2015

WATER QUALITY TRADING FROM THE POINT SOURCE PERSPECTIVE: WILLINGNESS TO PAY FOR ABATEMENT CREDITS AND PREFERENCES FOR WATER QUALITY TRADING MARKET MECHANISM

Andrew McLaughlin
University of Kentucky, andrew.mclaughlin.james@gmail.com

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Andrew McLaughlin, Student

Dr. Wuyang Hu, Major Professor

Dr. Carl Dillon, Director of Graduate Studies

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THESIS

A thesis submitted in partial fulfillment of
the requirements for the degree of Master of Science in Agricultural Economics
in the College of Agriculture, Food and Environment
at the University of Kentucky

By

Andrew McLaughlin

Lexington, Kentucky

Director: Dr. Wuyang Hu, Professor of Agricultural Economics

Lexington, Kentucky

2015

ABSTRACT OF THESIS

WATER QUALITY TRADING FROM THE POINT SOURCE PERSPECTIVE: WILLINGNESS TO PAY FOR ABATEMENT CREDITS AND PREFERENCES FOR WATER QUALITY TRADING MARKET MECHANISM

As part of the EPA's initiative to reduce the hypoxic zone in the Gulf of Mexico, a feasibility study for a potential water quality trading (WQT) program in the Kentucky River Watershed (KRW) was conducted. While theoretically, emission trading programs are among the most efficient means of reducing pollution, empirical evidence suggests low-trade volume as a primary concern for the long-term success of such programs. Some of the important reasons for the low volume of trade are due to lack of suitable market trading mechanism for point sources and lack of information on willingness to pay (WTP) for abatement credits. Our study aims to tackle these issues by gathering a profile of municipal sewage treatment plants as point source polluters in the KRW, while simultaneously analyzing their preferences for WQT market mechanisms and WTP using a survey based approach. The survey was conducted in 2012. Municipal sewage treatment plants' ranked preferences are analyzed using an exploded logit model and WTP is analyzed using Ordinary Least Squares and Tobit models.

KEYWORDS: Point Source, Water Quality Trading, Willingness to Pay for Abatement Credits, Preferences for Trading Market Mechanisms

Andrew McLaughlin

December 10, 2015

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By

Andrew McLaughlin

Wuyang Hu
Director of Thesis

Carl Dillon
Director of Graduate Studies

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ACKNOWLEDGMENTS

I would like to thank the entire Department of Agricultural Economics for their constant support throughout my undergraduate and graduate studies at the University of Kentucky. I would like to thank Lynn Robins for making my transition into the college as smooth as possible. I would like to thank Kenneth Burdine for taking me on my first extension run, as this was my first glimpse into agricultural economics beyond the classroom. And lastly, I would like to thank Wuyang Hu. You have been more than just an academic adviser. You have been a second father to me and I look forward to keeping in touch and collaborating for years to come. The entire department has been amazing and will be missed greatly.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

The Gulf of Mexico is currently facing extreme hypoxic conditions that have gone unresolved for several decades. According to the Environmental Protection Agency, excessive amounts of nutrients are discharged into subbasins of the Mississippi River, which contribute not only to the degradation of these individual subbasins, but also contribute to the hypoxic zone in the gulf (United States Environmental Protection Agency, 2015). In an effort to restore these waters to their optimal conditions, the EPA designated $3.7 million towards Targeted Watersheds Grants in 2008 (United States Environmental Protection Agency, 2008). The University of Kentucky was one of ten major organizations awarded and was tasked with assessing the feasibility of a water quality trading market for the Kentucky River Watershed, with the primary nutrients of interest being nitrogen and phosphorous.

While the EPA suggests that a water quality trading market can potentially provide a cost effective approach to implementing stricter water quality regulations (United States Environmental Protection Agency, 2014), one of the key concerns and challenges faced so far has been low trade volume within existing markets (Shortle & Horan, 2008). Prior to implementing a market in the Kentucky River Watershed, it is crucial to understand the participants. This thesis takes a survey based approach to gather a profile of the point source polluters within the Kentucky River Watershed. The survey instrument used not only gathers the characteristics of the facilities, but also gathers information on the willingness-to-pay for abatement credits and asks participants to rank their preferences among a list of market trading mechanisms for a potential market. These additional pieces of information take into account the perspective of the facility representatives, which can be valuable information during the implementation of a market where participation is voluntary. Therefore, the goal of this thesis is to shed light on the perspective of the point source polluters in order to help build a customized market for those who would actually be participants. Introducing a price for abatement credits that inaccurately represents the demands of the market leaves much room for improvement. Studies show that even minor variations of prices can have notable effects (Marn, Roegner, & Zawada, 2003).

In order to thoroughly present responses for willingness-to-pay for credits and ranked-preferences for market trading mechanisms, a variety of models will be used. For willingness-to-pay, the response variable is a continuous dollar amount, so we will first use Ordinary Least Squares. However, we quickly find that a large portion of the respondents report that they would only be willing to pay $0. For this reason, OLS might not be the most appropriate model due to censoring, and so we move beyond OLS and use a Tobit model. When modeling the ranked preferences for market trading mechanisms, a rank-ordered logistic regression model (ROL) is used. The ROL model is a generalization of the conditional logistic regression model (Allison & Christakis, 1994), with the added benefit of estimating the probability of an entire ranking of preferences, rather than simply the most preferred.

Following this chapter, Chapter 2 will provide the necessary background information to fully understand the problem at hand. We will define hypoxia, the nutrients of interest, look at the size and scope of the situation at hand, and discuss the current Action Plan set forth by the Hypoxia Task Force, which aims to tackle the water pollution problem, and we will discuss the concept of water quality trading. In Chapter 3, we will review the literature on the history of water quality trading. Chapter 4 will cover the EPA grant that funds the research for this thesis. Chapter 5 will discuss the survey based data collection process, followed by the descriptive statistics from the survey in Chapter 6. In Chapter 7we will focus on the theoretical models and empirical results used to analyze Willingness to Pay for abatement credits. Chapter 8 will walk through the theoretical models and empirical results used to understand the ranked preferences of possible market trading mechanisms. Chapter 9 concludes this thesis with a discussion of important findings and potential future research. SAS codes used to run the models found in this thesis along with the complete survey instrument used can be found in the appendices.

CHAPTER 2: BACKGROUND

Hypoxia is a worldwide problem with over 550 documented cases. Documentation on the northern Gulf of Mexico has shown evidence of hypoxia since 1972 and is now the largest human-caused hypoxic zone in the United States and the second largest in the world (Hypoxia Research Team at LUMCOM, n.d.). Due to the significance of this environmental phenomenon, government agencies and researchers have joined the effort to reduce the negative impact on the suffering estuary.

2.1 Defining Hypoxia, Eutrophication, & Nutrients

The United States Geology Survey (USGS) provides a detailed explanation of hypoxia, nutrients, and eutrophication on their website (United States Geological Survey, 2015). Most notably, hypoxia occurs when oxygen concentrations are below the minimum aquatic life sustaining levels, resulting from decomposing algae, where oxygen consumption outweighs oxygen production (Mississippi River Basin Watershed Nutrient Task Force, 2004). The minimum level of dissolved oxygen in order to sustain life is approximately 2mg/l (Committee on Environment and Natural Resources, 2000), which can be compared to 8-10 mg/l for a normal level (Stevenson & Wyman, 1991). Excessive nutrients in the water, i.e. eutrophication (typically nitrogen and phosphorous), promotes algal growth. Oxygen is then consumed as algae decomposes, which can result in low levels of oxygen in water (Mississippi River Basin Watershed Nutrient Task Force, 2010).

Eutrophication can be defined as, "an increased rate of supply of organic matter in an ecosystem" (Nixon, 1995). While eutrophication can occur naturally, humans can speed up the process (Art, 1993). However, excessively nourished water can have negative effects. Specifically, the decomposing algae blooms which compete for oxygen can deplete oxygen levels in a body of water. Oxygen depletion is an undesirable effect, and so eutrophication can be considered a form of pollution (Art, 1993).

Nutrients are the major elements necessary for organism growth (United States Environmental Protection Agency, 2012). Common nutrients include nitrogen and phosphorous (United States Geological Survey, 2007). Though nutrients are essential to aquatic life, high concentrations can contaminate water (Mueller & Helsel, 1996). The Gulf of Mexico contains high levels of nutrient concentration, which can be harmful to the fish and shellfish populations (Fuhrer, et al., 1999).

2.2 Location, Size, and Scope of the Hypoxic Zone in the Gulf of Mexico

The hypoxic zone in the Northern Gulf of Mexico has attracted a wide variety of researchers and organizations, all hoping to help reduce the massive negative impact on the area. Among those groups, the Louisiana Universities Marine Consortium (LUMCON), directed by Dr. Nancy Rabalais, has been documenting the temporal and spatial extent of the hypoxic zone since 1985 (Hypoxia Research Team at LUMCOM, n.d.). Their documented methods include long-term deployment of instruments on stationary moorings, monthly cruises of fixed offshore transects, and an annual shelfwide cruise, mapping the widest extent of the hypoxia each summer. In order to reduce seasonal variability in measurements, summer readings are conducted annually between July and

August (Hypoxia Research Team at LMUCON, 2015). The current fiver-year (2011-2015) hypoxic zone is 14,024 square kilometers. The 30-year (1985-2015) average hypoxic zone is 13,725 square kilometers. In 2002, the hypoxic zone peaked at approximately 22,000 square kilometers, which is roughly the size of Maryland (Hypoxia Research Team at LMUCON, 2015). Table 2.1 below shows the yearly readings (when available) from 1985-2015. The final rows in the table show the goal, the 30-year average, and the 5-year running average. The 30-year average is simply the average size of the hypoxic zone over the previous 30 years, from 1985-2015, with the exception of 1989 where data was not available. The 5-year running average provided below is the average size of the hypoxic zone from 2011-2015. It is important to note fluctuations in the size and concentration of the hypoxic zone due to uncontrollable circumstances, for example drought or hurricanes (Hypoxia Research Team at LMUCON, 2015). Thus a 5-year average is used for setting benchmark goals. Lastly, the federal-state goal for 2015 was to meet a 5-year running average of 5,000 square (Mississippi River Gulf of Mexico Watershed Nutrient Task Force, 2008). Obviously, this goal has not currently been met.

Table 2.1 Hypoxic Zone, Shelfwide Cruises

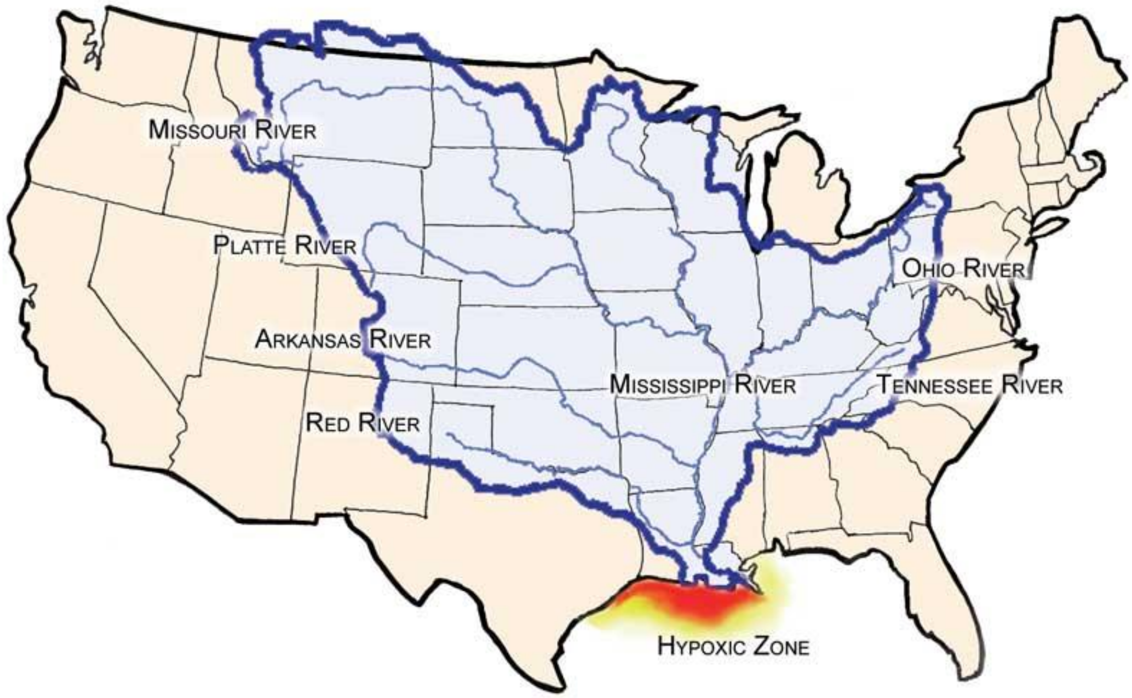
Year	Kilometers²	Miles²	Year	Kilometers²	Miles²
1985	9,774	3,775	2002	22,000	8,497
1956	9,592	3,705	2003	8,320	3,214
1987	6,688	2,583	2004	14,640	5,655
1988	40	15	2005	11,800	4,558
1989	n.d.	n.d	2006	16,560	6,396
1990	9,420	3,638	2007	20,480	7,910
1991	11,920	4,604	2008	21,764	8,406
1992	10,804	4,173	2009	8,240	3,183
1993	17,520	6,767	2010	18,400	7,107
1994	16,680	6,443	2011	17,680	6,829
1995	17,220	6,651	2012	7,480	2,889
1996	17,920	6,922	2013	15,120	5,840
1997	15,950	6,161	2014	13,080	5,052
1998	12,480	4,820	2015	16,760	6,474
1999	20,000	7,725	**Goal**	**5,000**	**1,991**
2000	4,400	1,699	**30-yr Ave.**	**13,752**	**5,312**
2001	19,840	7,663	**5-yr Ave.**	**14,024**	**5,543**

n.d. = no data, entire area not mapped

Source: (Hypoxia Research Team at LMUCON, 2015)

While the above mentioned hypoxic zone is located in the Gulf of Mexico, the source of the hypoxia spans across most of the United States. There are currently nine subbasins of the Mississippi-Atchafalaya River Basin being sampled for nutrient fluxes. In addition to the Mississippi River, the Missouri River, Ohio River, Arkansas River, Red River, and Atchafalaya River all contribute to the nutrient flux and are thus monitored. Figure 2.1 below shows the scope of the contributing basins across which span across most of the United States.

Figure 2.1 Hypoxic Zone



Source: (Rosen, 2015)

There are currently 16 sampling stations as of 2006 monitoring both flow and quality (USGS, 2007). The station located in the Mississippi River at Thebes, Ill has the largest drainage area of 1,847,000 km^2 (USGS, 2007). Of particular interest to our study, we can focus on the three stations along the Ohio River, because the Kentucky River flows into the Ohio River. Of the three stations, Station ID 03303280 has data on both flow and quality (USGS, 2007). The drainage area is 251,000 km^2 (USGS, 2007). Station 03612500 has data on quality and station 03611500 has data on flow (USGS, 2007). Their respective drainage areas are 526,000 km^2 and 525,800 km^2 (USGS, 2007). The Ohio sub-basins are part of the National Stream Quality Accounting Network (USGS, 2007).

2.3 Action Plan Reassessment 2013

For an issue as serious as the one effecting the Gulf of Mexico, a logical question might be to ask, “What’s being done?” Most recently, the Hypoxia Task Force has reassessed the action plan of 2008.

As of 2013, members of the Hypoxia Task Force include state agencies, regional groups, federal agencies, and tribes. The state agencies involved include Arkansas Natural Resources Commission, Illinois Department of Agriculture, Indiana State Department of Agriculture, Iowa Department of Agriculture and Land Stewardship, Kentucky Department for Environmental Protection, Louisiana Governor’s Office of Coastal Activities, Minnesota Pollution Control Agency, Mississippi Department of Environmental Quality, Missouri Department of Natural Resources, Ohio Environmental Protection Agency, Tennessee Department of Agriculture, and Wisconsin Department of Natural Resources (Mississippi River Gulf of Mexico Watershed Nutrient Task Force, 2013). The regional groups involved are Lower Mississippi River Sub-basin Committee and the Ohio River Valley Water Sanitation Commission (Mississippi River Gulf of Mexico Watershed Nutrient Task Force, 2013). Federal agencies include U.S. Army Corps of Engineers, U.S. Department of Agriculture: Natural Resources and Environment, U.S. Department of Agriculture: Research, Education, and Economics, U.S. Department of Commerce: National Oceanic and Atmospheric Administration, U.S. Department of the Interior: U.S. Geology Survey, and U.S. Environmental Protection Agency (Mississippi River Gulf of Mexico Watershed Nutrient Task Force, 2013). Lastly, the tribe involved is National Tribal Water Council (Mississippi River Gulf of Mexico Watershed Nutrient Task Force, 2013).

Since the 2008 Gulf Hypoxia Action Plan, the Task Force has targeted funding towards agricultural producers with the goal of nutrient reduction (Mississippi River Gulf of Mexico Watershed Nutrient Task Force, 2013). Many improvements have been made including stronger member relations and better data monitoring.

The primary goal of the Task Force is to alleviate the hypoxic zone in the Gulf of Mexico by reducing the nutrient load into the Mississippi/Atchafalaya River Basin. In order to do so, the Task Force devised a Ten Point Action Plan. The first item on the list focuses on state-level nutrient reductions strategies. Of particular interest for this thesis, key points for Kentucky's strategy includes the continued use of the Kentucky Agricultural Water Quality Act which focuses on best management practices to control nitrogen and phosphorus, along with Kentucky joining the Ohio River Basin Water Quality Trading Project in 2012, which will be revisited in the discussions portion of the thesis.

