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Precision agriculture technology adoption and technical efficiency

Nathan D. DeLay | **Nathanael M. Thompson** | **James R. Mintert**

Department of Agricultural Economics, Purdue University, West Lafayette, IN, USA

Correspondence
Nathan D. DeLay, Department of Agricultural Economics, Purdue University, West Lafayette, IN 47907, USA.
Email: ndelay@purdue.edu

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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). Efficiency gains from PA are likely cumulative, that is, the true impact of precision farming depends on the integration of complementary tools. To examine the efficiency benefits of different PA bundles, we perform a two-step analysis. First, we use cluster analysis to identify distinct producer groups based on patterns in PA technology adoption. These producer groups map naturally onto the classic technology adoption curve (laggards, late majority, early majority, innovators). Second, we use stochastic frontier analysis (SFA) and stochastic meta-frontier analysis (SMFA) to estimate differences in technical efficiency between PA adoption groups. We find that farms with advanced PA technology bundles are significantly more technically efficient than non-adopters. Differences in technical efficiency are not found to be driven by heterogeneous production technologies, but rather inefficiencies in input usage at the farm level. Our results have strong implications for farm consolidation in US agriculture.

KEYWORDS

precision agriculture, stochastic frontier analysis, stochastic meta-frontier analysis, technology adoption, technical efficiency

JEL CLASSIFICATION

Q16; Q12

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1 | INTRODUCTION

Precision agriculture (PA) uses inter- and intra-field variation in soil, topography and climate to optimise input application and increase profitability. PA promises to enhance efficiency by spatially targeting inputs to where they are most productive, thereby maximising overall output for a given mix of resources. Technologies such as automated guidance systems, variable rate technology (VRT), and yield mapping have grown in popularity since their introduction in the 1990s, and newer technologies, including unmanned aerial vehicles (UAVs) and multispectral sensors, are being adopted more widely now. 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 (Erickson, Lowenberg-DeBoer, & Bradford, 2017; Griffin et al., 2004; Lambert, Paudel, & Larson, 2015; Miller et al., 2018; Schimmelpfennig & Ebel, 2016; Shockley, Dillon, & Stombaugh, 2011). Schimmelpfennig (2016) uses ARMS data to show 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 & Bullock, 2000; Bullock & Lowenberg-DeBoer, 2007; Bullock, Lowenberg-DeBoer, & Swinton, 2002; Bullock et al., 2009; Tenkorang & Lowenberg-DeBoer, 2008). 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 view 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 US cotton farmers: (i) yield monitors and grid soil sampling; (ii) digital maps and farm data software; and (iii) aerial imagery, handheld GPS devices, and soil survey maps. Khanna, Epouhe, and Hornbaker (1999) describe PA technologies as performing either diagnostic, positioning or application tasks. Extending their work, Miller et al., (2018) categorise 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 fertiliser 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. A large body of work finds positive technical efficiency benefits associated with agricultural technology adoption (Chen, Huffman, & Rozelle, 2009; Mayen, Balagtas, & Alexander, 2010). However, in some cases positive efficiency effects may be driven by scale economies enjoyed by larger operations (Mugera & Langemeier, 2011; Page, 1984; Xin et al., 2016).

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—for example, 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—for example, detailed soil nutrient maps inform precise nutrient application rates, thus lowering the operation's fertiliser 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 whereas 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 technologies. Second, we use stochastic frontier analysis (SFA) and stochastic meta-frontier analysis (SMFA) 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), Miller et al., (2018) and Schimmelpfennig and Ebel (2016) 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 practised by US 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, summarise our results, and discuss their implications.

2 | 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, labour 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.

TABLE 1 2016 ARMS summary statistics

		N	Mean	Std. Error
Production variables (ARMS Phase II)				
Corn yield	Corn yield for the surveyed field in bushels per acre	1,594	176.81	1.52
Nitrogen	Lbs of commercial and manure nitrogen applied to the field	1,594	7249.62	282.64
Pesticides	Lbs of herbicide, insecticide, and fungicide active ingredients applied to the field	1,594	971.53	39.19
Labour	Total hours of paid and unpaid labour 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	5793.02	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
Field rented	Dummy =1 if the observed field is rented under a cash rent or crop share agreement	1,594	0.49	0.02
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 fertiliser	Dummy =1 if variable rate fertiliser 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 was 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

(Continues)

TABLE 1 (Continued)

		N	Mean	Std. Error
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 age	Age 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)	1,038	0.54	0.02
Ownership share (%)	Operator's share in the business of the farm field	1,038	86.20	0.75

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.

Phase II of the 2016 corn survey provides much greater detail on PA technology adoption than the 2010 survey, which was the previous 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 analyse 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, and ag-tech services).

Summary statistics for variables relevant to this study are shown in Table 1. Means are expanded to represent all corn fields in the United States using NASS-provided expansion weights. Our sample consists of 1594 farms that completed the Phase II questionnaire, of which 1038 also completed Phase III.[3] Observed fields represent over 75 million corn acres nationwide, equivalent to approximately 80% 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 & Ebel, 2016).

