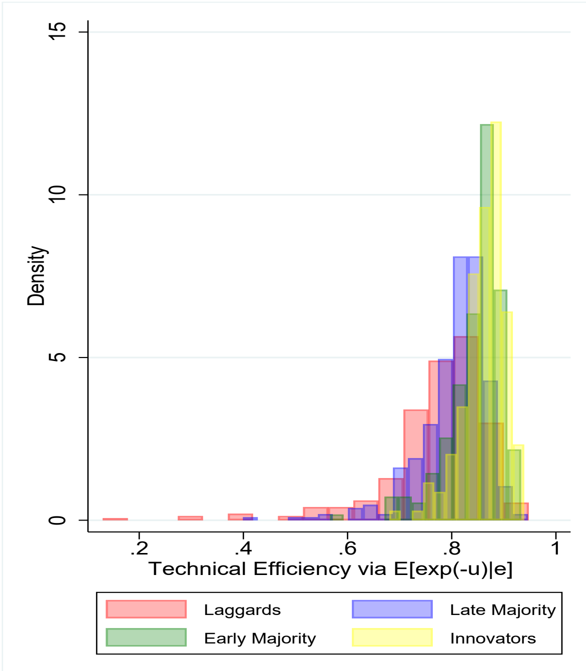

Figure 3a. Distributions of Technical Efficiency by PA Adoption Group

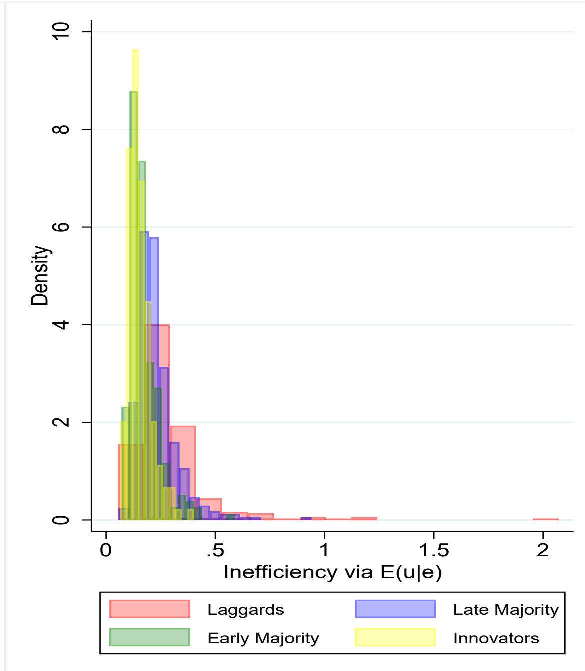

Figure 3b. Distributions of Inefficiency by PA Adoption Group

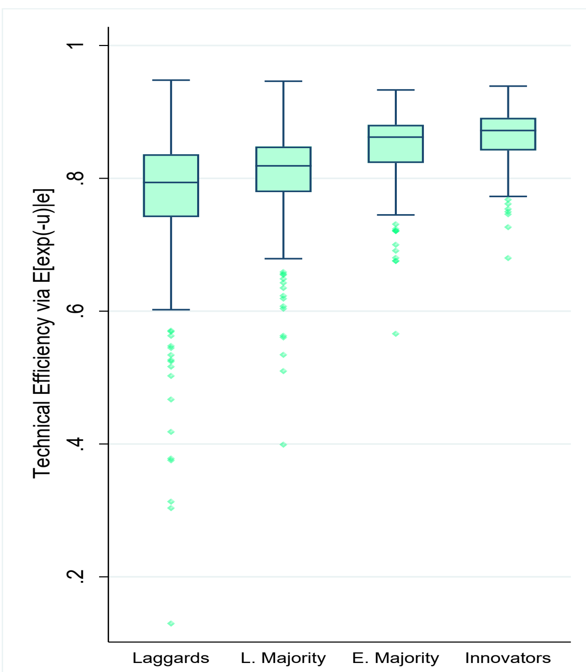

Figure 4a. Boxplots of Technical Efficiency by PA Adoption Group

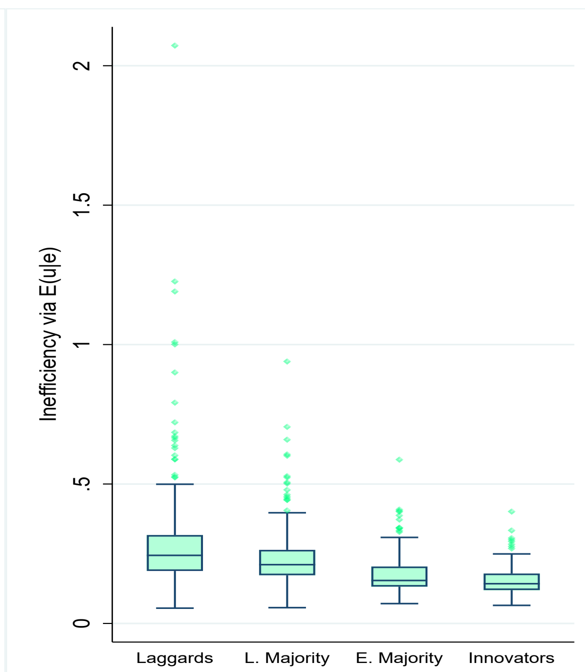

Figure 4b. Boxplots of Inefficiency by PA Adoption Group

Table 1. 2016 ARMS Summary Statistics.