The second item of the action plan covers the comprehensive federal strategy. This item focuses on monitoring water quality improvement, building decision support tools, predictive modelling for water quality, nitrogen and phosphorus regulation, financial assistance, overall awareness. The third item aims to utilize opportunities under currently existing programs to enhance protection of the gulf and local water quality. Programs to be leveraged include the USGS Cooperative Water Program and the USACE/USGS Long-Term Resource Monitoring Program. The USDA has taken the lead on point four of the action plan, with the task of managing efficient nutrient conservation practices for nonpoint and point sources in the Mississippi/Atchafalaya River Basin. In order to track progress, action item five aims to quantify many of the aspects of the hypoxic zone, ranging from scientific to economic in nature. In conjunction with item five, item six then aims to increase access to data and improve upon the basin and coastal data collection process. The three primary goals of the 2008 Action Plan were to reduce the size of the hypoxic zone, restore the MARB waters, and improve the MARB economy. The seventh action item is for the Task Force to track the progress of those three goals. Items eight and nine both focus on gaining a better understanding of the current situation and focus heavily on improved modelling techniques. Item eight focuses more the geographic aspects of the nutrients whereas item nine focuses more the impact those nutrients have on the hypoxic zone and how to improve upon these models. Lastly, item ten aims to increase public awareness of hypoxia by managing a website, developing annual reports, and promoting existing means of communication.

2.4 Water Quality Trading

"Its victory is made decisive by the fact that it lends itself easily to a market mechanism, whereas the subsidy scheme does not." (Dales, Land, Water, and Ownership, 1968)

Water quality trading is a relatively new concept and is explained by the Environmental Protection Agency as a voluntary exchange of pollutant reduction credits, stating that a facility with higher pollutant control cost can buy a pollutant reduction credit from a facility with a lower control cost, thus reducing their cost of compliance (United States Environmental Protection Agency, 2014). However, this definition was not derived overnight. The concept of water quality trading is a generalization of emissions trading, which was first introduced several decades prior to the conceptualization of water quality trading. The overall goal is to meet a specified level, or "cap", of pollution within a social setting, while simultaneously reducing deadweight loss. By social, this means there are a series of players that must interact. The players in this case being buyers and sellers, or more specifically, point and nonpoint source polluters. And when we speak of a cap in regards to water quality, we are referring to the total maximum daily load (TMDL) which is defined as the maximum amount of a pollutant a body of water can sustain.

TMDLs are regulated by the National Pollutant Discharge Elimination System (NPDES) and regulation requirements can be found in section 303(d) of the Clean Water Act (Clean Water Act, 2002) and the Code of Federal Regulations Title 40 Chapter I Subchapter D Part 130 (40 C.F.R. §130, 1985). TMDLs are linked to waters that are known to be impaired. When TMDLs are assigned to a geographic location, three key components must be identified. 40 C.F.R. §130.2 (i) defines two of the key components to be Load Allocations (LAs) for nonpoint sources and Wasteload Allocations (WLAs) for point sources (Cornell). Additionally, 40 C.F.R. §130.7 (c)(1) mandates the inclusion of a Margin of Safety (MOS) when implementing TMDLs to account for unpredictable error in calculations. Because TMDLs are typically set as a target level in response to water impairment, we can infer that the current level of pollutants in the water are already in excess of what is deemed to be socially optimal level, and thus abatement is necessary. Pollution abatement comes at a price though. A variety of methods can be implemented, ranging from municipal sewage treatment facilities investing in new technology to agricultural contributors investing in best management practices. For obvious reasons, several factors can play a role in the marginal cost of abatement, meaning we should assume heterogeneity in abatement costs among violators. The equation for a TMDL can be expressed as:

$$TMDL = \sum WLA + \sum LA + MOS \tag{2.1}$$

(United States Environmental Protection Agency, 2013), where on the left hand side of the equation, we have a TMDL. On the right hand side of the equation, we have the sum of three components. From left to right, we have the sum of waste load allocation from point source polluters, plus the sum of load allocations for nonpoint source polluters, plus the margin of safety which can be interpreted as a fixed error term. We can simply subtract the MOS from the TMDL, and as long as we are able to maintain the following equation, the TMDL has not been violated.

$$TMDL - MOS \geq \sum WLA + \sum LA \tag{2.2}$$

We can already see the possibility of fluidity between WLA and LA. Because we can view the above formula as a social issue, there is no reason why we cannot view the solution in the same way we would view any other economic problem. We would simply need to view this as a cost minimization problem, subject to meeting the TMDLs set forth by the NPDES. It should be clear that WLA and LA are going to be inversely related. While inverse means that as one increases, the other decreases, a fair argument could present itself when both WLA and LA decrease. However, we are assuming that from a static point, we are beginning from a less than optimal quantity, and we are also assuming that marginal costs are different between the two groups. Thus, in order for this to be a cost minimizing problem, it would be necessary for abatement to be carried out by the player with the lowest marginal costs. In perhaps the early stages, both parties might be required to reduce, independent of one another. However, in that scenario neither party would be trading, i.e. they would not be truly participating in water quality trading. Therefore, we could exclude that scenario from the example. Because this is a social problem with a regulated outcome, assigning tradable property rights, or in this case the right to pollute in the form of a tradable permit, could assist in the trading process. We can now arrive at the conclusion that if players have the ability to choose who bears the cost of abatement, it would make sense that so long as the cost of abatement exceeds the cost of a credit, there would be an incentive for a purchase to take place. Conversely, so long as the price of a credit exceeds the cost of abatement, there would be an incentive to sell a credit. When there is an incentive on both sides, we should then see a trade take place, which by definition would reduce the overall cost to society, in turn reducing the deadweight loss.

CHAPTER 3: LITERATURE REVIEW

3.1 Brief History of Emission Trading and Water Quality Trading

Jan-Peter VoB discusses in great detail the development of emissions trading as a policy instrument in the paper *Innovation Processes in Governance: The Development of 'Emissions Trading' as a New Policy Instrument* (VoB, 2007). Specifically, the paper covers the journey of emissions trading through four key phases: gestation, proof of principle, as a prototype, and regime formation. Emissions trading is observed simply as a policy instrument which addresses the need for regulation through the use of market mechanisms (VoB, 2007). In the section on gestation and proof-of-principle, it is explained that Coase, Dales, and Montgomery all played key roles in the fruition of emissions trading. Coase conceptualized tradable permits (Coase, 1960), Dales introduced the idea of establishing an emissions market (Dales, Land, Water, and Ownership, 1968), and Montgomery provided a formal theoretical proof of the superiority of emissions trading over taxes (Montgomery, 1972).

The US EPA had initially focused on a command-and-control approach regarding the Clean Air Act. Between 1972 and 1975, the EPA began implementing a more flexible approach, including offset mechanisms (VoB, 2007). By 1977, the command-and-control framework of the CAA began to see legal framework adjustments (VoB, 2007). The Office of Planning and Evaluation which later became the Office of Planning and Management led the reform of the EPA (VoB, 2007). Shortly thereafter, emission reduction credits were first introduced in 1979 (VoB, 2007).

In response to the overwhelming success of the carbon emissions trading programs used to meet the requirements of the Clean Air Act, it was only a matter of time before those policy techniques were extended into other programs with similar goals. Impaired waters across the United States led the government to get involved, first with the Federal Water Pollution Control Act of 1948, which over time evolved into the Clean Water Act of 1972 (United States Environmental Protection Agency, 2015). Emissions trading has since been adopted in the form of water quality trading. Though it is still a relatively new concept, water quality trading has been gaining traction and programs are currently in place all over the world. Suzie Greenhalgh of New Zealand's Landcare Research and Mindy Selman of World Resources Institute collaborated on a comprehensive assessment of 63 water quality trading programs, where 33 were active and 30 were in the consideration/developmental stages (Greenhalgh & Selman, 2012). Programs evaluated are provided in Table 3.1 and known trading program initiative are in Table 3.2. When comparing programs, key hurdles and factors for success were identified. The three primary hurdles to any water quality trading program were identified as design, development, and operations. In the design process, it is important to develop appropriate market drivers. For example, TMDLs are great market drivers, but in some instances, they are set higher than the current discharge level, and thus do not drive the market, as was the case for the Cherry Creek program, which has had only 3 trades since 1999 (Greenhalgh & Selman, 2012).

There is currently no general consensus upon which type of market structure is best for a water quality trading program. Several trading mechanisms have been introduced and are currently being used. Sole-source offsets, bilateral negotiations, clearinghouse, and exchange markets are some of the more prevalent markets (Woodward, Kaiser, & Wicks, 2004). A reoccurring issue is low trade volume (Shortle & Horan, 2008). Different authorities are experimenting with a variety of methods in an attempt to increase trade volume and improve market performance. Recently, Chesapeake Bay of Pennsylvania was the first program of its type to regulate point sources and nutrient credits via arms-length market transactions (O'Hara, Walsh, & Marchetti, 2012). The Pennsylvania Infrastructure Investment Authority, the state authority responsible for financing water projects, partnered with Chicago Climate Exchange to design and implement a clearinghouse for the water quality trading program (O'Hara, Walsh, & Marchetti, 2012). The necessity for the clearinghouse stemmed from the low trade volume. Due to high transaction costs and other potential risks and uncertainties, the clearinghouse should help to reduce the burden of transaction costs between trading parties while simultaneously eliminating some of the potential risks associated with trading (O'Hara, Walsh, & Marchetti, 2012). However, additional factors contributing to the low trade volume addressed include the low number of participants within an appropriate geographic scope, heterogeneous abatement costs, and that trade ratios that are not cost-effective for non-point sources (O'Hara, Walsh, & Marchetti, 2012), and so it is uncertain whether a clearinghouse will solve all of these problems.

Table 3.1 Active Water Quality Trading Programs

Program Name	State/Country	Participants	Type of Market	Inception
Hunter River Salinity Trading Scheme	New South Wales, Australi	PS-PS	Exchange	1995
South Creek Bubble Licensing Scheme	New South Wales, Australia	PS-PS (trialing NPS)	Clearinghouse (bubble permit)	1996
Murray-Darling Basin Salinity Credits Scheme	South-Eastern Australia	States[c]	Bilateral	1998
South Nation Total Phosphorus Management Program	Ontario, Canada	PS-PS	Clearinghouse	1998
Lake Taupo Nitrogen Trading Program	New Zealand	NPS-NPS	Bilateral	2009
Grassland Area Farmers Tradable Loads Program	California, U.S.	Irrigation districts[c]	Bilateral	2009
Bear Creek Trading Program	Colorado, U.S.	PS-PS/NPS	Bilateral	2006
Chatfield Reservoir Trading Program	Colorado, U.S.	PS-PS/NPS	Clearinghouse/bilateral	1996
Cherry Creek Basin Water Quality Authority Trading Program	Colorado, U.S.	PS-PS/NPS	Clearinghouse	1997
Dillon Reservoir Pollutant Trading Program	Colorado, U.S.	PS-NPS	Bilateral	1984
Long Island Sound Nitrogen Credit Exchange Program	Connecticut, U.S.	PS-PS	Clearinghouse	2002
Delaware Inland Bays	Delaware, U.S.	PS-NPS	Sole-source	2007
Lower St Johns River Water Quality Credit Trading Program	Florida, U.S.	PS-PS/NPS	Bilateral	2010
Maryland Nutrient Trading Programa	Maryland, U.S.	PS-PS/NPS	Exchange/bilateral	2010
Minnesota River Basin Trading Program	Minnesota, U.S.	PS-PS	Bilateral	2005
Rahr Malting Company Permit	Minnesota, U.S.	PS-NPS	Bilateral	1997
Southern Minnesota Beet Sugar Cooperative Permit	Minnesota, U.S.	PS-NPS	Clearinghouse	1999
Las Vegas Wash	Nevada, U.S.	PS-PS	Clearinghouse (bubble permit)	2010
Taos Ski Valley	New Mexico, U.S.	PS-NPS	Sole-source/bilateral	2004
Fall Lake	North Carolina, U.S	PS-PS/NPS	Sole-source/bilateral	2011
Neuse River Basin Nutrient Sensitive Waters Management Strategy	North Carolina, U.S	PS-PS/NPS	Clearinghouse	1998
Jordan Lake	North Carolina, U.S	PS-PS/NPS	Sole-source/bilateral	2009
Tar-Pamlico Nutrient Reduction Trading Program	North Carolina, U.S	PS-PS/NPS	Clearinghouse (bubble permit)	1989
Great Miami River Watershed Water Quality Credit Trading Program	Ohio, U.S.	PS-PS/NPS	Third-party broker	2005
Ohio River Basin Trading Program	Ohio, U.S.	PS-PS/NPS	To be determined	2012
Sugar Creek (Alpine Cheese Trading Program)	Ohio, U.S.		Third-party broker	2006
Clean Water Services Permit, Tualatin River	Oregon, U.S.	PS-PS/NPS	Third-party broker/sole-source	2004
Williamette Partnership (Rogue)	Oregon, U.S.	PS-NPS	Sole-source	Missing
Williamette Partnership (Williamette)	Oregon, U.S.	PS-NPS	Sole-source	Missing
Williamette Partnership (Lower Columbia)	Oregon, U.S.	PS-NPS	Sole-source	Missing
Pennsylvania Nutrient Credit Trading Program	Pennsylvania, U.S.	PS-PS/NPS	Clearinghouse	2006

Table 3.1 Active Water Quality Trading Programs (Continued)

Virginia Water Quality Trading Program	Virginia, U.S.	PS-PS/NPS	Clearinghouse/bilateral	2006
Red Cedar River Nutrient Trading Pilot Program	Wisconsin, U.S.	PS-NPS	Third-party broker	1997

Source: (Greenhalgh & Selman, 2012)

Table 3.2 Known Water Quality Trading Programs/Initiatives

Program Name	State/County	Participants	Type of Market
Moreton Bay Nutrient Trading Scheme	Queensland, Australia	PS-PS/NPS	TBD
Lake Simcoe Watershed	Ontario, Canada	TBD	TBD
Lake Winnipeg Basin	Manitoba, Canada	TBD	TBD
Lake Rotorua	New Zealand	NPS-NPS	TBD
Lower Colorado River	Colorado, U.S.	TBD	TBD
Lake Allatoona	Georgia, U.S.	PS-PS OR PS-PS/NPS	TBD
Charles River Flow Trading Program	Massachusetts, U.S.	PS-PS	Bilateral
Vermillion River	Minnesota, U.S.	TBD	TBD
Upper Mississippi River Basin	Minnesota, U.S.	PS-NPS	Clearinghouse
Passaic River	New Jersey, U.S.	PS-PS/NPS	TBD
Lake Tahoe	Nevada, U.S.	NPS-NPS	Third party broker
Truckee River Water Quality Settlement Agreement	Nevada, U.S.	PS-NPS	TBD
Shepherd Creek	Ohio, U.S.	PS-NPS	Third party broker
Upper Little Miami River Basin	Ohio, U.S.	PS-NPS	TBD
Portland Tradable Stormwater Credit Initiative	Oregon, U.S.	PS-PS	TBD
Bear River	Utah/Wyoming/Idaho, U.S.	TBD	TBD
West Virginia-Potomac Water Quality Bank and Trade Program	West Virginia, U.S.	PS-PS/NPS	Exchange
Clear Creek (I)	Colorado, U.S.	PS-PS	Sole-source
Boulder Creek Trading Program (I)	Colorado, U.S.	PS-NPS	Sole-source
Lower Boise River Effluent Trading Demonstration Project (I)	Idaho, U.S.	PS-NPS	Bilateral
Middle Snake River (I)	Idaho, U.S.	PS-PS	Bilateral
Upper Moquoketa and South Fork Moquoketa Watersheds Nutrient Trading Directory (I)	Iowa, U.S.	NPS-NPS	Bilateral
Sudbury River, Wayland (I)	Massachusetts, U.S.	PS-PS	Bilateral
Kalamazoo River (I)	Michigan, U.S.	PS-NPS	Third party broker
Passaic Valley Sewerage Commission Pretreatment Trading (I)	New Jersey, U.S.	PS-PS	Bilateral
New York City Watershed Phosphorus Offset Pilot Programs (I)	New York, U.S.	PS-PS	Sole-source
Lake Champlain (I)	New York/Vermont, U.S.	PS-PS	Sole-source
Cape Fear (I)	North Carolina, U.S.	NPS-NPS	TBD
Fox-Wolf Basin (I)	Wisconsin, U.S.	NPS-NPS	Bilateral
Rock River (I)	Wisconsin, U.S.	NPS-NPS	Bilateral

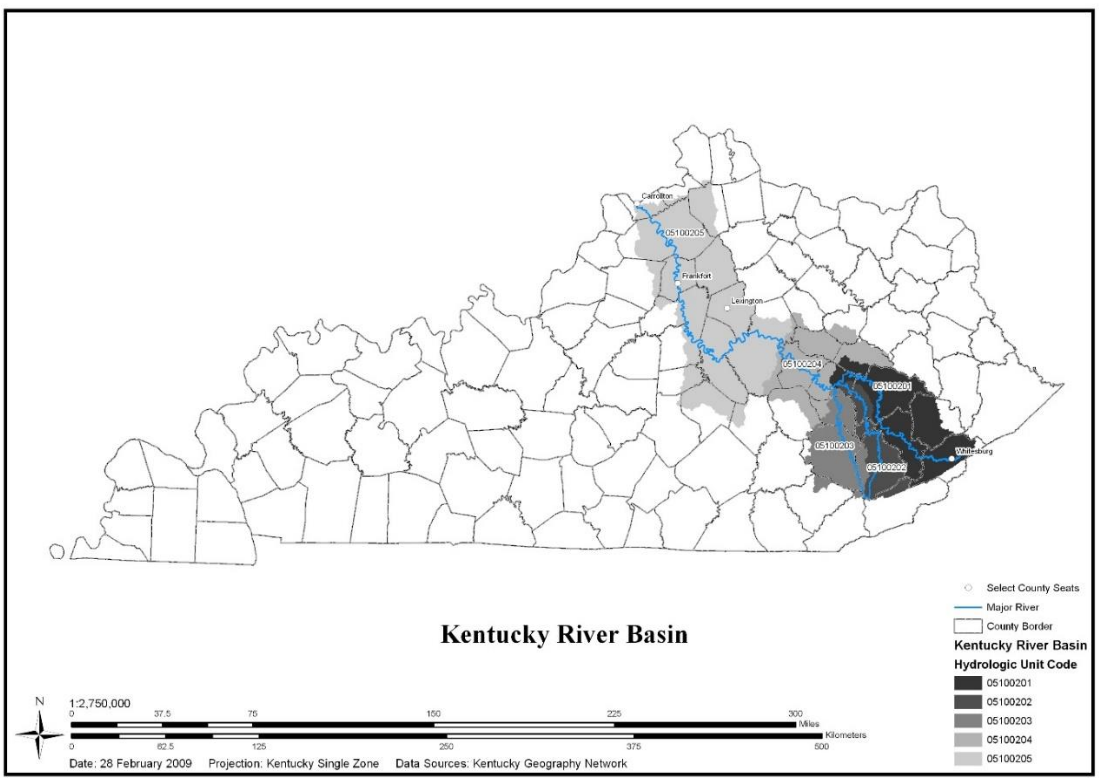
Note: (I) indicates the program is now inactive

Source: (Greenhalgh & Selman, 2012)

CHAPTER 4: EPA GRANT

Funding for this study was awarded as a grant by the U.S. EPA Assistance ID No. was WS-95436409 and the budget date began on May 1, 2009. The proposed project geographic location would include Watershed HUC Codes 05100201, 05100202, 05100203, 05100204, and 05100205, which correspond respectively to North Fork, Middle Fork, South Fork, Upper, and Lower Kentucky River sub-basins. The area examined can be seen below in Figure 4.1.

