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Farmers' willingness to participate in a big data platform

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Abstract

This paper uses a hypothetical choice experiment to examine farmers' willingness to share their farm data with a big data platform. We found that, on average, 36% of farmers are willing to join such a platform. Participation is affected by the characteristics of both the platform and the farmer. The organization operating the big data platform is particularly important: farmers are most willing to share their data with university researchers and least willing to share their data with government. Not surprisingly, farmers with strong privacy preferences are less likely to join a big data platform. However, we found that relatively small financial and nonfinancial benefits significantly increased participation, even among farmers who stated strong privacy preferences. [EconLit classifications: Q12, Q16, Q18]

1 | INTRODUCTION

Over the past two decades, agriculture has been undergoing a data revolution. Agricultural machinery, such as combines, seeders, and soil sensors, are now capable of capturing vast amounts of geographically-specific data. Whereas this field-level data has some benefit to the farm that generates it, most researchers agree that the full promise of the agricultural data revolution will only be realized when farm data is uploaded to a data platform where it can be combined with satellite imagery, drone scans, and information from weather sensors.

By aggregating data across a range of farms and weather conditions, algorithms can make agronomic recommendations such as the optimal rate and timing of fertilizer and pesticide application. These recommendations can be made at the sub-field level and inputted directly into precision agricultural machinery, which can apply inputs at variable rates according to GPS coordinates (Sonka, 2016; Weersink, Fraser, Pannell, Duncan, & Rotz, 2018; Wolfert, Ge, Verdouw, & Bogaardt, 2017). These precise recommendations should improve upon the decision heuristics and rules of thumb that farmers generally use when making input decisions.

Despite the promise that many see in the agricultural data revolution, few farmers are currently participating in a big data platform (Poppe, Wolfert, Verdouw, & Renwick, 2015). Instead, farm data is generally kept within the operation and is often not analyzed at all (Brown, 2017). There is little research that explores whether farmers are interested in joining a big data platform and, if so, what elements of the platform would maximize participation.

In this paper, we address this shortcoming in the literature using a hypothetical choice experiment. In the experiment, farmers are asked if they would enroll in a hypothetical big data platform. We vary the type of organization running the data platform, the financial cost or incentive for participating, and the nonfinancial benefits from participating. Overall, we find a relatively low participation rate: On average, 36% of respondents stated that they would join a hypothetical big data platform. However, the participation rate was influenced by the characteristics of both the respondent and the platform.

Not surprisingly, individuals who placed a higher value on their privacy were significantly less likely to participate. However, we also find evidence of a privacy paradox; consistent with previous research, respondents (including those who stated that privacy was very important to them) agreed to participate in the platform when offered relatively small financial incentives (Athey, Catalini, & Tucker, 2017; S. B. Barnes, 2006; Norberg, Horne, & Horne, 2007). Participation rates were also sensitive to the organization operating the big data platform: respondents were most likely to participate in a platform run by a university and least likely to join a platform run by the government.

The results contribute to the ongoing discussion surrounding the future of big data in agriculture, which is summarized in Weersink et al. (2018). Much of this literature speculates about the potential benefits of big data and precision agriculture technologies. The most important direct benefit for farmers is improvements in input decisions, such as seeding rates and fertilizer application (Lesser, 2014; Sonka, 2016; Wolfert et al., 2017). However, big data could also assist with other farm-level decisions such as environmental quality management (K. H. Coble, Mishra, Ferrell, & Griffin, 2018) and crop rotations.

Farmers might also benefit from big data indirectly if researchers are able to take advantage of big data in plant breeding and other agricultural research. The aggregation of field-level data would allow researchers to determine the performance of seed varieties under different fertilizer rates, weather conditions, and soil types, potentially accelerating the development of new varieties (Weersink et al., 2018). Likewise, machinery manufacturers and input companies could use big data to refine their marketing activities and new product development.

Capturing field-level data would also allow for real-time predictions of the size of the crop. Such information is valuable to a variety of actors in the supply chain, including buyers, transport companies, and processors. Evidently, the owner of this information would stand to gain significant information rents if the data was proprietary.

The major obstacle to the development of a big data platform is a concern about data ownership and privacy (Weersink et al., 2018; Wolfert et al., 2017). Legal protections surrounding farm ownership of agricultural data in Canada and the US are generally seen as weak and are yet to be tested in court (Booker, 2018; Ferris, 2017). According to Leon (2017), agricultural data is difficult to regulate, as it contains elements of real, personal, and intellectual property. In spite of these challenges, Ferris (2017) argues that specific laws are required for agricultural data, just as there are industry-specific regulations government financial and health data.

In the absence of government regulation, for-profit and not-for-profit entities are attempting to assuage farmers concerns by laying out clear privacy statements and agreeing to submit to industry codes of conduct. Notably, the American Farm Bureau, together with other farm organizations and agricultural technology providers, drafted *The Privacy and Security Principles of Farm Data*. Many agricultural technology companies have agreed to adhere to these principles, and the Farm Bureau has since established the *Ag Data Transparent* certification, which verifies that technology companies are compliant (Ag Data Transparent, 2019).

Despite such certifications, privacy concerns continue to loom large for farmers. In a 2016 survey by the American Farm Bureau, 77% of American farmers stated that they were “concerned” or “extremely concerned” about the entities that can access their data and whether this data can be used for regulatory purposes (American Farm Bureau, 2016). Similarly, in a 2018 survey by Farm Credit Canada (FCC), 71% of Canadian farmers stated that the use of their data by an outside party was either “extremely important” or “very important" in selecting which technology or service provider to use (Wall, 2018). Brown (2017) argues that farmers are particularly concerned that their data can be accessed by competing farms or input companies, who may use it to price discriminate against farmers. However, farmers' stated concerns contrast with their behavior—65% of respondents in the FCC survey were unsure of how their data was governed in their existing agreements and contracts.