Production Variables (ARMS Phase II)		N	Mean	Std. Error
Corn yield	Corn yield for the surveyed field in bushels per acre	1,594	176.81	1.52
Nitrogen rate	Lbs. of commercial and manure nitrogen applied per acre	1,594	139.99	2.44
Pesticides	Lbs. of herbicide, insecticide, and fungicide active ingredients applied per acre	1,594	19.62	0.39
Labor	Total hours of paid and unpaid labor used on the field	1,594	63.50	2.55
Capital	Total recovery cost of capital (equipment and machinery) used to grow corn on the field	1,594	5,793.02	198.36
Total farm acres	Total acres of corn planted by the farm	1,594	654.26	34.75
Field acres	Acres of corn planted in the observed field	1,594	48.70	1.53
Irrigated	Dummy =1 if the corn field was irrigated	1,594	0.05	0.01
Precision Ag Variables (ARMS Phase II)				
Collect data	Dummy =1 if any data collection tools were used on the field	1,594	0.66	0.02
Yield monitor	Dummy =1 if a yield monitor was used	1,594	0.55	0.02
GPS Yield map	Dummy =1 if yield monitor data was used to create a yield map	1,594	0.32	0.02
Map interpret	Dummy =1 if a technical consultant was hired to interpret or develop yield or remote sensing maps	1,594	0.04	0.01
Soil core data	Dummy =1 if data was collected from soil core sample tests	1,594	0.20	0.01
Soil sensors	Dummy =1 if data was collected from soil sensor tests	1,594	0.02	0.00
GPS soil map	Dummy =1 if soil data was used to create a map	1,594	0.15	0.01
VR seeding	Dummy =1 if variable rate seeding was performed	1,594	0.16	0.01
VR fertilizer	Dummy =1 if variable rate fertilizer application was performed	1,594	0.20	0.01
VR pesticides	Dummy =1 if variable rate pesticide application was performed	1,594	0.07	0.01
GPS guidance	Dummy =1 if GPS guidance tools such as auto-steer or light bar used	1,594	0.42	0.02
Drone/UAV	Dummy =1 if drone/UAV, aircraft, or satellite was used to collect imagery data	1,594	0.04	0.01
Crop sensors	Dummy =1 if crop condition sensors were used	1,594	0.03	0.00
Data public	Dummy =1 if public data was downloaded from online sources	1,594	0.03	0.00
Data computer	Dummy =1 if data was accessed on a personal computer	1,594	0.33	0.02
Data mobile	Dummy =1 if data was accessed on a mobile device	1,594	0.14	0.01
Ag-tech company	Dummy =1 if data was accessed through an ag-tech provider website	1,594	0.08	0.01
Share farm data	Dummy =1 if farm data was used by an outside service provider or extension agent to provide crop management recommendations	1,594	0.31	0.02
Operator Characteristics (ARMS Phase III)				
Operator age	Age in years of the primary farm operator	1,038	57.05	0.51
Operator experience	Number of years the primary operator has been farming	1,038	32.58	0.53
College	Dummy =1 if the primary operator has some college (Associates degree or more)	1,594	0.54	0.02
Ownership share (%)	Operator's share in the business of the farm field	1,038	86.20	0.75
Field rented	Dummy =1 if the observed field is rented under a cash rent or crop share agreement	1,594	0.47	0.02

Notes: Summary statistics represent all corn fields in 2016 using expansion weights provided by USDA NASS. Standard errors are estimated using standard delete-a-group jackknife procedure.

Table 2. Precision Agriculture Mean Adoption Rates by Hierarchical Cluster Assignment.

VARIABLES	Cluster 1: Laggards (n = 305)	2: Late Majority (n = 364)	3: Early Majority (n = 210)	4: Innovators/Early Adopters (n = 159)
Collect data	0.00	1.00	1.00	1.00
Yield monitor	0.00	0.68	0.98	0.99
Yield map	0.00	0.06	0.90	0.97
Map interpret	0.00	0.02	0.08	0.20
Soil core data	0.00	0.19	0.06	0.98
Soil sensors	0.00	0.00	0.01	0.09
GPS soil map	0.00	0.06	0.00	0.94
VR seeding	0.00	0.05	0.35	0.49
VR fertilizer	0.00	0.11	0.31	0.73
VR pesticides	0.00	0.08	0.10	0.24
GPS guidance	0.00	0.40	0.81	0.94
Drone/UAV	0.00	0.01	0.07	0.19
Crop sensors	0.00	0.03	0.06	0.08
Data public	0.00	0.01	0.04	0.13
Data computer	0.00	0.28	0.63	0.83
Data mobile	0.00	0.08	0.27	0.42
Ag-tech company	0.00	0.01	0.19	0.29
Share farm data	0.00	0.41	0.42	0.69
Corn yield	169.60	172.26	189.77	194.15
Nitrogen rate	129.67	135.97	145.32	161.52
Pesticides	17.81	21.23	19.54	21.40
Labor	43.84	62.48	66.47	100.40
Capital	3,249.41	5,036.89	7,035.86	10,654.42
Total farm acres	277.88	549.80	931.04	1,484.66
Irrigated	0.03	0.05	0.03	0.08
Operator age	59.39	57.58	53.98	54.22
Operator farming experience	33.33	33.89	29.61	31.97
College	0.41	0.53	0.69	0.66
Field rented	0.36	0.46	0.59	0.61
Operator ownership share	90.96	87.46	80.94	78.70

Notes: Means expanded to represent all corn fields in 2016 using a NASS-provided base weight. Standard errors (omitted) were estimated using standard delete-a-group jackknife procedure. The cluster analysis is performed on all 1,594 farms that filled out ARMS Phase II. Only the 1,038 farms that completed both Phase II and Phase III are summarized above. Differences in PA adoption rates between the full-sample cohort and the restricted sample are negligible.