Sixty-six per cent of corn farms collect at least one type of farm data. Due to the greater propensity of large farms to engage in precision agriculture (Schimmelpfennig, 2016), data-collecting farms represent 79% of all corn acres planted. Yield monitors are the most popular data collection tool at 55% of corn farms (70% of corn acreage), up from 48% of farms in 2010. Using data from yield monitors to generate GPS yield maps is typically the first step taken towards making yield data actionable for input decisions. However, only 32% of farms (46% of acres) report using 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% of corn farms and 54% of corn acreage in 2010 to 42% of farms and 63% of acres in 2016. The difference between farm-level and acre-level growth rates in guidance systems adoption implies that small operations were more likely to adopt the technology after 2010. VRT for

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

seeding, fertiliser or pesticides was used on 26% of corn farms (39% of corn acres) in 2016 compared to 19% of farms (28% of acres) in 2010. PA technology adoption paths are conditional, however (Khanna, Epouhe, & Hornbaker, 1999). For example, 57% of farms using variable rate fertiliser performed soil core testing in the survey year versus 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.[4]

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. Among producers that collect some type of farm data, about half share that data with an outside service provider or extension agent. One-third of producers access farm data on a personal computer whereas 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 just 8% of farms. This is not surprising as ag-tech software platforms were still relatively new in 2016. Like other PA technologies, farm data management tools are disproportionately used by large farms. Farms that use computers, mobile devices, or ag-tech platforms to access their data represent 36% of corn operations, but are responsible for over half of all corn acres planted.

3 | PRECISION AGRICULTURE ADOPTION 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.[5] Despite the complementary nature of these technologies, PA adoption is often done sequentially. Producers invest in technologies piece-meal and evaluate their effectiveness before adding more advanced tools (Khanna, 2001; Leathers & Smale, 1991; Miller et al., 2017). Khanna, Epouhe, and Hornbaker (1999) show that adoption of novel site-specific crop management (SSCM) practices is conditional on prior adoption of older, simpler technologies. This path dependency in PA is driven by a number of factors: uncertainty surrounding the costs and benefits of whole package implementation, producer risk-aversion, returns-to-scale, credit constraints, and human capital accumulation (Aldana et al., 2011; Feder, 1982; Leathers & Smale, 1991).

Early diffusion of innovation models help explain differences in sequential adoption timing across farms. The seminal work by Rogers (1962) predicts that innovations are embraced in stages, first by risk-loving innovators and eventually by risk-averse laggards. Mansfield (1961) likens the adoption process to an epidemic, spreading gradually as information about the innovation is shared with potential users. When innovators are few, information about their experience will spread slowly, leading to sluggish take-up (Khanna, Epouhe, & Hornbaker, 1999). The speed of diffusion in PA—and the shape of its adoption S-shaped curve—will depend on the distribution of farms across adoption groups, operator characteristics, and the newness of the technology.

[4]Note that the ARMS only asks about soil core testing in the current survey year. Farmers typically perform soil tests every 3–4 years. The true proportion is likely higher than reported here.

[5]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).

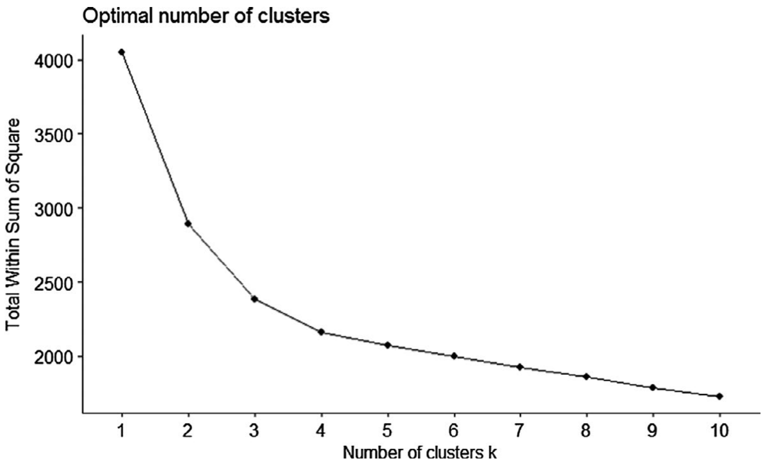

FIGURE 1 Cluster analysis scree plot

We apply the path dependency and diffusion of innovation framework to the PA variables in ARMS. Though ARMS data is cross-sectional, preventing us from analysing a farm's technological progression over time, examining adoption patterns across multiple technologies makes assessing farms' state of PA adoption at a given time possible.

We perform an agglomerative hierarchical cluster analysis (HCA) of observations based on the PA variables shown in Table 1.[6] Ward's linkages method is used to join clusters that minimise total within-cluster variance.[7] 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 & Shook, 1996).[8] Retaining four clusters balances the desire to minimise cluster variance with the need to group farms parsimoniously. Inspection of the clustering dendrogram confirms this choice (see Figure A1 in the Appendix S1).

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 Rogers (1962) classic technology adoption curve. A complete lack of PA adoption characterises 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 although farms in cluster 1 are 29% of our sample, they expand to represent 34% of US corn farms based on NASS-provided expansion weights, making laggards the largest single segment on 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 GPS yield maps, meaning their yield data is not likely to influence future input decisions. Rates of adoption for most other PA technologies are similarly low among this group, with the exception of GPS guidance, soil core sampling,

[6]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 (see Online Appendix).

[7]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.

[8]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.

