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Application of Multiple Imputation in Dealing with Missing Data in Agricultural Surveys: The Case of BMP Adoption

Hua Zhong, Wuyang Hu, and Jerrod M. Penn

Missing-data problems are common in farmer surveys but are often ignored in the literature. Conventional methods to address missing data, such as deletion and mean replacement, assume that data are missing completely at random, which rarely holds. This study compares these approaches to the multiple imputation method, which produces different parameter estimates. The mean replacement method increases the central tendency of data, leading to more significant but smaller coefficients than the other methods. We recommend using both the deletion and multiple imputation methods to deal with missing data; results generated by the mean replacement method may not be as reliable.

Key words: best management practices, multivariate imputation by chained equation, nonpoint source

Introduction

Missing-data problems are common in surveys of farmers and frequently occur in other types of primary data collection as well. Weber and Clay (2013) replicate previous studies to compare estimation results using population data from the USDA's quinquennial Census of Agriculture to its annual, but more limited, Agricultural Resource Management Survey (ARMS) to study nonresponse issues in the latter. They conclude that nonresponse occurs because of the time required and disutility to answer questions. Further, larger farms are more likely to have missing values, consequently having the most pronounced nonresponse bias. As opposite to "complete" nonresponse, "item-wise" nonresponse has been overlooked in agricultural and resource economics. Failure to address missing data and nonresponse bias can lead to spurious conclusions (Groves, 2006), especially when missing values constitute more than 5% of the data (Schafer, 1999).

Our study aims to investigate methods to address missing responses in surveys of farmers. The first method considered is deletion, a naïve method that omits observations with missing data. This method assumes that missing values are independent of the observed and unobserved data, an assumption rarely satisfied in empirical studies and that may lead to nonresponse bias (Lin and Schaeffer, 1995; Groves, 2006; Groves and Peytcheva, 2008). The second method considered is mean replacement, which replaces missing values with the observed mean. Both methods represent

Hua Zhong is an assistant professor in the Department of Applied Economics at the Beihang University School of Economics and Management and a visiting postdoctoral fellow in the Department of Economics at the University of Nevada, Reno. Wuyang Hu (corresponding author) is a professor in the College of Economics and Management at Huazhong Agricultural University, China, and a professor in the Department of Agricultural, Environmental, and Development Economics at the Ohio State University. Jerrod M. Penn is an assistant professor in the Department of Agricultural Economics and Agribusiness at Louisiana State University.
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conventional approaches to handling missing data and are common practices in agricultural and resource economics. We also consider a third, often-superior method of dealing with missing data, multiple imputation (MI), which is frequently used by the U.S. Census Bureau, the Bureau of Labor Statistics, and medical and environmental social science studies. Introduced by Rubin (1978), MI first imputes each missing cell with m plausible values, analyzes and estimates m complete datasets, and averages m results to produce a final estimate. Lall (2016) re-examines recent publications in two leading political science journals and finds that many of the conclusions in these publications could have been nullified if the more appropriate MI had been used.

This application of missing data involves a survey of farmers in the Kentucky River watershed to investigate farmer willingness to adopt best management practices (BMPs) through a hypothetical water quality trading (WQT) program through which farmers may be compensated by point sources (PSs). The WQT program, first introduced by the U.S. Environmental Protection Agency (EPA) in 2003, assists dischargers in a watershed to trade emission permits, thus improving water quality at a lower cost than traditional regulations. In WQT programs, agricultural nonpoint sources (NPSs) can create credits for the WQT market by adopting BMPs. PSs pay NPSs through the trading program by purchasing these credits. The goal of the survey is to understand farmer willingness to further reduce agricultural runoff, factors that may affect their intention, and by how much they would adopt additional BMPs given payment from a trading program. Thus, we asked farmers about current BMPs implemented and whether they would adopt more BMPs if compensation were offered through WQT and provided different types of WQT-related information to each farmer to test how this information affects BMP adoption.

Five BMPs were included in the survey: riparian buffers, animal fences, no-till, waste storage facilities, and nutrient management; 21.5%, 26.9%, 24.2%, 23.2%, and 18.2% of respondents did not indicate how much they would adopt for each type of BMP, respectively. As a result, our primary contribution is to address issues of missing data, in addition to assessing the feasibility of a WQT program in the Kentucky River watershed. In our study, we apply a multivariate imputation by chained equation (MICE) method, introduced by Raghunathan et al. (2001), one of multiple MI algorithms, to impute the multivariate missing data.

Mechanism of Missing Data and the MICE Method

Missing Mechanism

This section formally describes three types of missing data. Let Y denote a variable with missing data, $\mathbf{X}$ denote a vector of variables completely answered, and R be an indicator variable that equals 1 if Y is missing and 0 if Y is observed. The first type of missing data is missing completely at random (MCAR), defined as

$$\Pr(R=1|\mathbf{X},Y) = \Pr(R=1). \tag{1}$$

MCAR implies that missing data are independent of any observed or unobserved variables. If MCAR applies, deletion—which removes observations with missing data—is an effective strategy. The mean replacement method is also justified by MCAR, which incorporates observations with missing data by replacing missing cells with observed means. However, MCAR rarely holds empirically because it suggests that missing responses arise completely by chance (Kenward and Carpenter, 2007).

The second type of missing data is missing at random (MAR), represented as

$$\begin{aligned} \Pr(R=1|\mathbf{X},Y) &= \Pr(R=1|\mathbf{X}) \\ \text{or } \Pr(R=1|\mathbf{X},Y) &= \Pr(R=1|Y_{observed}). \end{aligned} \tag{2}$$

MAR assumes that the probability of missing data is related to the observed data but not to unobserved data. Empirical research commonly assumes MAR, and it is the fundamental assumption for most imputation methods. If MAR holds, a variety of methods can address the missing data, such as the Hot Deck method, MI, and full information maximum likelihood (FIML).

Given the MAR assumption, MI can effectively deal with missing data in empirical surveys because it considers the true variance of data, outlined in the following steps (van Buuren and Oudshoorn, 1999):

1. Identify the missing variables, the posterior predictive density, and predictor variables.
2. Draw m plausible values for the missing data from the density to generate m complete datasets.
3. Conduct m complete-data analyses for each of the m complete datasets.
4. Combine the m data analyses into one estimate.

The third type of missing data is missing not at random (MNAR), which implies that the probability of being missing is related to the unobserved value in the missing variable. Verifying MNAR is impossible unless we obtain the unobserved value or other external information beyond the survey. Current strategies to deal with MNAR are complex, and the results are sensitive to the methods chosen (Allison, 2012). At present, there is no consensus on the best approach, and only Heckman-type modelling may alleviate MNAR issues (Grittner et al., 2011).

The MICE Method

Multivariate imputation by chain equation (MICE) is an MI algorithm introduced by van Buuren and Oudshoorn (1999) and Raghunathan et al. (2001) to impute categorical and continuous variables simultaneously and without the multivariate normal assumption. The MICE algorithm has the advantage of accommodating various types of missing data, regardless of whether the underlying analytical models are discrete, continuous, categorical, or mixed. MICE decomposes the multivariate problem into a series of univariate problems using an iteration algorithm. The procedure is as follows (van Buuren and Oudshoorn, 1999; Raghunathan et al., 2001; Schenker et al., 2006; Azur et al., 2011):

1. Let X denote variables fully observed, and $Y^{(1)}$, $Y^{(2)}, \ldots, Y^{(n)}$ denote n variables with missing data, ordered by the amount of missing data from the least to the most.
2. In iteration 1, regress observed $Y^{(1)}$ on $\mathbf{X}$ and impute the missing values of $Y^{(1)}$ using the predicted distribution based on the fitted regression. Then, regress $Y^{(2)}$ on $\mathbf{X}$ plus the observed value and recently imputed values of $Y^{(1)}$ and impute the missing values of $Y^{(2)}$. For $Y^{(k)}$, regress $Y^{(k)}$ on $\mathbf{X}$, $Y^{(1)}$, $Y^{(2)}$, $\ldots$, $Y^{(k-1)}$, where $Y^{(1)}$, $Y^{(2)}$, $\ldots$, $Y^{(k-1)}$, including all observed and imputed values, to impute $Y^{(k)}$ using predictive distribution based on the fitted regression of $Y^{(k)}$. Repeat this procedure until all incomplete variables $Y^{(n)}$ are imputed.
3. In iteration 2, the imputation process is repeated as in iteration 1, but predictors in each regression include all variables except for the variable being imputed. To be specific, regress imputed values in iteration 1 and observed values of $Y^{(1)}$ on $\mathbf{X}, Y^{(2)}, Y^{(3)}, \ldots, Y^{(n)}$, where $Y^{(2)}$, $Y^{(3)}$, $\ldots$, $Y^{(n)}$ are imputed in the last round, and re-impute the missing values of $Y^{(1)}$ using predictive distribution based on the fitted regression. Regress $Y^{(2)}$ on X and $Y^{(1)}$, $Y^{(3)}$, $\ldots$, $Y^{(n)}$, including all observed and imputed values, where $Y^{(1)}$ is the most recent imputed value and $Y^{(3)}$, $\ldots$, $Y^{(n)}$ are imputed in the last round; and then re-impute the missing values of $Y^{(2)}$. For $Y^{(k)}$, regress $Y^{(k)}$ on $\mathbf{X}$, $Y^{(1)}, Y^{(2)}, \ldots, Y^{(k-1)}, Y^{(k+1)}, \ldots, Y^{(n)}$, where $Y^{(1)}, Y^{(2)}, \ldots,$ $Y^{(k-1)}$ are the most recent imputed value in current iteration and $Y^{(k+1)}, \ldots, Y^{(n)}$ are from the imputed values in the last iteration; then re-impute $Y^{(k)}$ using predictive distribution based on

the fitted regression of $Y^{(k)}$. This procedure is executed c iterations until the equation chains converge.

Surveys and the Missing-Data Problem

Survey

Survey questionnaires were mailed to randomly chosen farmers across 35 counties located in the Kentucky River watershed from 2011 to 2012. A total of 2,000 farmers were identified using a list of farmers in the watershed maintained by local University of Kentucky extension offices and contacted by a packet through U.S. mail. To improve response rates, the packet included a cover letter printed on University of Kentucky letterhead and hand-signed by the project's principal investigator. The survey questionnaire and a postage-paid return envelope were also included in the packet. A total of 459 returned their questionnaires for a final response rate of 23%. This was achieved after an initial mailing and two rounds of postcard reminders. Of the returned responses, 357 contained at least some completed answers regarding to BMP-related questions and were used in the final analysis. The survey questions included farmer participation in current government-funded environmental or conservation programs, their potential adoption of additional BMPs through a WQT program, farm characteristics, and demographic characteristics. Our sample is not significantly different from the state average of farm and farmer characteristics compared to the 2012 U.S. agricultural census.

The key BMP adoption question asked in the survey was:

> Regardless of whether you are currently participating in any government cost share programs, if you knew that by using water quality management practices on your land, a nearby waste/sewage water treatment plant or factory will cover X% of your cost of implementing these practices, would you be interested in using additional water quality management practices (BMPs) in the form of the following activities?

Each respondent received a table listing five BMPs: riparian buffers, animal fences, no-till, waste storage facilities, and nutrient management. In the actual survey, X% is a possible value from 75% to 120% in 5% increments, each with equal probability. Each respondent saw only one level of compensation. A respondent could give one of three answers to each BMP: "yes," "no," or "not possible for me" in case a specific BMP was inapplicable or the adoption capacity has been reached on their land.

If respondents answered yes, the follow-up question asked, "In addition to what you have adopted already, by how much would you like to adopt this practice?" The respondents provided exact values for how much they would adopt the practice (i.e., open-ended). The units of measure were "feet" for riparian buffers and animal fences, an "acre" for the practices of no-till and nutrient management, and "number of facilities" for waste storage.

The survey also included four WQT program descriptions to determine their impact on adoption. The baseline treatment provided a basic explanation of WQT programs. The second and third information treatment groups received additional information on cost savings and environmental benefits of WQT programs, respectively. The fourth treatment provided information on both cost savings and environmental benefits. Different treatments were randomly assigned with equal probability across the sample. As explained later, these treatments are integral to the imputation strategies.

Table 1 presents all variables and summary statistics for the entire sample. Table 2 explains discrete levels in explanatory variables.

Table 1. Variable Summary Statistics ($N = 357$)

Variable	Definition of Variables	Mean	Std. Dev.
Current use of BMPs:			
y_1	Any BMPs =1; else 0	0.739	0.440
y_2	Riparian buffers =1; else 0	0.367	0.483
y_3	Animal fences =1; else 0	0.465	0.499
y_4	No-till =1; else 0	0.311	0.464
y_5	Waste storage facilities =1; else 0	0.067	0.251
y_6	Nutrient management =1; else 0	0.241	0.428
Cost coverage compensation:			
Offer	The percentage of implementation costs for additional BMPs that will be covered by a wastewater treatment plant or factory. Each participant was randomly assigned to one of ten compensation levels: 75%, 80%, 85%, 90%, 95%, 100%, 105%, 110%, 115%, and 120%.	0.970	0.150
Explanatory variables:			
Land size	Land size, includes rented and owned land. (unit: 1,000 acres)	0.282	0.537
Rent percentage	Rented farmland / Total farmland	0.142	0.275
Surface water	Surface water on farmland =1; else 0	0.860	0.348
Percentage of household income from farming[a]	Share of pre-tax household income from farming	2.417	1.815
Total household income reinvested in farm[a]	Share of pre-tax household income reinvested into farm	2.529	1.542
Farms with crop	Farmers earning revenue from crops or who plant crop on their land =1; else 0	0.423	0.495
Farms with livestock	Farms earning revenue from livestock or raising livestock =1; else 0	0.798	0.402
Age	Farmer's age	60.154	11.908
Male	Male =1; else 0	0.857	0.350
Education[a]	Farmer's education level	4.078	1.920
Income level[a]	Household annual pre-tax income level	4.359	1.499
Farming experience	Farming experience (year)	32.220	15.307
Water recreation	1 if participating in water related recreation at least once a year =1; else 0	0.661	0.474
CRP	1 if currently participating in Conservation Reserve Program (CRP) =1; else 0	0.118	0.323
WLP	1 if currently participating in Working-Land Program (WLP) =1; else 0. WLP includes Conservation Stewardship Program (CSP), Environmental Quality Incentives Program (EQIP), and Wildlife Habitat Incentives Program (WHIP)	0.204	0.404
Water quality	Seven levels from poorest (1) to best (7) water quality nearest to farmers' properties.	5.038	1.365
Environmental cognizance	Respondent's self-reported awareness of environmental issues; seven levels from very aware (7) to unaware (1).	4.947	1.556
Beginning farmer	1 if farming less than ten years; else 0	0.120	0.326
Minority farmer	1 if operator's race is not white; else 0	0.045	0.207

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Table 1. – continued from previous page

Variable	Definition of Variables	Mean	Std. Dev.
Answers "not possible for me" for:			
z_1	=1 if all BMPs; else 0	0.345	0.476
z_2	=1 if riparian buffers; else 0	0.583	0.494
z_3	=1 if animal fences; else 0	0.490	0.501
z_4	=1 if no-till; else 0	0.501	0.501
z_5	=1 if waste storage facilities; else 0	0.577	0.495
z_6	=1 if nutrient management; else 0	0.507	0.501
Respondent's Information Treatment:			
Baseline	=1 if baseline; else 0	0.235	0.425
Cost savings	=1 if cost savings; else 0	0.261	0.440
Environmental	=1 if environmental benefits; else 0	0.210	0.408
Combined	=1 if combined information; else 0	0.294	0.456

Notes: [a] Discrete levels in table are interpreted in table 2.