Currently, there are a number of data platforms operating under a variety of business models. Most platforms offer farmers an app or farm management software that provides insight into farm agronomics and profitability, based on the data uploaded by the farmer. Some of these platforms are standalone software firms, such as FarmersEdge or CropLogic, whereas others are owned by agricultural input companies, such as Granular (owned by Corteva) and Climate Corporation (owned by Bayer, formerly Monsanto). Input companies may have an additional incentive to invest in data platforms, as they can benefit from complementarities between the data services and other products or services they sell to farmers. For example, an input company could use farmers' data to recommend a particular seed variety that would perform well in a particular field.

Agricultural machinery companies, such as John Deere and Case New Holland, are also leveraging their relationship with customers to develop data platforms. Machinery companies have an obvious advantage, as it is their equipment that generates the data. There is, in fact, considerable uncertainty about the legal ownership of the machine-generated data (Sykuta, 2016), though John Deere has tried to obviate this concern by signing *The Privacy and Security Principles of Farm Data*.

Finally, some big data platforms are operated by not-for-profit organizations. One example is the Ag Data Coalition (ADC), which provides a neutral environment for farmers to upload their data. After scrubbing and syncing farmers' data, the ADC shares the data with third parties that farmers have approved.

Other not-for-profits have focused on ensuring interoperability across data-sharing platforms. The Open Ag Data Alliance's mandate is to "develop open reference implementations of data storage and transfer mechanisms with security and privacy protocols" (Open Ag Data Alliance, 2019). Other not-for-profits, such as the Midwest Big Data Hub, are spurring the development of big data technologies by connecting industry players with interest or knowledge of big data, to spur further innovation in the field (About the Midwest Big Data Hub, 2019).

While the number of big data platforms appears to be expanding, only a handful of these organizations are likely to survive in a mature industry (Wolfert et al., 2017). Industry consolidation is primarily driven by network effects; the benefits a big data platform can provide to farmers are generally increasing in the size of the platform, giving large platforms an advantage in recruiting farmers. This implies that the industry will be close to a winner-take-all model, with a handful of firms gaining dominant market shares that serve as a barrier to entry for new platforms. The asymmetry in power between data platforms and farmers can result in higher prices and contract terms that are more favorable to the data platform (Carbonell, 2016; Carolan, 2018). For example, in the absence of competition, farmers may have no choice but accept privacy and security provisions that are not to their liking.

The potential market power created by big data could also have spillover effects in agricultural input markets, exacerbating the existing trend towards consolidation (MacDonald, 2017; Sexton & Xia, 2018). As agribusinesses expand their data platforms, they gain private information about the farmers that participate in their platform. As mentioned, this information can be used by input companies to make farm-specific recommendations. New entrants, or firms without a data platform, will be put at a competitive disadvantage vis-à-vis established firms with access to farm-level data.

Our research also contributes to the ongoing scholarship related to the adoption of precision agricultural technology and the adoption of big data in other industries. Barnes et al. (2019) distinguish between embodied knowledge technologies that require no additional skills or training, from information-intensive technologies that require significant farmer investment in additional knowledge and skills. They argue that embodied knowledge technologies should have higher adoption rates, as there are lower costs of adoption. Among precision agricultural technologies, GPS guidance (auto-steer) could be thought of as an embodied knowledge technology, whereas variable rate technology, and field mapping are information-intensive technologies.

A. P. Barnes et al. (2019) find that significantly more European farmers use GPS guidance (56%) than variable-rate technology (23%). A survey of Kansas farmers found that 60% used yield monitors (an embodied technology), while only 33% used variable rate technology (Griffin et al., 2017). In a survey of agricultural service providers, Mitchell, Weersink, and Erickson (2018) note a smaller difference in adoption among Ontario agricultural service providers—92% of providers offered GPS guidance in 2017, whereas 88% offered fertilizer prescriptions to aid variable rate application.

Data sharing cannot be neatly categorized as either an embodied and information-intensive technology. Most new agricultural machinery is capable of automatically generating and uploading farm-level data (Kamilaris, Kartakoullis, & Prenafeta-Boldú, 2017). However, utilizing the information gleaned from a data service (e.g., prescription maps and seeding recommendations) requires complementary information intensive technologies, such as variable-rate technology.

Research has also linked adoption of precision agriculture to farmer characteristics, finding that adoption is negatively correlated with age, and positively correlated with farm size, computational literacy, and education (Daberkow & McBride, 2003; Larson et al., 2008; Tamirat, Pedersen, & Lind, 2018). In nonagricultural sectors, Sun, Cegielski, Jia, and Hall (2018) find that the factors affecting a firm's willingness to adopt big data technologies include the firm's human resources, technology resources, and management support.

The rest of this paper unfolds as follows: in the next section we outline our survey and the resulting data, in Section 3 we detail our conceptual and empirical models, in Section 4 discuss our results, and in section 5 we conclude.

2 | SURVEY AND DATA

The data come from an online hypothetical choice experiment administered by Kynetec, a market survey company. The survey was completed by grain farmers in Saskatchewan in the fall of 2017. Respondents were initially offered $10 in compensation for completing the survey. Due to lower than normal response rates, compensation was raised to $20 then to $30. Out of the 561 survey respondents, 344 were compensated with $10, 129 were compensated with $20, and 88 were compensated with $30. Payments are controlled for in the analysis and do not have a statistically significant impact on the results.