TABLE 2 Precision agriculture mean adoption rates by hierarchical cluster assignment

	Cluster			
	1: Laggards	2: Late majority	3: Early majority	4: Innovators/ Early adopters
Variables	**(*n* = 305)**	**(*n* = 364)**	**(*n* = 210)**	**(*n* = 159)**
Collect data	0.00	1.00	1.00	1.00
Yield monitor	0.00	0.68	0.98	0.99
GPS 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 fertiliser	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	4,080.85	6,698.80	10,017.21	12,679.54
Pesticides	530.30	925.14	1,328.70	1,693.63
Labour	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 expansion weights provided by USDA NASS. 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 summarised above. Differences in PA adoption rates between the full-sample cohort and the restricted sample are negligible.

accessing data on a desktop computer, and data sharing, which are moderately common. The late majority cohort is most recognisable for adopting PA passively—for example, upgrading to a yield monitor equipped combine but failing to fully utilise 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 fertiliser 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 13% of all US 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 versus 4% of all corn producers.

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 occurring relatively slowly among farm operators. However, diffusion appears more rapid in terms of planted acreage (Lowenberg-DeBoer & Erickson, 2019). Figure 2 shows that farms in mature stages of the adoption curve represent fewer farms, but are responsible for a greater share of planted corn acreage and production. Laggards, by contrast, represent over one-third of US corn farms and are the single largest producer group identified, but operate just 21% of 2016's corn acreage. 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—suggesting there could be 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. These farms' operators are also younger, more highly educated, and more likely to rent farmland. Differences in corn yields across cluster groups suggest that farms actively using PA are more productive. The largest productivity jump appears between the late and early majority stages, 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.

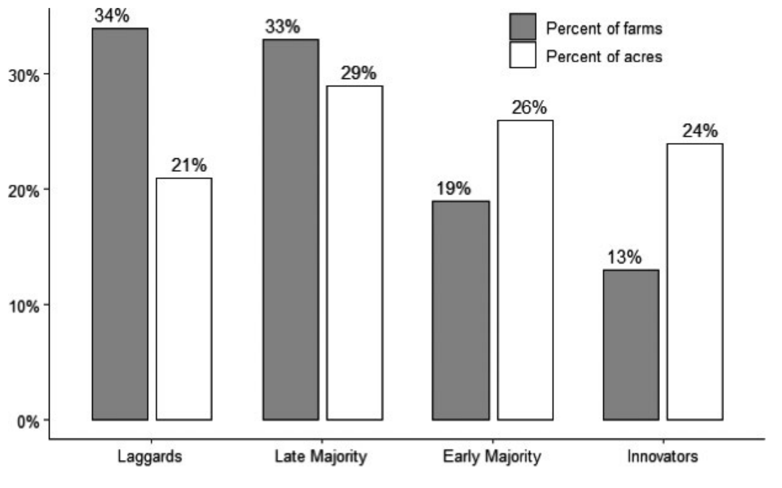

FIGURE 2 PA adoption group distribution

4 | STOCHASTIC FRONTIER ANALYSIS

Stochastic frontier analysis (SFA) has been used throughout the agricultural production literature to estimate farm technical efficiency (Kumbhakar & 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 Caudill and Ford (1993), Caudill, Ford and Gropper (1995), and Reifschneider and Stevenson (1991) (referred to as the RSCFG model) as follows:

$$\begin{gathered} \ln y_i = \ln \boldsymbol{x}'_i \boldsymbol{\beta} + v_i - u_i \\ v_i \sim N\left(0, \sigma_{vi}^2\right) \\ u_i \sim N^+\left(0, \sigma_{ui}^2\right) \\ \operatorname{cov}\left(v_i, u_i\right) = 0 \end{gathered} \tag{1}$$

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 fertiliser, pesticides, capital value, labour 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.[9]

Productive inputs were selected following related literature using ARMS data (McFadden, 2017; Schimmelpfennig, 2016). Nitrogen fertiliser 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 labour is measured by the total hours of labour (both paid and unpaid) 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 whereas 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 parameterising the variance of u_i, we can model the determinants of technical efficiency (Kumbhakar & Lovell, 2000; Wang & Schmidt, 2002).

$$\begin{gathered} \sigma_{vi}^2 = \exp\left(\boldsymbol{z}'_i \Theta_v + \boldsymbol{d}'_i \boldsymbol{\Omega}_v\right) \\ \sigma_{ui}^2 = \exp\left(\boldsymbol{z}'_i \Theta_u + \boldsymbol{d}'_i \boldsymbol{\Omega}_u\right) \end{gathered} \tag{2}$$

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 modelled 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 ($E(u_i) = g(z_i)$), scale its variance ($\sigma_{ui}^2 = f(\boldsymbol{z}_i)$), or both. However, this is computationally demanding and the log-likelihood

[9]A trans-log functional form for the production frontier was tested against the Cobb–Douglas. Results of the trans-log and comparison of technical efficiency and inefficiency scores are found in the Online Appendix.

function is unlikely to converge for a large number of determinants, as 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. Instead, we opt for the more parsimonious dual-heteroscedasticity model used elsewhere in the production literature (Hadri, 1999; Hadri, Guermat, & Whittaker, 2003; Mayen et al., 2010).