Figure 4.1 Kentucky River Watershed



Source: (Hu, 2009)

The region of interest which can be seen on the map spans across most of central and eastern Kentucky. Within this basin, there is a population of approximately 775,000 people spread across 42 counties. The basin spans 15,000 miles of stream and drains into the Ohio River. Within the Kentucky River alone, there have been over 17,000 pollution violations between 2000 and 2003.

4.1 Assessment of a Market-Based Water Quality Trading System for the Kentucky River Watershed: Overview

We can begin by reviewing the proposal for this EPA funded project, as the empirical data in this thesis was derived from a survey implemented as part of the EPA's feasibility study. The full assessment describes the technical approach, which includes the pollutant and economic suitability analysis, followed by the environmental results and measuring processes to be used. In this overview, we will focus on the pollutant suitability of analysis. We will discuss the economic suitability analysis in greater detail throughout the remainder of the thesis.

4.2 Pollutant Suitability Analysis

The Kentucky Division of Water identifies nitrogen and phosphorous as two of the primary nutrient pollutants in Kentucky's watershed (KDOW 2008) and will thus be the primary nutrients of interest in our study.

As mentioned previously, the Kentucky River flows into the Ohio River, which flows into the Mississippi River, all contributing to the excess sediment and nutrient discharge in the

Gulf of Mexico. For this analysis, the Kentucky River watershed will be our primary focus for data collection and analysis.

The implementation of stricter targeted discharge quantities, i.e. Total Maximum Daily Loads (TMDLs) set in place by the National Pollutant Discharge Elimination System (NPDES) will be the primary driving force of the proposed market. At the start of our analysis, TMDLs are not set in place for all dischargers in the proposed market. Buyers and sellers are comprised of point source and nonpoint source polluters, where point source polluters are municipal waste water treatment facilities and nonpoint source polluters are agricultural participants. Agricultural participants are expected to be the sellers, as their abatement costs are expected to be lower than those of the point sources, who would then opt to purchase credits from the nonpoint sources.

Supply and demand estimates can be approached most accurately when incorporating sufficient trade ratios. Trade ratios must be accounted for when considering a market for tradable permits, due to factors including equivalency, distance, location, uncertainty, and retirement. These factors are important to keep in mind because one pound of a pollutant in scenario A might not be equivalent to one pound of pollutant in scenario B. We can turn to Wisconsin and Michigan, as they have already adopted models to address uncertainty and equivalency. On the demand side, we can focus on the 256 municipal point sources reported by KPDES, as those will be the key participants in the survey analyzed in this thesis. However, we can also note the 7,156 industrial point sources and 1,217 private point sources discharging into the basin. The nonpoint sources, which are made up of agricultural participants reportedly affect 1477.2 river miles, according to the KDOW. On the supply side, geospatial models can be implemented to analyze nonpoint sources and mining lands.

In order to prevent high levels of pollution, the potential for hotspots needs to be addressed. In the proposal, monitoring data, implementing trading ratios, and introducing temporal and regional limits on trades are all suggested as viable options to be included. Timing is another important factor to keep in mind. Trades must occur when the timing of the supply is available and there is already demand in place. Additionally, for certain types of abatement practices, implementation can be a lengthy process. Thus, it is necessary for TMDL compliance to be met, even if abatement measures are scheduled to be made in the future.

CHAPTER 5: METHODOLOGY

5.1 Data Collection and the Survey

In order to collect primary data on point sources, a questionnaire was drafted to collect information from sewage treatment facilities, as they are identified as the primary buyers in the region. Multiple focus groups were held with treatment plant representatives in February 2011, prior to the launch of the finalized survey.

The survey questionnaire was distributed to municipal point sources in the Kentucky River Basin beginning June of 2011 and ending in August of 2012. According to the Kentucky Pollutant Discharge Elimination System, there are 256 municipal point sources located throughout the North Fork, Middle Fork, South Fork, Upper, and Lower sub-basins of the Kentucky River. The Kentucky Division of Water supplied our team with a list of 260 distinct contacts. The data provided included a facility name, telephone number, and an official representative, along with other information that could be used to identify the facility. The representatives on the list were exhaustively contacted via the telephone numbers provided. Representatives were offered a choice to complete the survey over the phone, in-person, via e-mail, or via fax. There were 81 out of 256 possible surveys completed, or a 31.6% response rate.

Several issues can arise with a non-mandatory survey questionnaire with the complexity of the one we provided. Though participants might be initially willing to participate, as they discover the technical aspect of the questions, some tend to lose confidence in their ability to provide an accurate response while others simply lose interest. For these and potentially other reasons, it is not uncommon to find several questions go unanswered within a survey.

Cheap talk was lightly implemented in order to alleviate the concerns of respondents and encourage respondents to answer questions honestly and accurately.

The survey collection process started off rather slowly. In the earliest attempts to gather information, we found respondents were hard to reach. We began by mailing surveys to the representatives on our list with very little participation. Because of the importance of the information we were hoping to collect, we began to schedule a series of in-person interviews. Once the facility representatives were contacted, we gave a light introduction to the study we were conducting in order to make sure they would be able to provide the necessary information. We then visited and collected surveys from 20 facilities within the watershed. The process was quite timely and we even found that in certain cases, the representatives were not present for the scheduled appointments. Additionally, we found that some representatives grew cautious about providing inaccurate information, and refused to answer certain questions. The remaining 61 surveys collected were conducted through a series of phone interviews, where the survey questions were read to the respondent and their responses were recorded. Due to the small sample size, we do not account for the mode of the response (i.e. in-person, phone, etc) within the models we implement, though that information is available should the need arise.

One of the benefits of collecting surveys in-person was less quantifiable, but highly rewarding. In person, you are able to discuss topics outside of the survey. For example, we were able to discuss the overall process of the treatment plant and even take a tour of the facility, which brings an additional level of authenticity to our research.

Figure 5.1 Aeration Tank, Ultra Violet Lights, and Point Source

The pictures above in Figure 5.1 were taken at one of the larger treatment facilities visited. The first image is a picture of tanks used for aeration. The picture in the middle shows the ultraviolet light treatment used for disinfecting the water. Finally, the picture on the right is a true "point source", as this is the point where the water leaves the treatment facility and returns back to the streams. Additional steps in the process include sediment scraping and chemical treatment, along with many other potential steps. The aeration process photographed above requires a large up-front investment, as can be seen by the sheer size of the tank. However, once running, the process is almost completely free, as it lets nature do most of the biological work. The larger facilities tend to vary more from location-to-location, as they were more customized to meet the needs of the community. Smaller communities commonly use "package plants" which are essentially purchased as an entirely predesigned unit. When asking representatives for the breakdown of the equipment used and the cost of the equipment, many were not prepared, and so answers varied widely among respondents. In future studies, it will be crucial to first determine whether the facility is custom designed or if it is a packaged plant. Additionally, it will be highly valuable to work with a municipal sewage treatment operator to focus on building a comprehensive list of equipment prior to finalizing the surveys for distribution. That would help to reduce the forgetfulness of survey respondents.

CHAPTER 6: SURVEY RESULTS AND DESCRIPTIVE STATISTICS

A total of 81 surveys were collected from point source representatives. Questions on the survey aimed to gather as much information as possible, ranging from basic characteristics of each facility, to the detailed cost structure of the treatment plants, to the personal preferences of the primary decision makers within each municipal treatment plant.

When stricter regulations are in place, a common factor in the decision making process is whether to invest in new equipment, or to build an entirely new treatment plant. Older facilities could be more likely to rebuild, whereas newer facilities could be more likely to upgrade or opt to purchase a credit. From our results, we find the newest facility had been in operation for less than one year, whereas the oldest facility had been in operation for 92 years. The average facility had been in operation for slightly over 35 years with a median of 31 years and a standard deviation of 21 years. Nearly all participants responded to this question; 79 out of 81.

In addition to the length of time a facility has been in operation, we can also consider the number of patrons served. Though a focus group was initially consulted in the development stages of the survey, we quickly realized that information was not collected uniformly across facilities, therefore rather than using a single method for collecting population size, we provided two options to the respondents. Respondents could choose to answer with the number of households served, the number of people served, or both.

There were 30 responses for the number of households served and 51 responses for the number of people served. We then adjusted the responses to create an adjusted population variable. When the respondent gave a response for people served, we used their response with no change necessary. When the respondent gave a response for the number of people served, we used a multiplier of 2.49, which was the average number of persons per household in the state of Kentucky from 2007-2011, according the 2010 United States Census Bureau (United States Census Bureau, 2015). For example, if the reported number of households served was 100, then the adjusted population would be 100 x 2.49 = 249. We then observe 75 responses when considering the adjusted population. The average number of households served was 2,723, the average number of people served was 19,548, and the average adjusted population was 17,713. The minimum number of households served was 65 and the maximum number of households served was 14,000. The minimum number of people served was 30 and the maximum number of people served was 200,000. The minimum and maximum adjusted population did not change from the minimum and maximum for the number of people served. When we begin to model our data, we use the adjusted population, and refer to it as "People Served".

We can also take a look at the cost structure of the treatment facilities. We will first look at the average annual operating cost of each facility, followed by the total cost of water quality treatment equipment. There were 55 and 61 responses for average annual operating cost and total water quality treatment equipment costs respectively. The mean annual operating cost was just over $1.1 million, with a median of $400,000 and a standard deviation of nearly $1.8 million. There was an enormous range where the lowest reported average annual operating cost was $2,500 compared to the maximum reported cost of nearly $61 million.

In a later section, we will discuss willingness to pay in greater depth. For now, we can simply look at the descriptive statistics for the willingness to pay responses. When respondents were asked how much they would be willing to pay for a nitrogen credit, 36 responded with values ranging from $0 to $200,000. The mean response was $5,862 with a median value of only $1.50 and a standard deviation just over $33,000. Similarly, respondents were asked how much they would be willing to pay for a phosphorous credit. There were 38 responses with values ranging from $0 to $400,000. The mean response was $11,614 with another low median value of $3.50 and large standard deviation just short of $65,000.

Table 6.1 Survey Results for Continuous Variables

Variable	Mean	Median	Std. Dev	Min	Max	N
Years	35.40	31.00	21.29	0.25	92.00	79
Households	2,723.50	1,200.00	4,088.47	65.00	14,000.00	30
People	19,548.16	3,300.00	45,699.13	30.00	200,000.00	51
Population^{A}	15,713.86	3,000.00	38,497.95	30.00	200,000.00	75
An Op Cost	$1,105,179.00	$400,000.00	$1,770,691	$2,500.00	$60,784,826.00	55
WTP N	$5,862.11	$1.50	$33,297.74	$0.00	$200,000.00	36
WTP P	$11,614.24	$3.50	$64,883.93	$0.00	$400,000.00	38

Note: Superscript ^{A} denotes an adjusted population variable

Figure 6.1 Willingness to Pay for Phosphorous Credits

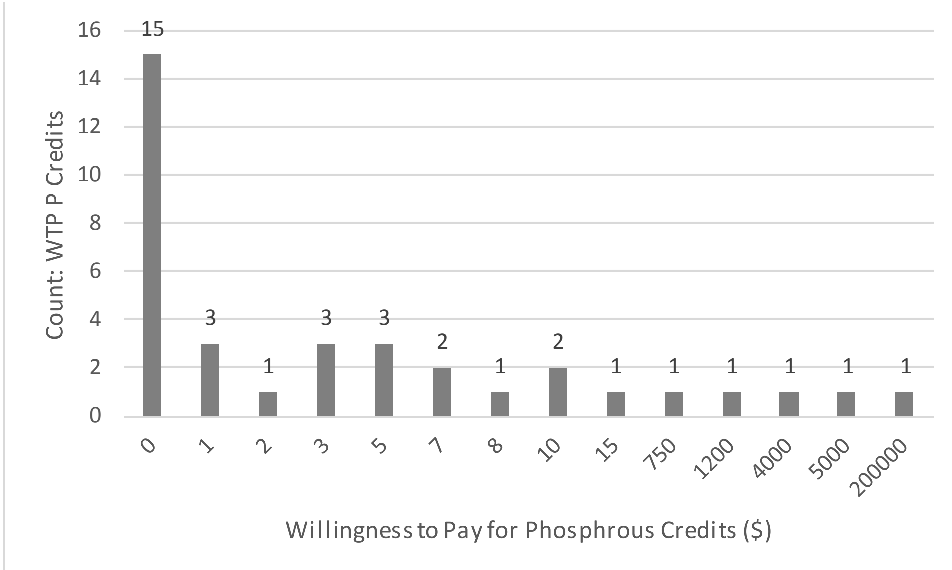
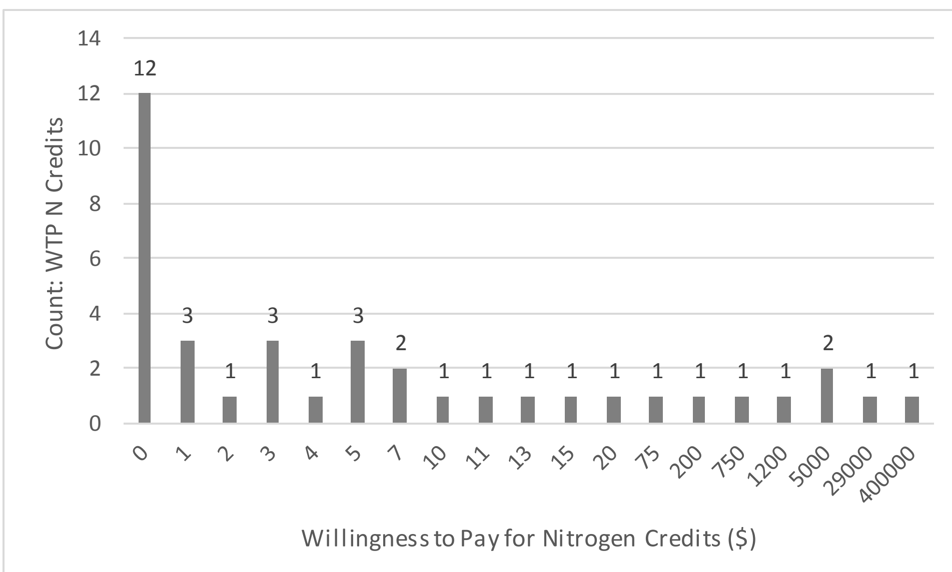


Figure 6.2 Willingness to Pay for Nitrogen Credits



Next, we can consider the current financial status of each facility. Specifically, is the facility improving or doing worse compared to the previous year? We asked respondents to rank the current financial status of the facility in comparison with the previous year, on a scale from 1-7, where 1 represents “much worse”, 4 is “about the same”, and 7 is “much better”. There were 77 responses for this question. Responses ranged from “much worse” to “much better”, with 36 ranking their facility “about the same”.