Table 2. Frequency Distribution of Discrete Variables

Level	% of Household Income from Farming	Freq.	Percent	Level	Total Household Income Reinvested in Farm	Freq.	Percent
1	0–15%	162	45.40%	1	0–15%	106	29.70%
2	16–30%	77	21.60%	2	16–30%	116	32.50%
3	31–45%	36	10.10%	3	31–45%	48	13.50%
4	46–60%	28	7.80%	4	46–60%	45	12.60%
5	61–75%	17	4.80%	5	61–75%	20	5.60%
6	75–90%	17	4.76%	6	75–90%	13	3.60%
7	>90%	20	5.60%	7	>90%	9	2.50%

Level	Income ($ thousands)	Freq.	Percent	Level	Education	Freq.	Percent
1	0–14.9	14	3.90%	1	Less than high school	17	4.80%
2	15–24.9	21	5.90%	2	High school	88	24.70%
3	25–49.9	60	16.80%	3	Some college, no degree	64	17.90%
4	50–74.9	110	30.80%	4	Associate	14	3.90%
5	75–99.9	64	17.90%	5	Bachelor	83	23.30%
6	100–149.9	56	15.70%	6	Master	51	14.30%
7	>150	32	9.00%	7	Professional	26	7.30%
				8	Doctorate	14	3.90%

Missing-Data Problem

We analyze missing responses to BMP adoption questions for two cases.[1] In the first case, respondents answered "yes" to the yes/no question, but did not answer the follow-up question. Because respondents have already stated they would like to adopt the BMP, the plausible values for the missing data should be a positive, continuous value for riparian buffers, animal fences, no-till and nutrient management, and a discrete count for the number of waste storage facilities.

The second case exists when respondents failed to answer the yes/no question, thus missing the follow-up question as well. If respondents answered the yes/no question for at least one practice but

[1] We investigate missing data associated only with respondents who answered at least part of the survey. Respondents who did not answer the survey were not included in our analysis.

Table 3. Frequency Distribution of BMP Responses ($N = 357$)

	Riparian Buffer	Animal Fence	No-Till	Waste Storage	Nutrient Management
Yes: amount provided	37	71	68	45	78
Yes: no amount	32	49	43	25	32
No	80	62	67	81	66
Not possible	70	60	49	69	38
Missing	138	115	130	137	143
Percentage of observations in the first case of missing data	9.00%	13.70%	12.00%	7.00%	9.00%
Percentage of observations in the second case of missing data	38.70%	32.20%	36.40%	38.40%	40.10%

not the other practices, their responses to the other practices are treated as missing. In this case, the plausible values for missing data in the yes/no questions are either "yes," "no," or "not possible for me." If respondents are imputed to belong to the "yes" category, then the plausible values for the quantitative questions are the same as in the first case. We exclude respondents who did not answer all five yes/no BMP adoption questions, treating them as uninterested and unwilling participants.[2] Table 3 summarizes the missing data for each BMP.

Empirical Strategy for Dealing with Missing Response

Following previous empirical studies in health, medical, environmental, and household areas (van Buuren and Oudshoorn, 1999; Schenker et al., 2006; Azur et al., 2011; White, Royston, and Wood, 2011; Miyama and Managi, 2014), we assume MAR applies in our research for several reasons. First, MCAR rarely holds empirically. Even if the MCAR assumption is satisfied, imputation based on MAR mechanisms will not bias the analysis (Little and Rubin, 1989). Second, as mentioned above, the MNAR assumption cannot be justified or tested without obtaining the unobserved values. One method to handle MNAR is to still use the imputation method under the MAR assumption but include as many predictor variables as possible (Miyama and Managi, 2014). Adding more predictor variables increases the chance that missing data are correlated with predictor variables, thus converting the missing mechanism from MNAR to MAR. Finally, our preliminary test shows that the MCAR condition does not hold in our case.[3]

Simulation-based methods such as MI can perform well even with up to 50% missing data (Allison, 2002), but one caveat of MI is that higher percentages of missing data will cause estimation problems and can weaken the MAR assumption (Johnson and Young, 2011). Compared to 20%–87% of missing data in previous empirical studies (Lall, 2016), our 18%–27% of missing data is relatively low.

Given the MAR assumption, we use deletion, mean replacement, and MICE to treat each BMP's missing data. The number of missing variables, n, is initially five, corresponding to the five BMPs, but will change when we impute missing values in both the yes/no question and corresponding follow-up question for each BMP. Although mean replacement and deletion rely on the same assumption, we include both for comparison. Many empirical studies prefer to use mean replacement over deletion because deleting observations decreases available information and the efficiency of estimation. We apply MICE under four scenarios to discuss different MI strategies.

[2] Other circumstances exist, in which a respondent answered "no" or "not possible for me" to the yes/no question, so their response to the follow-up implementation rate is missing. Some reasons include if respondents refused to consider the BMPs (i.e., "no"), inability to implement the BMP on their land, or if maximum BMP adoption had already taken place. In these cases, the appropriate value for the missing data in the follow-up question is 0 and thus no longer considered missing.

[3] To test whether nonresponses are related to the observed variables, we estimated a logit model with an indicator of missing data as the dependent variable and all observed variables as independent variables. Results show that nonresponses were correlated with several observed variables, so the MCAR assumption fails.

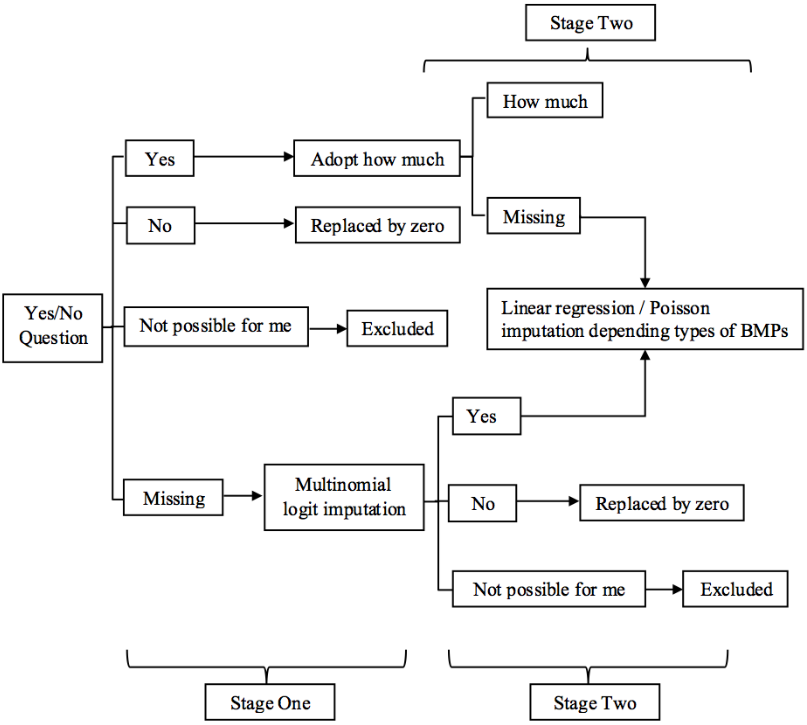

Figure 1. Execution Route of the Second Scenario

MICE Scenario 1: One-Stage Imputation

The first scenario imputes missing responses to each BMP's follow-up question. Missing values for respondents who answered "no" are replaced with 0 because they would not adopt additional BMPs. This is true for those who had additional capacity on their farms to adopt additional BMPs but chose not to so or those who had already reached their maximum capacity. For the respondents who answered "yes" but did not indicate how much they would adopt, we impute the missing values of the five BMPs simultaneously using MICE.

MICE Scenario 2: Two-Stage Imputation

The second scenario imputes missing values both in the yes/no question and in the corresponding follow-up question for each BMP such that there are missing values in 10 variables. The possible responses to the yes/no questions are "yes," "no," or "not possible for me." If the answer is yes, the possible response to the follow-up question is a positive, continuous or discrete value. If it is no, adoption is 0. Therefore, we impute "yes," "no," or "not possible for me" for the missing data in the yes/no question using a multinomial logit model. For those observed or imputed to be in the "yes" group, we impute missing data in the follow-up question. The imputation steps are also described in figure 1.

MICE Scenario 3: Two-Stage Imputation with Restriction

The third scenario is procedurally similar to the second scenario in that it imputes missing values in both the yes/no question and the follow-up question for each practice using a two-stage approach, but it restricts the imputation of missing values in the yes/no question to only "no" or "not possible for me." This more conservative approach assumes that missing responses to the yes/no question

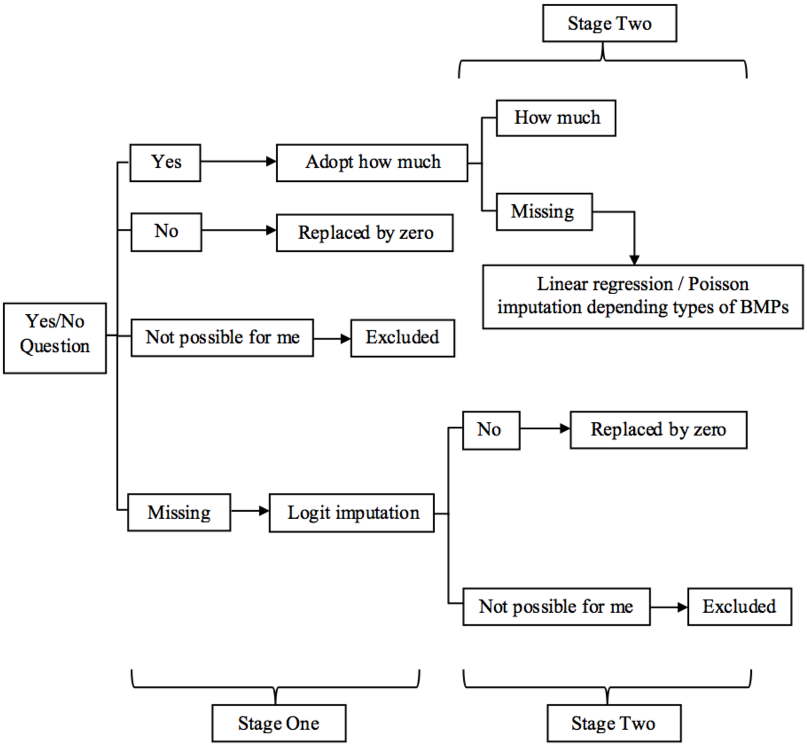

Figure 2. Execution Route of the Third Scenario

are more likely answer "no" or "not possible for me." There are also 10 missing variables for the imputation as well.

We first impute the missing values to be either "no" or "not possible for me" in the yes/no question using the logistic regression model, then restrict the sample to the "yes" group and impute missing values for the follow-up question. The imputation steps are outlined in figure 2.

MICE Scenario 4: Three-Stage Imputation

Scenario 4 considers the nature of the missing response of the yes/no question. "Yes" and "no" represent a personal preference to implement BMPs given the compensation through WQT programs, but "not possible for me" is principally different, implying that a farm cannot implement a practice, regardless of preferences. As a result, we first determine farm capability by using a logistic regression model to impute the missing response as "possible" or "not possible." For those imputed as "possible," we then impute "yes" and "no" using the logistic regression model again; for the sample that either answered "yes" or imputed as "yes," we impute missing data of the follow-up adoption rate question, outlined in figure 3. In this case, the number of missing variables for the imputation to consider is 15, corresponding to five possible/not possible imputations in the first stage, five yes/no imputations in the second stage, and five missing value imputations in the third stage.

Some explanatory variables have missing-data issues as well. However, the percentage of missing data is less than 5%. Schafer (1999) suggested that if the percentage of missing data is around 5%, it may not be considered severe, so mean replacement is utilized.

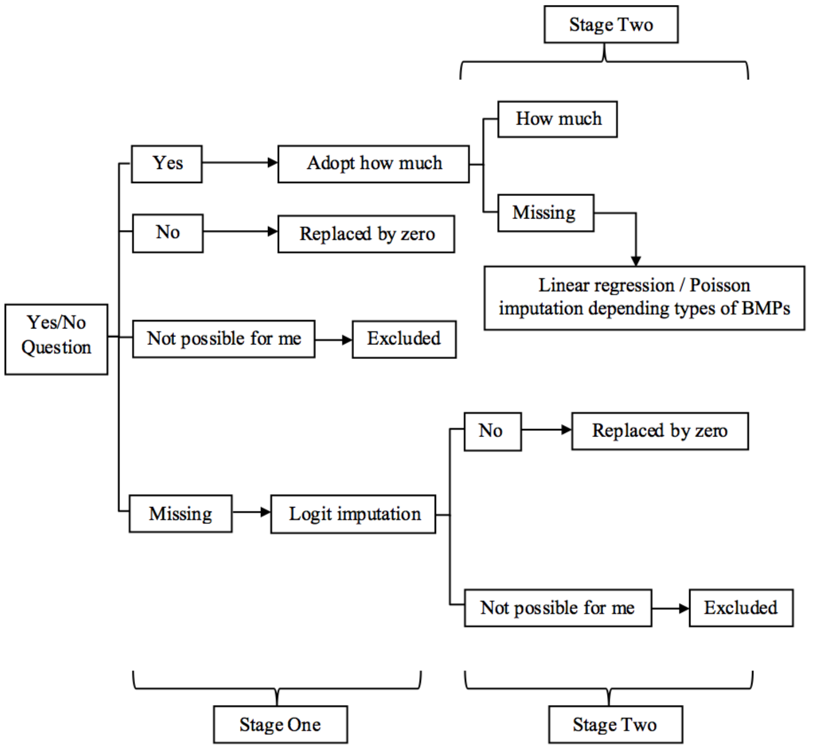

Figure 3. Execution Route of the Fourth Scenario

Imputation

As indicated above, MICE can accommodate discrete or continuous variables. In our study, adoption choices are discrete variables, so missing data are imputed by logit or multinomial logit models depending on the previously described scenarios. The follow-up adoption-rate questions are continuous or discrete count variables, so the missing data are imputed by linear or Poisson regression method. Online Supplement A lists the models used in imputation in our study.

