Cost Efficiency in BMP Adoption: Aspects of Conservation Auctions and Spatial Targeting

By

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Abstract

Improving water quality by inducing agricultural producers to implement Beneficial Management Practices (BMPs) is one of the top environmental concerns in Canada and worldwide. Conservation auctions can be a cost-effective mechanism to achieve this goal. The first two papers in this thesis focus on analyzing the performance of conservation auctions depending on various characteristics of the underlying BMPs. The last paper presents an optimization model and compares the social optimum to various agri-environmental government programs including conservation auction.

The first paper shows that not all BMPs are created equal, and conservation auctions can perform well if the potential BMPs' cost has low heterogeneity and the corresponding supply curve is flat, especially at the beginning. In our study area, the cost curves of structural BMPs (run-off ponds and wetland restoration) exhibit low cost heterogeneity. On the other hand, the cost curves of non-structural BMPs (permanent perennial cover and conservation tillage) exhibit high cost heterogeneity because they are affected by the profitability of the land to a larger degree. Fortunately, the typical "hockey-stick" shape environmental abatement curve is an ideal candidate to use in conservation auctions.

The second paper shows that if there is a diminishing marginal rate between BMP adoptions in close proximity, ignoring this so called "subadditivity" can significantly reduce the effectiveness of conservation auctions. The paper offers a potential solution by incorporating this diminishing marginal rate into the bid ranking and winner selection process. The technique was tested in the laboratory, and resulted in significant auction performance improvements if the subadditivity was present between neighbouring producers. The paper also shows that separately analyzing bidding and participation decisions for a conservation auction can lead to biased estimates; and hence, bidding behaviour should be analyzed in a selection model setting.

The third paper applies a binary integer programming model to estimate the maximum achievable pollution abatement and the optimal BMP adoption pattern with a given budget in a small watershed on the Canadian Prairies. The model incorporates the notion of diminishing marginal returns between BMP adoptions on the same agricultural field. While ignoring these interdependencies between BMPs can lead to efficiency losses, the magnitude of the loss is considerably lower than efficiency loss resulting from typical restrictions in agri-environmental programs, such as size and payout limitations. As obtaining the necessary cost and abatement assessment to carry out such optimization can be costly, a conservation auction can be used instead. The paper estimates the performance of a potential conservation auction assuming rent seeking level equivalent to what was observed by bidders in the second paper. The result shows that even if the auction ignores the interdependencies between BMP adoptions, it can be highly effective. However, the effectiveness of conservation auctions deteriorate to a large extent if the market structure is less than ideal. Having separate conservation auctions for each BMP type, or imposing size and total payment restriction hinders the performance to a large extent.

Preface

All the research reported in this thesis was approved by the University of Alberta Research Ethic Board:

- Ethics approval for the laboratory experiment in chapter 2: "Incentive program experiments in agriculture", No. Pro00017935
- Ethics approval for the laboratory experiment in chapter 3 "Experimental evaluation of incentive programs with synergy among neighbours", No. Pro00011917
- Ethics approval for the student pool database that was used to recruit participants for the laboratory experiment in chapter 2 and 3: "Student pool database for economics research ", No. Pro00011626,

Research funding for this project was provided by Agriculture and Agri-Food Canada (AAFC) through the Watershed Evaluation of BMPs (WEBs) program.

Dedication

I would like to dedicate this thesis to my husband, Gyorgy Ilyes. Thank you for your continued love and support during the challenges of graduate school and life.

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1 Introduction to the Thesis

As water quality problems become a growing concern worldwide, public administrators are looking into various new ways to reduce water pollution arising from different sources, including agricultural runoff. Public dollars are scarce; hence, it is crucial to investigate the cost effectiveness of solutions. Doole (2012) showed that reaching a 30% target runoff reduction in agriculture costs almost three times more to the economy using a traditional threshold policy which forces each farmer to comply with a fixed emission standard, compared to differentiated solutions. This illustrates the magnitude that can be saved if regulators can target farmers that are able to reduce their emissions in the most cost-effective ways.

The main problem with agricultural water pollution compared to industrial pollution is that there is not a single point source where individual contributions could be easily measured and monitored. Precipitation washes out nitrogen and phosphorus from the top soil, which gets diffused in the water that runs off from the fields and disperses in various water channels. It is difficult and costly to identify where exactly these nutrients originate from. This is called a Non-Point Source (NPS) emission problem. Traditional pollution policies like an emission tax, subsidies or trading cannot be applied to NPS pollution problems because they require identifying the actual emission levels of each contributor. While the theoretical foundation of group-based tax and subsidy focused policies for non-point source pollution was developed decades ago, their application requires the ability of monitoring the group ambient pollution level (Segerson 1988; Spraggon 2002, 2004). In practice, this would mean a constant monitoring of nutrient runoff at the watershed level, for which the necessary technology was not available until recently. In the past few years, specialized sensors have been developed that could be used to measure water contamination on a constant basis, but they are still too costly for widespread application (Pellerin et al. 2014). Moreover, there are some experimental studies that tested the performance of potential ambient-based tax and subsidy programs and analyzed how much monitoring they would require to produce acceptable performance (Fooks, Messer and Suter 2018; Miao et al. 2016). While these policies could be the future of environmental policies when the required sensors can be mass produced, currently governments focus on inducing firms to adopt more environmentally friendly production approaches instead. These new, potentially more environmentally friendly practices are often called Beneficial Management Practices or BMPs. The advantage of focusing on BMPs, instead of the actual emissions, is that their adoption can easily be monitored.

Currently, the approach to induce producers to adopt BMPs is financial compensation for the incurred adoption costs. These policies are often referred to as Payment for Environmental Services (PES) or “green payments”. These programs have various forms. One of the most commonly used in Canada is the cost share program, which is currently part of the various Growing Forward (GF) initiatives. The GF programs replaced the previous similar cost-share based program called the National Farm Stewardship Program (NFSP). Within these programs farmers are encouraged to adopt certain BMPs on their land, and they can obtain compensation for a given proportion of their direct costs. As a result, BMPs that produce economic benefits to the farmers have high participation rates, such as top soil testing or GPS controlled variable fertilization rates (Sparling and Brethour 2007). BMPs with net economic costs to the farmers, such as wetland restoration, experience low adoption rates across Canada regardless of the potential environmental benefits to the public (Boxall 2018).

Aside from the participation levels, the major problem with the cost sharing approach is that there is no consideration of cost efficiency. The government has no way of controlling whether the most or the least efficient producers adopt BMPs. As a result, cost-share based programs cost significantly more per unit of abatement than programs that target cost effective BMP adoptions (Maringanti, Chaubey and Popp 2009). As a common alternative, fixed payment programs have also been used by various regulatory bodies in the majority of the OECD countries (OECD 2010). Fixed payment programs pay a given amount for every producer who is willing to adopt a certain BMP. These programs are attractive to regulators because of their ease of implementation, transparency, low transaction cost and apparent fairness. However, the cost of implementation is only known to the farmers and can vary significantly among them. This information asymmetry can lead to very ineffective and costly programs. Such programs tend to lead to adverse selection problems, where farmers with low cost will enter the contract regardless of the resulting environmental benefit (OECD 2010).

In order to achieve cost efficient policy, the regulator needs to be able to engage in an environmental contract with those producers who are the most cost efficient in BMP adoption. One way to target the most cost-efficient BMP adopters is to eliminate the information asymmetry, obtain cost and emission estimates, and run an optimization model using potential adoptees. Based on the optimization results, government agencies can offer contracts to the most cost-efficient producers that compensate for adoption costs without overpaying them. The 3rd chapter in this thesis follows this approach and develops a model that maximizes the pollution reduction given a government budget using real field data that incorporates cost and pollution heterogeneity arising from landscape characteristics. The contribution of that chapter to the literature is that it incorporates actual heterogeneous field data for both the cost and emission sides. It also incorporates potential interdependencies between land parcels, and uses a binary mathematical programming optimization model to calculate the socially optimal BMP adoption pattern in a small watershed on the Canadian

Prairies. This allows us to set a potential benchmark and assess the effectiveness of various environmental policies.

Unfortunately, obtaining abatement values and cost estimates usually has large upfront costs and is often quite time consuming, which reduces the feasibility of using mathematical targeting models. As an alternative mechanism, so called "conservation auctions" started to be held to overcome the information deficiencies. Conservation auctions, or green auctions, are procurement auctions held by agencies where potential BMP adopters bid for a limited number of environmental contracts. After the theoretical concept was introduced by Latacz-Lohmann and Van der Hamsvoort (1997), various programs were implemented worldwide. These initial programs reported significant cost savings: Stoneham, Chaudhri and Strappazzon (2003) estimated 700% cost efficiency improvements; and White and Burton (2005) reported between 200% and 315% improvements. However, these efficiency improvements are only estimates, and may erode quickly in repeated conservation auctions. Before wider implementation, the circumstances need further investigating in controlled laboratories experiments (Latacz-Lohmann and Schilizzi 2005). The first two chapters in this thesis are devoted to this investigation.

There are existing laboratory studies that focus on specific regulatory aspects of auction mechanisms such as the information regulators provide to potential BMP adoptees *(*Cason, Gangadharan and Duke 2003a) or pricing methods used in the auction (Cummings, Holt and Laury 2004; Cason and Gangadharan 2004, 2005; Boxall, Perger, and Weber 2013). While these studies focus on how the agencies can tweak the auction to be more successful, there is very little focus on how external factors may influence the auction's success. For simplicity, most studies assume the producers' cost structures are evenly distributed along a "text-book" cost curve. However, environmental abatement cost curves often have unusual shapes (Tisdell 2007). Moreover, conservation auctions tend to be limited to a specific geographical area where entry is restricted to local farmers, which may lead to concentrated markets with high potential for collusion among bidders. The aim of the first chapter is to understand how these may affect or potentially hinder the cost effectiveness of conservation auctions for water quality improvements.

Another common underlying assumption in these conservation auctions is that costs and the environmental benefits provided by the BMPs are independent from each other. However, as water runoff flows from one field to another, neighbours' actions potentially affect each other's abatement possibilities and may significantly change the optimal adoption pattern and environmental outcome. The second chapter investigates how diminishing marginal rate of BMP adoptions affects conservation auctions in laboratory settings.

The research conducted in this dissertation stems from the Watershed Evaluation of BMPs (WEBs) project, which is a Canadian nation-wide program funded by Agriculture and Agri-Food Canada (AAFC) and Ducks Unlimited Canada to examine the efficacy of BMP adoption.

1.1 Theoretical and Empirical Literature of Auctions

Auctions have been used for centuries as a market mechanism that aims to sell a single item to a bidder who values it the most. Originally, auctions were often open when the bidders could observe each other's bidding behavior. In an open auction, the price may start low and then ascend (English auction), or start very high and then descend (Dutch auction) until a single bidder is left to pay the winning price. In the case of a sealed bid auction, bidders submit their bid directly to the auctioneer without knowledge of other bidders' activities, and the one who submitted the highest bid wins the auction. The highest bidder either pays their own bid (first or discriminatory price auction) or the bid of the highest losing bid (second price or Vickrey auction). Despite the long history of auctions, their theoretical foundations only started to be investigated in the 60's when Vickrey (1961) showed that English and second price auctions are equivalent under certain circumstances. Later the result was generalized to be the Revenue Equivalence Theorem (RET), which states that under certain assumptions all these 4 types of auctions (English, Dutch, first and second price sealed bid auctions) are equivalent (Myerson 1981). The result was even expanded to multi-unit auctions. Dasgupta and Maskin (2000) showed that the Vickrey auction is efficient in multi-unit auction settings and Ausubel (2004) proved that the English auction equivalence with the sealed bid Vickrey auction holds in multi-unit settings.

The RET states that all four auction types (English, Dutch, first and second price sealed bid auctions) lead to the same winner, which is called allocative efficiency. It also declares that all lead to the same amount of revenue for the seller, which is called economic efficiency. However, this doesn't mean that firms bid the same way in all auctions. The four types of auctions can be divided into two groups. In the case of open descending auctions (Dutch) and sealed second price auctions, the dominant strategy of the bidders is to bid their actual value (Milgrom 1989). While in case of ascending and first price auction, the bidders' best strategy is to shade their bids. In conservation auctions this means that English and Vickrey auctions are superior to the first price auction in terms of cost revealing mechanisms (Latacz-Lohmann and Van der Hamsvoort 1998). However, RET results are only true under the assumption of a) bidders are risk neutral, b) bidders have independent private values, c) there is symmetry among bidders, d) payment is the function of the bid alone, and e) there is a zero cost of bid construction and implementation. The problem is that these assumptions are more often than not violated in conservation setting. There are theoretical models that show what happens if one of the assumptions is violated. For example, Riley and Samuelson (1981) showed that if bidders are risk averse, first price auction leads to larger expected revenue for the auctioneer. At the same time, Klemperer (1999) argues that the bidders' risk attitude has no effect on their bidding strategy in case of uniform price sealed auctions. When other assumptions are violated, for example the symmetry, the result is ambiguous (Myerson 1981; Klemperer 1999). If more than one assumption is violated the model becomes extremely complex to analyze (Riley and Samuelson 1981). Hence, there is no conclusive result from theory to decide which auction format is best to use in real life settings. Although certain types of markets traditionally operate using one auction type, (e.g. US treasury bonds are usually sold in uniform price sealed bid auctions) there is no compelling evidence that suggests that one of the auction formats is superior to others (Binmore and Swierzbinski 2000).

In addition to the problem that auction theory assumptions are violated in real life, conservation auctions are reverse auctions that have not been studied as extensively as forward auctions. There are only a few studies that provide theoretical foundations for reverse auctions. Engelbrecht-Wiggans and Katok (2006) provided a formalization of reverse auctions that mimics an open price descending Dutch auction and is often used in Business to Business (B2B) internet auctions. In this reverse auction model, the auctioneer wants to purchase a given quantity of goods and there are multiple suppliers, each with a single unit of supply and a privately known cost. The auctioneer openly announces a high starting price, which is descending over-time, and the auction ends when the remaining number of suppliers equals the demand quantity. Just as the forward Dutch auction, this is a uniform price auction, and all the winners get the same price. Authors note that their formulation is equivalent to the Vickery (1961) auction concepts except the bidders are providing and not acquiring. This results in the bidders' dominant strategy being to drop out when the price equals their true cost; hence it is a true cost revealing mechanism (Engelbrecht-Wiggans and Katok 2006 pg 584). While this type of reverse auction is very common in B2B supplier management, it is not very common in conservation. There are only a handful of conservation auctions that use the uniform pricing mechanism. A small scale Indonesian program aimed at reducing soil erosion on coffee farms used a Vickrey-type auction applied to a reverse auction setting, but instead of using a quantity target used a budget limit (Jack, Leimona and Ferraro 2009).

Since government agencies usually have fixed budgets for environmental programs, setting a budget limit in an auction instead of a quantity targeted is more practical for a conservation auction. To accommodate this type of auction setting, an alternative framework using discriminatory pricing mechanism was developed specifically for conservation auctions by Latacz-Lohmann and Van der Hamsvoort (1997). Their model is fundamentally different from other general auction models as instead of having a quantity goal, the auctioneer has a budgetary limitation and buys contracts until its budget is exhausted. The model assumes risk averse bidders with homogenous expectations toward the lowest and highest bid prices that are accepted. Later this model was adapted by Vukina et al. (2008) by assuming bidders with heterogeneous expectations towards price. This model was further expanded by Wichmann et al. (2017) to study bidding behaviour when bidders face uncertain cost. Since the model developed by Latacz-Lohmann and Van der Hamsvoort (1997) was the only one that was developed specifically in conservation auction contexts using budget limitations, it became the most widespread auction setting in conservation auctions across the world. It is used in the US Conservation Reserve Program (CRP), which aims to buy cropland from farmers to set aside for conservation purposes, and it is the largest program of its kind. It has also been used in various Australian programs inducing BMP adoptions such as the BushTender, the EcoTender, the Auction for Landscape Recovery (ALR) program and the Western Australian Conservation Auction program (Latacz-Lohmann and Schilizzi 2005). It is also used in the Challenge Funds in the United Kingdom, which aim to alter tree planting methods in commercial forestry; used in Canada for wetland restoration (Hill et al. 2011); and in Germany for the Grassland Conservation Pilot Tender, which aimed to retire cultivated cropland and to compare auction effectiveness with previous fixed rate take it or leave it programs (Groth 2005). This auction was also used in Finland in a multiunit discriminatory auction to reduce phosphorus loads from waterways (Iho et al. 2014)

2 Effects of the Underlying Supply Function Heterogeneity on Conservation Auction

2.1 Introduction

Inducing farmers to adopt Beneficial Management Practices (BMPs) in agriculture has become an important tool to control multiple aspects of water pollution in Canada and worldwide. Initially, governments relied on emphasising stewardship motives to farmers, but BMP adoptions often have substantial costs, hence financial compensation is often necessary. Governments frequently use various cost sharing programs for BMP adoptions, but these can have low adoption rates as landowners still have to endure a certain proportion of the cost (Sparling and Brethour 2007). Moreover, cost sharing programs only compensate landowners for their direct cost, for example, building a retaining pond or fencing off water stream from cattle. However, many BMP adoptions often have substantial indirect costs. For example, the main cost driver of Forage Conversion is the lost crop revenue over time; but a typical cost sharing program, like NSFP or Growing Forward, only compensates the producers for the initial seeding cost (Boxall et al. 2008). Rational agents won't willingly increase their production cost or decrease their potential revenue unless they are compensated for it. The problem is that the actual cost of the adoption is only known to the farmers themselves.

Fixed payment government programs are also very popular in OECD countries. The problem with these programs is that the hidden information about the underlying cost can lead to an adverse selection problem. Often the low-cost farmers are participating regardless of the level of environmental benefits they produce, which results in very high cost per unit abatement achieved (OECD 2010).

In the past two decades, reverse auctions have been successfully used by private businesses and government agencies as a cost revealing mechanism when purchasing various services. A reverse auction is essentially the flip side of a regular or forward auction. In a regular auction there is a single seller, the auctioneer, who has a single item to sell and wants to obtain the highest price for its item from one of multiple buyers. In a reverse auction, the auctioneer is a single buyer who wants to purchase one or more items or often services at the lowest cost from multiple sellers. When a reverse auction is used to purchase environmental services, they are often called conservation auctions or "green" auctions. Generally, there are multiple services the auctioneer wants to purchase, making them multi-unit auctions. There is very limited theory to guide us regarding conservation auctions, and studying empirical program evaluations requires cost estimates since the actual true cost is unknown to the researchers. As a result, laboratory experiments have been frequently employed to study the effectiveness of conservation auctions and this study will also utilize that methodology.

There are two types of pricing mechanisms that exist in such conservation auctions: discriminatory and uniform pricing. When using discriminatory pricing, the winners receive a payment equal to their bid. In the case of uniform pricing each winner receives an equal payment or equal amount per unit of service provided. While some laboratory studies find that discriminatory conservation auctions are more efficient than their uniform counterparts (Cason, Gangadharan and Duke 2003a; Cason and Gangadharan 2004; 2005), others find the opposite (Boxall, Perger and Weber 2013). Although both sides of the debate used similar settings, the underlying cost functions that each employed were quite different.

This leads to our research objective, which is to analyze how the underlying cost function affects auction effectiveness by testing a wide variety of supply curves and market structures in experimental settings. Most previous studies used a single hypothetical cost structure with randomly drawn homogenous sized firms. This study uses various different cost functions that were calculated based on actual BMPs' adoption costs and environmental benefit estimates from the Canadian Prairies. The data includes estimates for the following BMP types: retention pond, Forage Conversion and zero or conservation tillage. Depending on the BMP types, some of these cost curves represent fairly even "markets" with similar sized firms, resembling perfect competition. Others have large heterogeneity in firm sizes due to the considerable variation in farming operation sizes. In addition to the market structure differences, these adoption costs also vary in terms of shapes. Structural BMPs often have a fairly flat supply curve as the cost is driven by the building structure, which is often proportionate to the size of the land or the size of the cattle herd and the provided benefits. On the other hand, non-structural BMPs' costs tend to vary to a larger degree because the adoption cost is driven by the opportunity cost of the land, which is affected by heterogeneous landscape characteristics such as soil quality and slope. As a result of using multiple cost curves and treatments, this study has a substantially larger dataset than most other previous sets of laboratory experiments. This allows rigorous statistical analysis to be carried out in order to determine the characteristics of the cost function that actually drives various results of the auction. This provides useful insights for regulators when it comes to deciding how to organise a potential conservation auction program.

2.2 Background

While there is no existing formal theoretical formulation for uniform price auctions with budgetary limitations, Latacz-Lohmann and Schilizzi (2005) provided a graphical illustration of how the uniform and the discriminatory pricing auction results would relate to each other as illustrated in Figure 2.1A. Assuming bidders are following their dominant strategy, under the uniform pricing rule bidders submit bids equal to their actual cost (dotted line). Under the discriminatory rule they shade their bids (dashed line). Depending on how much bid shading is present in the discriminatory auction, it can perform better than uniform (Figure 1A) or worse (Figure 1B). If there is excessive bid shading on the discriminatory auction, the achieved abatement on the discriminatory auction may be less than the achieved abatements on the uniform auction ($X_F > X_D$). If there is a lesser amount of bid shading in the discriminatory auction, the achieved abatement quantity can be higher than on the uniform auction ($X_F < X_D$)

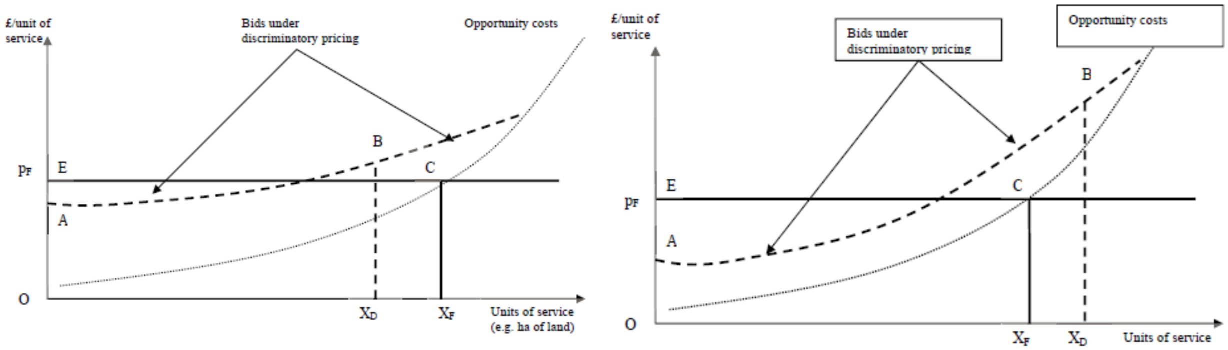

Figure 2.1. Uniform vs. Discriminatory Pricing, Latacz-Lohmann and Schilizzi 2005 pg 58

The question is what factors contribute to more significant bid shading in some cases than others? More importantly, which of the two potential cases are realized in the conservation programs? The problem is that the hidden information prevents us from accurately assessing the effectiveness of conservation auctions held by regulatory agencies. Studying conservation auctions in the laboratory gives us the opportunity to compare auction outcomes to the achievable optimal abatement quantity, as this cannot be done by examining field conservation auctions. It also allows us to have control of certain aspects, so we can isolate the correlation between certain design elements and the effectiveness of the auction.

The pioneer study in this field was the paper by Latacz-Lohmann and Van der Hamsvoort (1997), which laid the theoretical foundation. The authors' main purpose was to examine how their proposed auction setting would work out against various fixed payment schemes. The result showed that the auction setting can outperform the fixed payment programs, which were the standard in conservation programs at the time of the study. Their study was followed by a handful of others using similar settings. Cason, Gangadharan and Duke (2003a) also compared fixed payment schemes with discriminatory sealed bid conservation auctions by varying the amount of information bidders received. Their findings verified that the conservation auction setting outperforms the fixed price scheme, but the effectiveness greatly depends on the information the landowners have about their competitiveness in the market.

Later, various laboratory studies focused on the uniform versus discriminatory pricing debate using single hypothetical cost functions (Cummings, Holt and Laury 2004, Cason and Gangadharan 2004, 2005). Their findings were consistent with the regular (forward) auction findings in the literature, which is that the uniform auction is a superior cost revealing mechanism, compared to the discriminatory auction, where larger bid shading is present. They also found that despite being better at revealing the true cost, the uniform auctions were outperformed by the discriminatory auctions in terms of economic efficiency, as they generated less environmental benefit per dollar.

Since real field data are hard to come by, most conservation auction experiments use hypothetical data. It is common to draw random data along smooth cost curves, with constant elasticity, or draw from a uniform distribution between a given range as indicated by Cason, Gangadharan and Duke (2003a). This imposes a potentially unrealistic shape on the underlying cost curve. Real field data often shows that environmental abatement functions are not smooth with constant elasticity. Tisdell's (2007) trading experiment used cost based on estimated environmental services, and it can be seen that a realistic abatement cost curve is anything but smooth and that elasticities may change multiple times along the curve (see Figure 2).

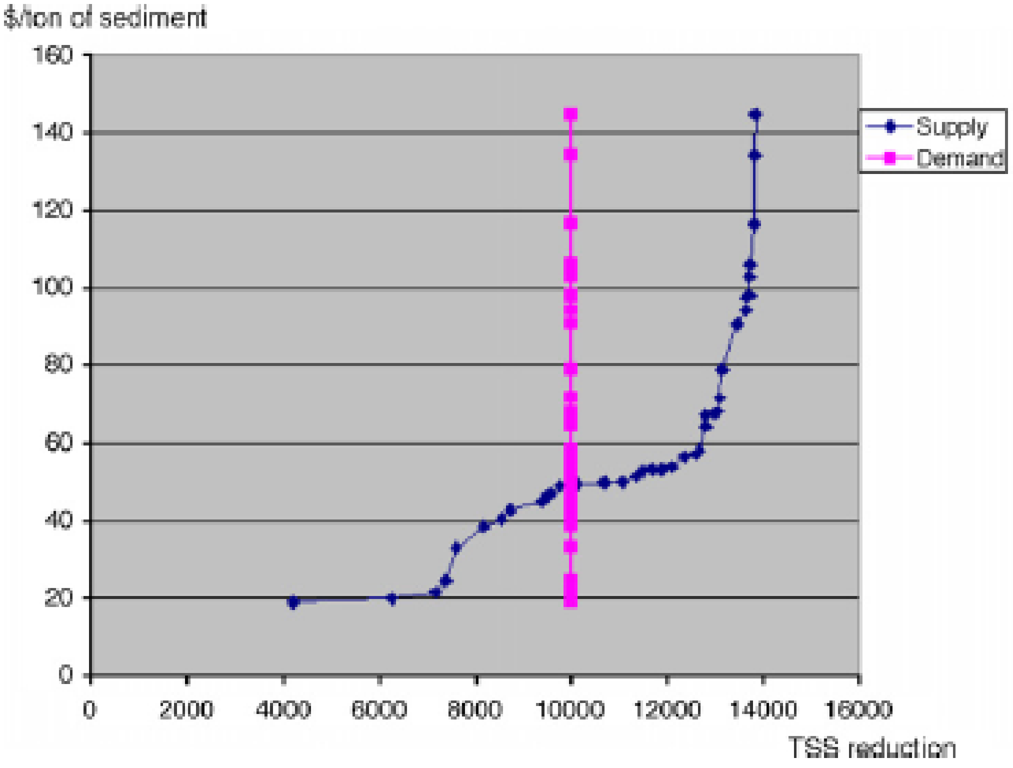

Figure 2.2. Supply Curve used by Tisdell (2007 Pg 587)

While studies that used hypothetical cost curves found that discriminatory pricing is better than uniform in terms of economic efficiency, this may not be the case under certain conditions. One set of laboratory experiments, which used costs derived from actual BMP adoption costs, in the Canadian Prairies, found different results (Boxall, Perger and Weber, 2013). Their experimental settings mimicked the earlier studies by Cason and Gangadharan (2004, 2005), but concluded the opposite. Moreover, the authors used three different ranking criteria, and the uniform pricing outperformed the discriminatory in all of them albeit by different degrees. Using different ranking criteria essentially means assigning different orders to the bids, therefore leading to different supply curves. This raised suspicion that there may be a close relation between the underlying supply curve and the effectiveness of the pricing mechanism.