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.

$$\begin{aligned} TE_i &= \frac{y_i}{\exp\left(\ln \boldsymbol{x}'_i \boldsymbol{\beta} + v_i\right)} \\ &= \frac{\exp\left(\ln \boldsymbol{x}'_i \boldsymbol{\beta} + v_i - u_i\right)}{\exp\left(\ln \boldsymbol{x}'_i \boldsymbol{\beta} + v_i\right)} \\ &= \exp\left(-u_i\right) \end{aligned} \quad . \tag{3}$$

To estimate (3) empirically, we use the conditional expectation proposed by Battese and Coelli (1988).

$$\widehat{TE}_i = E\left[\exp\left(-u_i\right) \mid \varepsilon_i\right] . \tag{4}$$

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

$$E\left[u_i | \boldsymbol{z}_i, \boldsymbol{d}_i\right] = \sqrt{\frac{2}{\pi}} \hat{\sigma}_{ui} = \sqrt{\frac{2}{\pi}} \exp\left[\frac{1}{2}\left(\boldsymbol{z}'_i \widehat{\Theta}_u + \boldsymbol{d}'_i \widehat{\Omega}_u\right)\right] \tag{5}$$

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

$$\begin{aligned} \frac{\partial E\left[u_i | \boldsymbol{z}_i, \boldsymbol{d}_i\right]}{\partial z_k} &= \sqrt{\frac{1}{2\pi}} \widehat{\Theta}_{uk} \frac{1}{n} \sum_{i=1}^{n} \hat{\sigma}_{ui} \\ \frac{\partial E\left[u_i | \boldsymbol{z}_i, \boldsymbol{d}_i\right]}{\partial d_k} &= \sqrt{\frac{1}{2\pi}} \widehat{\Omega}_{uk} \frac{1}{n} \sum_{i=1}^{n} \hat{\sigma}_{ui} \end{aligned} \tag{6}$$

Note that the coefficients in $\widehat{\Theta}_u$ 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.

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, that is, $u_i > 0$. See the Appendix S1 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 et al., (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 A7 of the Appendix S1). 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, ungrouped 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 undetected 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—farms that have not adopted 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 8% less output than dryland corn fields, though the difference is not significant at conventional levels. Capital and applied nitrogen have 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 et al., 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 falls short of its feasible maximum by 23%. 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 the total error variance, on average. Concurrently, we perform a likelihood-ratio test of the null hypothesis that $\sigma_{ui}^2 = 0$, that is, that no inefficiency is present and the OLS estimator is sufficient (Coelli, 1995). 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 parameterisation shown in Equation (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 noise component of the composite error term.

Conversely, the variance of inefficiency—and consequently, its mean—is 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. Farm

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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 labour 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: Estimates expanded to represent all corn fields in 2016 using expansion weights provided by USDA NASS. Standard errors calculated using standard 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).

***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 4 Average marginal effects on inefficiency (u)

Variables	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	−7764.07	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: Average marginal effects of regressors on the unconditional expectation of u, $E(u_i|z_i, d_i)$. Standard errors calculated using standard delete-a-group jackknife procedure.

***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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. Although 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 (unconditional) mean inefficiency. Marginal effects are calculated according to the formulas shown in Equation (6) and standard errors are constructed using the delete-a-group jackknife procedure.[10] All marginal effects are statistically significant at the 0.01 level. In contrast to other findings (Sabasi, Shumway, & Astill, 2019; Wang, 2002) 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 4% 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 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 reveals a clear pattern of improved efficiency (reduced inefficiency) as farms advance along 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 achieve 16% more output (corn bushels) on average than laggards with the same amount of inputs, conditional on

[10]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.

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

[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).

relevant covariates. To interpret these effects in context, we report mean technical efficiency and inefficiency by PA adoption group in Table 5.

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 5 are largely consistent with average marginal effects.[11] 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 whereas innovators are 57% less inefficient. Comparing mean levels of technical efficiency across PA groups shows that late majority farms are 4% 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.

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 scores 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 centred at the lower tail of the distribution for early majority and innovator farms. The spread of these distributions also varies by group. The boxplots in Figure 4 show that, not only the mean and median, but also the variability of efficiency and inefficiency improve significantly for farms further up the PA adoption curve.

5 | STOCHASTIC META-FRONTIER ANALYSIS

Our analysis up to this point assumes that all farm groups share a common production technology. This assumption implies two things about farms in different PA groups. One, a common frontier means that productivity does not vary across farm groups. However, differences in productivity may emerge if different bundles of PA technology shift the production frontier up (or down). Observed differences in technical efficiency may be driven by differences in the underlying production technologies. Second, estimates of technical efficiency and inefficiency will be biased if calculated relative to an incorrect frontier (Mayen et al., 2010). A homogenous frontier prevents us from disentangling productivity and efficiency gaps between farms and across groups.

[11]Note that marginal effects are conditional on farm and operator characteristics whereas Table 5 reports unconditional means. The slight differences observed between marginal effects and mean comparisons is attributable to this.