For predictor variables x, we follow a general rule that the number of predictors should be as large as possible to improve the possibility the MAR condition is satisfied (van Buuren and Oudshoorn, 1999). Furthermore, using all information increases the precision of prediction and decreases imputation bias. Lastly, imputation algorithms do not require causality between predictor and imputed variables. The goal of imputation is to predict the distribution of a missing variable, and the imputations are drawn from the posterior distribution of the imputed variable but do not change the joint distribution (Schafer, 1997; King et al., 2001). Thus, it is necessary to include dependent variables in the analytic model as predictors to improve the precision of prediction in the imputation.

However, White, Royston, and Wood (2011) stated that imputation models with too many variables may face difficulties of convergence, especially for complex imputation models. van Buuren and Groothuis-Oudshoorn (2011) recommended no more than 15–25 variables. Given this debate, we choose the following 21 predictor variables: the levels of compensation, land size, rent percentage, having surface water on the farm, percentage of household income from farming, total household income reinvested in the farm, types of farming production, age, gender, education, income, race, water recreation activities, farming experience, water quality near the farm, participation in government programs, current usage of different types of BMPs, and the four different WQT information treatments. Because the riparian buffer, animal fence, no-till, and

Table 4. Example of Imputation for a Two-Stage Scenario

		Imputation Model	Imputation Condition	Dependent Variable	Independent Variable										X (Fully Observed Variables)
					c_1	c_2	c_3	c_4	c_5	y_1	y_2	y_3	y_4	y_5	
Stage One	Riparian buffers			c_1		✓	✓	✓	✓						
	Animal fences	Multinomial logit		c_2	✓		✓	✓	✓						Fully
	No-till	($c_i = 1$ if "yes", $c_i = 0$ if "no",		c_3	✓	✓		✓	✓						observed
	Waste storage facilities	$c_i = 2$ if "not possible for me")		c_4	✓	✓	✓		✓						variables
	Nutrient management			c_5	✓	✓	✓	✓							
Stage Two	Riparian buffers	Linear regression	$c_1 = 1$	y_1							✓	✓	✓	✓	
	Animal fences	Linear regression	$c_2 = 1$	y_2						✓		✓	✓	✓	Fully
	No-till	Linear regression	$c_3 = 1$	y_3						✓	✓		✓	✓	observed
	Waste storage facilities	Predictive mean matching	$c_4 = 1$	y_4						✓	✓	✓		✓	variables
	Nutrient management	Linear regression	$c_5 = 1$	y_5						✓	✓	✓	✓		

Notes: c_i is the adoption choice of BMPs. If respondents agree to adopt a BMP, y_1 is the adoption rate of the BMP.

nutrient management BMPs are continuous, imputation uses the linear regression model. Waste storage facilities are added in discrete quantities, so imputation relies on the Poisson regression method.

Table 4 displays an example of scenario 2's two-stage imputation. Ten variables are missing, including both adoption choices and adoption rates. In stage one, missing data of adoption choices are imputed sequentially by multinomial logit regression; in stage two, missing data of adoption rates are imputed by linear regression method, conditional on adoption choices of observed and imputed data. This procedure to sequentially impute data from stage one to stage two represents one round of imputation. Online Supplement B contains detailed imputation models and predictors for each scenario.

Online Supplement C reports some clarification for choosing a specific data algorithm and transformation of variables to address divergence issue in our imputation. In addition, we use 30 iterations as the burn-in period. Online Supplement D provides justification and evidence of convergence. Specifying additional burn-in iterations did not change the results. For waste storage facilities, a predicted mean matching (PMM) method was used in the simulation, instead of the Poisson method, to achieve convergence.

After imputing missing values for each BMP's follow-up question, we replace imputed extreme values, values that exceeded the minimum and maximum of the observed data, by the corresponding minimum and maximum of each BMP. These extreme values accounted for less than 5% of all imputed values.

Empirical Model for BMP Adoption

Previous studies have estimated BMP adoption rates by using OLS models, Tobit models, double-hurdle models, and switching-regression models (Ervin and Ervin, 1982; Norris and Batie, 1987; Adesina and Zinnah, 1993; Uri, 1997; Ma et al., 2012; Abdulai and Huffman, 2014). Following previous literature, with each imputed dataset, we estimate the factors affecting how much farmers may engage in each BMP, specified by equation (3) using Tobit or Poisson regressions. The dependent variable, Y_i, is how much of each BMP farmers would like to implement. For riparian buffer (Y_1), animal fence (Y_2), no-till (Y_3), and nutrient management (Y_5), the dependent variables is continuous if the decision is "yes" and 0 if the decision is "no." Because usage of BMPs is censored at 0, we use a Tobit model to estimate how much farmers may implement these practices. Since waste storage facilities (Y_4) are count values, we estimate the number of facilities adopted using Poisson regression. We exclude respondents who indicated "not possible for me" from the analysis.

$$Y_i = \mathbf{X}'\boldsymbol{\beta} + \varepsilon, \tag{3}$$

where Y_i is a continuous value if "yes" for $i = 1, 2, 3, 5$ and a count number for $i = 4$ and $Y_i = 0$ if "no." Previous studies show mixed results of factors affecting choices and rates of BMP adoption. Two syntheses of BMP adoption conclude that no single factor can consistently explain BMP adoption (Knowler and Bradshaw, 2007; Prokopy et al., 2008). Baumgart-Getz, Prokopy, and Floress (2012) conducted a meta-analysis of BMP adoption among farmers, concluding that their environmental awareness and attitudes are important factors but that researchers must carefully define and use these indicators. Admittedly, previous syntheses of BMP adoption cannot find any factor consistently explaining adoption, but these studies still conclude that farm characteristics, farmer characteristics, and environmental attitude and awareness are the most used and recognized variables to explain BMP adoption. Accordingly, we use the following explanatory variables for each BMP: compensation, land area, rent area percentage, the presence of surface water on the farm, farm with livestock,[4] percentage of household income from farming, total household income reinvested in the farm, income, nearby water quality, and participation in the Conservation Reserve Program (CRP) and Working-Land Program (WLP). We also examine the cross-effect of BMP adoption by including the current use of the five types of BMPs to explain adoption. Finally, to examine whether complementarity exists in adopting BMPs, we include the respondent's decision to adopt other practices j as explanatory variables in the adoption of practice i. Following equation (3), the estimable model is

$$Y_i = \beta_0 + \beta_i C + \left(\sum_{n=1}^{N} \beta_{in} x_n\right) + \left(\sum_{i=1}^{5} \theta_{ii} y_i\right) + \left(\sum_{j=1}^{5} \mu_{ij} y'_j\right) \quad (i \neq j) \tag{4}$$

where, $i = 1,2,3,4,5,6$ (each i also identifies a model of a BMP, and there are five regressions in total); β_0, β_i, β_{in}, μ_{ij}, and θ_{ii} are coefficients; $j = 1,2,3,4,5$, where each j denotes a BMP, either riparian buffers, animal fences, no-till, waste storage facilities, or nutrient management, respectively; N is the number of variables; Y_i represents dependent variables of how much of each BMP farmers would like to implement; C, x_n, y_n, and y'_n are independent variables; $x_n =$ farm characteristics, farmer characteristics, environmental aspects, targeted farm status, and the type of WQT program information farmers received; C is the compensation offered to a farmer by NPSs, which will cover a certain percentage of the cost of implementing the BMPs; y_i is current adoption of all surveyed BMPs; and y'_j is respondent's decision to adopt other BMPs.

Combining Final Estimates

The last step of MI is to calculate the m estimation results using Rubin's (1987) method. Let Q denote a parameter estimate, such as a regression coefficient, in each imputed dataset. The point estimate $\bar{Q}$ of Q is the average of the m separate estimates:

$$\bar{Q} = \frac{1}{m}\sum_{j=1}^{m} Q_j. \tag{5}$$

Let U_j denote the estimated squared standard error of Q_j, written as equation (6), and B denote the between-imputation variance across the m point estimates, written as equation (7). The estimated variance of point estimate of MI, T, is

$$\bar{U} = \frac{1}{m}\sum_{j=1}^{m} U_j; \tag{6}$$

$$B = \frac{1}{m-1}\sum_{j=1}^{m} (Q_j - \bar{Q})^2; \tag{7}$$

$$T = \left(1 + \frac{1}{m}\right) B + \bar{U}. \tag{8}$$

[4] In a preliminary model, we included two indicators for crop production and for livestock production to control for farm type. However, the MI method requires that imputation predictors should include all variables that appear in the analytic model (van Buuren and Groothuis-Oudshoorn, 2011). Including the crop production indicator in imputation stymied model convergence. Thus, we chose to include the indicator of livestock production but exclude crop production in our analytic model. Nevertheless, our preliminary models were estimated including these variables and the results are largely identical to those without them.

The tests and confidence intervals follow a Student's t-approximation: $(\bar{Q} - Q)/\sqrt{T} \sim t_v$ with degrees of freedom v represented as

$$(9) \qquad v = \left(\frac{1}{m-1}\right)\left[1 + \frac{\bar{U}}{(1+m^{-1})B}\right]$$

Previous studies have shown that, after convergence, five or ten imputations are sufficient unless there is a severe degree of missing data. However, White, Royston, and Wood (2011) recommend larger numbers of imputation m due to efficiency loss and reproducibility. Since the variance of parameters is calculated using equation (8), they propose that the relative efficiency of infinitely many imputations, a, compared to m imputations is

$$(10) \qquad \lim_{a\to\infty} \frac{\left(1+\frac{1}{m}\right)B + \bar{U}}{\left(1+\frac{1}{a}\right)B + \bar{U}} = \frac{\left(1+\frac{1}{m}\right)B + \bar{U}}{B + \bar{U}} = 1 + \frac{B}{B+\bar{U}} \times \frac{1}{m} = 1 + \frac{FMI}{m},$$

where $\frac{B}{B+\bar{U}}$ is the fraction of missing information (FMI), which ranges between 0 and 1 (Schafer, 1997).

If we allow 1% loss of efficiency in our imputation, $1 + \frac{FMI}{m}$ should be less than or equal to 1.01, then $\frac{FMI}{m} \leq 0.01$, so the imputation times m are greater than or equal to $(100 \times FMI)$. FMI is calculated based on the analytic model using imputation data and can be obtained from most statistical software packages. In the estimation, each parameter has its own FMI. We use the largest FMI value (i.e., 1) to determine m. This also improves the reproducibility of our imputation, regardless of "seeds" or software packages. Intuitively, a larger m improves similarity in reproduced results. After some preliminary trials, we use $m = 100$.

Results

Imputation is executed using the "rseed" option in Stata 13.0. To improve coefficient interpretation, we convert income level, percentage of household income from farming, and total household income reinvested in the farm from categories to continuous data using the midpoint of each corresponding category (Online Supplement E). Tables 5–9 display the results of how much farmers may increase each BMP.[5] Each table compares the results of all six imputation methods per BMP. The largest FMI values for each model are reported at the bottom of respective tables.

Assessment of Imputation

We show that results using conventional imputation methods are misleading. First, the MCAR condition fails in our data. Given the appropriateness of the MAR assumption, MI is superior to conventional missing-data methods, which tend to exaggerate significance of coefficients, generating erroneous policy implications (Lall, 2016). Taking the result in table 7 as an example, the conventional methods show that larger farms or farms with more rented land are significantly more likely to adopt no-till, while MI methods show these relationships are inconclusive.

Theoretically, replacing missing values by a constant (sample mean) decreases data variability (i.e., increases central tendency of the distribution of the data) and, as a result, underestimates variances that causes biased significance tests (Johnson and Young, 2011). When significant, coefficients using mean replacement are the smallest in magnitude across all six scenarios for all five BMPs. However, t-values calculated from this method are greater than in any of the other

[5] We test for and find no evidence to support overdispersion in the Poisson model in the deletion method (Cameron and Trivedi, 1990). Since MI does not change the distribution of data, tests of overdispersion will be consistent before and after imputation. Therefore, we use the Poisson model across all six scenarios.

Table 5. Tobit Regression for Factors Affecting Farmers' Riparian Buffers Adoption

			MICE Method			
	Deletion	Mean Replacement	One-Stage	Two-Stage	Restricted Two-Stage	Three-Stage
Offer	252.21	1,262.02	6,038.36*	2,399.99	3,892.89	6,524.32
	(1,823.69)	(1,044.37)	(3,265.62)	(3,225.84)	(3,062.33)	(3,070.73)
Land acre	−348.12	−261.87	−855.63	−658.48	−523.85	−57.10
	(791.51)	(327.50)	(1,211.16)	(1,081.18)	(952.25)	(768.20)
Rent percentage	471.37	−80.48	789.84	1,206.70	330.97	34.13
	(1,086.16)	(597.57)	(1,816.96)	(1,625.48)	(1,604.54)	(1,644.90)
Surface water	1,196.30	133.88	726.85	243.20	182.05	424.81
	(928.47)	(484.61)	(1,264.12)	(1,167.88)	(1,195.40)	(1,121.46)
Farm with livestock	−993.62	−192.82	−987.45	−1,167.85	−943.91	−1,152.16
	(868.77)	(436.25)	(1,442.57)	(1,202.70)	(1,195.02)	(1,231.92)
HH income	6.17	−2.53	−1.90	−2.96	−2.57	−4.09
	(4.34)	(2.45)	(7.17)	(6.53)	(6.70)	(7.00)
%HH income from farming	−1,779.14	−1,147.17	−2,968.57	−2,629.59	−3,336.01*	−1,926.24
	(1,359.75)	(743.51)	(2,161.91)	(1,921.82)	(1,898.44)	(1,910.29)
%HH income reinvested in farm	2,353.53	1,735.31**	4,981.63**	4,274.05**	4,866.53**	3,069.42
	(1,472.19)	(877.36)	(2,454.51)	(2,151.58)	(2,366.86)	(2,330.12)
Water quality	−231.21	−136.75	−56.86	146.84	−242.93	17.52
	(191.50)	(115.71)	(309.26)	(256.38)	(290.15)	(278.51)
CRP	−661.85	225.05	1,200.70	480.79	1,200.10	969.55
	(792.88)	(456.45)	(1,256.99)	(1,173.41)	(1,210.86)	(1,311.56)
WLP	1,059.95	253.61	−888.60	−143.04	−202.93	−603.21
	(645.30)	(356.86)	(1,111.59)	(1,014.89)	(1,065.55)	(1,007.54)
Current usage of other BMPs:						
Riparian buffers	1,628.61***	1,267.39***	2,810.33***	2,066.80**	2,744.15***	2,072.80**
	(605.12)	(336.13)	(973.05)	(896.49)	(888.43)	(903.51)
Animal fences	−959.05	−658.66	−987.20	−963.56	−1,145.92	−5.26
	(646.53)	(379.37)	(1,102.66)	(990.16)	(927.65)	(1,074.51)
No-till	−664.72	216.05	1,280.76	1,089.14	1,419.69	1,685.38
	(763.36)	(420.11)	(1,337.12)	(1,121.57)	(1,102.79)	(1,143.07)
Waste storage facilities	−2,614.14*	−1,388.77**	−2,451.86	−1,973.32	−2,210.02	−3,439.98*
	(1,535.59)	(665.72)	(1,964.89)	(1,959.34)	(1,918.21)	(1,858.17)
Nutrient management	−363.96	−174.85	−472.88	−860.92	−15.96	−790.41
	(636.13)	(373.31)	(1,135.26)	(959.69)	(969.10)	(1,037.33)
Choices of other BMPs:						
Animal fences	3,608.54***	2,026.57***	4,120.23***	4,060.74***	4,015.39***	2,402.14***
	(714.09)	(388.50)	(1,241.75)	(1,259.47)	(1,160.68)	(869.25)
No-till	83.85	258.29	935.85	1,197.78	1,259.19	320.01
	(686.32)	(389.67)	(1,160.80)	(984.32)	(1,031.05)	(894.26)
Waste storage facilities	−917.66	−665.85	−1,189.65	−1,191.82	−1,599.76	18.69
	(736.45)	(422.56)	(1,347.95)	(1,090.81)	(1,245.81)	(1,065.52)
Nutrient management	637.78	210.97	365.66	861.18	917.16	408.31
	(701.61)	(345.46)	(1,107.78)	(1,015.60)	(1,098.75)	(937.77)
WQT Information Treatment:						
Cost-savings information	−1,509.39**	−474.56	−488.92	−210.12	−94.68	−485.51
	(746.33)	(428.96)	(1,195.09)	(1,017.59)	(1,133.19)	(1,148.11)
Environment information	−23.03	181.65	746.78	606.96	1,255.00	239.82
	(802.67)	(456.54)	(1,484.95)	(1,366.12)	(1,346.05)	(1,265.11)
Combined information	−411.98	−296.11	−210.79	−92.38	−166.82	−209.24
	(631.24)	(421.42)	(1,177.61)	(991.09)	(1,024.50)	(1,071.08)
Constant	−2,752.69	−2,006.60	−9,961.93**	−6,888.15*	−7,872.08**	−8,954.43***
	(2,458.34)	(1,387.10)	(4,380.66)	(3,922.50)	(4,032.93)	(3,899.99)
Sigma	1,695.34***	1,364.46***	3,291.63***	2,989.19***	3,294.86***	3,428.87***
	(203.97)	(120.66)	(671.00)	(572.11)	(588.35)	(555.24)
N	119	149	149	225	199	218
				256	237	251
Largest FMI	–	–	0.8153	0.8833	0.7472	0.8168