Another recent study analyzing the Scottish fishing vessel decommissioning program speculated that discriminatory pricing may perform better than uniform if the underlying supply curve is steep (Schilizzi and Latacz-Lohmann, 2012). Although both rounds of the auction used discriminatory pricing, the authors estimated the potential uniform bids based on their previous laboratory experiments. The estimation revealed that one of the auctions would have yielded better results if uniform pricing were used, while in the other the discriminatory was the best decision. Based on this result the authors hypothesized that potentially the steepness of the underlying cost structure may have been the reason. The main contribution of our research is to provide statistical evidence to support or refute this hypothesis by employing various different underlying cost curves in a conservation auction experiment.

Beside the shape of the cost curve, other aspects of the supply curve, like the market structure, can be important in conservation auctions. Klemperer's (2002) auction design guide points out that the market structure and presence of a strong bidder is one of the key aspects of an auction outcome. Most conservation auction experiments employ very simple market structures, often using single units or multiple units but there is typically not a significant variation among sizes. For example Cason, Gangadharan and Duke (2003a) used a market where the size of the offered environmental services varied, but the firms are evenly distributed along the cost curve. This implies that the bidding firms were similar in size, i.e. there is perfect competition. However, in agricultural settings BMP adoption costs and abatement potentials are often strongly related to the size of a farm. For example, the size of a run-off Holding Pond and the related cost of construction are strongly related to the number of cattle a producer has (Boxall et al. 2008). Since in North America farm sizes can vary from small hobby farms to large-scale industrial operations, this means that assuming evenly sized market structures can be quite unrealistic in conservation auctions. Using various data driven underlying cost functions allowed us to assess the role of the market structure in conservation auctions, which is another contribution to the literature.

Laboratory experiments, including conservation auctions, often prohibit participants from talking to each other during the experiment to prevent collaboration and increased bid shading (Cummings, Holt, and Laury 2002; Cason and Gangadharan 2004, 2005). However, actual government auctions often face communication problems, and one of the main challenges in auction design is to prevent or minimize collusion (Klemperer 2002). Although sealed bid auctions, as opposed to open auctions, can somewhat alleviate the collusion problem, participants cannot be prevented from talking to each other in an actual field conservation auction. In a small-scale, locally concentrated, conservation auction, participants likely know each other and may share information to "game" the auction. Cason, Gangadharan and Duke (2003a) found that providing additional information to the bidders in conservation auction leads to increased rent seeking activities in their laboratory experiments. However, Glebe (2013) provided a theoretical formulation showing that disclosing environmental benefit information to farmers can change bidders' expectation of the bid cap and can encourage participation, which leads to thicker market and potentially increased efficiency. Allowing participants to communicate may potentially provide them the opportunity to obtain information from their fellow bidders and may alter the outcome of the auction. Our study employs multiple communication treatments to control for potential information exchange among bidders.

2.3 Experiment Design

This section describes the set of experiments that have been used in this study to explore the role of underlying cost functions on conservation auction outcomes.

2.3.1 Experimental Procedures

The experiments in this study were designed to induce incentive comparable behaviour in our subjects similar to agricultural producers in a potential conservation auction and were similarly structured to other laboratory experiments in the literature (e.g. Cason, Gangadharan, and Duke 2003a; Cummings, Holt and Laury 2004; Schilizzi and Latacz-Lohmann 2007; Boxall, Perger and Weber 2013; Wichmann et al. 2017; Boxall et al. 2017).

The experiments utilized Ztree software, which was developed for the specific purpose of conducting economic experiments, and allowed us to customize the auction to our needs

(Fischbacher 2007). The subjects were recruited from the participant database maintained by our department, Resource Economics and Environmental Sociology, and managed using the ORSEE software (Greiner 2015). The data pool contained a mix of undergraduate and graduate students as well as some employees from the University of Alberta. While laboratory experiments cannot replace fields experiments, they produce incentive compatible behavior that allows us to generalize their findings with their external validity being established in the literature (Roe and Just 2009). External validity of laboratory auctions has been confirmed by multiple studies (Brookshire et al. 1987; List and Shogren 1998). Students participating in conservation auctions in the laboratory are assumed to behave similarly to rational profit maximising firms (Cason and Gangadharan 2004, 2005; Cason, Gangadharan and Duke 2003). Moreover, a very similarly structured previous version of these experiments was carried out with the actual agricultural producers in our study area and showed identical behaviour to the university students (Boxall et al 2008)

During the data collection, 48 experimental sessions were carried out with 12 participants each, resulting in 578 participants in total. The average age among the participants was 24.6 years, and 46% of them were female. An experimental session lasted between 45-60 minutes including reading the instructions, the actual auction rounds, and the handling of the cash payments at the end. At the beginning of an experimental session, participants were given PowerPoint instructions explaining the course of the experiment (see Appendix), which was followed by one-minute long auction rounds. Before the incentive based auction rounds started, two practice rounds had been executed ensuring the participants understood the rules of the auction.

The experiments employed sealed bid budget based conservation auctions using both discriminatory and uniform pricing mechanism that were repeated multiple times through the course of the experimental sessions. Each session had 12 participants representing producers. Each of them could adopt a single BMP of a specific size. The size of the BMPs varied among the participants. Participants were only provided information about their own BMP adoption, which included their total cost given in dollars, and the size of their BMP in number of units[1]. They were also informed about the auction rules, such as how the government ranks the bids from the lowest bid per unit supplied to the highest and allocates the budget until it is exhausted.

Each sessions had 15 independent auction rounds divided into 3 blocks. The participants kept their BMP cost and size within each block, but received new randomly assigned values

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[1] The unit may represent different things depending on the supply function used in the given treatment, e.g. units can refer to a kg of phosphorus abated, head of cattle or hectare of land covered.

at the beginning of each block. The flowchart (Figure 2.3) below shows the sequence within an experimental session. This type of session structure has been used previously in the literature (Cason, Gangadharan and Duke 2003a; Cason and Gangadharan 2004; Tisdell 2007). As previous studies showed that conservation auctions tend to lose their edge in as few as 3 repetitions (Latacz-Lohmann and Schilizzi 2007), we chose the 5 round block length to ensure that the entire learning effect of possible cost advantage could be captured. In total, 15 rounds were chosen to ensure sufficient data collection without expanding the sessions so long that the focus of subjects deteriorates.

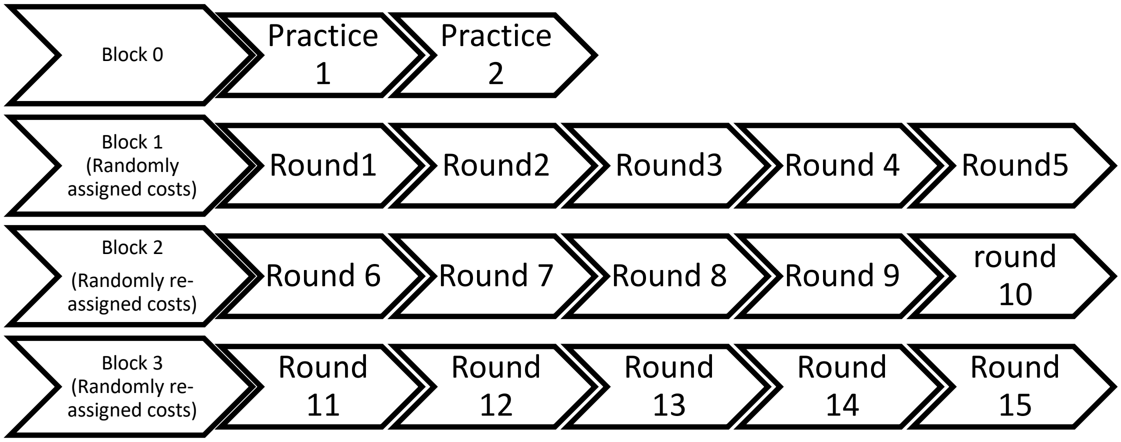

Figure 2.3. Flowchart of an Experimental Session

Participation in each auction round was voluntary, and ensured a one dollar fixed payment for those who decided not to participate or did not win in the auction. This fixed payment was meant to represent the notion that producers do have farming income even if they do not take part in a potential BMP adoption program, and we wanted to mimic real life situations as closely as possible. Also, there is evidence in the literature that endowment effects may play a role in subject behaviour in experiments. Subjects who participated and won in the auction got paid the difference between the government payout and their adoption costs on top of their fixed income payment. The payment accrued through the 15 rounds, and total payment per participants ranged between $15 to $35 with an average payment of $27.50.

2.3.2 Auction Treatments

Since the focus of this research is to investigate how the underlying cost function affects performance of conservation auctions, the main treatment was changing the cost functions. This has not been done before in conservation auction experiments. Instead of selecting randomly created curves that most experiments use (e.g. Cason and Gangadharan 2004; 2005), this research used cost curves based on actual BMP cost estimates, because their shapes may be significantly different than text book cost curves (Tisdell 2007). The experiments employed 6 different underlying cost curves, which were estimated based on BMP adoption cost data from a small watershed in Manitoba.

Since one of the BMPs examined in our study area could be adopted by 12 producers, it was a natural choice to have 12 subjects in the experiments. Also, existing studies suggest having at least 2-3 subjects representing identical or similar situations in order to ensure efficient trading in the lab (Plott 1982; Smith 1962). Using 12 participants, each cost curve can be divided into 3 groups: low-, medium- and high-cost producers. Low-cost refers to the producers who are the most cost-efficient, and always should submit a bid. These bidders could easily win in the auction if they bid close to their costs and thus always should adopt BMPs. Since these producers' costs are significantly lower than the potential budget cut-off line, they have a significant opportunity to seek rent. High-cost refers to the type of producers who are not cost efficient enough and should not adopt the practice, hence they have limited to no rent-seeking potential. Medium-cost refers to the producers whose costs are around the budget cut-off line, and they may or may not win on the auction depending on how much rent-seeking is going on among the low-cost producers. These producers have limited rent seeking potential, as they are already close to the budget cut off in the auction.

Different cost curves have different numbers of producers in these 3 categories. Some have an even distribution of suppliers, and have 4 producers in each category. Other curves have a more uneven distribution. For example, if there is a sharp bend in the curve around the budget line, there are more low- and high-cost producers, but there are very few medium-cost ones.

The second treatment in the experiments was the use of the two different pricing methods: discriminatory and uniform pricing. Conservation auctions, both in the lab and in the field, often employ discriminatory pricing mechanisms, where winning participants are paid their bid in the auction. The laboratory experiments are designed to mimic actual conservation auctions and are similarly structured to other laboratory experiments in the literature (Cason, Gangadharan, and Duke 2003a; Cummings, Holt and Laury 2004; Schilizzi and Latacz-Lohmann 2007). Discriminatory pricing is an attractive method for its simplicity, transparency and generally regulators do not like the idea of willingly paying more than the bids, which would occur under uniform pricing (Latacz-Lohmann and Schilizzi 2005). However, theory suggests that discriminatory auctions are inferior to uniform auctions as a cost revealing mechanism (Latacz-Lohmann and Hamsvoort 1997; 1998). Also, there is no clear conclusion in the literature about which of the two pricing methods result in more cost-effective outcomes in practice (Latacz-Lohmann and Schilizzi 2005; Hailu and Thoyer 2006). Moreover, there is speculation that the cost effectiveness of the two mechanisms may be dependent on the underlying cost functions (Boxall, Perger and Weber 2013; Schilizzi and Latacz-Lohmann 2012). Thus, one of the chosen experimental treatments was to vary the pricing mechanism and in half of the sessions we used uniform and in the others used discriminatory pricing. This allows us to test the hypothesis that the shape of the underlying cost function influences which pricing mechanism a regulator should choose.

The third treatment in this study was the presence of communication among bidders. In all sessions the auctions used the sealed bid format where each participant only knows about their own bid and their own auction result. In half of our sessions, however, no communication was allowed, and participants were prohibited to talk to each other during the experiment. These treatments are referred to as silent sessions. The other half of the sessions allowed communication in a face-to-face free chat format. The subjects were informed that they were allowed to talk and share any information they want, but their actual bids and auction result still would not be seen by their fellow participants unless communicated. The study employed a full factorial design in order to allow us to study all the potential interactions between the different treatments. The 1st treatment was the 6 different cost curves, the 2nd treatment was the two different pricing methods, and the 3rd treatment was the 2 different communication options. This led to 24 unique treatments, and each experimental treatment was repeated twice with different participants, hence we had 48 experimental sessions in total using the 6 cost curves.

Table 2.1. Summary of the Laboratory Experiment Auction Design

	Discriminatory Pricing	**Uniform Pricing**
Communication Allowed	6 cost curves x 2 repetitions = 12 sessions	6 cost curves x 2 repetitions = 12 sessions
Communication Prohibited (Silent)	6 cost curves x 2 repetitions = 12 sessions	6 cost curves x 2 repetitions = 12 sessions

2.4 Conceptual Framework

2.4.1 Measuring Auction Success

Government agencies that hold conservation auctions are mainly concerned with the overall performance of the auctions such as how much environmental benefit the auction generates given their budget, how cost efficient the auction is in general, and how much money is wasted and paid above the actual cost. We used three measurements adapted from the literature: rent, environmental and cost efficiency as they are described below. During the econometric analysis, these variables served as dependent variables.

2.4.1.1 Information Rent

The main reason a regulator would run a conservation auction in the first place is to overcome the information asymmetry between themselves and the producers. This information asymmetry allows the producers to extract payment above their actual adoption cost, which is called the information rent. Our first and foremost measure of auction success is the magnitude of this information rent. Some studies simply use the actual value of the information rent which equals the total payment to the winners minus the actual BMP adoption cost of those producers (Cason and Gangadharan 2004, 2005[2]). In this study, the underlying cost curves and the scales of auctions vary significantly between sessions; hence the absolute value of the information rents cannot be directly compared. In order to be able to compare different sessions, we need to scale this information rent and use some kind of proportional relative measure. Schilizzi and Latacz-Lohmann (2007; 2013) use a proportional measure they call the information rent rate, which is the ratio of the total payment and the opportunity cost. Their measure signifies the percentage the government overpaid the producers; other studies call this measure the overcompensation rate (Latacz-Lohmann and Latacz-Lohmann 2007b). Based on construction, a value of 1 or 100% represents the case when there is zero overpayment, and the amount this value is above the 100% represents the percentage overpaid. Other studies use a measure where the information rent is scaled to the total government payment (Boxall, Perger and Weber 2013; Boxall et al. 2017; Kits, Adamowicz, and Boxall 2014; Wichmann et al. 2017). Based on the construction, the rent rate values fall between 0 and 100%, where 0% means no rent was extracted and 100% means that only rent was paid. Our study adapted this latter measure called PRENT, which stands for the

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[2] Authors called it "Sellers profit", but information rent is more accurate

percentage of the government payment spent on information rent and is calculated by the following formula:

$$PRENT = \frac{\text{information rent}}{\text{payment}} * 100\% = \frac{\text{payment - actual cost}}{\text{payment}} * 100\% \qquad (2.1)$$

2.4.1.2 Environment Efficiency

The other important issue in a conservation auction is how much environmental benefit has been generated. Many studies use the absolute value of this quantity simply by adding up the size of the winners' BMP inputs (Latacz-Lohmann and Hamsvoort 1997; Cummings, Holt and Laury 2004; Schilizzi and Latacz-Lohmann 2007b; Kits, Adamowicz and Boxall 2014; Boxall et al 2017). However, in this present study, the environmental benefits cannot be directly compared between sessions due to the magnitude difference between sessions. Instead of comparing the actual quantity, the quantity was scaled to the maximum or optimum quantity potentially achievable in the given auction. This type of measurement is also commonly used in the literature (Cason and Gangadharan 2004, 2005;[3] Schilizzi and Latacz-Lohmann 2013[4]; Banerjee, Shortle, and Kwasnica 2015; Krawczyk et al. 2016[5]). Although various names have been used for these measurements, it is referred to as Environmental Efficiency (EE) in this present study after Banerjee, Shortle, and Kwasnica (2015). Environmental efficiency ranges between 0 and 100%, where 100% represents the optimal case where the auction reached the maximum quantity that could be achieved with the given budget and covering producers' BMP adoption costs. Based on construction, the higher this number is, the more successful the auction.

$$EE = \frac{\text{realized quantity}}{\text{maximum achiavable quantity}} * 100\% \qquad (2.2)$$

2.4.1.3 Cost Efficiency

The third measurement used is a proxy for cost or economic efficiency. Cost efficiency is often defined as the average cost of the environmental benefit achieved, which is simply the unit cost. Schilizzi and Latacz-Lohmann define the cost of a unit of abatement to the producers as *Economic cost-efficiency* and define the cost of a unit of abatement to the public as *Budgetary cost-efficiency* (2007, 2013). Alternatively, the reciprocal measure can be used,

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[3] Authors called this "P-MAR" for the Percentage of Maximum Abatement Realized

[4] Authors called this "% max N abated" for the percentage of maximum nitrogen abatement

[5] Authors called this relative environmental value, as it was the proportion of the maximum environmental value that could have been achieved.

which can be interpreted as the purchasing power of the auctioneer's dollar, meaning the number of abatement units per dollar. Cason and Gangadharan take this concept of reciprocal measurement even further and scale it to the optimal value (2005). They call this P-OCER, which stands for Percentage of the Optimal Cost Effectiveness Realized. P-OCER is calculated as follows:

$$P-OCER=\frac{payment\ per\ unit\ required\ to\ achive\ the\ optimum\ quantity}{payment\ per\ unit}*100\% \quad (2.3)$$

P-OCER ranges between 0 and 100%, where 100% represents the case where optimal cost efficiency is achieved. As cost efficiency also requires scaling in order to compare results from different sessions, this concept is followed here. Generally, the higher the number is, the more successful the auction. However, this measure can assign a value above 100% for a suboptimal situation. This happens, as noted by Cason and Gangadharan (2005 pg 63), when the auction expends considerably lesser amounts than the total budget, leading to a situation where the abatement per dollar exceeds the abatement per dollar at the optimal winner selection. This is because the government purchases only the units that are at a much lower part of the supply curve than the optimal quantity is. While this phenomenon rarely occurred for flat supply curves, it was almost always the case with steeper curves. To avoid this problem, the measurement was modified: instead of using the payment per unit required to achieve the optimum quantity as a scale, we used the payment per unit required to receive at least the quantity that was realized on this particular auction. This measurement is referred to as Cost Efficiency (CE) here and a value of 100% signifies the situation where the auctioneer spent exactly as much as needed to achieve this particular quantity. This measure cannot exceed 100% unless bidders are accepting payments below their actual cost. CE is formulated as follows:

$$CE=\frac{payment\ per\ unit\ required\ to\ achieve\ at\ least\ the\ quantity\ realized}{payment\ per\ unit}*100\% \quad (2.4)$$

2.4.2 Supply Curve Measurements

The focus of this paper is to analyze the effect of the underlying cost curves on conservation auction success in terms of the above defined variables such as the percentage of information rent. In order to carry out quantitative analysis, we need to quantify the supply curve characteristic and associate the used supply curves with some kind of measurement. Before moving to the actual measurement calculations, we first begin by examining supply curve graphs. Supply curves are illustrated on a graph where the horizontal axis is the number of units[6] of output produced, and the vertical axis is the price or the cost of producing a unit of output (Figure 2.4).

2.4.2.1 Firm Size Heterogeneity

Two different types of supply characteristics can be distinguished based on the two dimensions of the supply graph. For simplicity, we call the vertical variation of the supply curve "cost heterogeneity" and the horizontal variation as "firm size heterogeneity". Although supply curves are often displayed as smooth continuous curves, in environmental conservation issues a BMP is either implemented or it is not, which actually makes the curve non-continuous. This leads to the situation where the quantity or the size of the BMP for each firm may matter. If the potential achievable quantities are evenly distributed we have small firm size heterogeneity, and when the quantities are unevenly distributed, we have larger firm size heterogeneity.

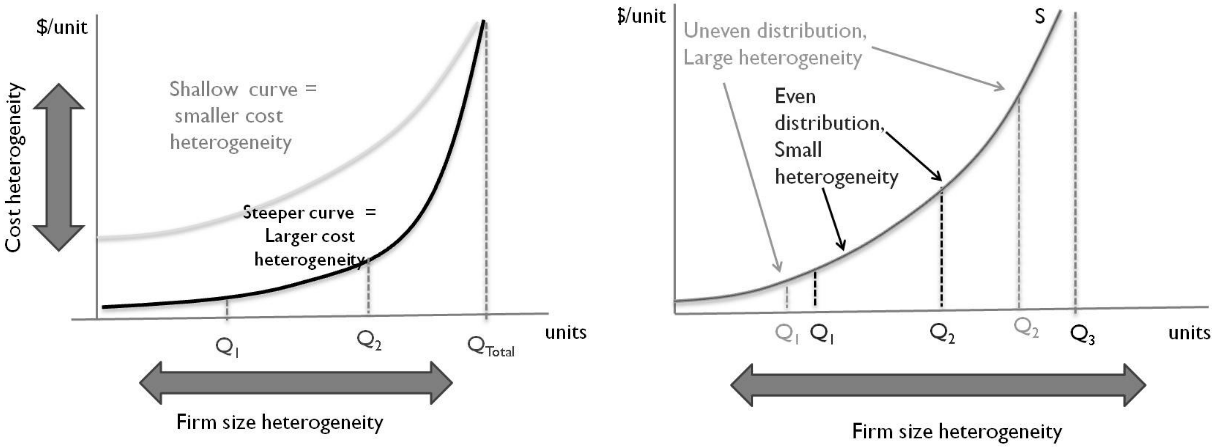

Figure 2.4. Graphical Illustration of the Supply Curve Heterogeneity

There are various measurements that exist in the industrial organization literature that describe firm size heterogeneity in a market, and they are most often calculated based on the market share (m) of the firms. For this analysis the Herfindahl-Hirschman Index (HHI) was used, which is one of the most well-known and accepted measures for market concentration[7]. The HHI is used in assessing the market concentration in industries by the US Trade Commission and the Canadian Competition Bureau for merger guidelines and other

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[6] Here unit is used in a broad sense as different curves had different units

[7] Besides the HHI, alternative measurements were also considered, such as market concentration ratio, Entropy coefficient; and variance of the market shares. However, they lead to the same result, and therefore HHI was chosen because it is the most widespread in the literature.

competition related issues (2010). The HHI index is the sum of the producers' squared market shares: $HHI = \sum_{j=1}^{N=12} m_j^2$. Based on the construction, the HHI values range from 1/N to 1, where N is the number of firms in the industry – the higher the value, the more concentrated the market is. Often HHI is used based on the percentage values (0 - 100%), which essentially scales the index to be between $1/N * 100^2$ and 10,000. For HHI calculation purposes, the market share can either be based on output dollar value or output quantity. Since we want to separate out cost heterogeneity from firm size heterogeneity, the market shares are strictly based on output quantity.

2.4.2.2 Cost Heterogeneity

While several firm size heterogeneity measurements exist, there are no generally accepted curvature measures that could distinguish between supply curves based on their overall shape. The price elasticity of supply (PES) is the only measurement that is known to measure the "curviness" of a supply curve; but it is a point measure and can differ for each point on the supply curve. If a curve has constant elasticity of supply, PES can provide an overall measurement. However, as discussed earlier, the typical abatement curve has a "hockey-stick" shape with a bend, which means the price elasticity is changing along the curve. Using a weighted average of the PES measure of the points could provide an overall measurement, but it has the same problem as all the other potential overall measurements considered, such as producer's surplus (PS) and the Gini coefficient. First, they all use the quantity and not just the price in their calculation, which means that resulting values are not independent from the firm size heterogeneity measurement (HHI). In order to avoid the multi-collinearity problem and separate the cost heterogeneity measurement from the firm size heterogeneity, the measurement had to be purely based on the price and its construction should not involve the quantity. While using statistical moments, such as the mean and the variance of the prices, are independent from the quantity, they have another problem. A single overall measurement potentially assigns the same values to very different shapes of curves if there is a curvature change in them, as is illustrated in Figure 2.5.

Supply curve A and B have visually different shapes, but the single measures of cost heterogeneity described above would assign the same value for both curves, assuming firms produce the same output quantity. They would produce the same Gini value, the same PS, the same overall weighted PES, and even the mean and the variance of the prices could be the same. They both have a flatter section and a steeper section, but in curve A the flat portion is at the beginning and the steep portion at the end; while in curve B it is the opposite. Since environmental abatement functions often have a unique shape with a bend in them, sometimes referred to as the "hockey stick" shape (Brown et al. 2011), this is not just a theoretical problem. In order to accurately distinguish between curves like the ones illustrated in Figure 2.5, we needed more than just a single overall measurement.

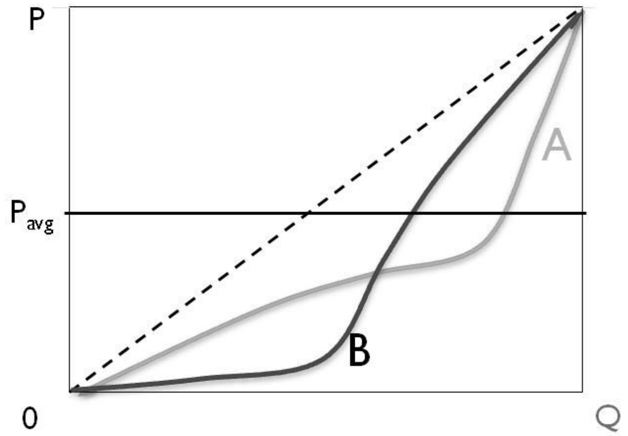

Figure 2.5. Graphical Illustration of the Problem with Single Measurements Describing Curve Shapes

As a solution, measurements were constructed based solely on the price of a unit[8] of output, which will be simply referred to as a price. The measurements derived are the price differences from the no cost heterogeneity case (see Figure 2.6). If there is no cost heterogeneity, and all the firm prices are the same, the supply function is a perfectly elastic horizontal line and all the prices are equal to the same price ($\overline{P}$), hence our measures are the difference between a price at a given point and the mean price.

