2016

ESSAYS ON FARMER WILLINGNESS TO PARTICIPATE IN BEST MANAGEMENT PRACTICES IN THE KENTUCKY RIVER WATERSHED

Hua Zhong
University of Kentucky, hua.zhong@uky.edu
Digital Object Identifier: http://dx.doi.org/10.13023/ETD.2016.234

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Hua Zhong, Student

Dr. Wuyang Hu, Major Professor

Dr. Carl R. Dillon, Director of Graduate Studies

ESSAYS ON FARMER WILLINGNESS TO PARTICIPATE IN BEST MANAGEMENT PRACTICES IN THE KENTUCKY RIVER WATERSHED

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

By Hua Zhong

Directors: Dr. Wuyang Hu, Professor of Agricultural Economics

Lexington, KY

ABSTRACT OF DISSERTATION

ESSAYS ON FARMER WILLINGNESS TO PARTICIPATE IN BEST MANAGEMENT PRACTICES IN THE KENTUCKY RIVER WATERSHED

This dissertation explores the adoption of Best Management Practices (BMPs) in the Kentucky River watershed. Through a survey of farmers in the Kentucky River watershed, chapter two investigates farmers' current BMP adoption and their willingness to engage in additional adoption incentivized through a proposed Water Quality Trading (WQT) program. This chapter includes two parts: the first part is to investigate the factors influencing farmers' current usage of BMPs; the second part is to estimate farmers' willingness to implement BMPs given different levels of compensation specified in the survey. Farmers' experiences about BMPs are more likely to persuade them to adopt additional BMPs. The activities of using riparian buffers, fencing off animals and building up waste storage facilities are found to be responsive to the levels of compensation offered.

The third chapter discusses farmers' expected economic benefits from BMP adoption, and addresses the missing data issue. In the survey, of those respondents who indicated that they accept the offered level of compensation, about 20% of them did not answer the follow-up question of how much they would adopt the practice, creating missing data. We compare three methods to handle the issue of missing data: deletion method, mean imputation, and multiple imputation method. Following these methods, we estimate factors affecting how much farmers may engage in BMPs using a Tobit or Poisson model. The results show that increasing the compensation for using BMPs is more likely to encourage farmers to adopt riparian buffers. Results obtained using the method of multivariate imputation by chained equation are more promising than using the deletion or mean imputation method.

The fourth chapter examines whether wealth change and local community interaction may affect BMP adoption. Survey data on BMP adoption are combined with the local community data from publically available sources. Results show that the decrease in land values between 2007 and 2012 discouraged the adoption of riparian buffers; the equine inventory in local communities has positive impact on the adoption of animal fences and nutrient management; the more rural the local communities are, the less likely farmers would fence off livestock from water resources.

KEYWORDS: Best Management Practice, Water Quality Trading,
Multivariate Imputation by Chained Equation, Local Community
Interaction, Wealth Effect

Hua Zhong

May 6th, 2016

ESSAY ON FARMER WILLINGNESS TO PARTICIPATE IN
BEST MANAGEMENT PRACTICES IN THE KENTUCKY RIVER WATERSHED

By

Hua Zhong

Dr. Wuyang Hu
Director of Dissertation

Dr. Carl R. Dillon
Director of Graduate Studies

May.6th, 2016

ACKNOWLEDGEMENTS

The following dissertation, while an individual work, benefited from the insights and direction of several people. First, my Dissertation Chair, Wuyang Hu, exemplifies the high quality scholarship to which I aspire. I want to acknowledge Wuyang who provided timely and instructive comments and evaluation at every stage of the dissertation process, allowing me to complete this project on schedule. Your advices on both research as well as on my career have been priceless. Also, I wish to thank the entire Dissertation Committee, and the outside reader, respectively: Seong-Hoon Cho, Michael Reed, John Schieffer, Stephen Workman, and Phillip Bridges. Each individual provided insights that guided and challenged my thinking, substantially improving the finished product.

In addition to the technical and instrumental assistance above, I received equally important assistance from family and friends. My mother, Yanjun Wang, instilled in me, from an early age, the desire and skills to obtain my doctor degree. My aunt, Wanyun Zhong, provided me a great support for everything during my Ph.D. program. Finally, words cannot express how grateful I am to all my friends in the U.S. and in Beijing.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURE

Chapter 1 Introduction

1.1 Background

Water quality trading (WQT) programs are market-based programs that establish a mechanism allowing the party with higher abatement costs to purchase emission permits directly or indirectly from the party with lower abatement costs (EPA 2004). As a result, those with higher abatement costs will abate less while those with lower costs will abate more but be compensated by the permit buyers. The overall goal is to maintain or improve the water quality in a watershed where the buyers and sellers of permits coexist (EPA 2004).

The WQT programs are initiated to assist dischargers in a watershed to meet the Total Maximum Daily Load (TMDL) provisions of the Clean Water Act of 1972 (CWA) (Wainger and Shortle 2013). The provisions authorize the Environmental Protection Agency (EPA) to establish a cap on pollution discharges in a watershed to achieve CWA goals, and TMDLs are designed as a cap on point and nonpoint sources (PSs and NPSs) to limit pollutant loadings. Under TMDLs in an impaired watershed, dischargers are encouraged to trade emission permits, thus water quality standards are achieved at a lower cost than traditional regulations. WQT experiments began in the US in the early 1980s, mostly in the form of pilot or demonstration projects (OECD 2012). United States EPA officially introduced the WQT program in 2003, which led to at least 22 activated trading programs across 14 states (Selman et al. 2009).

Traditionally, the primary U.S. water quality law, the CWA, regulates point sources pollution from factories, plants, or pipes. In contrast to pollution from point sources, emissions from agricultural NPSs are mostly exempt from federal and state regulation directly (Braden and Boyle 2013; Fowler, Royer and Colburn 2013). However, agriculture run-off is a main source of pollution for water resources, and agricultural NPSs contribute a relatively large share of the pollutant load in some impaired watersheds. The WQT is a promising mechanism to provide an opportunity for farms to abate agricultural run-off while farmers also can obtain a new source of income. In WQT programs, agricultural NPSs are considered as the suppliers of emission credits to create offsets for the trading market by implementing Best Management Practices (BMPs). As a supplier in trading market, one of the advantages of agricultural NPSs is a lower abatement cost than PSs. In addition, the traditional solutions to control PSs discharges are not available for agricultural NPSs (Segerson 1988). As an alternative, pollution from agriculture is always regulated by voluntary approaches, thus agricultural NPSs are encouraged to engage in BMPs to abate. These advantages allow agricultural NPSs to supply water quality credits and abate farm run-off loading in a WQT program.

However, point-nonpoint WQT programs have not been developed successfully. To date, only 4 programs have had trading occur in 15 established point-nonpoint trading programs, especially in trading markets related to agricultural NPSs. Ribaudo and Gottlieb (2011) summarize several issues which may limit trading, such as stringency of the cap, practice uncertainty, cost of finding trading partners, fear of regulation, limit of flexibility, baseline requirements, and interactions with conservation programs. The problem of stringency of the cap is that the discharge cap, TMDLs, are not developed well so there is no demand for nonpoint source credits. The practice uncertainty is that the performance of implementing BMPs is hard to be measured and monitored, so credits generated by NPSs are not reliable. One of the important reasons for practice uncertainty is the compensation from PSs cannot meet farmers expected economic benefits from implementing BMPs. The cost of finding trading partners is the transaction costs to identify farmers' willingness to participate in BMPs through WQT programs. Fear of regulation is due to the fact that agricultural NPSs are exempted from regulation. Farmers may not be used to inspection on their lands. The limiting flexibility means that the practices for generating WQT credits are limited, and farmers may not be able to use their private practice to produce trading credits. The baseline requirements indicate that farmers are required to adopt a set of conservation practices prior to trading programs to make themselves eligible to generate credits from additional run-off abatement. The interactions with conservation programs describe the situation that if farmers in a watershed have already adopted large percent of BMPs on their land, the farm's capacity to use additional BMPs may limit the amount of trading. Shortle (2013) states that most of the economic studies on WQT have focused on market design instead of market prediction and uncertainty. Market prediction and uncertainty includes understanding the factors influencing farmers' engagement in BMPs and participation in WQT programs, how much participants will trade, and what factors are likely to hinder trading. All in all, this study is motivated by the above challenges.

1.2 Objective and Structure

The purpose of this thesis is three-fold. The first is to investigate farmers' current usage of BMPs in Kentucky, and the factors affecting farmers' choices of BMPs through WQT programs. These steps will improve the market prediction, and help local agency identify farmers' willingness to participate in WQT programs. Second, this study examines how much farmers may engage their lands in BMPs if they decide to implement BMPs, thus to discuss farmers' limited ability to produce trading credits. In addition to economic and demographic characteristics, the third is to explore how wealth changes and local community interactions influence farmers' BMP adoption.

Chapter two is intended to investigate farmers' willingness to participate in BMPs through a proposed WQT program in Kentucky. A contingent valuation method (CVM) is used in this section through a survey of farmers in the Kentucky River watershed. The survey data were collected from 2011 to 2012. The WQT program did not exist in Kentucky when the data were collected, and still does not exist to date. Since the WQT program is designed to offer farmers compensation for implementing BMPs, the CVM question is whether the respondent will accept the offer of some compensation for using the BMPs specified by the WQT program. Five BMPs are featured: riparian buffers, animal fences, no till, waste storage facilities, and nutrient management. The analysis in this section includes two parts: the first part is to investigate the factors influencing farmers' current usage of BMPs; the second part is to estimate farmers' willingness to implement BMPs given different levels of compensation given in a survey.

Chapter three is motivated to explore how much farmers may engage their lands in BMPs through a WQT program in Kentucky. This section is conducted using a survey of farmers in the Kentucky River watershed introduced in Chapter two. Besides asking the question of farmers' willingness to implement BMPs, the survey also asked a follow-up question that how much farmers may adopt the BMPs (in addition to what they have already used) if they are offered compensation through WQT. With respect to five different types of BMPs, about 21.5%, 26.9%, 24.2%, 23.2%, and 18.2% of respondents did not indicate how much they would adopt BMPs. Before data can be analyzed, missing responses in our survey need to be addressed since the percentage of missing data is more than 5% (Schafer, 1999). We compare three methods to handle the issue of missing data: deleting the observations with missing values, mean imputation, and Multivariate Imputation by Chained Equation (MICE). Following these missing data treatments, we estimate factors affecting how much farmers may engage in BMPs using a Tobit or Poisson model.

Chapter four is to investigate effects of wealth changes and interactions with local communities on BMP adoption in addition to farmers' demographic and socioeconomic variables. The farm investment as BMP adoption is subject to farm financial condition. The urban housing market bust during 2007-2008 significantly decreases farmland values (Zhang and Nickerson 2015).The decrease of farm wealth therefore discourages environmental investments such as BMP adoption on farmlands in the future. In addition to economic factors, previous studies also show that social interactions could motivate farmers to commit to environmental services (Michel-Guillou and Moser 2006). However, most studies use self-rated variables to capture effects of social interactions on BMP adoption which may overestimates adoption. To our knowledge, few studies have explicitly examined the effect of wealth changes on BMP adoption, and no study to date has examined the social interaction effects using local community characteristics data. To proceed, we develop a conceptual framework to model decisions of BMP adoption, and the decisions are subject to farm's wealth condition. Then, we specify the linkage between BMP decisions and social interactions with local communities. In the empirical analysis, we combine survey data on BMP adoption conducted between 2011 and 2012 in Kentucky with publicly available data. The wealth change is approximated by percentage differences of land value between 2007 and 2012; the social interaction effects of local community include urban and rural effect, residential effect, and local agricultural recreation business effect.

Chapter 2 Farmer Willingness to Participate in Best Management Practices in Kentucky

2.1 Introduction

The purpose of this paper is to explore farmers' willingness to implement BMPs in order to prepare them to participate in a proposed WQT program. A contingent valuation method (CVM) is used through a survey to farmers in the Kentucky River watershed. The Kentucky River watershed, also known as the Kentucky River basin, contains 7,000 square miles across 42 counties with 16,000 miles of streams. The 700,000 residents in this area use about 100 million gallons of water per day from streams and reservoirs in the watershed. More than 2,075 square miles of the watershed have been designated as priority watersheds (sub-watershed), impacted by pathogens, nutrients, habitat, alterations, siltation, low dissolved oxygen, and metals (Carey 2009). The Kentucky River basin discharges into the Ohio River, which together with the Upper and Lower Mississippi River sub-basins discharges significant quantities of nutrients to the Gulf of Mexico. The excess of nutrients directly causes the hypoxic zone, an oxygen-depleted area that cannot support aquatic life. The survey data were collected from 2011 to 2012. The WQT program did not exist in Kentucky when the data were collected, and still does not exist. Since the WQT program is designed to offer farmers compensation for implementing BMPs, the CVM question is whether the respondent will accept the offer of some compensation for using the BMPs specified by the WQT program. After searching for historical agricultural BMP information and consulting with experts in agronomy and relevant government agencies, we have chosen five BMPs that are feasible and realistic in our study area. The five BMPs are: riparian buffers, animal fences, no till, waste storage facilities, and nutrient management[1].

The empirical study includes two parts. The first part is to discuss who is participating in BMPs in Kentucky, so the empirical model investigates the factors influencing farmer current usage of BMPs. The second part is to investigate who may participate in additional BMPs propagate by WQT programs. The empirical model estimates farmer willingness to implement BMPs given different levels of compensation that could be offered by WQT programs. Explanatory factors considered in this analysis are farm characteristics, farmer demographic characteristics, environmental characteristics, and targeted farmers. Finally, the results present the probabilities of farmers implementing BMPs at the different levels of compensation.

---

[1] The BMPs are also called conservation practices in USDA. The name of each practice may change. The definition of each practice are described in following link: http://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/technical/?cid=nrcs143_026849

2.2 Literature Review

The actual design of the trading market is one of the most frequently discussed topics in WQT programs. The research on the design of trading markets includes determining the participants, calibrating the trading ratio, evaluating the efficiency of institutions in the market, examining market barriers, and comparing different trading systems (Horan, Shortle and Abler 2002; Horan and Shortle 2005; Breetz et al. 2005; Ghosh, Ribaudo and Shortle 2011; Horan and Shortle 2011). However, few studies focus on understanding the choices farmers make given the context of WQT programs (Shortle 2013). One of the reasons is that most researchers are interested in market mechanism issues. Another reason is that the qualitative data that are typically collected are insufficient to support any substantive statistical analysis (Windle et al. 2005; Peterson et al. 2007).

In order to investigate farmers' choices of BMPs through WQT programs, it is necessary to review the research on farmers' choices of conservation programs and BMPs. This is because both WQT programs and conservation programs aim to encourage farmers to implement BMPs to abate pollution discharge. The conservation program sponsored by the USDA is a voluntary incentive program to address natural resource issues, to avoid the difficulties of regulation, and to reduce economic hardship to farmers through payment and assistance. It includes land retirement programs, working-land programs, agricultural land preservation programs, and conservation technical assistance (USDA 2014). Past research on farmers' choices in conservation programs is to investigate the determinants of farmers' participation in the programs. In addition to demographic characteristics, some other characteristics are considered as explanatory factors, such as farms' geographic characteristics and the targeted farm group (Lynch and Lovell 2003; McCann and Núñez 2005; Lambert, Sullivan, et al. 2006; Nickerson and Hand 2009). Targeted farmers are defined as beginning (farming less than 10 years), limited-resource (farm gross sales less than $105,000), and socially disadvantaged (nonwhite) farmers. Nickerson and Hand (2009) find that targeted farms, accounting for 40% of all US farms, have different conservation priorities and receive different levels of payments from the government. In our study, we also include targeted farms to examine whether disadvantaged groups have different preferences and willingness to use BMPs.

In the earlier literature, a large number of studies have been published investigating adoption choices for conservation practices. Most these studies research the factors influencing farmers' choices of BMPs using a revealed preference method. These analyses consider the observed variables, such as farmer household characteristics and farm characteristics, as the independent variables to explain BMP adoption using ordinary least squares or binary choice models. In the early stage, Ervin and Ervin (1982) develop a two-stage decision-making framework to explain farmer adoption of BMPs. The two stages are recognition and adoption. Besides the two-stage model, several studies discuss the effect of investment decisions, monetary compensations, types of BMPs, land tenure, and conservation programs on the adoption of BMPs (Featherstone and Goodwin 1993; Cooper and Keim 1996; Wu and Babcock 1998; Soule, Tegene and Wiebe 2000; Núñez and McCann 2004; Claassen and Duquette 2012).

Knowler and Bradshaw (2007) synthesize 31 analyses of factors affecting the adoption of conservation agriculture from a total of 23 published papers in order to identify explanatory variables consistently influencing adoption. Their synthesis groups the factors into four categories including farmer and farm household characteristics, farm biophysical characteristics, farm financial/management characteristics, and exogenous factors. In their aggregated analysis, no evidence points to a set of universal or consistent factors that can explain adoption choices. They conclude that the choices of the analytical methods, the influence of region and the conservation agriculture practices considered by researchers may lead to the divergence of the significance and signs of the factors across 31 distinct analyses.

Prokopy et al. (2008) conduct an analysis to review 55 studies about the determinants of farmer adoption of BMPs in the USA using a vote count methodology. They categorize the determinants as four groups−capacity, attitudes, awareness and farm characteristics. Their results also cannot conclude the factors consistently influencing BMP adoption. However, they find that education levels, income, farm sizes, capital, farm operation diversification, labor, information, land tenure, landscape and land quality have significant relationships with BMP adoption. Other factors show mixed results of significance and signs across the investigated studies. In addition, factors influencing BMP adoption have different impacts on the adoption of different types of BMPs.

We include several plausible factors chosen from the previous literature to explain farmers' choices of BMPs in our empirical analysis. The choices of relevant variables in this study and how we estimated these variables have also been described in the empirical model section.

As such, our intention in this paper is not to offer a definitive answer to the question on why farmers adopt conservation practices −there is unlikely to be such an answer. Our main contribution is to add to the discussion and enrich the evidence supporting these different factors, including the economic incentives farmers may receive from adopting conservation practices.

This study conducts a survey using a CVM to investigate the factors influencing farmers' willingness to participate in BMPs under the context of WQT programs. Although some researchers criticize the bias results of CVM in some cases (Arrow et al.1993; Diamond and Hausman 1994; Hausman 2012), this method is still employed for two reasons. First, the CVM is suited to estimate health choices, transportation choices, and farmers' operation choices, and the CVM estimates are useful as baselines for valuation (Haab et al. 2013), even if the CVM may not perform well in all circumstances (Hanemann 1994). Second, the CVM is a simple and flexible method for investigating goods or services not on the market yet, and create different what-if conditions under which the goods and services can be evaluated. Third, previous studies show that choice experiment methods may be too complicated for farmers to comprehend, thus may not collect sufficiently high quality data to support substantive statistical analysis (Windle et al. 2005; Peterson et al. 2007).

This study follows Cooper and Keim's (1996) work. They estimate the factors encouraging farmers' adoption of BMPs, and predict the probability of farmers adopting practices as a function of the compensation. They use a sample selection model and the double hurdle model in their econometric estimation because the CVM question in their survey is conducted only if a farm is not currently using water quality practices. In our survey, the CVM question is conducted regardless of whether a farm is currently using BMPs, in order to avoid sample selection issues.

2.3 Data

The survey data were collected from randomly chosen farmers across 35 counties in the Kentucky River watershed from October 2011 to March 2012. The response rate is 23%[2], and there are 357 valid observations out of 459 responses. Table 2.1 displays the demographic summary of the Kentucky farmers included in this study and the state average from the US agricultural census data in 2012. As can be seen in this table, except higher than average farm size, our sample does not appear to be drastically different to the state average. The survey questions include current usage of BMPs, willingness to participate in BMPs, participation in environmental programs, farm's characteristics, and respondents' demographic characteristics.

In the survey, the key questions involve two parts. The first question is phrased "are you currently using any of the following water quality management practices on the farm you are operating?" These practices include riparian buffers, animal fences, no till, waste storage facilities and nutrient management. The respondent could answer yes/no with respect to each practice.

The second key question follows the first one and is phrased "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)

[2] Our study has a comparable response rate to the existing literature on farmers' choices of BMPs. From the synthesis of Knowler and Bradshaw (2007) and Prokopy et al. (2008), very high response rates are often observed in studies with very small sample sizes (often in two digits or in low hundreds).

in the form of the following activities: riparian buffers, animal fences, no till, waste storage facilities and nutrient management?" The respondents are asked to specify their answer for each of the BMPs separately given the level of compensation. In the survey, X% is replaced with one of the following levels with equal probability: 75%, 80%, 85%, 90%, 95%, 100%, 105%, 110%, 115% and 120%. When answering the survey, each respondent will see only one questionnaire with one of these levels. In other words, respondents are randomly assigned to a questionnaire with different levels of compensation. In order to avoid the sample selection problem, CVM questions are asked regardless of whether a respondent is currently using the BMPs.

In the second key question, a respondent could answer "yes", "no", or "not possible for me" with respect to each practice[3]. The "not possible for me" option captures the possibility that farmers have already maximized their potential to adopt BMPs. Table 2.2 presents the frequency of responses who were willing to adopt additional BMPs, the frequency of respondents assigned to each level of compensation, and the percentage of yeses to the question when respondents faced each level of compensation.

Furthermore, the survey is designed with four types of information explaining the meaning of WQT programs. One of the four levels of the information is randomly

[3] The "not possible for me" category is an agrarian or geographic issue but not a decision issue. During focus group discussions and pretests before the survey, the "not possible for me" category was repeatedly confirmed by respondents that it was clear in the survey that these practices were physically not feasible or applicable on their land. The numbers of farmers not possible to adopt riparian buffers, animal fences, no till, waste storage facilities, and nutrient management are 208, 175, 179, 206 and 181 respectively. In addition, we have conducted a robustness test for "not possible for me" responses. Following Adamowicz et al. (1998), we have run a multinomial logit analysis of "yes", "no" and "not possible for me" responses to test whether "not possible for me" responses were consistent with either the "yes" or "no" response. These results show that there are no systematic factors determining the "not possible" group and the other two groups.

assigned with equal probability to the survey. This design is to examine whether the different levels of information will influence an individual's response. The first type of information is the baseline with basic explanation of WQT programs. The information does not contain any further description or interpretation of WQT programs. The second type of information includes the information in the first type but also includes an additional message on WQT programs, focusing on their cost saving implications. The third type contains the baseline information and also information emphasizing the environmental benefit from WQT programs. The fourth type provides the baseline as well as an explanation of WQT programs, focusing on both cost saving and environmental benefit information. Appendix 2.1 displays the four types of information. Tables 2.3 and 2.4 present all variables and summary statistics for the entire sample. Fig 2.1 shows the spatial distribution of respondents in our survey at the zip code level. The size of blue circles represents number of observations coming from a particular zip code in our survey. The map base is the population density at zip code levels obtained from the U.S. census 2010. Generally, our sample covers most of the Kentucky River watershed, and the spatial distribution of our survey is consistent with the population density.

2.4 Theoretical Model

A farmer's choice is understood through random utility theory (McFadden 1974). U_a and U_b denote the individual utility from two choices, "yes" or "no". In this article, for the first key question, "yes" means the respondent is currently using BMPs; "no" means otherwise. For the second key question, "yes" indicates the respondent accepts the offer to implement additional BMPs through WQT programs; "no" indicates otherwise. The following equation is the utility functions of U_a and U_b.

$$U_a = x'\beta_a + \varepsilon_a \quad and \quad U_b = x'\beta_b + \varepsilon_b \qquad (2.1)$$

where x is a vector of observed variables in individual utility function, including compensation (C) offered from the survey (for the second key question); β is a vector of coefficients; ε is the $i.i.d.$ random variable with zero mean. If $U_a > U_b$, an individual will choose "yes", then the observed indicator y equals 1. If $U_a \leq U_b$, an individual will choose "no", then the observed indicator y equals 0. Therefore, the probability that an individual will choose "yes" could be written as equation 2.2 (Greene 2007).

$$\begin{aligned}
&Prob[y = 1|x] = Prob[U_a > U_b|x] \\
&= Prob\left[x'\beta_a + \varepsilon_a > x'^{\beta_b} + \varepsilon_b \,\middle|x\right] \\
&= Prob[x'(\beta_a - \beta_b) + (\varepsilon_a - \varepsilon_b) > 0 \,|x] \\
&= Prob[x'\beta + \varepsilon > 0 \,|x] \qquad (2.2)
\end{aligned}$$

In this paper, the binary choice is estimated using a logit model. Thus, the probability function, equation 2.2, is rewritten as logistic cumulative distribution function, equation 2.3. Equation 2.4 is derived from equation 2.3 to represent the commonly known odds ratio (in log form):

$$Prob[y = 1|x] = \frac{e^{x'\beta}}{1 + e^{x'\beta}} \qquad (2.3)$$

$$\log\left[\frac{P(y = 1)}{1 - P(y = 1)}\right] = x'\beta \qquad (2.4)$$

2.5 Empirical Model

2.5.1 First Part: Current Usage of BMPs Models

The first part of the empirical model estimates farmers' actual usage of BMPs. The survey question used in this part is "are you currently using any of the following water quality management practices on the farm you are operating? Those practices are riparian buffers, animal fences, no till, waste storage facilities and nutrient management." The answer for each BMP is a binary choice, yes/no, and is estimated using logit models.

There are six regressions in the current usage of BMP models[4]. One regression is to analyze all BMPs included. If a farmer uses any of the five practices, the decision is a "yes", otherwise "no." The other five regressions are separate for the five different types of BMPs. Regardless, the dependent variables are the yes/no answers. Equations 2.5 and 2.6, derived from equation 2.4, are mathematical representations of logit regression, estimating all of the current usage of BMP models:

$$\log\left[\frac{P(y_1 = 1)}{1 - P(y_1 = 1)}\right] = \alpha_{10} + \left(\sum_{n=1}^{N} \alpha_{in} x_n\right) \tag{2.5}$$

$$\log\left[\frac{P(y_i = 1)}{1 - P(y_i = 1)}\right] = \alpha_{i0} + \left(\sum_{n=1}^{N} \alpha_{in} x_n\right) + \left(\sum_{n=2}^{6} \gamma_{ij} y_j\right) \quad (i \neq j) \tag{2.6}$$

[4] Our preliminary work considered the multivariate probit model to reflect joint adoption of several BMPs by each respondent, but the model could not be implemented in our case for two reasons. First, since farm biophysical characteristics are different across farms, BMPs that are possible to be adopted for each respondent are different across our sample. None of the farms could implement all types of BMPs, and the multivariate probit model cannot be applied. Second, even if we treat "not possible" as "no", the multivariate probit model could not converge. As a result, we use five separate probit models but in each model the decision of whether to adopt the other BMPs are included to control for the correlation between different BMPs.

where, $i = 2, 3, 4, 5, 6$; each i also identifies a model, and there are six regressions in total.

j = $2, 3, 4, 5, 6$; each j denotes a BMP such as riparian buffers, animal fences, no till waste storage facilities and nutrient management respectively. N is the number of variables. Other notations are explained below:

α_{10} α_{i0}, α_{in} ,and γ_{ij} are coefficients

Dependent variable: y_1, y_2, y_3, y_4, y_5 ,y_6

$P(y_1 = 1)$= probability of currently using any BMPs among riparian buffers, animal fences, no till, waste storage facilities or nutrient management

$P(y_2 = 1)$= probability of currently using riparian buffers

$P(y_3 = 1)$= probability of currently using animal fences

$P(y_4 = 1)$= probability of currently using no till

$P(y_5 = 1)$= probability of currently using waste storage facilities

$P(y_6 = 1)$= probability of currently using nutrient management

Independent variable: x_n

x_n= farm's characteristics, farmer's characteristics, environmental aspects and variables indicating whether a farm is a targeted farm.

Most of those variables are considered from previous research (Ervin and Ervin 1982; Featherstone and Goodwin 1993; Cooper and Keim 1996; Traore, Landry and Amara 1998; Wu and Babcock 1998; Soule, Tegene and Wiebe 2000; Lynch and Lovell 2003; Núñez and McCann 2004; McCann and Núñez 2005; Lambert, Schaible, et al. 2006; Hand and Nickerson 2009; Claassen and Duquette 2012).

Farm characteristics capture the effects of farm’s biophysical characteristics and farm management characteristics on BMP adoption, and these variables include land size, rent percent, surface water, percentage of household income from farming, total household income reinvested back to farm, farms with crop, and farms with livestock. Farmer characteristics examine the impact of farmer’s demographic characteristics on BMP adoption, and the variables include age, gender, education, income level, farming experience, and water recreation activities (Knowler and Bradshaw 2007; Prokopy et al. 2008).

The environmental aspects include farmers’ participation in the Conservation Reserve Programs, participation in Working-Land Programs, farms’ water quality, and farmers’ concern of environmental issues. The Conservation Reserve Program (CRP) is the land retirement program from conservation programs sponsored by the USDA. Participants in the CRP are compensated annually to retire environmentally sensitive land from agricultural production for 10 to 15 years. The Working-Land Program (WLP) is one of the conservation programs that encourage farmers to adopt BMPs on working land to achieve environmental benefits (USDA 2014). In our survey, the WLP includes the Conservation Stewardship Program, Environmental Quality Incentives Program, and Wildlife Habitat Incentives Program. Participations in CRP and WLP are introduced as binary variables. Farm’s water quality is a discrete variable rated by farmers themselves. The variables of farmers’ awareness are obtained from a survey question that asks farmers to rate their concern for environmental issues.

Targeted farmers are represented in the models by two dummy variables: socially disadvantaged and beginning farmers. The variable income level is a proxy for the targeted farmers with limited resources. In addition, we also include dummy variables showing the current BMP usages. These dummy variables are added to examine whether there is any synergy to using BMPs.

2.5.2 Second Part: Willingness to Implement Additional BMPs Models

The second part of the empirical model estimates farmers' willingness to implement additional BMPs given different levels of compensation. Farmers who responded "not possible for me" are not included in the logit analysis of farmers' willingness to participate in additional BMPs. The binary outcome is whether farmers will implement additional BMPs (1 if yes, 0 if no) following the compensation offered through WQT programs, and is estimated using logit regressions.

In equation 2.7, the binary dependent variable (y'_1) indicates whether farmers would accept the offer to adopt additional BMPs for any of the five different types (1 if yes, 0 if no). Equation 2.8 shows whether farmers may say yes to one of the five BMPs respectively ($y'_2, y'_3, y'_4, y'_5, y'_6$),

$$\log\left[\frac{P(y'_1 = 1)}{1 - P(y'_1 = 1)}\right] = \beta_0 + \beta_1 C + (\sum_{n=1}^{N} \beta_{1n} x_n) + \theta_{11} y_1 \qquad (2.7)$$

$$\log\left[\frac{P(y'_i = 1)}{1 - P(y'_i = 1)}\right] = \beta_0 + \beta_i C + (\sum_{n=1}^{N} \beta_{in} x_n) + (\sum_{n=2}^{6} \theta_{in} y_n) \qquad (2.8)$$

where, $i = 2,3,4,5,6$; each i also identifies a model, and there are five regressions in total. $\beta_0, \beta_1,, \beta_{1n}, \theta_{11}, \beta_i, \beta_{in}, \mu_{ij}$ *and* θ_{ii} are coefficients.

j = 2,3,4,5,6; each j denotes a BMP such as riparian buffers, animal fences, no till, waste storage facilities and nutrient management respectively.

N is the number of variables.

C, x_n, y_1, y_n are independent variables

x_n= farm's characteristics, farmer's characteristics, environmental aspects, targeted farm status and the type of WQT program information farmers received

C = the compensation offered, which will cover a certain percentage of the cost of implementing the BMPs.

The current usage of BMPs (y_1 , y_n) is the proxy to measure the unobserved variable: previous experience with BMPs. Cameron and Englin (1997) find that respondent's experiences, defined as numbers of years in which individual has been a user of environmental goods, could influence the contingent valuation of those resources. In our research, we consider the current usage of BMPs to capture the effect of experiences with environmental practices on the willingness to adopt additional BMPs.

In this analysis, we examine the cross-effect of adopting BMPs through including the current usage of the five types of BMPs. Finally, for the action to adopt additional BMPs, we also allow the decision to adopt one practice to explain the adoption of the others, to examine whether there is the synergy of using BMPs in the future.

2.6 Results

2.6.1 First Part: Current Usage of BMPs

Table 2.5 reports the results of logit regressions for farmers' current usage of BMPs. Model 1 is the current usage of any BMP model; models 2-6 are the current usage of the five different types of BMP models.

For farms' characteristics, types of farm production are highly significant factors explaining the current usage of BMP. Holding other factors constant, farms having crop production are more likely to use riparian buffers and no till; farms having livestock production are more likely to use animal fences, since this practice is designed for farms with livestock.

In addition, the results in farms' characteristics tell that the current usage of BMPs is also determined by the percentage of household income from farming, rent area, and surface water on farmland. Holding other factors constant, farms with surface water resources tend to build up riparian buffers along the surface water, but are less likely to use nutrient management. Farmers earning mainly from farming prefer to adopt no till. If farmers rent more acres for operating, they would like to adopt no till on their land. Movafaghi, Stephenson and Taylor (2013) state that no till is a production improvement practice, which has more than environmental benefits. Based on their findings, if farmers rent a large area or have a higher percentage of household income from farming, they are more likely to adopt no till for higher productivity.

For famers' characteristics, farmer's education and water recreation activities would affect the current usage of BMPs. Holding other factors constant, farmers with higher education prefer to adopt BMPs, especially adopting riparian buffers and nutrient management. Farmers participating in water related recreation activities at least once a year would like to use BMPs, especially using riparian buffers. In addition, older farmers are more likely to build up waste storage facilities. However, no evidence is found that farmers' gender and farming experience are related to the current usage of BMPs.

An interesting result in farmers' characteristics is that income level does not affect the current usage of BMPs. This finding is consistent with Featherstone and Goodwin's (1993) result that the income level is not a determinant factor for conservation investment decisions. Instead, the source of income influences the current usage of BMPs. Table 2.5 shows that the more farmers earn from farms, the more likely they would use BMPs. Lynch and Lovell (2003) and Núñez and McCann (2004) also conclude a similar result that a lower percentage of off-farm income will encourage farmers to participate in BMPs or environmental programs.

For environmental aspects, participation in the CRP and the WLP are important contributors to the current usage of BMPs. Concerns for the environment is another factor affecting farmers' current usage of BMPs, but poor water quality near farms may not stimulate farmers to implement BMPs. The results show that farms participating in the WLP prefer to adopt animal fences; farms participating in CRP tend to use no till and animal fences. Claassen and Duquette (2012) have a similar result that farms' payment programs have high levels of additionality. Additionality refers to farms that would not achieve environmental gains without payment incentives. The finding in this paper confirms the additionality of farmers' payment programs that the government payment is a significant incentive mechanism affecting the current use of BMPs. Furthermore, if farmers are concerned about environmental issues near their farms, they are more likely to use riparian buffers and nutrient management.