Notes: In the last three scenarios, "yes/no" choices are imputed, affecting the numbers of observations across different imputation data. We report the smallest (upper row) and the largest number (lower row) of observations used during estimation. Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) imply 10%, 5%, and 1% significance levels, respectively.

Table 6. Tobit Regression for Factors Affecting Farmers' Animal Fences Adoption

			MICE Method			
	Deletion	**Mean Replacement**	**One-Stage**	**Two-Stage**	**Restricted Two-Stage**	**Three-Stage**
Offer	1,595.78	1,070.10	3,145.69	2,596.27	2,057.25	3,188.58
	(1,646.66)	(1,035.28)	(2,025.59)	(2,067.17)	(1,803.73)	(2,143.73)
Land acre	−1,673.14**	−970.69*	−2,739.97**	−2,667.73**	−2,489.65**	−2,702.89***
	(856.26)	(550.68)	(1,112.02)	(1,101.72)	(1,024.45)	(1,016.09)
Rent percentage	50.92	487.46	999.03	854.22	955.99	1,279.91
	(959.33)	(580.28)	(1,270.45)	(1,385.80)	(1,102.67)	(1,310.78)
Surface water	−164.23	−299.20	−742.06	−1,137.32	−1,004.94	−432.25
	(859.03)	(517.27)	(1,083.09)	(1,158.66)	(958.09)	(860.73)
Farm with livestock	618.18	153.34	−509.84	−442.35	−65.03	−301.45
	(954.67)	(521.23)	(1,154.61)	(1,194.73)	(1,056.65)	(1,208.81)
HH income	2.23	0.32	5.08	5.36	2.42	1.55
	(4.53)	(2.69)	(5.39)	(6.03)	(5.24)	(5.78)
%HH income from farming	2,161.51	988.66	2,510.39	5,311.77***	1,639.60	4,016.02**
	(1,536.92)	(882.25)	(1,748.43)	(1,967.42)	(1,755.90)	(1,965.13)
%HH income reinvested in farm	−1,223.12	−367.69	120.90	−4,041.02*	872.55	−2,312.96
	(1,746.35)	(1,054.12)	(2,037.00)	(2,152.72)	(1,914.50)	(2,098.21)
Water quality	−320.04*	−298.13**	−344.31	−275.46	−360.08	−391.09*
	(190.89)	(124.16)	(233.54)	(234.56)	(220.47)	(227.68)
CRP	104.59	−7.19	−1,018.53	−198.59	−224.73	−217.39
	(825.86)	(513.02)	(958.98)	(999.10)	(993.95)	(976.61)
WLP	−758.13	−181.45	11.73	−768.85	−319.35	−472.27
	(668.12)	(385.97)	(856.71)	(797.99)	(766.13)	(827.71)
Current usage of other BMPs:						
Riparian buffers	1,088.93**	451.93	769.53	706.17	1,078.44*	928.56
	(519.27)	(344.52)	(652.60)	(702.98)	(616.24)	(672.47)
Animal fences	1,985.10***	1,067.09***	1,975.42***	2,005.71***	1,920.26***	2,005.42***
	(583.56)	(364.75)	(716.45)	(732.19)	(688.65)	(726).00
No-till	1,270.70*	675.76	2,513.68**	1,235.00	1,580.20*	1,510.77*
	(752.04)	(437.16)	(1,002.68)	(943.23)	(935.16)	(914.27)
Waste storage facilities	1,980.49*	376.44	1,308.00	2,385.30*	1,619.69	1,917.57
	(1,133.39)	(679.09)	(1,305.55)	(1,358.75)	(1,242.95)	(1,543.73)
Nutrient management	−1,952.46***	−940.34**	−2,597.18***	−2,008.29**	−2,145.99**	−2,238.97***
	(692.98)	(429.19)	(850.44)	(860.55)	(895.60)	(845.06)
Choices of other BMPs:						
Riparian buffers	1,075.81*	479.27	1,496.68**	1,877.22***	1,649.58**	1,098.85*
	(568.45)	(344.87)	(679.76)	(685.34)	(682.88)	(620.65)
No-till	18.46	78.54	−552.15	236.71	600.98	154.99
	(651.84)	(408.58)	(769.94)	(882.48)	(778.56)	(664.59)
Waste storage facilities	697.40	422.57	1,042.17	1,376.18	972.34	707.56
	(690.61)	(408.74)	(821.65)	(832.53)	(825.03)	(780.67)
Nutrient management	−275.76	3.24	−388.19	−132.05	−135.21	119.77
	(634.45)	(408.34)	(783.74)	(780.35)	(787.86)	(718.49)
WQT Information Treatment:						
Cost-savings information	1,542.20**	838.91**	1,600.37*	1,314.34	1,901.27**	1,174.46
	(711.43)	(431.30)	(910.48)	(905.02)	(837.94)	(876.17)
Environment information	508.58	108.81	474.66	414.85	263.20	34.14
	(722.10)	(477.12)	(952.33)	(873.60)	(851.06)	(933.93)
Combined information	−443.79	−303.91	−519.57	−983.39	−155.92	−1,090.90
	(682.03)	(428.70)	(836.56)	(860.11)	(741.54)	(860.44)
Constant	−2,652.10	−81.45	−2,634.74	−2,286.91	−2,845.88	−2,123.55
	(2,397.51)	(1,479.62)	(2,819.25)	(2,745.98)	(2,614.28)	(3,163.88)
Sigma	2,238.97***	1,833.18***	2,752.05***	2,750.88***	2,819.08***	2,841.68***
	(198.54)	(124.69)	(332.43)	(296.09)	(327.22)	(332.99)
N	134	182	182	249	216	253
				276	255	276
Largest FMI			0.6864	0.7625	0.6467	0.7609

Notes: In the last three scenarios, "yes/no" choices are imputed, affecting the numbers of observations across different imputation data. We report the smallest (upper row) and the largest number (lower row) of observations used during estimation. Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) imply 10%, 5%, and 1% significance levels, respectively.

Table 7. Tobit Regression for Factors Affecting Farmers' No-Till Adoption

			MICE Method			
	Deletion	**Mean Replacement**	**One-Stage**	**Two-Stage**	**Restricted Two-Stage**	**Three-Stage**
Offer	−96.65	−50.71	−9.49	−39.30	−22.21	−23.45
	(75.74)	(51.38)	(113.65)	(94.38)	(106.01)	(87.55)
Land acre	23.05*	20.58**	23.44	27.32	31.55	20.96
	(12.96)	(10.20)	(20.05)	(19.86)	(20.20)	(18.11)
Rent percentage	93.34**	42.98*	105.12	129.01*	100.40	77.26
	(37.03)	(25.58)	(74.21)	(68.69)	(62.61)	(56.28)
Surface water	1.43	−6.11	21.73	32.46	46.55	17.09
	(37.06)	(26.17)	(52.77)	(49.56)	(53.72)	(38.31)
Farm with livestock	−85.03***	−47.99**	−52.99	−48.11	−77.28*	−42.41
	(33.10)	(22.69)	(46.44)	(37.63)	(44.09)	(33.16)
HH income	0.49***	0.30***	0.40	0.35	0.43*	0.36*
	(0.18)	(0.11)	(0.27)	(0.24)	(0.26)	(0.22)
%HH income from farming	135.83**	110.85***	169.21**	171.74**	163.04**	158.73**
	(57.45)	(39.44)	(85.99)	(84.57)	(79.80)	(75.10)
%HH income reinvested in farm	−66.28	−61.92	−52.38	−77.01	−93.23	−7.91
	(64.76)	(47.44)	(92.97)	(86.98)	(92.07)	(78.35)
Water quality	−11.06	−7.00	−10.24	−9.35	−6.88	−12.51
	(7.96)	(5.75)	(11.55)	(9.97)	(11.37)	(10.17)
CRP	−31.29	−23.64	−76.66	−75.96	−60.02	−71.89*
	(30.53)	(22.08)	(51.27)	(48.88)	(47.39)	(42.94)
WLP	22.15	17.64	3.30	18.04	−3.16	18.26
	(29.05)	(18.90)	(47.84)	(40.72)	(41.11)	(34.12)
Current usage of other BMPs:						
Riparian buffers	−14.62	5.71	1.56	−14.69	−16.58	0.08
	(24.48)	(16.60)	(36.97)	(31.91)	(34.02)	(32.57)
Animal fences	35.10	17.48	23.75	14.62	10.39	28.76
	(30.15)	(19.79)	(42.05)	(38.68)	(37.57)	(33.60)
No-till	95.17***	70.52***	127.56***	119.25***	126.52***	121.15***
	(25.14)	(17.18)	(43.34)	(38.60)	(41.02)	(37.73)
Waste storage facilities	−107.87**	−60.33**	−119.78*	−115.79**	−119.66*	−114.18**
	(42.85)	(27.43)	(66.64)	(58.69)	(63.80)	(53.53)
Nutrient management	−20.57	−18.38	−9.27	−16.88	7.74	−17.71
	(27.54)	(19.18)	(41.03)	(36.87)	(40.11)	(33.95)
Choices of other BMPs:						
Riparian buffers	14.84	9.96	47.19	35.26	64.78	15.38
	(27.82)	(17.55)	(48.06)	(38.30)	(44.30)	(31.22)
Animal fences	2.03	12.64	3.91	9.71	24.95	−4.74
	(30.91)	(20.23)	(43.76)	(43.51)	(39.53)	(31.01)
Waste storage facilities	49.72	21.63	47.82	36.10	78.98*	32.81
	(30.66)	(19.77)	(42.90)	(38.94)	(43.43)	(33.67)
Nutrient management	39.26	37.00**	44.33	76.64*	74.61*	21.38
	(27.44)	(17.75)	(37.73)	(40.09)	(40.22)	(29.49)
WQT Information Treatment:						
Cost-savings information	14.99	27.34	51.05	34.32	25.70	32.74
	(29.95)	(20.70)	(46.09)	(39.29)	(44.73)	(36.29)
Environment information	14.96	19.91	69.30	48.54	51.34	26.44
	(35.36)	(22.36)	(62.72)	(51.51)	(51.82)	(44.97)
Combined information	−1.03	4.29	8.35	−19.55	−11.09	−0.43
	(28.92)	(21.14)	(41.82)	(40.55)	(39.68)	(35.29)
Constant	37.79	14.95	−134.41	−114.58	−178.24	−63.10
	(105.07)	(66.85)	(164.27)	(121.62)	(155.70)	(116.88)
Sigma	96.38***	84.60***	141.44***	136.20**	145.94***	128.24***
	(8.50)	(5.87)	(26.34)	(21.63)	(26.07)	(20.94)
N	136	178	178	254	226	254
				285	264	283
Largest FMI			0.8701	0.8719	0.8521	0.8835

Notes: In the last three scenarios, "yes/no" choices are imputed, affecting the numbers of observations across different imputation data. We report the smallest (upper row) and the largest number (lower row) of observations used during estimation. Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) imply 10%, 5%, and 1% significance levels, respectively.