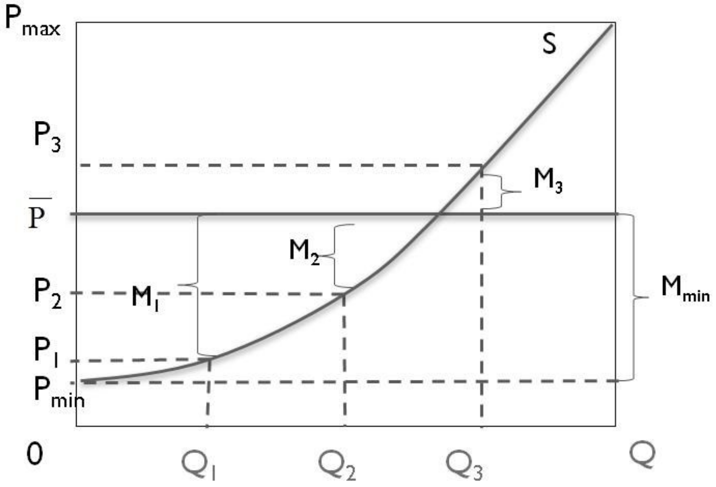

Figure 2.6. Graphical Illustration of the Curvature Measurements Used

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[8] The unit may represent different things for different supply functions, e.g. units can refer to a kg of phosphorus abated, head of cattle or hectare of land covered.

These measurements were calculated at the quartile points (Q1, Q2, Q3) as well as for the minimum price. Since the underlying cost curves represent significantly different scales of the auction, the price differences cannot be directly compared between sessions. Hence, they were scaled to the maximum price of the given curve, which resulted in a proportional measure calculated as follows:

$$M_i = \frac{\overline{P} - P_i}{P_{max}} \tag{2.5}$$

Each of these measures has a different interpretation. M_{min} essentially represents a proxy measure for the overall size of cost heterogeneity. The lower the number the closer all the firms are to each other cost-wise; the higher the number the more cost heterogeneity there is among the firms. The 1st quartile point measurement (M_1) represents a proxy for the cost heterogeneity at the beginning of the curve where the low-cost firms are located; the smaller the number the flatter the curve initially. The 3rd quartile point measurement (M_3) is a proxy of the curviness at the end of the supply. Since the budget for auctions is either 30 or 50% of the total market, this point is always above the budget cut-off line. Hence, it describes the shape of the curve at the end, where the high-cost firms are located, which are not cost efficient enough to adopt the BMP. The 2nd quartile point measurement (M_2) represents the proxy for the middle of the curve, where the medium-cost firms are located. Medium-cost firms may or may not be able to adopt the BMP depending on how much rent seeking is going on at the earlier part of the curve. M_2 was dropped from the final analysis due to collinearity issues, and M_3 remained because it has a more straightforward interpretation.

Analysis of the created measurements related to the curves illustrated on Figure 2.5 demonstrates that they in fact can capture the information they are designated for. Both curves start at the same price point, hence both curve A and B would have the same M_{min} value. The curves are such that they cross at the median point; hence, they also would have the same M_2 values. However, curve B is flatter at the beginning than curve A, hence its M_1 value would be higher. At the same time, curve B is steeper at the end; hence, it has lower M_3 value than curve A.

2.4.3 Econometric Models

Given the repetitive nature of these types of experiments coupled with the fact that the treatment variables do not change over time, random effect panel data models are the most straightforward econometric approach, which is consistent with methods in similar studies (Cason, Gangadharan and Duke 2003a; Cason and Gangadharan 2004, 2005, Kits, Adamowicz and Boxall 2014; Boxall et al. 2017). The models were also thoroughly tested to prevent misspecification; the details of the testing procedures can be found in the Appendix (0).

The notion of a single overall measure for the auction requires a panel structure where each auction has one corresponding data point. As described earlier (Figure 2.3), each experimental session (48) consisted of 3 blocks each, and participants received new farm parameters for each block. We chose these blocks to be the base of our cross-sectional dimension ($i \in [1..48 * 3 = 144]$). The corresponding time variable is the sequential round number within each block where the subjects maintain a constant BMP adoption cost and size ($t \in [1..5]$).[9] The conceptual advantage of this structure is that there is no exogenous parameter change within a cross sectional panel unit. Additionally, long panels are likely to have more issues related to the time variable, which may cause estimation bias (Cameron and Triveldi 2010).[10]

Since we are interested in the pricing mechanisms and their potential interaction effect on other treatment variables, we run separate regressions for the uniform and for the discriminatory pricing in order to simplify results and to eliminate the need for interaction terms. This means we divide the data into two parts; each of which has 72 blocks. The econometric models are set up to determine the various treatments' effect on auction performance; more specifically their effect on each of the three performance measurements: rent, environmental and cost efficiency. This results in three separate models, which can be written as follows[11]:

$$\begin{aligned} PRENT_{it} &= \beta_0 + \beta_1 lnt + \beta_2 dchat_i + \beta_3 HHI + \beta_4 Mmin_i + \beta_5 M1_i + \beta_6 M3_i + u_i + \varepsilon_{it} \qquad (2.6) \\ EE_{it} &= \beta_0 + \beta_1 lnt + \beta_2 dchat_i + \beta_3 HHI + \beta_4 Mmin_i + \beta_5 M1_i + \beta_6 M3_i + u_i + \varepsilon_{it} \\ CE_{it} &= \beta_0 + \beta_1 lnt + \beta_2 dchat_i + \beta_3 HHI + \beta_4 Mmin_i + \beta_5 M1_i + \beta_6 M3_i + u_i + \varepsilon_{it} \end{aligned}$$

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[9] An alternative method would have been to set the sessions to be the base of the cross-sectional grouping and the previously mentioned overall time variable (T=1..15) would have been the time variable. This approach has been tested and essentially gave the same result.

[10] An alternative approach would be pooled OLS regression with clustered standard errors. The clustering could be based on either the 48 sessions, or could be based on the 144 blocks, which is the panel group variable chosen in the model. While this later approach is not uncommon in the experimental literature, it is generally used when individual bids are analyzed (Wichmann et al. 2017; Banerjee, Shortle and Kwasnica 2009) as opposed to the overall auction performance that is analyzed here.

[11] A potential alternative structure to analyze possible learning effects as auctions are repeated within a session, is to use dummy variables identifying the 5 rounds. Such a model was considered, and its result can be found in the Appendix. This alternative model produced the same result, and confirmed that the learning effect diminishes over time, and as a result the final model with the lnt variable was chosen as it can represent the diminishing learning effect with a single variable, instead of using 4 dummy variables for the consecutive rounds.

where
$i \in [1..144]$ – *panel identifier (identifies the blocks)*
$t \in [1..5]$ – *time variable (round # within a block)*

PRENT – *percentage of information rent out of the total spending*
EE – *environmental efficiency given as percentage of quantity achieved*
CE – *cost efficiency given as percentage of optimal payment per unit for the given quantity*

lnt – *natural logarithm of the time variable*
dchat – *communication dummy variable (=1 if communication was allowed)*
HHI – *firm size heterogentity measurement, Herfindahl-Hirschman Index*
Mmin – *cost heterogentity measurement, for overall variability*
M1 – *cost heterogentity measurement, variability at the 1st quartile*
M3 – *cost heterogentity measurement, variability at the 3rd quartile*

2.5 Testable Hypotheses

The main focus of this paper is to assess the supply curve's effect on reverse auction performance demonstrated in laboratory experiments. We have specified two main features of the underlying supply curves: cost heterogeneity (measured by M_{min}, M_1, and M_3) and firm size heterogeneity (measured by HHI). The third hypothesis focuses on the communication treatment's effect on the auction outcome and the preferred pricing method.

Hypothesis 1: Cost Heterogeneity

The first hypothesis focuses on the cost heterogeneity aspect of the supply function. More specifically it describes how the steepness or the variation of costs along the supply curve affects the cost effectiveness of the different pricing methods. This hypothesis has been discussed in the literature (Schilizzi and Latacz-Lohmann 2012; Boxall et al. 2013), but has not been tested empirically in a controlled laboratory setting. Regulators often avoid uniform pricing because the method provides rent to bidders by construction, as the auctioneer pays more to bidders than their bid was in the auction. However, often pollution abatement functions have very unique shapes where they start out very flat, are elastic until a given point, and then sharply turn into a very inelastic portion (Brown et al. 2011). This may actually mean that in the case of conservation auctions, uniform pricing is more desirable.

Furthermore, the uniform pricing method has other favourable features, such as better cost revelation (Krishna 2002).

> Hypothesis: if the supply curve is steep, especially at the beginning, the discriminatory auction mechanism is favoured. In case of a flat supply curve, a uniform auction is better.

The hypothesis can be observed by the significance, sign and magnitude of the cost heterogeneity variables: M_{min}, M_1, and M_3. As separate models are run on each pricing mechanism, the effect is easily distinguishable between uniform and discriminatory pricing methods. In terms of rent seeking, a positive sign means the steeper the curve, the more rent seeking happens. In the case of environmental efficiency, a negative sign is expected, as it means the steeper the curve, less abatement is achieved. Similarly, for the cost efficiency measure, a negative sign is expected, which means the cost effectiveness of the auction is decreasing with the steepness of the curve.

Hypothesis 2: Firm Size Heterogeneity

The second hypothesis focuses on the firm size heterogeneity aspect of the supply function. As the regulator often has little or no information about actual adoption costs, and therefore cost heterogeneity, knowing how the observable aspect of the supply curve affects the outcome is more practical. Hence, addressing the market characteristics with regard to firm sizes can potentially provide crucial information to regulators.

> Hypothesis: Firm size heterogeneity in an auction influences the overall effectiveness of the auction. More specifically, the higher the firm size heterogeneity (higher HHI), the worse the auction performs.

This hypothesis can be validated by the coefficient related to the HHI variable. For the rent equation, a positive sign means that the more market power is in the market, the more rent seeking is going on. In case of environmental efficiency, a negative coefficient signifies that the increasing market power reduces the achieved abatement and hence the environmental efficiency. Similarly, a negative coefficient in the cost efficiency equation means that larger market power reduces the overall cost effectiveness of the auction.

Hypothesis 3: Communication

The third hypothesis focuses on the communication treatment. Under the uniform pricing rule, the dominant strategy for the individuals is to bid their actual adoption cost regardless of other factors. On the other hand, for a discriminatory auction, participants' dominant strategy is to overbid in order to extract information rents. In small scale conservation auctions, potential communication among participants may further reduce the effectiveness of the discriminatory pricing mechanism as the potential for collusion may lead to increased bid shading.

> Hypothesis: Communication negatively affects conservation auction effectiveness, and discriminatory pricing further exacerbates this problem.

In our regressions, a dummy variable coefficient for the communication treatment shows how the presence of communication affects auction performance. In terms of rent, a positive sign means communication enhances the rent seeking ability of the participants. For the EE and CE equations, we expect negative signs, as it would mean the communication reduces the effectiveness of the auction: lowers the abatement level and worsens the cost efficiency. Again, since the pricing mechanism is analyzed separately, we can observe whether the effect of communication among bidders differs between the two pricing mechanisms.

2.6 Data

2.6.1 Study area

The BMP adoption costs that were used in the experiment were based on actual cost and agronomic data that was collected through a Canadian national environmental program called the Watershed Evaluation of Beneficial Management Practices (WEBs). Our study used the data that was collected from one of the Prairie sites called the South Tobacco Creek Watershed (STC) located close to Miami, Manitoba. The study area was a small (206 ha) watershed with 36 producers, with 12 of them holding livestock in the base year, 2004. The economic cost information was provided by the Deerwood Soil and Water Management Association. This is a group of producers in the STC who have collected this information from watershed residents. The main environmental concern in this particular watershed is nutrient runoff from the agricultural fields, especially dissolved phosphorus. This ends up in Lake

Winnipeg, contributing to the lake's eutrophication process and resulting water quality problems (Daniel, Sharpley and Lemunyon 1998; Environment Canada 2011).

The cost curves used in the experiment were derived from 3 BMPs out of several that were identified in the area to alleviate water pollution (AAFC 2011): establishment of run-off retention ponds (Holding Pond), tillage management (Zero Till), and establishment of perennial cover (Forage Conversion)[12]. This present study used the adoption costs estimation by Boxall et al. (2008). They calculated adoption costs based on the initial establishment cost, the potential maintenance costs, and accounted for the foregone net revenue for a 10 year period (Boxall et al. 2008).

In addition to adoption costs, the potential environment benefit was also studied in this watershed and the values were obtained from a study by Yang et al. (2008) who used a SWAT hydrological model to estimate water flow, sediment and nutrient runoff outcomes from different land management practices. At the time of the experiments, abatement data was available on the Holding Pond and the Zero Till BMPs, but not on the Forage BMP. Although abatement values included sediment, nitrogen and phosphorus abatement estimates, the number of kg of phosphorus abatement was chosen as the critical environmental benefit (EB) since it is important in the region.

2.6.2 Supply Curve Construction

Some BMPs can only be implemented for the entire farm; while others can be executed on a field by field basis. In order to be consistent, we used aggregated farm level data for all BMP projects. From this aggregate farm based cost data, we constructed various marginal cost curves, referred to simply as cost curves in this thesis. Industry supply curves are generated by adding up individual supply curves. In our case individual supply curves are vertical and if the price is above the cost, the producer will supply their capacity. If the price does not cover the cost, the producer won't supply anything.

In the true sense of environmental supply curves, these curves were constructed based on the price of a unit of abatement. This means ranking the producers from the one who can produce a kg of phosphorus abatement at the cheapest price to the one who can produce abatement in the most expensive way for the given BMP. In other words, we sorted the producers based on the dollar per environmental benefit ($/EB). For each price point, the amount of abatement is equal to the total capacity of those suppliers whose cost is no higher than the given price. So, this is simply the cumulative sum of the EB of those producers that

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[12] There were other BMPs that were recommended by the AAFC in the study area, such as Wetland Restoration and Riparian Area Management, but their data was not available at the time of the experiment.

have costs per unit of EB equal to or lower than the given price. Curves 1 and 4 were constructed with this method (Table 2.2)[13].

Since the actual abatement is often unknown in a conservation auction, the number of agricultural units is often used as a proxy for the magnitude of the abatement; for example the number of hectares of land converted to forage. Using this, we constructed additional curves based on the number of agricultural units[14] for each BMP project. We ranked the producers based on their abatement cost per agricultural unit, referred to as *unitcost* in our tables. Curves 2, 5 and 6 were constructed with this method (see Table 2.2).

Table 2.2. Supply Curves Used in the Experiments

		Holding Pond BMP			**Zero Till BMP**		**Forage BMP**
Total Cost		$1,125			$720		$873
Budget		$56,231			$215,950		$261,790
		Curve 1	**Curve 2**	**Curve 3**	**Curve 4**	**Curve 5**	**Curve 6**
Ranking rule		$/EB	$/unit	$/total cost	$/EB	$/unit	$/unit
Total Unit		73.85	1336	12	1082.54	8365.56	4457.37
Market power (HHI)		High (1631)	V. High (1852)	Low-Medium (833)	High (1669)	Medium (1394)	Medium (1310)a
Description		Flat with sharp bend at the end "hockey stick"	Moderately Steep everywhere	Very Steep everywhere	Moderately Steep overall, but flatter first half	Steep overall, but flatter first half.	Very Steep, everywhere, Steepest overall
Cost Heterogeneity Measurements[a]	**Overall Variability (Mmin)**	17.28%	26.48%	36.11%	32.49%	46.02%	42.54%
	Variability at the 1st Quartile (M1)	11.53%	14.35%	32.13%	9.21%	0.24%	30.53%
	Variability at the 3rd Quartile (M3)	0.01%	15.73%	32.04%	26.90%	22.23%	12.21%

a) Construction of the cost heterogeneity measurements (M_{min}, M_1,M_3) are explained in the previous section (2.4.2). The lower the number, the less variability among the adoption costs.

Sometimes government agencies measure their success based on the number of producers that adopt the given BMP (see Boxall, Perger and Weber 2013). Maximizing the

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[13] At the time of the experiment, abatement data was not available for the 3rd BMP (Forage), hence only 2 curves were calculated this way (Holding pond and Zero Till).

[14] Agricultural units mean different things for different BMPs. For the Holding pond BMP, it means the number of head of cattle, while in the other BMPs the agricultural unit is the hectares of land affected.

number of producers adopting BMPs means that producers would be ranked based on total costs, regardless of their environmental contribution. If there is a large variation in the producers' size, this would lead to an inefficient outcome. For demonstration purposes we include one cost function generated with this method (curve 3). Overall, using these methods, 6 cost curves were generated and used in the experiments.

While the Holding Pond BMPs could only be adopted by 12 livestock producers, the other BMPs could be potentially implemented by any of the 36 farmers in the study area. In order to use these cost functions in the lab experiments with the same number of participants, we needed to draw a sample of bidders from the other BMPs. To preserve the shape and structure of the 36 producer cost functions, systematic sampling was employed. The producers were ranked from the lowest cost per agricultural unit to the highest cost per unit, and 3 producers were randomly drawn from each of the 4 quartiles[15]. During the sampling, any outliers were not selected. Also, a couple of producers, which would obtain a net benefit from adoption (i.e. negative cost) were not selected either. The sampling preserved the mean values and the standard deviation of the original data quite well. Descriptive statistics of the full data set and the sampled producers can be found in the Appendix (Table.2.7 to

Table 2.9). We also verified visually that the selected samples in fact kept the shape of the original industry supply curves.

In addition to the costs and the size of the potential BMP adoption, conservation auction experiments also need to establish a government budget. Since the cost data was calculated in 2004 dollars, the budget was calculated based on funding levels from existing environmental programs at the time, similar to other studies using this data (see Boxall et al. 2008; Packman 2010; Boxall, Perger and Weber 2013; Kits, Adamowicz, and Boxall 2014; Wichmann et al. 2017; Boxall et al. 2017). In the given year the producers in this watershed could have participated in the National Farm Stewardship Program (NFSP), which offered cost sharing incentives for implementing these BMPs. Generally, the NFSP program provided financial assistance to farmers in the form of reimbursement of a certain[16] % of their direct cost up to a given maximum[17]. Although the NFSP program has been discontinued, subsequent programs called "Growing Forward" use a similar cost sharing approach.

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[15] Alternatively, we could have ranked the producers based on cost per EB. However, EB data was not available for one of the BMPs (Forage), so to keep consistency among the BMPs, the unit cost ranking was chosen for all BMPs for sampling purposes.

[16] The Holding Pond and Zero Till BMPs had a 30% cost sharing from the NFSP, while the wetland and the Forage BMPs had 50% cost share offered.

[17] NSFP contribution was maxed out at $20K for the Holding Pond and Wetland Restoration, while Zero Till and Forage BMPS had a $15K and a $5K maximum respectively.

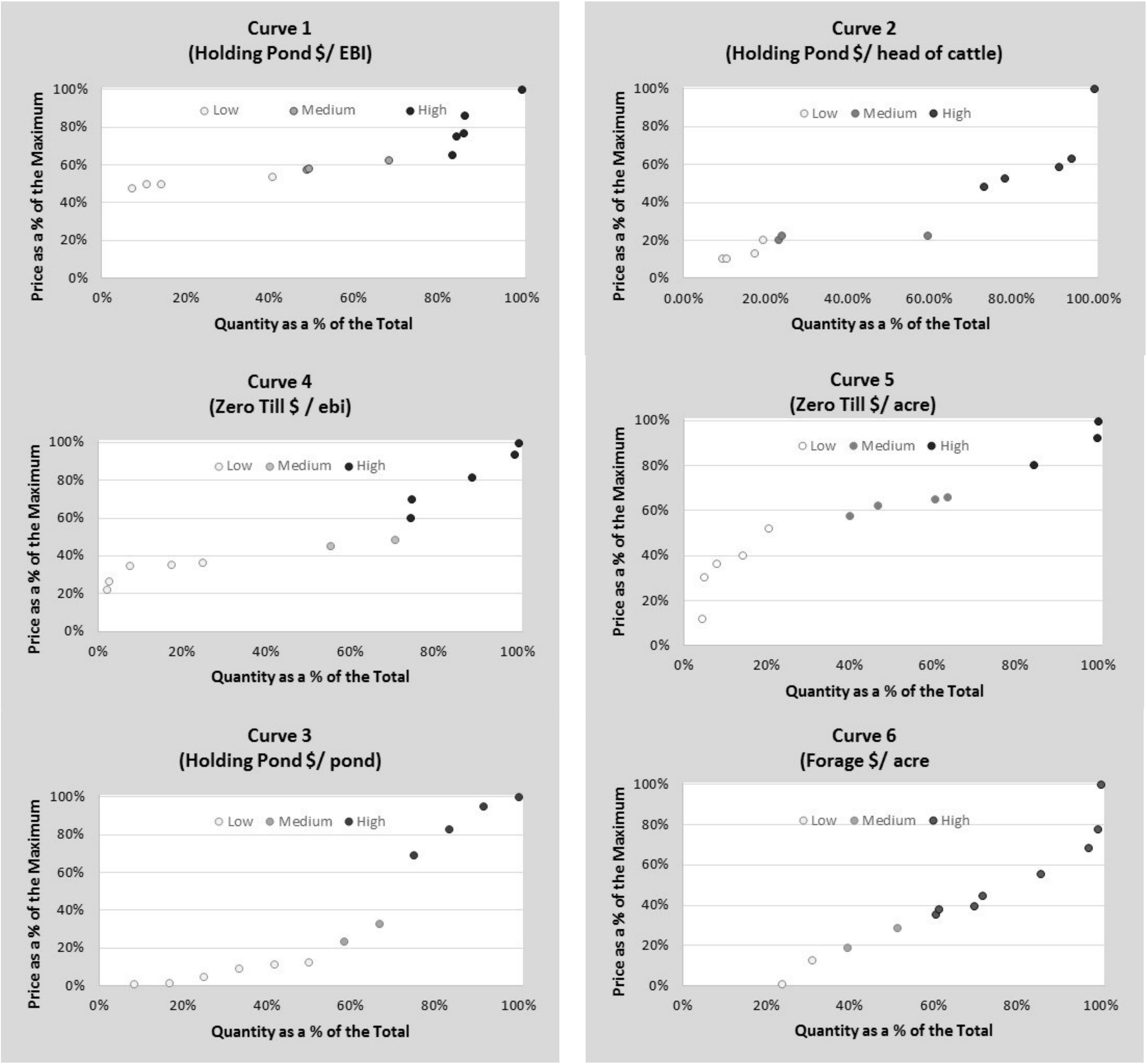

Figure 2.7. Graphical Illustration of the Used BMP Cost Curves

The cost curves present variation regarding magnitude, curvature and market power (Table 2.2), which are represented by the measurements discussed earlier (2.4.2). The size or magnitude of the market where curves 1, 2, and 3 were used is less than a quarter than the markets where curves 4, 5 and 6 were used. The values show that these markets are generally concentrated, with HHI ranges from low-medium to very high, which is not surprising as each market only had 12 producers. Visual inspection of the shapes (Figure 2.7) and the cost range measures also indicates that curves range from flat, shallow to very steep curves. Also there are various combinations of market power and cost range measures present in the curves, which makes the data analysis more accurate as they do not seem to be correlated. For example, curve 1 is flat with high market power, curve 2 is steep with very high market power and curve 3 is very steep but only has a low-medium amount of market power.

2.7 Results

The following section summarizes the results of the conducted experiments. Before the results are discussed in terms of the previously created measurements (PRENT, EE, CE), the next subsection provides an overview of other aspects of the auction such as participation and adoption patterns, as well as an overview of the observed communication levels. The second subsection provides the results of the econometric models described in section 2.4.3.

2.7.1 General observations

2.7.1.1 Qualitative Observations on Communication

During sessions where communication was allowed, we observed various levels and types of communication among the participants. Often during the practice and the initial rounds, subjects discussed the rules of the auction and were helping each other to understand the bidding process. Although communication levels varied among sessions, there was always some level of communication when it was allowed. Students frequently shared with each other whenever they won or not in the auction, and often they also shared the bidding price they submitted. However, the sharing was not always with everyone. Often the subjects only shared information with the person physically sitting beside them. Students frequently signed up for the same session with their friends or classmates, which created a pre-existing social tie between some of the participants. As people who knew each other tended to sit close to each other, this potentially facilitated the information sharing. In some cases, subjects went that far in information exchange that they showed their computer screen to their neighbour who was sitting beside them. This type of communication can conceivably happen among producers in an actual government auction program whose farms are located in close proximity to each other and have social connections between them.

Moreover, there was often more than just simple information exchange. Often participants were suggesting bidding behaviours to each other, and tried to collude. The short amount of time between auctions was generally not enough to establish agreement among the participants and to create a viable plan that everybody would keep. However, there was one occasion when the subjects managed to carry out a perfect collusion strategy, which led to an excessive payment to them. In that particular session their combined earnings were two and half times larger than in an average session due to almost the entire budget being spent on rent. This auction used the data from curve 6, which was the steepest curve of all cost curves; hence the opportunity of rent seeking was the largest to begin with. In this session, during the practice periods the participants figured it out that if they know the government budget they can take turns in bidding and earn the entire budget for themselves.[18] They used the initial rounds to estimate the budget and after that in each auction round only one person participated, the rest of them refrained from bidding. This allowed for the sole bidder to receive a payment equivalent to the entire budget and earn excessive rent. This strategy only worked out because of the repetitive nature of the experiment allowed each subject to have a turn in winning, and could not be a viable strategy in an actual conservation auction program. However, this is an important lesson that in case of budget based auction when the budget is established ahead of time, an unusually low participation rate could lead to excessive rent seeking activity.

2.7.1.2 Participation and Adoption Patterns

Regulatory agencies often find that participation rates in actual conservation programs are quite low. As most laboratory conservation auction experiments do not have the option for subjects to abstain from participating (Cason, Gangadharan and Duke 2003a; Cummings, Holt and Laury 2004; Cason and Gangadharan 2004, 2005), this problem is not well-studied in the experimental lab. There has been an experimental study focusing on risk in conservation auctions where participation was voluntary (Wichmann et al. 2017). The authors did find that uncertainty regarding BMP adoption cost reduced participation in the laboratory (Wichmann et al. 2017). However, in this thesis there was no risk involved in participating: the subjects already committed their time and the winners and losers were not publicly announced. Still, the overall non-participation rate was 9.6%, which was likely the result of participants avoiding the disappointment of losing in the auction.