The survey queried farmers about their use of existing precision agriculture technologies, their attitudes towards privacy, technology, and farm management, and their sociodemographic characteristics. Respondents then answered a series of 12 choice questions. In the choice questions, respondents were asked if they would be willing to participate in a particular big data platform. The choice questions varied (a) the organization running the platform, (b) the financial incentive for participation, and (c) the nonfinancial incentive for participation. Table 1 shows the organizations and incentives that were considered. A sample choice question is provided in Figure 1.

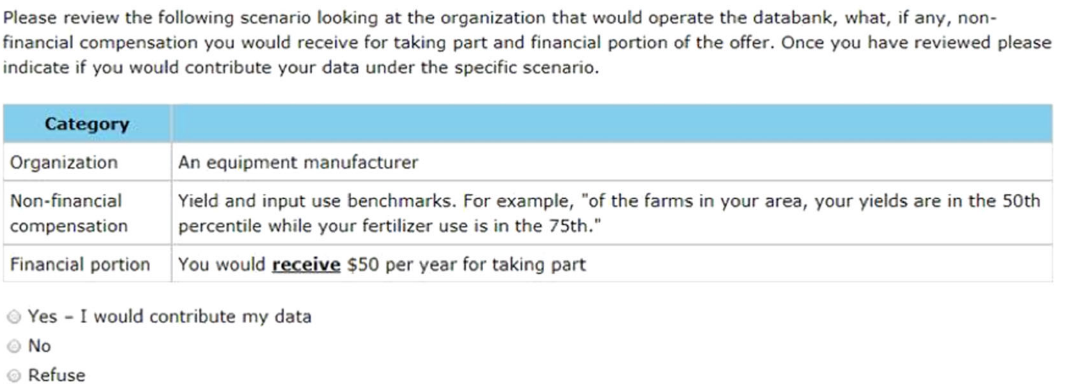
The survey design was pseudo-random. Given the options in Table 1, there are 72 unique combinations of organization, financial incentive, and nonfinancial incentive. The 72 unique scenarios were divided into six groups of 12, ensuring sufficient variation in the organization, financial incentive, and nonfinancial incentive within each group. Respondents were randomly assigned to a particular group of 12 questions—an approximately equal number of responses was received for each group of questions.

Before answering the choice questions, respondents were provided with an information script that explained the rationale for enrolling in a big data platform.[1] Importantly, the script asked respondents to assume that there were no transaction costs of participating in the platform.

[1]The information script read: "Much of the value of farm-level data comes from aggregating it into a databank. Researchers can use a databank to detect underlying trends that can only be seen with very large sample sized. For the following questions, assume your farm equipment has the relevant data collection capabilities. Also assume that if you decide to contribute your data to a databank, it can be done so remotely by the relevant organization, and requires no effort on your part."

TABLE 1 Organizations and incentives in the choice questions

Organization	Financial incentive	Nonfinancial incentive
University researchers	−$50	None
Crop input suppliers Grower associations Equipment manufacturers	$0 $50 $100	Prescription maps based on the data submitted. Depending on the data submitted these could be for fertilizer, seed, fungicide, or other inputs.
Financial institutions Government		Yield and input use benchmarks. For example, “of the farms in your area, your yields are in the 50th percentile while your fertilizer use is in the 75th.”


Please review the following scenario looking at the organization that would operate the databank, what, if any, non-financial compensation you would receive for taking part and financial portion of the offer. Once you have reviewed please indicate if you would contribute your data under the specific scenario.

Category	
Organization	An equipment manufacturer
Non-financial compensation	Yield and input use benchmarks. For example, "of the farms in your area, your yields are in the 50th percentile while your fertilizer use is in the 75th."
Financial portion	You would **receive** $50 per year for taking part

Yes – I would contribute my data
No
Refuse

FIGURE 1 Sample choice question [Color figure can be viewed at wileyonlinelibrary.com]

Respondents were asked to evaluate 11 statements, which measured their attitudes towards privacy, technology use, and farm management. Respondents denoted their level of agreement with each statement on a scale of one (low level of agreement) to five (high level of agreement). The first three statements measured privacy attitudes, the next four statements measured technology use attitudes, and the final four statements measured farm management attitudes. The statements and mean responses are given in Table 2. There is a high correlation between statements that measure the same attitude. We, therefore, use principal component analysis to combine the statements into three variables, which capture attitudes towards privacy, technology use, and farm management, respectively (details can be found in the online appendix).

To gauge farmers’ current level of technology, respondents were asked about their use of five precision agriculture technologies: yield monitors, GPS guidance, soil sampling, variable rate technology, and automatic section control.[2] Respondents were given the option of answering: “I do not use this technology”, “I use this technology and it doesn’t improve my farm’s performance”, or “I use this technology and it improves my farm’s performance”. The average responses to these questions are shown in Table 3.

Precision agriculture technologies are likely to be complementary to enrollment in a big data platform. Yield monitors and soil sampling generate the data that would be uploaded to the platform, while GPS guidance, variable rate technologies, and automatic section control would be necessary for a farmer to extract the full benefits from participating in a big data platform. For example, a big data platform may provide farmers

[2]GPS guidance provides farmers with their exact location on the field, helping reduce overlap when seeding, spraying, and harvesting. GPS can be used alongside yield monitors to generate yield maps. Automatic section control turns off sections of seeders or sprayers when the seeder or sprayer covers a part of the field that has already been treated. Soil sampling requires the farmer or agronomist to take physical soil samples to a lab to be analyzed.