Table 8. Tobit Regression for Factors Affecting Farmers' Waste Storage Facilities Adoption

			MICE Method			
	Deletion	**Mean Replacement**	**One-Stage**	**Two-Stage**	**Restricted Two-Stage**	**Three-Stage**
Offer	0.19	−0.13	−0.61	−0.44	−0.29	−0.10
	(1.03)	(0.85)	(0.84)	(0.73)	(0.84)	(0.76)
Land acre	0.01	−0.01	0.02	0.01	0.10	0.03
	(0.27)	(0.20)	(0.17)	(0.19)	(0.16)	(0.17)
Rent percentage	−0.74	−0.38	−0.20	−0.12	−0.40	−0.25
	(0.57)	(0.46)	(0.44)	(0.36)	(0.44)	(0.37)
Surface water	−0.28	−0.13	0.04	0.18	0.06	0.05
	(0.52)	(0.43)	(0.44)	(0.40)	(0.43)	(0.36)
Farm with livestock	0.59	0.24	0.10	0.15	−0.04	0.16
	(0.60)	(0.42)	(0.42)	(0.38)	(0.42)	(0.38)
HH income	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
%HH income from farming	−0.26	−0.42	−0.54	−0.66	−0.68	−0.47
	(0.70)	(0.60)	(0.59)	(0.52)	(0.59)	(0.54)
%HH income reinvested in farm	1.83**	1.42**	1.13*	0.88	1.20*	1.19**
	(0.78)	(0.62)	(0.60)	(0.55)	(0.63)	(0.56)
Water quality	−0.02	−0.06	−0.07	−0.06	−0.10	−0.09
	(0.12)	(0.10)	(0.09)	(0.09)	(0.10)	(0.08)
CRP	0.43	0.27	0.18	0.20	0.22	0.28
	(0.43)	(0.31)	(0.32)	(0.29)	(0.31)	(0.30)
WLP	0.12	0.16	0.19	0.21	0.27	0.07
	(0.33)	(0.26)	(0.26)	(0.25)	(0.27)	(0.24)
Current usage of other BMPs:						
Riparian buffers	0.54	0.35	0.22	0.05	0.10	0.26
	(0.36)	(0.28)	(0.29)	(0.26)	(0.29)	(0.24)
Animal fences	−0.19	−0.13	−0.14	−0.22	−0.14	−0.07
	(0.35)	(0.29)	(0.29)	(0.26)	(0.27)	(0.27)
No-till	−0.55	−0.29	−0.02	0.01	−0.06	−0.01
	(0.45)	(0.34)	(0.34)	(0.28)	(0.34)	(0.31)
Waste storage facilities	0.50	0.27	0.20	0.32	0.35	0.15
	(0.42)	(0.35)	(0.34)	(0.31)	(0.34)	(0.31)
Nutrient management	−0.10	−0.16	−0.24	−0.25	−0.18	−0.18
	(0.36)	(0.30)	(0.29)	(0.25)	(0.29)	(0.26)
Choices of other BMPs:						
Riparian buffers	−0.17	−0.15	−0.14	−0.05	−0.15	−0.08
	(0.35)	(0.29)	(0.28)	(0.26)	(0.29)	(0.25)
Animal fences	1.19***	0.85***	0.76***	0.73**	0.84***	0.46*
	(0.38)	(0.30)	(0.30)	(0.33)	(0.30)	(0.25)
No-till	−0.18	0.03	0.11	0.15	0.39	0.06
	(0.36)	(0.29)	(0.30)	(0.31)	(0.31)	(0.26)
Nutrient management	1.09***	0.81***	0.84***	0.99***	1.04***	0.58**
	(0.37)	(0.29)	(0.29)	(0.36)	(0.31)	(0.25)
WQT Information Treatment:						
Cost-savings information	0.55	0.34	0.30	0.41	0.36	0.42
	(0.44)	(0.37)	(0.36)	(0.33)	(0.36)	(0.33)
Environment information	0.33	0.28	0.36	0.36	0.35	0.35
	(0.50)	(0.39)	(0.40)	(0.34)	(0.39)	(0.36)
Combined information	0.48	0.29	0.21	0.28	0.24	0.35
	(0.49)	(0.40)	(0.40)	(0.37)	(0.40)	(0.38)
Constant	−3.01*	−1.69	−0.88	−1.29	−1.51	−1.03
	(1.58)	(1.23)	(1.20)	(1.09)	(1.24)	(1.11)
N	128	151	151	211	200	223
				243	231	253
Largest FMI			0.1894	0.5798	0.2613	0.4859

Notes: In the last three scenarios, "yes/no" choices are imputed, affecting the numbers of observations across different imputation data. We report the smallest (upper row) and the largest number (lower row) of observations used during estimation. Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) imply 10%, 5%, and 1% significance levels, respectively.

Table 9. Tobit Regression for Factors Affecting Farmers' Nutrient Management Adoption

			MICE Method			
	Deletion	Mean Replacement	One-Stage	Two-Stage	Restricted Two-Stage	Three-Stage
Offer	62.82	54.06	107.19	77.77	141.76	148.60
	(143.69)	(107.51)	(166.49)	(151.42)	(157.89)	(146.35)
Land acre	28.37	25.16	28.27	27.17	15.12	29.82
	(28.62)	(22.52)	(33.72)	(31.74)	(34.16)	(33.87)
Rent percentage	27.97	39.36	95.52	120.49	66.40	113.87
	(74.79)	(55.39)	(93.72)	(102.11)	(92.81)	(97.53)
Surface water	−45.93	−38.51	−43.89	−63.54	−76.91	−6.64
	(65.67)	(49.21)	(70.97)	(64.81)	(69.04)	(58.55)
Farm with livestock	26.83	36.73	46.70	64.14	27.88	44.45
	(71.66)	(50.48)	(78.71)	(71.44)	(70.23)	(60.03)
HH income	0.29	−0.08	0.22	0.24	0.54	0.00
	(0.33)	(0.23)	(0.40)	(0.41)	(0.39)	(0.38)
%HH income from farming	47.68	46.89	22.94	63.80	−2.50	28.86
	(104.37)	(75.63)	(116.90)	(127.58)	(109.39)	(102.86)
%HH income reinvested in farm	42.17	−13.33	20.15	−9.69	−6.90	69.84
	(137.86)	(89.78)	(148.28)	(137.11)	(146.93)	(133.10)
Water quality	−4.74	−0.52	−2.32	8.78	8.75	−3.76
	(16.28)	(12.81)	(19.99)	(17.90)	(19.34)	(17.54)
CRP	38.59	53.88	68.35	59.46	10.02	53.37
	(70.88)	(49.58)	(89.13)	(76.24)	(84.74)	(71.09)
WLP	−72.25	−83.80**	−103.51	−119.48*	−97.93	−73.32
	(54.51)	(41.11)	(74.33)	(66.48)	(67.08)	(62.96)
Current usage of other BMPs:						
Riparian buffers	100.59**	87.88**	108.61*	108.59*	96.73*	96.93*
	(50.38)	(35.38)	(57.58)	(56.57)	(52.72)	(51.29)
Animal fences	−17.41	−8.09	9.34	5.69	31.66	29.65
	(50.59)	(37.79)	(59.58)	(52.05)	(52.66)	(47.18)
No-till	69.91	57	92.08	71.86	99.15	117.32
	(57.74)	(41.11)	(65.93)	(56.65)	(66.01)	(65.47)
Waste storage facilities	−140.50*	−95.19	−136.67	−130.61	−130.11	−157.81
	(84.69)	(58.56)	(105.69)	(98.82)	(96.99)	(103.60)
Nutrient management	147.10***	110.10***	142.65**	131.73***	172.79***	107.75**
	(48.56)	(35.13)	(56.81)	(51.36)	(56.64)	(48.47)
Choices of other BMPs:						
Riparian buffers	26.41	36.58	46.24	30.41	58.83	34.03
	(53.39)	(37.90)	(61.21)	(56.07)	(59.96)	(52.85)
Animal fences	16.04	5.83	9.67	12.88	18.66	13.42
	(55.62)	(40.14)	(63.13)	(60.41)	(57.85)	(55.51)
Waste storage facilities	74.33	83.99**	102.08	131.67**	147.94**	53.28
	(54.53)	(39.62)	(63.69)	(67.40)	(62.87)	(53.69)
Nutrient management	137.56***	103.25***	143.25**	155.49**	163.19**	88.21*
	(52.36)	(38.11)	(62.36)	(64.89)	(64.10)	(52.38)
WQT Information Treatment:						
Cost-savings information	3.06	16.52	13.53	1.38	36.47	26.28
	(65.35)	(47.35)	(74.37)	(67.61)	(77.47)	(74.86)
Environment information	−13.73	−21.87	12.49	−42.21	24.06	−11.30
	(66.14)	(48.51)	(81.12)	(68.44)	(78.56)	(77.02)
Combined information	62.72	43.73	48.30	44.33	36.88	46.27
	(61.15)	(46.97)	(69.08)	(62.20)	(64.94)	(66.26)
Constant	−328.43	−246.17*	−422.14*	−457.00*	−582.94**	−420.96*
	(208.79)	(148.33)	(251.70)	(243.87)	(255.60)	(220.95)
Sigma	209.05***	179.62***	235.06***	225.08***	245.26***	228.81***
	(17.10)	(12.37)	(44.03)	(49.07)	(47.39)	(46.38)
N	145	176	176	254	239	264
				288	272	290
Largest FMI			0.8724	0.9418	0.8752	0.9276

Notes: In the last three scenarios, "yes/no" choices are imputed, affecting the numbers of observations across different imputation data. We report the smallest (upper row) and the largest number (lower row) of observations used during estimation. Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) imply 10%, 5%, and 1% significance levels, respectively.

methods,[6] which verifies that mean replacement increases central tendency of the data and artificially provides more significant coefficients than the deletion and MI methods. The deletion method is a less distorted strategy than mean replacement because it does not replace missing data with a constant. However, it is still based on the unrealistic MCAR assumption.

Unlike conventional methods, the MICE algorithm imputes missing data from predictive distribution considering the true variance of data. Thus, it decreases central tendency of the data and generates more variance, which leads to relatively greater estimates but more conservative significance than conventional methods. Summing up, if a variable is statistically significant across all scenarios, absolute values of coefficient magnitudes should have the following order:

$$(11)\quad \left|\boldsymbol{\beta}_{one-stage}\right| \geq \left|\boldsymbol{\beta}_{two-stage}\right| \approx \left|\boldsymbol{\beta}_{two-stage\ restricted}\right| > \left|\boldsymbol{\beta}_{deletion}\right| > \left|\boldsymbol{\beta}_{mean}\right|.$$

For several reasons, we choose to use results from the one-stage imputation method to examine farmer willingness to adopt BMPs, factors that may affect their willingness, and how much more they would adopt each BMP. First, as discussed above, MICE methods are equivalent to or better than deletion and mean replacement. Second, deviations between the imputed and observed data are expected under the MAR assumption, but researchers should be especially careful of extreme departures (Abayomi, Gelman, and Levy, 2008). Following van Buuren and Groothuis-Oudshoorn (2011) and Azur et al. (2011), a visual examination of the observed and imputed distributions shows that the one-stage and three-stage imputed values have fewer deviations than the other two strategies. Consequently, scenarios 1 and 4 are preferable due to fewer departures. Third, the one-stage imputation and the two-stage with restricted imputation have smaller FMI values than the other two scenarios. The FMI value represents the fraction of missing information. In other words, for a given fixed percentage of efficiency loss from the imputation, the greater FMI is, and the more imputation times *m* needed (White, Royston, and Wood, 2011). Therefore, under the same imputation time, the one-stage imputation and the two-stage with restricted imputation have smaller losses of efficiency than other scenarios.

The one-stage imputation generally performs best among the four imputation scenarios because its imputed value has less variation and lower FMI across the five BMPs. In addition, the extra steps to determine whether a farm is able to adopt BMPs or whether they would like to use a BMP can also be a strong assumption.

Discussion of the BMP Adoption: Additional Abatement

Table 10 shows the average marginal effect of the coefficients from the one-stage imputation. Models of riparian buffers, animal fences, no-till, and nutrient management are Tobit models indicating the average marginal effect is calculated as $F(\mathbf{X}'\boldsymbol{\beta}) \times \boldsymbol{\beta}$ (McDonald and Moffitt, 1980), while waste storage facilities utilizes a Poisson model, so the average marginal effect is $\boldsymbol{\beta} \times \exp(\mathbf{X};\boldsymbol{\beta})$. After calculating the average marginal effect and standard error using the delta method for each imputation, we apply Rubin's method (equations 8–10) to derive a final estimate of marginal effects in the one-stage imputation. It is possible that BMP adoption among farmers is not just a function of willingness; their capacity to adopt may be limited by how close they were to their farms' maximum adoption capacity. This question was asked in the survey and initially included in the analysis but subsequently dropped due to strong collinearity.

All else equal, a 1% increase in compensation suggests an additional 22.77 feet in riparian buffers. Farms with one additional acre are predicted to decrease adoption of animal fences by 1.46 feet, meaning that larger farms are less likely to add fences to restrict animal access to streams. One possible explanation is that the expected total expense of installing fences for large farms should

[6] t-values of the coefficient of %HH Income from farming are deletion (2.36), mean replacement (2.81), one-stage (1.97), two-stage (2.03), two-stage restricted (2.04), three-stage (2.11). t-values of the coefficient of current use of no-till are deletion (3.79), mean replacement (4.10), one-stage (2.94), two-stage (3.09), two-stage restricted (3.08), three-stage (3.21).

Table 10. Average Marginal Effect of Factors Affecting BMP Adoption after One-Stage Imputation

	Riparian Buffers	Animal Fences	No-Till	Waste Storage Facilities	Nutrient Management
Offer	2,277.48*	1,678.34	−4.68	−0.42	48.25
	(1,246.76)	(1,074.72)	(55.59)	(0.58)	(74.87)
Land acre	−322.50	−1,463.55**	11.48	0.02	12.78
	(458.66)	(594.24)	(9.78)	(0.12)	(15.18)
Rent percentage	296.48	534.72	51.53	−0.13	43.13
	(687.38)	(679.26)	(36.38)	(0.30)	(42.21)
Surface water	275.15	−396.83	10.61	0.03	−19.83
	(481.06)	(579.40)	(25.80)	(0.30)	(31.92)
Farm with livestock	−375.19	−274.04	−25.97	0.07	21.08
	(551.19)	(618.23)	(22.66)	(0.29)	(35.38)
Income	−0.73	2.71	0.19	0.00	0.10
	(2.72)	(2.87)	(0.13)	(0.00)	(0.18)
%HH income from farming	−1,115.98	1,339.90	83.00**	−0.37	10.45
	(816.78)	(932.87)	(42.23)	(0.41)	(52.68)
%HH income reinvested in farm	1,876.91**	67.33	−25.70	0.77*	9.09
	(930.82)	(1,090.01)	(45.53)	(0.42)	(66.64)
Water quality	−21.33	−184.07	−5.03	−0.05	−1.05
	(117.12)	(124.71)	(5.66)	(0.06)	(9.00)
CRP	453.47	−544.56	−37.58	0.12	30.79
	(478.22)	(512.67)	(25.06)	(0.22)	(40.06)
WLP	−337.48	7.34	1.64	0.13	−46.72
	(424.44)	(459.11)	(23.39)	(0.18)	(33.39)
Current usage of other BMPs:					
Riparian buffers	1,058.22***	409.79	0.77	0.15	49.02*
	(370.26)	(346.80)	(18.06)	(0.19)	(25.83)
Animal fences	−371.44	1055.23***	11.66	−0.10	4.18
	(418.93)	(378.73)	(20.58)	(0.20)	(26.81)
No-till	487.95	1342.58**	62.49***	−0.01	41.57
	(510.53)	(535.95)	(20.97)	(0.23)	(29.66)
Waste storage facilities	−922.38	698.06	−58.69*	0.14	−61.65
	(740.36)	(696.81)	(32.55)	(0.23)	(47.36)
Nutrient management	−180.12	−1,386.68***	−4.55	−0.16	64.36***
	(432.36)	(450.65)	(20.06)	(0.20)	(25.19)
Choices of other BMPs:					
Riparian buffers	–	799.28**	23.12	−0.09	20.83
	–	(360.23)	(23.49)	(0.19)	(27.49)
Animal fences	1,557.10***	–	1.90	0.52**	4.39
	(490.42)	–	(21.40)	(0.21)	(28.43)
No-till	351.17	−294.42	–	0.08	46.06
	(438.32)	(410.60)	–	(0.20)	(28.58)
Waste storage facilities	−446.25	555.79	23.42	–	64.63**
	(509.24)	(437.50)	(20.93)	–	(27.72)
Nutrient management	139.17	−206.81	21.70	0.57***	–
	(421.10)	(419.06)	(18.40)	(0.21)	–
WQT Information Treatment:					
Cost-savings information	−184.66	856.10*	25.03	0.20	6.08
	(453.18)	(486.99)	(22.63)	(0.25)	(33.48)
Environment information	285.80	253.59	33.97	0.25	5.58
	(565.50)	(508.43)	(30.74)	(0.28)	(36.53)
Combined information	−80.90	−277.01	4.10	0.14	21.80
	(446.76)	(446.84)	(20.47)	(0.27)	(31.06)

Notes: Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) imply 10%, 5%, and 1% significance levels, respectively.

exceed small farms, although the expense on a per animal basis may be lower for large farms, potentially suggesting that farmers consider the total expenditure rather than cost per unit in BMP adoption decisions.