Although the extreme cases mentioned in the previous section, such as perfect collusion, and unsuccessful auctions only occurred a few times, the communication generally changed participation levels (see Table 2.3). On average, 7.7% of the subjects did not participate during the silent sessions and 10.9% during the communication sessions and the difference was statistically significant (p=0.0000). The difference was significant in both pricing mechanisms, but more apparent in the uniform auction. During uniform auctions, 9% of the participants did not submit bids in the silent sessions and 14% in the communication sessions

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[18] This session was taken out from the data and the session was repeated so it doesn't skew the results.

(p=0.0000). During discriminatory auctions, 6.4% of the subjects did not submit a bid in the silent sessions, and 7.7% in the communications session (p=0.0484).

Table 2.3. Non-Participation and Adoption Rates by Auction and Cost Types

	# Producers	% Did not participate	% Adopted (# Winners/12)
No Communication (Silent)			
Discriminatory Auction	2160	6.4%	39.6%
Low Cost	780	1.3%	78.5%
Mid Cost	450	2.7%	49.3%
High Cost	930	12.6%	2.3%
Uniform Auction	2160	9.0%	39.8%
Low Cost	780	0.9%	87.8%
Mid Cost	450	5.3%	32.7%
High Cost	930	17.5%	2.9%
Both Pricing	4320	7.7%	39.7%
Communication			
Discriminatory Auction	2160	7.7%	38.5%
Low Cost	780	0.5%	78.8%
Mid Cost	450	4.2%	41.8%
High Cost	930	15.5%	3.0%
Uniform Auction	2160	14.0%	37.6%
Low Cost	780	2.1%	86.8%
Mid Cost	450	15.1%	23.6%
High Cost	930	23.4%	3.1%
Both Pricing	4320	10.9%	38.0%
Grand Total	**8640**	**9.3%**	**38.9%**

However, the presence of communication affected various groups differently. As described in the experimental design section (see section), we divided BMP adoption costs that were given to participants into 3 categories: low-cost, medium-cost and high-cost. Dividing participation rates into these cost categories, we counted the percentage of the participants who decided not to participate in the Table 2.4.

Table 2.4. Non-Participation Rates by Repetition and Cost Types

Repetition within a block	Low Cost Producer		Medium Cost Producer		High Cost Producer	
	No Chat	***Chat***	***No Chat***	***Chat***	***No Chat***	***Chat***
1	1.6%	0.6%	2.8%	6.7%	3.5%	7.5%
2	0.6%	0.0%	1.7%	7.2%	11.6%	13.7%
3	1.%	0.6%	6.1%	10.6%	18.3%	22.6%
4	1%	1.9%	5.6%	7.8%	20.4%	26.1%
5	1%	.2%	3.9%	16.7%	21.5%	29.0%
Average	**1.1%**	**1.3%**	**4.0%**	**9.8%**	**15.1%**	**19.7%**

The overall participation rate was the lowest among participants who received high-cost producer's data. The average non-participation rate in the communication sessions (19.7%) was higher than that in the silent sessions (15.1%) and the difference was statistically significant (p-value= 0.0002)[19]. In the high-cost group, the non-participation rate was sharply increasing with repetition even without communication. Communication seemed to increase non-participation in this group, and by the 5th repetition, 29% of them stopped participating. A laboratory study, which analyzed the emotions evoked by losing or winning on reverse auction, produced similar patterns (Ding et al. 2005). The authors found that losing in the auction not only generated negative emotions, but repeatedly losing significantly increased participants' frustration level and reduced their propensity to participate in the consequent auction rounds.

The non-participation level of high-cost producers may suggest that many of the farmers who do not participate in real life conservation auction programs may do so because they know they would not be as cost efficient as the other producers. However, the problem is that non-participation was present in the medium-cost and even in the low-cost group. Based on data construction, students who receive BMP costs from a low-cost producer should always participate and adopt the given BMP. We can view non-participation by low-cost subjects as a form of "Loser's curse". This is a phenomenon in auctions when bidders do not bid as aggressively as they should because they underestimate their winning potential (Holt and Sherman 1994). Non-participation rates were lowest among subjects with low cost. On average, 1.1% of the low-cost subjects in the silent sessions and 1.3% of the low-cost subjects in the communication sessions did not participate in the auctions, but the difference is not statistically significant (p-value=0.6199). However, the non-participation rate was increasing with repetition if communication was allowed. This may be due to the cost variation

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[19] This value is the result of a 2-tail parametric mean-comparison test (T-test). All p-values in brackets are similarly calculated through this section.

within the low-cost group. Some low-cost subjects underestimated their chance to win after they learned that there are others with even lower costs.

This behaviour was even more prominent among the medium-cost participants, and 1 in 6 subjects in this group did not participate by the 5th round if communication was allowed. At the same time, in the silent sessions non-participation rates did not show an increasing pattern with auction repetitions in this cost group. On average, 4% of the medium-cost producers did not submit a bid in the silent sessions, and 9.8% in the communication sessions and the difference was statistically significant (p=0.0000) When medium-cost producers did not adopt a BMP, it is not necessarily a problem, but when they do not participate, the competitive pressure of the auction is decreasing. This may allow low-cost participants to increase their rent seeking activities. This trend went so far that there were 2 occasions where the absence of the participation of the medium-cost producers caused the auction to be unsuccessful. Both cases occurred in the same experimental session, where the steepest supply curve (curve 6) was used in a uniform auction with the communication treatment. This particular curve is not just steep, but there is also a jump in the curve between the low-cost and the medium-cost producers (see Figure 2.7). In this particular session, the medium-cost producers stopped participating and the low-cost producers kept increasing their bids. This resulted in a situation where the required payout would have exceeded the budget even if only the single lowest bidder would have been selected as the winner. When this happened, the medium-cost producers started to participate again, and the market corrected itself within 2 repetitions and the percentage of rent extracted went from an average of 84% down to an average of 44% for the rest of the session.

The participation and adoption rates showed distinct patterns based on the pricing mechanism (Table 2.3). Uniform pricing auctions led to lower participation rates among all groups, except in the low-cost group during the silent sessions. On average, 4.6% fewer subjects participated in uniform pricing auctions compared to discriminatory auctions, and the difference was statistically significant as confirmed by a *t*-test (p-value=0.000). However, while participation rates differed, the overall adoption rate was not significantly different between the pricing mechanisms. The average adoption rate was 39.8% in the uniform auction and 39.6% in the discriminatory action during the silent sessions, but the difference was not statistically significant (p-value=0.9010). In the communication sessions the average adoption rate was 37.6% in the uniform auction and it was 38.5% in the discriminatory auction, and again the difference was not statistically significant (p-value=0.5516).

While participation rate was lower, the adoption pattern was actually better in the case of the uniform auctions. Under the uniform pricing rule, on average, the adoption rate among the low-cost subjects was 8.7% higher than it was under the discriminatory pricing and the difference was statistically significant (p-value=0.0000). This pattern persisted regardless of the communication treatment. At the same time, the medium-cost group's adoption level was 17.4% higher in the discriminatory auctions and again the result was statistically significant (p-value=0.0000). There was no statistical difference in the adoption rates of high-cost participants between the pricing mechanisms (p-value=0.4885).

2.7.2 Econometric Model Results

The regression analyses were performed using Stata software utilizing random effect panel estimators as described in section 2.4.3. There are three main models based on the three auction performance measurements variables (rent, CE, EE). Each model was run separately on the discriminatory and on the uniform pricing sessions, which resulted in six equations, presented in Table 2.5. As most models suffered from autocorrelation, these equations were estimated as random effect panel data models with first order autocorrelation, AR1, using Prais-Winsten error correction. As autocorrelation is a frequent problem in repetitive laboratory experiments, using random effects model with an AR1 error correction is not uncommon in the literature (Shogren et al. 2001; Burtraw et al. 2009; Vossler, Suter and Poe 2013; Iftekhar and Tisdell 2014). While most studies don't report the exact type of AR1 correction they use, there are examples where it is specified, and the same Prais-Winsten error correction is used (Suter et al. 2008; Suter, Vossler and Poe 2009). The uniform pricing EE model was estimated with a random effects panel data model using FGLS estimates as it did not show signs of autocorrelation. Details of the model selection and discussion of the econometric challenges can be found in the Appendix (0). The final model selection was based on specification tests; however, none of the significance levels or the magnitude of the coefficients differed in the final model selection from the simple uncorrected regression results.

2.7.2.1 The Regression Constant

The constant represents the level of rent, environmental and cost efficiency that would be achieved in the case where treatment variables are zero.[20] This refers to a hypothetical case of a single shot auction with no communication coupled with HHI being zero along with all the curvature measurements (M_{min}, M_1, M_3) also being zeros. This scenario would represent a perfectly competitive market with no market power, where the supply curve is perfectly

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[20] The Lnt learning effect measure is equal to zero if t=1 (the first round of auction).

elastic and there is an infinite amount of abatement supply available at the same price per unit. The constant is not statistically significant for the rent regression for either the uniform or the discriminatory pricing. This means there would be zero rent extracted in a perfectly competitive market where each firm had the exact same cost per unit of abatement. In the case of environmental and cost efficiency, the constants are statistically significant and above 100, which means that more than the optimal abatement would be realized in such case. The constant is higher in the uniform auction for both the EE (123.05% vs. 116.73%) and the CE (139.43% vs. 135.14%) equation. This means that in a perfectly competitive market without communication the uniform auction would achieve 6.32% more abatement and 4.29% higher cost effectiveness than an auction with discriminatory pricing. However, such a perfectly competitive market is just a hypothetical scenario and none of the cost curves employed were close to representing such markets.

Table 2.5. Auction Performance Regression Results, Random Effect Panel Model

		Dependent Variables					
		PRENT: Information Rent Rate (%)		EE: Environmental Efficiency (%)		CE: Cost efficiency (%)	
		Discr.	Uniform[a]	Discr.	Uniform	Discr.	Uniform
	Learning Effect (Lnt)	14.17***	0.32	-6.45***	2.34	-13.15***	0.34
		-(2.16)	-(1.18)	-(1.83)	-(1.44)	-(2.79)	-(0.55)
	Communication Dummy	7.49**	-0.01	-1.3	-5.44**	-7.63***	-4.65***
		-(3.21)	-(0.01)	-(3.60)	-(2.61)	-(1.56)	-(0.80)
	Firm Size Heterogeneity (HHI)	-0.01	0.2	0.01	0.00	0.01	0.00
		-(0.01)	-(2.05)	-(0.01)	-(0.01)	-(0.01)	(0.00)
Cost Heterogeneity Measurements	**Overall Variability (Mmin)**	0.46***	1.37***	-1.43***	-2.01***	-0.77***	-1.70***
		-(0.33)	-(0.20)	-(0.18)	-(0.18)	-(0.16)	-(0.09)
	Variability at the 1st Quartile (M1)	1.32***	1.41***	-0.25***	-0.34**	-1.79***	-1.91***
		-(0.28)	-(0.13)	-(0.06)	-(0.16)	-(0.15)	-(0.06)
	Variability at the 3rd Quartile (M3)	0.09	-0.19	0.69***	0.83***	-0.09	0.30***
		-(0.43)	-(0.12)	-(0.20)	-(0.16)	-(0.26)	-(0.04)
	Constant	-15.29	-15.98	116.73***	123.05***	135.14***	139.43***
		-(30.90)	-(13.26)	-(9.82)	-(15.33)	-(21.37)	-(7.54)
	R^2	0.26	0.51	0.45	0.51	0.61	0.69
	χ^2	478.58	32976.65	106.46	188.9	6116.07	24762.49
	ρ	0.529	0.425	0.401	N/A	0.524	0.447
	# Obs.[a]	360	358	360	358	360	358

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level
Standard errors in parentheses

a) There were 2 observations where the auction was unsuccessful as the required payout to the sole winner would have exceeded the budget, hence there was no payout to anybody and there was no adoption.

2.7.2.2 Communication

In the case of the uniform auctions, the extracted rent was not significantly different between the communication and the silent sessions. However, in the discriminatory auctions communication increased the extracted information rent by 7.49%. Interestingly, the opposite can be observed in the case of environmental efficiency. The uniform auction abatement level was reduced by 5.44% if communication was allowed, and the discriminatory auctions were unaffected. However, as the constant for the environmental efficiency model was higher than in the case of the uniform auctions, this result can be interpreted as communication reducing the uniform pricing advantage from 6.32% to 0.88% in terms of achieved abatement levels. The overall cost effectiveness went down in both types of auctions, but the magnitude of this efficiency loss was higher for discriminatory auctions (7.63%) than it was for uniform auctions (4.65%). Since the uniform auction regression parameters had a higher constant, we can interpret this as communication further increasing the gap in cost effectiveness between the uniform and the discriminatory auction, from 4.29% to 7.27%. Overall, the presence of communication had a negative effect on the auction performance, and it affected the discriminatory auctions at a larger extent. Communication facilitates information exchange, and the additional information obtained via communication can alter a bidder's expectation of the maximum accepted bid cap. In discriminatory conservation auctions, bidders shade their bid to a larger extent, and theory tells us that their optimal bid is increasing when the expected bid cap is higher (Latacz-Lohmann and Van der Hamsvoort 1998). While there is no theoretical foundation for reverse auctions with uniform pricing, the theory of forward auctions tells us that the bidders' dominant strategy is to bid their own cost when uniform pricing is used (Vickery 1961). This is confirmed in the laboratory in the case of forward auction (Engelbrecht-Wiggans and Katok 2006).

2.7.2.3 Market Power

The HHI index was not statistically significant in any of the regressions, suggesting that increases in the seller's market power has no effect on auction performance regardless of the pricing mechanism. Supply side market power has been extensively studied in bilateral markets such as double auctions, both theoretically and experimentally. While some studies have found clear indications of its effects on markets (Davis and Holt 1991; 1994, Isaac and Reynolds 2002; Sturm 2008), others found that effects of market power was only present initially and faded away with repetition (Cason, Duke and Gangadharan 2003b). There are a few studies that examined supply side market power in reverse auction settings with ambiguous results. A laboratory study that used multi-unit uniform reverse auctions found that the Vickery pricing mechanism, which we employed in the uniform auctions here, was not significantly affected by the seller's market power (Bernard, Schulzeb and Mount 2005). Cong and Wei (2010) found that uniform auctions are less sensitive to market structure than discriminatory auctions. Empirical evidence from treasury markets generally does not support market power's effect on auctions. Keloharju, Nyborg, and Rydqvist (2005) analysed treasury auctions that used uniform pricing in Finland and found that market power had a very small effect on the market outcome. Nyborg, Rydqvist and Sundaresan (2002) found the same analyzing the Swedish treasury auctions, which used discriminatory auctions. At the same time, there is one experimental study on government procurement auctions employing the uniform auction pricing format found that higher supply side market power had a statistically significant effect on auction performance and lowered government revenue (Dormany 2016).

This latter study also provided HHI values for measuring market power, and compared auction performance between markets where HHI was equal to 1000, with markets with HHIs equal to 2000. As the US law of merger guidelines considers a 200 point increase in HHI to be large enough to need to be addressed (2017), the jump in market concentration in Dormany's study was quite extreme, as it was 5 times the merger guideline limit. This thesis utilized data based on actual BMP adoptions costs, and while the jump between the market with the lowest (833) and the highest HHI (1851) value is similarly high, it includes multiple markets between the two extremes and represents many smaller jumps, which might be the reason for the differences. Moreover, the cost curves in this study were not specifically designed to analyze the differences in market structure. The cost curves used were derived from cost estimates of actual BMP adoptions in the study area and as such may not present enough variability. This may cause an identification problem between market power and cost heterogeneity. Consequently, while the absence of market power in this study is not unusual in the literature, it may not provide robust evidence that market power doesn't play a role in conservation auctions.

2.7.2.4 Cost Heterogeneity

The main focus of this study was addressing how cost heterogeneity affects auction outcomes. The results clearly show that the supply curve curvature had major effects on auction performance (see Table 2.5). M_{min}, which represents the overall steepness of the supply curve, was statistically significant in all models. The coefficients were positive in the PRENT equations and negative in the EE and CE ones, which means that the steeper the supply curve, the worse is auction performance. While M_{min} represents overall "curviness", the exact interpretation is the percentage difference between the lowest and the average price based on its construction. The result shows that 1% increase in cost difference between the lowest and the average price would lead to a 0.46% increase in rent extraction for the discriminatory auction and 1.37% in the case of uniform auction. This means that the overall steepness of the cost curve reduced uniform auction performance almost 3 times the rate it reduced the discriminatory auction performance in terms of rent extraction. For the M_1 measurement, which represents the steepness of the curve at the 1st quartile point where the low-cost producers are located, was highly significant in both models, and their magnitudes were quite similar. At this point, a 1% increase in curve steepness increases the percentage rent extracted by 1.32% in case of the discriminatory and 1.41% in case of the uniform auctions.

When it comes to abatement quantity, the steepness of the supply curve sharply reduced the environmental efficiency. The M_{min} coefficient shows that 1% increase in cost difference between the lowest and the average price would lead to a 1.43% reduction in abatement for the discriminatory auction and a 2.01% reduction for the uniform auction. Increased steepness at the 1st quartile point was also detrimental to the auction, but at a much lower magnitude. At this point a 1% increase in steepness reduced the achieved objective by 0.25% in discriminatory auctions and 0.34% in uniform auctions. On the other hand, steepness at the end of the supply curve, at the 3rd quartile point, helped auction performance for both pricing mechanisms and increased the realized abatement level by 0.69% for discriminatory and 0.83% the uniform auction.

The same trend can be seen in the CE measure. Overall steepness, represented by M_{min}, was detrimental for both auction types, but at a lesser degree for the discriminatory auction. An additional 1% distance increase between the lowest and the average price lead to 0.77% cost effectiveness loss for the discriminatory and 1.7% loss for the uniform auction. Steepness at the 1st quartile point was similarly negative for both pricing mechanisms: 1% increase in curve steepness lead to a 1.79% loss for discriminatory and 1.91% for uniform auction. The steepness of the 3rd quartile of the cost curve didn't affect cost effectiveness of the discriminatory auction, but improved uniform auction cost effectiveness by 0.3%.

2.7.2.5 Learning effects

The variable *Lnt* represents the effect of repetition; or how the market performance would change if the auction were repeated multiple times and the subjects had a chance to learn how competitive their own cost structure was compared to others. In the case of the uniform auction, this treatment variable was not statistically significant in any of the three models. This shows that the uniform auction was unaffected by repetition and there was no learning effects present in them. On the other hand, this treatment was statistically significant at the 1% significance level in all three discriminatory regressions. The coefficient is 14.17 in the rent equation, which means that the percent of rent extracted increased by 14.17% for the first repetition, half of that in the 2nd repetition, and a third of that in the 3rd repetition and so on. An alternative model was run using a linear functional form for this repetition variable, and the result was that on average, each additional repetition increased rent extraction by 4.65%. However, the data fit the logarithmic functional form better, which is consistent with the literature in that the most learning happens at the beginning and then fades away. Hence, the log (time variable) or 1/(time variable) are the functional forms used in most laboratory studies focusing on conservation auctions (e.g. Cason and Gangadharan 2004; 2005). The learning effect was also significant for the EE and CE equation in the discriminatory auctions. In those equations the sign was negative, showing that repetition reduced abatement levels and cost effectiveness over time. The first repetition reduced the abatement level by 6.45% and cost effectiveness by 13.15% and the effect faded away over repetitions. This finding is consistent with the general auction literature, which reports that uniform pricing prevents learning effects compared to discriminatory pricing (Scherer 1990, Von and We 1990).

Another interesting pattern was how the auction performance changed within the sessions. The cost efficiency of the auctions within a session shows a distinctive pattern. In case of the flatter curves, the cost efficiency is really high for both types of auctions and never goes below 70% (Figure 2.8)

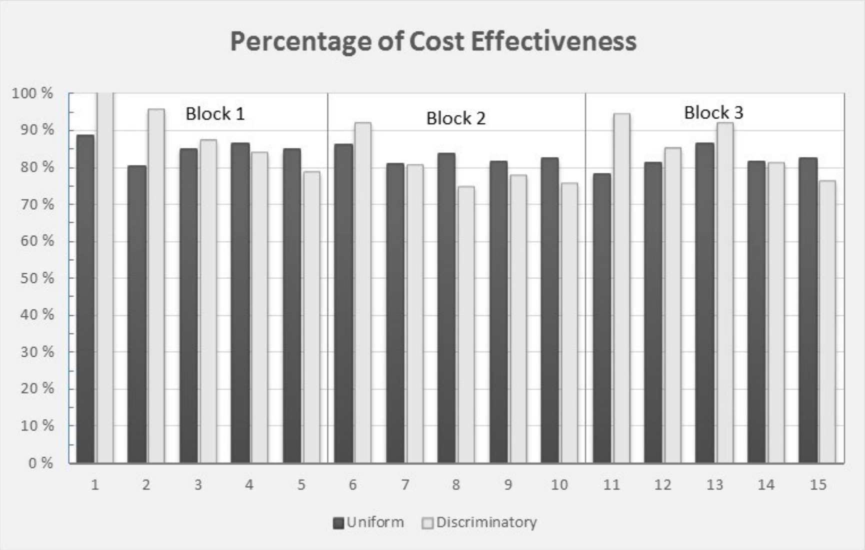

Figure 2.8. Percentage of Cost Effectiveness for the Flat Curves (Curve 1, 2)[21]

As a design structure, the experimental sessions were divided into 3 blocks, the subjects repeated the auction 5 times with the same cost and then they received new parameters for the next block. In case of discriminatory auction, shown by the light bar, the cost efficiency started out around 95% at the beginning of each block when the subjects were unfamiliar with their cost, but it deteriorated with each repetition. At the same time, in the uniform auction, shown by the dark bar, performance doesn't seem to follow any consistent distinct pattern within the blocks, and it fluctuates in a seemingly random fashion. These were only 2-minute long repetitions without much time to think about their rent seeking strategy. Still, the cost efficiency of the discriminatory auction dropped almost 20%, and fell below the uniform auction performance after a few repetitions within each block for the two cost curves

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[21] The illustration shows the average percentage of cost effectiveness per repetition for all sessions for the specified curves.

In case of the steep curves, curve 3 and 6, the discriminatory auction started around the 50% cost efficiency at the beginning of each block, and again fell roughly 20% by the end of each block (Figure 2.9). However, despite the quick efficiency loss, for these steep curves the discriminatory pricing still performed better than the uniform auction, which had efficiency levels hovering around 20%.

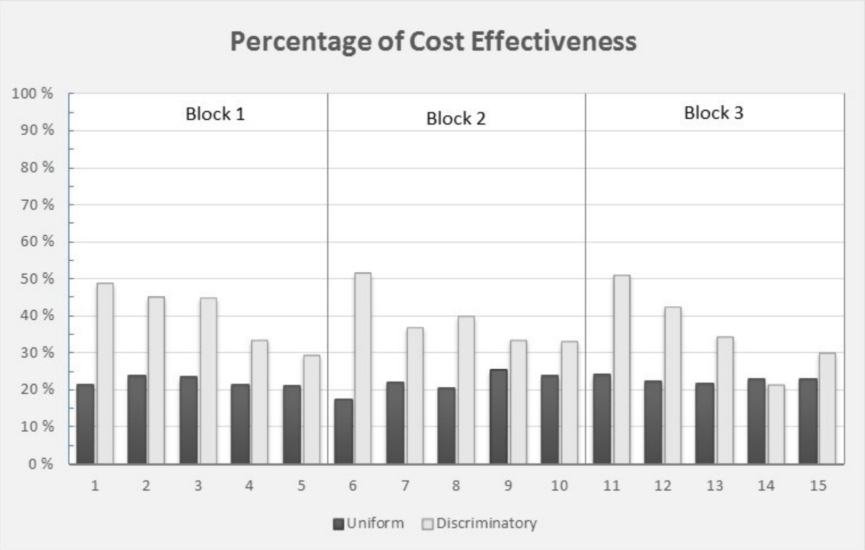

Figure 2.9. Percentage of Cost Effectiveness for the Steep Curves (Curve 3, 6)[21]

2.8 Discussion

2.8.1 Importance of Participation in Auction Success

While the focus of this thesis was not on the participation rate in conservation auctions, the importance of participation level emerged throughout the experiment. While high participation rates may not be as crucial when the cost heterogeneity is very low among producers as the cost heterogeneity rises, keeping participation high is essential. In the case of curve 6, which had the highest cost heterogeneity of all curves, the low participation rate, especially among medium-cost producers was critical. The absence of competitive pressures of the medium-cost participants rendered the auction unsuccessful on multiple occasions. Moreover, in some instances it allowed those who did participate to engage in perfect collusion to game the auction.

Although participation in the auction did not have any risk to the participants in terms of financial cost or additional time requirement, almost 1 in 10 students decided not to participate in the auctions. Additionally, learning about their cost relative to others either via communication or repetition sharply decreased participation across the mid- and high-cost producers. Moreover, in some cases more than one third of the high-cost group refrained from participation. This verified what had been concluded by others (Ding et al. 2005), that people may avoid participating in a reverse auction purely to avoid potential frustration caused by losing. In real life conservation auctions there are other reasons producers may not participate. BMP adoption can change future income, and thus imposes uncertainty, which is also known to reduce participation rates in reverse auctions (e.g. Wichmann et al. 2017). Furthermore, formulating and submitting a bid in real-life conservation auctions is not actually costless, but takes time, effort and potentially imposes transaction costs to farmers. Even basic auction theory tells us that transaction costs reduce participation in conservation auctions (Latacz-Lohmann and Van der Hamsvoort 1998).

Since high rates of participation are crucial in auction success, it may be worth offering small monetary or other types of incentives to farmers just for participation. While this may increase the total administration costs of the auction, the improvement in cost effectiveness due to higher participation rates could potentially compensate for it. The amount and the type of additional incentives required to induce optimal participation level could be a topic for further research. Laboratory experiments could be a suitable platform to analyze the level of monetary compensation that leads to sufficient participant levels in various situations. However, other non-monetary incentives may work too, and potentially surveys or focus group discussions could help regulators to better understand the type of incentives that can improve participation levels in conservation auctions.

2.8.2 Cost Heterogeneity and Auction Success

The results provided robust evidence that cost heterogeneity plays an important role in auction performance as all measurements got worse as the supply curve got steeper. The uniform auction is more sensitive to the magnitude of cost heterogeneity than discriminatory auctions. This sensitivity increases as cost heterogeneity increases because the auctioneer hands out surplus willingly, even without overbidding. However, uniform auctions prevent learning, and do not worsen over time regardless of how much bidders learn about their own cost effectiveness when compared to others. Therefore, uniform auctions outperform discriminatory pricing mechanisms when cost heterogeneity is very low. However, there is a tipping point when the cost heterogeneity is high enough that discriminatory auctions become superior. Moreover, when cost heterogeneity is extremely high, the auction performance is poor regardless of pricing mechanism or learning effects, and as a result the auction mechanism may not be the best tool to induce BMP adoption in such cases.