Table 3. Stochastic Frontier Model: PA Groups Based on Hierarchical Clustering.

	Dependent variable: ln total output (corn bsh.)				
VARIABLES	Estimate	Std. Error	z value	Pr(>|z|)	
Production Frontier					
ln N	0.30	0.04	6.89	0.00	***
ln pest	0.14	0.03	5.42	0.00	***
ln labor hrs.	0.15	0.04	3.84	0.00	***
ln capital	0.33	0.06	5.55	0.00	***
ln farm acres	0.03	0.02	1.45	0.15	
Irrigated	-0.08	0.07	-1.17	0.24	
Northern Crescent	-0.19	0.05	-3.75	0.00	***
Northern Great Plains	-0.08	0.07	-1.22	0.22	
Prairie Gateway	-0.31	0.07	-4.27	0.00	***
Eastern Uplands	-0.12	0.14	-0.84	0.40	
Southern Seaboard	-0.64	0.09	-6.93	0.00	***
Fruitful Rim	-0.45	0.09	-5.15	0.00	***
Cons	2.16	0.29	7.48	0.00	***
ln sigma v					
Operator experience	0.03	0.04	0.87	0.39	
Operator experience^2	0.00	0.00	-0.82	0.41	
College	-0.11	0.26	-0.42	0.67	
Rent field	-0.46	0.22	-2.07	0.04	**
Ownership share	0.00	0.00	0.61	0.54	
PA - Late majority	0.43	0.38	1.13	0.26	
PA - Early majority	0.04	0.25	0.16	0.87	
PA - Innovators	-0.13	0.38	-0.34	0.74	
Cons	-2.60	0.72	-3.61	0.00	***
Mean sigma v	0.38	0.00	123.73	0.00	***
					***
ln sigma u					
Operator experience	0.04	0.05	0.74	0.46	
Operator experience^2	0.00	0.00	-0.73	0.47	
College	-0.13	0.45	-0.28	0.78	
Rent field	0.79	0.45	1.75	0.08	*
Ownership share	0.00	0.01	-0.29	0.77	
PA - Late majority	-0.63	0.43	-1.48	0.14	
PA - Early majority	-1.13	0.50	-2.23	0.03	**
PA - Innovators	-1.40	0.59	-2.35	0.02	**
Cons	-2.66	0.95	-2.79	0.01	***
Mean sigma u	0.30	0.00	72.53	0.00	***
Mean technical efficiency[a]	0.81	0.004	212.14	0.00	***
Mean inefficiency[b]	0.23	0.005	43.57	0.00	***
Observations	1,038				
Log-pseudolikelihood	-487,194.15				

Notes: *** p<0.01, ** p<0.05, * p<0.1. Estimates expanded to represent all corn fields in 2016 using expansion weights provided by USDA NASS. Standard errors calculated using delete-a-group jackknife procedure. [a] Output-oriented efficiency score computed $E(\exp(-u_i|\varepsilon_i))$ following Battese and Coelli (1988). [b] Inefficiency term computed $E(u_i|\varepsilon_i)$ following Jondrow et al. (1982).

Table 4. Average Marginal Effects on Inefficiency (u).

	dy/dx	Std. Error	z value	Pr(>|z|)	
Operator experience	0.005	0.000	117.44	0.00	***
Operator experience^2	-0.00007	0.000	-7,764.07	0.00	***
College	-0.01	0.003	-5.35	0.00	***
Rent field	0.09	0.003	33.20	0.00	***
Ownership share	-0.0002	0.000	-403.93	0.00	***
PA - Late majority	-0.07	0.002	-29.71	0.00	***
PA - Early majority	-0.13	0.003	-38.01	0.00	***
PA - Innovators	-0.16	0.005	-33.87	0.00	***

Notes: *** p<0.01, ** p<0.05, * p<0.1. Average marginal effects of regressors on the un-conditional expectation of u, $E(u_i|z_i)$. Standard errors calculated using standard delete-a-group jackknife procedure.

Table 5. Mean Technical Efficiency and Inefficiency Scores by PA Group.

	TE[a]		$E(u\|\varepsilon)$[b]	
	Mean	Std. dev.	Mean	Std. dev.
PA - Laggards	0.77	0.10	0.29	0.19
PA - Late majority	0.80	0.07	0.23	0.10
PA - Early majority	0.85	0.05	0.17	0.07
PA - Innovators	0.86	0.04	0.15	0.05

Notes: [a] Output-oriented technical efficiency score computed $E(\exp(-u_i|\varepsilon_i))$ following Battese and Coelli (1988). [b] Inefficiency term computed $E(u_i|\varepsilon_i)$ following Jondrow et al. (1982).

Supplementary appendix for: Precision Agriculture Technology Adoption and Technical Efficiency

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Cluster Analysis Alternatives

The dendrogram displayed in Figure A1 confirms the choice of four clusters (outlined in color). The height of each bracket denotes the "merging cost" of combining two clusters in terms of their dissimilarity to one another. Four clusters balances the desire to minimize cluster variance with the need to group farms parsimoniously. A Gower dissimilarity matrix is employed to differentiate farms/clusters and we used the Ward's linkages method to combine clusters. Multiple iterations of our clustering approach did not produce substantial differences in farm-to-cluster assignment. The largest movements were observed between the Late Majority and Early Majority groups (clusters 1 and 2). This is expected given that these are the least distinguishable groups in the dataset. Little movement is detected in and out of the Laggard and Innovators groups across iterations.