In addition, we observe a synergy effect that farmers tend to implement some BMPs as a bundle. Our result shows that no till, waste storage facilities, and nutrient management are more likely to be practiced together.

No statistical evidence suggests that targeted farms have any special preference for BMPs. Also, ten years of farming experience is not a threshold period for farming decisions on BMPs. Socially disadvantaged farmers do not have any different preference for BMPs compared to other farmers.

2.6.2 Second Part: Farmers' Willingness to Participate in Additional BMPs through WQT Programs

Table 2.6 presents the results of logit regressions for the willingness to participate in additional BMPs. Model 7 describes the willingness to participate in any additional BMPs; models 8-12 are for the willingness to participate in a specific type of BMP.

In expectation, compensations could influence farmers' participation in BMPs, so the offer (C) would be statistically significant with a positive sign. However, the regression results show that the compensations do not change the probability of participation in practices of no till and nutrient management, and only positively affect the probability of participating in riparian buffers, animal fences and waste storage facilities.

For farms' characteristics, farm size, rent area, surface water on farmland, percentage of household income from farming, total household income reinvested back to farm and types of farm production all play a role in participation in additional BMPs. Large-size farms are less likely to use animal fences. Farmers who rent more farmland are less likely to implement no till, but this result is opposite to that in the model describing current usage of the BMP. Farms with surface water resources prefer to build up waste storage facilities, because this practice is designed to prevent a farm from contaminating water flows. However, these farms are less likely to fence off animals from water resources and adopt nutrient management on their land. Previous studies show that off-farm work (and thus income) may limit the time that farmers can invest in labor-intensive practices (e.g., building fences), but others find off-farm work/income increases the resources that can be used for capital intensive practices (e.g., precision agriculture) (Knowler and Bradshaw 2007; Prokopy et al. 2008). Our result shows that the percentage of income coming from the farm (which is opposite to income from off-farm) only has significant impact on the adoption of animal fences. Animal fences can be both labor and capital intensive. Famers investing large shares of their income in their farms prefer to implement additional riparian buffers and build up more waste storage facilities. Farms with livestock production have no interest in putting in additional effort to fence off animals, but farmers having crop production prefer to implement additional no till and nutrient management.

For farmers' characteristics, the factors affecting farmers' willingness to implement additional BMPs are age, gender, farming experiences, education, income levels and water recreation activities. Specifically, older farmers may refuse to spend more effort in fencing off animals and no till. Male farmers prefer to build up additional animal fences, but are less likely to use waste storage facilities. Farmers with more farming experience tend to adopt additional no till, but may refuse to use more riparian buffers on their farms.

Farmers with higher education are in favor of having additional no till and nutrient management. This implies that if education raises willingness to adopt BMPs, it is more likely to encourage farmers to adopt BMPs by providing more information through agricultural extension services. Farmers with water related recreation activities at least once a year prefer to adopt more nutrient management. The results also show that income level only influences farmers' decisions to implement additional waste storage facilities.

For environmental aspects, our results show that although conservation programs are important contributors to the current usage of BMPs in Kentucky, there is no statistical evidence that these programs would encourage farmers to implement additional BMPs in the future. However, perceiving worse water quality near the farm could encourage farmers to adopt BMPs. Poor water quality near farms would lead farmers to use more riparian buffers, animal fences, and no till in the future, but could not influence the current usage of BMPs.

One interesting finding in environmental aspects shows that the coefficient of the CRP is significant with negative sign in the willingness to implement an additional no till model but is significant with positive sign in the current usage of the no till model. In other words, it implies that if farmers currently participate in the CRPs, they are more likely to use no till currently, but are less likely to use no till generated through WQT programs in the future. One possible explanation is that farmers with the CRP have already adopted no till as much as they could, so there is no eligible land for them to expand the scope of this practice.

Table 2.6 shows that previous experiences of BMPs have significant effects on encouraging farmers to expand the scope of the BMPs through WQT programs. If farmers are currently using a BMP on their farm, they are more likely to use more of the same BMP in the future, except for waste storage facilities. Table 2.7 summarizes the result from Table 2.6 that explains the effect of farmers' current experience of BMPs on their adoption of additional BMPs. The results show that if farmers are currently using riparian buffers, they are more likely to build up waste storage facilities, and less likely to use no till. If farmers are currently using waste storage facilities on the farm, they may not adopt additional riparian buffers and use nutrient management in the future. If farmers are currently using nutrient management, they will not consider animal fences and waste storage facilities through WQT programs.

In addition, we observe the synergy of using BMPs in that there are certain sets of BMPs often/almost always chosen together in the survey. Table 2.8 summarizes the results from Table 2.6 displaying the synergy of future BMP adoption. If farmers would like to use riparian buffers, they are more likely to adopt animal fences and nutrient management together. If farmers would like to build up animal fences on their land, they tend to implement riparian buffers, build up waste storage facilities, and adopt no till on their farms. If farmers would adopt more no till on their land, they are more likely to use riparian buffers, waste storage facilities and nutrient management at the same time. If farmers would like to build up waste storage facilities, they are more likely to build up animal fences, and use nutrient management through the WQT program as well. If farmers tend to use nutrient management in the future, they are more likely to implement no till, and build up animal fences and waste storage facilities at the same time.

For targeted farms, most results are similar to the ones in the current usage of the BMP model. There is no statistical evidence that targeted farms have systematically different preferences to the implementation of additional BMPs currently, and in the future, except that socially disadvantaged farmers prefer to build up waste storage facilities.

Results also show that the information about cost savings from the WQT programs is an effective form to introduce the WQT programs. In model (7), the result implies that the cost saving information positively motivates choices of using a BMP. To be specific, the results from models (9) and (12) show that the cost saving information about WQT programs is more likely to encourage famers to consider adopting animal fences and nutrient management on their land. Furthermore, combined information about cost savings and environmental benefits from WQT programs is more likely to encourage farmers to consider adopting nutrient management. There is no evidence to show that the information about environmental benefits from WQT programs alone has any effect on motivating farmers to consider BMPs. All of these results indirectly imply that cost savings or economic benefits are more likely to trigger the adoption of BMPs instead of environmental awareness. This finding, in turn, suggests that different types of information may generate different rationales and differing responses by farmers. Although it is not the intention in this paper to investigate what specific decision heuristics farmers use under these circumstances, it remains an interesting future research venue. The fact that WQT programs may bring additional financial benefits to farmers raises the issue of whether WTP questions may only tap into a particular set of cognitive processes and farmers' decision-making.

Finally, Figures 2.2 and 2.3 present graphs of the relationship between the percentage of cost compensation and the probability of implementing BMPs. Holding other explanatory variables at sample median,4 the probabilities that farmers implement additional BMPs at different levels of compensation are calculated from Equation 2.3 using the estimated coefficients. Since offer (C) variables are only significant in the willingness to build up riparian buffers, animal fences and waste storage facilities models, Figures 2.2 and 2.3 show the probabilities of implementing these three BMPs as a function of the percentage of the compensations. Our results also show that cost saving information about WQT programs is effective in triggering farmers to use additional animal fences. Figure 2.2 shows that the predicted probabilities of using animal fences when cost saving information is presented are significantly higher than the ones without the information. At 75%, 100% and 120% of cost compensation, predicted probabilities of using animal fences with cost saving information are 98.9%, 99.6%, and 99.8% respectively. The predicted probabilities of using animal fences without the information treatment are 94.5%, 98.1% and 99.2%, respectively. In Figure 2.3, the trend shows that if the compensation rises, the probabilities that a farmer adopts riparian buffers and builds waste storage facilities through WQT programs increase. At 75%, 100% and 120% of cost compensation, the probabilities of using riparian buffers are 0.8%, 2.6% and 5.3% respectively, and the probabilities of building waste storage facilities are 1.1%, 2.6% and 5.3%, respectively. Finally, our prediction shows that the probabilities of adopting animal fences are much greater than adopting riparian buffers and waste storage facilities. One possible explanation is that in addition to economic factors, biophysical characteristics may also determine the adoption of riparian buffers and waste storage facilities. Generally, farms with livestock only need one or two waste storage facilities; and areas of water resources on farms limit the adoption of riparian buffers. Oppositely, animal fencing is a more flexible practice than any other practices investigated in our study. Thus, it may be adopted by more farms.

2.7 Conclusion and Implications

This paper explores farmers' willingness to participate in BMPs through WQT programs in Kentucky. The study includes two parts. The first part is to investigate the factors influencing farmers' current usage of BMPs. The second part is to estimate farmers' willingness to participate in additional BMPs given different levels of compensation that may be offered through the WQT programs.

In the first part, the most significant result is that farmers who are already participating in conservation programs are more likely to use BMPs. Farms with different types of production, as well as the source of income, affect farmers' current usage of BMPs, but the actual level of income does not. Furthermore, targeted farmers who are limited in their production and social reach do not have any different preference to adopt BMPs compared to other farms, and 10 years of farming experience does not appear to be a threshold for the decisions on using BMPs.

In the second part, the most important finding is that higher compensations from WQT programs only encourage farmers to further implement three of the five BMPs considered: building up riparian buffers, fencing off animals and building up waste storage facilities. Another interesting finding is that the experience on BMPs is more effective in influencing farmers to implement additional BMPs than the compensation they may receive. In contrast to the result in the first part, farmers participating in the CRP or WLP have no apparent interest in implementing additional BMPs. The results show the probabilities of farmers adopting additional BMPs based on the different levels of compensation. This will help policy makers facilitate the WQT market by encouraging the trading partners to properly set up the price of the tradable permits.

There are two implications from the results. First, farmers in Kentucky are likely to be encouraged to build up riparian buffers, animal fences and waste storage facilities through the compensation potentially provided by buyers in the WQT market. It implies that the water quality trades related to, or targeted at, the three types of BMPs are possible through a proposed WQT program in Kentucky. In contrast, there is no statistical evidence supporting that farmers could be encouraged to implement no till or nutrient management through the compensation from these programs. It indicates that tradable permits related to these two practices may not be available in the WQT market. This implication will provide the buyers with the information about potential permits in the market, and assist policy makers to design the trading ratios and allocate budgets with respect to specific practice.

The second implication from the results is that farmers who are currently using riparian buffers, animal fences, no till, and nutrient management are more likely to expand the scope of these practices to generate additional credits for WQT. It implies that when buyers in the WQT market intend to purchase the emission permits generated from the above four practices, it is efficient for buyers to trade with farmers who are currently using these practices. This implication could also help policy makers target who may participate in WQT programs to supply the trading permits.

The goal of WQT programs is not only to fulfill the mission of conservation in agriculture, but also to promote PS and NPS trading as a way of reducing the cost of meeting water quality goals in a watershed. If the market mechanism is likely to motivate those who are already using some BMPs to adopt more, or utilize additional effort, the market mechanism can facilitate the mission of WQT programs. Our study shows this. For non-adopters, and except for those where adoption is physically impossible or irrelevant, the compensation generated through the market mechanism may incentivize them to become an adopter. As our results show, once they become an adopter, they will be more likely to adopt more in the future. Finally, since we show that the market mechanism is likely to have a stronger impact toward those who are already using some BMPs, if WQT programs or other conservation programs can provide nonusers with more education, training, and other assistance to help them become an adopter of BMPs, the effectiveness and efficiency of WQT programs may be improved substantially.

2.8 Tables in Chapter 2

Table 2.1 Demographic Summary of Kentucky Farmers from the U.S. Agricultural Census Data in 2012 and Our Sample

Variable	U.S. agricultural census 2012 (Kentucky)	Our sample
Age	57.6	60.15
Male percentage	89.36%	85.7%
Farming experience	25.1	32.2
Race (Percentage of white)	98%	95.5%
Land acre (average per farm)	169	282

Table 2.2 Frequency Distribution of Willingness to Adopt BMPs

				Levels of compensation									
				75%	80%	85%	90%	95%	100%	105%	110%	115%	120%
Number of respondents assigned to each compensation level (Total N=357)				41	37	46	32	30	28	34	35	30	44
Percentage of respondents assigned to each compensation level to total sample size				11.5%	10.4%	12.9%	9.0%	8.4%	7.8%	9.5%	9.8%	8.4%	12.3%
	Frequency of responses			The percentage of "yes" responses (Yes /(Yes+No)) to each practice with respect to each level of compensation									
	Yes (=1)	No (=0)	Not possible /missing										
All BMPs included	57.4%	8.1%	34.5%										
Riparian buffers	19.3%	22.4%	58.3%	40.0%	31.6%	44.4%	43.8%	63.6%	50.0%	53.8%	46.2%	54.5%	47.1%
Animal fences	33.6%	17.4%	49.0%	64.0%	52.6%	70.0%	56.3%	73.3%	63.2%	71.4%	63.2%	71.4%	76.2%
No-till	31.0%	18.8%	50.1%	76.2%	42.1%	60.9%	61.1%	81.3%	57.9%	46.2%	70.6%	63.6%	61.9%
Waste storage facilities	19.6%	22.7%	57.7%	33.3%	40.0%	47.1%	41.2%	53.3%	37.5%	41.7%	46.2%	60.0%	68.8%
Nutrient management	30.8%	18.5%	50.7%	68.2%	50.0%	54.2%	64.7%	64.3%	64.7%	66.7%	50.0%	64.3%	76.2%

Note:
1. The frequency of responses is from the question on the willingness to adopt new BMPs based on the compensation offered in the survey.
2. For the row "All BMPs included", if farmers answer "yes" to adopt at least one of five different types of BMPs, we count them as "yes"; if farmers answer "no" to all of BMPs, we count them as "no".

Table 2.3 Variable Summary Statistics

Variable N=357	Definition of Variables	Mean	Std. Dev.
Current BMPs adoption:			
y_1	Currently using any BMPs (=1); otherwise (=0)	0.74	0.44
y_2	Currently using riparian buffers (=1); otherwise (=0)	0.37	0.48
y_3	Currently using animal fences (=1); otherwise (=0)	0.47	0.50
y_4	Currently using no-till (=1) ; otherwise (=0)	0.31	0.46
y_5	Currently using waste storage facilities (=1) ; otherwise (=0)	0.07	0.25
y_6	Currently using nutrient management (=1) ; otherwise (=0)	0.24	0.43
Cost coverage compensation:			
Offer	The percentage that treatment plant or factory will cover the cost of implementing the BMPs if the farmer uses the additional BMPs, there are ten different levels of compensation. Those levels are 75%, 80%, 85%, 90%, 95%, 100%, 105%, 110%, 115% and 120%.	0.97	0.15
Explanatory variables:			
Land size	Land size includes rented and owned land for operating. (unit: 1000 acre)	0.28	0.54
Rent percent	Rented land for operating / Total land for operating	0.14	0.28
Surface water	Surface water on farmland (=1) ; otherwise (=0)	0.86	0.35
Percentage of household income from farming	Share of pre-tax household income from farming (see table 2.4)	2.42	1.82
Total household income reinvested back to farm	Share of pre-tax household income back to farming (see table 2.4)	2.53	1.54
Farms with crop	Farms earning revenue from crop or farmers planting crop on their land (=1) ; otherwise (=0)	0.42	0.50
Farms with livestock	Farms earning revenue from livestock or raising livestock (=1) ; otherwise (=0)	0.80	0.40
Age	Farmer's age	60.15	11.91
Male	Male =1; otherwise (=0)	0.86	0.35
Education	Farmer's education level (see table 4)	4.08	1.92
Income level	Household annual pre-tax income level (table 2.4)	4.36	1.50
Farming experience	Farming experience (year)	32.22	15.31

(Continued)

Table 2.3 Continued

Variable	Definition of Variables	Mean	Std. Dev.
Water recreation	Participating in water related recreation at least once a year (=1) ; otherwise (=0)	0.66	0.47
CRP	Currently participating in Conservation Reserve Program (CRP) (=1) ; otherwise (=0)	0.12	0.32
WLP	Currently participating in Working-Land Program (WLP) (=1); otherwise (=0). WLP includes Conservation Stewardship Program (CSP), Environmental Quality Incentives Program (EQIP), Wildlife Habitat Incentives Program (WHIP)	0.20	0.40
Water quality	Discrete levels from 1 to 7 indicating the poorest to the best water quality nearest to farmers' properties	5.04	1.37
Concern of environmental issue	Respondents' awareness of issues concerning the environment Self-rated with seven levels. Level seven is very aware, and level one is unaware.	4.95	1.56
Target farmers:			
Beginning farmers	Farming less than ten years (=1) ; otherwise (=0)	0.12	0.33
Socially disadvantage farmers	Operator's race is not white (=1) ; otherwise (=0)	0.05	0.21
Infeasible to implement BMPs			
z_1	Answer "not possible for me" to all BMPs (=1) ; otherwise (=0)	0.35	0.48
z_2	Answer "not possible for me" to riparian buffers (=1) ; otherwise (=0)	0.58	0.49
z_3	Answer "not possible for me" to animal fences (=1) ; otherwise (=0)	0.49	0.50
z_4	Answer "not possible for me" to no-till (=1) ; otherwise (=0)	0.50	0.50
z_5	Answer "not possible for me" to waste storage facilities (=1) ; otherwise (=0)	0.58	0.50
z_6	Answer "not possible for me" to nutrient management (=1) ; otherwise (=0)	0.51	0.50
Information: The survey was designed with 4 levels of information explaining the meaning of WQT programs			
Level 1	The least detailed information level (=1); otherwise (=0)	0.24	0.43
Level 2	The less detailed information level(=1); otherwise (=0)	0.26	0.44
Level 3	The more detailed information level(=1); otherwise (=0)	0.21	0.41
Level 4	The least detailed information level(=1); otherwise (=0)	0.29	0.46

Note: Discrete levels in table are interpreted in table 2.4.

Table 2.4 Frequency Distribution of Discrete Variables

Level	Percentage of household income from farming	Frequency	Percent
1	0-15%	162	45.38%
2	16-30%	77	21.57%
3	31-45%	36	10.08%
4	46-60%	28	7.84%
5	61-75%	17	4.76%
6	75-90%	17	4.76%
7	above 90%	20	5.6%
Level	Total household income reinvested back to farm	Frequency	Percent
1	0-15%	106	29.69%
2	16-30%	116	32.49%
3	31-45%	48	13.45%
4	46-60%	45	12.61%
5	61-75%	20	5.6%
6	75-90%	13	3.64%
7	above 90%	9	2.52%
Level	Income ($)	Frequency	Percent
1	0 to 14999	14	3.92%
2	15000 to 24999	21	5.88%
3	25000 to 49999	60	16.81%
4	50000 to 74999	110	30.81%
5	75000 to 99999	64	17.93%
6	100000 to 149999	56	15.69%
7	above 150000	32	8.96%
Level	Education	Frequency	Percent
1	Not a high school graduate	17	4.76%
2	High school graduate	88	24.65%
3	Some college, no degree	64	17.93%
4	Associate degree	14	3.92%
5	Bachelor degree	83	23.25%
6	Master degree	51	14.29%
7	Professional degree	26	7.28%
8	Doctorate	14	3.92%

Table 2.5 First Part: Logit Regressions for Current Usage of BMPs

	All BMPs included (1)	Riparian buffers (2)	Animal fences (3)	No till (4)	Waste storage facilities (5)	Nutrient management (6)
Farms' characteristics:						
Land acre	1.409	0.484	-0.190	0.371	-0.244	0.245
	(0.892)	(0.384)	(0.237)	(0.282)	(0.479)	(0.243)
Rent percentage	0.109	-0.175	0.121	0.905*	0.272	0.325
	(0.634)	(0.509)	(0.474)	(0.510)	(0.904)	(0.545)
Surface water	-0.271	1.094**	0.361	-0.501	0.493	-0.984**
	(0.409)	(0.467)	(0.378)	(0.404)	(0.933)	(0.417)
Percentage of household income from farming	0.227*	0.0686	0.00423	0.190**	0.0286	-0.000484
	(0.132)	(0.0940)	(0.0892)	(0.0963)	(0.177)	(0.102)
Total household income reinvested back to farm	0.0997	-0.0137	0.0251	-0.0079	0.234	0.159
	(0.138)	(0.107)	(0.105)	(0.117)	(0.196)	(0.120)
Farms with crop	1.031***	0.672**	-0.0028	1.123***	-0.517	0.373
	(0.337)	(0.275)	(0.267)	(0.289)	(0.546)	(0.320)
Farms with livestock	1.034***	-0.102	2.192***	0.377	1.361	-0.0261
	(0.376)	(0.373)	(0.415)	(0.398)	(1.118)	(0.432)
Farmers' characteristics:						
Age	-0.0180	-0.0170	0.00503	0.0155	0.0536*	-0.0198
	(0.0154)	(0.0142)	(0.0133)	(0.0151)	(0.0290)	(0.0158)
Male	0.161	0.561	0.0153	0.340	0.259	-0.641
	(0.432)	(0.419)	(0.371)	(0.438)	(0.984)	(0.407)
Education	0.244***	0.160**	0.0584	0.129	-0.208	0.247***
	(0.0893)	(0.0759)	(0.0735)	(0.0823)	(0.153)	(0.0882)
Income	0.0381	-0.0495	0.0485	0.113	0.0491	-0.0141
	(0.112)	(0.0970)	(0.0919)	(0.103)	(0.180)	(0.109)
Farming experience	-0.0145	0.00609	-0.0132	-0.0032	-0.00551	-0.00114
	(0.0147)	(0.0134)	(0.0129)	(0.0143)	(0.0260)	(0.0155)
Water recreation activities	0.743**	0.513*	0.152	0.242	-0.0752	0.0739
	(0.309)	(0.287)	(0.267)	(0.308)	(0.544)	(0.335)

(Continued)

Table 2.5 Continued

	All BMPs included (1)	Riparian buffers (2)	Animal fences (3)	No till (4)	Waste storage facilities (5)	Nutrient management (6)
Environmental aspects:						
CRP	1.857**	-0.0955	0.692*	1.117***	0.330	0.238
	(0.798)	(0.409)	(0.408)	(0.412)	(0.585)	(0.454)
WLP	1.370**	0.244	0.879***	-0.0938	0.570	0.524
	(0.546)	(0.326)	(0.326)	(0.357)	(0.554)	(0.349)
Water quality	0.0644	0.0634	0.0290	-0.0489	0.268	-0.140
	(0.107)	(0.100)	(0.0912)	(0.105)	(0.213)	(0.113)
Concern of environmental issue	0.123	0.229**	0.0546	-0.0466	-0.185	0.308**
	(0.0925)	(0.0980)	(0.0869)	(0.101)	(0.186)	(0.120)
Target farmers:						
Beginning farmers	-0.280	-0.473	-0.175	0.309	0.314	0.341
	(0.561)	(0.520)	(0.484)	(0.529)	(1.141)	(0.545)
Socially disadvantage farmers	0.181	-0.498	0.508	0.204	0.00737	0.273
	(0.679)	(0.687)	(0.595)	(0.634)	(1.167)	(0.729)
Current usage of other BMPs:						
Riparian buffers	-	-	0.389	0.436	0.651	0.503
	-	-	(0.275)	(0.299)	(0.549)	(0.323)
Animal fences	-	0.410	-	0.175	-0.352	0.283
	-	(0.281)	-	(0.299)	(0.529)	(0.321)
No till	-	0.470	0.119	-	1.104*	0.607*
	-	(0.298)	(0.295)	-	(0.577)	(0.332)
Waste storage facilities	-	0.882*	-0.513	1.168**	-	1.700***
	-	(0.525)	(0.502)	(0.559)	-	(0.548)
Nutrient management	-	0.505	0.218	0.558*	1.627***	-
	-	(0.321)	(0.318)	(0.325)	(0.551)	-
Constant	-2.174*	-4.461***	-3.639***	-4.462***	-9.559***	-2.203
	(1.319)	(1.248)	(1.151)	(1.308)	(2.520)	(1.343)
N	357	357	357	357	357	357
pseudo R^2	0.267	0.195	0.161	0.227	0.252	0.228

Standard errors in parentheses; *, **, and *** imply significant at the 10%, 5%, and 1% significance levels, respectively.

Table 2.6 Second Part: Logit Regressions for Willingness to Participate in Additional BMPs

	All BMPs included (7)	Riparian buffers (8)	Animal fences (9)	No till (10)	Waste storage facilities (11)	Nutrient management (12)
Cost coverage compensation:						
Offer	2.326	3.888*	4.266*	0.351	3.620*	1.475
	(1.962)	(2.193)	(2.247)	(2.014)	(2.081)	(2.464)
Farms' characteristics:						
Land acre	-0.00196	-1.508	-2.655**	1.501	0.0782	-0.270
	(0.393)	(1.204)	(1.292)	(1.030)	(0.326)	(0.375)
Rent percentage	-0.786	2.324	-0.650	-2.586**	-0.645	0.428
	(1.056)	(1.518)	(1.124)	(1.293)	(1.059)	(1.224)
Surface water	0.476	1.246	-1.937**	0.140	1.947**	-3.088**
	(0.721)	(0.944)	(0.964)	(1.068)	(0.891)	(1.263)
Percentage of household income from farming	0.197	-0.169	0.823**	0.132	-0.153	0.0752
	(0.232)	(0.230)	(0.331)	(0.248)	(0.195)	(0.286)
Total household income reinvested back to farm	0.244	0.802***	0.0132	-0.142	0.662***	0.0984
	(0.250)	(0.269)	(0.329)	(0.255)	(0.241)	(0.310)
Farms with crop	1.333**	-0.493	-0.416	1.225*	-0.651	1.233*
	(0.612)	(0.651)	(0.726)	(0.655)	(0.564)	(0.686)
Farms with livestock	-0.666	-0.856	0.266	-2.494**	-0.250	0.307
	(0.780)	(0.844)	(1.010)	(0.971)	(0.816)	(1.205)
Farmers' characteristics:						
Age	-0.0350	0.0649	-0.123***	-0.123***	0.00572	-0.0459
	(0.0297)	(0.0396)	(0.0439)	(0.0381)	(0.0294)	(0.0371)
Male	1.123	-1.063	3.647***	-1.114	-1.959*	1.090
	(0.803)	(1.045)	(1.199)	(1.048)	(1.095)	(1.167)
Education	0.107	-0.0191	0.454**	0.00815	-0.0459	0.572**
	(0.158)	(0.177)	(0.197)	(0.180)	(0.162)	(0.239)
Income	0.0177	0.153	0.0683	0.270	-0.410*	-0.0474
	(0.210)	(0.244)	(0.218)	(0.230)	(0.221)	(0.279)
Farming experience	-0.0136	-0.0915***	0.0140	0.0757**	-0.0262	0.0354
	(0.0272)	(0.0353)	(0.0336)	(0.0316)	(0.0265)	(0.0325)
Water recreation activities	0.434	1.016	0.212	0.741	-0.996	1.480**
	(0.546)	(0.643)	(0.633)	(0.653)	(0.649)	(0.741)

(Continued)

Table 2.6 Continued

	All BMPs included	Riparian buffers	Animal fences	No till	Waste storage facilities	Nutrient management
Environmental aspects:						
CRP	-	-0.0351	-1.446	-3.329***	1.038	1.757
	-	(0.827)	(1.305)	(1.070)	(0.772)	(1.262)
WLP	-0.742	-0.256	-0.309	-0.0914	0.753	-1.845*
	(0.639)	(0.738)	(0.881)	(0.740)	(0.655)	(0.952)
Water quality	-0.755***	-0.431**	-1.040***	-0.451**	-0.329	0.425
	(0.262)	(0.217)	(0.370)	(0.225)	(0.213)	(0.289)
Target farmers:						
Beginning farmers	0.520	-0.247	-1.615	-0.0479	1.223	1.824
	(1.248)	(1.171)	(1.499)	(1.098)	(1.139)	(1.304)
Socially disadvantage farmers	2.401	1.316	4.159	3.211	3.805**	2.611
	(1.921)	(2.507)	(3.849)	(2.403)	(1.866)	(2.926)
Experiences of BMPs:						
Current use any of BMPs	2.450***	-	-	-	-	-
	(0.659)	-	-	-	-	-
Riparian buffers	-	2.607***	-0.819	-1.442**	1.516**	0.520
	-	(0.791)	(0.725)	(0.690)	(0.688)	(0.717)
Animal fence	-	-0.535	4.296***	0.313	-0.385	0.445
	-	(0.664)	(1.035)	(0.680)	(0.654)	(0.757)
No till	-	0.300	-0.637	4.390***	-0.448	1.211
	-	(0.908)	(1.061)	(0.994)	(0.767)	(0.905)
Waste storage facilities	-	-5.039***	2.780	-0.288	0.484	-4.179***
	-	(1.543)	(2.031)	(1.156)	(0.934)	(1.585)
Nutrient management	-	-0.957	-1.672**	-1.436	-1.688**	2.894***
	-	(0.822)	(0.853)	(0.875)	(0.727)	(0.913)
Choices of other BMPs:						
Riparian buffers	-	-	4.749***	-0.0370	-0.648	2.152**
	-	-	(1.275)	(0.753)	(0.664)	(0.972)
Animal fences	-	3.792***	-	1.343*	1.833***	0.170
	-	(0.831)	-	(0.796)	(0.649)	(0.807)
No till	-	1.566*	0.509	-	1.527**	2.470***
	-	(0.888)	(0.762)	-	(0.730)	(0.919)
Waste storage facilities	-	-0.547	2.292**	1.104	-	5.291***
	-	(0.873)	(1.145)	(0.804)	-	(1.282)
Nutrient management	-	0.688	1.805**	1.861**	3.050***	-
	-	(0.792)	(0.901)	(0.729)	(0.743)	-

(Continued)

Table 2.6 Continued

	All BMPs included	Riparian buffers	Animal fences	No till	Waste storage facilities	Nutrient management
Information about WQT:						
Cost saving	1.482*	-0.336	1.675*	0.0480	0.278	1.927*
information	(0.865)	(0.853)	(0.945)	(0.763)	(0.730)	(1.018)
Environmental	0.364	-0.362	-1.093	0.437	1.225	0.0265
aspect Info	(0.750)	(0.980)	(0.956)	(0.853)	(0.832)	(1.089)
Combined	0.335	0.763	-1.233	-0.941	0.366	1.879*
Information	(0.649)	(0.855)	(0.775)	(0.724)	(0.840)	(1.024)
Constant	1.444	-7.746**	1.438	6.707*	-2.986	-9.060**
	(3.261)	(3.938)	(3.476)	(3.911)	(3.573)	(4.565)
N	234	149	182	178	151	176
pseudo R^2	0.355	0.531	0.606	0.548	0.451	0.631

Standard errors in parentheses; *, **, and *** imply significant at the 10%, 5%, and 1% significance levels, respectively.

Note: The CRP in environmental aspects is omitted because of the collinearity.

Table 2.7 Correlation between Current Usage and Future Choices of BMPs

		Future choices of BMPs (Dependent variables)				
		Riparian buffers	Animal fences	No till	Waste storage facilities	Nutrient management
Current choices of BMPs (Independent variables)	Riparian buffers	Positive	-	Negative	Positive	-
	Animal fences	-	Positive	-	-	-
	No till	-	-	Positive	-	-
	Waste storage facilities	Negative	-	-	-	Negative
	Nutrient management	-	Negative	-	Negative	Positive

.

Table 2.8 Correlation between Future and Future Choices of BMPs

		Future choices of BMPs (Dependent variables)				
		Riparian buffers	Animal fences	No till	Waste storage facilities	Nutrient management
Future choices of BMPs (Independent variables)	Riparian buffers	-	Positive	-	-	Positive
	Animal fences	Positive	-	Positive	Positive	-
	No till	Positive	-	-	Positive	Positive
	Waste storage facilities	-	Positive	-	-	Positive
	Nutrient management	-	Positive	-	Positive	-

2.9 Figures in Chapter 2

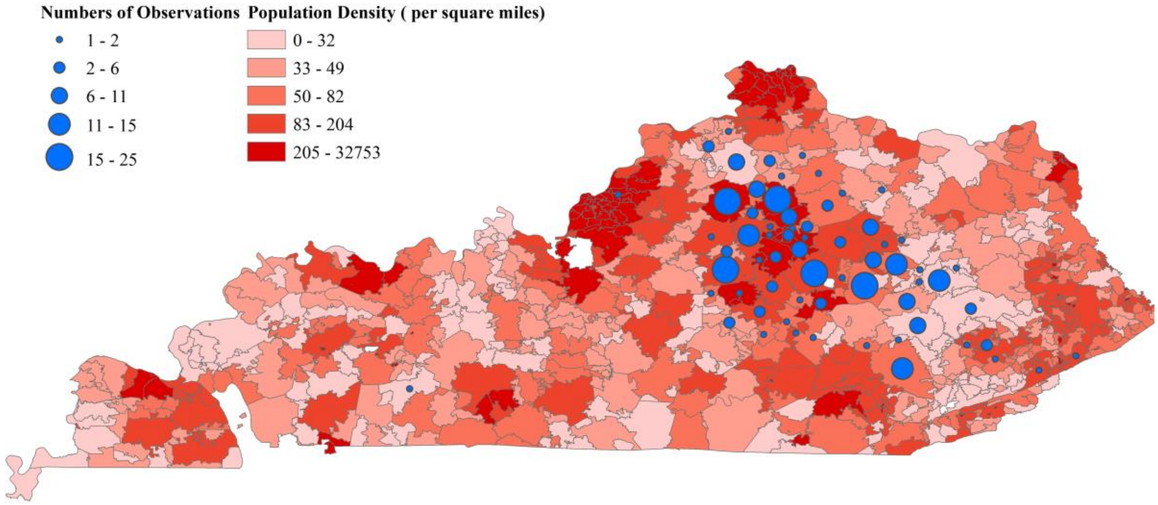

Figure 2.1 Spatial Distribution of Respondents in Our Survey

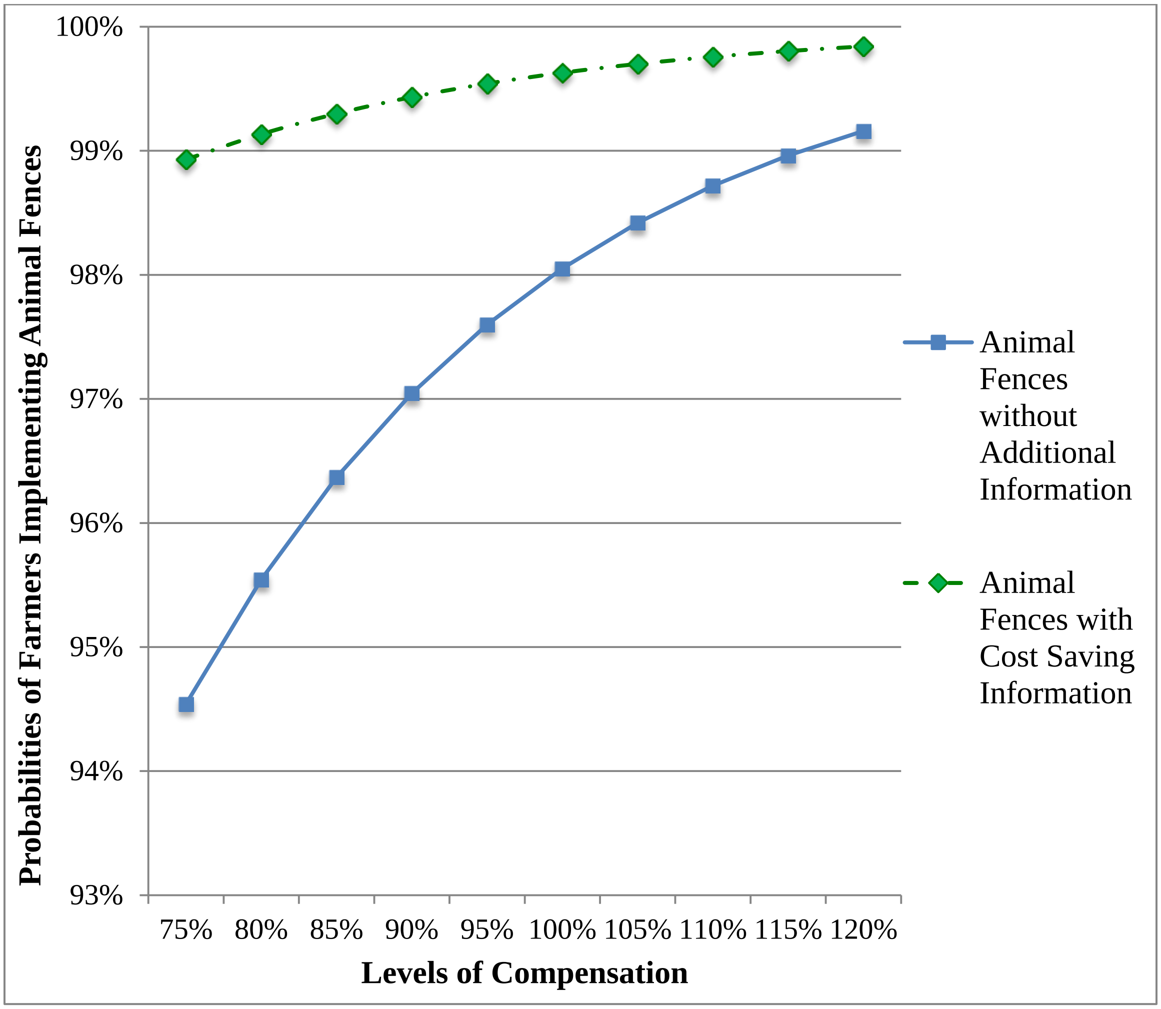

Figure 2.2 Probabilities of Implementing Animal Fences with or without Cost Saving Information

Note: The probabilities of farmers implementing additional animal fences appear to be high. This is because the figure is created based at sample median. A typical farmer in the sample is already having animal fences. According to our models, whether farmers have already implemented animal fences is one of the most important predictors on whether they will adopt in the future. As a result, these farmers are predicted by our models to have a high probability of using additional animal fences.