TABLE 2 Responses to attitude questions[a]

	Mean	*SD.*
Privacy		
Privacy is important to me	4.0	1.00
I would be put at a disadvantage if other could access info about my farm	3.1	1.10
I feel comfortable sharing information about my farm	3.2	0.95
Technology use		
I like to have the latest technology	3.4	1.00
I find new technologies easy to use	3.3	0.99
New technology is more hassle than it is worth	2.5	1.02
I am getting maximum use out of available tech on my farm	3.3	1.04
Farm management		
I have implemented new techniques that have been recommended	3.6	0.87
I am proactive in seeking advice	3.9	0.85
Precision ag will transform agriculture over the next 20 years	4.0	0.97
I know better than others how to manage risk on my farm	3.6	0.89

[a]Respondents were asked to denote their level of agreement on a scale of 1–5, with 5 being strongly agree.

TABLE 3 Responses to technology use questions

	Use technology improves performance	Use technology, does not improve performance	Does not use technology
Yield monitors	42%	33%	25%
GPS guidance	90%	4%	5%
Soil sampling	68%	9%	23%
Variable rate	24%	5%	71%
Automatic section control	56%	1%	44%

with prescription maps that specify different rates of fertilizer application in different areas of a field—both GPS and variable rate technologies would be necessary for these prescriptions to be implemented automatically.

The average age of those surveyed was 56.1, close to the average age of Saskatchewan farm operators found in the 2016 census of agriculture—55 years.[3] Women were underrepresented in the survey: they made up just 5.5% of respondents, while the census found that 24.9% of Saskatchewan farm operators were female. Of those surveyed, 5% did not have a high school diploma, whereas 23% had a university degree. In contrast, the census found that only 11.7% of Saskatchewan farmers held a university degree. Farmers with a university degree may be more likely to communicate through email (the method of delivery for the survey) or to respond to a survey about technological adoption.

Annual sales revenue was collected as a categorical variable. Table 4 provides a comparison of the revenue of farms in our survey and the revenue of farms in the census. The discrepancies between the survey data and the census data might be explained by the differences in sample frames. Our survey was restricted to grain farmers. In contrast, the census captures all farms, including specialty crop and hobby farms, which tend to be smaller. A significant portion of those surveyed (12%) refused to disclose their annual sales revenue.

[3]The census of agriculture data is available at https://www.statcan.gc.ca/eng/ca2016.

TABLE 4 Farms by revenue class

Revenue range	Survey (Grain farmers in SK)	Statistics Canada[a] (All farmers in SK)
<$100,000	3%	43%
$100,000–$499,999	29%	35%
$500,000–$999,999	27%	12%
$1 million–$2 million	20%	7%
$2 million–$3 million	4%	3%[b]
>$3 million	5%	

[a]Statistics Canada. Table 32-10-0157-01.
[b]The final two categories are combined in Statistics Canada data.

In our analysis, we drop all observations with missing covariates. This results in the removal of 1,467 observations, creating a final analysis sample of 5,265 observations. The results are virtually unchanged when we use the full data set with dummy variables to account for nonresponse.

On average, 36% of farmers are willing to participate in a big data platform. Figure 2 shows how the participation rate changes with the platform attributes. The organization running the platform has a particularly important impact on the participation rate. The hypothetical participation rate is highest when the platform is run by university researchers and lowest when the government runs the platform. Participation rates are also higher in the presence of financial and nonfinancial incentives. Providing even a small monetary benefit for participating increases participation rates by over ten percentage points. Similarly, participation rates increase by 9 percentage points when prescription maps are offered and by 12 percentage points when benchmark statistics are offered.

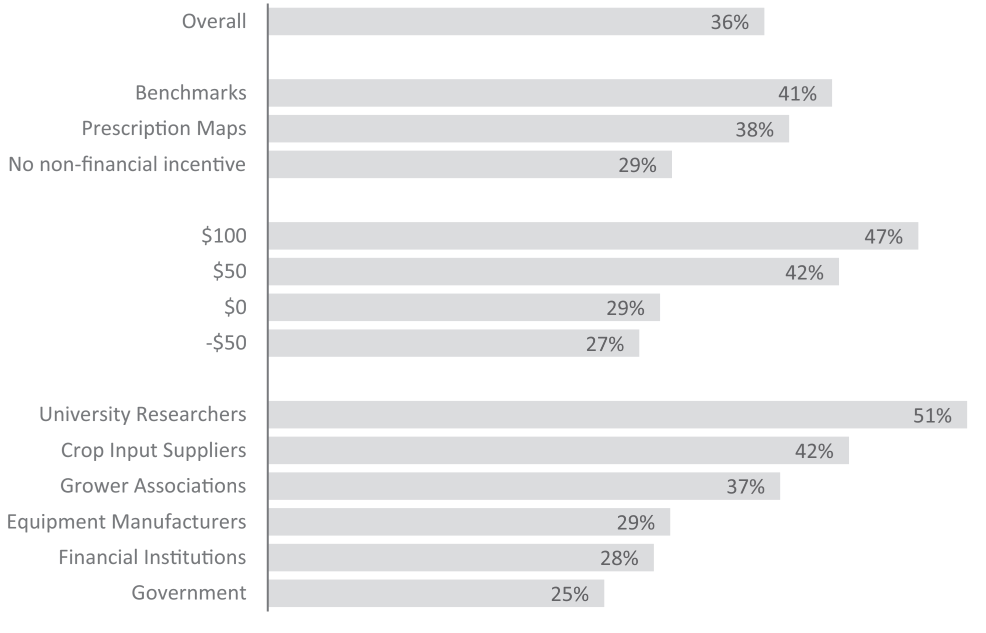


FIGURE 2 Percent of respondents who agreed to participate in a big data platform depending on the program characteristics[a]. [a]The choice task varied three characteristics of the hypothetical big data program: the nonfinancial incentive (benchmarks or prescription maps), the financial cost/incentive, and the type of organization running the program