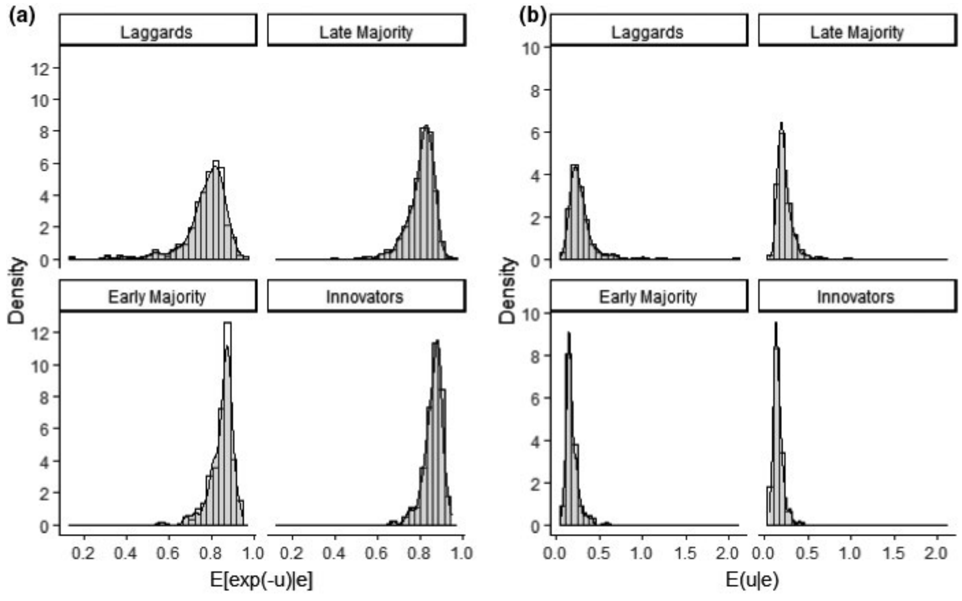

FIGURE 3 (a) Distributions of technical efficiency by PA adoption group. (b) Distributions of inefficiency by PA adoption group

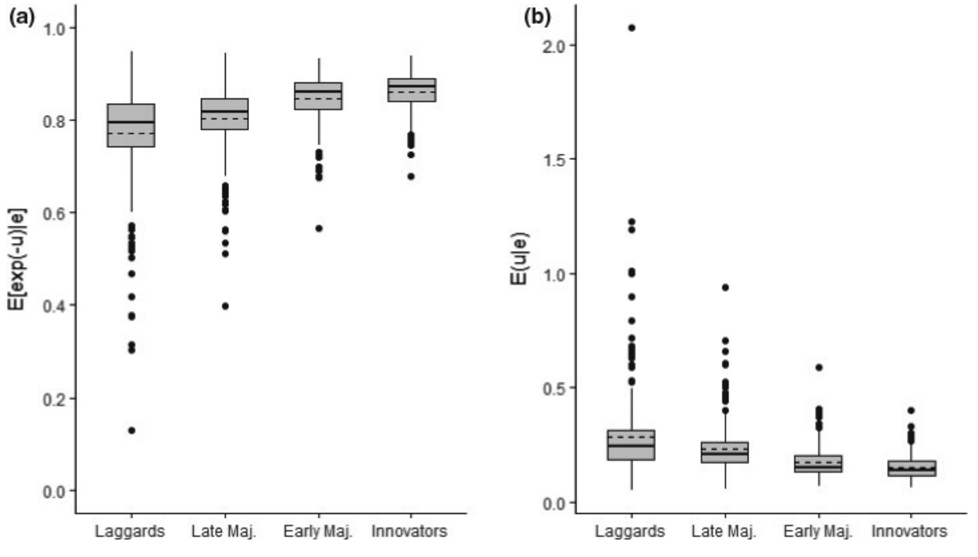

FIGURE 4 (a) Boxplots of technical efficiency by PA adoption group. (b) Boxplots of inefficiency by PA adoption group. *Note*: Solid line = median, dashed = mean

To test the robustness of our results to this possibility, we adapt the two-step stochastic meta-frontier analysis (SMFA) approach proposed by Huang, Huang, and Liu (2014). This strategy allows us to compute technical efficiency scores based on group-specific frontiers, then test for differences in the underlying production technology for farms at different stages of PA adoption by comparing them to a common meta-frontier.

In the first step, we estimate stochastic frontier models separately for each PA technology group $j = 1, \cdots, 4$.

$$\ln y_{ij} = \ln \boldsymbol{x}'_{ij} \boldsymbol{\beta_j} + v_{ij} - u_{ij}. \tag{7}$$

As before, u_{ij} follows a half-normal distribution with variance $\sigma^2_{uij}\left(\boldsymbol{w}'_{ij}\Theta_{uj}\right)$ whereas v_{ij} is mean-zero normally distributed with variance $\sigma^2_{vij}\ \boldsymbol{w}'_{ij}\Theta_{vj}$. Random noise and inefficiency variances are explained by farm-specific characteristics $\boldsymbol{w}_{ij}$ that vary within and across groups. Conformability issues in estimating the log-likelihood function limit the variables in $\boldsymbol{w}_{ij}$ to farm size and operator age. Within-group technical efficiency scores are:

$$TE_{ij} = \frac{y_{ij}}{\exp\left(\ln \boldsymbol{x}'_{ij} \boldsymbol{\beta_j} + v_{ij}\right)} = \exp\left(-u_{ij}\right). \tag{8}$$

Here, TE_{ij} measures how close farm i is to achieving its output potential, given the production technology specific to group j. We use predicted output from Equation (7) to fit a common stochastic meta-frontier that envelops all individual frontiers,

$$\widehat{\ln y_{ij}} = \ln \boldsymbol{x}'_{ij} \boldsymbol{\beta}^M + v^M_{ij} - u^M_{ij}, \tag{9}$$

where v^M_{ij} is mean-zero normally distributed as $N(0, \sigma^2_v)$ and u^M_{ij} is half-normally distributed as $N^+(0, \sigma^2_u)$. Both distributions are assumed to have constant variances.[12] Technical efficiency relative to the meta-frontier constitutes the technology gap ratio (TGR), a measure of distance between group-specific production technologies and the meta-technology available to all farms (Battese et al., 2004).

$$TGR_{ij} = \frac{\widehat{\ln y_{ij}}}{\exp\left(\ln \boldsymbol{x}'_{ij} \boldsymbol{\beta}^M + v^M_{ij}\right)} = \exp\left(-u^M_{ij}\right). \tag{10}$$

In calculating Equations (9) and (10), we can decompose total inefficiency into farm-level technical inefficiency with respect to the farm's chosen technology and shortfalls in efficiency due to the production technology itself.