In order to have a better understanding of when this tipping point occurs, PRENT values were predicted for various levels of steepness from M_{min}=0% to 45% assuming communication among bidders[22] (Table 2.6). In the table, the marked cells represent the tipping points, where the cost heterogeneity is large enough for the discriminatory auction to overtake the uniform in terms of performance. In the table, values where the proportion of the rent is higher than 30% of the total payment are shaded with grey. In these scenarios, the auction performance is so poor that it would no longer be an appealing option for auctioning conservation contracts.

Table 2.6. Predicted Rent Percentages for Supply Curves by Various Overall Cost Heterogeneity Levels

Curve close to it	Overall Cost Heterogeneity M_{min}[a]	Uniform Pricing	Discriminatory Pricing No Learning	With Learning Equivalent with # of Repetitions 1	2	3	4
	0%	0	7.5	7.5	7.5	7.5	7.5
	5%	6.9	9.8	19.6	25.4	29.4	32.6
	10%	13.7	12.1[b]	21.9	27.7	31.7	34.9
Curve 1 (13.88%)	15%	20.6	14.6	24.4	30.2	34.3	37.4
Curve 2 (26.%)	25%	28.2	18.3	28.1[b]	33.9	37.9	41.1
Curve 4 (32.49%)	30%	37.1	22.6	32.5	38.2	42.3	45.5
Curve3 (36.11%)	35%	46.6	27.6	37.5	43.2[b]	47.3	50.5
Curve 6 (42.54%)	40%	56.8	33.3	43.2	48.9	53.0[b]	56.1[b]
Curve5 (46.02%)	45%	67.8	39.6	49.5	55.2	59.3	62.5

a) M1 and M3 are assumed to be proportionate to M_{min}, and the average proportion that prevailed in the existing curve was used in the table.

b) Flipping points, where the discriminatory pricing becomes favorable over uniform pricing.

c) Shaded cells represent auctions with poor performance with over 30% rent extraction.

The values show that if we can prevent producers from learning anything about their cost effectiveness compared to others, uniform pricing is only better than discriminatory pricing if the supply curve is very flat M_{min}<10%. For scaling purposes, the table shows M_{min} values of the different cost curves, and it can be seen that even the flattest curve, curve 1, is

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[22] Communication increases rent extraction in discriminatory pricing by 7.49%, which is shown in the table by the value assigned to the discriminatory pricing for M_{min}=0% case.

slightly steeper than 10%. However, the moment we assume that the bidders obtain some information about how their cost compares to others (assuming the learned information is equivalent with what they could obtain in a single repetition lasting only one minute), then the tipping point is twice as high (M_{min}=20%). At this point the flat curve (curve 1) is better off with the uniform auction. If we assume bidders obtain even more information, equivalent to 2 repetitions, this tipping point is at M_{min}=30% and uniform auction performance becomes superior for the next cost curve (curve 2) as well. As apparent from the table, when the cost heterogeneity goes beyond M_{min}=35%, auction performance drops, and the rent extraction becomes so high in most scenarios that the reverse auction tool loses its appeal as a cost-effective conservation mechanism.

While the regulator cannot know the value of M_{min} ahead of time, analyzing the BMP costs that are associated with the different curves can give regulators indications regarding cost heterogeneity. The relatively flat curves are associated with the Holding Pond BMPs (curves 1 and 2), which is a structural BMP, and only a small amount of land is taken out from production. The biggest cost associated with the Holding Pond BMP is the actual construction cost of the retention pond (Boxall et al. 2008). This cost is independent from the soil productivity and has a linear relationship to livestock herd size. As a result, curve 2, which is the Holding Pond BMP ranked based on the cost per head of cattle, is a moderately flat curve. When cost related to this BMP is ranked based on cost per unit of abatement, the resulting cost curve is even flatter (curve 1). This shows that cost heterogeneity is mainly driven by the cost structure rather than by the diversity of the underlying abatement values. In fact, curve 1 exhibits the typical environmental hockey-stick abatement curve shape. This curve is flat at the beginning, manifesting in low M_{min} and M1 values, and has a sharp upward bend that leads to an increased M3 value. Since our study showed statistical evidence that low M_{MIN} and M1 values prevent excessive rent seeking, and that high M3 values actually improve reverse auction performance, confirming that reverse auctions are a suitable tool in conservation.

Since the experiments, the cost and the potential environmental abatement of Wetland Restoration, which is also a structural BMP, also became available in the study area. For Wetland Restoration, the main cost component is the construction cost, which is accounting for approximately two-thirds of the total cost even if 10 years worth of opportunity cost is included in the calculation (Packman 2010). Again, this cost is independent from soil productivity and the type of crops growing on the land. As a result, the Wetland BMP supply curve is quite flat initially based on both $/acre and $/kg of phosphorus abated (Packman 2010, pg 73-74). In fact, these wetland supply curves are very similar to the Holding Pond

BMP supply curve, and also exhibit the "hockey-stick" shape. Moreover, we calculated the M_{min}, M1, and M3 values for the Wetland Restoration BMP, and the values are very similar to the flattest curve (1) used in the experiment.

By analyzing the curves that performed poorly, it can be noted that their cost structure is vastly different from the cost structure of the flat curves. This occurs for two reasons. First, one of the worst performing curves (curve 3) was the only one constructed with an unusual ranking selection to maximize the number of BMPs adopted. Since there was a very large variation in farm size, which is not unusual in North America, this approach was destined to produce very high cost heterogeneity leading to poor auction performance. While the unattractiveness of this approach was shown by Boxall, Perger, and Weber (2013), this study provided measurable explanation of why such an objective leads to very ineffective results cost-wise. While this particular curve happened to be using the Holding Pond BMP data, this type of supply curve construction and ranking criteria would have produced the same large cost heterogeneity in all other BMPs because farm size, and hence total adoption cost, varies tremendously across all the BMPs examined.

The second reason that some supply curves showed large cost heterogeneity was because the costs associated with the BMP are strongly dependent on soil productivity and on what the land was producing before the BMP was adopted. The other poorly performing very steep curve (curve 6) was associated with Forage Conversion. In this case, when the producer converts the field from crops to perennial cover the entire crop revenue has to be given up. The potential revenue a field could produce per hectare primarily depends on the soil type and productivity, which varies significantly even in a small geographic area such as our study area. The moderately steep curves (4 and 5) were associated with the Zero Till BMP. While changing tillage practices changes labour and machinery costs that are largely independent from the field's physical characteristics, it also changes herbicide requirements and crop yields at different rates, depending on the crop (Boxall et al. 2008). For example, the herbicide requirements for canola increase at a much higher rate than for other crops. Moreover, Zero Tillage leads to an increase in yield for some crops, such as wheat and barley, but results in a significant yield decrease for others such as flax and canola (Boxall et al. 2008). As a result, the cost heterogeneity of Zero Tillage BMP is expected to be higher than BMPs like the Holding Pond and Wetland Restoration where cost is largely independent from field characteristics. On the other hand, as the producers are still able to continue to grow crops on the field, and the entire crop revenue is not sacrificed as it is in forage conversion, Zero Till cost heterogeneity is still expected to be lower than Forage Conversion, which is exactly what the cost estimates reveal.

Generally, it can be concluded that structural BMPs (fencing, wetland restoration, retention ponds etc), where the actual amount of land that needs to be taken out of production is small (hence their cost is largely independent from soil productivity), are prime candidates for conservation auctions. On the other hand, BMPs that require changing farming practices on the entire field and are expected to affect different crops in different ways should be carefully evaluated. Moreover, BMPs that require the entire field crop revenue to forgone, such as forage conversion or retiring land from agricultural production, are generally not good candidates for conservation auctions. Even if the auctioneer can prevent any learning, information exchange and any type of communication, the extracted information rent is expected to be excessive because of the high cost heterogeneity. This makes conservation auctions an unappealing tool in such cases, and alternative policy mechanisms may be more cost efficient; for example, spatial contracting or offering fixed payments per hectare for anyone who would adopt the practice in a take-it-or-leave-it manner.

In addition to the type of BMP, the bid ranking criteria can also influence cost heterogeneity of the supply curves. As discussed by Boxall, Perger and Weber (2013), ranking bids based on total cost to maximize the number of producers that adopt the practice leads to inefficient auction outcomes with extreme rent seeking activity. As actual abatement estimates are often not available, regulators may use prices per agricultural unit as the base of their ranking criteria such as \$/acre, \$/hectares or \$/head of cattle. However, in this study area, supply curves that were constructed based on \$/EBI values showed lower cost heterogeneity than their counterparts that were constructed based on \$/agricultural unit. In the case of Holding Pond BMP, M_{min} was 26.48% for the \$/head ranking and 17.28% for \$/EBI ranking. For the Zero Till BMP, the M_{min} value was 42.02% for the \$/ha ranking and 32.49% for the \$/EBI ranking. While the Wetland Restoration BMP curve was not used in the experiment, we calculated its cost heterogeneity values, and observed the same trend. The Wetland Restoration BMP supply curve constructed based on \$/ha ranking would have a 16.92% M_{min} value, while the curve constructed based on \$/EBI ranking would have a M_{min} value equal to 13.88%.

These results may be specific to this particular geographic location and BMP, but the degree of difference in cost heterogeneity is large enough to merit further investigation to determine if there is a general pattern or just a coincidence. If this is actually a trend in conservation cost, the cost efficiency improvements of lower cost heterogeneity could potentially cover the cost of conducting environmental assessments to estimate EBI values. Moreover, conducting an environmental assessment and distributing its details among the producers could potentially serve as a non-monetary incentive that induces participation, which can further improve the cost effectiveness of the auction.

When it comes to choosing between pricing mechanisms for conservation auctions, the regulator should consider potential information exchange and learning opportunities among bidders as well as the expected cost heterogeneity. If cost heterogeneity is expected to be at a moderate level because cost is strongly related to the type of crops or other field characteristics, the discriminatory auction is probably better than uniform. However, for those BMPs where cost heterogeneity is expected to be low, this might not be the case. Uniform auctions can prevent increased rent seeking if bidders communicate, which could be expected if they are located in a smaller geographic area. Moreover, using uniform auctions can help avoid price inflation over time if the auction is planned to be repeated.

However, one of the limitations of the study is that the economic model had a single variable identifying the learning effect, which was not interacted with the curvature measurements. Our finding that discriminatory pricing worsened with repetition and that uniform pricing prevents this, is well-documented in the literature (Scherer 1990, Von and We 1990). However, it is possible that the magnitude of learning in discriminatory auctions depends on the curviness of the curve. This could not be assessed in this current study due collinearity issues, but could be tested in further experiments.

Another concern with regard to the result is the lack of significance of the HHI variable in any of the six regressions. Market power is not extensively studied in reverse auction settings, and the results are ambiguous as some studies found no sign of market power (Bernard, Schulzeb and Mount 2005) while others did (Dormany 2005). While our results support the theory that market power doesn’t play much role in reverse auction if there are at least 12 bidders, this might have been the result of an identification problem. All the supply curves used in this study are estimated from actual BMP adoption, hence not particularly designed to be able to separate the cost and the firm size heterogeneity from each other. Including an additional supply curve with the exact same HHI value as one of the existing curves but different cost heterogeneity, could improve the statistical identification, and perhaps improve the results. Moreover, adding a “text-book” supply curve with an even steepness that is typically used in experimental studies (e.g. Cason and Gangadharan 2004, 2005) could also help emphasise the change in auction performance resulting in the unique supply curve shapes present in conservations.

2.9 Appendix

Table.2.7. Descriptive Statistics, Zero Tillage

	ALL PRODUCERS					DRAW				
	Unit (acre)	**EBI (kg TP)**	**Cost ($2004)**	**UnitCost ($/acre)**	**EBICost ($/kg TP)**	**Unit (acre)**	**EBI (kg TP)**	**Cost ($2004)**	**UnitCost ($/acre)**	**EBICost ($/kg TP)**
Min	4.1	0.7	-$147	-$8.2	-$83.7	31.2	4.8	$2,033	$15.8	$271.3
Max	1734.0	330.2	$183,532	$170.4	$2,787.9	1734.0	330.2	$183,532	$131.8	$1,221.2
Mean	470.3	57.8	$40,116	$70.7	$718.8	697.1	90.2	$59,985	$76.5	$668.3
Std	479.1	72.1	$48,234	$39.5	$600.5	597.4	94.3	$63,827	$33.8	$321.4

Table 2.8. Descriptive Statistics, Forage

	ALL PRODUCERS			DRAW		
	Unit (acre)	**Cost ($ 2004)**	**UnitCost ($/acre)**	**Unit (acre)**	**Cost ($ 2004)**	**UnitCost ($/acre)**
Min	4.1	-$78	-$19.1	31	$6,486	$6.2
Max	1673.6	$503,697	$608.5	1048	$212,355	$608.5
Mean	372.4	$79,465	$260.9	376.47	$50,177	$241.0
Std	364.9	$96,944	$162.9	293	$71,819	$172.1

Table 2.9. Descriptive Statistics, Holding Pond

	Unit (number of animal)	EBI (kg TP)	Cost ($2004)	UnitCost ($/animal)	EBICost ($/kg TP)
Min	8	0.14	$280	$24.81	$1,146.37
Max	475	19.62	$25,179	$232.52	$2,382.17
Mean	111	6.15	$9,372	$86.37	$1,557.78
Std	129	6.29	$9,685	$64.39	$385.25

Table 2.10. Auction Budgets

BMP		Budget for the entire industry	Budget for the sample
BMP1 (Holding Pond)	Curve1,2,3	$56,231	-
BMP2 (Zero Till)	Curve 4 5	$433,253	$215,950
BMP4 (Forage)	Curve 6	$858,218	$261,790

2.9.1 Regression testing

2.9.1.1 Model selection

Before selecting the random effect panel data specification, alternative possibilities were considered. First, all models were run as a fixed effect model in Stata using the xtreg command fe option. This provides an F-test on the joint significance of the panel-specific dummy variables. The null hypothesis that all panel specific dummies are zero has been rejected in all models, suggesting that pooled OLS is not the appropriate regression specification for the data. Secondly, a Breusch-Pagan (BP) test was performed on all 6 models, and the null hypothesis that the variance of the error term is zero ($\sigma_u^2 = 0$) was rejected for all models (1980). Based on these results, pooled OLS would have been inconsistent with the data, and a panel data model is needed (Baum 2001).

In order to verify that the random effect model is consistent, hence more appropriate for the data, Hausman tests were performed. However, the test did not produce results for two of the discriminatory pricing models, as the difference between the estimated covariance matrices were not positive definite in those models. The test could not reject the consistency of the random effect model in 3 out of the 4 models where it produced results. There was only one model where the Hausman test rejected the random effect model, but with only 10% significance. When the Hausman test cannot be executed, it doesn't mean that the random effect model is inconsistent, but only that the model does not satisfy the assumptions of the test. The orthogonality hypothesis (Var(X,u)=0) can also be tested with an alternative test developed by Mundlak and Yahav(1981), which includes adding the mean of the regressors into the regression (Wooldridge 2002 pg 332). However, as all of our variables are time invariant, this test cannot be performed on our models (Cameron and Triveldy 2010). When these tests reject the null hypothesis that regressors are orthogonal to the panel error terms (Var(X,u)=0), Haussmann Taylor model (1981) could be used as a remedy (Wooldridge 2010 ch 11.3). However, the Haussmann-Taylor model requires having an endogenous variable in the model that is not time-invariant, and we do not have such a variable in our model.

As the statistical tests did not produce strong evidence against it, the random-effect model was chosen for estimation as it is more appropriate given the regressors in the models. All our treatment variables with regards to the cost curves are time invariant, hence can only be estimated in a random-effect specification. Moreover, random-effect models are extensively used in the conservation auction literature when it comes to laboratory experimental data (Cason, Gangadharan and Duke 2003a; Cason and Gangadharan 2004, 2005; Tisdell 2011; Kits, Adamowicz, and Boxall 2014, Boxall et al. 2017),

2.9.1.2 Econometric challenges and remedies

As the Feasible Generalised Least Square (FGLS) estimation in Stata offers both homoskedastic and heteroskedastic options, a simple Likelihood Ratio (LR) test between the two can be used to test whether the model has heteroskedasticity (Wiggins, 2002). The LR test showed that none of the 6 models had panel-level heteroskedasticity problem (the Chi-square values can be found in Table 2.11. Despite the fact that the panel was structured in such a way that we had a short panel with only 5 time periods, autocorrelation had been detected in most of the models. It was examined if this was due to a lagged variable exclusion. However, the serial autocorrelation problem persisted even if the lagged variables were included and often the autocorrelation significance increased with lags. For example, in the CE discriminatory pricing model the autocorrelation was only significant at 10% level, but with the lag included it was significant at less than 1%. Moreover, the only model where autocorrelation was not detected, in the EE uniform pricing, showed signs of autocorrelation if we included any lag variables. The F-values of the Wooldridge panel data autocorrelation test can be found in Table 2.11. Based on these tests the final models did not include the lag of the dependent variables.

There are various options in Stata for estimating panel data that allow serial autocorrelation depending on assumptions imposed on the error structure. The most common assumption is to assume that the error terms follow a first order autocorrelation AR(1) process: $u_{it} = \rho \quad * u_{i\,t-1} + \varepsilon_{it}$,. In Stata, *xttest1* provides the Baltagi and Li (1995) test for first-order serial correlation, and according to these results ρ =0 was rejected in all the discriminatory pricing models (results in Table 2.11); hence first order autocorrelation is a reasonable assumption. As there are 2 missing data points in the uniform models' data, this test cannot be performed on these models. However, one of the uniform models did not suffer from autocorrelation. The FGLS regression, using the *xtgls* command in Stata, allows this assumption using the *corr(ar1)* option. However, FGLS estimation, which uses maximum likelihood methods to estimate ρ , has been criticized on the grounds that it provides unacceptably optimistic standard errors (Beck and Katz, 1995). The most common error term transformation, called Prais-Winston (P-W), is already implemented in Stata in multiple ways. The P-W correction can be transformed on FGLS estimation using the *xpcse* command. The P-W correction is also available for pooled OLS estimation using the *prais* command; this estimation is referred to as OLS-PW from now on. Cochrane and Orcutt (1949) introduced an alternative error correction, which involves dropping the first time period during the transformation. This correction is also implemented in Stata on pooled OLS estimation using the *corc* option in the *prais* command and is referred to as OLS-CO in the tables.

However, the strict assumption that all panels have the same correlation coefficient may not hold for our model. Both FGLS and FGLS with P-W correction estimates allow panel-specific corrected standard errors structure ($u_{it} = \rho_i * u_{i\,t-1} + \varepsilon_{it}$) using *corr(psa1)* option. Alternatively, the *xtscc* command offers an even more generalized solution without restricting the error term to follow an AR(1) process. This command uses pooled OLS/WLS model introduced by Driskoll and Kraay (1998) that allows error terms to be in a general form and even allows correlation across panels. This is often called spatial correlation (Cameron and Triveldy 2006).

Table 2.11. Model Testing Results

Test name (stata command)	Null Hypothesis	Percentage of Rent form the total payout (PRENT)		Percentage of he maximum objective realized (EE)		Percentage of cost effectiveness realized (CE)	
		Disc.	Uniform	Disc.	Uniform	Disc.	Uniform
F test (xtreg,fe)	All ui=0	2.51***	2.11 ***	1.44**	2.37***	3.23 ***	2.69 ***
LR test for heteroskedasticity (lrtest)		-605.82	-457.23	-823.19	-228.67	-823.19	-228.67
Breusch Pagan LM test (xttest0)	var(U)=0	37.82**	21.72***	4.49**	32.74***	67.14 ***	44.68***
Haussmann test	E(x,u)=0	N/A	3.39*	0.00	0.42	N/A	0.2418
Wooldridge test (xtserial)	rho =0	4.865**	4.296**	15.467***	0.945	4.677**	2.854*
including lag		12.186***	6.759**	25.694***	16.324***	13.790***	31.696***
including 2 lags		15.468***	6.509**	6.799**	19.436***	8.516***	19.700***
Baltagi and Li LM test (xttest1)		46.22***	N/A	30.68***	N/A	96.23***	N/A
Adjusted LM test (xttest1)		14.11**	N/A	29.38***	N/A	35.69 ***	N/A

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level

Table 2.12. PRENT Regression Results, Uniform Pricing

			Autocorrelation addressed						
			AR(1) common correlation coefficient				AR(1) panel specific		Generalized
		Uncorrected	OLS-CO	OLS-PW	FGLS-AR1	PW-AR1	FGLS-PSAR1	PW-PSAR1	D-K
	Learning Effect (Lnt)	-0.16	-5.66*	0.19	0.32	0.32	0.53	0.53	-0.25
		-(1.35)	-(3.12)	-(1.85)	-(1.68)	-(1.18)	-(1.53)	-(1.40)	-(0.76)
	Communication Dummy	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
		-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	(0.00)
	Firm Size Heterogeneity (HHI)	0.89	2.19	0.4	0.19	0.2	1.34	1.34	0.98
		-(2.27)	-(2.39)	-(2.28)	-(2.50)	-(2.05)	-(2.19)	-(1.42)	-(1.10)
Cost Heterogeneity Measurements	**Overall Variability (Mmin)**	1.39***	1.27***	1.38***	1.37***	1.37***	1.38***	1.38***	1.40***
		-(0.15)	-(0.17)	-(0.16)	-(0.17)	-(0.20)	-(0.17)	-(0.27)	-(0.17)
	Variability at the 1st Quartile (M1)	1.42***	1.36***	1.42***	1.41***	1.41***	1.32***	1.32***	1.43***
		-(0.14)	-(0.15)	-(0.14)	-(0.15)	-(0.13)	-(0.14)	-(0.17)	-(0.11)
	Variability at the 3rd Quartile (M3)	-0.2	-0.12	-0.2	-0.19	-0.19	-0.11	-0.11	-0.21**
		-(0.14)	-(0.14)	-(0.13)	-(0.15)	-(0.12)	-(0.15)	-(0.16)	-(0.09)
	Constant	-17.7	-5.04	-16.58	-15.98	-15.98	-19.2	-19.2	-18.2
		-(13.31)	-(15.81)	-(13.61)	-(14.70)	-(13.26)	-(13.97)	-(16.96)	-(11.95)
	R^2	0.68	0.62	0.55		0.51		0.67	0.68
	χ^2	408.88	125.85	104.4	336.44	32976.65	387.36	42153.17	200.47
	# ρ^a		1	1	1	1	72	72	
	ρ		0.200	0.337	0.426	0.425			
	# Obs.	358	286	358	358	358	358	358	358

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level, Standard errors in parentheses

a) ρ is the correlation coefficient of the error term: $\boldsymbol{u_{it}} = \boldsymbol{\rho} \ * \boldsymbol{u_{i\,t-1}} + \boldsymbol{\varepsilon_{it}}$

Table 2.13. PRENT Regression Results, Discriminatory Pricing

			Autocorrelation addressed						
		Uncorrected	Common AR(1)				Panel specific AR(1)		Generalized
			OLS-CO	OLS-PW	FGLS-AR1	PW-AR1	FGLS-PSAR1	PW-PSAR1	D-K
	Learning Effect (Lnt)	12.86***	6.18**	13.85***	14.17***	14.17***	13.27***	13.27***	12.86***
		-(1.57)	-(2.92)	-(2.38)	-(2.10)	-(2.16)	-(1.85)	-(2.14)	-(1.18)
	Communication Dummy	6.85**	4.66*	7.30**	7.49**	7.49**	10.38***	10.38***	6.85***
		-(2.94)	-(2.51)	-(3.09)	-(3.47)	-(3.21)	-(2.94)	-(3.14)	-(2.27)
	Firm Size Heterogeneity (HHI)	-0.01	0	-0.01	-0.01	-0.01	-0.02***	-0.02	-0.01
		-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.02)	-(0.01)
Cost Heterogeneity Measurements	Overall Variability (Mmin)	0.45**	0.50***	0.46**	0.46**	0.46**	0.73***	0.73***	0.45***
		-(0.20)	-(0.19)	-(0.18)	-(0.23)	-(0.33)	-(0.18)	-(0.23)	-(0.08)
	Variability at the 1st Quartile (M1)	1.35***	1.53***	1.33***	1.32***	1.32***	1.20***	1.20***	1.35***
		-(0.17)	-(0.17)	-(0.16)	-(0.21)	-(0.28)	-(0.16)	-(0.31)	-(0.14)
	Variability at the 3rd Quartile (M3)	0.19	0.38**	0.12	0.09	0.09	-0.23	-0.23	0.19*
		-(0.18)	-(0.15)	-(0.21)	-(0.21)	-(0.43)	-(0.19)	-(0.55)	-(0.11)
	Constant	-19.8	-32.89**	-16.7	-15.29	-15.29	-0.49	-0.49	-19.8
		-(17.23)	-(14.68)	-(14.72)	-(20.39)	-(30.90)	-(18.78)	-(42.64)	-(12.87)
	R^2	0.53	0.53	0.33		0.26		0.56	0.53
	χ^2	233.25	88.42	90.03	167.24	478.58	320.14	21782.77	4878.87
	# ρ[a]		1	1	1	1	72	72	
	ρ		0.188	0.412	0.517	0.529			
	# Obs.[a]	360	288	360	360	360	360	360	360

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level, Standard errors in parentheses

a) ρ is the correlation coefficient of the error term: $u_{it} = \rho * u_{i\,t-1} + \varepsilon_{it}$

Table 2.14. EE Regression Results, Discriminatory Pricing

			Autocorrelation addressed						
		Uncorrected	Common AR(1)				Panel specific AR(1)		Generalized
			OLS-CO	OLS-PW	FGLS-AR1	PW -AR1	FGLS-PSAR1	PW-PSAR1	D-K
	Learning Effect (Lnt)	-5.81***	3.1	-6.45***	-6.45***	-6.45***	-6.92***	-6.92***	-5.81***
		-(1.63)	-(5.37)	-(1.89)	-(1.88)	-(1.83)	-(1.69)	-(1.62)	-(1.33)
	Communication Dummy	-2.03	-3.16	-1.29	-1.3	-1.3	-4.35*	-4.35	-2.03
		-(2.30)	-(2.98)	-(2.19)	-(2.74)	-(3.60)	-(2.34)	-(3.66)	-(1.52)
	Firm Size Heterogeneity (HHI)	0.00	0.00	0.01	0.01	0.01	-0.01	-0.01	0.00
		-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	(0.00)
Cost Heterogeneity Measurements	**Overall Variability (Mmin)**	-1.40***	-1.29***	-1.43***	-1.43***	-1.43***	-1.49***	-1.49***	-1.40***
		-(0.16)	-(0.16)	-(0.13)	-(0.19)	-(0.18)	-(0.15)	-(0.17)	-(0.08)
	Variability at the 1st Quartile (M1)	-0.26*	-0.25	-0.25**	-0.25	-0.25***	-0.41***	-0.41***	-0.26***
		-(0.14)	-(0.16)	-(0.12)	-(0.16)	-(0.06)	-(0.13)	-(0.04)	-(0.01)
	Variability at the 3rd Quartile (M3)	0.65***	0.59***	0.69***	0.69***	0.69***	0.66***	0.66***	0.65***
		-(0.14)	-(0.20)	-(0.14)	-(0.17)	-(0.20)	-(0.15)	-(0.22)	-(0.10)
	Constant	117.10***	102.37***	116.72***	116.73***	116.73***	136.80***	136.80***	117.10***
		-(13.55)	-(16.91)	-(11.82)	-(16.14)	-(9.82)	-(13.90)	-(10.34)	-(8.21)
	R2	0.34	0.19	0.45		0.45		0.75	0.34
	χ2	131.79	15.07	33.33	100.24	106.46	154.47	1121.55	129.64
	# ρ[a]		1	1	1	1	72	72	
	ρ		0.266	0.405	0.401	0.401			
	# Obs.	360	288	360	360	360	360	360	360