Figure 6.3 Current Financial Status Compared to Previous Year

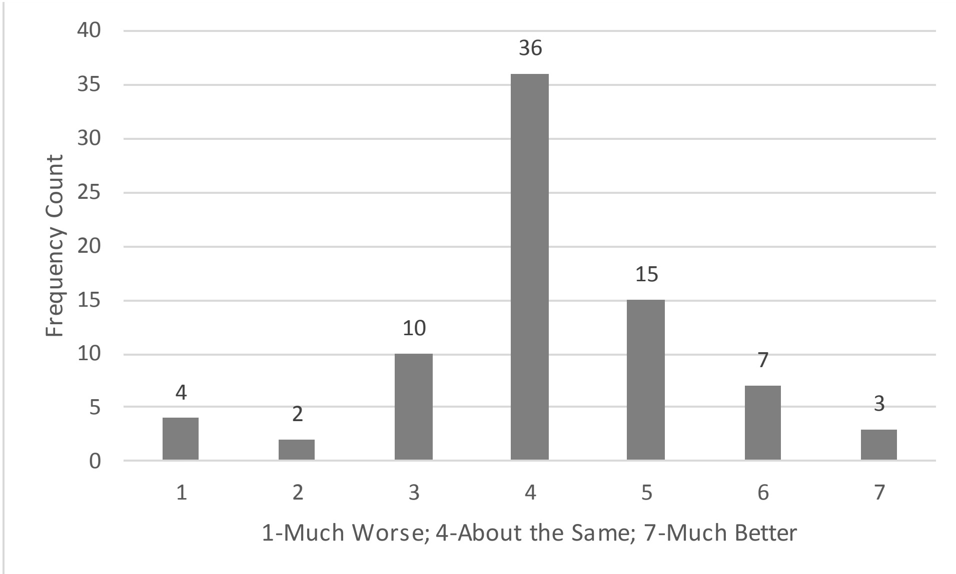
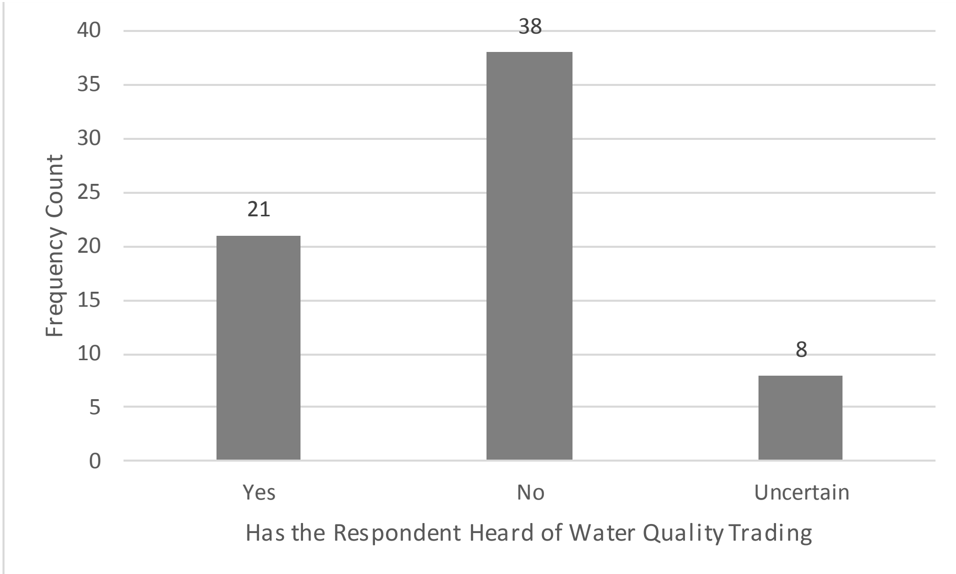


Table 6.2 Current Financial Status Compared to Previous Year

	Rank	Frequency	Percentage
Much Worse	1	4	5%
	2	2	3%
	3	10	13%
About the Same	4	36	47%
	5	15	19%
	6	7	9%
Much Better	7	3	4%

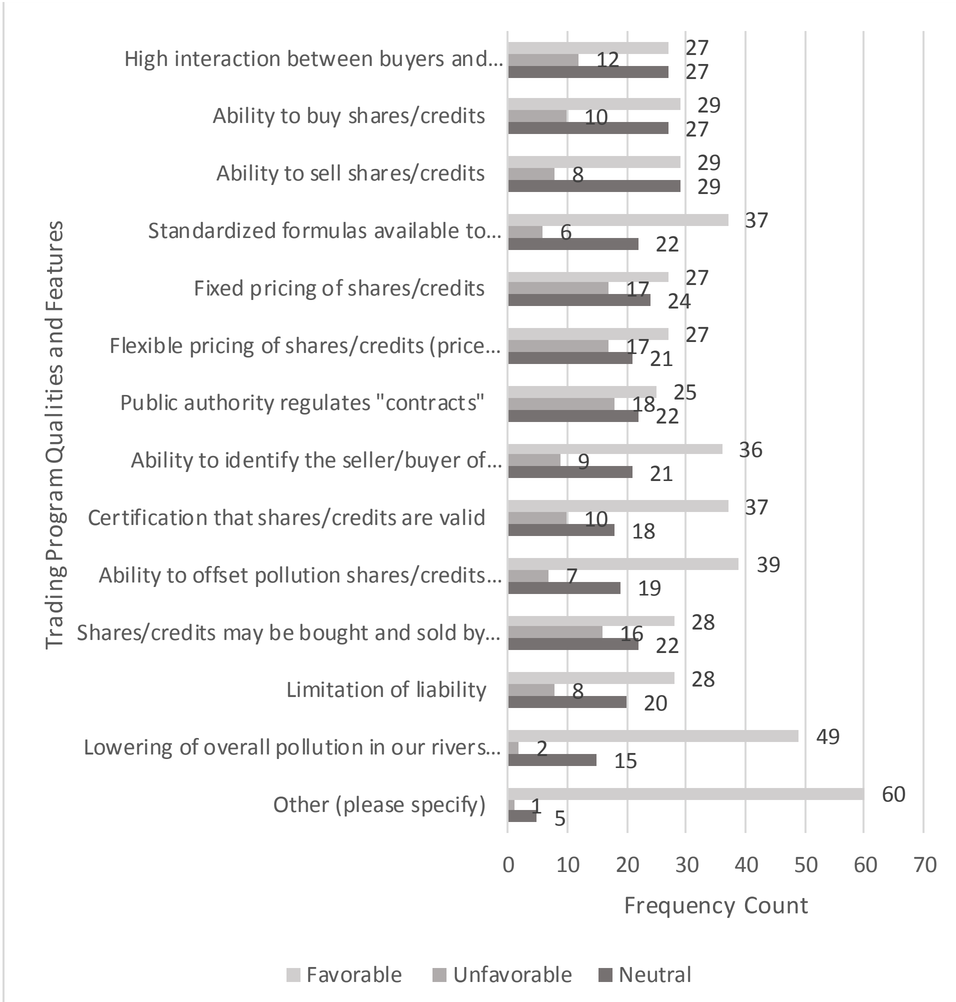
Additionally, we asked respondents to report if, prior to the implementation of this survey, if they had ever heard of water quality trading before. Responses could be “yes”, “no”, or “uncertain”. The majority of respondents, 36, had never heard of was water quality trading before. 21 respondents had heard of water quality trading prior to this survey, and 8 were uncertain.

Figure 6.4 Has Respondent Previously Heard of Water Quality Trading?



Additionally, we asked respondents how they felt about a variety of qualities and features for a potential water quality trading market. Popular characteristics can be incorporated, while less popular qualities can be avoided when possible. Responses for each quality could be "favorable", "unfavorable", or "uncertain".

Figure 6.5 Favorability for Trading Program Qualities and Features



It can also be important to see how much each facility spends on equipment used to control nitrogen and phosphorous. We can break this information down into aggregates. Specifically we ask:

Based on your best knowledge, please indicate your facility's expenses for equipment used mostly to control nitrogen and phosphorous averaged over the past five, ten, and twenty years.

Figure 6.6 Expense Breakdown (Survey Question)

	Average Annual Expense in Past Five Years	Average Annual Expense in Past Ten Years	Average Annual Expense in Past Twenty Years
Under $5,000	☐	☐	☐
$5,000 - $10,000	☐	☐	☐
$10,000 - $50,000	☐	☐	☐
$50,000 - $100,000	☐	☐	☐
$100,000 - $200,000	☐	☐	☐
$200,000 - $500,000	☐	☐	☐
$500,000 - $1M	☐	☐	☐
$1M - $1.5M	☐	☐	☐
$1.5M - $2M	☐	☐	☐
Over $2M	☐	☐	☐
For each of the cost you specified, please give the percentage of distribution over different methods:	____% biological method ____% chemical method ____% mechanical method	____% biological method ____% chemical method ____% mechanical method	____% biological method ____% chemical method ____% mechanical method
Other types of costs (please specify):			

The majority of respondents who reported on this question report spending less than $5,000 on average over the past 5, 10, and 20 years, while some responses exceeded $2,000,000. Unfortunately, this question went largely unanswered, with the highest number of responses being 16, for the average annual expense over the past five years. We attempt to get the percentage breakdown of where these costs were distributed, i.e. was the cost due to biological methods, chemical methods, or mechanical methods? Responses to these questions were spotty at best.

Finally, we can review the ranked preferences among a list of potential water quality trading mechanisms. After being provided with a list of descriptions for each market mechanism, respondents were asked to rank their preferences in the following question:

I would rank these market options as (1 being the most preferred; 2 is less preferred to 1, and so on):

_____ Seller/Buyer Negotiation

_____ Government Facilitation

_____ Market Exchange

_____ Sole-Source Offset

This question will be covered later in more detail. For now, we can review the responses. Each mechanism receives its own rank by each respondent. For Seller/Buyer Negotiation, 25 said they prefer this option most, 17 said they prefer it second most, 11 ranked it third, and 5 ranked it least preferred. For Market Exchange, 7 ranked this item as their most preferred, 16 ranked it as second most preferred, 14 ranked it third most preferred, and 19 ranked it least preferred, while one respondent ranked this mechanism with a 10. For Government Facilitation, 13 ranked this as most preferred, 10 ranked it second most preferred, 14 ranked it third, and 20 ranked it as their least preferred mechanism. Sole-Source offset received 13 responses for most preferred, 17 responses for second most preferred, 15 responses for third most preferred, and 11 responses for least preferred, with one response with a value of 10.

Figure 6.7 Ranking: Seller/Buyer Negotiation

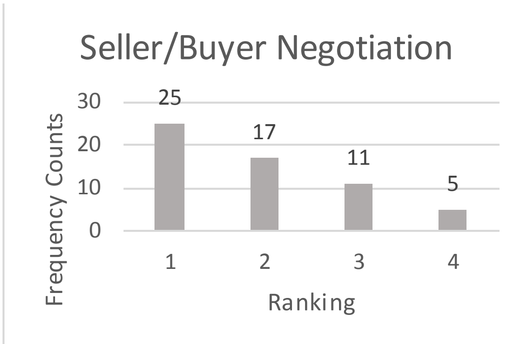


Figure 6.9 Ranking: Market Exchange

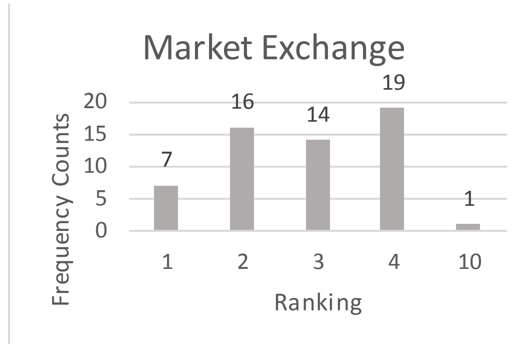


Figure 6.8 Ranking: Government Facilitation

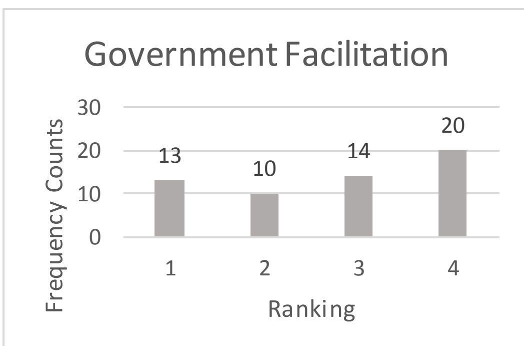
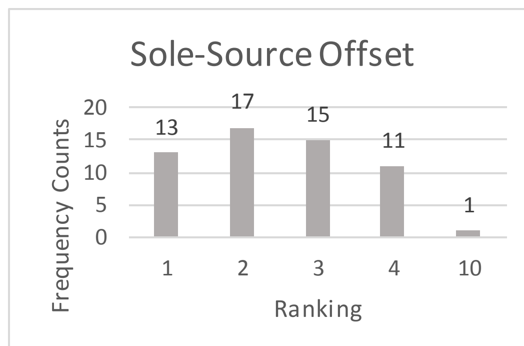


Figure 6.10 Ranking: Sole-Source Offset



CHAPTER 7: WILLINGNESS TO PAY FOR ABATEMENT CREDITS

In this chapter, we will discuss the willingness to pay for phosphorous and nitrogen abatement credits for a potential water quality trading market. The question is presented in the survey as follows:

Regardless of the characteristics you preferred above, what is the **maximum** amount your facility is willing to pay for these shares/credits? We understand that often times the facilities do not decide these amounts themselves. However, we would like you to specify the amounts based on your best guess or if you were to make the decision.

To reduce one "unit"; i.e., 1 mg in Total Nitrogen in discharge, the maximum your facility will be willing to pay per year is:

Figure 7.1 Willingness to Pay: Nitrogen (Survey Question)

☐ $0	☐ $5	☐ $10
☐ $1	☐ $6	☐ $11
☐ $2	☐ $7	☐ $12
☐ $3	☐ $8	☐ $13
☐ $4	☐ $9	☐ $__________

To reduce one “unit”; i.e., 1 mg in Total Phosphorous in discharge, the maximum your facility will be willing to pay per year is:

Figure 7.2 Willingness to Pay: Phosphorous (Survey Question)

☐ $0	☐ $5	☐ $10
☐ $1	☐ $6	☐ $11
☐ $2	☐ $7	☐ $12
☐ $3	☐ $8	☐ $13
☐ $4	☐ $9	☐ $__________

The respondent has the option of selecting any of the available boxes with values ranging from $0-13 or alternatively, the respondent can include an alternative response, if there is a more appropriate dollar amount. The range of possible responses was generated during the discussion with a focus group. This question focuses on abatement on a per-unit basis. Given publicly available information, the total quantity of abatement can be derived for each facility. In order to analyze the response for the two willingness-to-pay questions, we will first consider the type of dependent variable, which first appears to be continuous. Because the respondent can select any dollar amount they see fit, we first begin by implementing an Ordinary Least Squares model. However, we immediately notice that a large portion of the respondents reported they would be willing to pay $0. Respondents were limited to only recording positive dollar value responses, and thus we have unintentionally censored their possible responses. Therefore, we move beyond OLS and use a tobit model, which is a common model for censored regression analysis. Additionally, a quick look at the responses shows significant outliers. Specifically, while the majority of responses are single or double digit dollar amounts, we have some responses that reach as high as $200,000 and $400,000 for willingness to pay responses. Rather than choosing to keep or discard the outliers, analysis is conducted using OLS and tobit, first where the outliers are present and second where outliers are removed. To define outliers, we simply remove observations that are more than 1.5 times the inner quartile range above the third quartile. Additionally, tests for multicollinearity were conducted. A general rule of thumb is to further investigate variables when the variance inflation factor (VIF) is greater than 10. For our data, the highest VIF values were 3.8 (nitrogen model, all observations present), 3.7 (phosphorous model, all observations present), 2.4 (nitrogen model, outliers removed), and 2.5 (phosphorous model, outliers removed). Because there were no values indicating multicollinearity, we can move forward with our analysis.

For all models used in this section, the dependent variables are regressed against the following explanatory variables from the survey:

Table 7.1 Explanatory Variables

Explanatory Variable	Description
Years	The number of years the current facility has been in operation.
People Served	The number of households or people the facility serves.
Financial Status	The current financial status of the facility compared to the previous year. Responses range from 1-7, where 1 is much worse, 4 is about the same, and 7 is much better.
Operating Cost	The average annual operating cost of the water quality treatment equipment currently used in the facility (including labor, electricity/fuel, and materials, but excluding building costs, installation, and equipment depreciation.
Monitor	If the facility is required to monitor phosphorous, then the response is coded as '1'.
Reduce	If the facility is required to reduce phosphorous, then the response is coded as '1'.
Familiar	If the respondent has heard of water quality trading, then the response is coded as '1'.
Unfamiliar	If the respondent has not heard of water quality trading, the response is coded as '1'.

Note: Monitor and Reduce are both coded against "Neither". Familiar and Unfamiliar are both
coded against "Not Certain".

7.1 Ordinary Least Squares Model

When attempting to model the willingness to pay for abatement credits we first employ the Ordinary Least Squares model:

$$y_i = \beta_1 + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \varepsilon_i \quad (7.1)$$

Or

$$y_i = x_i'\beta + \varepsilon_i \quad (7.2)$$

Where y_i represents the willingness to pay for respondent i, $\mathbf{x}_i$ is the vector of explanatory characteristics which differ across respondents, β is the vector of parameter estimates, and ε_i is the random error term.

7.2 Tobit Model

The tobit model (Tobin, 1958), first introduced by James Tobin, is commonly used for censored data when several observations are found at either the upper and/or lower bound and the remaining responses are not censored. The basic concept is that there is a true latent variable which cannot be observed beyond a boundary, thus we only observe the censored response. The tobit model can be represented as follows:

$$y_i^* = x_i'\beta + \varepsilon_i, i = 1, 2, \ldots, N \quad (7.3)$$

$$y_i = y_i^* \ if \ y_i^* > 0 \quad (7.4)$$

$$y_i = 0 \ if \ y_i^* \leq 0 \quad (7.5)$$

Where y_i^* represents the latent dependent variable, which in our case is *desired* willingness to pay. Because respondents cannot pay a negative value, though they may wish to, several observations can be censored at $y_i = 0$, where y_i is the recorded willingness to pay. When the respondents are willing to pay a positive value, we will observe their true willingness to pay. The censored regression model describes both the probability of a censorship and the conditional expected value given a positive response. The probability of $y_i = 0$ can be shown as:

$$P\{y_i^* \leq 0\} \tag{7.6}$$

$$= P\{\varepsilon_i \leq -x_i'\beta\} \tag{7.7}$$

$$= P\left\{\frac{\varepsilon_i}{\sigma} \leq -\frac{x_i'\beta}{\sigma}\right\} \tag{7.8}$$

$$= \Phi\left(-\frac{x_i'\beta}{\sigma}\right) \tag{7.9}$$

$$= 1 - \Phi\left(\frac{x_i'\beta}{\sigma}\right) \tag{7.10}$$

And the conditional expected value of y_i given $y_i > 0$ can be shown as:

$$E\{y_i|y_i > 0\} = x_i'\beta + E\{\varepsilon_i|\varepsilon_i > -x_i'\beta\} \tag{7.11}$$

$$= x_i'\beta + \sigma\frac{\phi(\frac{x_i'\beta}{\sigma})}{\Phi(\frac{x_i'\beta}{\sigma})} \tag{7.12}$$

7.3 Empirical Results: Willingness to Pay for Abatement Credits

In this section, we will review the results obtained using Ordinary Least Squares and a censored regression model, i.e. the Tobit Model. The reason we will be implementing both models is due to the fact that while the dependent variable(s) is/are continuous in nature, there is a clustering of observations at zero. When clustering occurs at the extreme end of possible responses, that is an indication of censoring, and thus OLS will no longer be the appropriate model to use. Additionally, we will take note of the presence of extreme outliers in our dependent variables which can potentially skew our parameter estimates.