Table 6 shows the results of the group-level stochastic frontier analysis. Constant returns-to-scale cannot be rejected for laggards and innovators, though farms in the late and early

[12]Huang, Huang, and Liu (2014) use environmental characteristics specific to each industry group in their specification of the stochastic meta-frontier. As farm groups belong to the same industry and are relatively evenly distributed throughout regions, we opt for a homoscedastic error and inefficiency variance. However, our results are robust to different variance parameterisations.

TABLE 6 Stochastic meta-frontier analysis: Group-specific production frontiers

	Dependent variable: ln total output (corn bsh.)							
	Laggards		**Late majority**		**Early majority**		**Innovators**	
Variables	**Estimate**	**Std error**	**Estimate**	**Std error**	**Estimate**	**Std error**	**Estimate**	**Std error**
Production frontier								
ln N	0.28**	0.06	0.31***	0.06	0.30***	0.06	0.19***	0.06
ln pest	0.08***	0.04	0.14***	0.03	0.21***	0.05	0.10	0.04
ln labour hrs	0.18***	0.05	0.12***	0.05	0.31**	0.07	0.12***	0.09
ln capital	0.41	0.07	0.23	0.09	0.16***	0.08	0.60	0.12
ln farm acres	0.04	0.07	0.04	0.03	−0.12	0.03	−0.04**	0.03
Irrigated	0.02	0.13	−0.09***	0.07	−0.07	0.14	−0.24	0.11
Northern Crescent	−0.12**	0.09	−0.27**	0.10	−0.12	0.09	−0.12	0.10
Northern Great Plains	−0.49***	0.23	−0.15***	0.07	−0.03***	0.06	0.09	0.10
Prairie Gateway	−0.25	0.07	−0.40	0.08	−0.47	0.10	−0.20**	0.13
Eastern Uplands	−0.07***	0.19	−0.21***	0.17	0.22***	0.24	0.25	0.13
Southern Seaboard	−0.83***	0.16	−0.87***	0.09	−0.59***	0.11	−0.12***	0.18
Fruitful Rim	−0.67***	0.11	−0.42***	0.10	_	_	_	_
Cons	1.87	0.46	3.06	0.32	3.34	0.36	1.56	0.42
ln sigma v								
Farm acres	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operator age	0.00**	0.02	0.00**	0.02	0.01***	0.02	0.00	0.02
Cons	−2.08	1.02	−2.17	0.95	−2.81	0.90	−1.63	1.13
Mean sigma v	0.31	0.00	0.31	0.00	0.30	0.00	0.33	0.00
ln sigma u								
Farm acres	0.00***	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operator age	−0.04	0.01	0.00*	0.01	0.01	0.03	0.01*	0.03
Cons	0.71***	0.94	−1.41***	0.81	−1.89***	1.92	−5.26***	3.14
Mean sigma u	0.33	0.01	0.45	0.00	0.27	0.01	0.11	0.00
RTS, Pr(RTS=1)[a]	0.99	(0.90)	0.85	(0.00)	0.88	(0.00)	0.97	(0.49)
Observations	305		364		210		159	
Log-pseudolikelihood	−173,536.48		−170,196.35		−56,779.29		−18,523.59	

Notes: White's heteroscedasticity consistent standard errors shown next to parameter estimates.

[a]Estimated returns-to-scale for each group. The probability of the Chi-square statistic based on a Wald test for constant returns-to-scale is shown in parentheses.

***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

majority stages report decreasing returns to scale, suggesting PA groups access different production technologies. However, results of the pooled stochastic meta-frontier in Table 7 are comparable to the homogeneous production frontier estimated in Table 3. The estimate of σ_u^2 in Table 7 is not statistically different from zero, that is, we do not find evidence of inefficiency in the meta-frontier. Table 8 summarises group-specific technical efficiency scores, inefficiency scores, and TGRs by PA group.

Although the general pattern of improved technical efficiency and reduced inefficiency at advanced stages of technology adoption remains, the SMFA differs from the pooled SFA in

TABLE 7 Stochastic meta-frontier analysis: Meta-frontier

	Dependent variable: ln total output (corn bsh.)			
Variables	**Estimate**	**Std error**	**z value**	**Pr(>|z|)**
ln N	0.29	0.01	21.34	0.00***
ln pest	0.13	0.01	14.05	0.00***
ln labour hrs	0.14	0.01	9.97	0.00***
ln capital	0.33	0.03	12.52	0.00***
ln farm acres	0.00	0.01	0.46	0.56
Irrigated	−0.10	0.03	−3.74	0.00***
Northern Crescent	−0.20	0.02	−9.22	0.00***
Northern Great Plains	−0.06	0.03	−2.17	0.02**
Prairie Gateway	−0.32	0.03	−9.54	0.00***
Eastern Uplands	−0.12	0.03	−3.78	0.00***
Southern Seaboard	−0.66	0.03	−23.68	0.00***
Fruitful Rim	−0.50	0.07	−7.28	0.00***
Cons	2.45	0.10	25.47	0.00***
Mean sigma v	0.15	0.00	31.79	0.00***
Mean sigma u	0.00	0.00	16.37	0.00***
Lambda[a]	0.00	0.00	0.51	0.30
Observations	1,038			
Log-pseudolikelihood	492,156.87			

Notes: Estimates expanded to represent all corn fields in 2016 using expansion weights provided by USDA NASS. Standard errors calculated using standard delete-a-group jackknife procedure.