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level, Standard errors in parentheses

a) ρ is the correlation coefficient of the error term: $\boldsymbol{u_{it} = \rho * u_{i\,t-1} + \varepsilon_{it}}$

Table 2.15. CE Regression Results, Discriminatory Pricing

			Autocorrelation addressed						
		Uncorrected	Common AR(1)				Panel specific AR(1)		Generalized
			OLS-CO	OLS-PW	FGLS-AR1	PW-AR1	FGLS-PSAR1	PW-PSAR1	D-K
	Learning Effect (Lnt)	-12.15***	-5.39	-13.29***	-13.15***	-13.15***	-13.23***	-13.23***	-12.15***
		-(1.49)	-(4.43)	-(2.35)	-(1.97)	-(2.79)	-(1.69)	-(2.21)	-(0.66)
	Communication Dummy	-7.72**	-8.03**	-7.61**	-7.63**	-7.63***	-9.36***	-9.36***	-7.72***
		-(3.15)	-(3.10)	-(3.26)	-(3.24)	-(1.56)	-(2.67)	-(2.26)	-(0.49)
	Firm Size Heterogeneity (HHI)	0.00	0.00	0.01	0.01	0.01	0.02**	0.02	0.00
		-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	(0.00)
Cost Heterogeneity Measurements	**Overall Variability (Mmin)**	-0.77***	-0.71***	-0.77***	-0.77***	-0.77***	-0.93***	-0.93***	-0.77***
		-(0.21)	-(0.23)	-(0.22)	-(0.22)	-(0.16)	-(0.17)	-(0.09)	-(0.04)
	Variability at the 1st Quartile (M1)	-1.83***	-1.92***	-1.78***	-1.79***	-1.79***	-1.63***	-1.63***	-1.83***
		-(0.19)	-(0.21)	-(0.19)	-(0.19)	-(0.15)	-(0.15)	-(0.17)	-(0.08)
	Variability at the 3rd Quartile (M3)	-0.17	-0.31	-0.07	-0.09	-0.09	0.19	0.19	-0.17**
		-(0.19)	-(0.20)	-(0.22)	-(0.20)	-(0.26)	-(0.16)	-(0.24)	-(0.08)
	Constant	140.23***	140.90***	134.17***	135.14***	135.14***	120.28***	120.28***	140.23***
		-(18.48)	-(16.98)	-(15.87)	-(19.05)	-(21.37)	-(15.87)	-(21.43)	-(5.42)
	R2	0.64	0.55	0.6		0.61		0.83	0.64
	χ2	314.72	105.36	117.04	278.93	6116.07	462.62	1748.22	291.88
	# ρ[a]		1	1	1	1	72	72	
	ρ		0.315	0.585	0.524	0.524			
	# Obs.	360	288	360	360	360	360	360	360

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level, Standard errors in parentheses

a) ρ is the correlation coefficient of the error term: $\boldsymbol{u_{it}} = \boldsymbol{\rho} \; * \boldsymbol{u_{i\,t-1}} + \boldsymbol{\varepsilon_{it}}$

Table 2.16. CE Regression Results, Uniform Pricing

			Autocorrelation addressed						
		Uncorrected	**Common AR(1)**				**Panel specific AR(1)**		**Generalized**
			OLS-CO	**OLS-PW**	**FGLS -AR1**	**PW -AR1**	**FGLS -PSAR1**	**PW-PSAR1**	**D-K**
	Learning Effect (Lnt)	0.32	-5.39	0.34	0.34	0.34	0.36	0.36	0.26***
		-(1.16)	-(4.43)	-(1.39)	-(1.46)	-(0.55)	-(1.32)	-(0.66)	-(0.09)
	Communication Dummy	-5.00**	-8.03**	-4.64**	-4.65**	-4.65***	-4.55**	-4.55***	-4.94***
		-(2.23)	-(3.10)	-(2.14)	-(2.22)	-(0.80)	-(1.90)	-(1.33)	-(0.77)
	Firm Size Heterogeneity (HHI)	0.00	0.00	0.00	0.00	0.00	0.01	0.01*	0.00**
		-(0.01)	-(0.01)	-(0.01)	-(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Cost Heterogeneity Measurements	**Overall Variability (Mmin)**	-1.72***	-0.71***	-1.70***	-1.70***	-1.70***	-1.64***	-1.64***	-1.71***
		-(0.15)	-(0.23)	-(0.10)	-(0.15)	-(0.09)	-(0.19)	-(0.15)	-(0.06)
	Variability at the 1st Quartile (M1)	-1.89***	-1.92***	-1.91***	-1.91***	-1.91***	-1.89***	-1.89***	-1.89***
		-(0.13)	-(0.21)	-(0.12)	-(0.13)	-(0.06)	-(0.15)	-(0.09)	-(0.05)
	Variability at the 3rd Quartile (M3)	0.32**	-0.31	0.29**	0.30**	0.30***	0.29**	0.29***	0.31***
		-(0.14)	-(0.20)	-(0.12)	-(0.14)	-(0.04)	-(0.14)	-(0.10)	-(0.03)
	Constant	138.76***	140.90***	139.46***	139.43***	139.43***	136.11***	136.11***	138.43***
		-(13.06)	-(16.98)	-(12.24)	-(13.04)	-(7.54)	-(12.44)	-(8.14)	-(5.07)
	R^2	0.8	0.55	0.69		0.69		0.88	0.8
	χ^2	656.69	105.36	341.34	661.06	24762.49	705.79	4.30E+05	27046.64
	# ρ^a		1	1	1	1	72	72	
	ρ		0.316	0.455	0.448	0.447			
	# Obs.	358	288	358	358	358	358	358	358

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level, Standard errors in parentheses

a) ρ is the correlation coefficient of the error term: $\boldsymbol{u_{it} = \rho \ast u_{i\,t-1} + \varepsilon_{it}}$

3 Conservation Auction Effectiveness with Diminishing Marginal Return of BMP Adoptions

3.1 Introduction

Improving water quality is consistently ranked as the top environmental concern in most OECD countries (OECD, 2012). As the agriculture sector is often the main source of water pollution, policy makers are looking into different methods to provide incentives for farmers to adopt more environmentally friendly practices. Conservation auctions are considered to be one of the most cost-effective solutions and a meta-study reported that their cost saving can range from 16% to 315% compared to the traditional fixed payment or cost sharing programs (Latacz-Lohmann and Schilizzi 2005). Others reported even higher, 700%, cost saving by conservation auctions (Stoneham, Chaudhri and Strappazzon 2003). Thus, it is no surprise that policymakers have recently been investigating the potential usage of conservation auctions in BMP adoption in Canada.

Water quality affected by sediment runoff from fields is one of the leading environmental concerns regarding the agricultural industry. In Canada, farmers' actions targeting water quality improvements are often referred to as Beneficial Management Practices (BMPs). As the surface runoff is flowing from field to field, any BMP a farmer may adopt essentially affects the neighbouring farms' contamination of the water body as well. While the extent of the spatial dependencies between BMP adoptions is extremely complex and depends on various land and BMP characteristics, there is a general trend of diminishing marginal returns in water quality improvement due to increasing numbers of BMPs adopted as reported in the hydrology literature (Perez-Pedini, Limbrunner and Vogel 2005). If this spatial dependency is of a considerable magnitude, it may significantly change the marginal benefit of additional BMP adoptions. If conservation auctions are employed to select the farms to adopt BMPs, failure to account for these interdependencies could result in significant reduction of the cost effectiveness.

Depending on the environmental goal, multiple BMP adoption in close proximity can enhance or worsen each other. In habitat conservation, the effect is often positive and extensively studied in spatial targeting experiments (Parkhurst et al. 2002; Parkhurst and Shogren 2007), and also in auction context (Cai et al. 2013; Banerjee, Kwasnica and Shortle 2015). However, the negative side, when the value of the marginal benefit is diminishing between participating bidders has not been explored previously. As the environmental benefits provided by the two BMPs together are less than the sum of the individual benefits they would provide separately, this is called a "subadditivity" or "negative synergy" between these BMPs. Utilizing laboratory experiments, this study investigates the effect of the diminishing marginal return of BMP adoptions in conservation auctions. This present study analyses how the efficiency loss may occur and what is its magnitude. Additionally, as a potential solution, we explore how incorporating the negative synergy into the winner selection process could prevent or decrease the efficiency loss and improve auction performance.

3.2 Literature review

When auction literature started to expand from single unit auctions toward multi-unit ones, the initial underlying assumptions were that the sold goods and services are homogenous and their values are independent from each other (Myerson 1984). However, this is often not true, and the value of two items together is often different than the sum of the individual values; this is called synergy in values. When the items are considered to be complements, and the value of the set of items exceeds the value of the sum of the individual values; i.e. positive synergy or superadditivity ($f(A+B) > f(A)+f(B)$. Functions with this property are considered to be exhibiting economics of scope. On the other hand, when the items are considered substitutes, the value of the set of the items is lower than the sum of the value of the individual items, i.e. negative synergy or subadditivity ($f(A+B) < f(A)+f(B)$). Functions with this property are considered to be exhibiting diminishing marginal value.

The theoretical exploration of synergies in auctions started in the 90's focusing on positive synergies (Krishna and Rosenthal 1995; Fernando 1997; Ausubel 1997). Superadditivity or positive synergy is often present in bidders' valuation in large scale government procurement auctions, such as radio spectrum, transportation route deregulations etc. Combinatorial auctions, when bidders can place bids on packages containing multiple items, are designed to enhance auction efficiency in this situation (Cramton, Shoham and Steinberg 2006) .

There are various combinatorial auction methods in the literature. The ascending English auction was expanded into a so called "proxy" auction, where bidders use a proxy agent to bid for packages on their behalf (Ausubel and Milgrom 2002). The proxy auction is an iterative bidding process with provisional winner announcements, which ends if there are no changes in winners at the next iteration. This was later expanded into a clock-proxy auction where the final round of proxy auction was preceded by a non-combinatorial clock auction phase (Ausubel, Crampton and Milgrom 2006).

Ausubel and Milgrom (2006) provided a generalized format for the traditional Vickery auction that incorporates package bidding and named it the Vickery-Clark-Groves (VCG) mechanism. In this auction bidders submit their bid value for each potential item combination they are interested in, and they pay the incremental value if they win in the auction. This method, similarly to the Vickery auction, leads to a dominant strategy of submitting the true valuation for the packages. There is an extensive literature analysing the various aspects of these combinatorial auctions such as efficiency, winner determination, bundle package formation, empirical considerations and so on. These issues are discussed in detail in a textbook on combinatorial auction edited by Cramton, Shoham, and Steinberg (2006), and in various literature surveys (Abrache et al. 2007; de Vries and Vohra 2003).

While the literature initially was focused on positive synergies in auctions, lately the theory has been extended to negative synergy or subadditivity. Menezes and Monteiro (2003) demonstrated how the equilibrium price changes in uniform auctions if there is negative synergy between the sold goods. Trifunović (2014) formulated the optimal bidding strategy if the goods with negative synergy are sold on sequential auctions. There are even some experimental studies that include cases with negative synergy between items (Chenovis and Levin 2012). However, negative synergies are still not well understood in the literature.

In the case of regular (forward) auctions discussed above, the synergy appears on the bidder's side, as it is the result of the buyer valuing the items together differently from the individual items. In the case of reverse auctions, such as conservation auctions, the auctioneer is the buyer, hence the value interdependency between the goods and services is realised on the auctioneer's side. Therefore, bidders have no incentive to coordinate their bidding strategy unless this information is provided to them. For example, the landowners' cost of implementing various BMPs often remains independent, but the benefits provided by these Environmental Goods and Services (EG&S) are dependent on the spatial configuration of the land and the pattern of adoption.

The most studied area regarding the interdependency and conservation contracts is the scenario when the synergy is positive. In habitat conservation, there are often advantages to conserving neighbouring parcels, because many species thrive more successfully if protected lands are clustered rather than fragmented (Polasky et al. 2014). This is sometimes referred to as the economics of scope effect, with the buyer placing a higher value on buying larger sizes of conservation offsets (Nemes, Plott and Stoneham 2008). Additionally, certain spatial formations, such as wildlife corridors, are preferred over randomly fragmented conservation effects (Parkhurst et al. 2002). There are several ways to deal with this positive synergy. In the case of fixed payment schemes, the regulator can create an additional incentive payment called the agglomeration bonus that is paid if the conservation action takes place in adjoining land parcels. Since there is very little theory to guide us, the effectiveness of such mechanism has been studied in the lab (Parkhurst et al. 2002; Parkhurst and Shogren 2007), as well using simulation (Drechsler et al. 2010; Wätzold and Drechsler 2014). Banerjee, Shortle, and Kwasnica (2015) combined the agglomeration bonus system with the VCG mechanisms for conservation auctions to show how combinatorial conservation auctions can improve habitat connectivity. A repeated conservation auction in Australia aimed at improving habitat linkages using a benefit scoring mechanism that involved neighbouring parcels (Windle et al. 2009).

When synergy is studied in a bilateral trading context, the solution often involves creating a “smart” market mechanism that allows selling and buying in packages. The BushBroker exchange mechanism was introduced to accommodate conservation offset trading in Australia by allowing creation of packages by multiple sellers and buyers over a sophisticated online trading website organized by the government (Nemes, Plott and Stoneham 2008). The usefulness of combinatorial auctions in conservation has also been studied using agent based modelling (ABM) with simulated agents (Iftekar and Tisdell 2016). Tanaka (2007) set up laboratory experiments that aimed to consolidate fragmented land via various bilateral trading mechanisms such as call markets, double auctions and direct face-to-face negotiations. A similar study was conducted in Alberta to evaluate potential wetland restoration offset markets using call markets and packaged double auctions (Weber et al. 2011). Also, there are various studies that are not in the conservation context, but focus on reverse combinatorial auctions in general with positive synergies. These studies mainly focus on the challenge of the actual implementation such as winner determination, pricing mechanisms, executing package handling, moderating the auction mechanism, etc (Giovannucci et al. 2007; 2008; Giovannucci, Cerquides and Rodriguez-Aguilar 2010; Goreje and Holt 2010; Hsieh 2010).

The second area that is studied in the conservation and interdependency between bidder’s context revolves around group mechanisms. Certain ecosystems, such as lakes or coral reefs, accumulate pollutants and exhibit threshold effects (Jack, Leimona and Ferraro 2009). This means that the regulator needs to create a mechanism that only pays for contracts if the desired level of conservation is achieved, otherwise the payments are wasted. An alternative reason to implement such a mechanism is if individual abatement cannot be observed, but the group’s overall performance can. Taylor, Randall and Shogren (2003) provided a theoretical framework for this type of situation. Their model included a conservation auction where each landowner submitted individual bids, which was the basis of winner selection. However, the discriminatory pricing payment was only used if the aggregate level of abatement was achieved by the group. This model was tested using laboratory experiments that confirmed that the Nash equilibrium abatement level could be achieved in most cases, and landowners could cooperate to achieve the desired abatement level (Taylor et al. 2004). An alternative mechanism is to award payment to the group as a whole based on the achieved abatement level. Collins and Maille (2011) presented two different theoretical models following this approach. In their first model, the landowners implemented BMPs on their own and the group as a whole decided how to penalize or reward individual members from the received group payment. Their second model assumes that the group as a whole has invested in BMP adoption technologies and offers cost-share to individual members, who are then burdened with the actual implementation. The authors tested their second model in a field experiment in a small watershed during three consecutive years and found that the mechanism can work, but it requires a cohesive group and certain personal characteristics such as strong leadership. There are several other studies on this topic, both theoretical and experimental but they are not discussed here in detail as they mainly focus on traditional pollution control mechanisms such as subsidies and taxes or focus more on the monitoring / enforcement issues.

The third area of study is when the spatial dependency is negative and can be identified between parties. Negative spatial spillover has often been studied in resource extraction or common pool resource contexts (Janssen and Ostrom 2008; Schnier 2009; Ahn, Ostrom and Walker 2010; Janssen et al. 2010; Anderies et al. 2011). Another common area for negative spatial dependency is the spatial dispersion game, where the parties choose their location or market segment based on the magnitude and spatial structure of the negative spillover (Brow-Kruse, Cronshaw and Schenk 1993; Brown-Kruse and Schenk 2000; Blume, DeLong and Maier 2005; Kirchkamp and Nagel 2007; Orzen and Sefton 2008).

However, negative synergy or subadditivity is not typically studied in conservation auctions, which is our focus. When multiple BMP adoptions take place in the same watershed, their efficiency can impact each other just simply based on the law of diminishing marginal benefits. There is a rich literature on spatial optimization of BMP adoptions by hydrologists and they use various algorithms to model the interdependency between land units based on geophysical characteristics of the land. Although the relationship between BMP adoptions on different land parcels is extremely complex, Perez-Pedini, Limbrunner and Vogel (2005) provided a highly stylized illustration. The authors simplified the BMP adoption problem and provided a Pareto frontier that showed that increasing the number of BMPs in a watershed does not provide linearly increasing environmental benefits (see Figure 3.1).

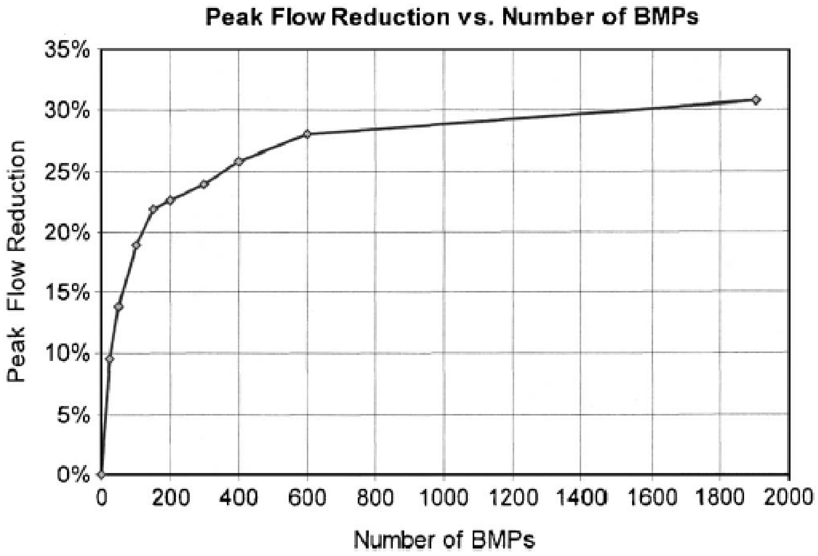

Figure 3.1. Diminishing Marginal Return of BMP Adoption, Perez-Pedini, Limbrunner and Vogel. 2005 p445

In fact, their graph is a perfect illustration of the concept of diminishing rate of returns. The authors also discussed that the spatial dispersion diminishes the farther the BMPs are from each other spatially. Hence, this is a typical case of subadditivity in BMP adoption that happens on the same field or fields that are in close proximity to each other. Although this notion is embedded into most spatial BMP optimization studies by hydrologists, it has not really entered the economics literature yet. Our study aims to fill this gap.

There are only two studies that incorporate some kind of negative dependency between landowners in conservation auctions. Espinola-Arredondo (2008) developed a model where the projects implemented by the auction winners imposed an externality on the non-participating landholders. While other conservation auction models focus on bid formation, this model focuses on the participation aspect of the auction. The author analyzed both negative and positive externalities, and found that the externality does have an effect on participation incentives in the auction. More precisely, it increased the participation rate if there was negative externality for non-participating neighbors and reduced participation if the externality was positive. Another study explored conservation auction performance where there is a potential synergy on the cost side and the winning landowners have negative effect on their neighbour's production cost (Calel et al. 2013). The authors provided a theoretical foundation of the optimal bidding behavior and explored the effectiveness of joint bidding in this scenario. However, there are no studies that explored negative synergy or subadditivity in the auctioneer valuation of the benefits in conservation auction.

Laboratory Experiment Design

This section describes the set of experiments that were used in this study to explore the role of negative synergy or subadditivity in reverse auctions, which represent the diminishing marginal rate of multiple BMP adoptions in close proximity..

3.2.1 Experimental Procedures

The experiments in this study were designed to induce incentive comparable behaviour in our subjects similar to agricultural producers in a potential conservation auction and were similarly structured to other laboratory experiments in the literature (e.g. Cason, Gangadharan, and Duke 2003a; Cummings, Holt and Laury 2004; Schilizzi and Latacz-Lohmann 2007; Boxall, Perger and Weber 2013; Wichmann et al. 2017; Boxall et al. 2017).

The experiments were implemented using the ZTREE experimental economic software system (Fischbacher 2007). Participants were recruited from the experimental database maintained by the Department of Resource Economics and Environmental Sociology at the University of Alberta using ORSEE software (Greiner 2015). While laboratory experiments cannot replace fields experiments, they produce incentive compatible behavior that allows us to generalize their findings with their external validity being established in the literature (Roe and Just 2009). External validity of laboratory auction has been confirmed by multiple studied (Brookshire et al. 1987; List and Shogren 1998). Students participating in conservation auctions in the laboratory are assumed to behave similarly to rational profit maximising firms (Cason and Gangadharan 2004, 2005; Cason et al. 2003). Moreover, a very similarly structured previous version of these experiments was carried out with the actual agricultural producers in our study area and showed identical behaviour to the university students (Boxall et al. 2008) During the recruitment process, the invitation email encouraged students who knew each other to sign up for the same sessions in order to encourage better social interaction[23]. At the end of the sessions, students were asked to complete a questionnaire, which had questions about how well they knew their group-mates in the session. The questionnaire can be found in the Appendix. Moreover, audio recording of the sessions was done in order to capture potential collaboration efforts among participants.

Data collection was performed at the University of Alberta using the same conference room and executed by the same researcher using the same instructions. During the data collection, 24 experimental sessions were carried out with 12 participants each, resulting in

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[23] The invitation email contained the following "In these sessions, we'd like to increase the number of people who know each other before the experiment. If you registered for a session and your friend didn't get an invitation please let us know and we gladly sign up your friend to the same session."

288 participants in total. The average age among the participants was 25.7 years, and 45% of them were female. An experimental session lasted between 60-80 minutes including reading the instructions, the actual auction rounds, answering the questionnaire and the handling of cash payments. Participants' total payment per session ranged between $20 to $50 with an average of $31.

At the beginning of an experimental session, participants were given PowerPoint instructions explaining the course of the experiment (see Appendix), which was followed by two and half minutes long auction rounds. Before the incentive-based auction rounds started, two practice rounds had been executed ensuring the participants understood the rules of the auction.

The auctions in the experiments in this study utilized budget based conservation auction framework using sealed bid discriminatory pricing, as this type of auction has an established theoretical foundation with regard to individual bidding behaviour (Latacz-Lohmann and Van der Hamsvoort 1997), and had also been extensively used in laboratory studies (Cason, Gangadharan, and Duke 2003a; Cummings, Holt and Laury 2004; Schilizzi and Latacz-Lohmann 2007; Boxall, Perger and Weber 2013; Wichmann et al. 2017; Boxall et al. 2017).

Each experimental session had 12 participants representing agricultural producers that are eligible to participate in the conservation auction. The data in the experiments represented the Wetland Restoration BMP from the Canadian Prairies. BMPs that had potential spillover effects in the experiment represented farms that were geographical neighbours. The next subsection provides details on the data selection process (Section 3.3). The participants' cost was the total wetland restoration cost and the quantity was the annual kg of phosphorus abatement associated with the restoration of wetlands on the given farm. However, the experiment used neutral language, and the subjects were unaware of the nature of the product they were selling, and were told they were partaking in a (reverse) auction selling products (product A and product B).

Each experimental session had a total of 15 rounds of auctions divided into 3 blocks of 5 preceded by two practice rounds. Each participant received a randomly assigned cost and quantity data at the beginning of each block. The participants kept their assigned data within each block, and could partake in an auction 5 times with the same cost and quantity before they received a new randomly selected data.

While laboratory experiments on auctions often do not allow subjects to refrain from bid submission (Cason and Gangadharan 2003; Cummings, Holt and Laury*.* 2004), submitting a bid in our experiments was voluntary. Allowing participants to refrain from bid submission allowed us to examine whether neighbours would accommodate each other and abstain from bidding if a negative synergy was incorporated into the winner selection process. Participants who decided not to submit a bid in the given round of auction received the same base payment as the participants who submitted a bid but did not win. Participants' final payment included a $5 base payment and an incentive payment they earned in 3 randomly selected rounds, one from each block.

3.2.2 Experimental Design

3.2.2.1 Subadditivity Treatments

Negative interdependency among BMPs can be implemented in multiple ways depending on the direction. It can be one-way (unilateral), which means that the activity of one firm (the source) has a negative impact on a neighbouring firm (the sink), but not vice versa. This situation is often present when the polluting activity of an upstream farm or manufacturer causes damage downstream. Alternatively, the interdependency can go both ways (bilateral), when both of the neighbouring farms have an impact on each other. Some authors explore both types of interdependencies. For example, Schnier (2009) reports a laboratory experiment analyzing the effects of both unilateral and bilateral directionality on common pool resource extraction. In our case, the interdependency is simply the result of diminishing marginal benefits of multiple BMP adoptions in close proximity. Hence, there is no reason to assume single directionality. The synergy is assumed to be negative, bilateral and symmetric in this study.

While the basic assumption here is that the subadditivity is always present between the neighbouring BMPs, the auctioneer may or may not include this information into the bidding process. Revealing additional information in conservation auctions can be a double-edged sword, as Cason, Gangadharan, and Duke. (2003a) note, when they showed that revealing the quality of their BMP to participants can worsen cost efficiency. At the same time, revealing information about the buyer preferences has been found to increase allocative efficiency in multiunit English auctions (Strecker 2010).