Farmers with a higher proportion of household income from farming are more likely to adopt no-till, with a 1% increase of household income from farming leading to 0.83 more acres of no-till. In addition to the environmental benefits of no-till, farmers also obtain economic benefits such as lower fuel and labor costs. The time saved from no-till means farmers can work on other tasks to improve crop production (Huggins and Reganold, 2008). Therefore, choosing no-till can concurrently improve long-term farm production, soil quality, and farm revenue. Farmers who reinvest more assets into their businesses tend to adopt more riparian buffers and waste storage facilities. A key result of this study is that previous BMP adoption significantly affects additional BMP adoption. Holding other factors constant, farmers already using riparian buffers will adopt 1,058.22 more feet of riparian buffers and apply nutrient management to 49.02 more acres relative to farmers not using buffers. Farmers who have already employed animal fences will increase animal fences by 1,055.23 feet compared to farmers who have not. Similarly, farmers currently using no-till are likely to adopt 1,342.58 additional feet of animal fences and 62.49 acres of no-till. If farmers already have a waste storage facility, they will reduce the practice of no-till on 58.69 acres. Farmers currently using nutrient management will reduce animal fences by 1,386.68 feet but will adopt nutrient management on 64.36 additional acres. Cameron and Englin (1997) also find that respondents' willingness to use environmental goods is influenced by their previous experiences with the goods.

Lastly, the type of information significantly affects farmers' BMP adoption decisions. Compared to the control group, which received only basic WQT information, the treatment featuring augmented cost-savings information induced farmers to adopt animal fences by an additional 856.10 feet. However, the treatment with augmented environmental information did not influence BMP adoption. As such, policy makers who wish to promote a WQT program or BMP adoption should carefully consider the type of information communicated with the farmers.

Table 10 also reveals the complementarity of adopting different BMPs. Farmers willing to use riparian buffers are more likely to adopt animal fences and vice versa. Farmers willing to build waste storage facilities also tend to implement nutrient management systems. These findings match previous literature that farmers who adopt technological innovation tend to attempt other similar innovations because of technical complementarity among the innovations (Lichtenberg, 2004; Khanal, Gillespie, and MacDonald, 2010) and adopters' preferences, such as risk attitudes (Rahelizatovo and Gillespie, 2004) or socioeconomic characteristics (Sharma, Bailey, and Fraser, 2011).

Conclusion

This study investigates methods to address missing responses in farmer surveys by comparing conventional methods and multiple imputation methods. We conduct a survey of Kentucky farmers' BMP adoption through a hypothetical WQT program. Roughly a fifth to a quarter of respondents did not indicate the amount adopted for the five BMPs investigated. We apply six approaches to address the missing data issues: the deletion method, the mean replacement method, and four MICE variants.

Our empirical findings show that compensation from WQT programs, socioeconomics characteristics, farm physical characteristics, WQT-related information, land area, percentage of household income from farming, percentage of total household income reinvested in the farm, and current experience of BMPs all affect BMP adoption. We also observe a complementarity of BMP adoption, with riparian buffers and animal fences as well as waste storage facilities and nutrient management often adopted together by farmers. Lastly, we find that WQT information with augmented cost-savings information induced farmers to adopt more animal fences.

While other disciplines routinely employ MI, many researchers using agricultural surveys continue to rely on the deletion method for missing data. We show that replacing missing data with MI-generated values enhances the economic analysis and implications. The MI method shows promise to specifically handle missing data for surveys involving farming decisions. The comparison between several popular schemes offers insights on their relative efficacy to address missing data.

As a conservative strategy, when the percentage of missing data is more than 5% or the MCAR assumption tenuous, we recommend dealing with missing data by providing results from both the deletion and the MI method (Schafer, 1999). The traditional approaches such as deletion and mean replacement methods may generate misleading conclusions. The mean replacement method is not advisable as it may generate unreliable results versus other methods, especially when the researcher is uncertain about the underlying reasons for the missing data.

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References

Abayomi, K., A. Gelman, and M. Levy. "Diagnostics for Multivariate Imputations." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 57(2008):273–291. doi: 10.1111/j.1467-9876.2007.00613.x.

Abdulai, A., and W. Huffman. "The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application." *Land Economics* 90(2014):26–43. doi: 10.3368/le.90.1.26.

Adesina, A. A., and M. M. Zinnah. "Technology Characteristics, Farmers' Perceptions and Adoption Decisions: A Tobit Model Application in Sierra Leone." *Agricultural Economics* 9(1993):297–311. doi: 10.1016/0169-5150(93)90019-9.

Albert, A., and J. A. Anderson. "On the Existence of Maximum Likelihood Estimates in Logistic Regression Models." *Biometrika* 71(1984):1–10. doi: 10.1093/biomet/71.1.1.

Allison, P. *Missing Data*. Thousand Oaks, CA: Sage Publications, 2002.

———. "Handling Missing Data by Maximum Likelihood." 2012. Paper presented at the SAS Global Forum. Available online at http://www.statisticalhorizons.com/wp-content/uploads/MissingDataByML.pdf.

Azur, M. J., E. A. Stuart, C. Frangakis, and P. J. Leaf. "Multiple Imputation by Chained Equations: What Is It and How Does It Work?" *International Journal of Methods in Psychiatric Research* 20(2011):40–49. doi: 10.1002/mpr.329.

Baumgart-Getz, A., L. S. Prokopy, and K. Floress. "Why Farmers Adopt Best Management Practice in the United States: A Meta-Analysis of the Adoption Literature." *Journal of Environmental Management* 96(2012):17–25. doi: 10.1016/j.jenvman.2011.10.006.

Cameron, A. C., and P. K. Trivedi. "Regression-Based Tests for Overdispersion in the Poisson Model." *Journal of Econometrics* 46(1990):347–364.

Cameron, T. A., and J. Englin. "Respondent Experience and Contingent Valuation of Environmental Goods." *Journal of Environmental Economics and Management* 33(1997):296–313. doi: 10.1006/jeem.1997.0995.

Ervin, C. A., and D. E. Ervin. "Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications." *Land Economics* 58(1982):277–292. doi: 10.2307/3145937.

Grittner, U., G. Gmel, S. Ripatti, K. Bloomfield, and M. Wicki. "Missing Value Imputation in Longitudinal Measures of Alcohol Consumption." *International Journal of Methods in Psychiatric Research* 20(2011):50–61. doi: 10.1002/mpr.330.

Groves, R. M. "Nonresponse Rates and Nonresponse Bias in Household Surveys." *Public Opinion Quarterly* 70(2006):646–675. doi: 10.1093/poq/nfl033.

Groves, R. M., and E. Peytcheva. "The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis." *Public Opinion Quarterly* 72(2008):167–189. doi: 10.1093/poq/nfn011.

Huggins, D. R., and J. P. Reganold. "No-Till: The Quiet Revolution." *Scientific American* 299(2008):70–77. doi: 10.1038/scientificamerican0708-70.

Johnson, D. R., and R. Young. "Toward Best Practices in Analyzing Datasets with Missing Data: Comparisons and Recommendations." *Journal of Marriage and Family* 73(2011):926–945. doi: 10.1111/j.1741-3737.2011.00861.x.

Kenward, M. G., and J. Carpenter. "Multiple Imputation: Current Perspectives." *Statistical Methods in Medical Research* 16(2007):199–218. doi: 10.1177/0962280206075304.

Khanal, A. R., J. Gillespie, and J. MacDonald. "Adoption of Technology, Management Practices, and Production Systems in US Milk Production." *Journal of Dairy Science* 93(2010):6012–6022. doi: 10.3168/jds.2010-3425.

King, G., J. Honaker, A. Joseph, and K. Scheve. "Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation." *American Political Science Review* 95(2001):49–69.

Knowler, D., and B. Bradshaw. "Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research." *Food Policy* 32(2007):25–48. doi: 10.1016/j.foodpol.2006.01.003.

Lall, R. "How Multiple Imputation Makes a Difference." *Political Analysis* 24(2016):414–433. doi: 10.1093/pan/mpw020.

Lichtenberg, E. "Cost-Responsiveness of Conservation Practice Adoption: A Revealed Preference Approach." *Journal of Agricultural and Resource Economics* 29(2004):420–435.

Lin, I.-F., and N. C. Schaeffer. "Using Survey Participants to Estimate the Impact of Nonparticipation." *Public Opinion Quarterly* 59(1995):236–258. doi: 10.1086/269471.

Little, R. J. A., and D. B. Rubin. "The Analysis of Social Science Data with Missing Values." *Sociological Methods & Research* 18(1989):292–326. doi: 10.1177/0049124189018002004.

Ma, S., S. M. Swinton, F. Lupi, and C. Jolejole-Foreman. "Farmers' Willingness to Participate in Payment-for-Environmental-Services Programmes." *Journal of Agricultural Economics* 63(2012):604–626. doi: 10.1111/j.1477-9552.2012.00358.x.

McDonald, J. F., and R. A. Moffitt. "The Uses of Tobit Analysis." *Review of Economics and Statistics* 62(1980):318–321. doi: 10.2307/1924766.

Miyama, E., and S. Managi. "Global Environmental Emissions Estimate: Application of Multiple Imputation." *Environmental Economics and Policy Studies* 16(2014):115–135. doi: 10.1007/s10018-014-0080-3.

Norris, P. E., and S. S. Batie. "Virginia Farmers' Soil Conservation Decisions: An Application of Tobit Analysis." *Journal of Agricultural and Applied Economics* 19(1987):79–90. doi: 10.1017/S0081305200017404.

Prokopy, L. S., K. Floress, D. Klotthor-Weinkauf, and A. Baumgart-Getz. "Determinants of Agricultural Best Management Practices Adoption: Evidence from the Literature." *Journal of Soil and Water Conservation* 63(2008):300–311. doi: 10.2489/jswc.63.5.300.

Raghunathan, T. E., J. M. Lepkowski, J. Van Hoewyk, and P. Solenberger. "A Multivariate Technique for Multiply Imputing Missing Values Using a Sequence of Regression Models." *Survey Methodology* 27(2001):85–96. Available online at http://www5.statcan.gc.ca/olc-cel/olc.action?objId=12-001-X20010015857&objType=47.

Rahelizatovo, N. C., and J. M. Gillespie. "The Adoption of Best-Management Practices by Louisiana Dairy Producers." *Journal of Agricultural and Applied Economics* 36(2004):229–240. doi: 10.1017/S1074070800021970.

Royston, P., and I. R. White. "Multiple Imputation by Chained Equations (MICE): Implementation in Stata." *Journal of Statistical Software* 45(2011):1–20. doi: 10.18637/jss.v045.i04.

Rubin, D. B. *Multiple Imputation for Nonresponse in Surveys*. New York, NY: Wiley, 1987.

Rubin, D. D. "Multiple Imputations in Sample Surveys – A Phenomenological Bayesian Approach to Nonresponse." In *Proceedings of the Survey Research Methods Section, American Statistical Association,* Alexandria, VA: American Statistical Association, 1978, 20–28.

Schafer, J. L. *Analysis of Incomplete Multivariate Data*. New York, NY: Chapman & Hall, 1997.

———. "Multiple Imputation: A Primer." *Statistical Methods in Medical Research* 8(1999):3–15. doi: 10.1177/096228029900800102.

Schenker, N., T. E. Raghunathan, P.-L. Chiu, D. M. Makuc, G. Zhang, and A. J. Cohen. "Multiple Imputation of Missing Income Data in the National Health Interview Survey." *Journal of the American Statistical Association* 101(2006):924–933. doi: 10.1198/016214505000001375.

Sharma, A., A. Bailey, and I. Fraser. "Technology Adoption and Pest Control Strategies Among UK Cereal Farmers: Evidence from Parametric and Nonparametric Count Data Models." *Journal of Agricultural Economics* 62(2011):73–92. doi: 10.1111/j.1477-9552.2010.00272.x.

Uri, N. D. "Conservation Tillage and Input Use." *Environmental Geology* 29(1997):188–201. doi: 10.1007/s002540050117.

van Buuren, S., and K. Groothuis-Oudshoorn. "MICE: Multivariate Imputation by Chained Equations in R." *Journal of Statistical Software* 45(2011):1–67. doi: 10.18637/jss.v045.i03.

van Buuren, S., and K. Oudshoorn. "Flexible Multivariate Imputation by MICE." TNO Report PG/VGZ/99.054, TNO Prevention and Health, Leiden, Netherlands, 1999. Available online at http://www.stefvanbuuren.nl/publications/Flexible%20multivariate%20-%20TNO99054%201999.pdf.

Weber, J. G., and D. M. Clay. "Who Does Not Respond to the Agricultural Resource Management Survey and Does It Matter?" *American Journal of Agricultural Economics* 95(2013):755–771. doi: 10.1093/ajae/aas171.

White, I. R., R. Daniel, and P. Royston. "Avoiding Bias Due to Perfect Prediction in Multiple Imputation of Incomplete Categorical Variables." *Computational Statistics & Data Analysis* 54(2010):2267–2275. doi: 10.1016/j.csda.2010.04.005.

White, I. R., P. Royston, and A. M. Wood. "Multiple Imputation Using Chained Equations: Issues and Guidance for Practice." *Statistics in Medicine* 30(2011):377–399. doi: 10.1002/sim.4067.

Online Supplement A: Imputation Models (Raghunathan et al., 2001)

Linear Regression Model

Define y as a variable that follows a normal linear regression model:

(A1) $$y|\mathbf{x} \sim N(x'\boldsymbol{\beta}, \sigma^2),$$

where $\mathbf{x} = (x_1,\ x_2,\ x_3,\ \ldots,\ x_k)'$ is a vector of k predictors of y and is fully observed, $\boldsymbol{\beta}$ is a $k \times 1$ vector of regression coefficients explaining the correlation between y and predictors x, and σ^2 is the scalar variance.