[a]The percentage of total error variance attributable to inefficiency u.

***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 8 Stochastic meta-frontier analysis: Mean technical efficiency, inefficiency, and technology gap ratio by PA group

	TE[a]		**E(u|z)**[b]		**TGR**[c]	
	Mean	**Std Dev.**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
PA – Laggards	0.79	0.10	0.26	0.17	0.9997	0.00
PA – Late majority	0.73	0.12	0.35	0.24	0.9997	0.00
PA – Early majority	0.90	0.09	0.12	0.12	0.9997	0.00
PA – Innovators	0.91	0.04	0.09	0.04	0.9997	0.00

Notes: Both technical efficiency and inefficiency are calculated based on group-specific production frontiers shown in Table 6.

[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).

[c]Technology gap ratio estimated from the meta-frontier.

two ways. One, the late majority group—farms that tend to adopt yield monitors but little else—report lower technical efficiency scores than laggards when evaluated against their own unique production frontier. Two, the degree to which the variability of efficiency and inefficiency shrinks for farms at advanced stages of PA adoption is slightly diminished in the SMFA. Figures 5 and 6 illustrate the kernel density and box-plot distributions of efficiency and inefficiency by PA group.

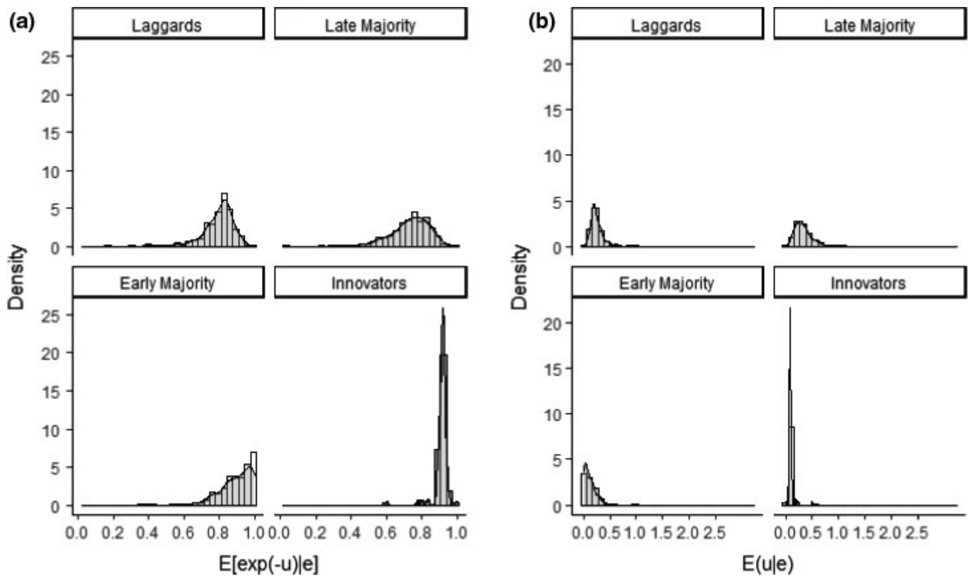

FIGURE 5 (a) Distributions of within-group technical efficiency by PA adoption group via SMFA. (b) Distributions of within-group inefficiency by PA adoption group via SMFA

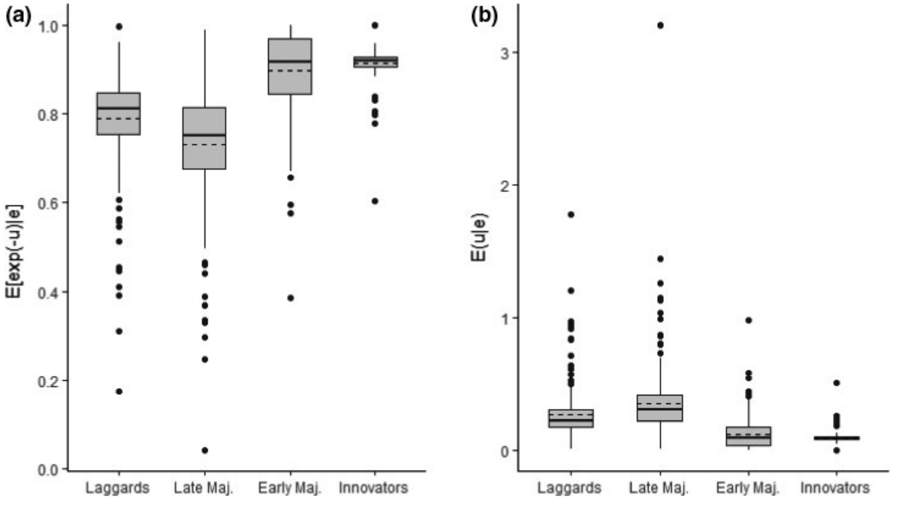

FIGURE 6 (a) Boxplots of within-group technical efficiency by PA adoption group via SMFA. (b) Boxplots of within-group inefficiency by PA adoption group via SMFA. *Note*: Solid line = median, dashed = mean

However, the meta-frontier analysis confirms the conclusion that efficiency gains are most apparent at the early majority stage; early majority farms are 14% more technically efficient than laggards and innovators are 16% more efficient than laggards according to the meta-frontier approach. Unlike farm-level efficiency measures, TGRs are nearly one for all PA groups. We therefore cannot conclude that farms at later stages of the PA technology adoption curve improve their ability to access the meta-frontier production technology (Huang et al., 2014).