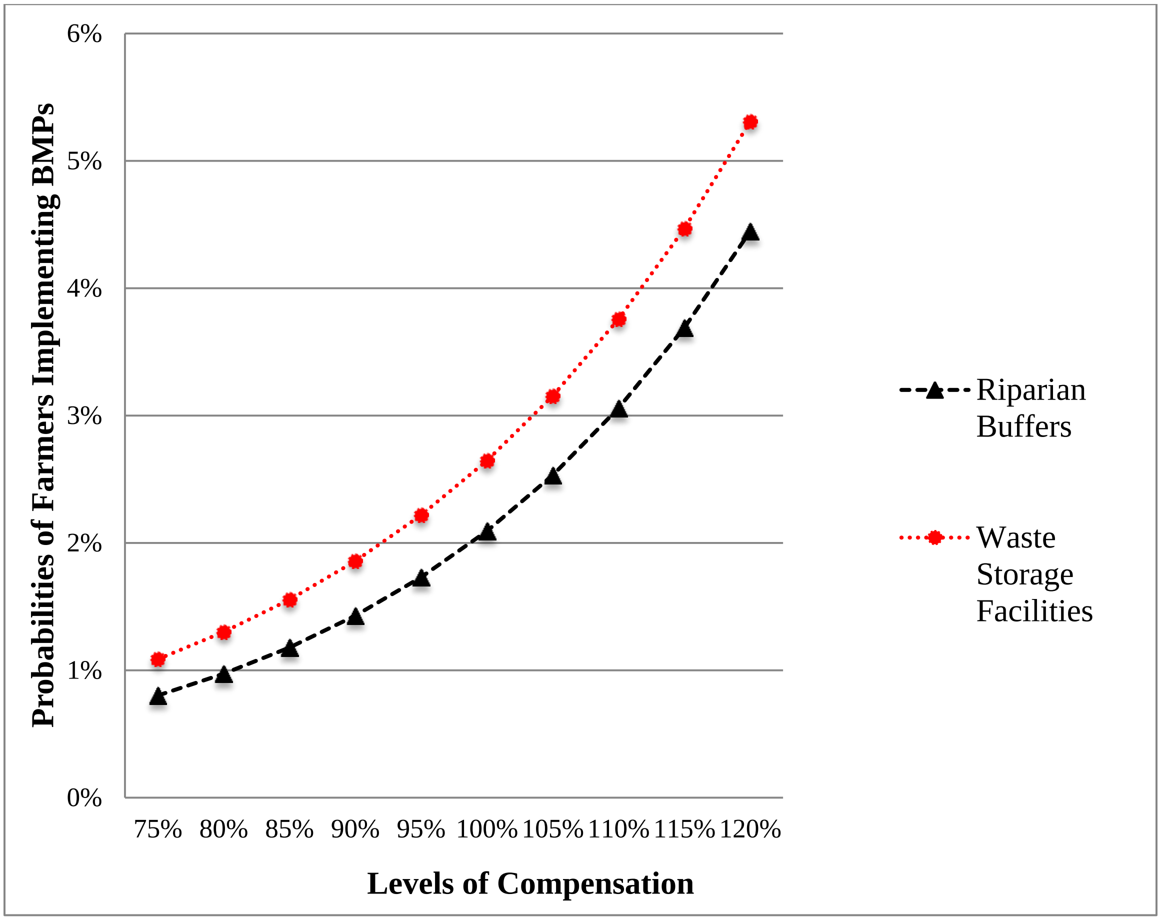

Figure 2.3 Probabilities of Implementing of BMPs: riparian buffers and waste storage facilities

Chapter 3 Farmer Willingness to Engage in Best Management Practices: a Comparison between Methods of Treating Missing Observations

3.1 Introduction

While in the previous chapter we examined whether farmers were willing to further reduce agricultural runoff and what are the factors affecting their choice, in this chapter, we investigate by how much farmers may be able to adopt additional BMPs on their land to generate trading credits. In this process, we consider specifically the impact of missing observations on the analysis by comparing different methods of treating the missing data.

We use the same survey as described in the previous chapter. The survey asked farmers questions about current BMPs implemented and the extent to which farmers would adopt more BMPs if compensated through WQT. The effect of farmers' knowledge of WQT on BMP adoption was tested by giving different types of WQT-related information to the respondents. Five BMPs were featured: riparian buffers, animal fences, no till, waste storage facilities, and nutrient management, and about 21.5%, 26.9%, 24.2%, 23.2%, and 18.2% of respondents did not indicate how much they will adopt for each respective BMP. Addressing missing responses is crucial since missing data can lead to spurious interpretation of the data (Groves, 2006), especially when missing values constitute more than 5% of the data (Schafer, 1999). Given its prevalence in our survey, we also study the survey's issues of missing values.

Missing data problems are common in surveys of farmers, and frequently occur in primary dataset collection. Weber and Clay (2013) replicate previous studies to compare estimation results using the population data from the USDA's quinquennial, comprehensive 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 time consumed and disutility from answering questions, and that larger farms are more likely to have missing values, consequentially having the most pronounced nonresponse bias. A conventional, naïve method to handle missing responses is to delete the observations with missing portions, known as listwise deletion. This method assumes that missing values are independent with the observed and unobserved data. This assumption is rarely satisfied in empirical studies and the listwise deletion method may lead to nonresponse bias (Lin and Schaeffer 1995; Groves, 2006; Groves and Peytcheva, 2008).

In this study, we focus on two types of variables facing the issue of missing responses: a yes/no question of whether farmers would accept the offer to implement each of the BMPs, and, if yes, its follow-up question on how much farmers would adopt BMPs. In this research, we use Multiple Imputation (MI) to address the issue of missing data. MI, introduced by Rubin (1978), is a statistical method that imputes *m* plausible missing values for each missing observation to create *m* completed datasets; each completed dataset is analyzed using a separate statistical method such as regression. Averaging the *m* results, the point estimates, and covariance matrices using Rubin's formula generates the final estimates of the model's coefficients (Raghunathan et al. 2001; King, Honaker, Joseph and Scheve 2001).

This current study includes three methods to address missing data. The first simply deletes observations with missing responses. The second uses mean imputation to replace missing values in the follow-up "how-much" question by the observed mean. In the third method, we use MI to impute missing responses in the willingness question and the follow-up question if farmers accepted the initial offer. Specifically, we apply a Multivariate Imputation by Chained Equation (MICE) method introduced by Raghunathan et al. (2001). The MICE method is preferred over the traditional, multivariate normal imputation method because it overcomes the multivariate normal imputation's inability to impute discrete and continuous missing data simultaneously. In addition, MICE does not rely on the multivariate normality assumption, as does multivariate normal imputation. In our research, discrete and continuous missing data coexist, so the multivariate normality is invalid, further supporting the use of MICE. We use the MICE method under four different scenarios to impute missing data. The first scenario imputes missing responses in the follow-up question if farmers accepted the initial offer. The second, third, and fourth scenarios are multi-stage procedures that first impute missing responses in the yes/no question; then impute missing values in the follow-up question if the answer to the first question is recorded or imputed as yes. The specific procedures are introduced in the empirical strategy section. Given the imputed value, we estimate the factors affecting how much farmers may engage in BMPs using Tobit or Poisson regression, and combine the *m* results to derive final coefficient estimates.

The next section describes the WQT survey and its missing value issues. We then introduce the theory of mechanisms to address missing data followed by a discussion of empirical strategies to address missing data in our survey and imputation procedures. The last two sections display results of the analysis, and conclude with policy implications of our research.

3.2 Survey and Missing Data Problem

The survey data were collected from randomly chosen farmers across 35 counties in the Kentucky River watershed from 2011 to 2012. The response rate was 23%. Out of the total returned 459 questionnaires, 357 contained at least some completed responses regarding to BMP-related questions and were used in the final analysis. 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.

The key BMP adoption questions asked farmers: "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?" A table was given to each respondent listing five BMPs: riparian buffers, fencing off animals, no till, waste storage facility and nutrient management." In the actual survey, X% is replaced by one of the following possible values with equal probability: 75%, 80%, 85%, 90%, 95%, 100%, 105%, 110%, 115% and 120%. Each respondent saw only one questionnaire and only one level of compensation. A respondent could answer "yes," "no," or "not possible for me" with respect to each practice. "Not possible for me" allows respondents to indicate if a specific BMP as not applicable on their land.

If respondents answered yes to adopt a BMP, 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 unit of measure for riparian buffers and animal fences is “feet;” an “acre” is the unit of measure unit for the practices of no till and nutrient management; and the measurement for the practices of waste storage facility is the number of installed “facilities.”

The survey also included four different explanations and descriptions of WQT programs. Each participant was randomly assigned to one of the information scenarios. This design examines whether the different levels of information may influence an individual’s response. The first information treatment gives a basic explanation of WQT programs with minimal interpretation of WQT programs. The second information treatment includes the information in the first, plus an additional description of WQT programs implied cost savings for farmers. The third type contains the baseline information and information emphasizes the environmental benefits from WQT programs. The fourth treatment provides both cost savings and environmental benefits information. As explained later, these treatments are an integral part of the imputation strategies. Table 2.3 presents all variables and summary statistics for the entire sample. Table 2.4 explains discrete levels in explanatory variables.

3.2.1 Missing Data Problem

We analyze missing responses to BMP adoption questions for three cases. Figure 3.1 illustrates the three cases of missing responses in our survey. The first case is if respondents answered “no” or “not possible for me” to the yes/no question, then the response to the follow-up implementation rate are treated as missing as well. Some reasons include if respondents refused to consider the BMPs (i.e. no), they are unable to implement the BMP on their land, or if they have already adopted BMPs as much as possible on their land. In these cases, the plausible value for the missing data in the follow-up question is “zero”, thus are no longer considered missing.

The second case of missing data is when respondents answered “yes” to the yes/no question, but did not respond to how much they would increase the BMP on their land. Because respondents have already stated they would like to adopt the BMP, the plausible values for the missing data in the follow-up question should be some positive, continuous value for riparian buffers, animal fences, no till and nutrient management, and a discrete count for waste storage facilities.

The third case includes the respondents who did not answer the yes-no BMP adoption question nor the follow-up adoption rate question. If respondents answered the yes/no question for at least one practice but not to the other practices, their responses to the other practices are treated as missing. In this third case, the plausible values for missing data in yes/no questions are either “yes,” “no,” or “not possible for me;” if respondents actually answered “yes” to the yes/no questions or are imputed to be “yes,” then the plausible values for the quantitative questions are the same as in the second case. If respondents did not answer any of the five yes/no BMP adoption questions, we exclude them from the analysis entirely, treating them as uninterested and unwilling market participants. In this research, we address the issue of missing data in the last two cases. Table 3.1 summarizes the missing data for each BMP.

3.3 Theory of Missing Mechanism and the Multivariate Imputation by Chained Equation

3.3.1 Missing Mechanism

This section formally introduces the mechanism of the three types of missing data. Let Y denote a variable with missing data, X denotes a vector of variables completely answered, and R be an indicator variable that equals one if Y is missing and zero if Y is observed. The first type of missing data is Missing Completely at Random (MCAR), and is defined as

$$\Pr(R = 1|X, Y) = \Pr(R = 1) \tag{3.1}$$

MCAR implies that missing data do not depend on any observed or unobserved variables. If the MCAR mechanism applies, the listwise deletion method that deletes the observations with missing data is the most efficient strategy to address missing values. However, the MCAR rarely holds in empirical analyses 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

$$\Pr(R = 1|X, Y) = \Pr(R = 1|\, X)$$

$$\text{or } \Pr(R = 1|X, Y) = \Pr(R = 1|\, Y_{observed}) \tag{3.2}$$

MAR assumes that the probability of missing is related to the observed data, but not to unobservable 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, Full Information Maximum Likelihood (FIML).

The third type of missing data is Missing Not at Random (MNAR). It 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 missing are complex, and the results are sensitive to the methods chosen (Allison 2012). Although various studies have introduced and developed solutions to the MNAR problem, there is no general agreement on the best approach, and only Heckman-type modelling may alleviate the MNAR missing data issue (Grittner et al. 2011).

Following the previous empirical studies in health, medical, environmental and household areas (Van Buuren, Boshuizen and Knook 1999; Schenker et al 2006; Burgette and Reiter 2010; Azur, Stuart, Frangakis and Leaf 2011; White, Royston and Wood 2011; Miyama and Managi 2014), we assume MAR applies in our research for several reasons. First, MCAR is an inefficient assumption in empirical research. 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 without obtaining the unobserved value. Even if a discernable pattern of missing values appears to follow MNAR, we cannot test the performance of those methods for MNAR since the missing data are not observable. The results may also significantly change depending on the correction method used. Weber and Clay (2013) find that a sample selection model does not reduce nonresponse bias from the ARMS data. A simple and plausible 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). The underlying idea is that using more predictor variables increases the chance the missing data are correlated with predictor variables, thus it may convert the missing mechanism from MNAR to MAR.

Finally, we tested whether nonresponses are related to the observed variables. We created an indicator variable denoting observations with missing data, treating this indicator as the dependent variable and all observed variables as independent variables. Next, we estimated a logit model to test whether any relationships exist between the nonresponse indicator and observed explanatory variables. The results show that nonresponses were correlated with several observed variables, so the MCAR assumption fails.

Given the MAR assumption, MI is useful to deal with missing data issues, outlined in the following steps (van Buuren, Boshuizen, and Knook 1999):

(1) Identify the missing variables, the posterior predictive density, and predictor variables given the MAR assumption.

(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 with final m estimates.

Rubin (1976) first introduced MI to analyze the nonresponse issue in survey data, and numerous statisticians have worked to improve MI (Andrew Gelman, Gary King, Roderick JA. Little, Xiao Li Meng, Trivellore E. Raghunathan, Patrick Royston, Donald B. Rubin, Joseph L. Schafer, Stef van Buurenand, Ian R. White), aiding its growth in popularity to address missing data in medical and social science fields. An advantage of

MI is that it considers the true variance of data because missing values are imputed with different plausible values and are averaged to conclude a final estimate.

3.3.2 The MICE Method

In this research, we apply the MI method using multivariate imputation by chain equation (MICE), introduced by van Buuren, Boshuizen and Knook (1999) and Raghunathan et al. (2001), to impute categorical and continuous variables simultaneously and without the multivariate normal assumption. MICE decomposes the multivariate problem into a series of univariate problems using an iteration algorithm. The procedure is displayed in Figure 3.2, and is demonstrated as follows (van Buuren, Boshuizen and Knook 1999; Raghunathan et al. 2001; Schenker et al. 2006; Azur et al. 2011):

Let X denote variables fully observed, and $Y^{(1)}, Y^{(2)}, \dots, Y^{(n)}$ denote k variables with missing data, ordered by the amount of missing data from the least to the most.

(1) In iteration 1, regress observed $Y^{(1)}$on X, and impute the missing values of $Y^{(1)}$ using the predicted distribution based on the fitted regression. Then, regress $Y^{(2)}$ on 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 X, $Y^{(1)}$, $Y^{(2)}$, … , $Y^{(k-1)}$ where $Y^{(1)}$, $Y^{(2)}$, … , $Y^{(k-1)}$ include observed value and all of imputed value, then 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.

(2) Iteration 2: the imputation process is repeated in the same manner as round 1, but predictors in each regression include all variables except for the variable to be

imputed. To be specific, regress imputed values in iteration 1 and observed values of $Y^{(1)}$on X $Y^{(2)}, Y^{(3)}, \ldots, Y^{(n)}$, where $Y^{(2)}, Y^{(3)}, \ldots, Y^{(n)}$ are imputed in 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 observed value and imputed value, where $Y^{(1)}$ is the most recent imputed value and $Y^{(3)}, \ldots, Y^{(n)}$ are imputed in last round; and then re-impute the missing values of $Y^{(2)}$. For $Y^{(k)}$, regress $Y^{(k)}$ on 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 value in 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.

MICE allows the use of different models in each regression. If $Y^{(k)}$ is a continuous variable, a normal linear regression is suitable; if $Y^{(k)}$ is a binary variable, logistic regression is preferable; if $Y^{(k)}$ is a categorical variable with more than two outcomes, a polytomous regression model is appropriate; if $Y^{(k)}$ is a count outcome, a Poisson loglinear regression, a negative binomial regression, or a Predictive Mean Matching (PMM) method are appropriate models, where the PMM method imputes predicted values by matching them with the observed values of the variable (Little, 1988). If $Y^{(k)}$ is mixed, such as a semi-continuous outcome, a two-stage model is applied. To be specific, it first uses a logistic regression to impute zero and non-zero status, and then uses a normal linear regression model to impute non-zero values for the non-zero group. We employ each of these types of regressions in this study's imputations, with the corresponding computation procedure introduced in Raghunathan et al (2001). Appendix 3.1 shows model specifications used in our study.

3.4 Empirical Strategy Dealing with Missing Response

Given the MAR assumption, we use the deletion method, the mean imputation method, and the MICE method to treat missing data for each BMP. In addition, we apply the MICE method with four scenarios to discuss different imputation strategies. The four scenarios are as follows:

(1) One-stage MICE: Only addresses missing responses in the follow-up questions when respondents answered "yes" to the choice questions, but failed to answer the follow-up questions.

(2) Two-stage MICE: Considers missing data issues in both the yes/no questions and in the follow-up quantity questions. We first impute missing responses in the choice questions with "yes" "no" and "not possible for me." For respondents who answered or were imputed as "yes," we then impute missing observations of the follow-up questions. The imputation processes used for the two missing variables are simultaneous.

(3) Two-stage MICE with restriction: Similar to scenario two, but this time it assumes that missing choices are more likely to be "no" or "not possible for me." Therefore, we first impute missing choices as either "no" or "not possible for me," then impute the missing data in the follow-up questions using MICE.

(4) Three-stage MICE: In this case, we recognize the fact that the outcome "not possible for me" was not the respondent's preference, but the reality. Accordingly,

we first impute whether it was possible for the respondents to adopt a BMP, but who did not answer the yes/no questions; then for the "possible" group, we impute missing choices as either "yes" or "no;" finally for respondents who answered or were imputed as "yes," we impute missing data in the follow-up questions. These steps were also computed simultaneously using the MICE method.

3.4.1 MICE Scenario 1: One-Stage Imputation

The first scenario imputes missing responses to each BMP's follow-up question. For respondents who answered "No," the missing value is replaced by zero because they would not adopt BMPs. For the respondents who answered "Yes" but did not indicate how much they would adopt, we impute the missing values with respect to the five BMPs simultaneously using the MICE algorithm.

For predictor variables X, we follow a general rule that the number of predictors should be as large as possible (van Buuren, Boshuizen and Knook, 1999) to improve the possibility the MAR condition is satisfied. Furthermore, using all of the information increases the precision of prediction, and decreases imputation bias. 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, Honaker, Joseph and Scheve, 2001). In addition, imputation algorithms do not require causality between predictor and imputed variables.

However, White, Royston and Wood (2011) state that imputation models that include too many variables may face difficulties of convergence, especially for complex imputation models. Van Buuren and Groothuis-Oudshoorn (2011) recommend no more than 15 to 25 variables. Given this debate, we choose the following 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 back to 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. For the riparian buffer, animal fence, no till, and nutrient management BMPs, the imputation uses a linear regression model because imputed variables are continuous. Waste storage facilities are added in discrete quantities, so we impute missing values based on the Poisson regression.

3.4.2 MICE Scenario 2: Two-Stage Imputation

The second scenario imputes missing values both in the yes/no question and in each BMP's follow-up question on the intended amount of adoption. 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 adoption question is a positive, continuous value. If it is no, adoption is zero. Therefore, we impute "yes," "no," or "not possible for me" for the missing data in the yes/no question using a multinomial logit model; then examine only the "yes" group. We impute missing data in the follow-up question. The imputation steps are outlined as follows, and also described in Figure 3.3:

(1) Missing data in the yes/no questions are imputed as discrete values such as "yes," "no," or "not possible for me" with respect to each BMP.

(2) For respondents who answered "no," the missing data in the follow-up questions are replaced by zero; for respondents who were imputed to answer "no," the missing data are also replaced by zero.

(3) For respondents who answered "yes," but did not answer how much they would implement, or respondents who were imputed to answer "yes," their missing responses in the follow-up questions are imputed by MI using each BMP's appropriate models.

3.4.3 MICE Scenario 3: Two-Stage Imputation with Restriction

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

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 described in Figure 3.4, and outlined as follows:

(1) Missing values for each BMP's yes/no questions are imputed as discrete values such as "no" or "not possible for me" using a logistic regression model.

(2) For respondents who answered or who were imputed to answer “no” and “not possible for me,” the missing data in the follow-up questions are replaced by zero.

(3) Among respondents who answered “yes” but did not answer how much they would like to implement BMPs, their missing responses in the follow-up questions are imputed using each BMP’s corresponding model.

3.4.4 MICE Scenario 4: Three-Stage Imputation

Scenario 4 carefully considers the nature of the missing response of the yes/no question. “Not possible for me” is principally different from yes and no. “Yes” and “no” represent a personal preference to implement BMPs given the compensation through WQT programs, but “not possible for me” implies a farm cannot implement a practice, regardless of their 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; and for the sample who either answered “yes” initially or were imputed to answer “yes,” we impute missing data of the question on the adoption rate. The imputation steps are described in Figure 3.5, and are outlined as follows:

(1) Missing data in the yes/no questions are imputed as either “possible” or “not possible for me” with respect to each BMP using logistic regression.

(2) For respondents who were imputed to be “possible,” we re-impute the BMPs with missing responses with “yes” or “no” using a logistic regression model.

(3) For respondents who answered or were imputed to answer “not possible for me,” the missing data in the follow-up questions are replaced by zero; for respondents

who answered or were imputed to answer "no," the missing data in the follow-up questions are replaced by zero;

(4) For respondents who answered or were imputed to answer "yes" to the yes/no questions, but did not answer how much they would like to implement BMPs, missing responses in the follow-up questions are imputed.

Appendix 3.2 provides the detailed imputation model and predictors for the four MICE scenarios.

3.5 Imputation

3.5.1 Fitting the Imputation Model

During imputation, 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 3.3 where y_{norm} is the log-transformed non-missing values, y_{obs} is the value of non-missing y, and k is an estimated parameter indicating skewness. If y_{obs} is negatively skewed, the sign in front of y_{obs} in equation 3.3 is negative, otherwise it is positive. After imputation, we use the inverse transformation in equation 3.4 to convert observed and imputed values of variable y back to the original scale, and label it as $y_{completed}$.

$$y_{norm} = \ln(\pm y_{obs} - k) \qquad (3.3)$$

$$y_{completed} = \mp(e^{y_{norm}+y_{imputed}} + k\ ) \qquad (3.4)$$

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 is more likely to have the perfect prediction issue (White, Daniel, and Royston, 2011), especially for logit and multinomial logit models. One can 'diagnose' the models by identifying and removing the covariates causing perfect prediction. However, removing a potential troublesome variable can potentially 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 augment approach in all imputation models with categorical data.

We use 30 iterations as the burn-in period. Specifying additional burn-in iterations did not change the results. For waste storage facilities, a PMM method was used in the simulation, instead of the Poisson model, to achieve convergence.

3.5.2 After Imputation

After imputing missing values for each BMP's follow-up quantity question, we replaced imputed extreme values, values exceeding 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 across all scenarios.

With each imputed dataset, we estimate the factors affecting how much farmers may engage in each BMP, specified by equation 3.5 using Tobit or Poisson regressions. The dependent variable, Y_i, is how much farmers would like to implement each of the BMPs. 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 zero if the decision is "no." Because usage of BMPs is censored at zero, we use Tobit model to estimate how much farmers may implement these practices. Since the dependent variable for waste storage facilities Y_4 is a count value, we estimate how many facilities may be adopted using Poisson regression. We exclude respondents who answered "not possible for me" from the analysis.

$$Y_i = X'\beta + \varepsilon \tag{3.5}$$

$$where\ Y_i = continous\ value\ if\ decision\ is\ \text{Yes}, i = 1,2,3,5$$

$$Y_i = count\ number\ if\ decision\ is\ \text{Yes}, i = 4$$

$$Y_i = 0\ if\ decsion\ is\ "No"$$

Previous studies show mixed results of factors affecting choices and rates of using BMP. Two syntheses of BMP adoption conclude that there is no factor that can explain BMP adoption consistently (Knowler and Bradshaw 2007; Prokopy et al. 2008). Baumgart-Getz, Prokopy, and Floress (2012) conduct a meta-analysis to understand why farmers adopt BMPs, and they conclude that farmers' environmental awareness and attitudes are important factors, but researchers must carefully define and use these indicators. Following previous syntheses of BMP adoption, we select the following explanatory variables to explain BMP adoption in our case: compensation, land area, rent area percentage, the presence of surface water on the farm, percentage of household income from farming, total household income reinvested back into the farm, income, nearby water quality, participation in the Conservation Reserve Program (CRP), and Working-Land Program (WLP). Each BMP's regression utilizes the same explanatory variables. 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 synergy exists in adopting BMPs, we include the respondent's decision to adopt one practice as an explanatory variable in the adoption of the others.

The last step of MI is to calculate the m estimation results using Rubin's method (Rubin 1987). Let Q denote a parameter estimate, such as a regression coefficient, in each imputed dataset. The point estimate $\overline{Q}$ of Q is the average of the m separate estimates, represented by equation 3.6

$$\overline{Q} = \frac{1}{m} \sum_{j=1}^{m} Q_j \tag{3.6}$$

Let U_j denote the estimated squared standard error of Q_j written as equation 3.7, and B denote the between-imputation variance across the m point estimates written as equation 3.8. The estimated variance of point estimate of MI, T, is represented by equation 3.9.

$$\overline{U} = \frac{1}{m} \sum_{j=1}^{m} U_j \tag{3.7}$$

$$B = \frac{1}{m-1} \sum_{j=1}^{m} \left(Q_j - \overline{Q}\right)^2 \tag{3.8}$$

$$T = \left(1 + \frac{1}{m}\right) B + \overline{U} \tag{3.9}$$

The tests and confidence intervals follow a Student's t-approximation $(\overline{Q} - Q)/\sqrt{T} \sim t_v$ with degrees of freedom v represented as equation 3.10.

$$v = \left(\frac{1}{m-1}\right)\left[1 + \frac{\overline{U}}{(1+m^{-1})B}\right] \tag{3.10}$$

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) argue for larger numbers of imputation m due to efficiency loss and reproducibility. Since the variance of parameters is calculated using equation 3.9, they propose that the relative efficiency of infinitely many imputations compared to m imputations is

$$\lim_{n\to\infty} \frac{\left(1+\frac{1}{m}\right)B + \overline{U}}{\left(1+\frac{1}{n}\right)B + \overline{U}} = \frac{\left(1+\frac{1}{m}\right)B + \overline{U}}{B + \overline{U}} = 1 + \frac{B}{B+\overline{U}} * \frac{1}{m} = 1 + \frac{FMI}{m}$$

where $\frac{B}{B+\overline{U}}$ is the fraction of missing information (FMI) (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 $\frac{FMI}{m} \leq 0.01$. FMI is calculated after the analytic model using imputation data, and can be obtained from most statistical software packages. So the imputation times m are greater or equal to $(100 * FMI)$ if we allow 1% loss of efficiency in our analysis. In the estimation, each parameter has its own FMI. We use the largest FMI value 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.

3.6 Results

The imputation procedure is executed using the "rseed" option in Stata 12.0. Income level, percentage of household income from farming, and total household income reinvested back to farm are variables with categorical values, and in order to improve coefficient interpretation, are converted to continuous variables by using the midpoint of each corresponding category (Appendix 3.3). Tables 3.2-3.6 display the results of Tobit or Poisson models of how much farmers may increase BMP use given the offered amount of compensation.[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.

3.6.1 Assessment of Imputation

For each BMP, the significance of coefficients is largely consistent across all six methods. The deletion method and mean imputation method produce more similar results than the four MICE scenarios. The magnitude of the statistically significant coefficients using mean imputation is smaller compared to the deletion method. This is because replacing missing values by a constant decreases the variability of data; i.e., increase central tendency of the distribution of the data. As a result, the mean imputation method may potentially distort the efficiency of the estimation, and even lead to biased results. In addition, the one-stage imputation, two-stage imputation, and two-stage imputation with

[5] We conducted a regression-based procedure in the first scenario to test overdispersion in the Poisson model (Cameron and Trivedi, 1990), and the result did not suggest overdispersion. Since the MI method 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.

restriction are mostly consistent with each other. The three-stage imputation departs from all others.

In this analysis, we use results from the one-stage imputation method to examine whether farmers may be able to reduce agricultural runoff; what factors may affect their ability to do so; and how much more they would adopt each BMP. First, as discussed before, MI is theoretically equivalent to or better than the deletion or mean imputation method with the MCAR or MAR assumption, so for the last four, MICE methods are preferable over the first deletion and mean imputation.

Second, the extra steps we take 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, which may cause unreasonable results. Abayomi, Gelman and Levy (2008) conclude that the deviations between the imputed and observed data can be expected under MAR assumption, but researchers should be especially careful of extreme departures. Following van Buuren and Groothuis-Oudshoorn (2011) and Azur, Stuart, Frangakis and Leaf (2011), we examine the distribution of the observed and imputed data visually, and find that the one-stage has less departures from the observed data than two strategies, and is also the most stable imputation across all scenarios (see Appendix 3.4).

In addition, the One-stage and the Two-stage with restricted imputation have less FMI values than the other two scenarios. The FMI value represents the fraction of missing information. In other words, for a given fixed percent of efficiency loss from the imputation, the greater FMI is, the more imputation times *m* needed (White, Royston and Wood, 2011). Therefore, under the same imputation time, a smaller FMI value implies the imputation has a smaller loss of efficiency. Of our methods used, the One-stage imputation generally performs better than the others because its imputed value has less variations and lower FMI across the five BMPs. Lastly, presenting the one-stage imputation provides a more conservative result, because it assumes MAR, so less distortionary than any other scenarios.

Finally, comparing with the deletion method, results using the one-stage imputation method are reasonable, and are consistent with the results in the chapter 2. For the model of riparian buffers, results in the deletion method show that if farmers are currently using animal fences, they are less likely to adopt additional riparian buffers. In opposite, results in chapter 2 and in the one-stage imputation method consistently show that current adoption of animal fences cannot affect farmers' choices of riparian buffers. In addition, results in the deletion method show that cost saving information will discourage the adoption of riparian buffer, but this result is contradicted with chapter 2 and those in the one-stage imputation. Similarly, we also find that several results are opposite to results in chapter 2 after using the deletion method, while results after using one-stage imputation are mostly consistent with chapter 2. All in all, both theory and empirical results provide evidence that one-stage imputation is preferred to other strategies.

3.6.2 Additional Abatement

Table 3.7 shows the average marginal effect of the coefficients from the one-stage imputation. Using a Tobit model for riparian buffers, animal fences, no till, and nutrient management means the average marginal effect is calculated as $F(X'\beta) * \beta$ (McDonald and Moffitt, 1980). Waste storage facilities utilizes a Poisson model, so the average marginal effect is $\beta * \exp(X'\beta)$. After calculating the average marginal effect and standard error using the delta method for each imputation, we apply Rubin's method (equation 3.6 – 3.9) to derive a final estimate of marginal effects in the One-stage imputation. Table 3.7 contains these results.

All else equal, a 1% increase in compensation for adopting riparian buffers will lead to an increase of adoption by an average of 22.05 feet. Farms with one additional acre are predicted to decrease adoption of animal fences by 1.48 feet. The result shows that holding the compensation level constant, larger farms are less likely to build up fences to keep animals from direct access to streams. One possible reason is that the expected expenses of adopting fences for large farms are larger on average relative to small farms. In addition, an interesting finding is that for farms larger than 280 acres (the sample mean), the average percentage of rented land is about 28%, while the mean for farms with less than 280 acres is about 8%. It implies that farmers who operate on more land are also more likely to operate on rented land, and are less likely to make capital investments, such as in animal fences.