3 | CONCEPTUAL AND EMPIRICAL MODEL

The utility that a farmer receives from joining a big data platform is a function of their individual characteristics and the characteristics of the platform. Specifically, we denote the utility the *i*th individual receives from the *j*th big data platform as,

$$u_{i,j} = \sum_{f\epsilon F}\beta_f D_{f,j} + \sum_{g\epsilon G}\beta_g D_{g,j} + \sum_{h\epsilon H}\beta_h D_{h,j} + \gamma Z_i + e_{i,j}, \tag{1}$$

where F is the set of organizations (government, university researchers, crop input suppliers, grower associations, equipment manufacturers, financial institutions), G is the set of financial incentives (−\$50, \$0, \$50, \$100), and H is the set of nonfinancial incentives (none, benchmark statistics, prescription maps). D are dummy variables equal to 0 or 1; for example, $D_{f,j}$ is equal to 1 if the *j*th platform is run by the *f*th organization and is equal to 0 otherwise ($D_{g,j}$ and $D_{h,j}$ are similarly defined). Z_i is a vector of individual-specific characteristics. Finally, β and γ are parameters, and e represents unobservable characteristics of the individual and the big data platform. Normalizing the utility that the individual receives from not enrolling in the platform to zero, the individual will join the big data platform if $u_{i,j} > 0$.

The responses to the choice questions are analyzed using logit and latent class logit models, which assume the unobservables follow a logistic distribution (we obtain nearly identical results using probit and linear probability models). In the logit model, the probability that an individual joins the *j*th big data platform is,

$$\Pr\,(y_{i,j} = 1) = \frac{\exp\{\bar{u}_{i,j}\}}{1 + \exp\{\bar{u}_{i,j}\}}, \tag{2}$$

where $\bar{u}_{i,j}$ is the non-stochastic component of $u_{i,j}$ ($\bar{u}_{i,j} = u_{i,j} - e_{i,j}$), and $y_{i,j}$ is the dependent variable which is equal to one if the respondent joins the hypothetical data platform, and is equal to zero otherwise. We present results from two different logit models. In the second specification, a set of interaction terms between organization and sociodemographic information is included as a check for heterogeneity in the results.

As an additional check for heterogeneity, we run a latent class logit model. The latent class model assumes that there are M classes of individuals, each with different preferences. The probability the *i*th individual belongs to *m*th class is estimated as,

$$\text{Prob (class} = m) = \frac{\exp\{\theta_m Z_i\}}{\sum_{c=1}^{M}\exp\{\theta_c Z_i\}}, \tag{3}$$

where Z_i are the individual-specific characteristics and θ are parameters to be estimated.

Within each class, the probability that the individual chooses to participate in the big data platform is,

$$Prob\,(y_{i,j} = 1 \mid class = m) = \frac{\exp\{\bar{u}_{i,j,m}\}}{1 + \exp\{\bar{u}_{i,j,m}\}}, \tag{4}$$

where,

$$\bar{u}_{i,j,m} = \sum_{f\epsilon F}\beta_f D_{f,j} + \sum_{g\epsilon G}\beta_g D_{g,j} + \sum_{h\epsilon H}\beta_h D_{h,j}. \tag{5}$$

Combining Equations ((3,4)), the probability the *i*th individual joins the *j*th big data platform is,

$$\text{Prob}\,(y_{i,j} = 1) = \sum_{m=1}^{M}\text{Prob}\,(y_{i,j} = 1|\text{class} = m)\,\text{Prob (class} = m). \tag{6}$$

4 | RESULTS

Table 5 contains the coefficients and marginal effects of the logit model. Standard errors are clustered on the respondent to account for correlated responses from the same individual. As mentioned in the preceding section, the dependent variable measures whether or not the respondent agreed to participate in the hypothetical big data platform. The explanatory variables include characteristics of the hypothetical big data platform (the organization running the platform, financial incentive, and Nonfinancial incentive), characteristics of the respondent (technology use, attitudes, revenue, education, age, and gender), and the compensation paid for survey completion (which had no effect on the probability of participation).

4.1 | Organization

Farmers' preferences for the organization running the big data platform are consistent across all models. The differences between the coefficients on the organizations are both statistically and economically significant. For example, the probability that a farmer would participate in a big data platform run by university researchers is 28 percentage points higher than the probability they would participate in a platform run by the government (the differences are statistically significant at the 1% level).

We find that farmers are the least willing to share their data with the government. K. Coble et al. (2016) note that farmers may fear that sharing their data with the government could spark new regulations or reveal violations of existing regulations. Farmers might also be skeptical about the benefits that government can provide relative to private organizations. Mazzucato (2015) argues that the public sector is often more innovative than the private sector, but admits that this is contrary to public perception. The skepticism of government echoes societal concerns about government surveillance in other spheres (Acquisti, Taylor, & Wagman, 2016; Marthews & Tucker, 2017)

Next to government, farmers are least willing to share their data with equipment manufacturers and financial institutions (there is no statistical difference in farmers preferences for these two organizations). Brown (2017) suggests that farmers may be concerned about the ability of these companies to use their data to price discriminate or deny future loan applications.

Crop input suppliers and grower associations are second only to university researchers in terms of maximizing farmer participation (there is no statistical difference between the coefficients on these two organizations). Grower associations represent the interests of farmers of a specific commodity (e.g., wheat, canola, and pulses). In Saskatchewan, grower associations are funded by a refundable checkoff.[4] Grower associations fund research, create educational programs and work to find new markets for the commodity they represent. Producers' general contentment with the work of grower associations as evidenced by the low refund rate of checkoff levies (generally under 10%), hence it is not surprising that producers may trust these organizations more than the government.