Alternative clustering approaches were employed which produce stochastic frontier analysis results similar to those shown in the main text. Most clustering techniques line up with the taxonomy proposed by Rogers (1962), but differ in the number of farms assigned to each group. A common alternative to hierarchical clustering is K-means clustering, which minimizes the Euclidean distance between observations and their respective cluster centroids. The K-means technique requires a pre-determined number of clusters, which are optimized iteratively until the total sum-of-squared distances is minimized.

We report the results of our K-mean clustering with three and four clusters in Tables A1 and A2 below. The scree plot shown in Figure 1 of the main text informed the choice of three and four clusters. Clustering via K-means produces cluster groups with similar adoption rates of PA as the hierarchical clustering approach with some exceptions. Most noticeably, the Laggards groups produced by K-means is significantly larger and includes farms with some adoption of basic PA technologies while the Innovators group is more exclusive—suggesting that K-means does a better job of identifying farms with highly advanced PA systems but fails to isolate those with zero adoption of PA. Ultimately, the hierarchical method was chosen as it provides the most useful distribution of farms across PA groups and identifies the no-PA group which forms a useful baseline against which to compare other groups. Stochastic frontier analysis results are robust to various clustering techniques.

Principal Components Analysis

A common alternative to cluster analysis is principal components analysis (PCA), a multivariate statistical technique for finding latent relationships among variables in high-dimensional data. To extend the findings of our cluster analysis, we conducted a PCA to uncover patterns in PA adoption that can be crosschecked with our clustering assignment. Four principal components were retained according to the Kaiser Rule (keep all components w/ eigenvalues > 1) and to maintain simplicity (see the eigenvalue scree plot in Figure A2. A varimax rotation was performed on the first four eigenvectors to force each PA variable to load as highly as possible on a single component. The rotated eigenvalue matrix is shown in Table A3.

PA variables that load highly (have a loading factor >= 0.2) are highlighted. Component 1 groups together "classic" PA technologies (yield monitor, yield mapping, guidance); Component 2 groups together sensors and aerial imagery data; Component 3 is defined by its disassociation with many PA technologies (particularly soil testing and mapping) and reflects the preponderance of non-adopter or "laggards." Component 4 groups "advanced" data technologies (using data on a mobile device, subscribing to an ag-tech data platform) and VRT. The first 3 components are generally in line with the results of our cluster analysis which groups farms by stages on the PA tech adoption curve. Laggards are defined as adopting few to no PA technologies, early/late majority adopt the "classic" technologies, and innovators adopt "classic" tech plus soil tests/VRT and "advanced" data tech. Taking this a step further, we perform a hierarchical cluster analysis of the first four principal components which leads to similar grouping of PA variables. The dendrogram in Figure A3 shows four clearly defined technology groups, which reflect the adoption patterns of the farm groups identified in our cluster analysis.

Cobb-Douglas OLS Model

To motivate our stochastic frontier analysis, we estimate an initial Cobb-Douglas production function using ordinary least squares (OLS). Implied in the OLS model is the assumption that no inefficiency is present in the conversion of inputs into output, i.e. it assumes that $u_i = 0$. If true, equation (1) of the main text collapses to:

$$\ln y_i = \ln \boldsymbol{x}_i' \boldsymbol{\beta} + v_i \tag{1}$$

where v_i is the sole residual term which is normally distributed and symmetric.

Results of the OLS Cobb-Douglas model are presented in Table A4. Output elasticities are generally in-line with expectations. We reject constant returns-to-scale at the 0.10 significance level in favor of weakly decreasing returns-to-scale. Figure A4 displays the distribution of OLS residuals, which is clearly asymmetric with a skewness of -0.65. Both the Coelli (1995) and D’Agostino, Belanger, and D’Agostino (1990) tests reject zero-skewness at the 0.01 level, justifying the use of a stochastic frontier model.

Stochastic Frontier Model with Individual PA Technologies

Table A5 shows the results of our stochastic frontier model using individual PA technologies to explain error and inefficiency variance. As discussed in the main text, 12 of 18 PA technologies enter the inefficiency variance model negatively, though none of the coefficients are statistically significant at conventional levels. The effects of PA adoption likely depend on how various tools are combined. Table A5 underscores the need to evaluate PA technologies in bundles, as represented by our PA groups (clusters).

Stochastic Frontier Model Robustness Checks

As large operations may be more likely to adopt PA technologies, the interplay between technical efficiency and farm size should not be ignored (Schimmelpfennig, 2016). Mugera and Langemeier (2011) show that technical efficiency is significantly different across farm size categories in Kansas while Xin et al. (2016) find that technical efficiency in China's broiler producing sector increases with farm size. Where present, the relationship between size and technical efficiency is likely driven by scale economies (Page, 1984). Table 2 of the main text shows significant differences in farm acreage across PA adoption groups. The differences in technical efficiency detected in our model could be driven by differences in economies of scale, which would bias our estimates. Furthermore, operation size is often used to explain heteroscedasticity in the random error (Hadri et al., 2003).