Assume that y contains missing data that need to be imputed. Define $y = (y_o,\ y_m)$ and $x = (x_o,\ x_m)$, where

	Number of Observations $n = n_o + n_m$	y with Missing Data	x Predictors Fully Observed
Fully observed part	n_o	y_o	x_o
Missing part	n_m	y_m	x_m

The imputation model is specified as follows:

1. Using observed y_o and x_o, calculate $\hat{\boldsymbol{\beta}} = [x_o',\ x_o]^{-1}x_o'y_o$ and $\hat{u} = (y_o - x_o\hat{\boldsymbol{\beta}})$.
2. Generate $\widehat{\sigma^2} = \hat{u}'\hat{u}/g$, where g is a draw from $\chi^2_{n_o-k}$ distribution.
3. Draw $\boldsymbol{\beta}|\sigma^2 \sim N[\hat{\boldsymbol{\beta}},\ \widehat{\sigma^2}[x_o',\ x_o]^{-1}]$.
4. Draw $y_m \sim N[x_m\hat{\hat{\boldsymbol{\beta}}},\ \hat{\sigma}^2]$, where $\hat{\hat{\boldsymbol{\beta}}}$ is the most recent draw of $\boldsymbol{\beta}$ in step 3.
5. Using $y[y_o,\ y_m]$ and $[x_o,\ x_m]$, repeat steps 1–4 after appropriate adjustments.

After the first round, $\hat{\boldsymbol{\beta}}$ is obtained using $y[y_o,\ y_m]$ and $x[x_o,\ x_m]$, where y_m is the imputed value from the most recent round, the degree of freedom of x^2 distribution in step 2 is replaced by $n - k$, and x_o in step 3 is replaced by $x[x_o,\ x_m]$.

Logit Model

Define y as a variable that follows a logistic model:

(A2) $$\Pr(y = 1|\mathbf{x}) = \frac{\exp(x'\boldsymbol{\beta})}{\exp(x'\boldsymbol{\beta}) + 1},$$

where $\mathbf{x} = (x_1,\ x_2,\ x_3,\ \ldots,\ x_k)'$ is a vector of k predictors of y and is fully observed and $\boldsymbol{\beta}$ is a $k \times 1$ vector of regression coefficients explaining the correlation between y and predictors x.

Assume that y contains missing data that need to be imputed. Define $y = (y_o,\ y_m)$ and $x = (x_o,\ x_m)$, where

	Number of Observations $n = n_o + n_m$	y with Missing Data	x Predictors Fully Observed
Fully observed part	n_o	y_o	x_o
Missing part	n_m	y_m	x_m

The imputation model is specified as follows:

1. Use observed y_o and x_o to fit a logistic model to obtain the maximum likelihood estimate, $\hat{\boldsymbol{\beta}}$, and its asymptotic covariance matrix, V.
2. Let T be the Cholesky decomposition of V, where $V = TT^t$.
3. Draw $\boldsymbol{\beta} : \hat{\hat{\boldsymbol{\beta}}} = \hat{\boldsymbol{\beta}} + T\mathbf{z}$, where vector $\mathbf{z}$ is a random normal deviate with dimension rows $\hat{\boldsymbol{\beta}}$.
4. Use $\hat{\hat{\boldsymbol{\beta}}}$, which is the most recent draw of $\boldsymbol{\beta}$ in step 3 to fit

$$P^* = \Pr(y_m = 1|x) = \frac{\exp(x_m'\hat{\hat{\boldsymbol{\beta}}})}{\exp(x_m'\hat{\hat{\boldsymbol{\beta}}}) + 1}. \tag{A3}$$

5. Generate a vector $\mathbf{u}$ of uniform random numbers between 0 and 1 with dimension rows y_m.
6. With respect to each individual, impute 1 if $\mathbf{u} \leq P^*$, and 0 otherwise.
7. Using $y[y_o,\ y_m]$ and $[x_o,\ x_m]$, repeat steps 1–7 after appropriate adjustments.

Multinomial Logit Model

Define y as a variable that contains l categories (outcome $q = 1$ is the base outcome) follows a multinomial logistic model:

$$\Pr(y = q|\mathbf{x}) = \frac{\exp(x'\boldsymbol{\beta}_\mathbf{q})}{1 + \sum_1^{l-1}\exp(x'\boldsymbol{\beta}_\mathbf{q})} \text{ if } q > 1, \text{ so, } \frac{\Pr(y = q|x)}{\Pr(y = l|x)} = e^{x'\boldsymbol{\beta}_\mathbf{q}}, \tag{A4}$$

where $\mathbf{x} = (x_1,\ x_2,\ x_3,\ \ldots,\ x_k)'$ is a vector of k predictors of y and is fully observed and $\boldsymbol{\beta}_\mathbf{q}$ is a $k \times 1$ vector of regression coefficients explaining the correlation between outcome q and predictors x.

Assume that y contains missing data that need to be imputed. Define $y = (y_o,\ y_m)$ and $x = (x_o,\ x_m)$, where

	Number of Observations $n = n_o + n_m$	y with Missing Data	x Predictors Fully Observed
Fully observed part	n_o	y_o	x_o
Missing part	n_m	y_m	x_m

The imputation model is specified as follows:

1. Use observed y_o and x_o to fit a multinomial logistic model to obtain the maximum likelihood estimates $(\hat{\boldsymbol{\beta}}_1,\ \hat{\boldsymbol{\beta}}_2,\ \hat{\boldsymbol{\beta}}_3,\ \ldots,\ \hat{\boldsymbol{\beta}}_q,\ \ldots,\ \hat{\boldsymbol{\beta}}_{l-1})$ and the asymptotic covariance matrix $V = TT^t$, where T is the Cholesky decomposition.

2. Draw $\boldsymbol{\beta}$: $\hat{\hat{\boldsymbol{\beta}}}_q = \hat{\boldsymbol{\beta}}_q + T\mathbf{z}$, where vector $\mathbf{z}$ is a random normal deviates with dimension rows $\hat{\boldsymbol{\beta}}_q$.
3. Use $\hat{\hat{\boldsymbol{\beta}}}$, which is the most recent draw of β_q in step 3 to fit

$$\text{(A5)} \quad P_q^* = \Pr(y_m = q|x) = \frac{\exp(x_m' \hat{\hat{\boldsymbol{\beta}}}_q)}{1 + \sum_1^{l-1} \exp(x_m' \hat{\hat{\boldsymbol{\beta}}}_q)} \quad \text{and} \quad P_l^* = 1 - \sum_1^{l-1} P_q^*$$

4. Generate a vector $\mathbf{u}$ of uniform random numbers with dimension rows y_m.
5. Let $R_0 = 0$, $R_q = \sum_1^{l-1} P_q^*$, and $R_l = 1$ be the cumulative sums of the probabilities. Impute outcome q if $R_{q-1} < u < R_q$.
6. Using $y[y_o, y_m]$ and $[x_o, x_m]$, repeat steps 1–6 after appropriate adjustments.

Predictive Mean Matching (PMM) Model

Define y as a variable that follows a normal linear regression model:

$$\text{(A6)} \qquad y|x \sim N(\mathbf{x}'\boldsymbol{\beta}, \sigma^2),$$

where $\mathbf{x} = (x_1, x_2, x_3, \ldots, x_k)'$ is a vector of k predictors of y and is fully observed, $\boldsymbol{\beta}$ is a $k \times 1$ vector of regression coefficients explaining the correlation between y and predictors x, and σ^2 is the scalar variance. Assume that y contains missing data that need to be imputed. Define $y = (y_o, y_m)$ and $x = (x_o, x_m)$, where

	Number of Observations $n = n_o + n_m$	y with Missing Data	x Predictors Fully Observed
Fully observed part	n_o	y_o	x_o
Missing part	n_m	y_m	x_m

The PMM method follows steps of the linear regression model except for the last two:

1. Draw $y_m \sim N[x_m \hat{\hat{\boldsymbol{\beta}}}, \widehat{\sigma}^2]$ to obtain $\widehat{y_m}$, the prediction of y_m.
2. Generate first s minimums determined based on the absolute differences between the linear prediction for incomplete observation i and linear predictions for complete observations, such as

$$\left|\widehat{y}_i - \widehat{y}_j\right|,\ j \in obs\, j_{min} \text{ determined based on } \left|\widehat{y}_i - \widehat{y}_j\right| = \min_{j \in\ obs} \left|\widehat{y}_i - \widehat{y}_j\right|.$$

3. For the missing observation i of y_m, y_m equals $y_{j_{min}}$, where j_{min} is randomly drawn from the set of indices $\{i_1, i_2, \ldots, i_k\}$ determined based on the first s minimums.

Table B1. Imputation Model Using Multivariate Imputation by Chained Equation

Variable	Type	Definition
c_1	unordered categorical variables	Choice to adopt riparian buffers: $c_1 = 1$ if "yes," $c_1 = 0$ if "no," $c_1 = 2$ if "not possible for me"
c_2	unordered categorical variables	Choice to adopt animal fences: $c_2 = 1$ if "yes," $c_2 = 0$ if "no," $c_2 = 2$ if "not possible for me"
c_3	unordered categorical variables	Choice to adopt no till: $c_3 = 1$ if "yes," $c_3 = 0$ if "no," $c_3 = 2$ if "not possible for me"
c_4	unordered categorical variables	Choice to adopt waste storage facilities: $c_4 = 1$ if "yes," $c_4 = 0$ if "no," $c_4 = 2$ if "not possible for me"
c_5	unordered categorical variables	Choice to adopt nutrient management : $c_5 = 1$ if "yes," $c_5 = 0$ if "no," $c_5 = 2$ if "not possible for me"
y_1	continuous	Follow-up question on how much riparian buffer will be adopted
y_2	continuous	Follow-up question on how much animal fences will be adopted
y_3	continuous	Follow-up question on how much no till will be adopted
y_4	count	Follow-up question on how many waste storage facilities will be installed
y_5	continuous	Follow-up question on how much nutrient management will be adopted
I_1	binary variables	Respondent is unlikely or unable to adopt riparian buffers: $I_1 = 1$ if "no," $I_1 = 0$ if "not possible for me"
I_2	binary variables	Respondent is unlikely or unable to adopt animal fences: $I_2 = 1$ if "no," $I_2 = 0$ if "not possible for me"
I_3	binary variables	Respondent is unlikely or unable to adopt no till: $I_3 = 1$ if "no," $I_3 = 0$ if "not possible for me"
I_4	binary variables	Respondent is unlikely or unable to adopt waste storage facilities: $I_4 = 1$ if "no," $I_4 = 0$ if "not possible for me"
I_5	binary variables	Respondent is unlikely or unable to adopt nutrient management: $I_5 = 1$ if "no," $I_5 = 0$ if "not possible for me"
p_1	binary variables	Respondent capability to adopt riparian buffers: $p_1 = 1$ if possible, either "yes" or "no," else $p_1 = 0$ if "not possible for me"
p_2	binary variables	Respondent capability to adopt animal fences: $p_2 = 1$ if possible, either "yes" or "no," else $p_2 = 0$ if "not possible for me"
p_3	binary variables	Respondent capability to adopt no till: $p_3 = 1$ if possible, either "yes" or "no," else $p_3 = 0$ if "not possible for me"
p_4	binary variables	Respondent capability to adopt waste storage facilities: $p_4 = 1$ if possible, either "yes" or "no," else $p_4 = 0$ if "not possible for me"
p_5	binary variables	Respondent capability to adopt nutrient management: $p_5 = 1$ if possible, either "yes" or "no," else $p_5 = 0$ if "not possible for me"
q_1	binary variables	Given capability, respondent willingness to adopt riparian buffers: $q_1 = 1$ if "yes" and $q_1 = 0$ if "no" when $p_1 = 1$
q_2	binary variables	Given capability, respondent willingness to adopt animal fences: $q_2 = 1$ if "yes" and $q_2 = 0$ if "no" when $p_2 = 1$
q_3	binary variables	Given capability, respondent willingness to adopt no till: $q_3 = 1$ if "yes" and $q_3 = 0$ if "no" when $p_3 = 1$
q_4	binary variables	Given capability, respondent willingness to adopt waste storage facilities: $q_4 = 1$ if "yes" and $q_4 = 0$ if "no" when $p_4 = 1$
q_5	binary variables	Given capability, respondent willingness to adopt nutrient management: $q_5 = 1$ if "yes" and $q_5 = 0$ if "no" when $p_5 = 1$

Notes: Table B1 variable definitions in the imputation model.

Table B2. Imputation Model for the One-Stage Case

Imputation Model	Imputation Condition	Dependent Variable	Independent Variable y_1	y_2	y_3	y_4	y_5	*X* (Fully Observed Variables)
Linear regression	$c_1 = 1$	y_1		✓	✓	✓	✓	Offer compensation, land size, rent percent, surface water, percentage of household income from farming, total household income reinvested in farm, farms with livestock, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs, and four WQT program information treatments.
Linear regression	$c_2 = 1$	y_2	✓		✓	✓	✓	
Linear regression	$c_3 = 1$	y_3	✓	✓		✓	✓	
Predictive mean matching	$c_4 = 1$	y_4	✓	✓	✓		✓	
Linear regression	$c_5 = 1$	y_5	✓	✓	✓	✓		

Table B3. Imputation Model for the Two-Stage Case

	Imputation Model	Imputation Condition	Dependent Variable	Independent Variable										X (Fully Observed Variables)
				c_1	c_2	c_3	c_4	c_5	y_1	y_2	y_3	y_4	y_5	
Stage One	Multinomial logit ($c_i = 1$ if "yes," $c_i = 0$ if "no," $c_i = 2$ if "not possible for me")		c_1		✓	✓	✓	✓						Offer compensation, land size, rent percent, surface water, percentage of household income from farming, total household income reinvested in farm, farms with livestock, age, gender, education, race, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs, and four WQT program information treatments.
			c_2	✓		✓	✓	✓						
			c_3	✓	✓		✓	✓						
			c_4	✓	✓	✓		✓						
			c_5	✓	✓	✓	✓							
Stage Two	Linear regression	$c_1 = 1$	y_1							✓	✓	✓	✓	Offer compensation, land size, rent percent, surface water, percentage of household income from farming, total household income reinvested in farm, farms with livestock, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs, and four WQT program information treatments.
	Linear regression	$c_2 = 1$	y_2						✓		✓	✓	✓	
	Linear regression	$c_3 = 1$	y_3						✓	✓		✓	✓	
	Predictive mean matching	$c_4 = 1$	y_4						✓	✓	✓		✓	
	Linear regression	$c_5 = 1$	y_5						✓	✓	✓	✓		

Table B4. Imputation Model for the Two-Stage with Restriction Case

	Imputation Model	Imputation Condition	Dependent Variable	Independent Variable I_1	I_2	I_3	I_4	I_5	y_1	y_2	y_3	y_4	y_5	X (Fully Observed Variables)
Stage One	Logit ($I_i = 1$ if "no," $I_i = 0$ if "not possible for me")	$c_1 = 0$ & $c_1 = 2$	I_1											Offer compensation, land size, rent percent, percentage of household income from farming, total household income reinvested in farm, farms with livestock, age, gender, education, race, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs, and four WQT program information treatments.
		$c_2 = 0$ & $c_2 = 2$	I_2											
		$c_3 = 0$ & $c_3 = 2$	I_3											
		$c_4 = 0$ & $c_4 = 2$	I_4											
		$c_5 = 0$ & $c_5 = 2$	I_5											
Stage Two	Linear regression	$c_1 = 1$	y_1							✓	✓	✓	✓	Offer compensation, land size, rent percent, percentage of household income from farming, total household income reinvested in farm, farms with livestock, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs, and four WQT program information treatments.
	Linear regression	$c_2 = 1$	y_2						✓		✓	✓	✓	
	Linear regression	$c_3 = 1$	y_3						✓	✓		✓	✓	
	Predictive mean matching	$c_4 = 1$	y_4						✓	✓	✓		✓	
	Linear regression	$c_5 = 1$	y_5						✓	✓	✓	✓		