We consider several other robustness checks in the supplemental appendix (online). These include a test for omitted variable bias resulting from scale economies in the inefficiency and random noise parameterisation and an alternative frontier specification using the trans-log. Our main findings are robust to these tests.

6 | DISCUSSION AND CONCLUSIONS

Pooled stochastic frontier analysis (SFA) results show statistically significant increases in average technical efficiency between farms at latter stages of the PA technology adoption curve, with efficiency gains exhibiting diminishing marginal returns. Results from a stochastic meta-frontier analysis (SMFA) confirm the general pattern in average technical efficiency when estimated relative to group-specific frontiers. Importantly, the SMFA does not show differences in efficiency to be driven by efficiency gaps in the underlying production technologies adopted by different groups. This finding suggests that farms that adopt advanced PA technology bundles use inputs more efficiently than laggards, but do not meaningfully change the production frontier relative to the industry-wide meta-frontier.

In addition to improvements in mean technical efficiency and inefficiency, we find that the variance in inefficiency (σ^2_{ui}) is lowest among early adopters. This is not, however, the case for the random error variance (σ^2_{vi}). This implies that farms using comprehensive PA technology bundles face less production risk due to inefficiency, but do not face less risk posed by random production shocks (e.g., drought). PA technologies may not be risk mitigating in the Just and Pope (1979) sense where certain inputs and farm practices attenuate the effects of random shocks. Rather, the adoption of PA may reduce the variability of output due to imprecise input application (e.g., variable vs. uniform application of nutrients across heterogeneous soil types).

To illustrate the possible mechanism for these findings, consider a farm that combines GPS guidance, digital soil maps, and VRT to apply soil nutrients on a site-specific basis while eliminating overlap. This farm has the same maximum feasible production for a given mix of inputs and is equally exposed to extreme weather events as a farm with no PA technology. However, on average, the advanced farm will more closely approach the shared production frontier and deviate from it less severely than the farm that does not invest in PA.

Looking at marginal differences between groups, we see that moving from the laggard stage with no adoption to the late majority stage—where some data is collected and yield monitors are often used—is associated with modest improvements in technical efficiency when evaluated against a pooled frontier. However, when estimated relative to their group-specific frontier, late majority farms exhibit a significant efficiency deficit relative to all other groups, possibly the result of adjustment costs incurred when farms transition from a no technology baseline to more advanced technologies. Regardless of estimation method, the largest improvements in technical efficiency are observed between the late and early majority stages. Based on a pooled SFA approach, mean technical efficiency rises by 6% whereas mean inefficiency falls by 26% between the late and early majority 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 input efficiency, most likely through the elimination of overlap or convenience (Miller et al., 2018; Thompson et al., 2019). 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.

In both the pooled SFA and SMFA, we observe small marginal improvements in efficiency for farms that advance to the innovators group, which is recognisable 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, although the incremental benefits appear to be relatively small.

However, small marginal improvements in efficiency may warrant investment in advanced PA and farm data technologies when aggregated over a large scale. Note that although innovators make up only 13% of corn farms, they are responsible for 24% of all US corn acreage due to their large average size. The ability of large farms to capture these small efficiency gains may increase their competitiveness. 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—whereas large operations are simultaneously more likely to adopt novel PA systems and to enjoy the associated efficiency benefits. Though the 2016 ARMS does not directly ask about access to credit, it documents farm debts and assets, which vary widely across PA adoption groups. For example, farms classified as innovators carry debt-to-asset ratios that are nearly twice as high as laggards (0.19 vs. 0.11). The implication is that innovators are more willing and able to use financial leverage when investing in their farm operations.

Though consolidation in row-crop agriculture has occurred steadily over the previous three decades, widespread use of PA among large operations could accelerate this trend, particularly in the presence of low operating margins (MacDonald et al., 2018). Moreover, the long-run efficiency gains may be more significant than our results imply. As data-intensive technologies such as ag-tech software and mobile apps are recent developments (particularly during the survey period), adjustment costs could disguise the true benefits afforded by these technologies in the short run (Silva & Stefanou, 2007).

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 provides suggestive evidence in support of this claim. Several papers attempt to quantify the productive value of information and data in agriculture (Chavas & Pope, 1984; Muller, 1974; Shapiro & Muller, 1977). 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.

Finally, although our results are robust to alternative specifications and control strategies, unobservable factors (e.g., innate farming ability) may nevertheless lead to self-selection of farms into different PA technology bundles. We are careful not to interpret our results as causal effects, but rather useful associations that can inform farm-level benchmarking and technology investment decisions. Policymakers, agribusiness professional, and extension educators wishing to incentivise PA adoption can use these results to identify farms that are good candidates for PA. Future research efforts should address both the inherent self-selection of PA technology adoption and the dynamic effects of PA, perhaps using longitudinal farm-level data.

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ORCID

Nathan D. DeLay https://orcid.org/0000-0003-3239-0798

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Additional supporting information may be found online in the Supporting Information section.

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