For that reason, we will look at our results with all observations present, and again with outliers removed for comparison.

Acknowledging the Presence of Outliers

Prior to reviewing the models implemented, we will first address the presence of outliers. It is important to note that while an observation may be deemed an outlier, it does not mean the observation is inaccurate. However, due to the scale of our responses, they should also not be overlooked. There were 81 surveys partially completed. Of the 81 surveys submitted, there were only 38 responses for willingness to pay for phosphorous and only 36 responses for willingness to pay for nitrogen. We then cleaned the data and created two new sets. These two new sets would not have any missing values, which is necessary for some of the Tobit coding to be done later. One set is for phosphorous and contains 29 observations. The other set is for nitrogen and contains 26 observations. Using a simple formula to calculate outliers from these two sets, we consider any observation which lies a distance greater than 1.5 times the inner quartile range above Q3 or below Q1 to be a potential outlier. For phosphorous, we found six outliers ranging from $75 to $400,000. For Nitrogen, we found three outliers ranging from $750 to $200,000.

7.3.A Reporting OLS Results: All Observations Included

Phosphorous

There were 29 observations used for this model. The overall p value was significant at the .0001 level which means we have significant evidence that at least one of the coefficients in our model is not equal to zero, meaning at least one variable is 'useful', i.e. that variable significantly captures a portion of the variance within the model. The adjusted R-Square was 0.83 which means 83% of the variance among the dependent variables can be explained by the model. However, with the presence of extreme outliers, the R-Square value provided can be misleading. Eight parameter coefficients were estimated in addition to the intercept. Of the parameter estimates, People Served was significant at the 10% level while Financial Status and the dummy variable Unfamiliar were approaching significance at the 15% level. No other variable was significant. It is important to note that while the overall fit of the model seems rather strong, one outlier in particular has a Cook's D value greater than 15, which is considered to be a high amount of leverage. Results can be found in Table 7.2.

Nitrogen

There were 26 observations used for this model. The overall p value was significant at the .0001 level and the adjusted R-Square was again 0.83. Of the parameter estimates, we find similar results to those from the phosphorous model. People Served was significant at the 10% level while Financial Status and the dummy variable Unfamiliar were approaching significance at the 15% level. No other variable was significant. Again, there was an observation with a Cook's D value greater than 15. Results can be found in Table 7.2.

Table 7.2 OLS Parameter Estimates with All Observations Present

Variable	Phosphorous		Nitrogen	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	13,243	38269	13,386	21836
Years	284.28	358.68	121.83	202.66
People Served	1,627.16*	818.06	804.40*	431.44
Financial Status	-9,245.15[A]	6245.20	-5,963.39[A]	3566.68
Annual Operating Cost	115.04	103.77	62.24	0.00
Monitor	23,139	19052	12727	10159
Reduce	10,064	22127	1,885.74	12345
Familiar	-4,941.81	20550	-3,585.29	11638
Unfamiliar	-28,373[A]	18504	-16,108[A]	9905.29

Note: Asterisks *,**, and *** denote variables significant at the 10%, 5%, and 1% levels, respectively. Superscript [A] denotes variables approaching significance at 15%.

7.3.B Interpreting OLS Results (Phosphorous Example)

The results for the two willingness to pay models (phosphorous and nitrogen) have nearly identical interpretations. The primary difference is that of course the respective estimates from each table correspond to the willingness to pay for their respective dependent variables. We can walk through the interpretation for the phosphorous results first, understanding we will have the same basic interpretation for the nitrogen results. Additionally, the results will have the same interpretation when for the second set of OLS models, when the outliers have been removed.

For phosphorous, an intercept of 13,243 means that with no additional information, we would expect WTP for phosphorous credits to be $13,243. For every additional year of operation, starting from 0 years, we can expect WTP for phosphorous credits to increase by $284.28. Results for the number of people served has been adjusted by a factor of 1,000. So for every additional 1,000 people served, we expect to see a $1,627 increase in WTP for phosphorous credits. Financial status was recorded using a likert scale, with values ranging from 1-7, were 1 represents the facility is doing “much worse” financially this year, as compared to the previous year, 4 represents the facility is doing “about the same”, and 7 means the facility is doing “much better”. For every additional point, starting from 0, we would expect the WTP for phosphorous credits to decrease by $9,245. Annual operating cost results were adjusted by a factor of 10,000. So for every additional $10,000 of annual operating cost incurred by the facility, we would expect to see an increase of $115 in WTP for phosphorous credits. Monitor and Reduce are both part of the same question. Respondents were asked if their facility was required to Monitor, Reduce, or do Neither, in terms of phosphorous discharge levels. Because respondents were given the option of choosing more than one box, both Monitor and Reduce were dummy coded against Neither, i.e. Neither was set to a value of 0. When the respondent's facility monitors for phosphorous, their expected WTP for phosphorous credits increases by $23,139 compared to a facility that does not monitor or reduce. Additionally, when a facility reduces phosphorous levels, WTP for phosphorous credits increases by $10,064 compared to a facility that does neither. Familiar and Unfamiliar were also both part of the same question, where respondents were asked if they had heard of water quality trading prior to filling out the survey. Respondents had the option of answering "yes", "no", or "uncertain". When a respondent said "yes", then we dummy code their response as a '1' for Familiar. Similarly, when they responded "no", we dummy code their response as '1' for Unfamiliar. Both Familiar and Unfamiliar are coded against Uncertain. When a response was '1' for Familiar, the expected WTP for phosphorous credits decreases by $4,941. When the response was '1' for Unfamiliar, the expected WTP decreases by $28,373.

7.3.C Reporting OLS Results: Outliers Excluded

Phosphorous

After removing the outliers, the OLS model for phosphorous contains 23 observations. The significance of the p value has been reduced from significant at the 0.0001 level to 0.29 and the adjusted R-Square value has been reduced to 0.12. While the overall fit of the model has been reduced, the number of significant parameter estimates has increased. We no longer see significance in People Served, however we now see Monitor is significant at the 1% level, Unfamiliar is significant at the 5% level, and Reduce and Familiar are both significant at the 10% level. Results are shown in Table 7.3.

Nitrogen

After removing the outliers, the OLS model for nitrogen contains 23 observations. The significance of the p value has been reduced from significant at the 0.0001 level to 0.48 and the adjusted R-Square is -0.0028. There were no significant variables in this model. Results are shown in Table 7.3.

Table 7.3 OLS Parameter Estimates with Outliers Removed

Variable	Phosphorous		Nitrogen	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	1.32	6.38	3.75	4.91
Years	0.02	0.07	0.06	0.05
People Served	-0.16	0.15	0.08	0.11
Financial Status	0.45	1.04	-0.14	0.85
Annual Op. Cost	0.01	0.02	-0.01	0.01
Monitor	-9.84***	3.51	-2.91	2.37
Reduce	-7.15*	3.68	-2.83	2.73
Familiar	7.02*	3.98	0.71	2.63
Unfamiliar	8.86**	3.82	-0.63	2.37

Note: Asterisks *,**, and *** denote variables significance at 10%, 5%, and 1% level, respectively. Superscript ^{A} denotes variables approaching significance at 15%.

7.3.D Reporting Censored Regression Results: All Observations Included

For the censored regression model, we implemented the QLIM procedure in SAS. There are multiple ways to perform a censored regression model in SAS. Another popular approach is to use the LifeReg procedure. According to the knowledge base on the SAS Support website, the primary difference between the two procedures is that the QLIM procedure satisfies all four Moore-Penrose conditions while the Lifereg procedure satisfies only two Moore-Penrose conditions (SAS Institute Inc., n.d.). To lean on the conservative side, we chose to satisfy all four conditions, hence using Proc QLIM.

Parameter estimation results from the Tobit model can be interpreted similar to those of the OLS model with a few exceptions. When the expected value is less than or equal to zero, we would then set our expected value equal to the zero, i.e. the lower bound, otherwise the interpretation is the same for positive values as it would be for OLS. Additionally, we must calculate marginal effects for the model, which will be addressed shortly.

Phosphorous Parameter Estimates (With Interpretation)

There were 29 observations included in the censored regression model for phosphorous (52 observations were missing). Of those 29 observations, 10 were censored at the lower bound where respondents said their willingness to pay for phosphorous credits was $0.00. For this model, all variables with the exception of Years and Annual Operating Cost were significant at the 1% level. Years and Annual Operating Cost were not significant at all. Perhaps the most important result is the estimate for _Sigma is significant at the 1% level which implies tobit has an advantage over OLS.

The results estimated for the tobit model can be interpreted as follows: The intercept for the latent, "desired" willingness to pay for phosphorous credits is $55,648 and is significant at the 1% level. For every additional year of operation, the respondent should be willing to pay an additional $4.15 per credit, but this number is not significant. For people served, we can say that for every additional 1,000 people served, desired willingness to pay increases by $299, but is not significant. When the financial status increases by one point, from 0, the willingness to pay decreases by $20,410 and is significant at the 1% level. For every $10,000 of annual operating cost, the willingness to pay should increase by $269 and is significant at the 1% level. When the facility monitors phosphorous levels, the willingness to pay decreases by $1159, compared to not monitoring or reducing, and is significant at the 1% level. Similarly, if the facility reduces phosphorous levels, their willingness to pay should decrease by $1617 and is significant at the 1% level. When the representative is familiar with water quality trading, willingness to pay increases by $18,623 and is significant at the 1% level. Lastly, when the respondent is unfamiliar with water quality trading, their willingness to pay for credits should decrease by $14,609 and is significant at the 1% level.

Monitor and reduce are both dummy coded against "neither monitor or reduce". A response can be both monitor and reduce, monitor or reduce, or neither. However, while familiar and unfamiliar were both dummy coded against "uncertain", regarding prior knowledge to water quality trading, it does not make sense for respondents to check more than one box.

When the results from the parameter estimates are applied to an individual respondent, those values should be interpreted as being applied to the "desired" willingness to pay.

When the value is less than or equal to zero, we would map their willingness to pay to zero. Alternatively, if their desired willingness to pay was greater than or equal to zero, we have no conflict, and can simply take the results without any necessary adjustments, similar to OLS. However, this is not OLS, so we will need to take additional steps to interpret the marginal effects of the explanatory variables on the latent dependent variable. The remaining estimates for willingness to pay for nitrogen credits (with all observations included), along with the estimates for willingness to pay when outliers have been removed will be identical to the interpretation of the estimates we just covered. Therefore, I will only lightly cover the remaining results until we move on to the marginal effects. These results can be found in Table 7.4.

Nitrogen Parameter Estimates

There were 26 observations included in the censored regression model for nitrogen (55 missing values). Of those 26 observations, 11 were censored at the lower bound. For this model, all variables were significant at the 1% level with the exception of Years which was significant at the 10% level and People Served, which was not significant at all. The value for _Sigma was also significant at the 1% level. Results are located in Table 7.4.

Table 7.4 Tobit Model Parameter Estimates with All Observations Included

	Phosphorous		Nitrogen	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	55,648***	4.22	28,435***	2.27
Years	4.15	190.90	184.26*	105.22
People Served	299.00	408.19	111.67	223.16
Financial Status	-20,410***	16.62	-11428***	8.56
Annual Operating Cost	268.77***	55.019	160.14***	29.60
Monitor	-1,158.95***	3.49	-304.35***	1.55
Reduce	-1,616.60***	3.44	-19,708***	1.12
Familiar	18,623***	1.85	6,072.51***	1.01
Unfamiliar	-14,609***	3.40	-11,264***	2.23
_Sigma	33277***	1.30	16,894***	0.64

Note: Asterisks *,**, and *** denote variables significant at the 10%, 5%, and 1% levels, respectively. Superscript [AA and A] denotes variables approaching significance at 20% and 15%, respectively.

7.3.E Reporting Censored Regression Results: Outliers Excluded

Phosphorous Parameter Estimates

With the outliers removed, there were 24 observations in our model for phosphorous. For this model, there was a reduction in the number of parameters estimated to be significant. The only variable significant at the 1% level was _Sigma. People Served was approaching significance at the 15% level and Familiar was approaching significance at the 20% level. The remaining estimates were not significant. Results are located in Table 7.5.

Nitrogen Parameter Estimates

With outliers removed, there were 23 observations in our model for nitrogen. For this model, _Sigma was significant at the 1% level. Monitor was significant at the 10% level. Years and Reduce were both approaching significance at the 20% level. Results are located in Table 7.5.

Table 7.5 Tobit Model Parameter Estimates with Outliers Removed

	Phosphorous		Nitrogen	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Intercept	1.35	26.76	3.63	7.12
Years	0.29	0.28	0.10^{AA}	0.07
People Served	0.36^{AA}	0.23	0.05	0.06
Financial Status	-0.38	4.55	-0.80	1.30
Annual Operating Cost	-0.06	0.06	-0.01	0.01
Monitor	1.01	10.51	-5.12*	2.69
Reduce	3.39	13.66	-5.73^{AA}	3.68
Familiar	-16.45^{A}	12.72	2.40	3.55
Unfamiliar	-10.32	12.34	0.93	3.36
_Sigma	17.58***	3.58	4.48***	1.01

Note: Asterisks *,**, and *** denote variables significant at the 10%, 5%, and 1% levels, respectively. Superscript $^{AA \text{ and } A}$ denotes variables approaching significance at 20% and 15%, respectively.

7.3.F Marginal Effects

To fully take advantage of the tobit model, it is important to remember that we are not only predicting a linear model, but a censored linear regression model. Specifically, we cannot forget the possibility of a censored response. Therefore, our marginal effects take the probability of a censorship into account during the estimation process:

$$\frac{\partial E(y|x)}{\partial x} = \beta \Pr(y^* > 0|x) \tag{7.13}$$

The formula we are estimating is the instantaneous change in the expected value of willingness to pay for credits, given the current values of the explanatory variables. From this static condition, if one of the continuous variables changes by one unit, we can expect to see the product of the parameter estimate multiplied by the probability of the latent dependent variable being greater than zero. The more certain we are that the latent variable is not censored, the more closely related the marginal effect will be to the actual parameter estimate.

When prompted, SAS provides marginal effects for each explanatory variable, for each response. However, rather than display the entire output, it is common to use the average marginal effects. Interpreting the marginal effects works best for continuous variables. Let's first look at the results for the average marginal effects on the willingness to pay for phosphorous credits when all observations are present. The average marginal effect of years on willingness to pay is 1.98, which means that from a static point, if the facility was to gain one year of operation, we would expect an average increase of $1.98 on the latent willingness to pay. Notice how the marginal effect differs from the parameter estimate, which was $4.15. People served is reported in units of 1,000 people, so when the number of people served increases by one unit, i.e. 1,000 people, we would expect willingness to pay to increase by $142.74. Financial status was reported on a likert scale, so we can say that when the financial status of the facility increases by one point, we would expect the willingness to pay to decrease by $9,744. Annual operating cost was recorded in units of $10,000, so when the annual operating cost increases by $10,000, we expect the willingness to pay to increase by $128. The remaining explanatory variables are dummy variables, and so it does not make sense to use marginal effects.

Table 7.6 Average Marginal Effects for Tobit Model: Outliers Present

	Phosphorous		Nitrogen	
Variable	**Mean**	**Standard Dev**	**Mean**	**Standard Dev**
Years	1.9822193	1.3319205	78.6689957	61.1277921
People Served	142.7436669	95.9143208	47.6745083	37.0442943
Financial Status	-9743.99	6547.32	-4879.00	3791.11
Annual Operating Cost	128.3164736	86.2201994	68.3709700	53.1259667
Monitor	-553.2922078	371.7758376	-129.9398014	100.9665002
Reduce	-771.7776056	518.5836014	-8414.09	6537.96
Familiar	8890.54	5973.85	2592.60	2014.51
Unfamiliar	-6974.27	4686.25	-4809.26	3736.91

Table 7.7 Average Marginal Effects for Tobit Model: Outliers Removed

	Phosphorous		Nitrogen	
Variable	**Mean**	**Standard Dev**	**Mean**	**Standard Dev**
Years	0.1447811	0.0600696	0.0574715	0.0237006
People Served	0.1786577	0.0741249	0.0266973	0.0110097
Financial Status	-0.1921431	0.0797200	-0.4668878	0.1925389
Annual Operating Cost	-0.0318747	0.0132248	-0.0038386	0.0015830
Monitor	0.5046805	0.2093914	-2.9798569	1.2288570
Reduce	1.7025707	0.7063949	-3.3302241	1.3733442
Familiar	-8.2592828	3.4267683	1.3943232	0.5750021
Unfamiliar	-5.1807266	2.1494783	0.5398613	0.2226323

CHAPTER 8: PREFERENCES FOR MARKET MECHANISMS

In this chapter, we will discuss the preferences for different types of market trading mechanisms for a potential water quality trading market, from the perspective of the representatives from each municipal sewage treatment facility, i.e. from the point source perspective. In the survey, we defined four trading mechanisms and then asked respondents to rank their preferences in the following question:

I would rank these market options as (1 being the most preferred; 2 is less preferred to 1, and so on):

_____ Seller/Buyer Negotiation

_____ Government Facilitation

_____ Market Exchange

_____ Sole-Source Offset

Not only were respondents asked to select their most preferred mechanism, but they were asked to rank their preferences from most preferred to least preferred. Ranking preferences gives a greater amount of insight than simply asking for the most preferred choice.