It is, however, interesting that crop input suppliers are preferred to equipment manufacturers, because one would expect that farmers would have the same concern about their information being "used against them" in a big data platform owned by any private company. One explanation is that the input companies are better positioned to make recommendations regarding input use (such as seeding rates and fertilizer application).

Farmers are, on average, most willing to share their data with university researchers. Sharing data with a university-run platform may be seen as less risky, as universities have neither a business nor regulatory relationship

[4]The only exception to this is the Saskatchewan Pulse Growers, whose checkoff is nonrefundable.

TABLE 5 Logit model[ab]

Choice variables	Coef.	*SE*	M.effect	*SE*
Organization				
Government	−1.84***	(0.58)	(base)	
University researchers	−0.47	(0.57)	0.28**	0.02
Crop input suppliers	−0.88	(0.57)	0.19	0.02
Equipment manufacturers	−1.41**	(0.58)	0.08***	0.02
Grower associations	−0.97*	(0.58)	0.17***	0.02
Financial institutions	−1.53***	(0.58)	0.05***	0.02
Nonfinancial incentive (base = none)				
Benchmarks	0.62***	(0.07)	0.12***	0.01
Prescription maps	0.45***	(0.07)	0.09***	(0.01)
Financial incentive (base = none)				
-$50	−0.08	(0.09)	−0.01	(0.02)
$50	0.63***	(0.08)	0.13***	(0.02)
$100	0.87***	(0.09)	0.18***	(0.02)
Yield monitors				
Use technology, improves farm performance	0.12	(0.19)	0.02	(0.04)
Use technology, does not improve farm performance	−0.05	(0.18)	−0.01	(0.04)
GPS guidance				
Use technology, improves farm performance	0.22	(0.36)	0.04	(0.07)
Use technology, does not improve farm performance	−0.14	(0.50)	−0.03	(0.09)
Soil sampling				
Use technology, improves farm performance	0.36**	(0.17)	0.07**	(0.03)
Use technology, does not improve farm performance	0.32	(0.30)	0.06	(0.06)
Variable rate technology				
Use technology, improves farm performance	0.07	(0.17)	0.01	(0.03)
Use technology, does not improve farm performance	−0.37	(0.32)	−0.07	(0.06)
Automatic section control				
Use technology, improves farm performance	−0.34**	(0.15)	−0.07**	(0.03)
Use technology, does not improve farm performance	1.5***	(0.51)	0.31***	(0.09)
Attitudes				
Privacy	−0.31***	(0.05)	−0.06***	(0.01)
Technology use	0.09	(0.07)	0.02	(0.01)
Farm management	0.09	(0.07)	0.02	(0.01)
Sociodemographics				
Revenue	−0.10	(0.07)	−0.02	(0.01)
Education	0.05	(0.05)	0.01	(0.01)
Age	−0.01	(0.01)	0.00	(0.00)
Female	0.32	(0.30)	0.06	(0.06)
Compensation for survey completion (base = $10)				
$20	−0.08	(0.16)	−0.02	(0.03)
$30	−0.07	(0.19)	−0.01	(0.04)

[a]Observations, 5265. Log-pseudolikelihood, -3078.10. Significance codes: *10%, **5%, ***1%.
[b]The marginal effect for indicator variables is the discrete change from the base level.

with farmers. Universities also touch the edges of a multitude of farm problems and could potentially use big data in a variety of ways to increase yields and profitability. Furthermore, universities have a track record of providing valuable agronomic research. As one example, hybrid canola (the most valuable crop in Saskatchewan) was first developed by researchers at the University of Manitoba.

4.2 | Financial and nonfinancial incentives

Farmers' willingness to participate in a big data platform increases in the presence of a financial incentive. Compared to platforms with no financial incentive, farmers are 13 percentage points more likely to participate if offered \$50 and 18 percentage points more likely to participate if offered \$100.

These financial rewards are small relative to total farm revenue, which can range to over \$3 million each year. One would think that if farmers have strong privacy preferences, then these financial incentives should have little impact on their participation rates. However, the effects of the financial incentives are no different for those with strong privacy preferences (the interaction of privacy attitudes and financial incentives are neither individually nor jointly significant). This result is consistent with prior work on the privacy paradox, which holds that individuals who have stated strong privacy preferences are often willing to trade their privacy for relatively small financial rewards (Athey et al., 2017).

In contrast, charging \$50 for the right to participate has no statistically significant effect on participation rates. This is counter to our expectations and surprising considering the statistical strength of the coefficients on the positive financial incentives.

The marginal effects for the nonfinancial incentives are also statistically and economically significant. Benchmark statistics increase the probability of participation by 12 percentage points, whereas prescription maps increase the probability of participation by nine percentage points.

4.3 | Technology use

We expected that farmers who use precision agriculture technologies would have a higher probability of joining a big data platform. This is both because precision agricultural technologies are necessary to extract maximal value from participating in a big data platform and because the use of precision agricultural technologies may signal that an individual is an early adopter of new technology. However, we find that the use of precision agricultural technologies generally has no significant effect on participation. The exceptions are soil sampling and automatic section control. Farmers who use soil sampling are more likely to join a big data platform (though the effect is only significant for those who use the technology and state that it benefits their farm). Conversely, those who use variable rate technology and see benefits from it are *less* likely to join a big data platform—the opposite of our expectations. This could be because farmers that see benefits from using variable rate technology believe they have already captured the value from the technology, and do not believe they would extract any further gains from contributing to a big data platform.

Conversely, farmers that don't see benefits from using variable rate technology may be more motivated to join a big data program in an attempt to realize benefits from the technology. Indeed, in our survey farmers who use variable rate technology and *do not* see benefits from it are *more* likely to join a big data platform, however, there are only four respondents in this category.