In order to investigate whether it is worthwhile to introduce the synergy into conservation auctions, half of the sessions incorporated this information into the bidding process and the other half did not. When the synergy was not included into the bidding process, the submitted bids were simply ranked on the basis price of a kg of phosphorus abated regardless of any spatial relationship between the underlying BMPs that the bids were associated with. In other words, ranking was simply based on $\frac{\text{bid}}{\text{quantity}}$. In the sessions where the subadditivity was introduced into the bidding, the subjects were informed that neighbouring BMPs would reduce each other's competitiveness by 10% when it comes to bid ranking for winner selection. If bids arrived for two BMPs with potential interdependency between them, their bids ranked at a 10% higher price per unit. Essentially their bid would be ranked based on the following formula:

$$\frac{bid}{quantity} * (1 + 0.1 * \#\ bid\ submitted\ for\ neighbouring\ BMPs) \qquad (3.1)$$

For example, assuming a $40 bid was submitted for a BMP with a 10 kg abatement potential, it was ranked as $4 / kg if there was no bid submission for neighbouring BMP(s). However, if there was a bid submitted for a neighbouring BMP in the auction, it was ranked as $4.4 / kg.

The diminishing marginal rate resulting from stacking BMPs in close proximity dissipates quickly by distance (Perez-Pedini, Limbrunner and Vogel 2005). Hence, the subadditivity of multiple BMP adoptions may happen within the same farm, in which case it is referred to as intra-farm subadditivity. Alternatively, the subadditivity associated with multiple BMP adoptions can happen between direct neighbours, and is referred to as inter-farm subadditivity.

The experiments explored three subadditivity options: a) bilateral intra-firm, b) bilateral inter-firm and c) multilateral inter-firm. During the bilateral intra-firm treatment, each of the 12 subjects had two potential BMPs to submit bids for (product A and B). In sessions when the subadditivity was incorporated into the bidding process, subjects had been told their two products were worsening each other competitiveness by 10% in the way described above. In each auction round, subjects were allowed to submit a bid for both BMPs, or just one of the BMPs, or they could completely refrain from bidding in the round. When the subadditivity was not incorporated into the bidding, the subjects simply had two unrelated BMPs to submit bids for.

In the case of the bilateral inter-firm synergy, the 12 subjects were divided into 6 pairs, and the diminishing effect existed within the pairs, but not across the pairs. Each subject had a single BMP to submit a bid for and had the option to refrain from submitting a bid in any given round. In sessions where the negative synergy was incorporated into the bidding, subjects were told how bid submissions between pairs were affecting both negatively due to the 10% competitiveness loss.

During the multilateral inter-firm treatment, the 12 subjects were divided into 4 groups of 3 potential bidders. Just as the bilateral inter-firm treatment, each subject had a single BMP to submit a bid for, or they could decide to refrain from bidding. In sessions where the diminishing rate was incorporated into the bidding, subjects were told how bid submissions within their group were affecting both negatively due to the 10% competitiveness loss. Hence, in these sessions, subjects could experience a 20% competitiveness loss if both of their group-mates submitted a bid.

3.2.2.2 Seating arrangements

During the experiments, the three types of subadditivity settings were emphasized by actual physical seating arrangements. In the case of the two inter-firm treatments, the subjects were divided into groups, and they were seated at separate tables with their group-mates. In the case of the bilateral inter-firm setting, the subjects were seated in pairs at 6 separate tables (see Figure 3.2A). In the case of multilateral inter-firm setting, the subjects were divided into groups of 3 and were seated at 4 separate tables (see Figure 3.2B). The seating arrangements were made so that subjects who knew each other outside of the experiment were seated together[24]. During these two inter-firm treatments, each of the 12 subjects was assigned a single BMP's data. They were informed about the quantity and the cost of their own BMPs. The neighbouring BMPs were selected to mimic actual spatial layouts in our study area. Details about the selected BMPS can be found in section 3.3.1.

In sessions with the intra-firm treatment, the subjects were seated around a single large table (see Figure 3.2C), and each subject was assigned two different BMPs (Product A and B). BMP pairs that a subject received were identical to the BMP pairs assigned to the subjects in the bilateral inter-firm treatment setting. In the illustrated example (Figure 3.2), farm 1 and farm 2 are considered neighbouring farms with a diminishing rate between their BMPs, and were assigned to a pair of participants that seated at the same table during the bilateral inter-firm treatment. In the bilateral intra-firm case, the same two farms were assigned together to a single person. This arrangement allowed us to explore how the subadditivity was handled when present between a producer own 2 fields, versus how it was handled if it manifested between fields owned by different producers.

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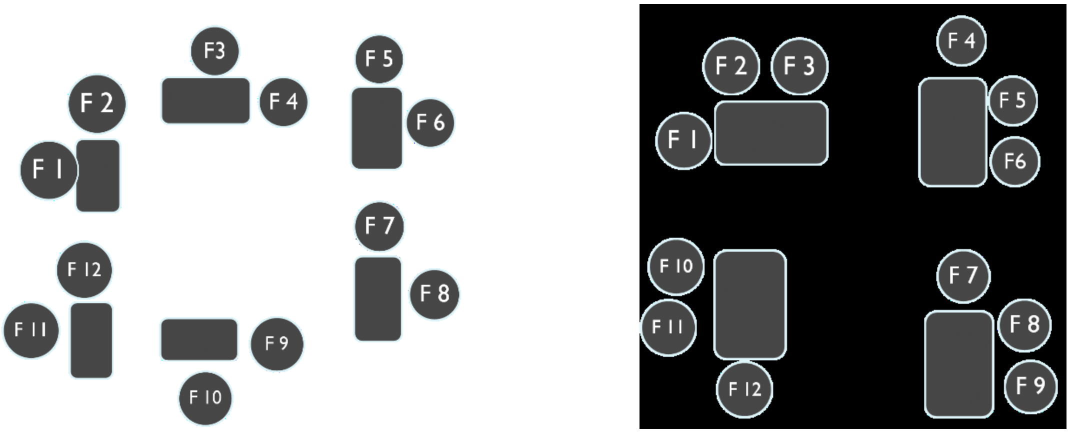
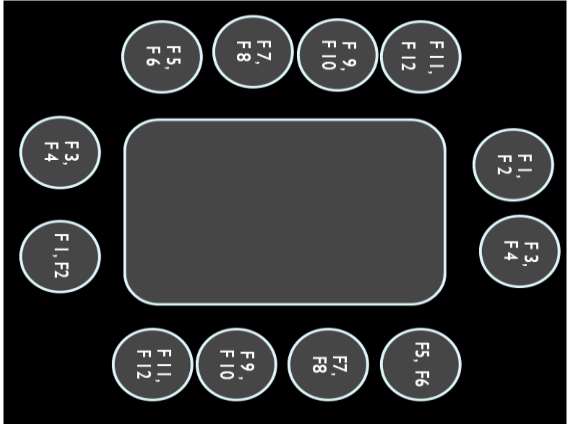
[24] Participants that arrived to the experiment together and apparently knew each other were asked to take seats next to each other. Participants who arrived to the experiment by themselves were asked if they knew anybody in the room, and if they did they were asked to seat next to the individual(s) they knew. However, this naturally happens in laboratory experiments anyway, and friends often come together and as human nature they sit next to each other unless advised otherwise.



A) Bilateral Inter-Firm **B) Multilateral Inter-Firm**



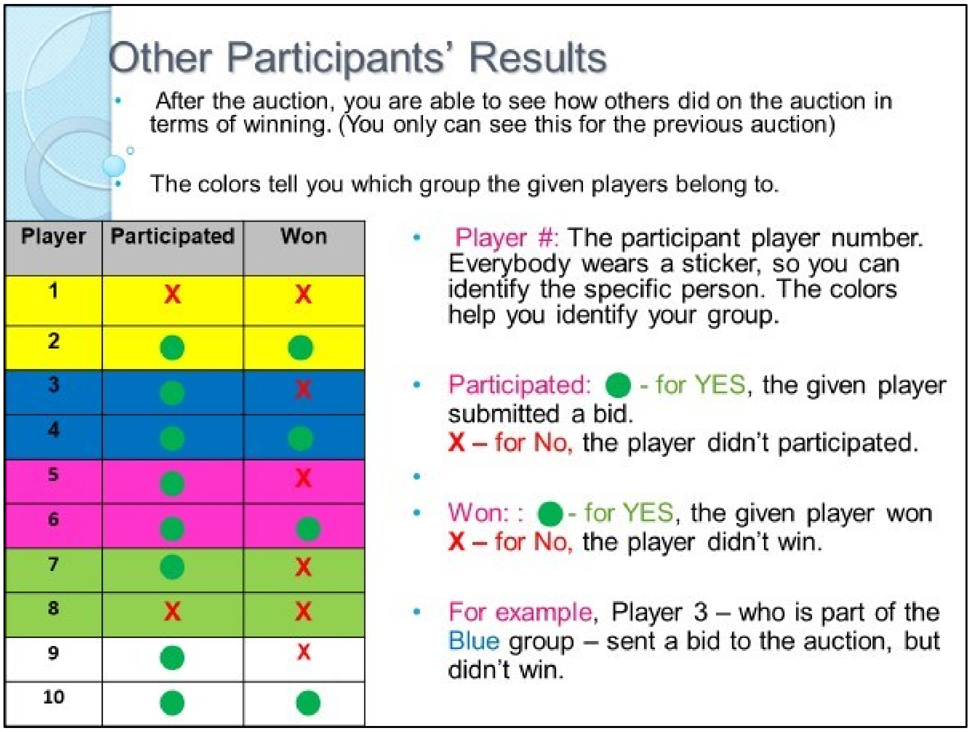
C) Bilateral Intra-Firm

Figure 3.2. Seating Arrangements and Farm Data Allocation at the Laboratory Experiments by Subadditivity Treatments

3.2.2.3 Information and Communication

The additional treatment involved investigating the role of communication among bidders. In order to accommodate communication and identification of other bidders, participants wore a sticker during the session with their number on it. In all the sessions, the auctions used the sealed bid format, where each participant only knew their own bid. Although this was a sealed bid auction, participants were able to see who submitted a bid and who won on the auction, but not the actual prices. The bidding behaviour of all the subjects was displayed on their computer screens in a table.

In the case of inter-firm treatments, participants' stickers were colour coded, and each table had its own colour. On their computer screens the table displaying the bidding result showed the subjects' numbers colored for easier identification (Figure 3.3).



Other Participants' Results

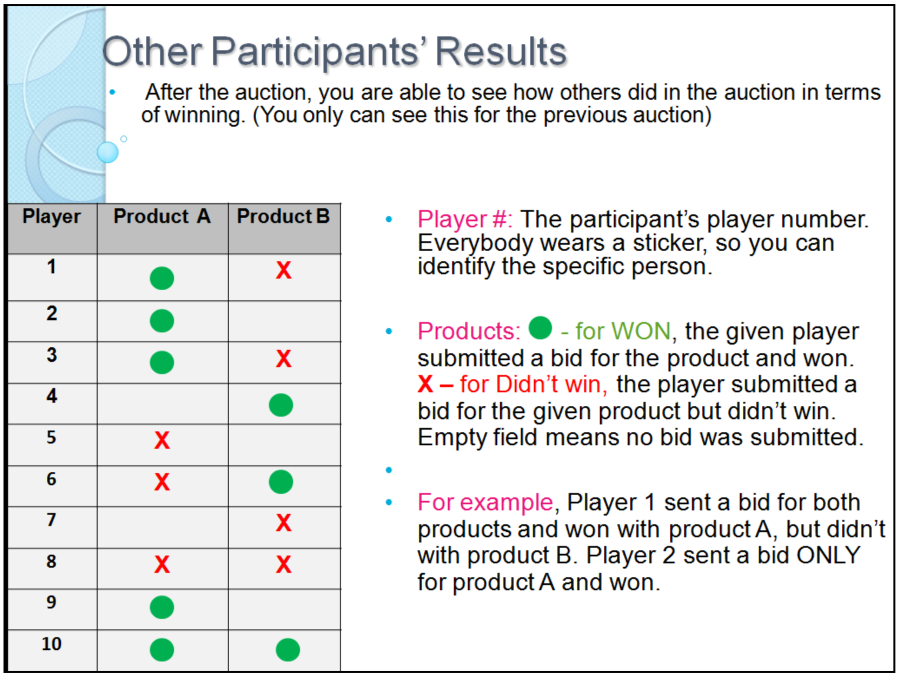
- After the auction, you are able to see how others did on the auction in terms of winning. (You only can see this for the previous auction)
- The colors tell you which group the given players belong to.

Player	Participated	Won
1	X	X
2	●	●
3	●	X
4	●	●
5	●	X
6	●	●
7	●	X
8	X	X
9	●	X
10	●	●

- Player #: The participant player number. Everybody wears a sticker, so you can identify the specific person. The colors help you identify your group.
- Participated: ● - for YES, the given player submitted a bid.
  X – for No, the player didn't participated.
- Won: : ●- for YES, the given player won
  X – for No, the player didn't win.
- For example, Player 3 – who is part of the Blue group – sent a bid to the auction, but didn't win.

Figure 3.3. Experimental Instruction Sample page, Explaining the Bidding Result, Bilateral Inter-Firm Treatment

During the intra-firm sessions, all the participants wore white stickers and the bidding result table had plain white background. Since each participant had two BMPs, the bidding results were shown separately for both of their BMPs (products A and B).



Other Participants' Results

- After the auction, you are able to see how others did in the auction in terms of winning. (You only can see this for the previous auction)

Player	Product A	Product B
1	●	X
2	●	
3	●	X
4		●
5	X	
6	X	●
7		X
8	X	X
9	●	
10	●	●

- Player #: The participant's player number. Everybody wears a sticker, so you can identify the specific person.
- Products: ● - for WON, the given player submitted a bid for the product and won.
  X – for Didn't win, the player submitted a bid for the given product but didn't win.
  Empty field means no bid was submitted.
- For example, Player 1 sent a bid for both products and won with product A, but didn't with product B. Player 2 sent a bid ONLY for product A and won.

Figure 3.4. Experimental Instruction Sample page, Explaining the Bidding Result, Bilateral Intra-Firm Treatment

The above information about the bidding results was provided in all sessions. Hence, participants knew which of their fellow participants submitted a bid and whether they won or not, but the actual submitted bid amounts were not disclosed to the others. In order to explore the potential effects of communication, in half the sessions communication was allowed among the subjects, while any type of communication was prohibited in the other half of the sessions. The sessions where communication was not allowed are referred to as silent sessions. When communication was allowed, the subjects were told they were allowed to share any information they wanted with anybody they wanted with. The communication was not facilitated electronically (i.e. there was no message sending possibility set up on their screens). Hence, the communication was mainly face-to face verbal communication. Moreover, the subjects were not prohibited from writing notes to each other on paper or even sharing their computer screen if they wanted to. Both of these behaviors were observed during the experiments.

3.2.2.4 Overall Design

The study employed a full factorial design in order to be able to study all the potential interactions between the different treatments (see Table 3.1). Each of the three subadditivity treatments had 8 sessions in total. In 4 of the 8 sessions, the subadditivity was incorporated into the bid ranking process, and it was ignored in the other 4 sessions. However, even in the sessions where the subadditivity was ignored, the subjects had been seated according to the seating arrangement relevant to the externality type. This allowed us to separate the effect of the seating arrangement from the effect of incorporating the subadditivity into the bid ranking. Two out of each 4 sessions mentioned earlier allowed communication among the subjects in a free chat format, and any type of communication was prohibited in the other 2 sessions. In total, 24 experimental sessions were carried out as shown in Table 3.1.

Table 3.1. Summary of the Laboratory Experimental Design

	Subadditivity incorporated into bid ranking	**Subadditivity ignored in bid ranking**
Bilateral Intra-Firm Seating (8 sessions in total)	Communication x2 repetitions Silent x2 repetitions = 4 sessions	Communication x2 repetitions Silent x2 repetitions = 4 sessions
Bilateral Inter-Firm Seating (8 sessions in total)	Communication x2 repetitions Silent x2 repetitions = 4 sessions	Communication x2 repetitions Silent x2 repetitions = 4 sessions
Multilateral Inter-Firm Seating (8 sessions in total)	Communication x2 repetitions Silent x2 repetitions = 4 sessions	Communication x2 repetitions Silent x2 repetitions = 4 sessions

3.3 Data

The BMP data used in the laboratory experiments was constructed based on wetland restoration cost information obtained from a small watershed on the Canadian Prairies. A detailed description of the study area can be found in the previous chapter (Section 2.6). Similar to the previous chapter, the environmental objective was to reduce phosphorus runoff from the agricultural lands. The abated phosphorus amount for each producer, assuming all the wetlands were restored on a given farm, was estimated by Yang et al. (2008) using a SWAT hydrological model. The wetland restoration costs used were estimated by Packman (2010) using a scenario in which 100% of the wetlands on each farm was restored. The estimated cost includes the actual physical restoration cost, the opportunity cost of the land is taken out of production, and the nuisance cost that is associated with the inconvenience of farm machinery having to go around the restored wetlands.

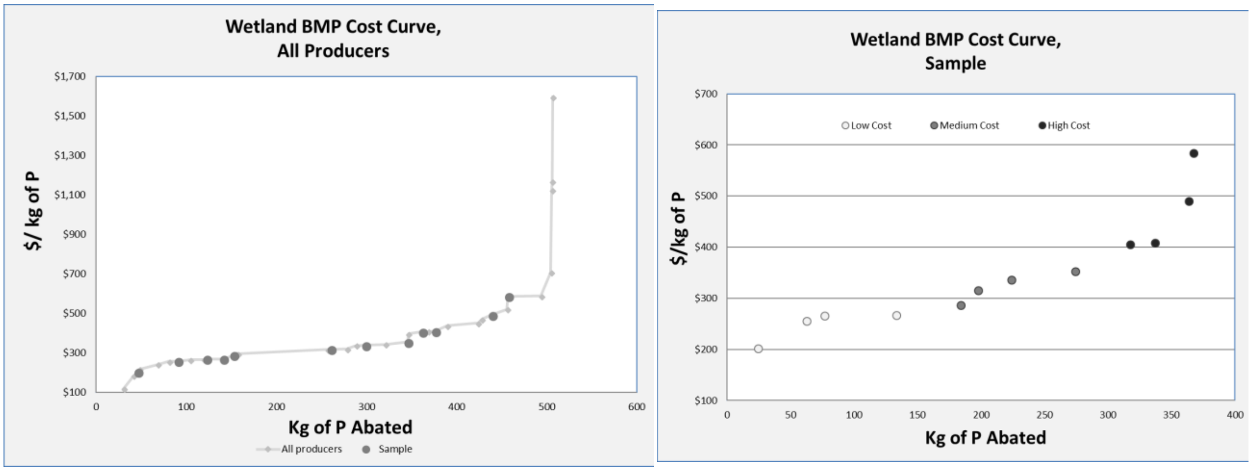


Figure 3.5. Supply Cost Curve for Wetland Restoration BMP

The budget used in the experiment was calculated similarly to the previous chapter and the various other studies using this dataset (see Boxall et al. 2008; Packman 2010 Boxall, Perger, and Weber 2013; Kits, Adamowicz, and Boxall 2014; Wichmann et al. 2017; Boxall et al. 2017) based on the National Farm Stewardship Program (NFSP) guidelines at the time of our base year[25] (2004). The actual NFSP program provided reimbursement for 50% of the direct cost of the wetland restoration up to a maximum of $20,000. The marginal cost curve

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[25] 2004 was chosen as the base year, because the cost values used from previous studies (Boxall et al. 2008; Packman 2010) were given in 2004 dollars. Moreover, the abatement level estimation used (Yang et al. 2008), was also calibrated for year 2004.

constructed was based on the selected wetland restoration BMP and resembles the "hockey stick" shape (see Figure 2.1), which is typical for conservation auctions (Brown et al. 2011).

3.3.1 Sampling and Group Selection

While the study area had a total of 36 producers, all of whom had potentially restorable wetland on their properties, 12 were selected to be used in the experiment for simplicity. The sampling was carried out in such a way that the mean, the variance (see Table 3.5) and the cost curve shape (see Figure 3.5) was preserved in order to have a fair representation of the producers' costs. Based on the cost per kg of phosphorus abated, the producers were divided into 3 cost categories: low, mid and high-cost. Since the aim of the experiment was to analyze potential diminishing marginal rate of BMP adoptions in close proximity, the geographical location of the farms was also considered during the sample selection. All the producers were mapped in the watershed and sample selection was intended to select producers that were representative of the various geographic locations across the watershed. Moreover, the selected producers in the sample were organized into groups where lands were geographical neighbours as much as possible (Figure 3.6).

Table 3.2. Sample Data Used

	Producer ID	Acre	Total Phosphorus Abated (kg)	Total Cost ($)	Unit cost ($/kg)	Cost Type	Group Setup	
							Bilateral Inter-Firm [a]	Multilateral Inter-Firm[b]
1	24	9.81	38.42	$9,910.97	$257.97	Low	1	1
2	28	15.72	43.40	$17,666.61	$407.03	High	2	2
3	29	3.78	13.73	$4,361.04	$317.74	Mid	1	1
4	32	8.01	19.64	$8,050.47	$410.00	High	5	2
5	33	11.71	50.95	$14,672.47	$287.98	Mid	6	3
6	36	10.97	26.55	$13,074.26	$492.35	High	6	4
7	40	18.43	56.33	$15,136.12	$268.70	Low	3	3
8	41	4.87	23.51	$4,799.23	$204.12	Low	3	3
9	43	1.24	3.49	$2,045.37	$585.85	High	2	2
10	50	2.79	14.07	$3,768.85	$267.94	Low	5	1
11	56	10.50	35.00	$12,000.00	$342.86	Mid	4	4
12	103	24.96	50.40	$17,854.68	$354.28	Mid	4	4
Total		**122.78**	**375.48**	**$123,340.08**	**$328.48**			

a) In the case of bilateral treatment, the 12 BMPs were divided into 6 groups with diminishing marginal rate of return between the pairs. The number denotes the group that the producers belong to.

b) In the case of the multilateral treatment, the BMPs were divided into 4 groups with diminishing marginal rate of return within the 3 BMPs. The number denotes the group that the producers belong to.

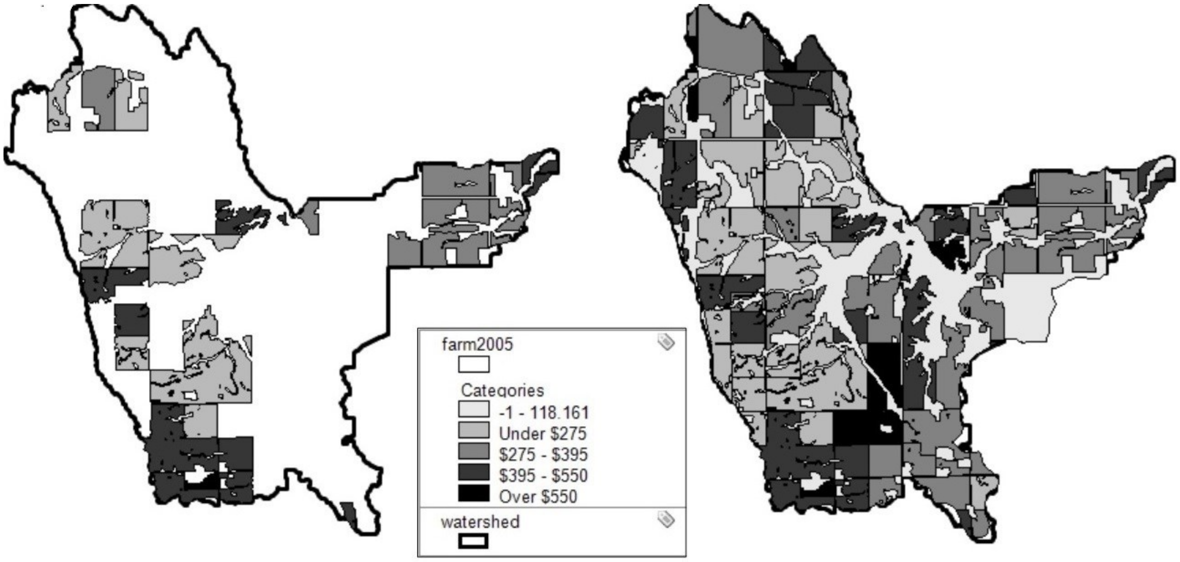

Figure 3.6. STC Watershed, Wetland Restoration Cost.
All Producers on the Left, Sampled Producers on the Right

3.4 Analysis Methods

This section describes the two main statistical methods that were used analyzing the experiment results. First, the overall auction performance was addressed by three measurements described below. These measurements were used to compare the overall auction successes between the treatments. The second step was to analyze the individual bidding behaviour in order to explore the mechanism that led to their bidding behaviour.

3.4.1 Overall Auction Performance

3.4.1.1 Measuring Auction Success

In general, the effectiveness of budget-based conservation auctions can be measured by three main factors: a) the quantity of the environmental benefit generated with the given budget, b) how much money is wasted and paid above the actual cost, and c) general cost efficiency, which usually combines both the quantity of environmental improvement and the monetary outlay.

As our objective is to address the diminishing marginal rate of returnamong BMPs, the main focus of the overall performance is the abatement quantity, which is based on the kg of phosphorus abated by the BMPs adopted by the winners. As there is a diminishing rate of return of abatement between neighbours' BMP adoption, we need to distinguish between different quantities of abatements, which are referred to as gross and net. Gross abatement

(Q_{Gross}) refers to the quantity that was calculated by simply adding up all the units abated (q_i) by producers (*i*) who won at the auction and adopted the BMP. This is shown as:

$$Q_{Gross} = \sum_{i \in winners} q_i \tag{3.2}$$

However, if there is a diminishing marginal rate between the producers' BMP adoption, this is not the true abatement amount. In order to calculate the true abatement amount, the amount of the negative synergy that would occur among the winners needs to be deducted from the overall amount. This is referred to as the net quantity (Q_{Net}). As the subadditivity was assumed to be a 10% reduction for each neighboring BMP, Q_{Net} is calculated as follows:

$$Q_{Net} = \sum_{i \in winners} q_i (1 - 0.1 * \sum_{j \in winners} d_{i,j}) \tag{3.3}$$

where $d_{i,j}$ is a dummy variable, which is 1 if the i^{th} and the j^{th} bidders are neighbours and 0 otherwise.

While all the treatments used the same BMP cost data, the optimal BMP adoption patterns and hence the optimal abated net quantities, were slightly different for the different treatments. In order to compare the performance between the three subadditivity treatments, the net abatement quantity achieved (Q_{Net}) is converted into a percentage measure and referred to as Environmental Efficiency (EE):

$$EE = \frac{Q_{Net}}{Q^*_{Net}} \times 100\% \tag{3.4}$$

where Q^*_{Net} is true abatement quantity achieved if all the potential bidders participated in the auction and submitted a bid equal to their own cost. EE ranges between 0 and 100%, where 100% represents the optimal case where the auction reached the highest level abatement quantity (Q^*_{Net}) that could be achieved with the given budget and covering producers' BMP adoption costs. Based on construction, the higher this number is, the more successful the auction.