To test the robustness of our results, we include total farm acres as a determinant of random noise and inefficiency variance. Column (1) of Table A6 shows the results of our stochastic frontier analysis following this approach. Farm size enters both equations significantly. In the case of random noise, an additional acre of total production raises field-level random error variance by 0.1% and one-sided inefficiency variance by 0.01%. Unlike our main model, a joint test for homoscedasticity in the random error is rejected at the 0.05 level. Point estimates of PA group identifiers in the inefficiency model shrink slightly but remain highly statistically significant. The associated average marginal effects are highly comparable to our original estimates in Table 4. Results confirm that existence of scale effects in inefficiency but show that any bias resulting from these effects to be negligible.

Another potential source of bias is heterogeneous production frontiers across PA adoption groups. Mayen et al. (2010) find organic dairy production to be significantly less efficient than conventional production if a homogenous production frontier is assumed. However, when computed relative to their own unique production frontiers, organic and conventional technical efficiencies are statistically indistinguishable. Their work points to the importance of formally testing for heterogeneous production technologies prior to calculating technical efficiency.

To do so, we include dummy variables for each PA group in the production frontier portion of the stochastic frontier model and present the results in Table A6 column (2). Testing the joint significance of these dummy variables is effectively a test for a shared production technology. The second column of Table A6 shows that all three of the PA group indicator variables enter the model insignificantly. Per a joint significant test, we cannot rule out a homogenous production frontier at the 0.10 level.

Nevertheless, we find some differences in the estimated effects of PA adoption on inefficiency. The coefficient on the early majority group becomes statistically insignificant and shrinks in magnitude. The effect size of late majority group assignment strengthens but remains insignificant. However, innovators remain significantly less (more) inefficient (technically efficient) than laggards and the associated marginal effect grows in magnitude.

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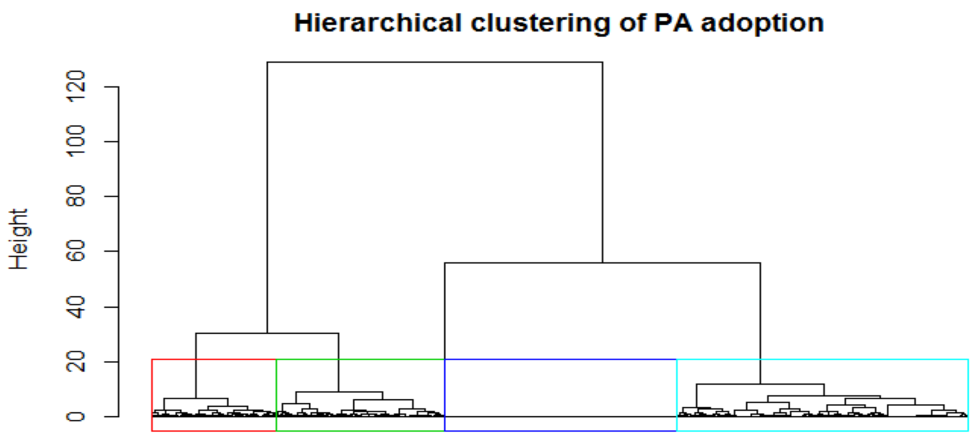