4.4 | Attitudes and sociodemographics

As expected, privacy attitudes have a negative and significant effect on the probability of participating in a big data platform: A one standard deviation increase in privacy preferences reduces the likelihood of participating by eight percentage points. Given that we had told respondents to assume that data could be inexpensively uploaded to a big data platform, the primary cost from participating in a big data platform is the loss of privacy. It is, therefore, unsurprising that privacy attitudes exert a strong influence on participation. Positive attitudes towards technology use and progressive farm management lead to slightly higher participation rates, though neither of these effects is statistically significant. We obtain the same results when we include responses to the 11 attitude questions individually and test whether the coefficients relating to each of the attitudes (privacy, technology use, and management) are jointly significant.

We had expected that age would decrease participation, as younger people generally have higher levels of technology adoption (Daberkow & McBride, 2003; Larson et al., 2008; Tamirat et al., 2018). However, age is not statistically significant. The coefficient on gender is large and appears economically significant: women are, on average, six percentage points more likely to participate in a data platform. However, the small number of women in our sample renders the coefficient statistically insignificant.

4.5 | Interaction terms

In our base model, we found that the organization running the big data platform has a particularly important effect on farmers' willingness to participate. In this section, we examine whether there is heterogeneity in preferences for the organization running the big data platform by adding the interaction of a dummy variable for each organization with respondents' sociodemographic characteristics. The estimates of the interaction terms are contained in Table 6 (for brevity we do not report the other coefficients in the model—they are all virtually unchanged from Table 5).

Few of the interaction terms are significant, suggesting that there is either very little heterogeneity in preferences for organizations, or that heterogeneity is related to factors other than sociodemographic characteristics. Notably, individuals with higher education are more likely to participate in platforms run by the government and universities. This is consistent with prior work that finds that political and social trust is generally increasing in education.[5] (Leigh, 2006; Schoon, Cheng, Gale, Batty, & Deary, 2010). Education also reduces participation in platforms run by input suppliers, though it has no effect on participation in platforms run by other private enterprises (such as financial institutions and equipment manufacturers). Women are also more likely to participate in a platform run by the government. Previous work on the relationship between gender and government trust has shown mixed results: Patterson (1999) finds that women are more trusting of government, whereas Leigh (2006) finds no relationship between gender and government trust.

4.6 | Latent class analysis

As an additional check for heterogeneity, we estimate a latent class logit model, which allows for multiple classes of individuals with differing preferences. As discussed in Section 4, the latent class model relies on two different equations: the class membership equation and the utility function. We include only the sociodemographic terms in the class membership equation (adding attitudes and technology use to the membership equation does not improve the model fit). In the utility function, we include the characteristics of the big data platform including the organization, the financial incentive, and the nonfinancial incentive. Using the Bayesian Information Criterion (BIC), a two-class model was selected, meaning that there are two different sets of coefficients estimated for the utility function.

The coefficients in the utility function of both classes are shown in Table 7. Membership is evenly split between the two classes. The most important difference between the two classes lies in the intercept term, which affects the probability of participation for all hypothetical big data platforms (regardless of their attributes). The intercept term is substantially lower in class one than class two, and, therefore, participation rates are far lower for individuals in class one.

The coefficients on organizations differ slightly across classes, but the ordering of the coefficients is the same in both classes and is consistent with the analysis in the preceding section. However, the impact of the financial incentive is different in the two classes: individuals in the second class value financial compensation more than those in the first.

[5]Dalton (2005) provides a more nuanced view of the relationship between government trust and education. In a cross-country study, he finds that education was strongly linked to trust in government in the 1950s, but that the relationship has faded over time, and, in some places, it is now nonexistent.

TABLE 6 Logit model with interaction terms[a,b,c]

		Coef.	*SE*	M. Effect	*SE*
Organization					
Government		−2.56***	(0.82)	*(base)*	
University researchers		−1.44**	(0.68)	0.22	(0.16)
Crop input suppliers		−0.1	(0.72)	0.49***	(0.16)
Equipment manufacturers		−0.69	(0.77)	0.37**	(0.16)
Grower associations		−0.73	(0.72)	0.36**	(0.15)
Financial institutions		−1.7**	(0.80)	0.17	(0.19)
Interaction terms					
Government	Revenue	−0.1	(0.09)	-0.02	(0.02)
	Education	0.18**	(0.08)	0.04**	(0.02)
	Age	0	(0.01)	0	(0.00)
	Sex: female	0.82*	(0.42)	0.16*	(0.08)
University researchers	Revenue	−0.07	(0.08)	-0.01	(0.02)
	Education	0.21***	(0.07)	0.04***	(0.01)
	Age	0	(0.01)	0	(0.00)
	Sex: female	0	(0.40)	0	(0.08)
Crop input suppliers	Revenue	−0.12	(0.08)	-0.02	(0.02)
	Education	−0.14**	(0.07)	-0.03**	(0.01)
	Age	−0.01	(0.01)	0	(0.00)
	Sex: female	0.41	(0.36)	0.08	(0.07)
Equipment manufacturers	Revenue	−0.13	(0.09)	-0.03	(0.02)
	Education	−0.04	(0.08)	-0.01	(0.02)
	Age	−0.01	(0.01)	0	(0.00)
	Sex: female	−0.07	(0.44)	-0.01	(0.09)
Grower associations	Revenue	−0.14	(0.09)	-0.03	(0.02)
	Education	0.01	(0.07)	0	(0.01)
	Age	−0.01	(0.01)	0	(0.00)
	Sex: female	0.53	(0.38)	0.11	(0.07)
Financial institutions	Revenue	−0.07	(0.09)	-0.01	(0.02)
	Education	0.1	(0.08)	0.02	(0.02)
	Age	−0.01	(0.01)	0	(0.00)
	Sex: female	0.2	(0.47)	0.04	(0.09)

[a]The model also includes all the same variables as are included in Table 5. For brevity these estimates are suppressed—their statistical significance is unchanged from Table 5.
[b]Observations: 5265. Log-pseudolikelihood: -3061.22. Significance codes: *10%, **5%, ***1%.
[c]The marginal effect for indicator variables is the discrete change from the base level.