If farmers receive more revenue from farming, they are more likely to adopt no till, and a 1% increase of household income from farming will encourage farmers to adopt no till on 0.81 more acres. 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, investing in no till is more likely to concurrently improve farm production, soil quality, and farming revenue in the long term. Farmers who reinvest more assets back into their businesses tend to adopt more riparian buffers and waste storage facilities. A 1% increase in total household income reinvested back into the farm will increase the adoption of riparian buffers by an additional 17.74 feet.

In addition to generating an environmental benefit, previous studies show that riparian buffers generate positive economic value and can increase property value (Qiu, Prato, and Boehm, 2006; Bin, Landry, and Meyer 2009). This property premium may explain why survey respondents choose it as an investment. On the other hand, building a waste storage facility has less economic return and higher construction and maintenance costs. Nevertheless, a waste storage facility will significantly improve environmental quality by diverting agricultural runoff from entering watersheds, and eventually provide economic advantages to farmers via nearby environmental amenities. Hence, building a facility is a long-term investment decision, and farms with higher household income reinvested back into their farms are more likely to build a waste storage facility.

One of the most important findings of this study is that previous BMP adoption significantly affects farmer adoption of additional BMPs. Holding other factors constant, farmers already using riparian buffers will adopt 1066.69 more feet of riparian buffers and apply nutrient management to 46.27 more acres relative to farmers not using buffers. Compared to farmers who have not adopted, farmers who already employ animal fences will increase animal fences by 995.95 acres. Similarly, farmers currently using no till are likely to adopt 1333.91 additional feet of animal fences and 63.81 acres of no till. If farmers already have a waste storage facility, they will reduce the practice of no till on 59.65 acres. Farmers currently using nutrient management will reduce animal fences by 1397.28 feet, but will adopt nutrient management on 63.81 additional acres. One possible explanation is that respondents' willingness to use environmental goods is influenced by their previous experiences about the goods (Cameron and Englin, 1997).

We find that the type of information has a significant impact on farmers' BMP adoption decisions. Compared to no additional information on WQT, the results also show that the WQT information treatment with augmented cost saving information induced farmers to adopt animal fences by an additional 842.86 feet; in contrast, the information about the environmental aspect did not influence BMP adoption. It implies that if policy makers wish to promote a WQT program or induce additional BMP adoption, they should scrutinize the type of information communicated with the farmers.

Table 3.7 also reveals the synergy between the decisions to adopt different types of BMPs. Certain sets of BMPs are often practiced together. First, farmers willing to use riparian buffers are more likely to adopt animal fences, and vice versa. Both practices' adjacency to surface water to prevent agricultural pollution from reaching water resources may explain the correlation. Buffers intercept agricultural runoff from crop production to remove pesticides and phosphorus, while fences prevent animals from accessing surface water. Another reason is that most respondents in our sample have both crop and livestock on their land. This bundled choice of BMPs verifies that farmers tend to implement similar practices together when they decide to adopt BMPs on their land.

Farmers willing to build waste storage facilities also tend to implement nutrient management systems. Both practices reduce pollution generated from production from reaching water resources; waste storage facilities store agricultural wastes such as manure in a confined area (NRCS, 2003), while nutrient management focuses on strategic use of fertilizer, animal manure and related substances to minimize water quality degradation

(NRCS Technical Resources). The U.S. Natural Resources Conservation Service (NRCS) offers guidelines for farmers and ranchers to use waste storage facilities and nutrient management together as a comprehensive management plan (NRCS, 2015). Our results are consistent with NRCS's guidelines, indicating that farmers are more likely to manage nutrients and runoff using a comprehensive plan through a WQT program.

3.7 Conclusion

This study explores whether farmers in Kentucky would like to reduce agricultural runoff by adopting additional BMPs subject to the compensation paid by buyers of water quality credits through WQT, and which factors affect the decision. 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 imputation method, the one-stage method using MICE, the two-stage method using MICE, the two-stage method using MICE with restriction, and the three-stage method using MICE. To varying degrees, these methods improve the estimation of how factors affect how much farmers employ BMPs on their lands.

Our findings show that the compensation from WQT programs, socioeconomics characteristics, farm physical characteristics, and WQT-related information influence frequencies of BMP adoption. For example, a 1% increase in the compensation offered for using BMPs encourages farmers to adopt an additional 22 feet of riparian buffers. In addition, land area, percentage of household income from farming, percentage of total household income reinvested back to farm, and current experience of BMPs all affect BMP adoption. We also observe a synergy of BMP adoption between riparian buffers and animal fences, and between waste storage facilities and nutrient management. The pairs tend to be adopted together by farmers. We also find that the WQT information treatment with augmented cost saving information induced farmers to adopt animal fences.

Although MI was introduced over 20 years ago, and has become an established method in political science, medical science and behavior science, many researchers still rely on the deletion method for missing data in agricultural surveys. We show that replacing the missing data with MI-generated values enhances the economic analysis and implications. While our research does not intend to offer a normative strategy, 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, we recommend dealing with missing data by providing results from both the deletion method and the MI method. The mean imputation method is not advisable as it may not generate results as reliable as the other methods especially when the researcher is uncertain about the underlying reasons for the missing data.

3.8 Tables in Chapter 3

Table 3.1 Frequency Distribution of Responses

	BMPs 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
Total	357	357	357	357	357

Table 3.2 Tobit Regression for Factors Affecting Farmers' Riparian Buffer Adoption

	Deletion	Mean Imputed	MICE method One-stage	Two-stage	Restricted Two-stage	Three-stage
Offer	148.39	1220.14	5844.58*	2285.81	3701.85	6412.12**
	(1774.11)	(1033.83)	(3254.79)	(3214.25)	(3027.58)	(3056.01)
Land acre	-456.93	-276.9	-926.19	-737.95	-583.55	-125.84
	(856.22)	(325.95)	(1196.95)	(1084.06)	(946.81)	(767.96)
Rent percentage	580.55	-71.66	814.53	1138.14	324.07	-25.76
	(1077.33)	(595.01)	(1814.07)	(1623.91)	(1589.47)	(1645.31)
Surface water	1202.77	117.48	664.56	116.78	147.55	344.27
	(935.51)	(481.15)	(1257.14)	(1180.68)	(1192.79)	(1119.89)
HH Income	5.49	-2.59	-2.73	-3.82	-3.34	-5.01
	(4.26)	(2.44)	(7.24)	(6.61)	(6.58)	(7.03)
%HH Income from farming	-1895.26	-1149.35	-3013.64	-2667.28	-3300.94*	-1980.11
	(1354.15)	(741.73)	(2160.84)	(1942.95)	(1899.53)	(1899.19)
%HH Income reinvested in farm	2085.75	1677.21*	4707.3*	3943.3*	4499.54*	2739.09
	(1423.19)	(864.28)	(2485.1)	(2124.31)	(2346.65)	(2325.5)
Water quality	-217.65	-134.7	-58.25	143.91	-247.15	13.89
	(187.78)	(115.17)	(309.29)	(257.06)	(289.95)	(279.94)
CRP	-452.92	237.62	1274.44	544.59	1242.17	1019.14
	(772.65)	(454.84)	(1253.61)	(1177.28)	(1207.5)	(1317.42)
WLP	1065.28	276.65	-743.54	-81.66	-89.58	-497.1
	(643.69)	(352.12)	(1116.72)	(1016.35)	(1072.98)	(1005.95)
Current usage of other BMPs:						
Riparian buffers	1577.12***	1267.72***	2831.04***	2121**	2754.91***	2095.24**
	(593.6)	(335.24)	(967.91)	(908.09)	(884.11)	(910.39)
Animal fence	-1204.81*	-695.18*	-1173.39	-1269.11	-1324.06	-248.89
	(611.44)	(369.24)	(1050.72)	(1008.1)	(911.06)	(1026.49)
No till	-731.74	184.27	1119.03	995.1	1308.1	1612.13
	(756.87)	(412.41)	(1299.82)	(1108.48)	(1100.15)	(1132.05)
Waste storage facility	-2419.11	-1370.3**	-2363.07	-1991.94	-2142.06	-3440.22*
	(1484.21)	(662.39)	(1943.83)	(1960)	(1903.22)	(1860.99)
Nutrient manage(*)	-275	-170.88	-449.41	-823.09	-3.8	-789.36
	(622.43)	(372)	(1125.2)	(962.36)	(966.26)	(1041.01)

(Continued)

Table 3.2 Continued

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Choices of other BMPs:						
Animal	3428.09***	2004.32***	4010.42***	4031.86***	3896.6***	2300.1***
fences	(679.85)	(383.24)	(1209.22)	(1275.85)	(1122.78)	(858.18)
No till	283.72	290.42	1098.67	1366.6	1365.59	421.93
	(661.76)	(382.08)	(1119.14)	(983.97)	(1019.47)	(888.47)
Waste storage	-1037.53	-697.42*	-1359.29	-1241.41	-1702.55	-57.96
facilities	(719.85)	(415.1)	(1308.26)	(1087.33)	(1248.52)	(1060.42)
Nutrient	601.73	218.56	427.57	800.82	966.3	452
manage	(693.89)	(344.1)	(1133.87)	(1010.98)	(1108.74)	(937.01)
Information about WQT:						
Cost	-1467.2**	-494.17	-582.07	-268.14	-179.45	-539.6
info(*)	(732.95)	(425.22)	(1210.91)	(1006.5)	(1129.82)	(1147.45)
Environ	-127.62	164.53	664.12	550.4	1188.01	187.72
Info(*)	(782.43)	(452.72)	(1468.57)	(1353.66)	(1320.7)	(1256.05)
Combo	-448.68	-321.88	-346.48	-139.22	-292.91	-271.78
Info(*)	(624.82)	(415.97)	(1213.4)	(991.47)	(1012.88)	(1069.11)
Constant	-3139.38	-2052.21	-10156.97**	-7200.64*	-8027.06**	-9291.2**
	(2372.58)	(1375.97)	(4304.47)	(3945.22)	(4005.27)	(3902.3)
Sigma	1690.19***	1361.95***	3308.4***	3025.59***	3309.37***	3459.3***
	(203.13)	(120.2)	(682.62)	(586.06)	(588.63)	(567.43)
N	119	149	149	225	199	218
				256	237	251
Largest FMI	-	-	0.8199	0.8859	0.7452	0.8211

Note:
(1) The “yes/no” choices are imputed in the last three scenarios, so numbers of observations used in the estimation varied across different imputation data. We report the smallest (upper row) and the largest numbers (lower row) of observations used in the estimation for the last three scenarios. Tables 3.3-3.6 also report the two numbers.
(2) Standard errors are in parentheses; *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.
(3) In (*), nutrient management abbreviates to nutrient manage for formatting the result in the one table; Cost info, environ Info, and combo info indicate cost saving information, environmental aspect information and combined information. Tables 3.3-3.7 also use the same abbreviation.

Table 3.3 Tobit Regression for Factors Affecting Farmers' Animal Fences Adoption

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Offer	1469.02	1057.82	3186.06	2615.7	2059.35	3207.67
	(1640.03)	(1035.47)	(2015.51)	(2066.06)	(1802.69)	(2140.37)
Land acre	-1685.91*	-957.62*	-2771.64**	-2691.97**	-2491.41**	-2715.9***
	(857.87)	(549.12)	(1129.81)	(1117.19)	(1037.2)	(1024.52)
Rent percentage	106.51	486.85	993	839.47	953.47	1266.29
	(956.73)	(580.61)	(1270.19)	(1388.32)	(1102.85)	(1306.33)
Surface water	-179.94	-283.98	-788.63	-1176.3	-1006.45	-460.42
	(855.98)	(514.83)	(1106.91)	(1178.09)	(965.1)	(875.08)
HH Income	2.59	0.39	4.75	5.12	2.36	1.37
	(4.51)	(2.68)	(5.44)	(5.99)	(5.18)	(5.79)
%HH Income from farming	2182.16	974.57	2551.81	5307.78***	1642.65	4006.3
	(1536.51)	(881.1)	(1761.24)	(1963.67)	(1755.76)	(1976.92)
%HH Income reinvested in farm	-1047.69	-317.66	-55.61	-4159.16*	851.64	-2383.9
	(1726.26)	(1040.45)	(2021.52)	(2156.11)	(1878.66)	(2080.62)
Water quality	-323.7*	-297.78**	-346.65	-274.07	-360.54	-392.36*
	(192.44)	(124.3)	(233.67)	(235.4)	(220.94)	(229.11)
CRP	49.14	-2.44	-1035.6	-197.15	-226.37	-232
	(824.82)	(513.16)	(964.84)	(1001.32)	(1002.23)	(987.01)
WLP	-742.25	-190.82	44.61	-757.05	-313.56	-454.49
	(668.87)	(385.01)	(869.01)	(804.03)	(775.26)	(842.22)
Current usage of other BMPs:						
Riparian buffers	1058.09**	445.21	790.18	724.08	1080.87*	939.95
	(518.25)	(343.92)	(650.75)	(709.87)	(616.99)	(669.21)
Animal fence	2108.27***	1100.1***	1866.46***	1900.53***	1906.62***	1935.93***
	(555.56)	(347.88)	(654.19)	(688.08)	(645.01)	(701.09)
No till	1316.6*	678.88	2499.37**	1227.24	1573.23*	1508.3
	(751.35)	(437.38)	(999.12)	(940.03)	(931.89)	(913.87)
Waste storage facility	1900.86*	375.21	1323.54	2373.2*	1621.97	1906.9
	(1131.87)	(679.77)	(1305.82)	(1360.33)	(1245.28)	(1547.76)
Nutrient manage	-1957***	-933.43**	-2618.8***	-2003.13**	-2148.27**	-2249.9***
	(695.79)	(428.86)	(856.41)	(863.8)	(900.82)	(855.37)

(Continued)

Table 3.3 Continued

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Choices of other BMPs:						
Riparian	1073.98*	476.89	1509.14**	1906.97***	1653.1**	1106.79*
Buffers	(568.51)	(344.96)	(683.06)	(698.16)	(687.26)	(625.37)
No till	-46.95	64.76	-506.06	302.38	611.49	181.41
	(643.94)	(406.13)	(767.88)	(877.25)	(772.81)	(657.55)
Waste storage	739.87	418.54	1053.9	1373.8*	976.21	709.18
facilities	(691.64)	(408.82)	(825.54)	(825.95)	(827.23)	(783.18)
Nutrient	-275.52	9.3	-396.68	-167.82	-135.29	115.84
manage	(636.64)	(408.15)	(786.34)	(781.51)	(788.94)	(723.61)
Information about WQT:						
Cost Info	1557.11**	844.07**	1576.89*	1298.35	1898.13**	1157.19
	(714.19)	(431.34)	(905.43)	(909.81)	(833.31)	(876.46)
Environ	503.06	105.31	478.65	412.75	260.87	33.14
Info	(724.79)	(477.44)	(955.09)	(878.6)	(851.38)	(937.62)
Combined	-437.96	-305.87	-519.48	-973.81	-151.72	-1091.03
Info	(682.44)	(428.89)	(839.71)	(860.9)	(744.84)	(863.53)
Constant	-2095.28	15.3	-2940.03	-2559.48	-2889.84	-2288.85
	(2221.91)	(1443.59)	(2644.73)	(2582.91)	(2520.92)	(3010.75)
Sigma	2245.07***	1834.23***	2766.97***	2771.55***	2829.42***	2863.08***
	(199.15)	(124.74)	(340.89)	(300.06)	(329.99)	(343.59)
N	134	182	182	249	216	253
				276	255	276
Largest FMI	-	-	0.6987	0.7581	0.65	0.7721

Standard errors are in parentheses; *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.

Table 3.4 Tobit Regression for Factors Affecting Farmers' No Till Adoption

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Offer	-97.79	-56.97	-16	-43.71	-30.39	-27.39
	(76.81)	(51.43)	(113.79)	(94.7)	(105.9)	(87.48)
Land acre	18.81	18.48*	21.37	25.25	28.38	19.07
	(13.14)	(10.22)	(19.96)	(19.74)	(20.22)	(18.05)
Rent percentage	99.47***	48.84*	110.67	129.45*	104.32*	77.76
	(37.44)	(25.51)	(73.79)	(68.73)	(62.9)	(56.1)
Surface water	-5.35	-16.35	10.39	25.26	33.82	11.04
	(37.15)	(25.51)	(52.16)	(49)	(53.11)	(37.62)
HH Income	0.41**	0.25	0.35	0.31	0.37	0.33
	(0.18)	(0.11)	(0.26)	(0.24)	(0.25)	(0.21)
%HH Income from farming	115.43**	106.63***	164.24*	168.35**	157.03**	156.13**
	(57.8)	(39.55)	(85.23)	(84.27)	(79.2)	(74.69)
%HH Income reinvested in farm	-71.86	-70.91	-62.77	-90.46	-111.54	-18.53
	(65.56)	(47.42)	(93.81)	(86.34)	(92.73)	(78.51)
Water quality	-8.46	-6.54	-9.71	-9.25	-6.5	-12.44
	(8.01)	(5.75)	(11.46)	(9.97)	(11.29)	(10.14)
CRP	-27.27	-22.36	-74.46	-74.19	-57.17	-71.03*
	(31)	(22.17)	(51.04)	(48.67)	(47.18)	(42.78)
WLP	19.19	18.9	5.34	20.63	0.8	20.31
	(29.66)	(18.97)	(47.91)	(40.53)	(41.26)	(33.94)
Current usage of other BMPs:						
Riparian buffers	-4.82	9.14	5.46	-12.85	-12.99	1.71
	(24.65)	(16.6)	(36.73)	(31.83)	(33.85)	(32.28)
Animal fence	2.67	2.51	7.39	1.09	-10.64	17.79
	(27.66)	(18.48)	(38.82)	(35.82)	(35.31)	(31.43)
No till	103.8***	72.72***	129.75***	119.5***	128.53***	121.21***
	(25.57)	(17.25)	(43.2)	(38.59)	(41.3)	(37.55)
Waste storage facility	-106.39**	-63.42**	-121.23*	-116.29**	-120.54*	-115.84**
	(43.22)	(27.39)	(66.23)	(58.2)	(63.48)	(53.2)
Nutrient manage	-20.66	-16.84	-8.3	-14.95	10.64	-16.31
	(28.08)	(19.24)	(41.04)	(36.83)	(40.08)	(33.98)

(Continued)

Table 3.4 Continued

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Choices of other BMPs:						
Riparian	19.51	10.11	47.8	38.17	66.86	16.69
Buffers	(28.25)	(17.64)	(47.96)	(37.88)	(44.2)	(31.13)
Animal	6.05	16.75	8.09	12.11	27.57	-4.66
fences	(31.25)	(20.17)	(43.96)	(43.22)	(39.41)	(30.98)
Waste	34.81	14.34	38.46	30.88	68.39*	28.86
storage facilities	(30.54)	(19.51)	(41.95)	(38.44)	(42.69)	(33.34)
Nutrient	43.79	37.33**	45.66	76.74*	77.35*	22.12
management	(27.8)	(17.81)	(37.77)	(39.44)	(40.4)	(29.42)
Information about WQT:						
Cost saving	25.67	28.23	52.48	33.87	26.1	31.51
information	(30.05)	(20.74)	(45.96)	(39.22)	(44.53)	(36.13)
Environmenta	14.09	20.73	70.8	48.88	51.54	25.83
l aspect Info	(35.74)	(22.39)	(62.6)	(51.42)	(51.61)	(44.97)
Combined	13.9	10.01	14.58	-18.06	-6.36	0.81
Information	(28.65)	(20.98)	(41.11)	(40.27)	(39.32)	(35.2)
Constant	-21.02	-1.54	-152.98	-130.48	-206.82	-76.64
	(104.2)	(66.57)	(160.8)	(121.15)	(154.09)	(116.22)
Sigma	98.78***	85.23***	141.83***	136.51***	146.96***	128.51***
	(8.75)	(5.93)	(26.25)	(21.52)	(26.11)	(20.89)
N	136	178	178	254	226	254
				285	264	283
Largest FMI	-	-	0.8684	0.8709	0.8501	0.8825

Standard errors are in parentheses; *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.

Table 3.5 Poisson Regression for Factors Affecting Farmers' Waste Storage Facilities Adoption

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Offer	0.091	-0.17	-0.633	-0.459	-0.281	-0.127
	(1.03)	(0.854)	(0.84)	(0.725)	(0.827)	(0.751)
Land acre	0.034	-0.012	0.024	0.016	0.1	0.033
	(0.264)	(0.2)	(0.172)	(0.187)	(0.156)	(0.171)
Rent percentage	-0.743	-0.389	-0.199	-0.119	-0.404	-0.251
	(0.577)	(0.468)	(0.446)	(0.364)	(0.442)	(0.377)
Surface water	-0.197	-0.104	0.056	0.181	0.058	0.055
	(0.514)	(0.426)	(0.439)	(0.403)	(0.429)	(0.362)
HH Income	-0.003	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
%HH Income from farming	-0.254	-0.388	-0.524	-0.63	-0.682	-0.448
	(0.69)	(0.598)	(0.584)	(0.516)	(0.592)	(0.537)
%HH Income reinvested in farm	1.746**	1.381**	1.11*	0.87	1.211*	1.179**
	(0.754)	(0.613)	(0.602)	(0.55)	(0.625)	(0.556)
Water quality	-0.035	-0.06	-0.072	-0.059	-0.099	-0.092
	(0.121)	(0.095)	(0.092)	(0.088)	(0.097)	(0.084)
CRP	0.393	0.249	0.175	0.197	0.219	0.271
	(0.425)	(0.31)	(0.314)	(0.294)	(0.313)	(0.294)
WLP	0.188	0.173	0.197	0.211	0.266	0.071
	(0.325)	(0.261)	(0.26)	(0.251)	(0.266)	(0.241)
Current usage of other BMPs:						
Riparian buffers	0.344	0.291	0.2	0.032	0.111	0.241
	(0.304)	(0.259)	(0.265)	(0.256)	(0.27)	(0.233)
Animal fence	-0.062	-0.088	-0.127	-0.196	-0.148	-0.044
	(0.332)	(0.283)	(0.278)	(0.247)	(0.265)	(0.261)
No till	-0.425	-0.239	-0.001	0.026	-0.071	0.016
	(0.434)	(0.325)	(0.327)	(0.272)	(0.329)	(0.297)
Waste storage facility	0.542	0.295	0.209	0.333	0.345	0.159
	(0.417)	(0.343)	(0.339)	(0.312)	(0.338)	(0.305)
Nutrient management	-0.065	-0.158	-0.233	-0.249	-0.178	-0.179
	(0.361)	(0.298)	(0.287)	(0.252)	(0.288)	(0.264)

(Continued)

Table 3.5 Continued

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Choices of other BMPs:						
Riparian Buffers	-0.07	-0.105	-0.12	-0.041	-0.154	-0.063
	(0.333)	(0.278)	(0.275)	(0.264)	(0.284)	(0.245)
Animal fences	1.146***	0.843***	0.757**	0.723**	0.841***	0.457*
	(0.38)	(0.296)	(0.296)	(0.328)	(0.3)	(0.247)
No till	-0.22	0.013	0.108	0.135	0.394	0.046
	(0.354)	(0.285)	(0.294)	(0.303)	(0.307)	(0.26)
Nutrient management	1.049***	0.799***	0.84***	0.993***	1.041***	0.575**
	(0.361)	(0.291)	(0.291)	(0.357)	(0.305)	(0.251)
Information about WQT:						
Cost Info	0.541	0.316	0.293	0.41	0.359	0.418
	(0.437)	(0.365)	(0.358)	(0.326)	(0.356)	(0.334)
Environ Info	0.34	0.272	0.35	0.351	0.35	0.346
	(0.49)	(0.391)	(0.397)	(0.34)	(0.391)	(0.358)
Combo Info	0.376	0.228	0.182	0.263	0.248	0.332
	(0.476)	(0.39)	(0.386)	(0.362)	(0.388)	(0.371)
Constant	-2.364	-1.473	-0.767	-1.157	-1.555	-0.887
	(1.443)	(1.176)	(1.137)	(1.045)	(1.155)	(1.054)
N	128	151	151	211	200	223
				243	231	253
Largest FMI	-	-	0.1766	0.5681	0.2519	0.4706

Standard errors are in parentheses; *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.

Table 3.6 Tobit Regression for Factors Affecting Farmers' Nutrient Management Adoption

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Offer	61.76	54.31	106.64	77.08	141.67	149.16
	(143.74)	(107.83)	(167.03)	(152.04)	(157.92)	(146.53)
Land acre	29.77	27.63	31.16	30.92	16.75	32.4
	(28.44)	(22.32)	(33.48)	(31.65)	(33.91)	(33.7)
Rent percentage	25.6	33.87	89.45	115.43	63.95	111.09
	(74.73)	(55.06)	(93.72)	(101.12)	(92.54)	(97.19)
Surface water	-41.14	-34.5	-38.88	-57.29	-74.49	-3.14
	(64.49)	(49.06)	(70.14)	(63.54)	(68.87)	(58.55)
HH Income	0.29	-0.05	0.24	0.27	0.55	0.02
	(0.33)	(0.23)	(0.41)	(0.4)	(0.39)	(0.38)
%HH Income from farming	44.41	46.31	21.74	66.86	-2.73	30.66
	(104.19)	(75.85)	(117.28)	(128.78)	(109.4)	(103.02)
%HH Income reinvested in farm	49.36	-7.46	27.45	-2.1	-2.85	76.11
	(136.86)	(89.67)	(148.35)	(137.03)	(146.52)	(132.95)
Water quality	-5.17	-0.22	-2.02	8.92	8.87	-3.63
	(16.12)	(12.84)	(20.09)	(17.95)	(19.39)	(17.58)
CRP	38.41	50.49	64.71	57.02	8.74	52.53
	(71.02)	(49.47)	(89.46)	(75.94)	(84.9)	(71.21)
WLP	-72.23	-84.61**	-104.71	-120.37*	-98.82	-74.71
	(54.59)	(41.16)	(74.43)	-66.82	(67.13)	(62.91)
Current usage of other BMPs:						
Riparian buffers	97.14**	82.94**	102.53*	102.82*	93.87*	93.28*
	(49.59)	(34.77)	(55.79)	(54.79)	(52.56)	(50.56)
Animal fence	-10.72	1.12	20.63	19.33	37.66	38.77
	(47.49)	(35.7)	(55.81)	(49.98)	(50.38)	(45.38)
No till	73.57	60.67	96.59	76.78	101.53	120.15*
	(57.06)	(40.9)	(66.18)	(56.61)	(65.89)	(65.77)
Waste storage facility	-139.59	-91.76	-133.35	-125.8	-128.2	-154.27
	(84.85)	(58.52)	(105.39)	(98.53)	(96.93)	(103.49)
Nutrient manage	147.99***	108.79***	141.46**	128.97**	172.09***	106.36**
	(48.59)	(35.15)	(57.02)	(51.25)	(56.71)	(48.36)

(Continued)

Table 3.6 Continued

	Deletion	Mean Imputed	MICE method			
			One-stage	Two-stage	Restricted Two-stage	Three-stage
Choices of other BMPs:						
Riparian Buffers	24.7	35.08	44.46	29.59	58.44	33.95
	(53.18)	(37.93)	(61.12)	(55.54)	(59.96)	(52.97)
Animal fences	15.97	9.01	13.11	15.7	20.63	16.46
	(55.77)	(40.02)	(63.24)	(60.13)	(57.57)	(55.34)
No till	70.64	78.6**	95.7	122.54*	144.86**	48.36
	(53.65)	(38.96)	(63.11)	(64.6)	(62.54)	(53.22)
Waste storage facilities	138.57***	104.59***	145.52**	157.73**	164.39**	89.14*
	(52.41)	(38.19)	(62.49)	(65.53)	(64.16)	(52.36)
Information about WQT:						
Cost Info	4.9	16.9	14.65	2.42	37.08	27.16
	(65.32)	(47.48)	(74.55)	(67.87)	(77.55)	(74.95)
Environ Info	-13.23	-19.75	15.38	-39.63	25.14	-9.91
	(66.26)	(48.52)	(81.61)	(68.75)	(78.53)	(77.17)
Combo Info	60.32	40.49	44.75	40.85	35.28	44.21
	(60.92)	(46.88)	(68.69)	(61.65)	(64.98)	(65.98)
Constant	-310.09	-225.54	-395.18	-416.3*	-566.63**	-395.25*
	(200.46)	(145.83)	(242.38)	(229.73)	(249.89)	(212.5)
Sigma	209.46***	180.13***	236.07***	226.54***	245.81***	229.56***
	(17.12)	(12.41)	(44.13)	(49.68)	(47.38)	(46.48)
N	145	176	176	254	239	264
				288	272	290
Largest FMI	-	-	0.8718	0.9376	0.8747	0.9274

Standard errors are in parentheses; *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.

Table 3.7 Average Marginal Effect of Factors Affecting BMP Adoption after One-stage Imputation

	Riparian buffers	Animal fences	No till	Waste storage facilities	Nutrient management
Offer	2205.12*	1698.90	-7.92	-0.44	47.99
	(1241.72)	(1069.02)	(55.88)	(0.58)	(75.11)
Land acres	-349.53	-1479.42**	10.51	0.02	14.08
	(453.65)	(603.32)	(9.78)	(0.12)	(15.07)
Rent percentage	305.99	531.11	54.45	-0.13	40.38
	(686.75)	(678.7)	(36.32)	(0.3)	(42.21)
Surface water	251.71	-421.47	5.06	0.04	-17.56
	(478.47)	(591.9)	(25.62)	(0.3)	(31.55)
Income	-1.04	2.53	0.17	0.00	0.11
	(2.75)	(2.89)	(0.13)	(0)	(0.18)
%HH Income from farming	-1133.85	1361.22	80.91*	-0.36	9.9
	(817.13)	(939.19)	(42.09)	(0.4)	(52.84)
%HH Income reinvested in farm	1773.77*	-27.55	-30.93	0.75*	12.38
	(941.17)	(1079.71)	(46.14)	(0.42)	(66.66)
Water quality	-21.86	-185.20	-4.79	-0.05	-0.91
	(117.17)	(124.69)	(5.64)	(0.06)	(9.04)
CRP	481.91	-553.31	-36.65	0.12	29.14
	(477.39)	(515.55)	(25.06)	(0.21)	(40.21)
WLP	-282.73	24.89	2.66	0.13	-47.24
	(426.16)	(465.5)	(23.52)	(0.18)	(33.43)
Current usage of other BMPs:					
Riparian buffers	1066.69***	420.65	2.69	0.13	46.27*
	(368.82)	(345.61)	(18.02)	(0.18)	(25.03)
Animal fences	-442.41	995.95***	3.66	-0.09	9.28
	(399.67)	(344)	(19.07)	(0.19)	(25.12)
No till	426.69	1333.91**	63.81***	0.00	43.59
	(495.71)	(533.29)	(20.93)	(0.22)	(29.77)
Waste storage facilities	-888.81	705.89	-59.65*	0.14	-60.14
	(731.68)	(696.45)	(32.49)	(0.23)	(47.22)
Nutrient management	-171.10	-1397.28***	-4.09	-0.16	63.81**
	(428.23)	(453.71)	(20.14)	(0.2)	(25.27)

(Continued)

Table 3.7 Continued

	Riparian buffers	Animal fences	No till	Waste storage facilities	Nutrient management
Choices of other BMPs:					
Riparian	-	805.36**	23.50	-0.08	20.02
buffers	-	(361.76)	(23.52)	(0.19)	(27.45)
Animal	1516.06***	-	3.98	0.51**	5.94
fences	(477.12)	-	(21.58)	(0.21)	(28.47)
No till	413.33	-269.48	-	0.07	43.17
	(422.95)	(408.99)	-	(0.2)	(28.33)
Waste storage	-510.95	561.66	18.91	-	65.64**
facilities	(494.79)	(439.23)	(20.56)	-	(27.77)
Nutrient	162.53	-211.23	22.45	0.57***	-
management	(431.02)	(420.1)	(18.49)	(0.21)	-
Information about WQT:					
Cost Info	-220.06	842.86*	25.83	0.20	6.59
	(459.39)	(483.73)	(22.65)	(0.25)	(33.55)
Environ Info	254.44	255.54	34.84	0.24	6.89
	(559.28)	(509.45)	(30.81)	(0.28)	(36.74)
Combo Info	-132.43	-276.73	7.18	0.12	20.19
	(460.92)	(448.15)	(20.2)	(0.26)	(30.89)
Number of censored at zero	80	62	67	-	66
N	149	182	178	151	176

Note: Standard errors calculated using Delta method are in parentheses; *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.

3.9 Figures in Chapter 3

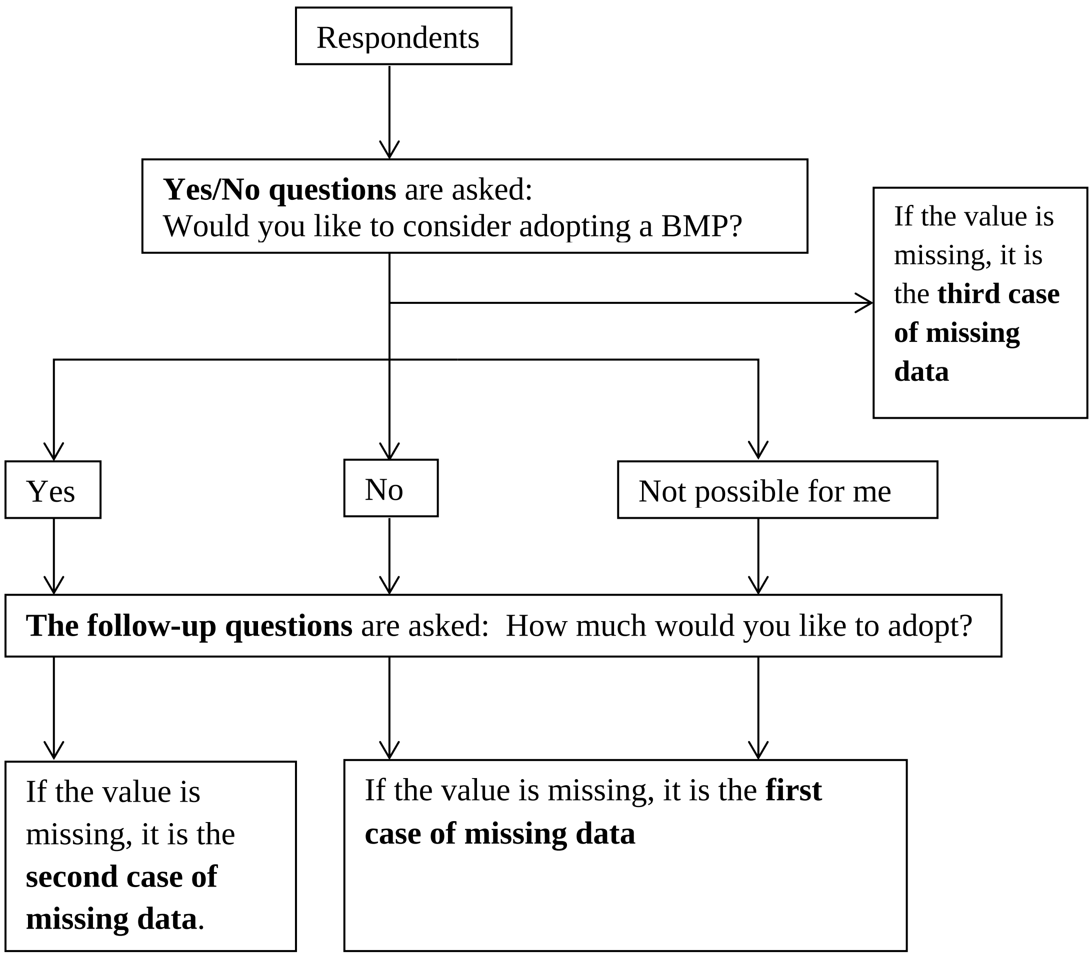

Figure 3.1 Figure 3.1 The Three Cases of Missing Data in the Survey

Define $Y^{(1)}, Y^{(2)}, \dots$ and $Y^{(n)}$ are variables with missing data;

X are fully observed variables in the dataset;

${Y^{(i)}}_{imp(j)}$ is the i th variable with observed data and imputed data in j th iteration.