Figure A1. Hierarchical Cluster Analysis Dendrogram

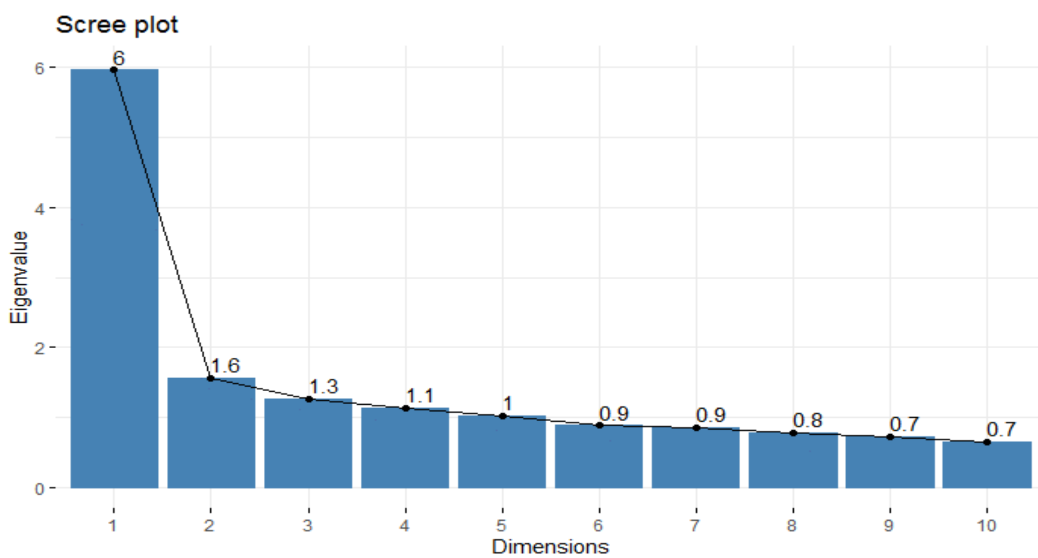

Figure A2. Principal Components Analysis Eigenvalue Scree Plot

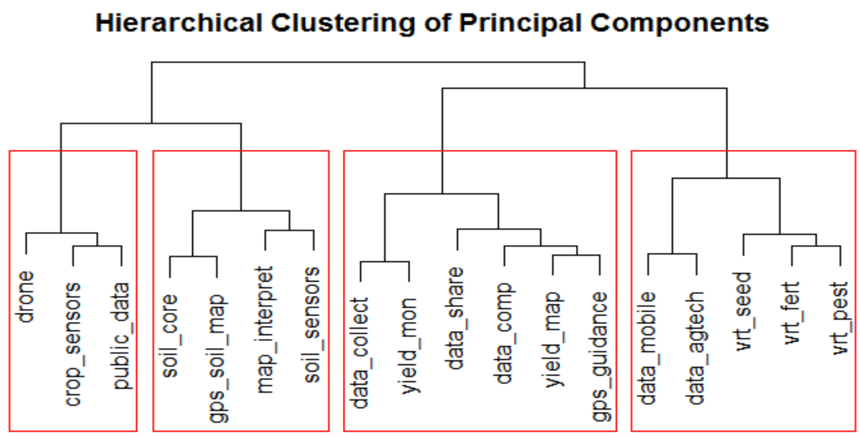

Figure A3. Hierarchical Cluster of Principal Components Dendrogram

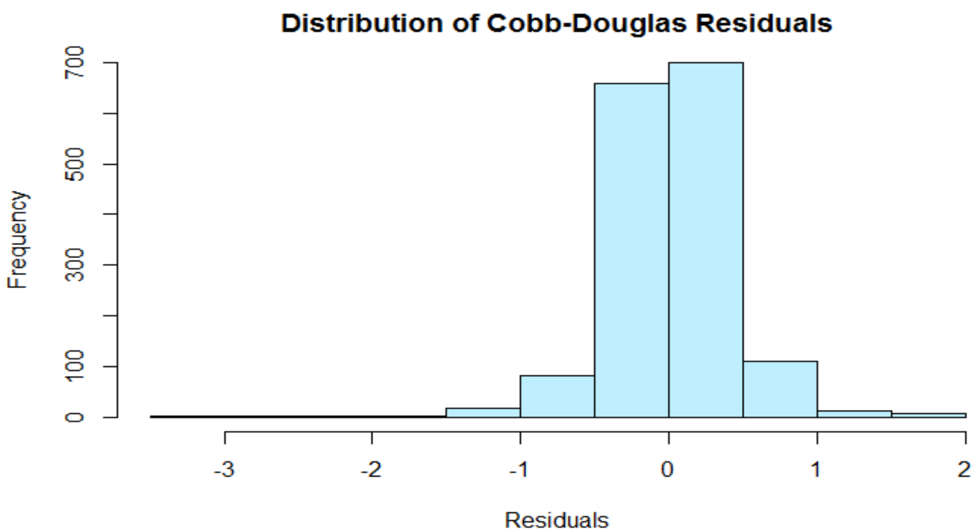

Figure A4. OLS Cobb-Douglas Error Skewness

Table A1. Precision Agriculture Mean Adoption Rates by K-means Cluster Assignment (K=3)

	Cluster		
	Laggards	Early/Late Majority	Innovators/Early Adopters
VARIABLES	435	407	196
Collect data	0.26	1.00	1.00
Yield monitor	0.12	0.90	0.96
GPS yield map	0.00	0.51	0.89
Map interpret	0.00	0.03	0.23
Soil core data	0.02	0.15	0.84
Soil sensors	0.00	0.00	0.08
GPS soil map	0.01	0.02	0.78
VR seeding	0.00	0.16	0.56
VR fertilizer	0.01	0.18	0.77
VR pesticides	0.00	0.10	0.25
GPS guidance	0.03	0.68	0.93
Drone/UAV	0.00	0.01	0.23
Crop sensors	0.00	0.05	0.09
Data public	0.00	0.01	0.14
Data computer	0.02	0.49	0.83
Data mobile	0.00	0.17	0.46
Ag-tech company	0.00	0.06	0.34
Share farm data	0.05	0.46	0.69
Corn yield	168.32	182.03	195.47
Nitrogen rate	130.84	141.40	157.42
Pesticides	19.10	19.94	20.95
Labor	44.94	70.43	91.50
Capital	3,385.42	6,675.11	9,393.32
Total farm acres	286.48	779.90	1,441.69
Irrigated	0.03	0.05	0.07
Operator age	58.84	56.48	53.20
Operator farming experience	33.33	32.56	30.54
College	0.42	0.62	0.70
Field rented	0.38	0.54	0.58
Operator ownership share	89.95	83.62	81.09

Notes: Means expanded to represent all corn fields in 2016 using a NASS-provided base weight. Standard errors (omitted) were estimated using standard delete-a-group jackknife procedure. The cluster analysis is performed on all 1,594 farms that filled out ARMS Phase II. Only the 1,038 farms that completed both Phase II and Phase III are summarized above. Differences in PA adoption rates between the full-sample cohort and the restricted sample are negligible.