To analyze the ranking of preferences, we will employ the use of a rank-ordered logistic regression model (Hausman & Ruud, 1987), also known as the exploded logit (Punj & Staelin, 1978). We will first introduce the theoretical model, then we will approach the analysis for these preferences in two distinct stages. The first stage will focus solely on item differences to determine if there are detectible differences among preferences for market trading mechanisms. In this stage, we can determine which mechanisms are most preferred, if any, and it will also serve as a nice introduction to the empirical model we will be implementing and how to interpret the results. For the second stage, we will expand our model to incorporate other information we have collected from the survey responses. In doing so, we can take the information gained here and use it to predict the probability of a particular ranking of preferences for a given facility. Additionally, we will be able to see how particular facility characteristics play a role in determining which trading mechanisms are most preferred, thus gaining better insight into which type of mechanism might have the greatest level of success in a given market.

8.1 Rank Ordered Logistic Regression: Theoretical Model

Discrete choice models offer a wide variety of ways to approach analyzing preferences. When respondents give complete ranks to their preferences, the rank ordered logistic regression model, aka the "exploded logit" captures the probability of the entire ranking of preferences. The exploded logit is derived from the Random Utility Model (Allison & Christakis, 1994).

Though the actual underlying utility may be a latent, unobservable value, the Random Utility Model attempts to account for the ranking of utilities in the following form:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (8.1)$$

Decomposing the Random Utility Model, U_{ij} represents the unobserved utility for respondent (i), given choice j, where j is an element of C_i, and C_i represents all possible choices for respondent (i). V_{ij} is the deterministic portion of the model, which will be represented as $x_{ij}'\beta$ where x_{ij}' is the vector of explanatory variables for respondent (i), associated with item j, and β is the vector of parameter coefficients associated with each of the explanatory variables. Lastly, ε_{ij} is the error term, which is distributed iid extreme-value, and represents the random component of the model. Notice, by construction, the deterministic portion of the model condenses to a simple scalar and can easily be written as:

$$x_{ij}'\beta \rightarrow \mu_{ij} \tag{8.2}$$

The deterministic portion of the model will be plugged into a likelihood function.

Regarding the response variables, we should look again at the Random Utility Model:

$$V_{ij} \rightarrow x_{ij}'\beta \rightarrow \mu_{ij} = y_i \tag{8.3}$$

Where $\mathbf{y_i} = (y_{i1},\ldots, y_{iJ})'$ and y_{ij} represents the response, in this case rank, from respondent (i) given to item j. The possible rankings will be $y_{ij} = 1,\ldots, J$ where a ranking of 1 is most preferred and J is least preferred. Similarly, $\mathbf{r}_i = (r_{i1},\ldots,r_{iJ})'$ where r_{ij} represents the item that received rank j by individual (i). We can then see the relationship between the rankings of items as:

$$y_{ij} = j \Leftrightarrow r_{ij} = k \tag{8.4}$$

Where y_{ij} is the response for item j, from respondent (i), and r_{ij} is the rank, k, for item j from respondent (i). We can then state that items most preferred will also give the highest utility, thus:

$$U_{ir_{i1}} > U_{ir_{i2}} > \cdots > U_{ir_{iJ}} \tag{8.5}$$

At this stage, we have acknowledged all components of the Random Utility Model. The next step is to estimate the probability of the above sequence of utilities:

$$\Pr[U_{ir_{i1}} > U_{ir_{i2}} > \cdots > U_{ir_{iJ}}] \tag{8.6}$$

We can begin by first estimating the probability of only one item being ranked as most preferred:

$$\Pr[U_{ir_{i1}}] \tag{8.7}$$

To do so, we can implement McFadden's conditional logit model (McFadden, 1974):

$$\frac{e^{\mu_j}}{\sum_{k=1}^{J} e^{\mu_k}} \tag{8.8}$$

In the above model, we are simply describing the likelihood of any item, j, being selected out of the entire list of possible items. The rank ordered logit model extends the conditional logit model to a product of conditional logits, where each additional term in the product sequentially removes the previously selected item from the denominator. Let $\delta_{ijk} = 1$ if $Y_{ik} \geq Y_{ij}$, and 0 otherwise. This gives us:

$$L_i = \prod_{j=1}^{J} [\frac{\exp\{\mu_{ij}\}}{\sum_{k=1}^{J} \delta_{ijk} \exp\{\mu_{ik}\}}] \tag{8.9}$$

First consider the term δ_{ijk}, which acts as an on/off switch, indicating which terms to include in the denominator and which terms to disregard. Next, consider the ambiguity of the indexing of the terms by the letter j. In this example, we can choose plug any sequential order of the J items and determine the likelihood of that sequence. We could just as easily replace the term j with r_{ij}, and thus implicitly seek out the likelihood of a particular sequence of ranked preferences. Extending the above equation to a sample size of n respondents, we have the log likelihood function:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J_i} \mu_{ij} - \sum_{i=1}^{n} \sum_{j=1}^{J_i} log\, [\sum_{k=1}^{J_i} \delta_{ijk} \exp(\mu_{ik})] \tag{8.10}$$

It should be obvious that the above equation translates to:

$$\log L = \sum_{i=1}^{n}\sum_{j=1}^{J_i} xij\,'\ \beta - \sum_{i=1}^{n}\sum_{j=1}^{J_i} log\,[\sum\nolimits_{k=1}^{J_i} \delta_{ijk} \exp(xij\,'\ \beta)] \tag{8.11}$$

Where our goal is to estimate the β coefficients that maximize the likelihood observing the particular sequence of preferences, given the available data from our respondents.

8.2 Empirical Results: Ranked Preferences

8.2.A Stage 1: Item Differences Only

Recall, respondents were asked to rank their preferences with the following question:

I would rank these market options as (1 being the most preferred; 2 is less preferred to 1, and so on):

_____ Seller/Buyer Negotiation

_____ Government Facilitation

_____ Market Exchange

_____ Sole-Source Offset

We will use the following abbreviations throughout:

Neg = Seller/Buyer Negotiation
Gov = Government Facilitation
Mkt = Market Exchange
SSoff = Sole-Source Offset

Where the responses can be recorded as:

$$Response = \left(Rank_{Neg}, Rank_{Gov}, Rank_{Mkt}, Rank_{SSoff}\right) \tag{8.12}$$

If for example, the respondent preferred Seller/Buyer Negotiations most, Government Facilitation second most, Market Exchange third, and least preferred Sole-Source Offset, their response would be:

$$Response = \left(1_{Neg}, 2_{Gov}, 3_{Mkt}, 4_{SSoff}\right) \tag{8.13}$$

Our first objective in this stage is to determine whether or not there is at least one item that is ranked differently among the rest with any level of statistical significance. In order to do so, we implemented the PHREG statement in SAS, which requires a special data loading process. The process requires each item (Neg, Gov, Mkt, SSoff) to be dummy coded for each rank (1, 2, 3, 4), and then stratified across respondents. Keeping the loading process in mind, we have 324 observations read and 230 observations used. Due to the structure of our model, this can be interpreted as roughly 324/4 = 81 survey responses read and 230/4 = 57.5 observations being used, where the trailing 0.5 is because one respondent only ranked 1/4 of the mechanisms. The difference between survey responses read and survey responses used is due to the fact that respondents were not required to fill out responses to every question.

In order to determine whether or not at least one item is ranked differently from the rest, we can look to the three tests provided by the PHREG statement for the global null hypothesis.

$$H_0: All\ \beta = 0$$

$$H_A: At\ least\ one\ \beta \neq 0$$

The three test statistics provided are the Chi-Square values for the Likelihood Ratio Test, the Score Test, and the Wald Test. When the Chi-Square value is large, we have significant evidence to reject the null hypothesis, suggesting that at least one beta is not equal to zero. The results from the global null hypothesis tests can be seen in Table 8.1.

Table 8.1 Testing Global Null Hypothesis: BETA = 0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	15.1463	3	0.0017***
Score	15.8162	3	0.0012***
Wald	15.1675	3	0.0017***

Note: Asterisks *,**, and *** denote variables significance at 10%, 5%, and 1% level, respectively.

As you can see above, the Chi-Square values for all three likelihood tests are significant at the 1% level, indicating that at least one beta is not equal to zero, meaning that at least one mechanism appears to be preferred differently from the others.

Our second objective in this stage of the analysis is to review the parameter estimates. Each of the four trading mechanisms (Neg, Gov, Mkt, SSoff) will have a parameter estimate. We should note that one of the parameter estimates will be set equal to zero and the results will be compared against that value. Sole-Source Offset was arbitrarily chosen to be the omitted mechanism. The parameter estimates for the item differences follow in Table 8.2.

Table 8.2 Exploded Logit Parameter Estimates: Item Differences

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
Neg	1	0.53095	0.2435	4.7539	0.0292**	1.701
Gov	1	-0.24422	0.2365	1.0663	0.3018	0.783
Mkt	1	-0.33527	0.2450	1.8722	0.1712[A]	0.715
SSoff	N/A	0	N/A	N/A	N/A	1

Note: Asterisks *,**, and *** denote variables significance at 10%, 5%, and 1% level, respectively. Superscript A denotes variable approaching significance at the 15% level
Note: Compared against SSoff

The null hypotheses being tested here are roughly translated to:

$$1.\, H_0: Preference\ for\ SSoff = Preference\ for\ Neg$$

$$1.\, H_A: Preference\ for\ SSoff \neq Preference\ for\ Neg$$

$$2.\, H_0: Preference\ for\ SSoff = Preference\ for\ Gov$$

$$2.\, H_A: Preference\ for\ SSoff \neq Preference\ for\ Gov$$

$$3.\, H_0: Preference\ for\ SSoff = Preference\ for\ Mkt$$

$$3.\, H_A: Preference\ for\ SSoff \neq Preference\ for\ Mkt$$

The standard output provided in the Table 8.2 above shows the parameter estimates for Neg, Gov, and Mkt. SSoff was included in addition to the typical results simply for comparison, and as you can see was set to zero.

We can see that Neg is significant at the 5% level, meaning there is significant evidence to suggest there is a difference in preference between Neg as compared with SSoff. Gov does not appear to be significant, thus we do not have significant evidence to suggest a difference in preference between Gov and SSoff. The parameter for Mkt is not significant, but it is approaching significance, meaning there is not quite enough evidence to suggest a difference in preference between Mkt and SSoff.

Next we can turn our attention to the Hazard Ratios, which can be interpreted as the odds of preferring that mechanism to SSoff. Going down the list, Neg is approximately 1.7 times as likely to be preferred compared to SSoff, Gov is 0.78 times as likely to be preferred compared to SSoff, and Mkt is 0.72 times as likely to be preferred compared to SSoff. The Hazard Ratio for SSoff is exactly 1, because it is being compared to itself. When simply looking at the ranking of the preferences, we can look at the value of the parameter estimates. The larger the value, the greater the preference. We observe:

$$0.53095_{Neg} > 0_{SSoff} > -0.24422_{Gov} > -0.33527_{Mkt} \tag{8.14}$$

Which, as should be expected, matches the mean value for the responses:

$$1.93_{Neg} < 2.53_{SSoff} < 2.72_{Gov} < 2.93_{Mkt} \tag{8.15}$$

These results simply mean on average, Neg is most preferred, SSoff is the second most preferred, Gov is the third most preferred, and Mkt is the least preferred of these possible trading mechanisms among our respondents.

We just ranked our preferences and tested for item differences when compared against SSoff. Next, we can exhaustively test for differences in preference among each pair of items. The remaining pairs to test will be Neg vs Gov, Neg vs Mkt, and Gov vs Mkt. The results are in Table 8.3 below:

Table 6.3 Linear Hypothesis Testing

Label	**Wald Chi-Square**	**DF**	**Pr > ChiSq**
Neg vs Gov	9.8388	1	0.0017***
Neg vs Mkt	12.6514	1	0.0004***
Gov vs Mkt	0.1366	1	0.7117

Note: Asterisks *,**, and *** denote variables significance at 10%, 5%, and 1% level, respectively.

These results show there is a significant difference in preferences between Neg and Gov, and also a significant difference in preferences among Neg, and Mkt, but there is not a significant difference in preferences between Gov and Mkt. Pairing this information with the results from earlier, we can now say:

Seller/Buyer Negotiations are most preferred by respondents. Sole-Source Offset is the second most preferred mechanism by respondents. The least preferred mechanisms are Government Facilitation and Market Exchange. Though Government Facilitation is slightly more preferred than Market Exchange, the difference is not significant, and thus the order of these trailing preferences could easily be reversed.

8.2.B Stage 1: Interpret Parameter Estimates (Exploded Logit)

Now that we have reviewed the parameter estimates, we can include them in the exploded logit model and interpret the results. The primary benefit of using this model is that we have the ability to take a series of ranked preferences and generate the probability of that order. We can begin by looking at the structure of the response:

$$Response = \left(Rank_{Neg}, Rank_{Gov}, Rank_{Mkt}, Rank_{SSoff}\right) \tag{8.16}$$

By the end, we should be able to determine the probability of a sequence of responses:

$$Response = \left(Rank_{Neg}, Rank_{Gov}, Rank_{Mkt}, Rank_{SSoff}\right) \tag{8.16}$$

In the above example, we are seeking the probability of a response where Neg is the most preferred, Gov is the second most preferred, Mkt is the third most preferred, and SSoff is the fourth most preferred. We will expand upon this when covariates are introduced in stage 2.

Recall:

$$x_{ij}'\beta \rightarrow \mu_{ij} = \beta_j' x_i \tag{8.17}$$

Because we are simply focusing on item differences without covariates, this model reduces to:

$$\mu_j = \beta_j \tag{8.18}$$

On the following page, we will replace μ_j, which is the deterministic portion of the random utility model for item j, with the parameter estimate for item j. We will walk through four steps. In each step, we will notate the probability we are capturing with a superscript letter. In the following step, that mechanism will be removed from the pool, and we will continue the process until we have captured all necessary probabilities.

Table 8.4 Step 1: Probability$\left(\mathbf{Response} = \left(\mathbf{1}_{\mathbf{Neg}}, \mathbf{0}_{\mathbf{Gov}}, \mathbf{0}_{\mathbf{Mkt}}, \mathbf{0}_{\mathbf{SSoff}}\right)\right)$

Variable	Item j	Parameter Estimate	e^{μ_j}	Hazard Ratio	$\frac{e^{\mu_j}}{\sum_{k=1}^{J=4} e^{\mu_k}}$
Neg	1	0.53095	$e^{0.53095}$	=1.7005	0.40499[A]
Gov	2	-0.24422	$e^{-0.24422}$	= 0.7833	0.18654
Mkt	3	-0.3357	$e^{-0.3357}$	= 0.7151	0.17031
SSoff	4	0.0000	e^{0}	= 1.0000	0.23816
Sum				$\sum_{k=1}^{J=4} e^{\mu_k} = 4.1989$	= 1

Table 8.5 Step 2: Probability$\left(\mathbf{Response} = \left(\cancel{\mathbf{1}_{\mathbf{Neg}}}, \mathbf{1}_{\mathbf{Gov}}, \mathbf{0}_{\mathbf{Mkt}}, \mathbf{0}_{\mathbf{SSoff}}\right)\right)$

Variable	Item j	Parameter Estimate	e^{μ_j}	Hazard Ratio	$\frac{e^{\mu_j}}{\sum_{k=2}^{J=4} e^{\mu_k}}$
~~Neg~~	Removed	Removed	Removed	Removed	Removed
Gov	2	-0.24422	$e^{-0.24422}$	= 0.7833	0.31352[B]
Mkt	3	-0.3357	$e^{-0.3357}$	= 0.7151	0.28622
SSoff	4	0.0000	e^{0}	= 1.0000	0.40025
Sum				$\sum_{k=2}^{J=4} e^{\mu_k} = 2.4984$	= 1

Table 8.6 Step 3: Probability$\left(\mathbf{Response} = \left(\cancel{\mathbf{1}_{\mathbf{Neg}}}, \cancel{\mathbf{1}_{\mathbf{Gov}}}, \mathbf{1}_{\mathbf{Mkt}}, \mathbf{0}_{\mathbf{SSoff}}\right)\right)$

Variable	Item j	Parameter Estimate	e^{μ_j}	Hazard Ratio	$\frac{e^{\mu_j}}{\sum_{k=3}^{J=4} e^{\mu_k}}$
~~Neg~~	Removed	Removed	Removed	Removed	Removed
~~Gov~~	Removed	Removed	Removed	Removed	Removed
Mkt	3	-0.3357	$e^{-0.3357}$	= 0.7151	0.41694[C]
SSoff	4	0.0000	e^{0}	= 1.0000	0.58306
Sum				$\sum_{k=3}^{J=4} e^{\mu_k} = 1.7151$	= 1

Table 8.7 Step 4: Probability$\left(\mathbf{Response} = \left(\cancel{\mathbf{1}_{\mathbf{Neg}}}, \cancel{\mathbf{1}_{\mathbf{Gov}}}, \cancel{\mathbf{1}_{\mathbf{Mkt}}}, \mathbf{1}_{\mathbf{SSoff}}\right)\right)$

Variable	Item j	Parameter Estimate	e^{μ_j}	Hazard Ratio	$\frac{e^{\mu_j}}{\sum_{k=4}^{J=4} e^{\mu_k}}$
~~Neg~~	Removed	Removed	Removed	Removed	Removed
~~Gov~~	Removed	Removed	Removed	Removed	Removed
~~Mkt~~	Removed	Removed	Removed	Removed	Removed
SSoff	4	0.0000	e^{0}	= 1.0000	1.0000[D]
Sum				$\sum_{k=4}^{J=4} e^{\mu_k} = 1.0000$	= 1

In the four steps above, rather than simply jumping to the overall probability of a sequence, we first captured the probability of a particular item being most preferred from all possible options:

$$Probability\left(Response = \left(1_{Neg}, 0_{Gov}, 0_{Mkt}, 0_{SSoff}\right)\right) \quad (8.19)$$

In order to do so, we first take the sum of the available hazard ratios to obtain our sample space. In the first round, that value was 4.1989. We then take the quotient of the hazard ratio of the item of interest as it relates to the sum of the hazard ratios, and we then have the probability of that event occurring. You will notice that for every step, the sum of probabilities should sum to 1. And with each subsequent step, the previous item has been removed, thus reducing the sample space within that step. For the fourth and final step in the probability collection process, you will notice there is only one item, and therefore its probability of being selected is 1.