Chain Equation Iteration 1:

Dependent variable	Predictor variables				Imputed variable
$Y^{(1)}$	X				${Y^{(1)}}_{imp(1)}$
$Y^{(2)}$	X	${Y^{(1)}}_{imp(1)}$			${Y^{(2)}}_{imp(1)}$
$Y^{(3)}$	X	${Y^{(1)}}_{imp(1)}$	${Y^{(2)}}_{imp(1)}$		${Y^{(3)}}_{imp(1)}$
$\dots \dots$					
$Y^{(n)}$	X	${Y^{(1)}}_{imp(1)}$	${Y^{(2)}}_{imp(1)}$	$\dots \dots {Y^{(n)}}_{imp(1)}$	${Y^{(n)}}_{imp(1)}$

Chain Equation Iteration 2:

Dependent variable	Predictor variables				Imputed variable
$Y^{(1)}$	X	${Y^{(2)}}_{imp(1)}$	${Y^{(3)}}_{imp(1)}$	$\dots \dots {Y^{(n)}}_{imp(1)}$	${Y^{(1)}}_{imp(2)}$
$Y^{(2)}$	X	${Y^{(1)}}_{imp(2)}$	${Y^{(3)}}_{imp(1)}$	$\dots \dots {Y^{(n)}}_{imp(1)}$	${Y^{(2)}}_{imp(2)}$
$Y^{(3)}$	X	${Y^{(1)}}_{imp(2)}$	${Y^{(2)}}_{imp(2)}$	$\dots \dots {Y^{(n)}}_{imp(1)}$	${Y^{(3)}}_{imp(2)}$
$\dots \dots$					
$Y^{(n)}$	X	${Y^{(1)}}_{imp(2)}$	${Y^{(2)}}_{imp(2)}$	$\dots \dots {Y^{(n-1)}}_{imp(2)}$	${Y^{(n)}}_{imp(2)}$

Chain Equation Iteration j:

Dependent variable	Predictor variables				Imputed variable
$\dots \dots$					
$Y^{(i)}$	X	${Y^{(1)}}_{imp(j)}$	${Y^{(2)}}_{imp(j)}$	$\dots {Y^{(i-1)}}_{imp(j)}$	${Y^{(i)}}_{imp(j)}$
		${Y^{(i+1)}}_{imp(j-1)}$	$\dots$	${Y^{(n)}}_{imp(j-1)}$	
$\dots \dots$					

Figure 3.2 Demonstration of the Multivariate Imputation by Chained Equation (MICE) Method

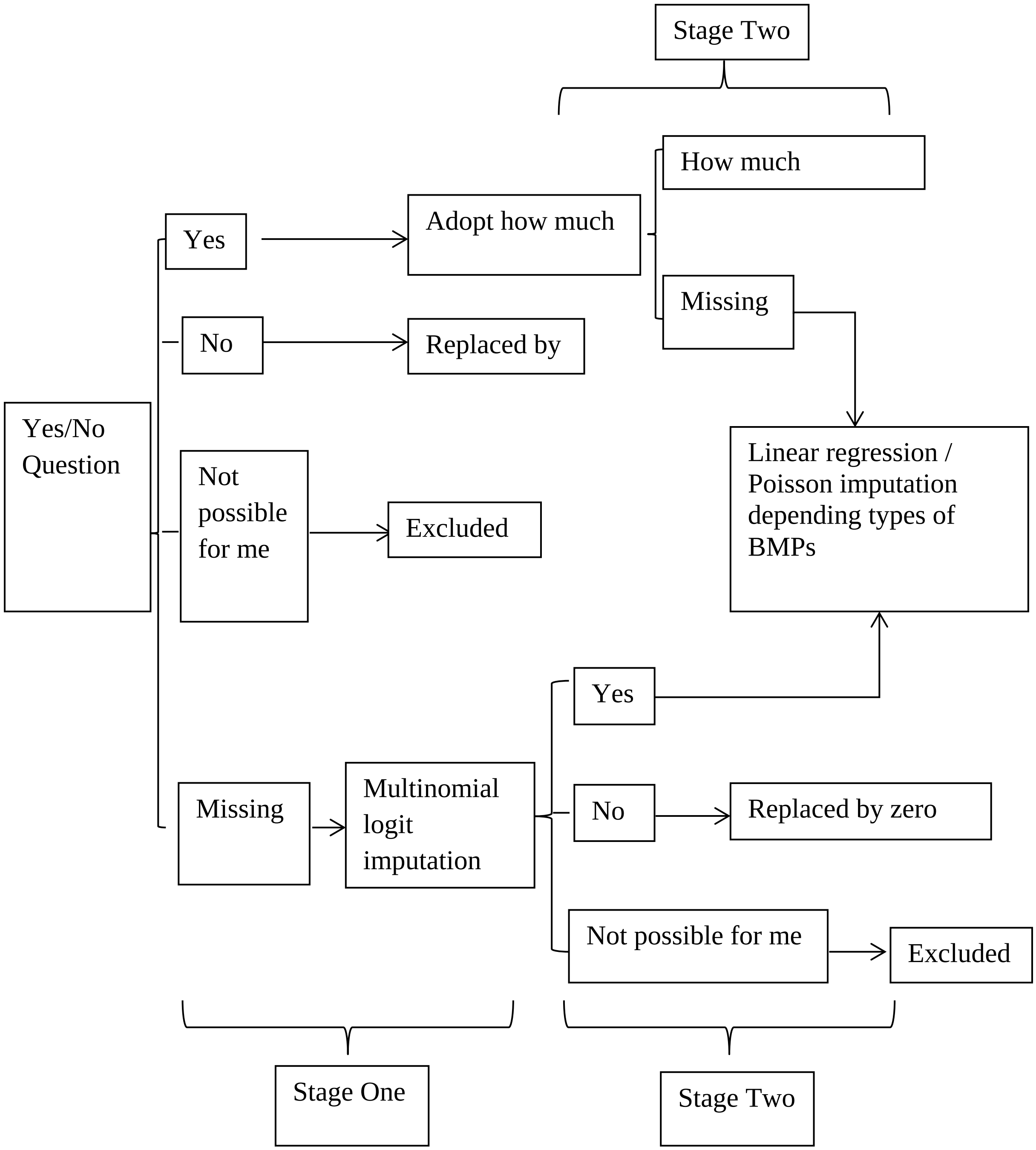

Figure 3.3 Execution Route of the Second Scenario

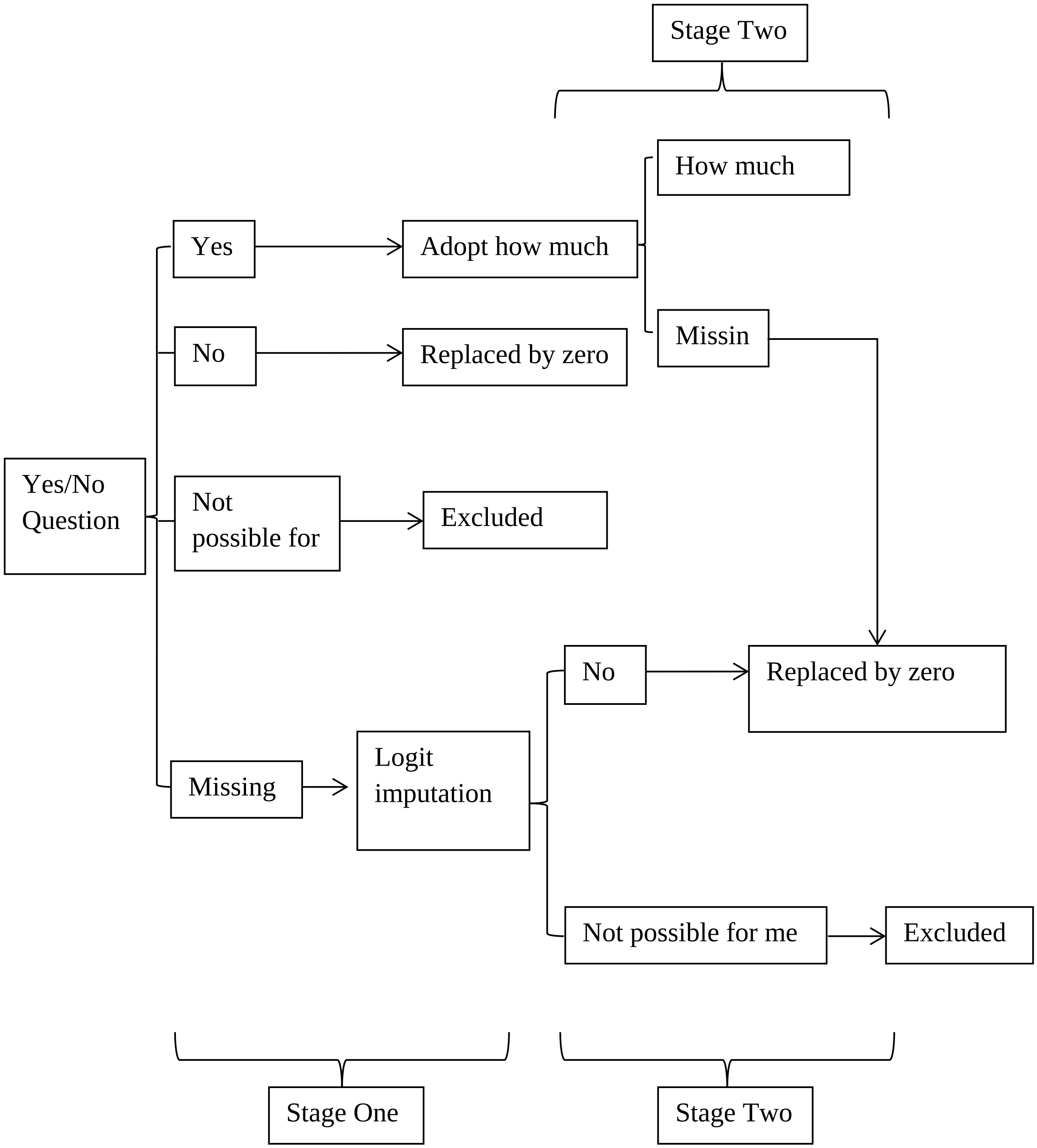

Figure 3.4 Execution Route of the Third Scenario

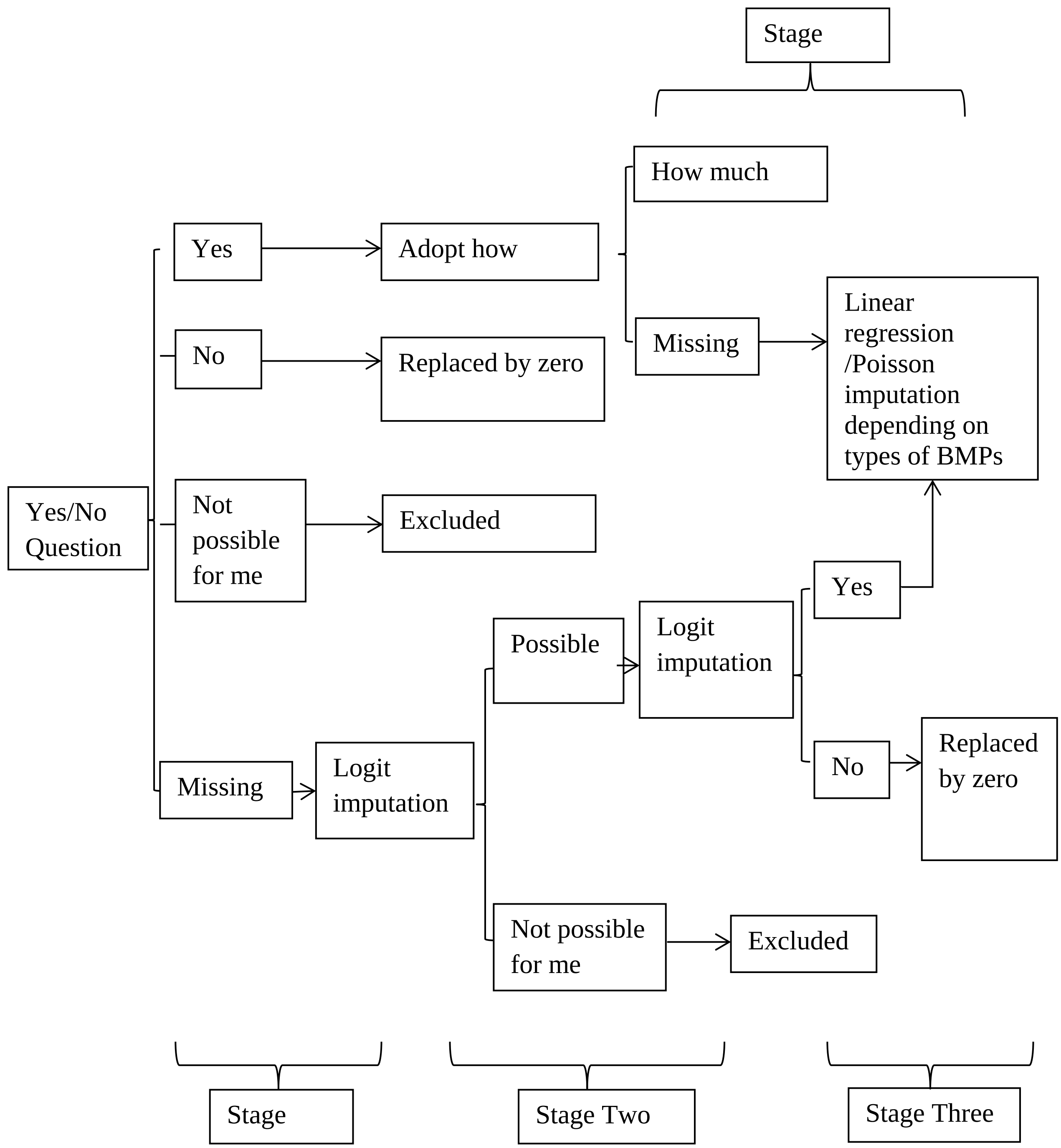

Figure 3.5 Execution Route of the Fourth Scenario

Chapter 4 The Effect of Land Wealth Change and Local Community Interaction on Best Management Practice Adoption

4.1 Introduction

Best Management Practices (BMPs) are schedules of activities, prohibitions of practices, maintenance procedures, and other management practices to prevent or reduce the pollution of waters (the U.S. EPA 2015). As increasing concerns about water pollutions from agriculture, the U.S. Environmental Protection Agency (EPA) introduces Best Management Practices (BMPs) to control agricultural run-off from the surface water, and intercept the pesticides and phosphorus diffusing into the underground water. The European Union (EU) Agriculture and Rural Development (AGRI) department also progressively encourages farm households to adopt BMPs to respond the increasing demand of environmental quality. Both the U.S. and the EU initiate incentive payment programs to promote BMPs installed on farmland, such as the Environmental Quality Incentive Program (EQIP) in the U.S., and the Agri-Environment Measures (AEM) in the EU.

BMP adoption as a type of farm investment is subject to farm financial conditions, especially the available amount of capital resources for investment. As the most valuable asset, farmland wealth determines a farm's financial health, and thus farmland values also affect decisions of environmental investment such as BMP adoption. Zhang and Nickerson (2015) find that the urban housing market bust during 2007-2008 significantly decreases farmland values. The decline of farm wealth drives landowners to leave farm business by selling out their lands, and also changes their risk attitudes. The decrease of farmland values therefore discourages environmental investments such as BMP adoption on farms in the future.

In addition to economic factors, previous studies also show that ethic and social pressure could motivate farmers to commit to environmental services (Lynne et al. 1988; Weaver 1996; Michel-Guillou and Moser 2006; Knowler and Bradshaw 2007; Chouinard et al. 2008; Prokopy et al. 2008; Mzoughi 2011; Baumgart-Getz, Prokopy, and Floress 2012; Sulemana and James Jr. 2014). For one thing, households in the urban fringe area or near farms have increasing demand for better water quality, farmland preservation, and biodiversity conservation (Leggett and Bockstael 2000; Roe et al. 2004; Ready and Abdalla 2005; Chen, Irwin, and Jayaprakash 2009), and strong disutility associated with the agricultural pollution from farming practices and livestock production (Palmquist, Roka and Vukina 1997; Herriges et al. 2005; Ready and Abdalla 2005). In response to water pollution issues, households would migrate out of local regions or appeal to local governments to control agricultural run-off (Chen et al. 2009; Irwin et al. 2014). For another, farmers' pro-environmental activities can protect social values, and improve their public images (Michel-Guillou and Moser 2006; Chouinard et al. 2008; Mzoughi 2011; Sulemana and James Jr. 2014). Improving farmers' social public images is one of the most important reasons to motivate farmers to commit to pro-environmental actions (Michel-Guillou and Moser 2006). Thus, social interactions with local communities may motivate farmers to adopt certain types of BMPs, such as plant buffers alongside a river or a waste storage facility preventing agricultural run-off from entering waterways.

Most previous studies use self-rated awareness variables to capture effects of social interactions on BMP adoption. When BMP adopters face a self-rated question, they are more likely to promote themselves that attribute their adoption to social commitments and altruism. Consequently, using self-rated variables may lead to overestimated adoption. To our knowledge, no study to date has examined the social interaction effects using local community characteristic data, and few studies have explicitly examined the effect of wealth changes on BMP investment. Our goal is to fill the research gap.

The objective of our research is to investigate effects of wealth changes and interactions with local communities on BMP adoption. To proceed, we closely follow Feather and Goodwin (1993) to model BMP adoption in terms of landowners' investment, and to show that the decisions of using BMPs are subject to farm's wealth. Then, we specify the linkage between BMP decisions and social interactions with local communities. In the empirical analysis, we combine survey data on BMP adoption conducted between 2011 and 2012 in Kentucky with publicly available data from the U.S. National Agricultural Statistics Service (NASS) and the U.S. census bureau. The survey is as described in the chapter two. Wealth changes are approximated by percentage differences of land value between 2007 and 2012; social interactions with local community are understood through three aspects: social pressure, residential effect, and local agricultural recreation business effect.

The article is organized as follows. The second section briefly reviews the previous literature. In the third section, we develop a conceptual model to explain BMP adoption where farmers are assumed to consider BMP adoption as an environmental investment. Then, we specify how local community characteristics influence farmers' BMP adoption. The fourth section introduces our study area, and the fifth section illustrates our empirical models. The last two sections discuss our empirical findings and conclude with the policy implication from our findings.

4.2 Literature Review

Given growing attentions of BMPs, numerous studies have attempted to understand the mechanism and factors explaining BMP adoption. Three syntheses summarize previous empirical studies to explain BMP or conservation practice adoption into four areas: farmer and farm household characteristics, farm biophysical characteristics, farm financial characteristics, and their attitudes and environmental awareness (Knowler and Bradshaw 2007; Prokopy et al. 2008; Baumgart-Getz, Prokopy, and Floress 2012). Due to the fact that previous studies have different research regions, data collection processes, BMP types considered, and analytic tools used, these syntheses show mixed results, and they do not point any factor consistently explaining BMP adoption.

4.2.1 Modelling BMP Investments

Most studies model BMP adoption grounded on the utility maximizing theory. Agricultural economists use expected net returns of agricultural and environmental production as the building blocks of utility function, BMP adoption can also be embedded into the utility function as the decision variable. The expected net return is subject to the budget constraint including the investment return, pecuniary costs, farm profits, farm wealth, and other economic factors (Feather and Goodwin 1993; Weaver

1996; Shively1997; Uris 1997; Fuglie 1999; Soule, Tegene and Wiebe 2000). After solving the first-order condition, BMP investments can be represented by a group of economic factors. Then, researchers can use a latent variable method to model BMP adoption. The latent variable method assumes that an unobserved latent value determines individual choices. Previous studies specify the latent value as a linear combination of economic factors, and use discrete choice models to estimate BMP adoption (Gould, Saupe, and Klemme 1989; Bosch, Cook, and Fuglie 1995; Soule, Tegene, and Wiebe 2000; Pautsch et al. 2001; Somda, Nianogo, Nassa, and Sanou 2002; Dupraz et al. 2003; Amsalu and Graaff 2007). In the next step, researchers can develop the latent variable method to model BMP adoption rates by using OLS models, Tobit models, double-hurdle models, and switching-regression models (Ervin and Ervin 1982; Norris and Batie 1987; Uri 1997; Ma et al. 2012; Abdulai and Huffman 2014).

The random utility model (RUM) of McFadden (1974) is an alternative method to interpret BMP adoption. Farmers would like to adopt BMPs when their utilities of adoption are greater than the utilities without adoption. The utility function is approximated by financial support, pecuniary costs, and income conditioning on farm physical and socioeconomic characteristics. Similar to the latent variable method, previous studies employ binary choice models to estimate BMP adoption (Rahm and Huffman 1984; Fuglie and Bosch 1995; Cooper and Keim 1996; Fernandez-Cornejo and Ferraioli 1999; Lambert, Sullivan, Claassen, Foreman 2007). Researchers also extend RUM to fit different research questions, such as polychotomous-choices of different farming plans by using a multinomial logit model or a nested logit model (Wu and Babcock 1998; Wu, Adams, and Kling 2004; Moreno and Sunding 2005; Lambert, Sullivan, Claassen, Foreman 2007), sequential choices of farming practices by using a bivariate probit model (Khanna 2001), interrelated strategies of BMP adoption by using system equations (Park and Lohr 2005), choice experiments of willingness to provide ecosystem services (Broch et.al 2013), and BMP adoption rates by using a Tobit model or a switching-regression model (Adesina and Zinnah 1993; Baidu-Forson 1999). Regardless of which theoretical frameworks researchers start from, their empirical models converge to a similar conditional mean function, and BMP adoption as the farm investment is always specified as being determined by a group of economic factors.

Following previous literature, in this study, BMP adoption as the farm investments is subject to farm financial conditions. As the most valuable asset, land determines a farm's financial health, and thus land wealth also affects BMP adoption. Moreno and Sunding (2005) as well as Davey and Furtan (2008) attempt to use assessed values of land and buildings to measure the wealth effect on BMP adoption, but cannot find evidences that the asset value has any significant impact on the adoption of conservation practices. One possible explanation is that landowners' decisions are more likely to respond to wealth changes but not wealth values. Zhang and Nickerson (2015) conclude that the urban housing market bust during 2007-2008 significantly decreases farmland values, but increased commodity demands over the period stabilize farmland wealth. The financial shock during 2007-2008 is an exogenous incident. We hypothesize that the decreasing farmland values during the period would affect landowners' decisions of BMP adoption.

4.2.2 Social Interactions

In addition to economic factors, numerous researchers interpret BMP adoption using psychological theory. Pioneered by Ervin and Ervin (1982), researchers try to understand BMP adoption by a two-stage framework: the perception stage and the decision stage (Norris and Baties 1987; Gould, Saupe, and Klemme 1989; McNamara, Wetzstein, and Douce 1991; Traore´, Landry, and Amara 1998; Daberkow and McBride 2003). At the perception stage, a farm household perceives that environmental problems such as the water pollution and the soil erosion have occurred near its farm, and may potentially affect its farm returns, asset values and the household health. At the decision stage, the household decides whether or not to adopt conservation plans to address these problems, and the decision is motivated by the first stage. To match the two-stage framework, the empirical model estimates the perception step firstly, and then estimates the BMP decision including an explanatory variable of the predict perception or the residual from the first step. Lynne et al. (1988) firstly explain the fundamental linkage between farmers' attitudes and their behaviors, and they conclude that conservation attitudes, social norms, and social situations lead to conservation behavioral intentions or actual conservation behaviors. Following these pioneer theories, Baumgart-Getz et al. (2012) summarize 46 studies of BMP adoption over 25 years, and show that both environmental awareness and attitude have positive effects on BMP adoption.

However, few studies have examined whether interactions with their communities affect farmers' contribution to environmental services. Pesticides and phosphorus from agricultural activities diffuse into the surface water and lead to eutrophication in water resources; livestock operations also become agricultural disamenity that worsens neighborhood living conditions and decreases residential property values (Ready and Abdalla 2005). Because farming activities affect public environment and residents' living conditions, controlling agricultural run-off by implementing BMPs becomes an ethical decision. Ford and Richardson (1994) review the empirical literature of how ethical beliefs affect individual decision, and they find that among other factors, situation variables such as referent groups, rewards and sanctions, and types of ethical conflict are determinants of ethical decision. Weaver (1996) explains individual contributions to agricultural impact on the environment using the theory of prosocial behavior, and he concludes that if farmers hold altruistic values, they are more likely to make environmental efforts even if they need to sacrifice their profits. Chouinard et al. (2008) also find the similar conclusion that some of farmers are willing to sacrifice their profits to undertake some levels of conservation practices.

In opposite to the ethical or altruistic theory, Michel-Guillou and Moser (2006) believe that social pressures lead farmer to commit to environmental protection, and these authors' results show that promoting farmers' public image is the most important reason for farmers' pro-environmental actions. Mzoughi (2011) finds that social concerns have impacts on farmers' adoption of integrated crop protection and organic farming, and these social concerns refer to satisfying landscape demands, being perceived as a leader by the other farmers, and showing to others one's environmental commitment. Sulemana and James Jr. (2014) show that farmers' identities are correlated with attitudes toward ethical environmental issues, and they define the identity as who they are, how they view themselves, how they view the world around them, and how they think as well as want others to perceive them.

Our study aims to expand previous research on how social interactions affect farmers' adoption of BMPs. Most previous studies use self-rated awareness variables to represent social interaction effects. Farmers are more likely to overstate their motivations for BMP adoption, and thus social interaction effects can be overestimated. Instead of using self-rated variables, our study uses local community demographic information, and community characteristics obtained from exogenous sources to capture social effects on BMP adoption.

4.3 The Conceptual Model

We closely follow Feather and Goodwin (1993)'s work, and assume that farmers consider BMP adoption as an environmental investment. In the long-term, the expected net present value (PV) of the BMP investment is:

$$NPV = \int_{t=0}^{T} e^{-rt}(R_t - C_t)dt \tag{4.1}$$

where T is the time, r is the discount rate, R_t are all of the expected net revenue from the BMP investment, and C_t are the expected costs associated with BMP adoption. Without the capital constraint, a positive NPV will lead to the BMP investment.

If farmers are facing several investment choices, they will need to compare investments of BMP adoption with other available alternative investments. Our conceptual model assumes that in the long-term farmers are rationing their investments with perfect foresight; BMPs that can be capitalized are durable capital. Farmers will maximize their total net present values of bundle of investments, subject to capital constraint, such as:

$$Max \sum_{j=1}^{J} NPV_j \left[\frac{r}{1-e^{-rT_j}}\right] y_j \tag{4.2}$$

$$Subject\ to: \sum_{j=1}^{J} I_j y_j \leq C$$

where NPV_j denotes the net present value for the investment j with associated continuous time amortization factor in the bracket; y_j is the a binary decision of BMP investment (if adopt a BMP, then $y_j = 1$). I_j is the amount of investment for project j, and C is the available amount of capital resources for investment. Farmers will compare the net present value of BMP investments with alternative investments, and maximize the total net present value in the long-term.

In addition, previous studies show that farm and farmer's characteristics, government requirements and incentive programs can also affect the choice of BMP investment (y_j), and thus change net present values of BMP investment (NPV_j). As a result, we include the biophysical constraint, the government regulation constraint, the technology constraint, and other constraints to restrict BMP investment. The fully specified conceptual model can be described as:

$$Max \sum_{j=1}^{J} NPV_j \left[\frac{r}{1-e^{-rT_j}}\right] y_j \tag{4.3}$$

$$Subject\ to: \sum_{j=1}^{J} I_j y_j \leq C$$

$$\sum_{j=1}^{J} \mathrm{A}_{ij} y_j \leq b_i \; for \; all \; i$$

where the group of constraints refers to all factors affecting BMP investment and other investments. The subscript i indicates the ith constraint, the A_{ij} is the coefficients for the ith constraint under the jth investment, and the b_i refers to the available resource for ith constraint. To satisfy the order condition, $i \geq j - 1$.

From the first order condition, solutions of our model are denoted as: y^*, a vector of optimal decisions of investment. The optimal decision of BMP investment ${y_j}^*$ is determined by an unobserved function v_j. The v_j consists of net present value of investments (NPV), available amount of capital resources for investment (C), technical coefficients affecting BMP adoption (A_i), resource limit (b_i), and investments of all projects except the amount of BMP investment (I_{-j}) conditioning on socioeconomic characteristics (θ). Formally, the optimal decision of BMP investment ${y_j}^*$ is described as follows:

$$\begin{aligned} {y_j}^* &= 1 \quad if \;\; v_j\left(NPV, C, \mathrm{A}_i, b_i, I_{-j} \middle| \theta\right) > 0 \\ {y_j}^* &= 0 \; if \;\; v_j \leq 0 \end{aligned} \tag{4.4}$$

where the subscript $(-j)$ denotes any investment other than project j.

In particular, the available capital resources (C) include available cash for investment and borrowing capacity. The available cash for investment is determined by income, costs and savings, while farmer borrowing capacity is evaluated by farm asset value. The available cash for investment can be measured by income level, income sources, and share of income contributed back to farming. Farmer borrowing capacity cannot be observed directly, but can be approximated by land wealth partially because farmland wealth is the most valuable asset on the farm. Increasing farm wealth can possibly improve landowners' borrowing capacity, and increase the possibility to invest on environmental improvement; oppositely, the decline of farm wealth may affect farmer borrowing capacity, change risk attitudes of landowners, and discourage their environmental investments in the future. In respond to decreasing land values, some landowners even leave farm business by selling out their lands. Therefore farmers are less likely to implement BMPs on their lands if land wealth is decreasing.

To simplify mathematical terms, let v^* be an unobserved value determining observed decisions of adopting BMPs (${y_j}^*$). v^* can be linear determined by a vector of economic variables (X) and an unobserved random term (u). To be specific, the latent value (v^*) is modelled as follows:

$$v^* = X'\beta + u \qquad where \quad u \sim N(0, \sigma_u^2) \tag{4.5}$$

$$y = 1\ (adoption) \qquad if \quad v^* > 0$$

$$y = 0\ (no\ adoption) \qquad if \quad v^* \leq 0$$

where β is the coefficient vector associate with variables X. X includes net benefit of BMP adoption, available capital, other investments, biophysical resource limit, and socioeconomic characteristics. Then, we can derive the probability of adopting a BMP ($y = 1$) conditioning on socioeconomic variables (θ):

$$Prob[y = 1|\theta] = Prob[v^* > 0|\theta] = Prob[x'\beta + \varepsilon > 0|\theta]$$

$$= 1 - F(-x'\beta|\theta) = F(x'\beta|\theta) \tag{4.6}$$

where $F(.)$ is a cumulative distribution function. As we discussed in the literature review, we hypothesize that in addition to economic factors, social interactions with local communities (s) may affect adoption decisions. To simplify the empirical estimation, we suppose that economic factors and social interactions are linear combination of the reduced form of our model. Finally, the equation 4.7 can be rewritten as follows:

$$Prob[y = 1|\theta, s] = F(x'\beta|\theta, s) \tag{4.7}$$

We assume that $F(.)$ follows the normal distribution function $\Phi(.)$, and a Probit model can be used to estimate the probability of using a BMP.

$$Prob[y = 1|\theta, s] = \Phi(x'\beta|\theta, s) \tag{4.8}$$

4.4 Study Area

The study area is in the Kentucky River watershed covering 7,000 square miles across 42 counties with 16,000 miles of streams. The 700,000 residents in this area use about 100 million gallons of water per day from streams and reservoirs in the watershed. More than 2,075 square miles of the watershed have been designated as priority watersheds (sub-watershed), impacted by pathogens, nutrients, habitat, alterations, siltation, low dissolved oxygen, and metals (Carey 2009). We use the same survey as described in the previous chapter. Data were from a mail survey of farmers in the watershed across 35 counties from 2011 to 2012 with 23% response rate. We selected 357 valid observations that contained at least some completed responses regarding to BMP-related questions and were used in the final analysis. Our survey questions included farmer participation in current government-funded environmental programs, their potential adoption of additional BMPs through a proposed Water Quality Trading (WQT) program, socioeconomic characteristics and their zip codes. The survey asked farmers questions about current BMPs implemented and the extent to which farmers would adopt more

BMPs if compensated through WQT. Table 2.3 presents all variables and summary statistics for the entire sample. Table 2.4 explains discrete levels in explanatory variables.

We also collected land value and local community data in our study area from the publicly available data. The land wealth data are obtained from the U.S. census of agriculture in the county levels. By using the zip code information, we can attach publicly available data to our survey data. The 2013 Urban Influence Codes (UICs) obtained from the U.S. Department of Agriculture Economic Research Service (USDA ERS). The UICs distinguish all counties, county equivalents, independent cities in the U.S. into 2 categories (metro and non-metro counties) with 12 groups. The metropolitan counties are further divided into two groups by the population size. The nonmetropolitan counties are categorized into 10 levels by the degree of urbanization and adjacency to metro areas. The USDA ERS releases UICs data every ten years. The 2013 UICs data is the closest date to match our 2012 survey data. Housing density, population density and residential housing values are collected from the U.S. census bureau.

4.5 Empirical Model

As shown in our conceptual model, we estimate decisions of BMP adoption by using Probit models. Farmers who answered “not possible for me” are excluded in the analysis of BMP adoption. In the model of each BMP, the dependent variable is a binary choice of whether farmers would like to accept our offer to adopt the corresponding BMP (1 if yes, 0 if no). In addition, we also use a dependent variable indicating whether farmers would accept our offer to adopt any of the five BMPs (1 if yes, 0 if no) to investigate whether there are common factors explaining BMP adoption in our study area. The independent variables include compensations for BMP adoption, wealth effects, local community characteristics, farming plans, socioeconomic characteristics, and information treatments. Except variables of farming plans, all models use the same set of independent variables to explain the adoption of five BMPs.