Table A2. Precision Agriculture Mean Adoption Rates by K-means Cluster Assignment (K=4)

	Cluster			
	Laggards	Late Majority	Early Majority	Innovators/Early Adopters
VARIABLES	444	389	169	36
Collect data	0.27	1.00	1.00	1.00
Yield monitor	0.12	0.93	0.96	0.98
GPS yield map	0.00	0.51	0.90	0.81
Map interpret	0.00	0.02	0.23	0.26
Soil core data	0.02	0.14	0.86	0.65
Soil sensors	0.00	0.00	0.06	0.15
GPS soil map	0.01	0.01	0.80	0.57
VR seeding	0.00	0.17	0.53	0.53
VR fertilizer	0.00	0.19	0.75	0.58
VR pesticides	0.00	0.10	0.24	0.24
GPS guidance	0.03	0.70	0.92	0.97
Drone/UAV	0.00	0.01	0.17	0.45
Crop sensors	0.00	0.05	0.06	0.30
Data public	0.00	0.00	0.00	1.00
Data computer	0.04	0.48	0.81	0.86
Data mobile	0.00	0.18	0.40	0.57
Ag-tech company	0.00	0.07	0.26	0.59
Share farm data	0.07	0.44	0.67	0.76
Corn yield	168.02	182.52	193.52	204.17
Nitrogen rate	130.68	140.84	157.80	161.91
Pesticides	19.35	19.75	20.59	20.75
Labor	44.83	71.61	91.17	81.72
Capital	3,368.22	6,839.67	9129.75	9,158.81
Total farm acres	287.04	801.64	1468.30	956.99
Irrigated	0.03	0.05	0.08	0.01
Operator age	58.78	56.42	53.81	52.15
Operator farming experience	33.24	32.58	30.84	30.70
College	0.42	0.61	0.70	0.73
Field rented	0.38	0.54	0.59	0.60
Operator ownership share	90.07	83.14	79.72	90.66

Notes: Means expanded to represent all corn fields in 2016 using a NASS-provided base weight. Standard errors (omitted) were estimated using standard delete-a-group jackknife procedure. The cluster analysis is performed on all 1,594 farms that filled out ARMS Phase II. Only the 1,038 farms that completed both Phase II and Phase III are summarized above. Differences in PA adoption rates between the full-sample cohort and the restricted sample are negligible.

Table A3. Principal Components Analysis Eigenvalue Matrix w/ Varimax Rotation

VARIABLES	PC1	PC2	PC3	PC4
Collect data	0.55	0.02	0.11	-0.10
Yield monitor	0.53	0.04	0.10	-0.07
Yield map	0.31	-0.04	-0.10	0.10
Map interpret	-0.06	0.10	-0.33	0.04
Soil core data	0.06	-0.01	-0.52	-0.06
Soil sensors	-0.01	0.36	-0.31	-0.19
GPS soil map	0.02	-0.06	-0.58	-0.03
VR seeding	0.03	-0.14	-0.08	0.42
VR fertilizer	0.08	-0.23	-0.30	0.22
VR pesticides	0.01	-0.29	-0.13	0.21
GPS guidance	0.35	-0.05	-0.01	0.12
Drone/UAV	-0.05	0.35	-0.11	0.24
Crop sensors	0.09	0.54	0.03	-0.02
Data public	-0.01	0.50	-0.03	0.14
Data computer	0.25	0.01	0.00	0.23
Data mobile	0.02	0.07	0.08	0.49
Ag-tech company	-0.05	0.14	0.07	0.52
Share farm data	0.31	0.04	-0.12	-0.11

Table A4. Cobb-Douglas Production Function

	Dependent variable: ln total output (corn bsh.)				
VARIABLES	Estimate	Std. Error	t value	Pr(>|t|)	
ln N	0.32	0.04	8.43	0.00	***
ln pest	0.17	0.02	8.12	0.00	***
ln labor hrs.	0.16	0.03	4.84	0.00	***
ln capital	0.27	0.05	5.76	0.00	***
ln farm acres	0.05	0.01	3.43	0.00	**
Irrigated	-0.01	0.05	-0.21	0.83	
Northern Crescent	-0.19	0.04	-4.59	0.00	***
Northern Great Plains	-0.08	0.05	-1.60	0.13	
Prairie Gateway	-0.30	0.04	-7.60	0.00	***
Eastern Uplands	-0.23	0.10	-2.41	0.03	*
Southern Seaboard	-0.63	0.07	-8.62	0.00	***
Fruitful Rim	-0.46	0.07	-6.68	0.00	***
Cons	1.96	0.19	10.28	0.00	***
Observations	1,594				
Log-likelihood	-1,103.92				
F-Stat	361.12				
Residual skew	-0.65				

Notes: *** p<0.01, ** p<0.05, * p<0.1. Estimates expanded to represent all corn fields using NASS base weights. Standard errors calculated using standard delete-a-group jackknife procedure.

Table A5. PA Adoption Variables as Exogenous Determinants of Inefficiency.

	Dependent variable: ln total output (corn bsh.)				
VARIABLES	Estimate	Std. Error	z value	Pr(>|z|)	
Production Frontier					
ln N	0.29	0.04	7.92	0.00	***
ln pest	0.17	0.02	6.98	0.00	***
ln labor hrs.	0.17	0.04	4.29	0.00	***
ln capital	0.30	0.05	5.47	0.00	***
ln farm acres	0.01	0.02	0.55	0.58	
Irrigated	-0.03	0.06	-0.59	0.56	
Northern Crescent	-0.17	0.05	-3.68	0.00	***
Northern Great Plains	-0.06	0.05	-1.22	0.22	
Prairie Gateway	-0.25	0.04	-5.63	0.00	***
Eastern Uplands	-0.18	0.11	-1.74	0.08	*
Southern Seaboard	-0.52	0.08	-6.73	0.00	***
Fruitful Rim	-0.37	0.09	-4.30	0.00	***
Cons	2.31	0.34	6.85	0.00	***
					***
ln sigma v					
Collect data	0.27	0.32	0.85	0.39	
Yield monitor	0.01	0.30	0.04	0.97	
Yield map	-0.40	0.20	-1.96	0.05	*
Map interpret	0.09	0.30	0.30	0.76	
Soil core data	0.01	0.43	0.02	0.99	
Soil sensors	0.19	0.57	0.34	0.74	
GPS soil map	0.04	0.40	0.10	0.92	
VR seeding	0.22	0.26	0.85	0.39	
VR fertilizer	-0.14	0.29	-0.49	0.62	
VR pesticides	-0.15	0.24	-0.61	0.54	
GPS guidance	-0.21	0.30	-0.72	0.47	
Drone/UAV	-0.07	0.55	-0.13	0.90	
Crop sensors	-0.39	0.83	-0.47	0.64	
Data public	0.51	0.51	0.98	0.33	
Data computer	-0.33	0.21	-1.56	0.12	
Data mobile	0.11	0.25	0.44	0.66	
Ag-tech company	-0.25	0.23	-1.07	0.28	
Share farm data	-0.04	0.30	-0.13	0.90	
Cons	-1.93	0.25	-7.59	0.00	***
Mean sigma v	0.36	0.00	201.12	0.00	***