To calculate the probability of the rank-order mentioned above:

$$Probability\left(Response = \left(1_{Neg}, 2_{Gov}, 3_{Mkt}, 4_{SSoff}\right)\right) \quad (8.20)$$

We can now apply our probabilities to the exploded logit model:

$$\left(\frac{e^{\mu_{Neg}}}{\sum_{k=1}^{J=4} e^{\mu_k}}\right)\left(\frac{e^{\mu_{Gov}}}{\sum_{k=2}^{J=4} e^{\mu_k}}\right)\left(\frac{e^{\mu_{Mkt}}}{\sum_{k=3}^{J=4} e^{\mu_k}}\right)\left(\frac{e^{\mu_{SSoff}}}{\sum_{k=4}^{J=4} e^{\mu_k}}\right) \quad (8.21)$$

As mentioned, each probability of interest was notated in order:

$$(A)(B)(C)(D) \rightarrow (0.40499)(0.31352)(0.41694)(1.0000) = 0.05294 \quad (8.22)$$

We can now say that based on our exploded logit model, the probability of a respondent ranking their preferences as Neg, Gov, Mkt, and lastly SSoff is 0.5294.

8.2.C Stage 2: Complete Model with Explanatory Variables

In the previous stage, we looked at the rankings of preferences for water quality trading mechanisms among municipal treatment facility representatives. We then used an exploded logit model to find the probability of a particular ranking of mechanisms. Expanding upon that model, we can include explanatory variables. The variables we will be adding to our model are:

Table 8.8: Explanatory Variables

Explanatory Variable	**Description**
Years	The number of years the current facility has been in operation.
People Served	The number of households or people the facility serves.
Financial Status	The current financial status of the facility compared to the previous year. Responses range from 1-7, where 1 is much worse, 4 is about the same, and 7 is much better.
Operating Cost	The average annual operating cost of the water quality treatment equipment currently used in the facility (including labor, electricity/fuel, and materials, but excluding building costs, installation, and equipment depreciation.
Monitor	If the facility is required to monitor phosphorous, then the response is coded as ‘1’.
Reduce	If the facility is required to reduce phosphorous, then the response is coded as ‘1’.
Familiar	If the respondent has heard of water quality trading, then the response is coded as ‘1’.
Unfamiliar	If the respondent has not heard of water quality trading, the response is coded as ‘1’.

Note: Monitor and Reduce are both coded against “Neither”. Familiar and Unfamiliar are both coded against “Not Certain”.

By including explanatory variables, we can return to the original case where we have the deterministic portion of the random utility model in the form of:

$$\mu_{ij} = \beta_j' x_i \tag{8.23}$$

The deterministic portion of the model can be expanded to:

$$\mu_{ij} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \tag{8.24}$$

Where

$$\begin{aligned} j &= Trading\ Mechanism \\ x_1 &= years \\ x_2 &= people\ served \\ x_3 &= financial\ status \\ x_4 &= operating\ cost \\ x_5 &= monitor \\ x_6 &= reduce \\ x_7 &= familiar \\ x_8 &= unfamiliar \end{aligned}$$

We should then pay special attention to the individual mechanism being reviewed. Because our dependent variable is not only the ranking, but also the order in which mechanisms are ranked, we first look at the individual mechanism. Take note of the ranking associated with that mechanism by the individual, then we can turn to look at the explanatory variables paired with the current item being ranked. For this reason, we will have a series of equations to interpret.

$$\mu_{iNeg} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \tag{8.25}$$

$$\mu_{iGov} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \tag{8.26}$$

$$\mu_{iMkt} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \tag{8.27}$$

$$\mu_{iSSoff} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \tag{8.28}$$

In the equations above, we can see that each line is associated with the deterministic portion of the model with respect to a particular mechanism. We can now turn our attention to the results for the exploded logit model with the explanatory variables included.

Again, we have 324 observations read, however only 152 observations were used. This can be interpreted as 324/4 = 81 survey respondents and 152/4 = 38 observations used, indicating a drop from 57.5 down to only 38 observations used. Due to the structure of the model, observations were only used when respondents completed all questions, hence 19 respondents ranked their preferences, but did not respond to all of the remaining questions, and so they are dropped from this portion of the analysis when using the PHREG statement.

In order to determine whether or not at least one of the interaction terms was significant, we can look to the three tests provided by the PHREG statement for the global null hypothesis.

$$H_0: All\ \beta = 0$$

$$H_A: At\ least\ one\ \beta \neq 0$$

The three test statistics provided are the Chi-Square values for the Likelihood Ratio Test, the Score Test, and the Wald Test. The interpretation is the same as for Stage 1, however, we have now expanded our model to include explanatory variables. When the Chi-Square value is large, we have significant evidence to reject the null hypothesis, suggesting that at least one beta is not equal to zero. The results from the global null hypothesis tests can be seen in Table 8.9.

Table 8.9 Global Test for All Beta = 0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	32.0438	27	0.2305
Score	31.0140	27	0.2706
Wald	25.2226	27	0.5620

Unlike Stage 1, none of our global tests show significance at the 1% level. However, we have lost a significant portion of our response variables due to incomplete surveys and we have also greatly increased the number of explanatory variables. These two factors both contribute to the loss of significance.

Next, we can look at the parameter estimates for our model. The results that are displayed below are divided into three sections. Each section corresponds to one of the four trading mechanisms. The first section represents the parameter estimates for the explanatory variables when paired with Buyer/Seller Negotiation, the second section represents Market Exchange, and the third section represents Government Facilitation. Within each section, the first item is "Mechanism". Mechanism is essentially an intercept term for the mechanism within each group. If for example, all explanatory variables were omitted, our model would reduce back to the same model from Stage 1. However, because we have now included additional variables, the parameter estimates between Stage 1 and Stage 2 will not be the same. Recall, this model is only an expansion of the model from Stage 1. Therefore, we are again comparing each variable against its Sole-Source Offset counterpart. The parameter estimates are provided in the Table 8.10 below.

Table 8.10 Exploded Logit Parameter Estimates, Complete Model

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
Buyer/Seller Negotiation						
Mechanism	1	-0.86954	1.88593	0.2126	0.6448	0.419
Years	1	0.01073	0.01763	0.3702	0.5429	1.011
People Served	1	-0.0000218	0.0000193	1.2732	0.2592	1.000
Financial Status	1	0.19307	0.27073	0.5086	0.4757	1.213
Operating Cost	1	5.63946E-7	3.66571E-7	2.3668	0.1239[AA]	1.000
Monitor	1	-0.90325	0.91216	0.9806	0.3221	0.405
Reduce	1	-1.58624	1.09837	2.0856	0.1487[AA]	0.205
Familiar	1	1.08263	1.22527	0.7807	0.3769	2.952
Unfamiliar	1	1.60336	1.26151	1.6154	0.2037[A]	4.970
Market						
Mechanism	1	0.18694	1.91370	0.0095	0.9222	1.206
Years	1	0.00227	0.01736	0.0171	0.8959	1.002
People Served	1	-0.0000541	0.0000319	2.8688	0.0903*	1.000
Financial Status	1	0.17297	0.28947	0.3570	0.5502	1.189
Operating Cost	1	8.80785E-7	4.57215E-7	3.7111	0.0541**	1.000
Monitor	1	-0.75665	0.90299	0.7021	0.4021	0.469
Reduce	1	-2.27761	1.19073	3.6587	0.0558*	0.103
Familiar	1	-0.73877	1.10142	0.4499	0.5024	0.478
Unfamiliar	1	-0.19067	1.08499	0.0309	0.8605	0.826
Government Facilitation						
Mechanism	1	-1.78416	1.87236	0.9080	0.3406	0.168
Years	1	0.00427	0.01729	0.0610	0.8050	1.004
People Served	1	-0.0000329	0.0000256	1.6570	0.1980[A]	1.000
Financial Status	1	0.12729	0.26362	0.2331	0.6292	1.136
Operating Cost	1	4.68078E-7	3.69692E-7	1.6031	0.2055[A]	1.000
Monitor	1	0.35065	0.92680	0.1431	0.7052	1.420
Reduce	1	-0.76789	1.12791	0.4635	0.4960	0.464
Familiar	1	0.36017	1.13414	0.1009	0.7508	1.434
Unfamiliar	1	1.31528	1.13675	1.3388	0.2472	3.726

Note: Asterisks *,**, and *** denote variables significance at 10%, 5%, and 1% level, respectively. Superscript A and AA denotes variable approaching significance at the 20% and 15% level, respectively.

Note: Compared against Sole-Source Offset

In the table of parameter estimates, there are several estimates that stand out. Under Buyer/Seller Negotiations, the parameter estimates for Operating Cost, Reduce, and Unfamiliar all appear to be approaching significance. Operating Cost is the most significant, with a p-value of 0.1239, followed by Reduce with a p-value of 0.1487, and lastly Unfamiliar with a p-value of 0.2037. Under Market, we observer our most significant variables. Operating Cost under Market is the single most significant variable from our results, with a p-value of 0.0541, followed closely by Reduce with a p-value of 0.0558, and lastly with People Served at 0.0903. The third and final section, Government Facilitation, has two variables approaching significance. Those variables are People Served and Operating Cost, with respective p-values of 0.1980 and 0.2055.

Before going any further, we should pause to understand what a p-value represents in for these estimates. Because we are comparing probabilities against Sole-Source Offset, we can consider a static preference for Sole-Source Offset. We can now consider one of the variables, for example Operating Cost. Under the Buyer/Seller Negotiation section, when the Operating Cost increases, does that increase (or decrease) the probability of the respondents preferring Buyer/Seller Negotiation, as compared to Sole-Source Offset? The null hypothesis says, “No”. However, when the p-value is small enough, we can say that we have significant evidence to reject the null hypothesis. In the Operating Cost example, where we are approaching significance. This means that as Operating Cost increases (or decreases), there is reason to believe the probability of preferring Buyer/Seller Negotiation will change. So how much will the probability of preferring Buy/Seller Negotiation change? If we are to increase the Operating Cost by a single dollar, due to the magnitude of data, we would see practically no change. Hence the Hazard Ratio is 1.00.

As there are a variety of explanatory variables, we can shift our attention to one of the dummy coded variables. If we were to look at Reduce, again for Buyer/Seller Negotiations, we see an estimate of -1.58624, and when exponentiated, we have a Hazard Ratio of 0.205. To interpret this type of response, we can say that when a respondent works in a facility that reduces phosphorous, the odds of the respondent preferring Buyer/Seller Negotiations to Sole-Source Offset is 0.205 compared to a respondent who works in a facility that is not required to reduce phosphorous. This is of course only one of several ways to interpret the results from this type of model.

The resulting parameter estimates have all been in contrast with Sole-Source Offset. We should also test the explanatory variables individually. The null hypotheses being tested are:

$$H_0: \beta_{Years,Neg} = \beta_{Years,Gov} = \beta_{Years,Mkt} = 0$$

$$H_A := At\ least\ one\ \beta_{Years,j} \neq 0$$

...

$$H_0: \beta_{Unfamiliar,Neg} = \beta_{Unfamiliar,Gov} = \beta_{Unfamiliar,Mkt} = 0$$

$$H_A := At\ least\ one\ \beta_{Unfamiliar,j} \neq 0$$

The results from the above hypotheses can be found in Table 8.11 below. Our objective is to determine if the explanatory variables are distinguishably different among the mechanisms. For example, when considering the variable Years, can it help us predict the ranking of Buyer/Seller Negotiations, Government Regulations, or Market Exchange? While none of the variables appear to be significant, we do see some common trends that agree with our findings when looking at the parameter estimates. For example, two of the most significant parameters were Operating Cost and Reduce, which are also the most significant here.

Table 8.11 Testing Significance of Explanatory Variables

Label	Wald Chi-Square	DF	Pr > ChiSq
Years	0.3980	3	0.9407
People Served	3.1267	3	0.3725
Financial Status	0.5975	3	0.8970
Operating Cost	4.2536	3	0.2353
Monitor	2.3795	3	0.4975
Reduce	4.2794	3	0.2328
Familiar	2.6244	3	0.4532
Unfamiliar	3.6375	3	0.3034

8.2.D Stage 2: Interpreting Results for the Exploded Logit Model with Explanatory Variables

Once the parameter estimates have been generated, the interpretation of the exploded logit model is nearly identical to what was discussed in Stage 1. We can again return to the deterministic portion of the model:

$$\mu_{ij} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \quad (8.29)$$

Where we can view all four components as:

$$\mu_{iNeg} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \quad (8.30)$$

$$\mu_{iGov} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \quad (8.31)$$

$$\mu_{iMkt} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \quad (8.32)$$

$$\mu_{iSSoff} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \beta_{3j}x_{3i} + \beta_{4j}x_{4i} + \beta_{5j}x_{5i} + \beta_{6j}x_{6i} + \beta_{7j}x_{7i} + \beta_{8j}x_{8i} \quad (8.33)$$

The explanatory variables are again:

$$j = Trading\ Mechanism$$
$$x_1 = years$$
$$x_2 = people\ served$$
$$x_3 = financial\ status$$
$$x_4 = operating\ cost$$
$$x_5 = monitor$$
$$x_6 = reduce$$
$$x_7 = familiar$$
$$x_8 = unfamiliar$$

Perhaps the best way to use and interpret the results from this model is with a hypothetical example. If we were to receive the following input values:

$$x_1 = years = 10$$
$$x_2 = people\ served = 75{,}000$$
$$x_3 = financial\ status = 6$$
$$x_4 = operating\ cost = 500{,}000$$
$$x_5 = monitor = 1$$
$$x_6 = reduce = 1$$
$$x_7 = familiar = 1$$
$$x_8 = unfamiliar = 0$$

We would simply place these values into the four deterministic equations:

Table 8.12 Exploded Logit Deterministic Equations

x_m	Explanatory Variable	Response	β_{Neg}	β_{Gov}	β_{Mkt}
x_0	*Mechanism*	1	-0.86954	0.18694	-1.78416
x_1	*Years*	10	0.01073	0.00227	0.00427
x_2	*People Served*	75,000	-0.0000218	-0.0000541	-0.0000329
x_3	*Financial Status*	6	0.19307	0.17297	0.12729
x_4	*Operating Cost*	500,000	5.63946E-7	8.80785E-7	4.68078E-7
x_5	*Monitor*	1	-0.90325	-0.75665	0.35065
x_6	*Reduce*	1	-1.58624	-2.27761	-0.76789
x_7	*Familiar*	1	1.08263	-0.73877	0.36017
x_8	*Unfamiliar*	0	1.60336	-0.19067	1.31528
			$\mu_{Neg} = 2.3636^A$	$\mu_{Gov} = -6.1427^B$	$\mu_{Mkt} = -4.8584^C$

Note: Superscript A, B, and C

$A: \mu_{Neg} = \sum x_m{}' \beta_{m,Neg}$

$B: \mu_{Gov} = \sum x_m{}' \beta_{m,Gov}$

$C: \mu_{Mkt} = \sum x_m{}' \beta_{m,Mkt}$

In the four deterministic equations above, we simply took the parameter estimates and introduced a hypothetical survey response. Given the values generated above, we can now return to the original objective of the exploded logit model, which is to estimate the probability of any rank-order of preferences:

$$Probability\left(Response = \left(Rank_{Neg}, Rank_{Gov}, Rank_{Mkt}, Rank_{SSoff}\right)\right) \quad (8.34)$$

Notice the values from the four equations above are located in the second column from the left, in Table 8.13 below. Given the set of responses from our example, we can now interpret the current model for Stage 2 in the same manner as we did in Stage 1.

Table 8.13 Begin: $\mathbf{Probability\left(Response = \left(Rank_{Neg}, Rank_{Gov}, Rank_{Mkt}, Rank_{SSoff}\right)\right)}$

$\boldsymbol{\mu_j}$		$\boldsymbol{e^{\mu_j}}$		$\boldsymbol{\frac{e^{\mu_j}}{\sum_{k=1}^{J=4} e^{\mu_j}}}$
μ_{Neg}	= -2.3636	$e^{-2.3636}$	= 0.9408	0.4823
μ_{Gov}	= -6.1427	$e^{-6.1427}$	= 0.0021	0.0011
μ_{Mkt}	= -4.8584	$e^{-4.8584}$	= 0.0078	0.0040
μ_{SSoff}	= 0.0000	$e^{0.0000}$	= 1.0000	0.5126
Sum			$\sum_{k=1}^{J=4} e^{\mu_j} = 1.9507$	= 1

CHAPTER 9: DISCUSSION

Throughout the course of this thesis, we were first introduced to the concept of the hypoxic zone in the Northern Gulf of Mexico, which is a phenomenon resulting largely from excessive nutrients pouring into the Mississippi-Atchafalaya River Basin. The phenomenon is so catastrophic that organizations and researchers all across the United States have taken an interest in finding a solution to this problem. Rivers, streams, and other waterways from several states and regions flow into the Mississippi River, contributing to nutrient loading in the gulf. Though the problem is quite large, the Mississippi River/Gulf of Mexico Hypoxia Task Force has devised a plan of action. That plan led to the recruitment of the University of Kentucky through targeted watershed grants awarded by the United States Environmental Protection Agency. While the Task Force is determined to restore the Gulf of Mexico to a non-hypoxic state, the actual implementation process still remained in question. One of the biggest concerns is how to efficiently and successfully impose new regulations.