4.5.1 Variable Specification

In our models, we measure wealth changes by using percentage differences of land values between 2007 and 2012. Due to limited access to the census data, we can only collect land value data at the county level from the U.S. census of agriculture. Percentage differences of estimated market values of land and buildings per acre between 2007 and 2012 ($\Delta L_{\%}$) are calculated as follows:

$$\Delta L_{\%} = \frac{\delta L_{2012} - L_{2007}}{L_{2007}} * 100\% \qquad (4.9)$$

where L_{2007} and L_{2012} denote market values of land and buildings per acre in 2007 and 2012 respectively, and δ =0.9 is the deflation index. We assume that if farmers have experienced land value decrease in the last five years, the decline of their land values would discourage their willingness to adopt BMPs in the future. Table 4.1 summarizes changes of land values in our study area and all of counties in Kentucky from 1997 to 2012. During 2007 -2012, there are 69% of counties in our study areas with decreased land values, and 61% of counties in the state with decreased land values. In addition, the table also shows that the average differences of farmland values in our study area have significantly decreased between 2007 and 2012, while average land values consistently increased between 1997 and 2002, and between 2002 and 2007. It indicates that the financial crisis has a significant shock on farmland values in our study area.

As we introduced in the literature, this study understands effects of social interactions from three aspects: social pressure, residential demands, and local agricultural and recreational business effect. The social pressure effect cannot be observed using secondary data. Even if our survey asks attitude questions about social pressure, the impact will likely be underestimated since most respondents may not acknowledge that their environmental behaviors are a result from social pressure. As a result, we approximate this effect by using an urban indicator and a rural index calculated from the 2013 UICs obtained from the USDA ERS. In our studies, if respondents are in metropolitan counties, metro dummies are equal to one, but rural indexes are equal to zero; if respondents are in the nonmetropolitan counties, metro dummies are equal to zero, and rural indexes are equal to corresponding UIC values of nonmetropolitan counties. Our hypothesis is that if farms are in rural counties, when they pollute water resources, they are less likely to be detected. Hence, without public supervision, farmers have the incentive not to adopt BMPs; in other words, living in rural counties may not have any effect on farmers' BMP adoption. In our study, we would like to consider these indexes to have controlled the effects of public supervision in our model rather than to capture social pressure effect precisely.

Expected results of urban effects are mixed. On the one hand, if farms are in metro counties, they are more likely to be exposed to the public if they produce water pollution. Thus, farmers in metro counties are more likely to adopt BMPs to control agricultural run-off because of social pressures. On the other hand, if farms are in metro counties, farmlands are more likely to be converted to non-agricultural usage lands- developed lands-in the future if they are not participating in conservation easement programs. At the same time, building up riparian buffers, animal fences and waste storage facilities are more likely to increase conversion costs from agricultural lands to developed lands. Agricultural land values are determined by agricultural production, nearby developed land values, and the conversion cost (Capozza 1989). Consequentially, adopting BMPs will increase the conversion cost, and may potentially decrease land values when landowners sell their lands. Therefore, farms in metro counties are also less likely to adopt BMPs if they are planning to sell their lands. Our research cannot separate positive and negative effects of metro areas on BMP adoption, but our result can provide the net effect.

We approximate residential effects by using housing densities and residential housing values. The housing density is the total numbers of residential housing units in the 2010 divided by the corresponding county area. The residential housing value is the 5 years average median housing value of owner-occupied housing units from 2008 to 2012. Similar to the metro effect discussed above, we hypothesize that surrounding residential development may increase attention to farmers' environmental awareness and exert social pressures, and thus have a positive effect to BMP adoption.

Local agricultural recreation effect can be measured by the income from agricultural tourism and recreational services from the U.S. census of agriculture. Unfortunately, data of agricultural recreational services are unavailable and a large portion of data is missing. In order to control for water quality demand from agricultural recreational business, our study selects the equine business to capture this effect. Based on the Kentucky equine survey (2012), the value added effect of total equine industry impacts, which is defined as new income paid to workers, profits earned by businesses or dividends paid to shareholders, is estimated to be 1.4 billion dollars in Kentucky. As one of major agricultural recreation industries in Kentucky, farms with equine business and horse riders also demand better environmental quality and amenity. Most of respondents live in counties with large amount of equine inventory. For example the Fayette county, the Bourbon county, and the Woodford county are top three equine inventory counties in Kentucky. Increasing equine recreational business in their communities or on their farms will motivate farm households to commit to pro-environmental actions. In our survey, although several respondents state that they have horses or ponies on their farms, whether or not having horses or ponies may not be appropriate to measure this effect. First, we cannot determine whether the horses or ponies on their farms are raised for recreational business such as riding or for farm owners' personal uses. Second, the presence of horses or ponies cannot capture the effect of the entire equine business in the community. Third, only a small portion of respondents mention they have horses or ponies on their farm, thus our data are limited. An alternative solution is to use inventory of horses and ponies owned by farms from the U.S. census of agriculture as a proxy variable to measure this effect. The equine inventory includes horses bred for sales or racing, and horses and ponies for recreation. As a result, the number of horses and ponies are positively correlated with equine recreational activities. As a result, we use the inventory of horses and ponies owned by farms to control for equine recreational business in local communities.

Farming planning is found to determine BMP adoption in previous literature. In addition to obtain economic benefit, farmers also consider whether BMPs can be incorporated into their current and future BMP plans. In our research, current BMP plans refer to farmers current BMP adoption, and future BMP plans denote synergy of BMPs in the future. Current BMP adoption is captured by a series of dummy variables of whether farmers are currently using any of five BMPs. The synergy effect implies some BMPs may be always adopted together, and these effects are also examined by a group of dummy variables of farmers' choices of other BMPs.

Socioeconomic characteristics are obtained from our survey, and include age, gender, education level, water recreation activities and farming experiences. Farm characteristics consist of farm sizes, whether farms have crop or livestock production, rent percentage, whether farms have surface water on the farmland, participation in Conservation Reserve Program (CRP) and Working-Land Program (WLP). In the end, as we introduced before, we use three dummy variables to measure the effect of information treatment of WQT knowledge on BMP adoption.

4.5.2 Spatial Consideration

Most of previous studies commonly assume that BMP investments are spatial independence or ignore spatial heterogeneity. Spatial dependence in choice outcomes indicates observed choices at one location are affected by choices made at nearby locations. Models without considering the spatial dependence will results in bias, and potentially amplify the omitted variable bias (LeSage and Pace 2009). Spatial heterogeneity arises from spatial error correlation in the model, and will result in inefficiency of estimation (Irwin 2002; Irwin and Bockstael 2004). In our study, dependent variables are stated preferences of BMP adoption. We assume that respondents' stated choices could not be influenced by other observations during the time of the survey, but their decisions are affected by other farmers' current BMP adoption or other unobserved spatial factors. Thus, the spatial correlation arises from the unobserved error term instead of dependent variables.

Deriving from equations 4.5 and 4.8, the probit model with spatial errors is specified as follows:

$$v^{*} = X'\beta + u \tag{4.10}$$

$$where \quad u = \rho W u + \varepsilon \;\; and \;\; \varepsilon \sim N(0, \sigma_{\varepsilon}^{2} I_{n})$$

$$y = 1\ (adoption) \qquad if \;\; v^{*} > 0$$

$$y = 0\ (no\ adoption) \qquad if \;\; v^{*} \leq 0$$

where $v^{*}$is a $n \times 1$ vectors of observations on the unobserved latent variable determining the observed choice of BMP adoption (y); X is a $m \times n$ vector of m observed explanatory variables, and β is a $m \times 1$ vector of parameter associated with X. Following the general framework of spatial error term model, equation 4.10 specifies the spatial correlated error term u. W is a $n \times n$ spatial weights matrix indicating spatial structure of our observations, ρ is a scalar parameter, and ε is assumed to be i.i.d. Furthermore, the reduced form of equation 4.10 can be rewritten as:

$$v^{*} = X'\beta + (I_{n} - \rho W)^{-1}\, \varepsilon \tag{4.11}$$

One technical challenge in our research is to generate the spatial weight matrix. We intend to use the zip code information to identify respondents' spatial correlation.

However, several observations share the same zip code information in our data, so not all of respondents have unique geographic information, and thus the weight matrix cannot be generated properly. One strategy is to aggregate respondents' binary choices in the same zip code into a new variable−the percentage of choices. For example, n% of respondents in the zip code XXXXX would like to adopt riparian buffers. This strategy may highly distort the distribution of data and omit large portions of information. First, some certain areas, such as rural areas, only contain one respondent, so the percentage variable would have extreme values such as 100% or 0%. The extreme value may result in a highly skewed distribution of dependent variable-percentage of choices. Second, numbers of observations are compressed from 356 to 71, and individual's preferences cannot be represented properly. Moreover, effects of socioeconomic characteristics cannot be measured either.

An alternative strategy is to treat respondents in the same zip code as their own neighbors. Thus, we can use full information in our data without any gross aggregation. But some zip codes only have one respondent which means they do not have neighbors, so these observations become "islands". In addition, this strategy only captures the spatial correlation within the same zip code. One solution is to apply two separate weigh matrices in a regression framework: one for the same zip code and define it as a first order continuity matrix, and another for the adjacency zip code and define it as a second order matrix. Incorporating spatial dependence in two spatial weight matrices will capture both neighborhood effect within the same zip codes and neighborhood effect between different zip codes. Bell and Bockstael (2000) propose the GMM approach to address the issue of higher order contiguity matrices, and specify a new spatial error structure as follows:

$$u = \rho_1 W_1 u + \rho_2 W_2 u + \varepsilon \quad (4.12)$$

Following their framework, we can estimate the spatial error model with a second order contiguity matrix by using Kelejian and Prucha's GMM approach (1998, 1999). However, Kelejian and Prucha's method require $|I - \rho_1 W_1 - \rho_2 W_2|$ to be inverted in each iteration. As we discussed in previous sections, several observations are "islands" so that $|I - \rho_1 W_1 - \rho_2 W_2|$ cannot be inverted. Following Pinkse and Slade (1998), Klier and McMillen (2008) linearize their GMM approach so that the computing process does not need to invert $|I - \rho_1 W_1 - \rho_2 W_2|$. Unfortunately, their linearized GMM approach cannot identify spatial error structure. Therefore, the weight matrix is still unsolved in our case. If our model does follow the spatial error structure, the disadvantage of not controlling spatial error term is inefficiency. In contrast, if we use an inappropriate weight matrix, the spatial correlation would be highly distorted, and results are even not reliable. At this stage, unless we find a more appropriate weight matrix, this study decides to not control the spatial error term issue in our research, and results using probit models will suffer inefficiency issues.

4.6 Empirical Results

Table 4.2 reports results of Probit models estimating decisions of five BMPs. In the table, the first column is the model investigating common factors explaining BMP adoption. Results in this model show that current experiences of BMPs, shares of farm investment, gender, education level, and water quality near their farms can influence their adoption decisions.

In particular, if respondents are currently using any BMP on their lands, they tend to adopt additional BMPs through the WQT compensation to abate more agricultural runoff. Respondents with large shares of farm investment are more likely to invest on BMP adoption in the future. Male respondents are more likely to implement BMPs, and farmers with higher education level prefer to use BMPs. Poor water quality near farms would motivate farmers to adopt BMPs. However, there is no statistical evidence found that wealth changes and local community characteristics would affect BMP adoption.

In models of specific BMPs, wealth changes and social interactions have significant impacts on adopting different types of BMPs. At first, the decline of land value between 2007 and 2012 discourage farmers to adopt riparian buffers, but would not affect the adoption of other BMPs. One possible explanation is that building up riparian buffers may need to take large areas on farmlands, and decrease agricultural profits. Increased commodity demands over the period stabilize farmland wealth during the economic recession during 2008 to 2012 (Capozza 1989; Zhang and Nickerson 2015). In order to stabilize farmland wealth, farmers are less likely to build up riparian buffers because it will sacrifice their farm profits.

Our results also find that social interactions with local communities have significant impacts on BMP adoption. If farms are in metro areas, farmers are less likely to adopt riparian buffers. As we discussed in variable specification, landowners in the metro counties are more likely to sell their lands. Farms with riparian buffers have higher conversion costs from agricultural lands to developed lands. Meanwhile, higher conversion costs will decrease farmland values in the land market (Capozza 1989). Therefore, landowners are less likely to build up riparian buffers on their lands in metro counties because they may exit their farm business at any time. When farms are located in rural counties, farmers are less likely to fence off livestock from water resources. This result is consistent with our hypotheses. If farms are located at rural counties, they are less likely to interact directly with the public, and thus social pressure for them to be more environmentally conscious may be less. Farms located at communities with large amount of equine inventory are more likely to adopt animal fences and nutrient management. Residential housing values have negative effects on implementing animal fences.

Our results show that increasing the compensation is more likely to incentivize farmers to adopt riparian buffers, animal fences, and waste storage facilities. The explanation of WQT programs focusing on cost saving information is more likely to encourage farmers to adopt animal fences and nutrient management. Explanations of WQT programs including both cost saving and environmental benefit information are more likely to persuade farmers to consider riparian buffers.

Our results also show some evidences of synergy of BMP adoption. If farmers would like to use riparian buffers, they are more likely to adopt animal fences or nutrient management together. If farmers would like to build up animal fences on their land, they tend to implement riparian buffers, build up waste storage facilities, and adopt no till on their farms. If farmers would adopt more no till on their land, they are more likely to use waste storage facilities and nutrient management at the same time. If farmers would like to build up waste storage facilities, they are more likely to build up riparian buffers and animal fences, and use nutrient management through the WQT program as well. If farmers tend to use nutrient management in the future, they are more likely to implement no till, and build up animal fences and waste storage facilities at the same time.

In addition, if farmers are currently using BMPs, they are more likely to expand the scope of BMPs through our proposed incentive payment program in the future. If farmers are currently using a BMP on their farm, they are more likely to adopt more of the same BMP in the future, except for waste storage facilities. If farmers are currently having riparian buffers on their farms, they are more likely to adopt waste storage facilities. However, not all of current experiences of BMPs have positive effects on the adoption of other BMPs. If farmers are currently having waste storage facilities on their farms, they are less likely to implement riparian buffers and nutrient management. If farmers are currently using nutrient management, they are less likely to adopt no till and build up waste storage facilities.

For demographic and socioeconomic variables, factors affecting BMP adoption include farming experience, land area, rent area, surface water on farmland, percentage of household income from farming, total household income reinvested back to farm, age, gender, education level, income level, water recreation activities, current participation in conservation reserve programs and working land programs, water quality, and minority. Farmers with more farming experiences prefer to adopt additional no till, but may be less likely to use riparian buffers. Large-size farms are less likely to build up animal fences. Farmers who rent more farmland are less likely to adopt no till. Farms with surface water resources are more likely to build up riparian buffers and waste storage facilities to intercept agricultural run-off diffusing into water resources, but are less likely to build up animal fences and use nutrient management on their farms. The percentage of income coming from the farm has positive significant impact on the adoption of animal fences. If farmers invest large shares of their income on their farms, they tend to build up more riparian buffers and waste storage facilities. Older farmers are more likely to adopt riparian buffers, but are less likely to build up animal fences and use no till and nutrient management. Male famers are more likely to use animal fences but are less likely to build up waste storage facilities. Farmers with higher education are in favor of having additional animal fences and nutrient management. Farmers with water related recreation activities at least once a year prefer to adopt riparian buffers. Farm household income has negative effect on the adoption of waste storage facilities. Poor water quality near farms would lead farmers to use more riparian buffers, animal fences, no till, waste storage facilities and nutrient management in the future. If farmers are currently participating in conservation reserve programs, they are less likely to adopt no till. If farmers are currently participating in working land programs, they would not like to adopt nutrient management in the future. Minority farmers are more likely to use waste storage facilities on their land.

4.7 Conclusion

Our study attempts to take into account effects of wealth changes and local community interactions in explaining BMP adoption. We combine our survey data on BMP adoption conducted between 2011 and 2012 in Kentucky with the public data through the geographic information. Wealth changes are measured by percentage differences of the estimated market value of land and buildings between 2007 and 2012; local community interactions are approximated by three aspects: rural effect, urban effect, residential effect, and local farm recreation business effect.

Our results show that decreasing farmland values during the financial crisis discourage the future adoption of riparian buffers. If farms are in metro counties, farm owners are less likely to adopt riparian buffers; when farms are in rural counties, they are less likely to fence off animal from water resources. If farms are located at counties with large amount of equine inventory, they are more likely to build up animal fences and use nutrient management. Residential housing values have negative effects on the adoption of animal fences. In addition, our result also find that increasing the cost coverage compensation can incentivize farmers to further implement riparian buffers, animal fences, and waste storage facilities. One of the interesting findings is that farmers who are currently using BMPs are more likely to expand the scope of their current adoption to abate more agricultural run-off. Our results can help policy maker design a more cost-effective payment scheme, and target willing sellers in the water quality trading market.

The policy implication of our research has two folds. First, if interactions with local communities motivate farmers' commitment to BMP adoption, policy makers could identify potential BMP adopters and promote the adoption in certain communities effectively. Second, if the decline of land wealth discourages farmers to invest on BMP in the future, the traditional cost-sharing payment scheme may not trigger BMP adoption when land values are tracking downward.

4.8 Tables in Chapter 4

Table 4.1 Comparison of Farmland Value in Kentucky and in our Study area

Name	In the study area	In the state
Number of counties with land value decreasing during 2007-2012	69%	61%
Number of counties with land value decreasing during 2002-2007	22%	12%
Number of counties with land value decreasing during 1997-2002	31%	28%
Average estimated market values of land and buildings per acre 2012	$ 2880.06	$ 2599.95
Average estimated market values of land and buildings per acre 2007	$ 2947	$ 2589.62
Average estimated market values of land and buildings per acre 2002	$ 2422.83	$ 2080.42
Average estimated market values of land and buildings per acre 1997	$ 2154.26	$ 1867.38
Average differences of land value between 2007 and 2012	$ -66.94	$ 10.33
Average differences of land value between 2002 and 2007	$ 524.17	$ 509.20
Average differences of land value between 1997 and 2002	$ 268.57	$ 213.03

Note: The dollar value in 2007 is the base value. The inflation calculation is calculated by using the U.S. inflation calculation from (http://www.usinflationcalculator.com/)

Table 4.2Table 4.2 Probit Model Estimating Decisions of BMP Adoption

	All BMPs included	Riparian buffers	Animal fences	No till	Waste storage facility	Nutrient manageme nt
Land value and local characteristics						
Percentage differences of land value between 2007 and 2012	0.687	29.349***	-0.004	0.738	-2.774	-1.243
	(0.785)	(11.397)	(2.317)	(2.05)	(1.843)	(2.194)
Housing density in 2012	0	0.001	0	-0.002	0	0
	(0.001)	(0.007)	(0.002)	(0.003)	(0.003)	(0.003)
Metro area (=1)	0.096	-5.669***	-1.144	-0.271	-0.373	-0.269
	(0.317)	(2.038)	(0.794)	(0.855)	(0.81)	(0.941)
Rural level	-0.022	-0.106	-0.502***	-0.011	0.049	0.128
	(0.05)	(0.24)	(0.163)	(0.108)	(0.095)	(0.164)
Equine Inventory (1000 unit)	-0.015	-0.922	0.409*	-0.057	0.048	0.517*
	(0.085)	(0.57)	(0.215)	(0.212)	(0.234)	(0.269)
5 years median housing value of owner-occupied housing units (1000 dollars	-0.002	-0.02	-0.034***	0.004	0.004	0.012
	(0.005)	(0.027)	(0.012)	(0.01)	(0.01)	(0.017)
Information provided in the survey: hypothetical cost coverage compensation and explanation of WQT						
Offer	0.004	5.866**	2.967*	0.439	2.707**	0.037
	(0.51)	(2.766)	(1.531)	(1.337)	(1.361)	(1.665)
Cost saving info	0.071	-2.138**	1.181*	-0.039	-0.113	1.552**
	(0.215)	(1.03)	(0.657)	(0.487)	(0.462)	(0.718)
Environmental info	-0.033	0.563	-0.446	0.398	0.707	-0.613
	(0.228)	(0.924)	(0.68)	(0.546)	(0.516)	(0.852)
Joint info	-0.058	1.993*	-0.626	-0.579	0.006	1.1
	(0.208)	(1.026)	(0.551)	(0.465)	(0.524)	(0.679)

(Continued)

Table 4.2 Continued

	All BMPs included	Riparian buffers	Animal fences	No till	Waste storage facility	Nutrient manageme nt
Synergy of BMPs: choices of other BMPs						
Choice of Riparian	-	-	2.675***	-0.31	-0.324	2.044***
	-	-	(0.73)	(0.518)	(0.432)	(0.758)
Choice of fence	-	4.697***	-	0.834*	1.171***	0.011
	-	(1.362)	-	(0.485)	(0.413)	(0.525)
Choice of no till	-	1.373	0.153	-	0.89**	1.557***
	-	(0.904)	(0.5)	-	(0.418)	(0.569)
Choice of waste management	-	-0.75	1.989**	0.848*	-	3.878***
	-	(0.917)	(0.81)	(0.495)	-	(0.886)
Choice of nutrient management	-	1.499	0.993*	1.363***	2.003***	-
	-	(0.953)	(0.542)	(0.462)	(0.474)	-
Current usage of BMPs						
Current use a BMP	0.746***	-	-	-	-	-
	(0.187)	-	-	-	-	-
Current Riparian	-	2.121***	-0.622	-0.729*	0.798*	0.402
	-	(0.788)	(0.491)	(0.408)	(0.424)	(0.482)
Current Fencing	-	-0.815	2.718***	0.369	-0.339	0.063
	-	(0.833)	(0.617)	(0.442)	(0.387)	(0.532)
Current No till	-	0.847	-0.724	2.83***	-0.122	0.825
	-	(1.018)	(0.707)	(0.633)	(0.459)	(0.602)
Current Waste	-	-7.584***	1.067	-0.399	0.353	-2.029**
	-	(2.441)	(1.348)	(0.769)	(0.6)	(0.925)
Current Nutrient	-	-0.907	-0.847	-1.128**	-1.32***	1.841***
	-	(0.84)	(0.548)	(0.562)	(0.495)	(0.566)
Demographic and socioeconomic variables						
Experience	0.001	-0.135***	0.02	0.042**	-0.021	0.036
	(0.008)	(0.046)	(0.021)	(0.019)	(0.017)	(0.023)
Land area	0.038	-0.449	-1.635*	0.514	0.056	-0.21
	(0.163)	(0.401)	(0.945)	(0.613)	(0.218)	(0.253)
Rent percentage	-0.122	0.576	-0.541	-1.373*	-0.402	0.373
	(0.29)	(1.431)	(0.792)	(0.765)	(0.642)	(0.815)
Surface water	-0.043	2.623**	-1.242*	0.228	1.079**	-1.874**
	(0.223)	(1.104)	(0.715)	(0.704)	(0.54)	(0.922)

(Continued)

Table 4.2 Continued

	All BMPs included	Riparian buffers	Animal fences	No till	Waste storage facility	Nutrient management
Percentage of household	-0.003*	-0.152	0.493**	0.033	-0.113	-0.07
income from farming	(0.058)	(0.227)	(0.214)	(0.15)	(0.12)	(0.177)
Total household income	0.113**	1.411***	-0.059	-0.016	0.451***	-0.074
reinvested back to farm	(0.063)	(0.437)	(0.225)	(0.161)	(0.147)	(0.209)
Farms with crop	0.364	-1.137	-0.174	0.67*	-0.264	1.131**
	(0.159)	(0.785)	(0.464)	(0.402)	(0.346)	(0.454)
Farms with	0.038	-1.114	-0.104	-1.502**	-0.114	0.667
livestock	(0.205)	(0.833)	(0.71)	(0.592)	(0.514)	(0.856)
Age	-0.012	0.121**	-0.08***	-0.068***	0.009	-0.05*
	(0.008)	(0.051)	(0.03)	(0.023)	(0.019)	(0.027)
Male	0.443**	-1.339	2.473***	-0.779	-1.43**	1.291
	(0.224)	(1.09)	(0.851)	(0.705)	(0.702)	(0.827)
Education	0.077*	0.082	0.335**	0.021	-0.05	0.442***
	(0.044)	(0.177)	(0.137)	(0.108)	(0.093)	(0.169)
Income level	0.083	-0.01	0.104	0.153	-0.227*	-0.141
	(0.057)	(0.237)	(0.149)	(0.143)	(0.132)	(0.209)
Water recreation	0.185	3.576***	0.556	0.414	-0.578	0.746
activities (=1)	(0.16)	(1.321)	(0.437)	(0.384)	(0.388)	(0.484)
CRP	-	-1.616	-1.272	-2.007***	0.612	1.059
	-	(1.076)	(0.843)	(0.609)	(0.445)	(0.839)
WLP	0.182	-0.445	-0.309	-0.177	0.682	-1.109*
	(0.197)	(0.771)	(0.583)	(0.448)	(0.422)	(0.609)
Water quality	-0.115**	-0.523**	-0.584***	-0.273*	-0.234*	0.312*
	(0.058)	(0.231)	(0.219)	(0.143)	(0.133)	(0.187)
Beginning	0.064	0.522	-0.987	-0.119	0.553	1.057
farmer	(0.302)	(1.061)	(0.972)	(0.674)	(0.685)	(0.92)
Minority farmer	0.204	-1.487	2.493	1.838	2.497**	0.505
	(0.378)	(1.481)	(2.218)	(1.484)	(1.23)	(1.581)
Constant	-0.332	-7.671	4.971*	3.414	-2.902	-7.228
	(1.077)	(6.138)	(2.857)	(2.816)	(2.55)	(3.623)
N	356	149	182	177	150	175
Pseudo R2	0.173	0.717	0.671	0.58	0.477	0.68

Note: 1. *, **, and *** imply 10%, 5%, and 1% significance levels, respectively.
2. Standard errors are below coefficients.

Chapter 5 Conclusion

My dissertation reflects part of my research interests regarding economic analysis of environmental services, and decisions of environmental investments. In particular, my dissertation investigates farmers' current usage of BMPs and their willingness to use additional BMPs through a proposed WQT program in Kentucky. Our results show that not only do economic benefits encourage farmers to adopt BMPs, farmers' current experiences of BMPs, information about payment programs, farming plans, wealth changes, and their social interactions can determine BMP adoption and adoption rates. Hence, BMP adoption is determined by a comprehensive decision making process including economic analysis, biophysical conditions, farming and investment plans in the long run, and social interests. On the one hand, market mechanisms are likely to motivate farmers to implement BMPs and supply trading credits to meet water quality goals; on the other hand, policy makers may need to advertise social values of protecting the environment, and provide more education, training, and other assistance to help farmers become an adopter of BMPs. These efforts will improve the effectiveness and efficiency of WQT programs.

The dissertation is organized around three objectives. The first objective is to investigate farmers' current usage of BMPs in Kentucky, and the factors affecting farmers' choices of BMPs through WQT programs. These steps will improve the market prediction, and help local agency identify farmers' willingness to participate in WQT programs. Chapter two is initiated by our first objective to investigate farmers' willingness to participate in BMPs through a proposed WQT program in Kentucky. A

CVM is used in this section through a survey of farmers in the Kentucky River watershed. The WQT program did not exist in Kentucky when the data were collected, and still does not exist to date. Since the WQT program is designed to offer farmers compensation for implementing BMPs, the CVM question is whether the respondent will accept the offer of some compensation for using the BMPs specified by the WQT program. Five BMPs are featured: riparian buffers, animal fences, no till, waste storage facilities, and nutrient management. The analysis in this section includes two parts: the first part is to investigate the factors influencing farmers' current usage of BMPs; the second part is to estimate farmers' willingness to implement BMPs given different levels of compensation given in a survey. The results show that farmers who participate in the conservation programs are more likely to use BMPs at present, but these farmers may not accept the offer to implement additional BMPs. Farmers' experiences about BMPs are more likely to persuade them to adopt additional BMPs than the level of compensation. The results also find that the practices of animal fences and waste storage facility are responsive to the levels of compensation offered.

Given the result of farmers' willingness to participate in BMPs through our proposed WQT program, my dissertation proposes a second objective: examine how much farmers may engage their lands in BMPs if they decide to implement BMPs, thus to discuss farmers' limited ability to produce trading credits. Chapter three pursues this objective by exploring farmers' potential adoption rates if they decide to participate in WQT programs. This section is conducted using a survey of farmers in the Kentucky River watershed introduced in Chapter two. In addition to asking the question of farmers' willingness to implement BMPs, our survey also asked a follow-up question that how much farmers may adopt the BMPs (in addition to what they have already used) if they are offered compensation through WQT. With respect to five different types of BMPs, about 21.5%, 26.9%, 24.2%, 23.2%, and 18.2% of respondents did not indicate how much they would adopt BMPs. We compare three methods to handle the issue of missing data: deleting the observations with missing values, mean imputation, and the MICE. Following these missing data treatments, we estimate factors affecting how much farmers may engage in BMPs using a Tobit or Poisson model. The results show that increasing the compensation for using BMPs is more likely to encourage farmers to adopt more riparian buffers. In addition, land area, percentage of household income from farming, percentage of total household income reinvested back to farm, and current experience of BMPs are found to affect BMP adoption. Results obtained using MICE are more promising than using the deletion or the mean imputation method.

In addition to economic and demographic characteristics, the third objective is to explore how wealth changes and local community interactions influence farmers' BMP adoption. Understand how social factors and farms' financial well-being affect BMP adoption can improve effectiveness and efficiency of WQT programs substantially, and reduce costs of searching for potential participants. Chapter four aims to address this objective. Chapter four is to investigate the effects of wealth changes and interactions with local communities on BMP adoption in addition to farmers' demographic and socioeconomic variables. BMP adoption as part of farm investment is subject to farm financial condition. The urban housing market bust during 2007-2008 significantly decreases farmland values. The decrease of farm wealth therefore discourages environmental investments such as BMP adoption on farmlands in the future. In addition to economic factors, previous studies also show that social interactions could motivate farmers to commit to environmental services. We develop a conceptual framework to model decisions of BMP adoption, and the decisions are subject to farm’s wealth condition. Then, we specify the linkage between BMP decisions and social interactions with local communities. In the empirical analysis, we combine survey data on BMP adoption conducted between 2011 and 2012 in Kentucky with the public data. Wealth changes are approximated by percentage differences of land values between 2007 and 2012; social interaction effects of local community include urban and rural effect, residential effect, and local agricultural recreation business effect. Our results show that decreasing farmland values discourage the adoption of riparian buffers. If farms are located at metro counties, farm owners are less likely to adopt riparian buffers; when farms are located at rural counties, they are less likely to fence off animal from water resources. If farms are located at counties with large amount of equine inventory, they are more likely to build up animal fences and use nutrient management. Residential housing values have the negative effect on the adoption of animal fences.

5.1 Implication

This dissertation provides four important implications. First, farmers in Kentucky are likely to be encouraged to build up riparian buffers, animal fences and waste storage facilities through the compensation potentially provided by buyers in the WQT market. It implies that the water quality trades that are related to, or targeted at, the three types of BMPs are more likely to succeed through a proposed WQT program in Kentucky. In contrast, there is no statistical evidence supporting that farmers could be encouraged to implement no till or nutrient management through the compensation from these programs. It indicates that tradable permits related to these two practices may not be available in the WQT market. This implication will provide the buyers with information about potential permits in the market, and assist policy makers to design trading ratios and allocate budgets with respect to specific practices.

The second implication from the results is that farmers who are currently using riparian buffers, animal fences, no till, and nutrient management are more likely to expand the scope of these practices to generate additional credits for WQT. It implies that when buyers in the WQT market intend to purchase the emission permits generated from the above four practices, it is efficient for buyers to trade with farmers who are currently using these practices. This implication could also help policy makers target who may participate in WQT programs to supply trading permits.

Third, we show that replacing the missing data with MI-generated values enhances the economic analysis and implications. While our research does not intend to offer a normative strategy, 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, we recommend dealing with missing data by providing results from both the deletion method and the MI method. The mean imputation method is not advisable as it may not generate results as reliable as the other methods especially when the researcher is uncertain about the underlying reasons for missing data.

The fourth implication is that if interactions with local communities motivate farmers' commitment to BMP adoption, policy makers could identify potential BMP adopters and promote adoption in certain communities effectively; if the decline of land wealth discourages farmers to invest on BMP in the future, the traditional cost-sharing payment scheme may not trigger BMP adoption when land values are decreasing.

Appendices

A 2.1 Four Types of Information Given to Farmers in the Survey

Types of the information	The text provide in the survey
Level 1	No additional information provided
Level 2	Information focuses on the cost aspect: The U.S. EPA estimates that annual private point source (e.g., a manufacture factory) control costs were about $14 billion and public point source (e.g., a municipal sewage water treatment plant) costs were about $34 billion. The National Cost to Implement Total Maximum Daily Loads (TMDLs) Draft Report estimates that flexible approaches, such as the water quality trading program, could save $900 million dollars annually compared to the least flexible approach. For example, nitrogen trading among publicly owned treatment works in Connecticut that discharge into Long Island Sound is expected to achieve the required reductions under a TMDL while saving over $200 million dollars in control costs. On the other hand, private non-point sources (e.g., farms) will obtain equal or better economic incentives than what they are currently receiving from government sources**.**
Level 3	Information focuses on the environment aspect: Market-based approaches can also create economic incentives for innovation, emerging technology, voluntary pollution reductions and greater efficiency in improving the quality of the nation's waters. The market-based approaches such as water quality trading provide greater flexibility and have potential to achieve water quality and environmental benefits greater than would otherwise be achieved under more traditional regulatory approaches. The U.S. government supports the creation of water quality trading shares/credits in ways that achieve ancillary environmental benefits and ecological services beyond the required reductions in specific pollutant loads, such as the creation and restoration of wetlands, floodplains and wildlife and/or waterfowl habitat. The government also encourages securing long-term improvements in water quality through the purchase and retirement of shares/credits by any entity.
Level 4	Information focus on both the environment and the cost: Give both pieces of information in scenarios 2 and 3.