Table B5. Imputation Model for the Three-Stage Case

	Imputation Model	Imputation Condition	Dependent Variable	p_1	p_2	p_3	p_4	p_5	q_1	q_2	q_3	q_4	q_5	y_1	y_2	y_3	y_4	y_5	*X* (Fully Observed Variables)
Stage One	Logit ($p_i = 1$ if it is possible to adopt BMPs ("yes" or "no"), $p_i = 0$ if "not possible for me")		p_1																Offer compensation, land size, rent percent, surface water, percentage of household income from farming, total household income reinvested in farm, farms with crop, farms with livestock, age, gender, education, race, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs.
			p_2																
			p_3																
			p_4																
			p_5																
Stage Two	Logit ($q_i = 1$ if "yes," $q_i = 0$ if "no"), conditional on $p_i = 1$	$p_1 = 1$	q_1							✓	✓	✓	✓						Offer compensation, land size, rent percent, percentage of household income from farming, total household income reinvested in farm, farms with livestock, age, gender, education, race, income level,water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of five BMPs, and four WQT program information treatments.
		$p_2 = 1$	q_2						✓		✓	✓	✓						
		$p_3 = 1$	q_3						✓	✓		✓	✓						
		$p_4 = 1$	q_4						✓	✓	✓		✓						
		$p_5 = 1$	q_5						✓	✓	✓	✓							
Stage Three	Linear regression	$q_1 = 1$	y_1							✓	✓	✓	✓						Offer compensation, land size, rent percent, percentage of household income from farming, total household income reinvested in farm, farms with livestock, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP, participation in WLP, current usage of the five BMPs, and four WQT program information treatments.
	Linear regression	$q_2 = 1$	y_2						✓		✓	✓	✓						
	Linear regression	$q_3 = 1$	y_3						✓	✓		✓	✓						
	Predictive mean matching	$q_4 = 1$	y_4						✓	✓	✓		✓						
	Linear regression	$q_5 = 1$	y_5						✓	✓	✓	✓							

Online Supplement C: Fitting the Imputation Model

During imputation, the normal linear regression model requires the normality assumption for observed values to predict value X. When the observed values are highly skewed, the normal linear regression model is invalid. Following Royston and White (2011), we apply a shifted log transformation to the observed value of missing data in order to satisfy the normality assumption. This process transforms the observed value in variable y into a log form toward normality using equation (C1), where y_{norm} is the log-transformed nonmissing values, y_{obs} is the value of nonmissing y, and k is an estimated parameter indicating skewness. If y_{obs} is negatively skewed, the sign in front of y_{obs} in equation (C1) is negative; otherwise it is positive. After imputation, we use the inverse transformation in equation (C2) to convert observed and imputed values of variable y back to the original scale, and label it as $y_{completed}$.

(C1) $$y_{norm} = \ln(\pm y_{obs} - k);$$

(C2) $$y_{completed} = \mp(e^{y_{norm}+y_{imputed}} + k).$$

In our research, the issue of perfect prediction occurs in several models. Perfect prediction arises when covariate variables can perfectly predict outcomes of the categorical data (Albert and Anderson, 1984). As a result, the imputation cannot be executed because the estimation has infinite coefficients with infinite standard errors. Categorical data, especially in logit and multinomial logit models, are more likely to have the perfect prediction issue (White, Royston, and Wood, 2011). One can "diagnose" the models by identifying and removing the covariates causing perfect prediction. However, removing a potentially troublesome variable may mislead the imputation because omitting a key determinant leads to a biased result. An alternative strategy uses an augmented-regression approach introduced by White, Daniel, and Royston (2010). We apply the augmented approach in all imputation models with categorical data.

Online Supplement D: Imputation Assessment

Online Supplement D displays our convergence tests for the imputation. van Buuren and Groothuis-Oudshoorn (2011) show that it is impossible to find a clear-cut method for determining whether the MICE algorithm has converged. The most-used strategy is to plot one or more parameters against the iteration number and then conduct a visual check. They also show that plotted parameters of nonconvergence of the MICE algorithm are flat or resolve into a steady state because values are locked to the starting imputation.

Following their method, we conducted 1,000 iterations to assess our imputation and convergence. Figures D1–D5 in display the convergence of all scenarios for each BMP model: one-stage, two-stage, restricted two-stage, and three-stage imputation. As can be seen in our figures, means of observed and imputed data oscillated. The oscillation indicates our imputations are not stuck with the starting values. In addition, the first full oscillation can be achieved within 10–30 iterations across all scenarios. This is a good signal that the imputations have converged. Thus, we opt to use 30 iterations as the burn-in period for all scenarios.

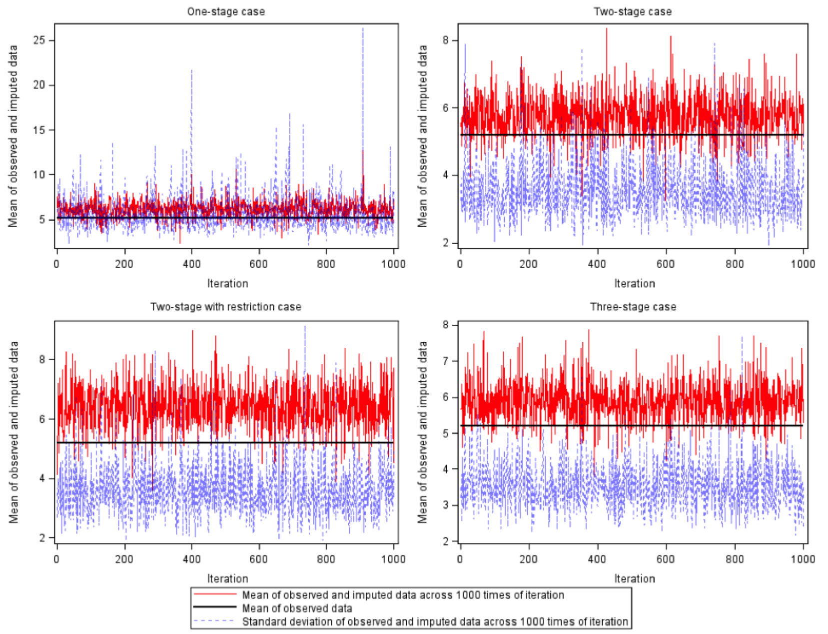

Figure D1. Assessment of Imputation Convergence for Riparian Buffers

Notes: Based on the visual check, the imputation results of riparian buffers are not stable as other models of BMPs, because missing rates for the riparian buffer are the highest among surveyed BMPs.

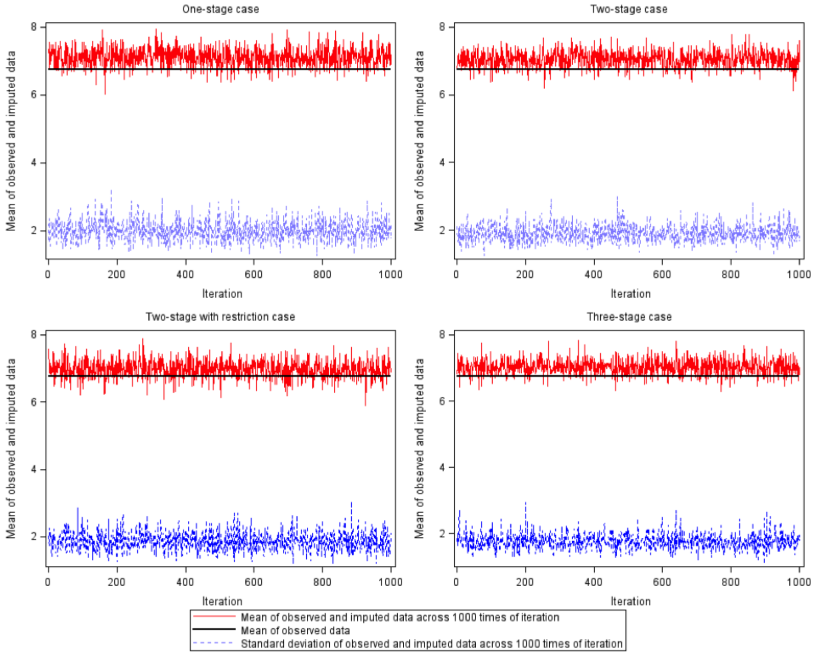

Figure D2. Assessment of Imputation Convergence for Animal Fences

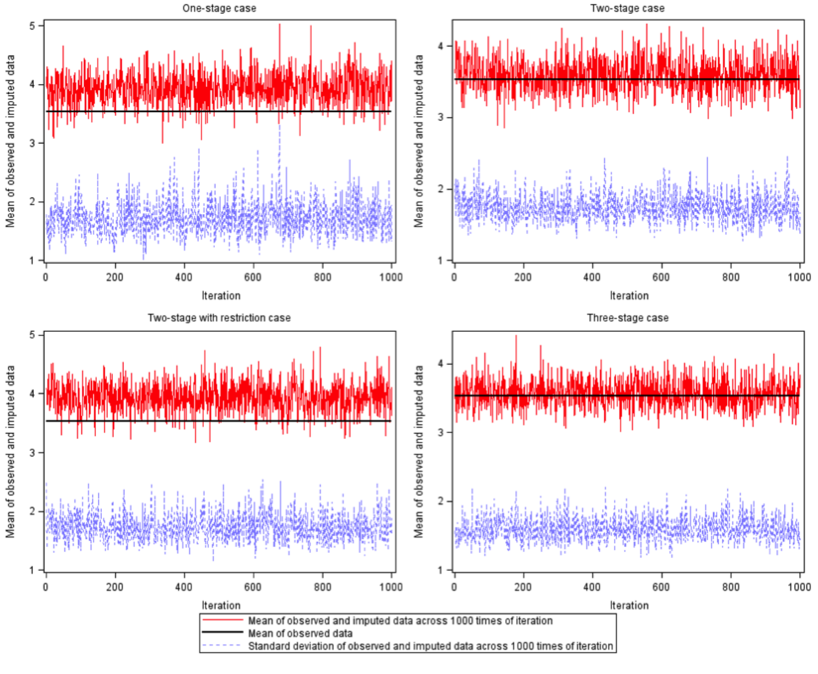

Figure D3. Assessment of Imputation Convergence for No Till

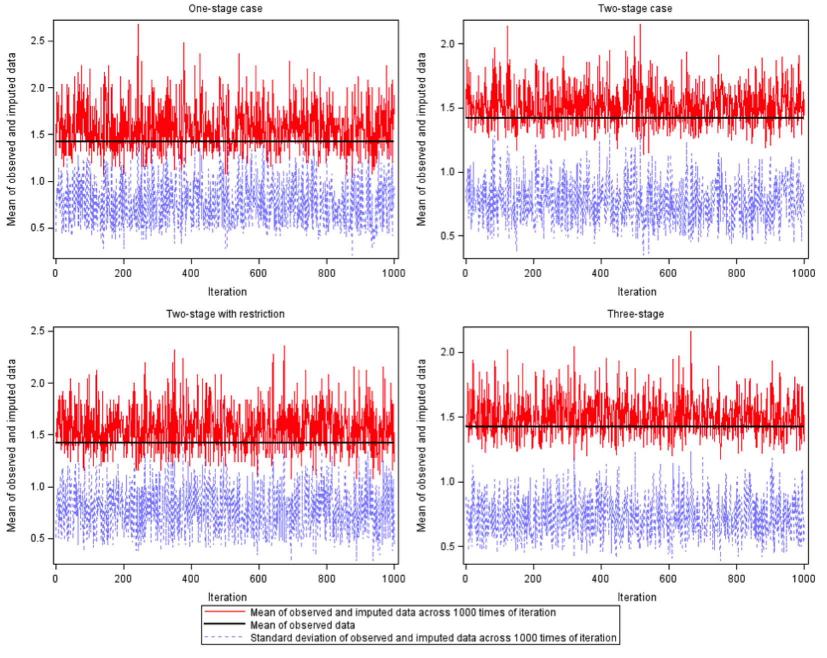

Figure D4. Assessment of Imputation Convergence for Waste Storage Facilities

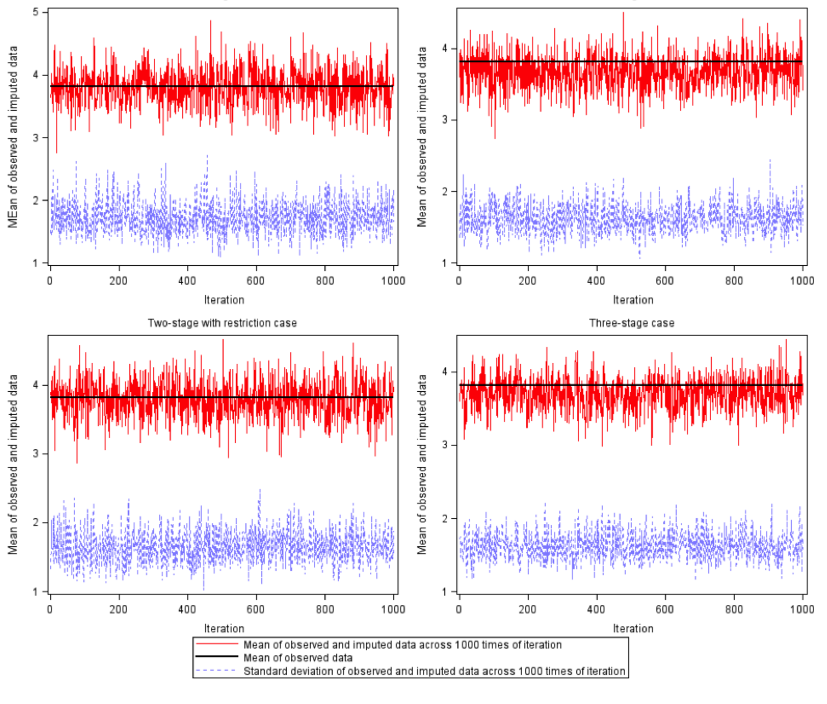

Figure D5. Assessment of Imputation Convergence for Nutrient Management

Online Supplement E: Rescaled Categorical Variables

Categorical Value	Percentage of Household Income from Farming	Total Household Income Reinvested in Farm	Income (1,000 Dollars)
1	8%	8%	0.5
2	23%	23%	20.0
3	38%	38%	37.5
4	53%	53%	62.5
5	68%	68%	87.5
6	82%	82%	125.0
7	97%	97%	233.3