The popularity of water quality trading has been rising, due to its theoretical superiority over previous methods used. However, theory and empirical evidence do not always agree with one another, which has historically been the case of water quality trading markets. For a variety of reasons, these markets have suffered from low-trade volume. Perhaps a contributing factor to the poor performance of these markets can be linked back to the lack of communication between those designing the market structure and those who would actually be participating in the market. For this reason, the goal of this thesis was to shed new light on the preferences of point source polluters, as this approach had never been taken before within the Kentucky River Watershed. Rather than simply provide a price for abatement credits or implement a market mechanism, we sought to gather the opinions and preferences of the official representatives from each municipal sewage treatment facility within the Kentucky River Watershed. Representatives from every facility were given the opportunity to voice their opinions so that no point source in the region was given preferential treatment. We then regressed their responses for willingness to pay and preferences among market mechanisms against a variety of explanatory variables ranging from facility characteristics to prior knowledge of water quality trading.

In order to explain their responses for willingness to pay, we first used ordinary least squares, but after quickly realizing the censored responses clustering at $0, we moved on to use a tobit model to account for the censorship. Upon further inspection, we noticed significant outlying responses for willingness to pay, that could potentially leverage our model and highly skew our parameter estimates for the explanatory variables. Because survey responses were gathered anonymously, we could not go back and contact the respondents to clarify the reasoning behind their responses, and so it was uncertain as to whether these responses were accurate or there was simply a misunderstanding while filling out the surveys. Therefore, we modeled the responses with outliers present and with outliers removed. Focusing our attention on the tobit model, we found that when all observations were present, nearly every parameter estimate appeared to be statistically significant at the 1% level for the phosphorous and nitrogen models. However, looking at the parameter estimates, we see extremely high values. For example, for willingness to pay for phosphorous credits, the intercept alone is estimated to be $55,648. Contrast that number against the market price in the Pilot Water Quality Credit Trading Program for the

Lower St. Johns River, which was only $68.87/pound (Florida Department of Environmental Assessment & Restoration, 2010). This difference suggests the outliers did play a role in inflating our estimates. Now turn to the tobit model where outliers have been removed and we find an estimated intercept of $1.35. In the model with outliers removed, significance is lost for all but one explanatory variable. This is to be expected for a model with less than 30 observations. Of the explanatory variables included in our analysis for phosphorous, the most significant variable was the number of people served is positively correlated with willingness to pay. The second most significant finding was that representatives who were already familiar with water quality trading were willing to pay less for credits. When looking at the responses for nitrogen, we found that representatives working in facilities that monitored phosphorous levels were willing to pay less for nitrogen credits. We also found that when facilities reduce phosphorous levels, their "latent" willingness to pay for nitrogen credits decreases. Lastly, we found that the age of the facility is positively correlated with the "latent" willingness to pay for nitrogen credits.

When looking at preferences among respondents for different types of market trading mechanisms, we found the most preferred choice was Seller/Buyer Negotiations, followed by Sole-Source Offsetting, followed by Government Facilitation, and the least preferred mechanism was Market Exchange.

Perhaps the program most relevant to this study is the Ohio River Basin Interstate Water Quality Trading Project. On August 9, 2012, the USDA awarded a conservation innovation grant to the Electric Power Research Institute (EPRI). The $1 million grant was awarded to assist in moving the ORV Pilot Water Quality Trading Program forward. The interstate program includes Indiana, Kentucky, and Ohio. The current pilot phase is scheduled to run from 2012 through 2015. While other states have implemented their own programs, the uniqueness of this program is the inclusion of interstate trading rules, which will allow for states to follow the same rules and will also allow for credit trading between states. The interstate trading program provides the same incentives as its single-state predecessors, being that it will provide flexibility for abating parties to seek more cost-effective means of abatement than installing on-site controls. However, one of the previous constraints to the success of former markets was the limitation of participants within a geographic scope. This program will now broaden that geographic bottleneck. As this project is a pilot, the program will be measuring the success in a variety of ways. Close attention will be paid to any obstacles that would hinder a full-scale roll-out. The pilot identifies an ultimate goal of creating a program that can be completely self-sustaining. In order to build a self-sustaining program, the program would require the implementation of trading mechanisms and voluntary participation. For a point source to voluntarily participate, knowing the preferences of point sources for a market trading mechanism is extremely valuable information, as it could guide a program towards implementing a program which is most desired by those who it is intended to be used by.

APPENDICES

Appendix 1: SAS Codes

Exploded Logit SAS Codes

```
proc means data = exlog;
run;

/*Appendix A*/
proc phreg nosummary;
model rank = dneg dgov dmkt / ties =
exact;
strata id;
Negotiation_Government: test dneg = dgov;
Negotiation_Market: test dneg = dmkt;
Government_Market: test dgov = dmkt;
run;

/*Interaction Terms*/
data explog; set exlog;

/*mkt*/
mktyrs = dmkt*yrs;
mktppl = dmkt*pplserved;
mktfin = dmkt*finstatus;
mktcost = dmkt*opcost;
mktmon = dmkt*mon;
mktred = dmkt*red;
mktneither = dmkt*neither;
mktfam = dmkt*familiar;
mktunfam = dmkt*unfamiliar;
mktuncertain = dmkt*uncertain;

/*neg*/
negyrs = dneg*yrs;
negppl = dneg*pplserved;
negfin = dneg*finstatus;
negcost = dneg*opcost;
negmon = dneg*mon;
negred = dneg*red;
negneither = dneg*neither;
negfam = dneg*familiar;
negunfam = dneg*unfamiliar;
neguncertain = dneg*uncertain;

/*gov*/
govyrs = dgov*yrs;
govppl = dgov*pplserved;
govfin = dgov*finstatus;
govcost = dgov*opcost;
govmon = dgov*mon;
```

```
govred = dgov*red;
govneither = dgov*neither;
govfam = dgov*familiar;
govunfam = dgov*unfamiliar;
govuncertain = dgov*uncertain;

/*ssoff*/
ssoffyrs = dssoff*yrs;
ssoffppl = dssoff*pplserved;
ssofffin = dssoff*finstatus;
ssoffcost = dssoff*opcost;
ssoffmon = dssoff*mon;
ssoffred = dssoff*red;
ssoffneither = dssoff*neither;
ssofffam = dssoff*familiar;
ssoffunfam = dssoff*unfamiliar;
ssoffuncertain = dssoff*uncertain;
run;
proc means data = explog; run;

/*Appendix C*/
proc phreg data=explog nosummary;

model rank = dneg dmkt dgov

negyrs
negppl
negfin
negcost
negmon
negred
negfam
negunfam

mktyrs
mktppl
mktfin
mktcost
mktmon
mktred
mktfam
mktunfam

govyrs
govppl
govfin
govcost
govmon
govred
govfam
govunfam
 ;

strata id;

Years: test negyrs, mktyrs, govyrs;
```

```
People_Served:test negppl, mktppl, govppl;
Financial_Status: test negfin, mktfin, govfin;
Operating_Cost: test negcost, mktcost, govcost;
Monitor: test negmon, mktmon, govmon;
Reduce: test negred, mktred, govred;
Familiar: test negfam, mktfam, govfam;
Unfamiliar: test negunfam, mktunfam, govunfam;

run;
```

Tobit SAS Codes

```
/*using tobit2*/
proc means data = tobit; run;
/*All Obs: Tobit WTP Phos*/
proc qlim data=tobit;
    model wtpp = yrs pplserved finstatus opcost mon red familiar unfamiliar;
    endogenous wtpp ~ censored(lb=0);
    output out=outtobit residual marginal;
  run;
/*All Obs: Average Marginal Effects, WTP Phos*/
proc means data = outtobit;
run;
/*All Obs: Tobit WTP Nit*/
proc qlim data=tobit;
    model wtpn = yrs pplserved finstatus opcost mon red familiar unfamiliar;
    endogenous wtpn ~ censored(lb=0);
    output out=outtobitn residual marginal;
  run;
/*All Obs: Average Marginal Effects, WTP Nit*/
proc means data = outtobitn;
run;


proc univariate data = tobit;
var wtpp wtpn;
run;
/*Outliers Removed: WTP P */
proc sql;
create table tobitp as
select wtpp, yrs, pplserved, finstatus, opcost, mon, red, familiar, unfamiliar
from tobit
where wtpp < 100;
run;
quit;
proc print data = tobitP; run;

/*Outliers Removed: WTP N */
proc sql;
create table tobitn as
select wtpn, yrs, pplserved, finstatus, opcost, mon, red, familiar, unfamiliar
from tobit
where wtpn < 100;
run;
```

```
quit;
proc print data = tobitn; run;

/*Outliers Removed: Tobit WTP Phos*/
proc qlim data=tobitp;
    model wtpp = yrs pplserved finstatus opcost mon red familiar unfamiliar;
    endogenous wtpp ~ censored(lb=0);
    output out=outtobitp residual marginal;
  run;
/*Outliers Removed: Average Marginal Effects, WTP Phos*/
proc means data = outtobitp;
run;
/*Outliers Removed: Tobit WTP Nit*/
proc qlim data=tobitn;
    model wtpn = yrs pplserved finstatus opcost mon red familiar unfamiliar;
    endogenous wtpn ~ censored(lb=0);
    output out=outtobitnn residual marginal;
  run;
/*Outliers Removed: Average Marginal Effects, WTP Nit*/
proc means data = outtobitnn;
run;
```

Appendix 2: Survey Instrument

Survey of Nitrogen and Phosphorous Discharge and Abatement in the Kentucky River Watershed

Thank you again for agreeing to take part in this research. We appreciate your time.

UK
UNIVERSITY OF KENTUCKY
College of Agriculture

First, we would like to know some characteristics of your facility.

1. How long has your current facility been in operation?
   ________________ years

2. About how many households or people is your facility serving?
   ________________ households OR ________________ people

3. Use the scale below to rank your facility's current financial status compared to last year.
   Much Worse About the same Much Better
   1 2 3 4 5 6 7

4. What is the average annual operating cost of the water quality treatment equipment currently used in your facility? This cost includes labor, electricity/fuel, and materials, but excludes building costs, installation, and equipment depreciation.
   $ ________________

5. How much does the water quality treatment equipment that you need to maintain your permit cost at your facility? Please use the table below for your answer.

Type/Name of equipment	Cost of purchasing equipment (please choose how it was measured)	Year purchased	Expected lifetime of the equipment
	□ Cost at the time of purchase □ Replacement cost as of 2011 $___________________		Years:
	□ Cost at the time of purchase □ Replacement cost as of 2011 $___________________		Years:
	□ Cost at the time of purchase □ Replacement cost as of 2011 $___________________		Years:
	□ Cost at the time of purchase □ Replacement cost as of 2011 $___________________		Years:
	□ Cost at the time of purchase □ Replacement cost as of 2011 $___________________		Years:

6. On average, how much total nitrogen and total phosphorous is removed from your facility's effluent stream per year? If your facility is not regulated for total nitrogen or phosphorous, please mark the closest substitutes (e.g., ammonia for nitrogen)
Total Nitrogen ________________ lbs (or closest substitute __________________)

Total Phosphorous ________________ lbs (or closest substitute __________________)

7. Regarding phosphorous, is your facility required to only monitor or to reduce it from your effluent?
□ monitor only
□ reduce
□ neither

8. Based on your best knowledge, please indicate your facility's expenses for equipment used mostly to control nitrogen and phosphorous averaged over the past five, ten, and twenty years.

	Average Annual Expense in Past Five Years	Average Annual Expense in Past Ten Years	Average Annual Expense in Past Twenty Years
Under $5,000	□	□	□
$5,000 - $10,000	□	□	□
$10,000 - $50,000	□	□	□
$50,000 - $100,000	□	□	□
$100,000 - $200,000	□	□	□
$200,000 - $500,000	□	□	□
$500,000 - $1M	□	□	□
$1M - $1.5M	□	□	□
$1.5M - $2M	□	□	□
Over $2M	□	□	□
For each of the cost you specified, please give the percentage of distribution over different methods:	____% biological method ____% chemical method ____% mechanical method	____% biological method ____% chemical method ____% mechanical method	____% biological method ____% chemical method ____% mechanical method
Other types of costs (please specify):			

Among other tools, water quality trading is one way to improve overall water quality in Kentucky while reducing the cost of compliance. Have you ever heard about the idea of water quality trading?

□ Yes □ No □ Not certain

Water quality trading is an innovative approach to achieve water quality goals more efficiently. Trading is based on the fact that sources in a watershed can face very different costs to control the same pollutant. Trading programs allow facilities facing higher pollution control costs to meet their regulatory obligations by purchasing environmentally equivalent (or superior) pollution reductions from another source at lower cost, thus achieving the same water quality improvement at lower overall cost.

While the most well known version of this kind of trading is the "cap-and-trade" design, there are several alternate methods of implementing a trading system that have been suggested for trading pollution shares/credits in water quality.

9. Please indicate the trading program qualities that you (your facility) might find favorable (F), unfavorable (U), or neutral (N):

Qualities/Features	Rating
High interaction between buyers and sellers	□ F □ U □ N
Ability to buy shares/credits	□ F □ U □ N
Ability to sell shares/credits	□ F □ U □ N
Standardized formulas available to calculate shares/credits	□ F □ U □ N
Fixed pricing of shares/credits adjusted annually by a third party	□ F □ U □ N
Flexible pricing of shares/credits (price varies with supply and demand)	□ F □ U □ N
Public authority regulates "contracts"	□ F □ U □ N
Ability to identify the seller/buyer of the shares/credits	□ F □ U □ N
Certification that shares/credits are valid	□ F □ U □ N
Ability to offset pollution shares/credits within your facility	□ F □ U □ N
Shares/credits may be bought and sold by anyone (companies, environmental organizations, farmers)	□ F □ U □ N
Limitation of liability	□ F □ U □ N
Lowering of overall pollution in our rivers (not your pollution discharges specifically)	□ F □ U □ N
Other (please specify) ________________________________	□ F □ U □ N

You are only 2 pages away from being done!

10. Below are some possible trading market descriptions that can be used as an alternative to be implemented. Based on the description provided, please rank the trading market description according to the needs and preferences of your facility (1 being the most preferred; 2 is less preferred to 1, and so on):

    Seller/Buyer Negotiation:
    Trades take place between buyers and sellers–not through an exchange where shares/credits may be purchased and sold. These trades are made through direct buyer/seller negotiations. For example, consider the market for used cars sold by private parties. Car buyers will choose among a variety of vehicles, each with unique characteristics. The market typically involves bilateral negotiations so that buyers can personally inspect the vehicles and parties can bargain over the price. A public authority could monitor the trades and may set rules to facilitate the trades.

    Government Facilitation:
    Under this system, facilities needing (wanting) to increase their discharges may purchase extra shares/credits at a fixed price to accommodate this increase. Shares/credits may be accumulated from many sellers and managed by a clearinghouse such as a public authority. For example, the state or some other entity pays for pollution reductions and then sells the shares/credits at a fixed price to polluters needing to exceed their allowable loads. A clearinghouse differs to a broker in a bilateral market in that clearinghouses eliminate all contractual or regulatory links between sellers and buyers so that parties interact only with the intermediary. Shares/credit buyers and sellers need not to know each other.

    Market Exchange:
    Shares/credits of pollution are traded in a market space, such as the New York Stock Exchange, where anyone may buy or sell shares/credits. Buyers and sellers meet in a public forum where prices are observed and quantities of shares/credits are traded. At any one time, there is a unique market-clearing price so that any interested parties can enter the market to make purchases or sales at the market price. Prices and market information are available to everyone and jointly determined by all sellers and buyers. This structure is similar to a stock market except that the pollution shares/credits not stocks are being transacted.

    Sole-Source Offset:
    Shares/credits can be generated and used within your facility. For example, if a facility has multiple points of pollutant discharge, an increase in one point could be possible by an equivalent decrease at another nearby site. Trades may be made within a facility or between multiple sites within one facility/organization as far as all sites are located within one watershed.

    I would rank these market options as (1 being the most preferred; 2 is less preferred to 1, and so on):

    _____ Seller/Buyer Negotiation
    _____ Government Facilitation
    _____ Market Exchange
    _____ Sole-Source Offset

11. Regardless of the characteristics you preferred above, what is the **maximum** amount your facility is willing to pay for these shares/credits? We understand that often times the facilities do not decide these amounts themselves. However, we would like you to specify the amounts based on your best guess or if you were to make the decision.

To reduce one "unit"; i.e., 1 mg in Total Nitrogen in discharge, the maximum your facility will be willing to pay per year is:

☐ $0	☐ $5	☐ $10
☐ $1	☐ $6	☐ $11
☐ $2	☐ $7	☐ $12
☐ $3	☐ $8	☐ $13
☐ $4	☐ $9	☐ $__________

To reduce one "unit"; i.e., 1 mg in Total Phosphorous in discharge, the maximum your facility will be willing to pay per year is:

☐ $0	☐ $5	☐ $10
☐ $1	☐ $6	☐ $11
☐ $2	☐ $7	☐ $12
☐ $3	☐ $8	☐ $13
☐ $4	☐ $9	☐ $__________

Thank you for participating. We appreciate your time.

Please use the space below to write any comments you may have.

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VITA

ANDREW MCLAUGHLIN

Education

Bachelor of Science — August, 2011
Major: Agricultural Economics
Minor: Business Administration

Graduate Certificate — May, 2015
Applied Statistics

Professional Experience

Data Analyst — March 2015-Present
Center for Clinical and Translational Science

Data Analyst — August, 2014-March, 2015
Institute for Pharmaceutical Outcomes and Policy

Research Assistant — January 2012-June 2014
Department of Agricultural Economics, University of Kentucky