A 3.1 Imputation Models (Raghunathan et al. 2001)

1 Linear Regression Model:

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

$$y|x \sim N(x'\beta, \sigma^2)$$

Where $x = (x_1, x_2, x_3, \dots \dots, x_k)'$ is vector of k predictors of y, and is fully observed, β is the $k \times 1$ vector of regression coefficients explaining the correlation between y and predictors x. 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 $\hat{\beta} = [x_o{}'x_o]^{-1}x_o{}'y_o$ and $\hat{u} = (y_o - x_o\hat{\beta})$
2. Generate $\widehat{\sigma^2} = \hat{u}'\hat{u}/g$ where g is a draw from $\chi^2_{n_o-k}$ distribution.
3. Draw $\beta|\sigma^2 \sim N[\hat{\beta},\ \widehat{\sigma^2}[x_o{}'x_o]^{-1}]$
4. Draw $y_m \sim N[x_m\hat{\hat{\beta}},\ \widehat{\sigma^2}]$, $\hat{\hat{\beta}}$ is the most recent draw of β 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, $\hat{\beta}$ 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 χ^2 distribution in step 2 is replace by $n - k$, and x_o in step 3 is replaced by $x = [x_o, x_m]$.

2 Logit Model:

Define y is a variable that follows a logistic model:

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

Where $x=(x_1,x_2,x_3,\dots\dots,x_k)'$ is vector of k predictors of y, and is fully observed, β is the $k\times 1$ 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. Using observed $y_o$and x_o to fit a logistic model to obtain the maximum likelihood estimates $\hat{\beta}$ and its asymptotic covariance matrix V.
2. Let T be the Cholesky decomposition of V where $V=TT^t$
3. Draw β : $\hat{\hat{\beta}}=\hat{\beta}+Tz$ where vector z is a random normal deviates with dimension rows $\hat{\beta}$
4. Using $\hat{\hat{\beta}}$, the most recent draw of β in step 3, to fit

$$P^*=\Pr(y_m=1|x)=\frac{\exp(x_m{}'\,\hat{\hat{\beta}})}{\exp\left(x_m{}'\,\hat{\hat{\beta}}\right)+1}$$

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

3 Multinomial Logit Model:

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

$$\Pr(y = q|x) = \frac{\exp(x'\beta_q)}{1 + \sum_1^{l-1} \exp(x'\beta_q)}\ if\ q > 1, \quad so, \quad \frac{\Pr(y = q|x)}{\Pr(y = l|x)} = e^{x'\beta_q}$$

Where $x = (x_1, x_2, x_3, \dots \dots, x_k)'$ is vector of k predictors of y, and is fully observed, β_q is the $k \times 1$ 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 $x = (x_o, x_m)$

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

2. Draw β : $\widehat{\widehat{\beta_q}} = \hat{\beta}_q + Tz$ where vector z is a random normal deviates with dimension rows $\hat{\beta}_q$

4. Using $\hat{\hat{\beta}}$, the most recent draw of β_q in step 3, to fit

$$P^*{}_q = \Pr(y_m = q|x) = \frac{\exp(x_m{}'\hat{\hat{\beta}}_q)}{1 + \sum_1^{l-1} \exp\left(x_m{}'\hat{\hat{\beta}}_q\right)}\ \ and\ P^*{}_l = 1 - \sum_1^{l-1} P^*{}_q$$

5. Generate a vector u of uniform random numbers with dimension rows y_m.

6. 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 $R_{q-1} < u < R_q$

7. Using y $[y_o, y_m]$ and $[x_o, x_m]$, repeat steps 1 – 6 after appropriate adjustments.

4 Predictive Mean Matching (PMM) Model:

Define y is a variable that follows a normal linear regression model

$$y|x \sim N(x'\beta, \sigma^2)$$

Where $x = (x_1, x_2, x_3, \dots \dots, x_k)'$ is vector of k predictors of y, and is fully observed, β is the $k \times 1$ vector of regression coefficients explaining the correlation between y and predictors x. 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

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

4. Draw $y_m \sim N[x_m\hat{\hat{\beta}},\ \widehat{\sigma^2}]$ to obtain $\widehat{y_m}$ the prediction of y_m.
5. 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

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

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

A 3.2 Imputation Model using Multivariate Imputation by Chained Equation

Table A.1 Variable Definition in the Imputation Model

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"

Continued

Table A1 continued

Variable	Type	Definition
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 $p_5 = 1$

Table A.2 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 back to 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 A.3 Imputation Model for the Two-stage Case

	Imputation model	Imputation condition	Dependent variable	Independent variable c_1	c_2	c_3	c_4	c_5	y_1	y_2	y_3	y_4	y_5	X (Fully observed variables)
	Multinomial logit		c_1		✓	✓	✓	✓						Offer Compensation, Land size, rent percent, surface water, Percentage of household income from farming, Total household income reinvested back to 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	✓		✓	✓	✓						
Stage one	($c_i = 1$ if yes, c_i = 0 if no, c_i =2 if not possible for me)		c_3	✓	✓		✓	✓						
			c_4	✓	✓	✓		✓						
			c_5	✓	✓	✓	✓							
	Linear regression	$c_1 = 1$	y_1							✓	✓	✓	✓	
	Linear regression	$c_2 = 1$	y_2						✓		✓	✓	✓	Offer Compensation, Land size, rent percent, surface water, Percentage of household income from farming, Total household income reinvested back to 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.
Stage two	Linear regression	$c_3 = 1$	y_3						✓	✓		✓	✓	
	Predictive mean matching	$c_4 = 1$	y_4						✓	✓	✓		✓	
	Linear regression	$c_5 = 1$	y_5						✓	✓	✓	✓		

Table A.4 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											Including: Offer, Land size, rent percent, Percentage of household income from farming, Total household income reinvested back to 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							✓	✓	✓	✓	Including: Offer, Land size, rent percent, Percentage of household income from farming, Total household income reinvested back to 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 A.5 Imputation Model for the Three-stage Case

	Imputation model	Condition	Dep variable	Independent 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 which means answer “yes” or “no”, p_i=0 if it is “not possible for me”)		p_1																Including: Offer, Land size, rent percent, Surface water, Percentage of household income from farming, Total household income reinvested back to 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& 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							✓	✓	✓	✓						Including: Offer, Land size, rent percent, Percentage of household income from farming, Total household income reinvested back to farm, farms with livestock, age, gender, education, race, income level, water recreation activities, farming experience, water quality near the farm, participation in CRP or WLP, current usage of BMPs, and information treatments.
		$p_2 = 1$	q_2						✓		✓	✓	✓						
		$p_3 = 1$	q_3						✓	✓		✓	✓						
		$p_4 = 1$	q_4						✓	✓	✓		✓						
		$p_5 = 1$	q_5						✓	✓	✓	✓							

Continued

Table A5 Continued

	Imputation model	Imputation condition	Dep variable	Independent 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)
	Linear regression	$q_1 = 1$	y_1							✓	✓	✓	✓						Including: Offer, Land size, rent percent, Percentage of household income from farming, Total household income reinvested back to 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						✓		✓	✓	✓						
Stage three	Linear regression	$q_3 = 1$	y_3						✓	✓		✓	✓						
	Predictive mean matching	$q_4 = 1$	y_4						✓	✓	✓		✓						
	Linear regression	$q_5 = 1$	y_5						✓	✓	✓	✓							

A 3.3 Rescaled Categorical Variables

Categorical value	Rescaled value		
	Percentage of household income from farming	Total household income reinvested back to farm	Income (1000 dollars)
1	8%	8%	0.5
2	23%	23%	20
3	38%	38%	37.5
4	53%	53%	62.5
5	68%	68%	87.5
6	82%	82%	125
7	97%	97%	233.3

A 3.4 Imputation Assessment

Following van Buuren and Groothuis-Oudshoorn (2011) and Azur, Stuart, Frangakis and Leaf (2011), we examine the distribution of the observed and imputed data visually. For each scenario, I conduct 1000 times of iteration and generate 1000 datasets for assessment. Figures from A1 to A10 display means and standard deviation of 1000 datasets for readers' references. Since the imputation is conducted using the log transformation, the means and standard deviations are also the log transformation term.

Then I conduct imputation assessment from three aspects. First, I compare the means between observed data and imputed data, in order to observe whether there are drastic changes after imputation. Abayomi, Gelman and Levy (2008) conclude that the deviations between the imputed and observed data can be expected under MAR assumption, but researchers should be especially careful of extreme departures. However, it does not imply that the observed mean is the benchmark of the imputation. This comparison is to diagnose the extreme departure.

Second, in datasets from 1000 iterations, I select the 10^{th} and 90^{th} percentile of mean as the bottom and top boundaries of convergence range. Then, I examine whether the means of observed and imputed data across 100 imputation results (the actual imputation for final results) fall into the confidence interval defined in our research. Following existing literature, the 1000 iterations are long enough to justify whether our chained equations are stable and convergence. The underlying idea is that the more numbers of mean of imputation are out of convergence range, the less stable the imputation is.

Third, we investigate whether the mean of observed and imputed data of 100 imputation iterations observed mean falls into the convergence assessment with 1000 iterations.

All in all, the above assessment is to evaluate whether our imputation process is stable and convincible, and the assessment is summarized in Tables A6-A11.

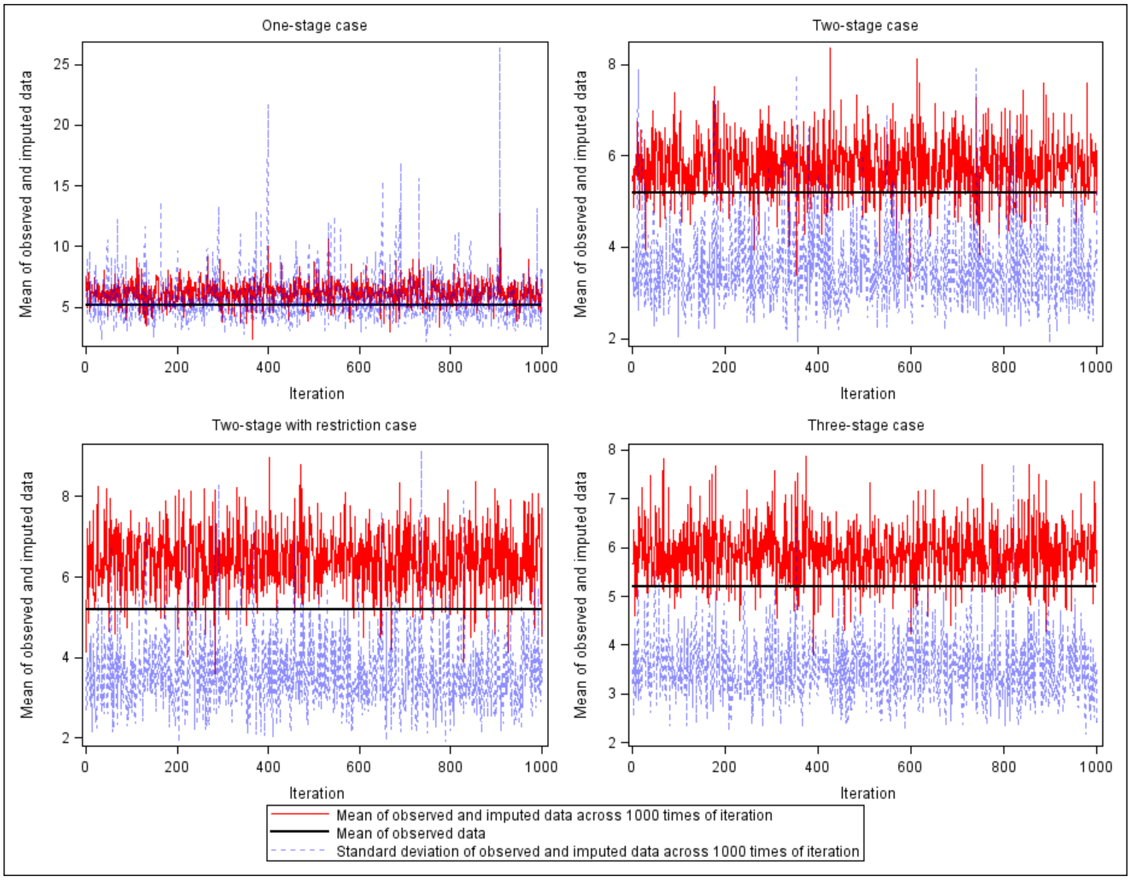

Figure A.1 Assessment of Imputation Convergence for Riparian Buffers

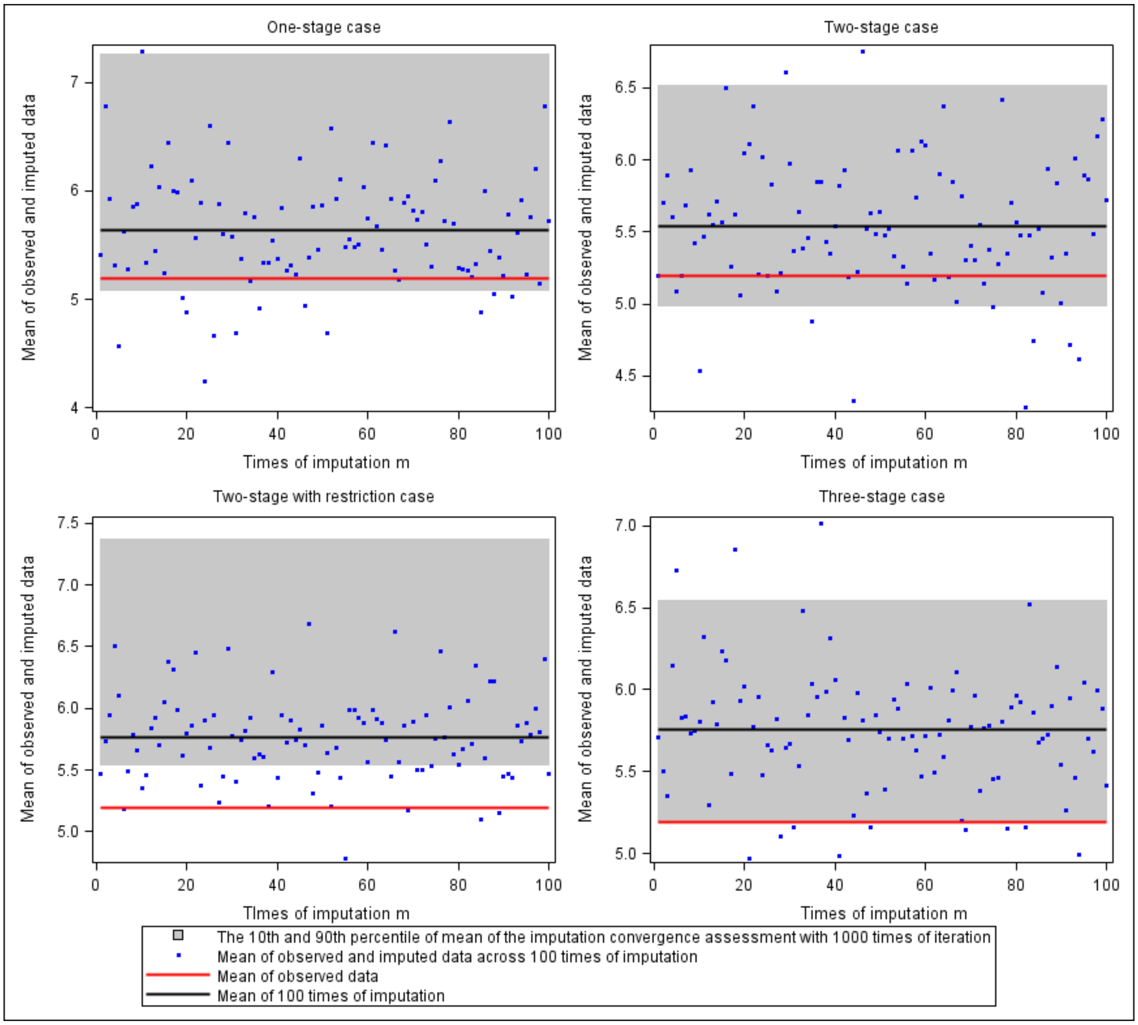

Figure A.2 Distribution of Imputing the Missing Data of Using Riparian Buffers

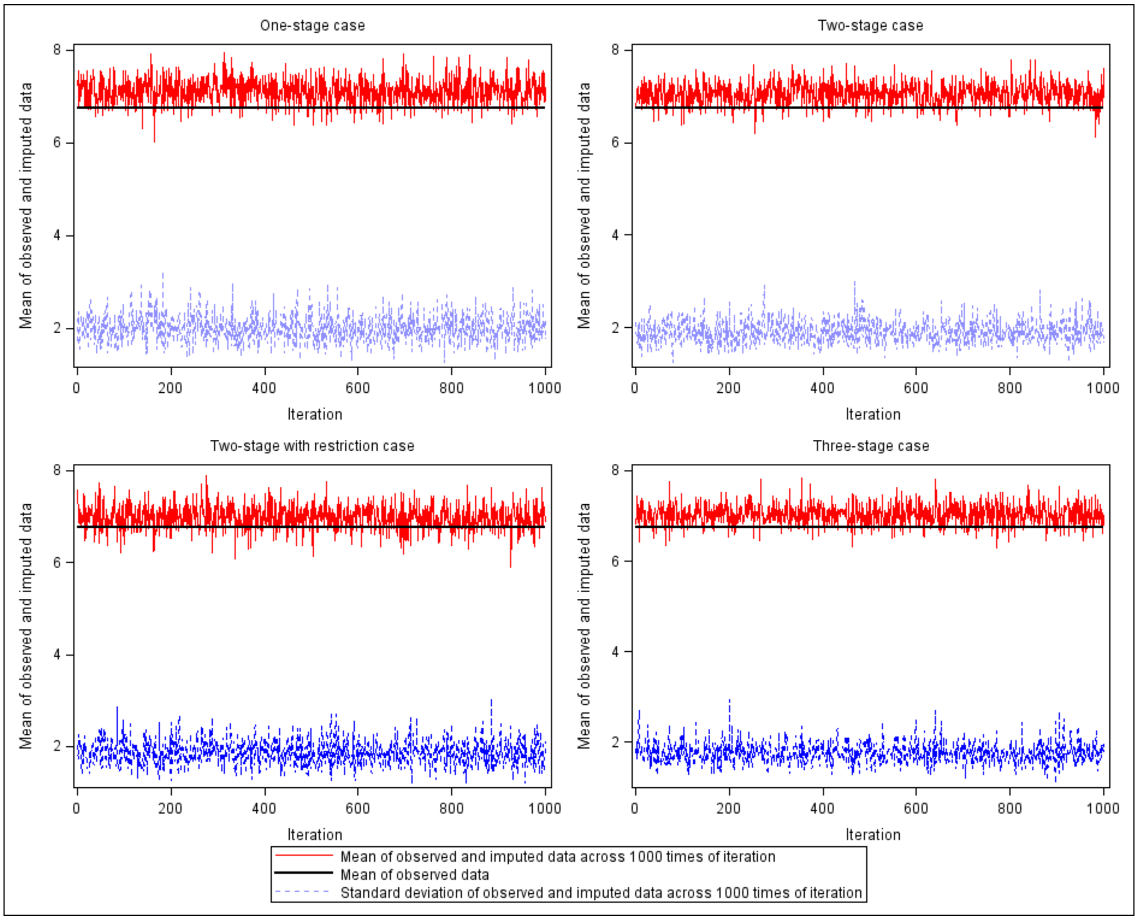

Figure A.3 Assessment of Imputation Convergence for Animal Fences

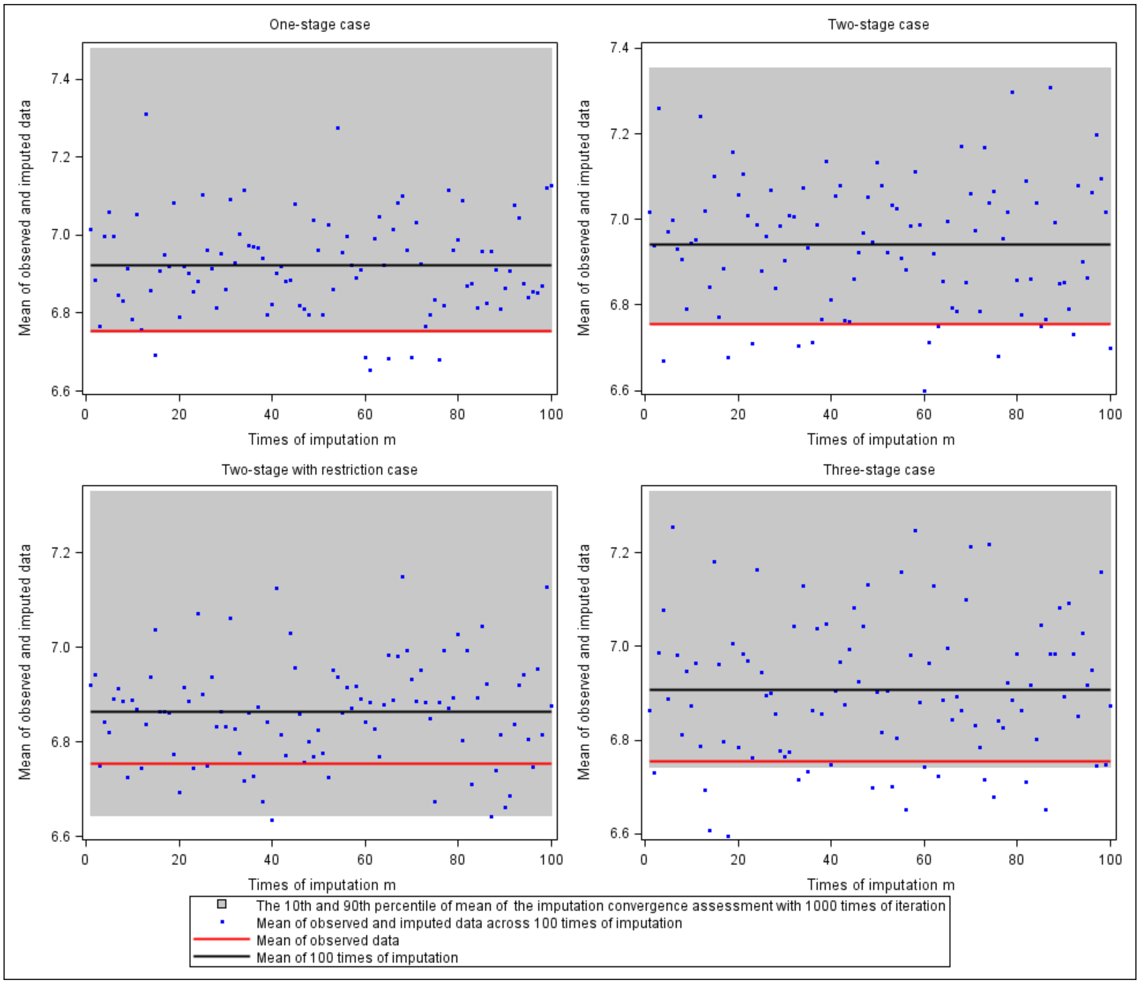

Figure A.4 Distribution of Imputing the Missing Data of Using Animal Fences

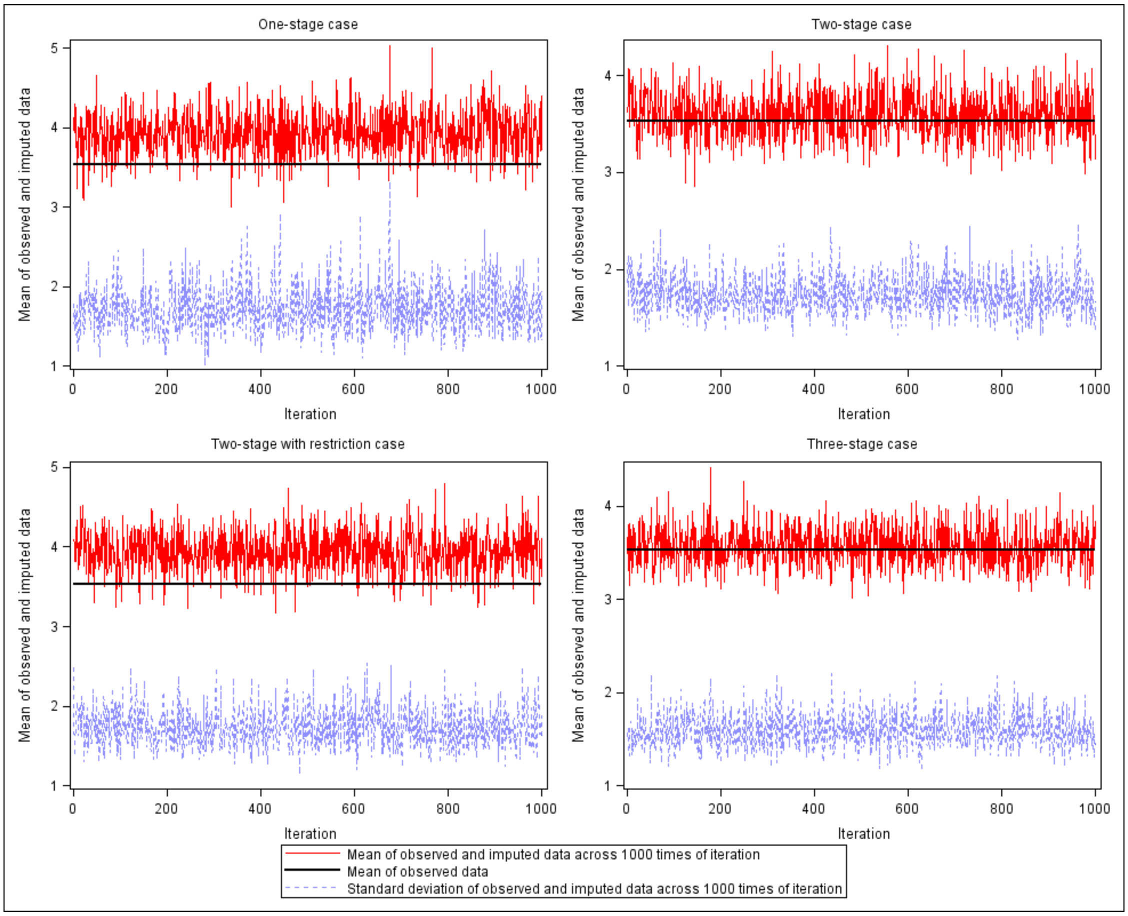

Figure A.5 Assessment of Imputation Convergence for No Till

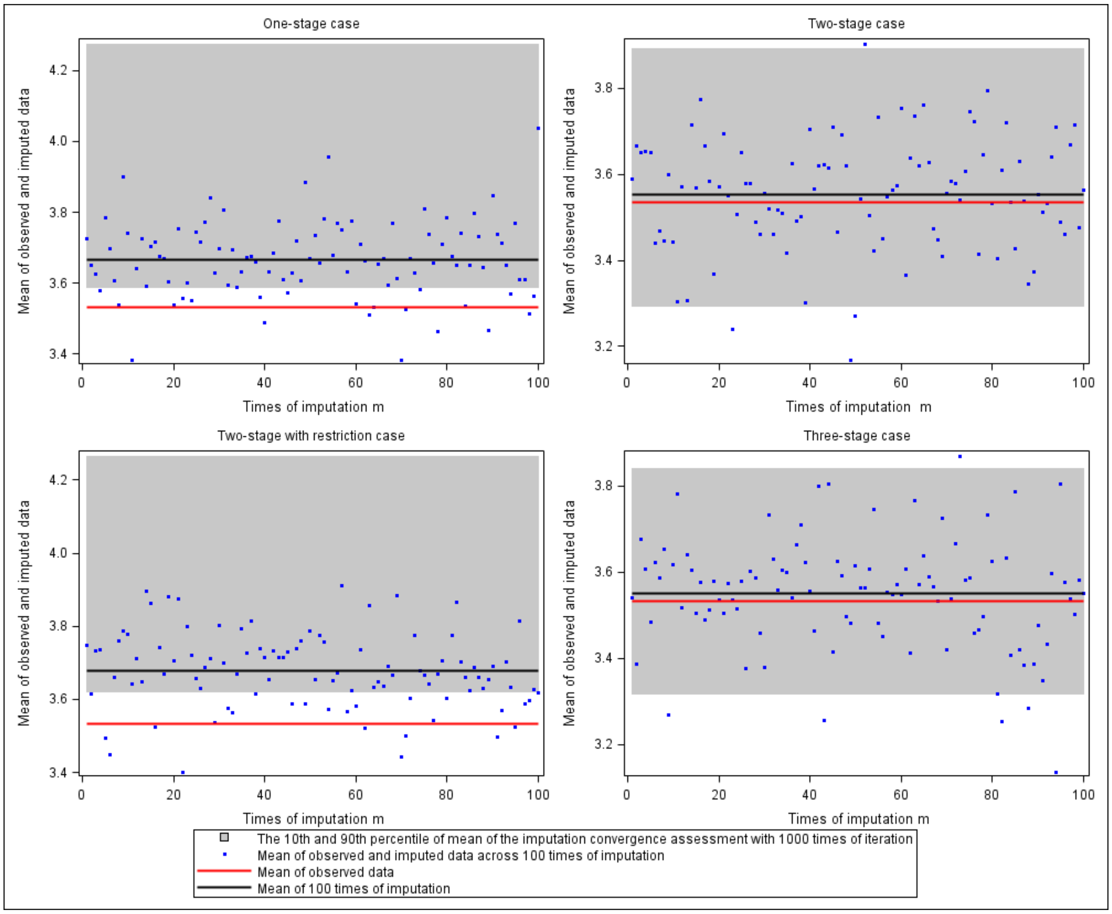

Figure A.6 Distribution of Imputing the Missing Data of Using No Till

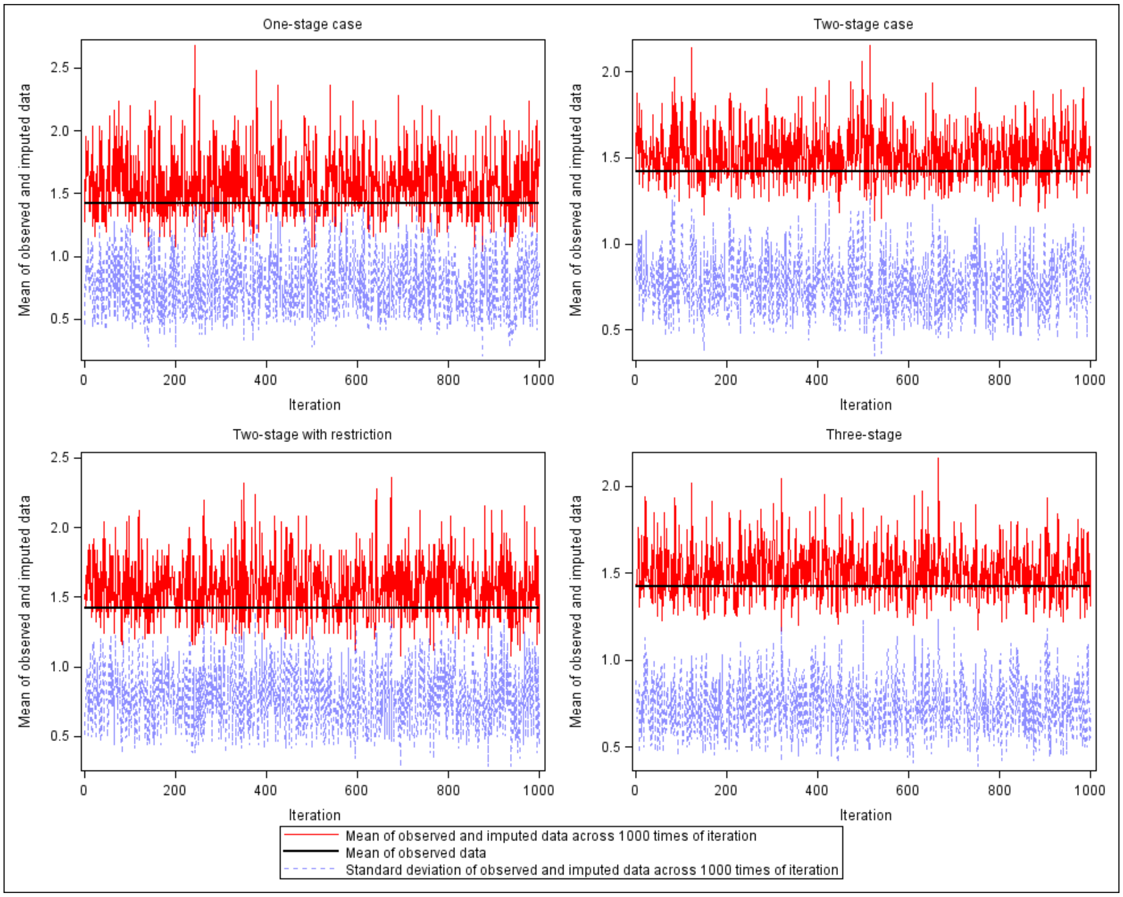

Figure A.7 Assessment of Imputation Convergence for Waste Storage Facilities

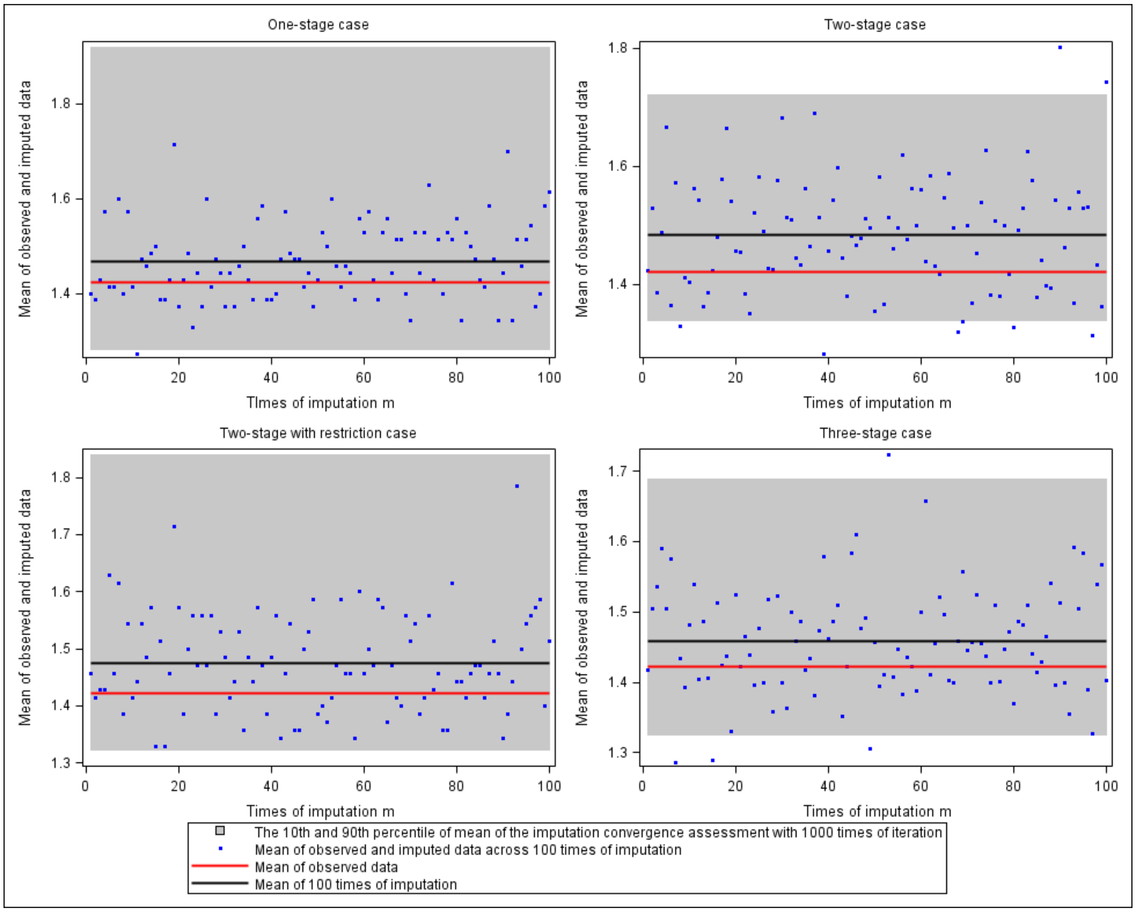

Figure A.8 Distribution of imputing the missing data of using waste storage facilities