(Table 3 continued)

ln sigma u					
Collect data	0.71	1.94	0.37	0.71	
Yield monitor	-2.01	7.18	-0.28	0.78	
Yield map	-0.11	2.20	-0.05	0.96	
Map interpret	-4.00	112.11	-0.04	0.97	
Soil core data	-0.90	1.17	-0.77	0.44	
Soil sensors	-0.41	6.16	-0.07	0.95	
GPS soil map	1.45	2.62	0.55	0.58	
VR seeding	-0.07	2.49	-0.03	0.98	
VR fertilizer	-1.14	1.19	-0.96	0.34	
VR pesticides	-0.46	1.33	-0.34	0.73	
GPS guidance	-0.25	1.46	-0.17	0.86	
Drone/UAV	0.99	37.38	0.03	0.98	
Crop sensors	1.40	6.32	0.22	0.83	
Data public	-4.39	81.52	-0.05	0.96	
Data computer	0.04	1.17	0.04	0.97	
Data mobile	-0.19	1.26	-0.15	0.88	
Ag-tech company	-0.82	1.43	-0.58	0.57	
Share farm data	0.59	1.56	0.38	0.71	
Cons	-2.49	1.76	-1.42	0.16	
Mean sigma u	0.21	0.00	47.03	0.00	***
Observations	1,594				
Log-pseudolikelihood	-698,383.31				

Notes: *** p<0.01, ** p<0.05, * p<0.1. Estimates expanded to represent all corn fields in 2016 using expansion weights provided by USDA NASS. Standard errors calculated using delete-a-group jackknife procedure.

Table A6: Robustness Checks for Scale Effects and Heterogeneous Production Frontiers.

	Dependent variable: ln total output (corn bsh.)			
	(1)		(2)	
VARIABLES	Estimate	Std. Error	Estimate	Std. Error
Production Frontier				
ln N	0.29***	0.04	0.29***	0.04
ln pest	0.12***	0.02	0.12***	0.03
ln labor hrs.	0.16***	0.04	0.16***	0.04
ln capital	0.36***	0.05	0.36***	0.05
ln farm acres	0.04**	0.02	0.05**	0.02
Irrigated	-0.13	0.08	-0.13	0.08
PA - Late majority			-0.07	0.15
PA - Early majority			0.00	0.11
PA - Innovators			-0.08	0.08
Northern Crescent	-0.18***	0.05	-0.19***	0.05
Northern Great Plains	-0.06	0.06	-0.06	0.06
Prairie Gateway	-0.31***	0.07	-0.31***	0.07
Eastern Uplands	-0.09	0.13	-0.09	0.13
Southern Seaboard	-0.65***	0.09	-0.65***	0.09
Fruitful Rim	-0.47***	0.08	-0.48***	0.08
Cons	2.05***	0.25	2.04***	0.26
ln sigma v				
Farm acres	-0.001**	0.00	-0.001*	0.00
Operator experience	0.04	0.04	0.04	0.04
Operator experience^2	-0.001	0.00	-0.001	0.00
College	-0.11	0.26	-0.11	0.26
Rent field	-0.42*	0.22	-0.43**	0.22
Ownership share	0.0002	0.00	0.0001	0.00
PA - Late majority	0.61	0.40	0.71*	0.42
PA - Early majority	0.37	0.26	0.36	0.35
PA - Innovators	0.38	0.44	0.47	0.51
Cons	-2.43***	0.66	-2.44***	0.64
Mean sigma v	0.35**	0.00	0.34***	0.00
ln sigma u				
Farm acres	0.0001*	0.00	0.0001**	0.00
Operator experience	0.04	0.05	0.04	0.05
Operator experience^2	-0.001	0.00	-0.001	0.00
College	-0.13	0.33	-0.1269892	0.34
Rent field	0.76**	0.36	0.82**	0.40
Ownership share	-0.0034423	0.00	-0.004	0.00
PA - Late majority	-0.71*	0.41	-1.27	1.63
PA - Early majority	-1.03*	0.53	-0.99	1.01
PA - Innovators	-1.26***	0.44	-1.83**	0.84
Cons	-2.58**	1.01	-2.45**	1.01
Mean sigma u	0.29***	0.00	0.28***	0.01
Observations	1,038		1,038	
Log-pseudolikelihood	-473,377.58		-471,923.00	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Estimates expanded to represent all corn fields using NASS base weights. Standard errors calculated using standard delete-a-group jackknife procedure.