Table 8 contains the estimates from the membership equation. Overall, there does not appear to be a strong relationship between socio-demographics and class membership. Revenue is weakly statistically significant, with larger farmers more likely to be in the first class.

5 | CONCLUSION

The aggregation of field-level data holds substantial promise for the future of agricultural innovation. Big data has the potential to optimize input use, crop choice, and improve research opportunities for agricultural

TABLE 7 Latent class logit model: Utility function[a]

Class probabilities	Class 1 50.0% Coef.	SE	Class 2 50.0% Coef.	SE
Intercept	−4.32***	(0.38)	−1.41***	(0.15)
Organization (base = government)				
University researchers	2.15***	(0.34)	1.72***	(0.17)
Crop input suppliers	1.57***	(0.36)	1.18***	(0.16)
Equipment manufacturers	0.69*	(0.37)	0.53***	(0.15)
Grower associations	1.40***	(0.35)	1.10***	(0.16)
Financial institutions	0.61	(0.39)	0.40***	(0.15)
Nonfinancial incentive (base = none)				
Benchmarks	0.94***	(0.19)	0.80***	(0.11)
Prescription maps	0.72***	(0.19)	0.60***	(0.11)
Financial incentive (base = $0)				
−$50	0.15	(0.22)	0.08	(0.12)
$50	0.51**	(0.20)	1.12***	(0.13)
$100	0.97***	(0.20)	1.40***	(0.13)

[a]Observations: 5265. Log-pseudolikelihood: -2683.63. Significance codes: *10%, **5%, ***1%.

innovators. The value of big datasets is increasing in their size, and, therefore, farmer participation rates are important.

In this paper, we used a hypothetical choice experiment to estimate participation in a big data platform. On average, 36% of farmers agreed to join the hypothetical big data program, however, participation rates depended on the characteristics of both the platform and the farmer. In particular, we found that the organization that runs the platform has a substantial effect on farmer participation. Participation is highest in platforms run by university researchers, followed by platforms run by crop input suppliers or grower associations, and then financial institutions or equipment manufacturers. Participants were least likely to join a big data platform operated by the government. We also found that relatively small financial incentives can greatly increase participation. A latent class logit model revealed some heterogeneities in the farm population—indicating some farmers are predisposed to participating in a big data platform than others.

Our results have implications for the creation of big data platforms. Farmers in our experiment are considerably more willing to join a platform that is run by a university, followed by crop input companies and grower associations. Universities and other not-for-profit groups with a similar level of trust are, therefore, uniquely positioned to operate a big-data platform. These platforms could even be two-sided: allowing farmers to upload data and third parties access to the data with the approval of farmers; this is precisely the goal of the Ag Data Coalition.

TABLE 8 Latent class logit model: Class membership equation (base = class 2)[a,b]

	Coef.	SE
Intercept	−1.09	(0.90)
Revenue	0.18*	(0.09)
Education	−0.07	(0.08)
Age	0.00	(0.01)
Female	0.6	(0.46)

[a]Observations: 5265.
[b]Significance codes: *10%, **5%, ***1%.

Given how strongly participants feel about government-run data platforms, it would appear ideal for government to remove itself as much as possible from the operation of these platforms, making clear that they will not be able to access the databanks run by private or not-for-profit entities. This is not to say that government has no role to play in this sphere. Though it is beyond the scope of our study, the government can likely increase trust in data platforms by crafting stronger privacy and security regulations (Ferris, 2017).

We also found that small rewards can dramatically increase participation rates. It is, therefore, critical for data platforms to provide tangible benefits to participants. This could be in the form of a financial incentive for participating, or, more likely, in the form of some nonfinancial benefit that is easily observable by farmers, whether it be prescription maps, advice on management practices, or benchmark statistics. Whereas universities seem to be the preferred organization to house a data bank, private companies (especially crop input companies), may be better positioned to provide these benefits to farmers.

Our hypothetical survey had a number of limitations. First, we examined only a few characteristics of a big data program (including financial incentives for participation and the provision of benchmark statistics and prescription maps). It is possible that organizations that had low hypothetical participation rates (such as governments and financial institutions) could use other program characteristics to increase their appeal to farmers. For example, these organizations could put in place strong privacy protections, offer other incentives for participation, or partner with a trusted third-party.

Another limitation of the study is the representativeness of the sample. The survey was administered online and a financial incentive was given to participants. Hence, our sample may be biased towards those who are more technologically savvy and value financial rewards. We surmise that this bias would act to increase participation rates (as farmers who take an online survey might also be more likely to participate in a big data platform) and cause an upward bias on the coefficients related to the financial incentive.

Our results highlight the importance of privacy attitudes on participation decisions. This suggests that questions around data security and ownership still loom large in farmers' minds. In previous surveys, farmers expressed strong concerns about data privacy but were unaware of how their data was handled by agricultural technology companies. This may lead some farmers to simply avoid joining a big data platform. Government policies that clarify rules around data ownership and security could, therefore, be Pareto improving—giving farmers confidence that their privacy is being protected, whereas ensuring higher participation rates for emerging big data platforms.

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SUPPORTING INFORMATION

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

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