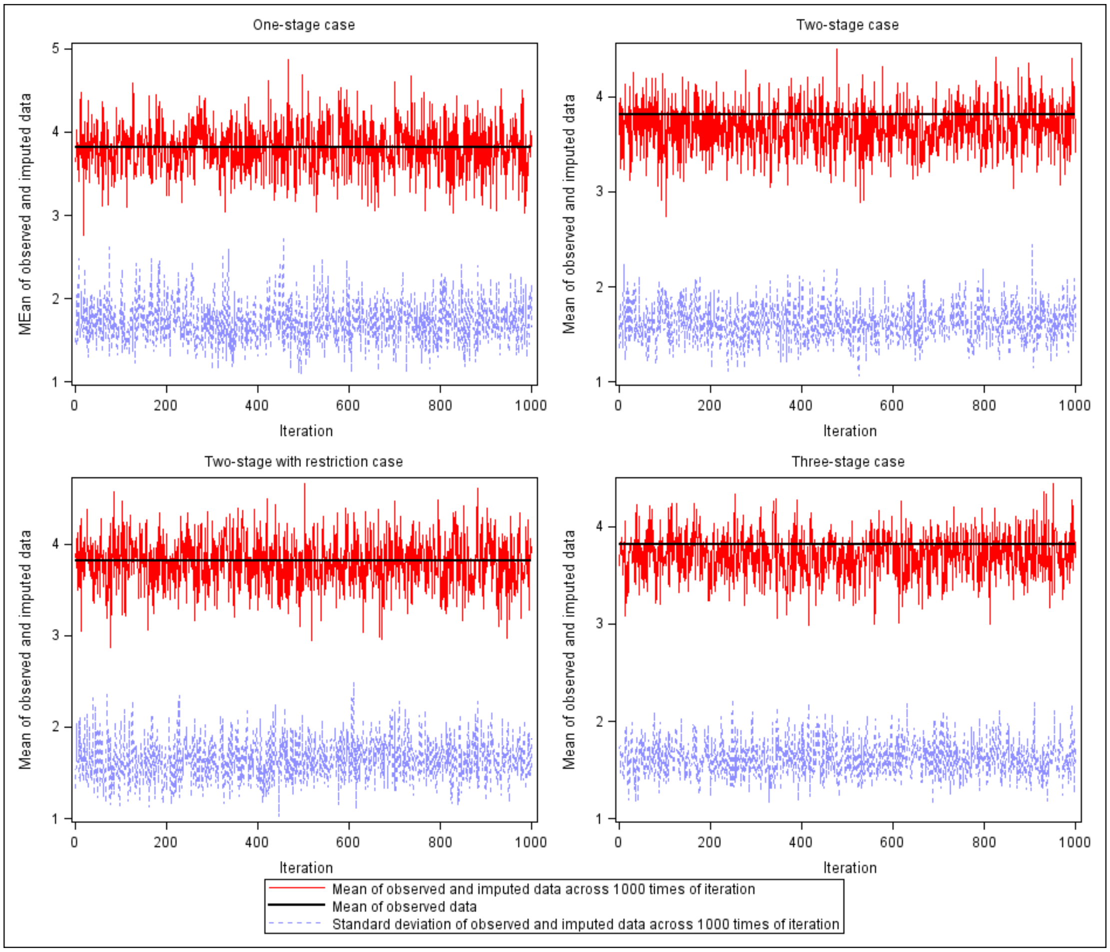

Figure A.9 Assessment of Imputation Convergence for Nutrient Management

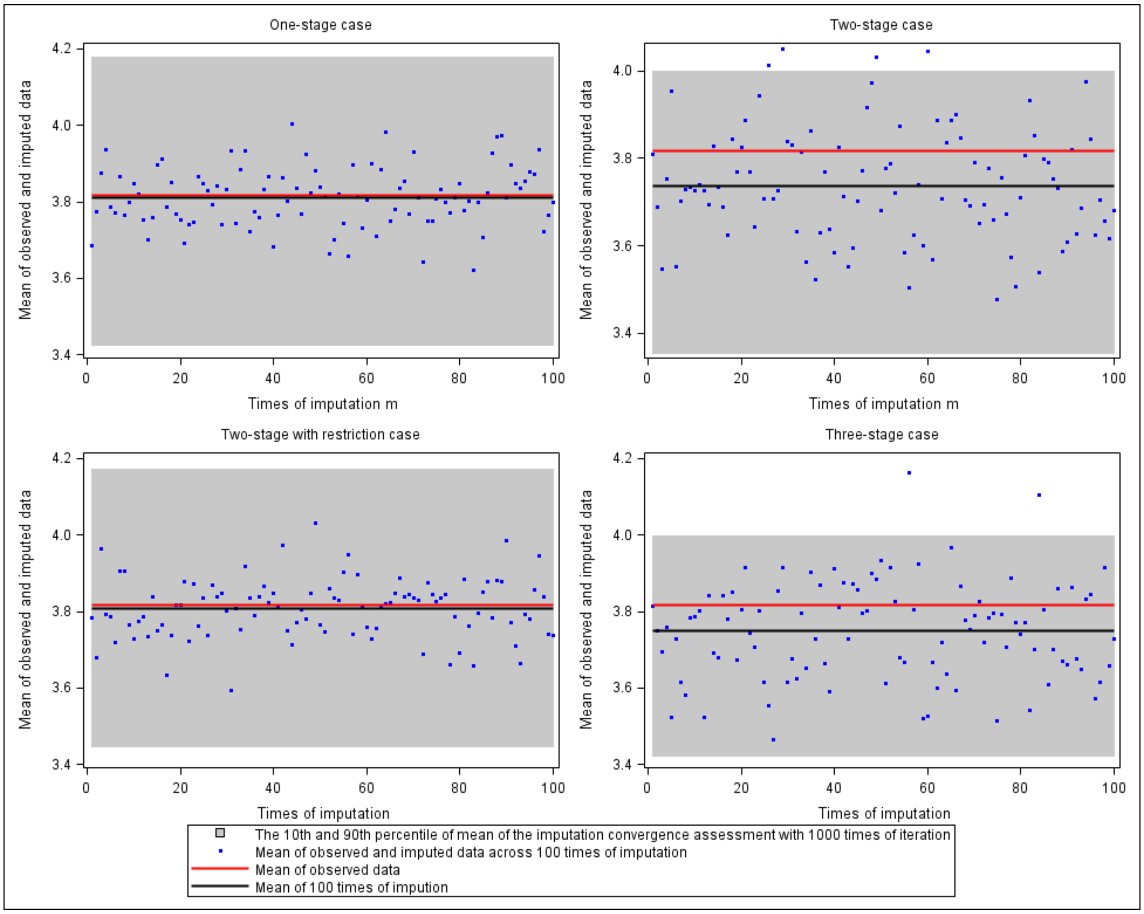

Figure A.10 Distribution of Imputing the Missing Data of Using Nutrient Management

Table A.6 Assessment of the Multiple Imputation for the Missing Data in Using Riparian Buffers

	Univariate	**Two-stage**	**Two-stage with restriction**	**Three-stage**
Distance between observed mean and mean of 100 imputations (The larger the worse)	0.441	0.3493	0.5738	0.5619
Numbers of mean of imputation out of convergence range of 10-90% percentile (The larger the worse)	13	10	21	9
Whether observed mean falls into the 10^{th} and 90^{th} percentile of mean of the convergence assessment with 1000 iterations	Yes	Yes	No	Yes
Rank (Ascending order)	2	1	4	3

Table A.7 Assessment of the Multiple Imputation for the Missing Data in Using Animal Fences

	Univariate	**Two-stage**	**Two-stage with restriction**	**Three-stage**
Distance between observed mean and mean of 100 times of imputation (The larger the worse)	0.1677	0.1881	0.1089	0.153
Numbers of mean of imputation out of convergence range of 10-90% percentile (The larger the worse)	6	12	2	14
Whether observed mean falls into the 10^{th} and 90^{th} percentile of mean of the convergence assessment with 1000 times of iteration	Yes	Yes	Yes	Yes
Rank (Ascending order)	2	3	1	4

Table A.8 Assessment of the Multiple Imputation for the Missing Data of Using No Till

	Univariate	**Two-stage**	**Two-stage with restriction**	**Three-stage**
Distance between observed mean and mean of 100 times of imputation (The larger the worse)	0.1322	0.0203	0.1442	0.0158
Numbers of mean of imputation out of convergence range of 10-90% percentile (The larger the worse)	21	3	26	5
Whether observed mean falls into the 10^{th} and 90^{th} percentile of mean of the convergence assessment with 1000 times of iteration	No	Yes	No	Yes
Rank (Ascending order)	3	1	4	2

Table A.9 Assessment of the Multiple Imputation for the Missing Data of Using Waste Storage Facilities

	Univariate	**Two-stage**	**Two-stage with restriction**	**Three-stage**
Distance between observed mean and mean of 100 times of imputation (The larger the worse)	0.0444	0.0619	0.0531	0.0362
Numbers of mean of imputation out of convergence range of 10-90% percentile (The larger the worse)	1	6	0	4
Whether observed mean falls into the 10^{th} and 90^{th} percentile of mean of the convergence assessment with 1000 times of iteration	Yes	Yes	Yes	Yes
Rank (Ascending order)	1	4	2	3

Table A.10 Assessment of the Multiple Imputation for the Missing Data of Using Nutrient Management

	Univariate	**Two-stage**	**Two-stage with restriction**	**Three-stage**
Distance between observed mean and mean of 100 times of imputation (The larger the worse)	0.0057	0.0798	0.0095	0.0681
Numbers of mean of imputation out of convergence range of 10-90% percentile (The larger the worse)	0	4	0	2
Whether observed mean falls into the 10^{th} and 90^{th} percentile of mean of the convergence assessment with 1000 times of iteration	1	1	1	1
Rank (Ascending order)	1	4	2	3

Table A.11 Summary of the Imputation Assessment

	Univariate	**Two-stage**	**Two-stage with restriction**	**Three-stage**
Riparian buffers	2	1	4	3
Animal fences	2	3	1	4
No till	3	1	4	2
Waste storage facilities	1	4	2	3
Nutrient management	1	4	2	3
Summary (the smaller, the better)	8	13	13	15

References

Abayomi, K., A. Gelman, and M. Levy. 2008. "Diagnostics for multivariate imputations." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 57(3):273-291.

Abdulai, A., and W. Huffman. 2014. "The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application." *Land Economics* 90 (1):26-43.

Adamowicz, W., et al. 1998. "Stated preference approaches for measuring passive use values: Choice experiments and contingent valuation." *American Journal of Agricultural Economics* 80:64-75.

Adesina, A.A., and M.M. Zinnah. 1993. "Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone." *Agricultural Economics* 9 (4):297-311.

Albert, A., and J. Anderson. 1984. "On the existence of maximum likelihood estimates in logistic regression models." *Biometrika* 71(1):1-10.

Allison, P. (2012) "Handling missing data by maximum likelihood." In *SAS Global Forum.* Orlando, FL.

Amsalu, A., and J. De Graaff. 2007. "Determinants of adoption and continued use of stone terraces for soil and water conservation in an Ethiopian highland watershed." *Ecological Economics* 61(2) :294-302.

Arrow, K., R. Solow, P.R. Portney, E.E. Leamer, R. Radner, and H. Schuman. 1993. *Report of the NOAA Panel on Contingent Valuation*. Washington, DC: National Oceanic and Atmospheric Administration.

Azur, M.J., et al. 2011. "Multiple imputation by chained equations: what is it and how does it work?" *International Journal of Methods in Psychiatric Research* 20 (1):40-49.

Baidu-Forson, J. 1999. "Factors influencing adoption of land-enhancing technology in the Sahel: lessons from a case study in Niger." *Agricultural Economics* 20 (3):231-239.

Baumgart-Getz, A., L.S. Prokopy, and K. Floress. 2012. "Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature." *Journal of environmental management* 96 (1):17-25.

Bell, K.P., and N.E. Bockstael. 2000. "Applying the generalized-moments estimation approach to spatial problems involving micro-level data." *Review of Economics and Statistics* 82:72-82.

Bin, O., C.E. Landry, and G.F. Meyer. 2009. "Riparian buffers and hedonic prices: a quasi-experimental analysis of residential property values in the Neuse River basin." *American Journal of Agricultural Economics* 91(4):1067-1079.

Bosch, D.J., Z.L. Cook, and K.O. Fuglie. 1995. "Voluntary versus mandatory agricultural policies to protect water quality: adoption of nitrogen testing in Nebraska." *Review of Agricultural Economics*:13-24.

Braden, J.B., and K.J. Boyle. 2013. "Innovations in Nonpoint Source Pollution Policy: Introduction." *Choices* 28 (3).

Breetz, H.L., et al. 2005. "Trust and communication: Mechanisms for increasing farmers' participation in water quality trading." *Land Economics* 81:170-190.

Broch, S.W., N. Strange, J.B. Jacobsen, and K.A. Wilson. 2013. "Farmers' willingness to provide ecosystem services and effects of their spatial distribution." *Ecological Economics* 92:78-86.

Burgette, L.F., and J.P. Reiter. 2010. "Multiple imputation for missing data via sequential regression trees." *American Journal of Epidemiology* 172 (9):1070-1076.

Buuren, S., and K. Groothuis-Oudshoorn. 2011. "MICE: Multivariate imputation by chained equations in R." *Journal of Statistical Software* 45(3).

Cameron, T.A., and J. Englin. 1997. "Respondent experience and contingent valuation of environmental goods." *Journal of Environmental Economics and Management* 33:296-313.

Carey, Daniel I. 2009. University of Kentucky Geological Survey, Map and Chart 188 Series XII, 2009 (http://kgs.uky.edu/kgsweb/olops/pub/kgs/mc188_12.pdf).

Capozza, D.R., and R.W. Helsley. 1989. "The fundamentals of land prices and urban growth." *Journal of Urban Economics* 26 (3):295-306.

Chen, Y., E.G. Irwin, and C. Jayaprakash. 2009. "Dynamic modeling of environmental amenity-driven migration with ecological feedbacks." *Ecological Economics* 68 (10):2498-2510.

Chouinard, H.H., et al. 2008. "Will farmers trade profits for stewardship? Heterogeneous motivations for farm practice selection." *Land Economics* 84 (1):66-82.

Claassen, R., and E. Duquette. 2012. "Additionality in US Agricultural Conservation Programs A Preliminary Analysis of New Data." Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Seattle, WA, U.S., August 12-14.

Cooper, J.C., and R.W. Keim. 1996. "Incentive payments to encourage farmer adoption of water quality protection practices." *American Journal of Agricultural Economics* 78:54-64.

Daberkow, S.G., and W.D. McBride. 2003. "Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US." *Precision agriculture* 4 (2):163-177.

Davey, K.A., and W.H. Furtan. 2008. "Factors that affect the adoption decision of conservation tillage in the prairie region of Canada." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 56 (3):257-275.

Diamond, P.A., and J.A. Hausman. 1994. "Contingent Valuation - Is Some Number Better Than No Number." *Journal of Economic Perspectives* 8:45-64.

Dupraz, P., et al. 2003. "The environmental supply of farm households: a flexible willingness to accept model." *Environmental and Resource Economics* 25 (2):171-189.

Ervin, C.A., and D.E. Ervin. 1982. "Factors Affecting the Use of Soil Conservation Practices - Hypotheses, Evidence, and Policy Implications." *Land Economics* 58:277-292.

Featherstone, A.M., and B.K. Goodwin. 1993. "Factors influencing a farmer's decision to invest in long-term conservation improvements." *Land Economics* 69:67-81.

Fernandez-Cornejo, J., and J. Ferraioli. 1999. "The environmental effects of adopting IPM techniques: the case of peach producers." *Journal of Agricultural and Applied Economics* 31(3):551-564.

Ford, R.C., and W.D. Richardson. 1994. "Ethical decision making: A review of the empirical literature." *journal of Business Ethics* 13(3):205-221.
Fowler, L.B., M.B. Royer, and J.E. Colburn. 2013. "Addressing Death by a Thousand Cuts: Legal and Policy Innovations to Address Nonpoint Source Runoff." *Choices* 28 (3).
Fuglie, K.O. 1999. "Conservation tillage and pesticide use in the Cornbelt." *Journal of Agricultural and Applied Economics* 31 (1):133-147.
Ghosh, G., M. Ribaudo, and J. Shortle. 2011. "Baseline requirements can hinder trades in water quality trading programs: Evidence from the Conestoga watershed." *Journal of Environmental Management* 92 (8):2076-2084.
Gould, B.W., W.E. Saupe, and R.M. Klemme. 1989. "Conservation tillage: the role of farm and operator characteristics and the perception of soil erosion." *Land Economics* 65(2):167-182.
Greene, W.H. 2007. Econometric Analysis. 6th ed. Englewood Cliffs, NJ: Prentice Hall.
Grittner, U., et al. 2011. "Missing value imputation in longitudinal measures of alcohol consumption." *International Journal of Methods in Psychiatric Research* 20 (1):50-61.
Groves, R.M. 2006. "Nonresponse rates and nonresponse bias in household surveys." *Public Opinion Quarterly* 70 (5):646-675.
Groves, R.M., and E. Peytcheva. 2008. "The impact of nonresponse rates on nonresponse bias a meta-analysis." *Public Opinion Quarterly* 72 (2):167-189.
Haab, T.C., M.G. Interis, D.R. Petrolia, and J.C. Whitehead. 2013. “From Hopeless to Curious? Thoughts on Hausman’s ”Dubious to Hopeless“ Critique of Contingent Valuation.” Applied Economic Perspectives and Policy 35: ppt029.
Hand, M.S., and C.J. Nickerson (2009) “The Role of Cost-Share Rates and Prices on the Size of Conservation Investments in EQIP.” Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Milwaukee, WI, U.S., July 26-28.
Hanemann, W.M. 1994. "Valuing the Environment through Contingent Valuation." *Journal of Economic Perspectives* 8:19-43.
Hausman, J. 2012. "Contingent valuation: from dubious to hopeless." *The Journal of Economic Perspectives* 26:43-56.
Herriges, J.A., S. Secchi, and B.A. Babcock. 2005. "Living with hogs in Iowa: the impact of livestock facilities on rural residential property values." *Land Economics* 81(4) :530-545.
Horan, R.D., and J.S. Shortle. 2005. "When two wrongs make a right: Second-best point-nonpoint trading ratios." *American Journal of Agricultural Economics* 87:340-352.
Horan, R.D., and J.S. Shortle. 2011. "Economic and Ecological Rules for Water Quality Trading." *Journal of the American Water Resources Association* 47:59-69.
Horan, R.D., J.S. Shortle, and D.G. Abler. 2002. "Point-nonpoint nutrient trading in the Susquehanna River basin." *Water Resources Research* 38:8-1-8-12.
Huggins, D.R., and J.P. Reganold. 2008. "No-till: the quiet revolution." *Scientific American* 299 (1):70-77.
Irwin, E.G. 2002. "The effects of open space on residential property values." *Land Economics* 78 (4):465-480.

Irwin, E.G., and N.E. Bockstael. 2004. "Land use externalities, open space preservation, and urban sprawl." *Regional Science and Urban Economics* 34 (6):705-725.
Irwin, E.G., P.W. Jeanty, and M.D. Partridge. 2014. "Amenity Values versus Land Constraints: The Spatial Effects of Natural Landscape Features on Housing Values." *Land Economics* 90 (1):61-78.
James Jr, H.S., and I. Sulemana. 2014. "Case studies on smallholder farmer voice: an introduction to a special symposium." *Agriculture and Human Values* 31(4):637-641.
Kelejian, H.H., and I.R. Prucha. 1998. "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances." The Journal of Real Estate Finance and Economics 17 (1):99-121.
Kelejian, H.H., and I.R. Prucha. 1999. "A generalized moments estimator for the autoregressive parameter in a spatial model." *International Economic Review* 40 (2):509-533.
Kenward, M.G., and J. Carpenter. 2007. "Multiple imputation: current perspectives." *Statistical Methods in Medical Research* 16:199-218.
Khanna, M. 2001. "Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model." *American Journal of Agricultural Economics* 83(1):35-51.
King, G., et al. (2001) "Analyzing incomplete political science data: An alternative algorithm for multiple imputation." *The American Political Science Review.* 95 (1): 49-69.
Klier, T., and D.P. McMillen. 2008. "Evolving Agglomeration in the Us Auto Supplier Industry*." *Journal of Regional Science* 48:245-267.
Knowler, D., and B. Bradshaw. 2007. "Farmers' adoption of conservation agriculture: A review and synthesis of recent research." *Food Policy* 32:25-48.
Lambert, D.M., G.D. Schaible, R. Johansson, and S. Daberkow. 2006. "Working-Land Conservation Structures: Evidence on Program and Non-Program Participants." Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Long Beach, CA, U.S., July 2326.
Lambert, D., P. Sullivan, R. Claassen, and L. Foreman. 2006. Conservation-Compatible Practices and Programs: Who Participates? Washington, DC: United States Department of Agriculture, Economic Research Service.Lambert, D.M., et al. 2007. "Profiles of US farm households adopting conservation-compatible practices." *Land Use Policy* 24:72-88.
Leggett, C.G., and N.E. Bockstael. 2000. "Evidence of the effects of water quality on residential land prices." *Journal of Environmental Economics and Management* 39 (2):121-144.
LeSage, J., and R.K. Pace. 2009. *Introduction to Spatial Econometrics* Boca Raton, FL: CRC Press.
Lin, I.-F., and N.C. Schaeffer. 1995. "Using survey participants to estimate the impact of nonparticipation." *Public Opinion Quarterly* 59 (2):236-258.
Little, R.J. 1988. "Missing-data adjustments in large surveys." *Journal of Business & Economic Statistics* 6 (3):287-296.
Little, R.J., and D.B. Rubin. 1989. "The analysis of social science data with missing values." *Sociological Methods & Research* 18:292-326.

Lynch, L., and S.J. Lovell. 2003. "Combining spatial and survey data to explain participation in agricultural land preservation programs." *Land Economics* 79:259-276.

Lynne, G.D., J.S. Shonkwiler, and L.R. Rola. 1988. "Attitudes and farmer conservation behavior." *American Journal of Agricultural Economics* 70 (1):12-19.

Ma, S., et al. 2012. "Farmers' Willingness to Participate in Payment-for-Environmental-Services Programmes." *Journal of Agricultural Economics* 63 (3):604-626.

McCann, L.M., and J. Núñez (2005) "Who Participates in EQIP?" Paper presented at the annual meeting of the American Agricultural Economics Association meeting, Providence, Rhode Island, ,U.S., July 24-26.

McDonald, J.F., and R.A. Moffitt. 1980. "The uses of Tobit analysis." *The Review of Economics and Statistics*:318-321.

McFadden, D. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics*, edited by P. Zarambka, 105142. New York: Academic Press.

McNamara, K.T., M.E. Wetzstein, and G.K. Douce. 1991. "Factors affecting peanut producer adoption of integrated pest management." *Review of Agricultural Economics* 13(1) :129-139.

Michel-Guillou, E., and G. Moser. 2006. "Commitment of farmers to environmental protection: From social pressure to environmental conscience." *Journal of environmental psychology* 26 (3):227-235.

Miyama, E., and S. Managi. 2014. "Global environmental emissions estimate: application of multiple imputation." *Environmental Economics and Policy Studies* 16:115-135.

Moreno, G., and D.L. Sunding. 2005. "Joint estimation of technology adoption and land allocation with implications for the design of conservation policy." *American Journal of Agricultural Economics* 87 (4):1009-1019.

Movafaghi, O.S., K. Stephenson, and D. Taylor. 2013. "Farmer Response to Nutrient Credit Trading Opportunities in the Coastal Plain of Virginia." Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Washington, D.C., U.S., August 4-6.

Mzoughi, N. 2011. "Farmers adoption of integrated crop protection and organic farming: Do moral and social concerns matter?" *Ecological Economics* 70 (8):1536-1545.

Nickerson, C., and M. Hand. 2009. *Participation in Conservation Programs by Targeted Farmers: Beginning Limited-Resource, and Socially Disadvantaged Operators' Enrolment Trends*. USDA-ERS Economic Information Bulletin. Washington, DC: USDA.

Norris, P.E., and S.S. Batie. 1987. "Virginia farmers' soil conservation decisions: An application of Tobit analysis." *Southern nJournal of Agricultural Economics* 19 (1):79-90.

Núñez, J., and L. McCann. 2004. "Crop Farmers' Willingness to Use Manure." Paper presented at the annual meeting of the American Agricultural Economics Association, Denver, CO, U.S., August 1-4.

Organisation for Economic Co-operation and Development (OECD). 2012. Water Quality and Agriculture: Meeting the Policy Challenge. OECD Studies on Water. Paris: OECD Publishing.

Palmquist, R.B., F.M. Roka, and T. Vukina. 1997. "Hog operations, environmental effects, and residential property values." *Land Economics* 73(1):114-124.
Park, T.A., and L. Lohr. 2005. "Organic pest management decisions: a systems approach to technology adoption." *Agricultural Economics* 33(s3):467-478.
Pautsch, G.R., et al. 2001. "The efficiency of sequestering carbon in agricultural soils." *Contemporary Economic Policy* 19(2):123-134.
Peterson, J.M., J.A. Fox, J.C. Leatherman, and C.M. Smith. 2007. "Choice Experiments to Assess Farmers' Willingness to Participate in a Water Quality Trading Market." Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Portland, OR, U.S., July 29-August 1.
Pinkse, J., and M.E. Slade. 1998. "Contracting in space: An application of spatial statistics to discrete-choice models." *Journal of Econometrics* 85 (1):125-154.
Prokopy, L., et al. 2008. "Determinants of agricultural best management practice adoption: evidence from the literature." *Journal of Soil and Water Conservation* 63(5):300-311.
Qiu, Z., T. Prato, and G. Boehm. 2006. "Economic valuation of riparian buffer and open space in a suburban watershed." *Journal of the American Water Resources Association* 42 (6):1583-1596.
Raghunathan, T.E., et al. 2001. "A multivariate technique for multiply imputing missing values using a sequence of regression models." *Survey methodology* 27(1):85-96.
Rahm, M.R., and W.E. Huffman. 1984. "The adoption of reduced tillage: the role of human capital and other variables." *American Journal of Agricultural Economics* 66 (4):405-413.
Ready, R.C., and C.W. Abdalla. 2005. "The amenity and disamenity impacts of agriculture: estimates from a hedonic pricing model." *American Journal of Agricultural Economics* 87 (2):314-326.
Ribaudo, M.O., and J. Gottlieb. 2011. "Point-Nonpoint Trading - Can It Work?1." *JAWRA Journal of the American Water Resources Association* 47(1):5-14.
Roe, B., E.G. Irwin, and H.A. Morrow-Jones. 2004. "The effects of farmland, farmland preservation, and other neighborhood amenities on housing values and residential growth." *Land Economics* 80 (1):55-75.
Royston, P., and I.R. White. 2011. "Multiple imputation by chained equations (MICE): implementation in Stata." *Journal of Statistical Software* 45 (4):1-20.
Rubin, Donald B. 1976. "Inference and missing data." *Biometrika* 63 (3):581-92.
Rubin, Donald B. 1978. "Multiple imputations in sample surveys-a phenomenological Bayesian approach to nonresponse." Paper presented at the Proceedings of the Section on Survey Research Methods.p20
Schafer, J.L. 1997. *Analysis of Incomplete Multivariate Data.*Boca Raton, FL: Chapman&Hall/CRC press.
Schafer, J.L. 1999. "Multiple imputation: a primer." *Statistical Methods in Medical Research* 8 (1):3-15.
Schenker, N., et al. 2006. "Multiple Imputation of Missing Income Data in the National Health Interview Survey." *Journal of the American Statistical Association* 101(475) :924-933.
Segerson, K. 1988. "Uncertainty and Incentives for Nonpoint Pollution-Control." *Journal of Environmental Economics and Management* 15:87-98.

Selman, M., et al. 2009. "Water quality trading programs: An international overview." *WRI Issue Brief* 1:1-15.
Shively, G.E. 1997. "Consumption risk, farm characteristics, and soil conservation adoption among low-income farmers in the Philippines." *Agricultural Economics* 17 (2):165-177.
Shortle, J. 2013. "Economics and Environmental Markets: Lessons from Water-Quality Trading." *Agricultural and Resource Economics Review* 42:57-74.
Somda, J., et al. 2002. "Soil fertility management and socio-economic factors in crop-livestock systems in Burkina Faso: a case study of composting technology." *Ecological Economics* 43 (2):175-183.
Soule, M.J., A. Tegene, and K.D. Wiebe. 2000. "Land tenure and the adoption of conservation practices." *American Journal of Agricultural Economics* 82:993-1005.
Traore, N., R. Landry, and N. Amara. 1998. "On-farm adoption of conservation practices: The role of farm and farmer characteristics, perceptions, and health hazards." *Land Economics* 74:114-127.
Uri, N. 1997. "Conservation tillage and input use." *Environmental Geology* 29 (3):188-201.
U.S. Environmental Protection Agency (EPA). 2004. Water Quality Trading Assessment Handbook. Washington DC: USEPA (http://water.epa.gov/type/watersheds/trading/handbook_index.cfm)
U.S. Environmental Protection Agency (EPA). 2015. "EPA Administered Permit Programs: The National Pollutant Discharge Elimination System." Code of Federal Regulations, 40 C.F.R. 122.2: https://www.gpo.gov/fdsys/pkg/CFR-2015-title40-vol22/xml/CFR-2015-title40-vol22-sec122-2.xml
U.S. Department of Agriculture (USDA). Technical Resources-Conservation Practices: Alphabetical Index. 2010. http://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/technical/?cidDnrcs143_026849
United States Department of Agriculture Natural Resources Conservation Service (USDA NRCS). 2003.
Conservation Practice Standard (Code 313)
U.S. Department of Agriculture (USDA). 2014. Conservation Programs. http://www.ers.usda.gov/ topics/natural-resources-environment/conservation-programs.aspx#.U2FJNZLVCb4
United States Department of Agriculture Natural Resources Conservation Service (USDA NRCS). 2015.
Nutrient Management Documents:
http://www.nrcs.usda.gov/wps/portal/nrcs/main/in/technical/ecoscience/nutrient/
University of Kentucky. "Kentucky Equine Survey 2012, Final Report." 2013 http://equine.ca.uky.edu/files/2012_equine_survey_report_final_4.pdf
Van Buuren, S., H.C. Boshuizen, and D.L. Knook. 1999. "Multiple imputation of missing blood pressure covariates in survival analysis." *Statistics in Medicine* 18:681-694.
Van Buuren, Stef, and Karin Oudshoorn. 2011. " mice: Multivariate imputation by chained equations in R." *Journal of Statistical Software* 45 (3).

Wainger, L.A., and J.S. Shortle. 2013. "Local innovations in water protection: Experiments with economic incentives." *Choices* 28 (3).

Weaver, R.D. 1996. "Prosocial behavior: private contributions to agriculture's impact on the environment." *Land Economics* 72(2):231-247.

Weber, J.G., and D.M. Clay. 2013. "Who Does Dot Respond to the Agricultural Resource Management Survey and Does It Matter?" *American Journal of Agricultural Economics* 95 (3):755-771.

White, I.R., R. Daniel, and P. Royston. 2010. "Avoiding bias due to perfect prediction in multiple imputation of incomplete categorical variables." *Computational Statistics & Data Analysis* 54 (10):2267-2275.

White, I.R., P. Royston, and A.M. Wood. 2011. "Multiple imputation using chained equations: issues and guidance for practice." *Statistics in Medicine* 30 (4):377-399.

Windle, J., J. Rolfe, S. Whitten, K. Alam, and D. Street. 2005. “Using Choice Modelling to Establish the Supply of Riparian Services and the Potential for a Water Quality Trading Scheme in Central Queensland.” Paper presented at the 49th Annual Conference of the Australian Agricultural and Resource Economics Society, Coffs Harbour, NSW, Australia, February, 9-11.

Wu, J., et al. 2004. "From microlevel decisions to landscape changes: an assessment of agricultural conservation policies." *American Journal of Agricultural Economics* 86 (1):26-41.

Wu, J.J., and B.A. Babcock. 1998. "The choice of tillage, rotation, and soil testing practices: Economic and environmental implications." *American Journal of Agricultural Economics* 80:494-511.

Zhang, W., and C.J. Nickerson. 2015. "Housing Market Bust and Farmland Values: Identifying the Changing Influence of Proximity to Urban Centers." *Land Economics* 91(4):605-626.

Vita

Hua Zhong

Education

M.S.	Economics	University of Kentucky	August, 2013
M.E.	Agricultural Engineering	China Agricultural University	July, 2011
B.A.	Bio-Engineering	China Agricultural University	July, 2009

Professional Experiences

Department of Agricultural Economics, University of Kentucky, Lexington, U.S.A.
Research Assistant 2012 ~ 2016
Teaching Assistant 2014 ~ 2015

Peer Reviewed Publications

Zhong, H., W. Hu, and P. Qing, (2016) "Farmers' Willingness to Participate in Best Management Practices" *Journal of Environmental Planning and Management* 59 (6): 1015 - 1039

Conference Presentations

• Southern Agricultural Economics Association Annual Meeting, 2016, San Antonio, Texas.
• Agricultural and Applied Economics Association Annual Meeting, San Francisco, California, July 26-28, 2015
• Chinese Economist Society Annual Meeting, Ann Arbor MI, March 14-15, 2015.
• Southern Agricultural Economics Association 2015 Annual Meeting, Jan 31-Feb 3, 2015, Atlanta, Georgia.
• Agricultural and Applied Economics Association Annual Meeting, Minneapolis MN, July 27-29, 2014.
• Southern Agricultural Economics Association 2014 Annual Meeting, February 1-4, 2014, Dallas, Texas.
• International Agriculture Engineering Conference, book exhibition, Shanghai in China, 2010.