The second measurement discussed is the information rent, which is one of the most commonly examined measurements in the reverse auction literature. The information rent is the difference between the auctioneers total payments and the actual total bidders' costs. Some studies used this value directly (Cason and Gangadharan 2004, 2005), others scale it to the cost (Schilizzi and Latacz-Lohmann 2007; 2007b; 2013). Alternatively, it can be scaled to the total spending (Boxall, Weber and Perger 2013; Boxall et al. 2017; Kits, Adamowicz and Boxall 2014; Wichmann et al. 2017). The latter approach is followed here, and the information rent was measured as follows:

$$PRENT = \frac{payment\text{ - }actual\ cost}{payment} \times 100\% \tag{3.5}$$

PRENT ranges between 0 and 100%, where 0% represents the case where there is no rent seeking present, and the entire auctioneer's outlay is just covering the costs of adoption. Based on construction, the lower the number is, the more successful the auction. This measurement cannot be negative unless some producers are implementing BMPs without getting compensated fully for their costs.

The third frequently used performance measure in auctions is cost effectiveness, which informs the auctioneer the average cost of a unit of abatement. However, the value of this measurement depends on what we use as the quantity of abatement. In order to measure the actual $/ kg P abated (C'_{Net}), the net quantity (Q'_{Net}) is used in the calculation is as follows:

$$C'_{Net} = \frac{budget\ spent}{Q'_{Net}} \tag{3.6}$$

Again, the scope of the underlying interdependency could lead to slightly different abatement quantities, hence different unit costs in the optimal case. In order to be able to compare the different treatments, the cost effectiveness measurement was turned into a percentage. The percentage of cost effectiveness measurement is referred to as Cost Efficiency (CE), and is calculated as follows:

$$CE = \frac{C^*_{Net}}{C_{Net}} \times 100\%, \tag{3.7}$$

where C^*_{Net} is the average cost of a kg of phosphorus abatement in the optimal case that would be achieved if all the potential bidders participated in the auction and submitted a bid equal to their own cost. CE ranges between 0 and 100%, where 100% represents the case where the cost of a kg of phosphorus abated is equal to the optimal cost (C^*_{Net}), realized with the highest level of abatement quantity (Q^*_{Net}). Based on construction, the higher this number is, the more successful the auction.

3.4.2 Bidding Behaviour

In addition to the overall auction performance, individual bidding behaviors were also analyzed. The analysis expanded the original bidding theory established for conservation auctions by Latacz-Lohmann and Van der Hamsvoort (1997). These authors present a theory where the optimal submitted bid is a function of 1) the individual cost, 2) the risk aversion level and 3) the expectation of lowest ($\underline{\beta}$) and highest ($\overline{\beta}$) accepted bid in the auction. The authors showed that the optimal bid is equal to the adoption cost plus a rent seeking amount, which depends on the agent risk aversion level and the expected bid caps ($\underline{\beta}$, $\overline{\beta}$). It is assumed that rational agents would submit a bid if their expected utility of participation is positive. This can be shown as:

$$bid^* = \text{cost} + f\left(risk\ aversion, \overline{\beta}, \underline{\beta}\right) \qquad (3.8a)$$

$$\text{Participate if: } U(bid^* - cost) * Prob(bid^* < \overline{\beta}) > 0 \qquad (3.8b)$$

For easier interpretation, studies of conservation auctions often scale the submitted bids to the cost and use the percentage of the *markup* the individual asks on top of their adoption cost (Cason, Gangadharan, and Duke. 2003a; Cason and Gangadharan 2004; 2005; Vukina et al. 2008). Using the markup instead of the actual bid as a left-hand side variable also shifts the focus of the analysis to the information rent instead of the submitted bid. The markup is simply calculated as shown below, and its value is equal to zero if the bid is equal to the cost of adoption:

$$markup^* = \frac{bid^* - cost}{cost} = \frac{f\left(risk\ aversion, \overline{\beta}, \underline{\beta}\right)}{\text{cost}} \qquad (3.9a)$$

$$\text{Participate if: } U(markup^*) * Prob(bid^* < \overline{\beta}) > 0 \qquad (3.9b)$$

The theory that risk aversion influences bidding behaviour in conservation auctions using discriminatory pricing has been confirmed in the laboratory (Wichmann et al. 2017). On the other hand, field conservation auctions in Indonesia using uniform pricing did not find statistical significance of risk aversion in their initial model, and they excluded risk aversion measures in their final model (Leimona and Carrasco 2017). The initial model in our study also included a risk aversion measure, but it was not statistically significant, and thus has been excluded from the final model. This present study used a risk score that was elicited by asking participants six lottery choices in a questionnaire adapted from the experimental literature (Holt and Laury 2002; Ferraro 2004; Leimona and Carrasco 2017). On the other hand, Wichmann and colleagues used Eckel-Grossman risk elicitation method (2016), which potentially could be a reason for the difference in results.

During an auction, bidders balance their net payout (bid-cost), with the probability payout with the acceptance possibility, which is the probability of the bid being less than the upper bid threshold $\text{Prob}(\text{bid} < \overline{\beta})$ (Latacz-Lohmann and Van der Hamsvoort 1997; Wichmann et al. 2017; Schilizzi and Latacz-Lohmann 2013). While this is accurate description of the bidding process when each bidder has a single unit to sell, this needs to be modified if the quantities offered by the bidders vary. In conservation auctions, where the quantity offered for sale by the bidders varies, bids are most often ranked on a per unit basis, such as \$/kg Phosphorus abated. As a result, the upper bid threshold, the bid, as well as the cost are considered on a per unit basis. Therefore, the net payout to a bidder is the difference between the bid and cost multiplied by the quantity: (bid-cost)*quantity. Since rational agents maximize their expected utility, which is monotone increasing in their net payout, this clearly gives an intuitive reason why the quantity of the BMP can influence the bidding behavior.[26] Moreover, this has been confirmed in a field conservation auction in an Indonesian watershed. Leimona and Carrasco (2017) analyzed a conservation auction that aimed to induce erosion control BMP adoption among coffee farmers, and found that the plot size played a significant role in bidding behavior. Hence, the quantity of abatement of the BMP (q_{ig}) is included in the regression.

While theory tells us that beside risk aversion, the expected bid thresholds ($\overline{\beta}$ and $\underline{\beta}$) are the basis for bidding behaviour, what factors influence the expectations related to these thresholds is less clear. The expectation of these bid thresholds could potentially be influenced by various socio-demographic characteristics. Basic personal traits, such as gender, have been found to play a significant role in bidding behaviour in various auctions such as eBay (Stafford and Stern 2002). Moreover, even non-object related laboratory auctions show that bidding behaviour differs between men and women (Ham and Kagel 2006). There is some empirical evidence that education has a significant effect on BMP adoption (Frisvold, Hurley and Mitchell 2009). On the other hand, others found that education, age, ethnicity and family size did not play a role in bidding behaviour in field conservation auctions (Leimona and Carrasco 2017). Thus, our initial analysis included the following collected personal traits: age, gender and education level. However, only the age variable turned out to be significant, and therefore the other variables were excluded from the final analysis. Moreover, even the age

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[26] Proof is in the appendix.

variable was only significant in the participation equation, and was excluded from the markup equation for simplicity.

While cooperation via communication can affect all laboratory auctions, it can be especially important when neighbours' behaviours can directly affect each other.. Windle et al. (2009) found that cooperation among bidders in auctions with positive synergy increased auction performance when communication was allowed. Jansen et al. (2010) found that allowing communication in a public pool experiment with negative spatial dependency improved social outcomes and prevented the tragedy of commons. However, in these studies cooperation benefited both parties. On the other hand, in this present study a participant who refrained from bidding to increase its neighbour's chance of winning on the auction, did not benefit from this cooperation, and hence was inspired by altruistic motives. Cooperation, especially altruistic cooperation has been reported to increase among people with higher social connections. Lorenze, Huffman and Meier (2011) found that pre-existing social ties increase cooperation and enforces altruistic patterns in a laboratory experiment. In order to capture the role of pre-existing social connections in the bidding behaviour, a social tie measurement was included in the bidding behaviour regression as a right-hand side variable ($socialtie_i$[27]). In this present study the subadditivity was set up in a way to affect the chance of winning, but not the payout in the case of winning. Hence, it was not surprising that the social tie variable was only significant in the participation equation, and hence excluded from the markup equation for simplicity.

In repetitive discriminatory auctions, individual bidding strategy can change over time, and this learning effect can be incorporated into the regression in various formats. If there are not many repetitions, dummy variables can be used to identify the repetitions (Kits, Adamowicz and Boxall 2014; Wichmann et al. 2017). However, as the learning effect has been observed to diminish over time, most studies use the time variable with a functional form that describes this notion. Some studies use the natural logarithm of the time variable (Cason and Gangadharan 2005; Boxall et al. 2017), others use functional forms based on the inverse of the time variable (Cason and Gangadharan 2004; Banerjee, Shortle, and Kwasnica 2015), and there are studies that report results using both of these formats (Cason,

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[27] Social tie measurement was calculated using the following scale: 0 = completely unknown individual, 1 = familiar face, 2 = acquaintance, 3 = friend, 4 = spouse/family member/ best friend. As most experimental studies simply compare the behavior of groups of random people vs. pre-existing social circles (clubs, associations), there are not many occasions when pre-existing social ties have been measured. However, Montjoye et al. (2014) used a similar scaling to our study (the 0-3 scores being identical to ours but the closest relationships being further distinguished from our category 4).

Gangadharan, and Duke 2003). In this study the natural logarithm of the time variable is used.

When the overall auction performance is analyzed, including the learning effect as an isolated variable can be sufficient as it describes how the auction performance changes over time. However, using a single learning effect variable at the individual bidder's level assumes that there is one general trend among all bidders regardless of their costs. However, the behavior of low-cost bidders that learn that their bid won on the first repetition is likely be different from high-cost bidders that learn that their first bid was not successful.

Theory tells us that low-cost producers are likely to shade their bids more than high-cost producers in an auction with discriminatory pricing (Latacz-Lohmann and Van der Hamsvoort 1997). This theory has been empirically verified in the BushTender conservation auction in Australia (Stoneham, Chaudhri and Strappazzon 2003) and is also supported by various laboratory experiments. Moreover, the cost is present in the denominator of markup equation (3.9), which suggests that the higher the cost, the lower proportion of the markup is asked for by the bidders. If there is no communication and bidders have no initial information about their cost related to others, participants are unlikely to know whether they are low- or high-cost producers. However, this is something they can learn over time with repetition. In order to capture this effect, dummy variables for the cost types are introduced: $dlow_{ig}$,$dmid_{ig}$ and $dhigh_{ig}$. The $dlow_{ig}$ variable is 1 if the individual was assigned one of the low-cost BMPs and zero otherwise; the $dmid_{ig}$ variable is 1 if the individual was assigned one of the mid-cost BMPs and zero otherwise; $dhigh_{ig}$ is 1 if the individual was assigned to one of the high-cost BMPs and zero otherwise.[28] In order to capture the different learning patterns of producers with different cost-types, the model included the natural logarithm of the round number (*lnt*) and its interaction terms with the above described $dlow_{ig}$ $dmid_{ig}$ and $dhigh_{ig}$ variables. This model setup assumes that players initially do not know how their cost compares to others'; but as they learn over time their reaction to it can differ based on their cost-type.

In addition to the variables discussed above, the regression model included treatment dummy variables ($dDMR_i$ and $dchat_i$). Since the main focus here is on the diminishing marginal rate of BMP adoptions , we ran separate regressions for the three subadditivity treatments in order to keep the model simple and to eliminate the need for interaction terms. This means that the data was divided into 3 segments based on the scope of the subadditivity: intra-firm,

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[28] Each observation was associated with exactly one cost group: $dlow_{ig} + dmid_{ig} + dhigh_{ig} = 1$.

bilateral, and multilateral inter-firm treatment. The three treatments were analyzed by separate regressions.

While random effects panel data regression is commonly used in the literature analyzing bidding behaviour (Cason and Gangadharan 2004, 2005; Kits, Adamowicz, and Boxall 2014), it cannot be employed in this dataset. In the case of the intra-firm treatments, each individual had two potential BMPs to bid on, which resulted in two observations for each subject at each auction. Instead of panel data, the data was analyzed using clustered standard errors at the experimental session and the subject level; another method which has been used in the literature (Wichmann et al. 2017; Banerjee, Shortle, and Kwasnica 2015).

In our model each subadditivity treatment had 8 sessions with 12 individuals each resulting in 96 clusters indexed by *i*. In the model *g* denotes the observation identifier. For the bilateral and multilateral inter-firm treatments each individual had 15 observations, one for each round of auctions, which resulted in 1440 (N) observations for each of these treatment options. In the case of the intra-firm treatment, each individual had 30 observations, 2 for each round of auctions, resulting in 2880 (N) observations for that treatment. The formal description of the markup estimation equation can be written as follows:

$$markup = X_{ig}\beta + e_i + u_{1ig}$$

$$\begin{aligned} &where: \\ &X_{ig}\beta = \beta_0 + \beta_1 dlow_{ig} * ln\,t + \beta_2 dmid_{ig} * ln\,t + \beta_3 dhigh_{ig} * ln\,t + \beta_4 dchat_i \\ &\qquad + \beta_5 dDMR_i + \beta_6 size_{ig} \end{aligned} \tag{3.10}$$

And where e_{1i} represents the time invariant unobserved individual characteristic and u_{1ig} is the normally distributed error term assumed to be uncorrelated among individuals ($\sim N(0,\sigma^2_{u1,g})$).

Auction participation (i.e. submitting a bid) was voluntary in each round of the experiment, which allowed investigation of participation decisions. Subjects could refrain from participation for various reasons. They may have decided not to bid because they did not think they had a chance to win, and they wanted to avoid the frustration that would result from losing on the auction. This behaviour has been identified in laboratory settings studying reverse auctions (Ding et al. 2005). Moreover, they could also decide strategically not to bid in order to not worsen their group-mates' (representing neighbouring BMPs) chance of winning in the auction. In the case of intra-firm treatments, participants may have chosen not to bid with one of their BMPs in order to not reduce their chance of winning with the other.

Since the participation (P) decision is a discrete choice, it can be analyzed using a latent variable model. If we assume the underlying participation decision is represented by a normal distribution, the model becomes a probit model. The probit model's standard error can also be clustered to the individuals just as it can be in the markup equation, and can be written formally as equation 3.11. Since most laboratory experiments on reverse auctions do not allow participants to refrain from bid submission, there are very few examples of this type of analysis in the experimental literature. Moreover, even studies that employ voluntary participation often do not execute formal econometric investigation of the participation decision, but focus their analysis on descriptive statistics (Ding et al. 2005; Kohler et al. 2013). To our knowledge, there is only one study (Wichmann et al. 2017) that used a formal regression for auction participation. Their participation model was set up in the following structure, and assumed either normal or linear underlying distributions:

$$P_{ig} = \begin{matrix} 1 \; if \;\; P^{*} = Z_{ig}\gamma + \eta_i + u_{2ig} > 0 \\ 0 \; otherwise \end{matrix} \qquad (3.11)$$

where η_i represents the time invariant unobserved individual characteristic and u_{ig} is the normally distributed error term assumed to be uncorrelated among individuals ($\sim N(0,\sigma^2_{u_g})$). The Z_{ig} represents the regressors matrix, which includes all the variables from the markup model. It also includes an additional variable ($socialtie_i$ and age_i) representing the average social tie of the ith individual to her group mates and the participant's age, respectively. In the case of intra-firm, this variable represents the average social of the individual to all the participants. It can be written as follows:

$$\begin{aligned} Z_{ig}\gamma = {} & \gamma_0 + \gamma_1 dlow_{ig} \ln t_{ig} + \gamma_2 dmid_{ig} * \ln t_{ig} + \gamma_3 dhigh_{ig} * \ln t_{ig} + \gamma_4 dchat_i + \\ & + \gamma_5 dDMR_i + \gamma_6 age_i + \gamma_7 socialtie_i + \eta_i + u_{2ig} \end{aligned} \qquad (3.12)$$

Assuming truncated normal distribution, the probability of submitting a bid given the characteristic of the observation can be written as:

$$Prob\left(P_{ig} = 1 \,\|\quad Z_{ig}\gamma\right) \qquad (3.13)$$

Estimating the participation decision (3.13) and the markup models (3.10) separately inherently assumes that they are independent decisions, which may not be the case. Heckman (1979) showed that if the error term of the two equations is not independent, the estimation result could suffer from sample selection bias. To prevent selection bias, participation and the markup, the model was set up as Heckman's two-step model. The probit model estimation result from the participation equation was included into markup equation as an additional regressor as follows:

$$E\left(markup_{ig}\ \| \qquad = X_{ig}\beta + \rho_{u_1u_2}\delta_{u_2}\lambda_i \frac{\Phi(-Z_{ig}\gamma)}{1-\Phi(-Z_{ig}\gamma)} \tag{3.14}$$

$$\begin{aligned} where\ \rho_{u_1u_2} &= corr(u_{1ig}, u_{2ig}) \\ \lambda_i &= inverse\ mill\ ratio \end{aligned}$$

If the two models are truly independent, and the covariances are zero, the $\rho_{\varepsilon u}$ estimation should be zero. However, if it is statistically significantly different from zero, without the selection model the markup estimation would have a selection bias.

While this type of selection model in laboratory auction has not been used before, it is quite common in studies analyzing bidding behaviours on actual government procurement auctions in the financial sector (Ayuso and Repullo 2001; Jofre-Bonet and Pesendorfer 2003; Bruno, Ordine and Scalia2005; Linzert, Nautz and Bindseil 2006, 2007). Selection models have also been used to compare bidding behaviours between internet and in-person auctions (Diekmann, Roe and Batte 2008; Liu, Shiu and Sun 2013), as well as analyzing the effect of online sellers' reputation on bidding behaviour (Livingston 2005).

3.4.3 Hypotheses

The focus of this paper is the effect of diminishing marginal return on reverse auction performance, demonstrated in laboratory experiments. While the previous experimental chapter's focus was the overall effectiveness of the auction, this chapter is more focused on the individual behaviour. More specifically, how bidding behaviour changes if the subadditivity is incorporated into the bid ranking. Our first hypothesis focuses on how conservation auction participation changes in cases where the diminishing marginal rate of return is incorporated into the winner selection process.

1) Hypothesis: Incorporating the subadditivity into the winner selection process can change the effectiveness of the auction.

To address this hypothesis, a *t*-test was carried out on the overall auction performance measurements: PRENT, EE, and CE. If incorporating the subadditivity into the bid ranking process enhances the auction, the percentage of information rent decreases and the environmental and cost efficiency increases.

2) Hypothesis: if bidders are informed about the subadditivity they bid less aggressively and participate less in the auction.

Generally, preventing collusion in government auctions is a main concern and several guidelines exist for minimizing it (Klemperer 2002). However, when the provided services among bidders have a subadditivity between them, collaboration may actually enhance the performance of the auction. If informing the participants about the subadditivity into the bid ranking is beneficial, the related dummy variable in the markup equation is negative.

3) Hypothesis: Coordination between bidders enhances auction outcome.

Higher levels of social interaction, such as communication, smaller group settings and higher levels of social ties among bidders, increase auction effectiveness when there is a diminishing marginal rate of return between the BMPs adopted. If the communication dummy variable is negative in the markup equation, the coordination via communication leads to even more bid shading and therefore worsens auction outcome. On the other hand, a negative communication dummy in the markup equation would show that communication enhances auction performance. If the social tie variable is statistically significant and negative, it would signify that participants are more likely to altruistically accommodate others if they have a stronger social relationship to them.

3.5 Results

3.5.1 General Observations

Most laboratory conservation auctions do not allow communication during the experiment (Banerjee, Shortle, and Kwasnica 2015; Boxall et al 2017; Boxall, Perger and Weber, 2013; Cason and Gangadharan 2005; Wichmann et al. 2017). However, in real life there is nothing that prevents participating landowners discussing their biding strategy with fellow producers. Some laboratory experiments allow communication to mimic this real-life situation (e.g. Cason and Gangadharan 2004; Kits, Adamowicz and Boxall 2014). However, in this study, communication was not just allowed in half of the sessions, but was also recorded, which gave us a unique opportunity to explore the nature of the communication that happens in a laboratory auction. Before the formal statistical analysis, the next section provides some insight on the communication observed.

3.5.1.1 Communication Patterns

When communication was allowed, some form of general discussion regarding the auction process was always present - such as discussion of the computer screens, payment calculation, bid ranking rules etc. However, the depth and the magnitude of information shared regarding their BMP costs, bids or bidding strategy varied among the sessions to a great extent. In some sessions, the discussion completely diminished after the trial rounds, and never went beyond the general discussion of the auction process even though the participants were reminded that communication was allowed. In some other sessions, detailed information about bidding prices were shared openly and even bidding strategies were discussed constantly over the entire session. According to voice recordings, this discussion changed bidding and participation decisions at least on occasion.

In the three different subadditivity treatments, participants were seated in 3 different layout patterns as described in section 0. As observed, this seating arrangement affected the scope of the communication even if the subadditivity was not introduced into the bidding and was not affecting the auction process. During the inter-firm treatments, participants were seated in groups and they shared more information with their own group than they shared with other participants in the lab. This behaviour was seemingly intentional as participants were often whisperings to each other, and voice recordings show that they even reminded each other to keep their voices down, ensuring only their group benefited from their information sharing. Participants turning their computer screen toward their group mates was not uncommon either, which meant complete sharing of every cost and bid submission during the session. People who knew each other were encouraged to sit in the same group, which encouraged this behaviour. However, it was often present even if the group mates previously did not know each other.

During the intra-firm sessions, participants were seated around a single conference table, but still showed preference to communicate and share information only with their neighbours. Again, people who knew each other tended to sit right beside each other, which facilitated this behaviour, but it was also often present among strangers. Generally, information sharing varied more during the intra-firm session than it did in the inter-firm session. When people were seated in groups of 2 or 3, there was always some information sharing among group mates, at least in some of the groups. When all participants were seated around the same table, sometimes the scope of the communication did not go beyond the general discussion about the auction procedure. However, in other sessions a few people started conversations about actual bidding prices early in the experiment, which then spread out to the entire group and continued during the entire span of the experiment. On the other hand, such full information sharing toward all other participants never happened during the inter-firm sessions, and the scope of information sharing mainly remained within their group.

3.5.1.2 Participants' Verbal Reactions to the Subadditivity

In sessions where the underlying hydrologic relationship between BMPs was introduced into the bidding process and communication was allowed, the effect of this subadditivity was frequently discussed during both types of inter-firm treatments, but not much during the intra-firm sessions. In some cases, participants did not completely understand when this dependency mattered, but they felt that they needed to respond to it somehow to be fair to their group mates. Voice recordings show that in one of the bilateral inter-firm sessions, participants in a group agreed at the beginning that they would alternate in bid submission in order not to diminish each other's chance of winning.

However, others were completely aware of how exactly the subadditivity worked and when it mattered most. In a bilateral inter-firm session, group mates discussed what the subadditivity meant to them at the very beginning, and agreed that it mattered if they were mid-cost producers. The following exchange recorded illustrates this:

> Player A: *"the problem is that it's possible for both of us to lose because we both bid…"*
>
> Player B: *"…it only makes sense not to participate if we are both really close to the edge…"*

Participants in this particular group knew each other before the experiment. They shared their computer screens and discussed participation and bidding decisions during the entire session. They both kept submitting bids when they had low-cost BMPs. When they got higher cost BMPs in the second block, they started to accommodate one another after the first repetition:

> Player A: *"How about I do not participate and you participate and see what happens"*

When their strategy seemed to be working, the bidder who accommodated the other was implying that he expected compensation for it: "*You're paying for lunch; you're totally paying for lunch…*"

Discussions about compensation for accommodation were present in other groups as well. In another group in the same session, a person offered to refrain from participation for compensation. As the other person did not respond affirmatively, neither of them stopped bidding.

During a multilateral inter-firm session when the subadditivity was incorporated into the bidding and communication was allowed, one of the groups decided to accommodate and compensate each other. They acted as a united group during the entire experiment. They turned all 3 computer screens towards each other and seemingly were making participation and bidding decisions together. When the session finished, instead of taking their individual earnings, they asked for their payout to be pooled and split equally among the group members. Unfortunately, they were whispering during the entire experiment to ensure nobody would hear their conversation, hence most of their voice recordings are inaudible and we do not know how exactly they came to this agreement.

3.5.2 Overall Auction Performance Analysis

If there is a diminishing marginal rate of BMP adoptions, it needs to be considered in the total abatement calculation regardless of whether it was incorporated into the bidding process. Failing to account for this subadditivity can be misleading and leads to inflated abatement quantities. When the subadditivity was not incorporated into the bidding process, the auctions apparently resulted in 185.6 kg phosphorus abatement (Q'_{Gross}) on average (see Table 3.3). However, the true abatement quantity (Q'_{Net}) was 168.4 kg on average. Introducing the subadditivity into the bid ranking apparently caused the total abatement to be slightly decreasing; the gross abatement became only 184.6 kg. However, the actual net abatement increased from 168.4 kg to 172.2 kg and the increase was statistically significant (P=0.009). Besides increasing the actual abatement quantity, incorporating subadditivity also reduced the proportion of the information rent paid out to the bidders from an average of 10.7% to 7.8% and the decrease was statistically significant (p=0.000). Although cost effectiveness was high, even if the subadditivity was not incorporated into the bid ranking process (89.5%), incorporating the subadditivity into the auction increased cost efficiency by 4.8% which was statistically significant (p=0.000).

However, the effect of incorporating the diminishing marginal rate into the bidding strongly depended on the scope of the subadditivity. While the average number of submitted bids slightly decreased in all 3 subadditivity treatments, this change was not significant for either inter-firm treatment (p=0.5278 for the bilateral and p=0.1255 for the multilateral inter-firm externality), but it was significant for the intra-firm treatment (p=0.0482). The extracted rent amount showed the opposite trend. The rent extraction rate dropped for both inter-firm treatments. It decreased from 11.3% to 8.0% (P=0.000) and 10.2% to 5.2% (P=0.000) in the bilateral and the multilateral inter-firm treatments, respectively. Simultaneously, the extracted rent only slightly decreased in case of intra-firm treatment from 10.7% to 10.4%, and it was not statistically significant (p=0.6163).

Table 3.3. Mean Values of Overall Auction Performance Measurements by Subadditivity Treatments

Subadditivity Treatments	Subadditivity Used in Bid Ranking	Number of Bids Submitted	PRENT: Percentage of Information Rent (%)	Budget Spent (%)	Phosphorus Abatement Quantities (kg)		EE: Environmental Efficiency (%)	CE: Cost Efficiency (%)
					Q'_{Gross}	Q'_{Net}		
Bilateral Intra-Firm	-	11.0	10.7%	94.8%	191.0	179.7	85.4%	89.3%
	Yes	10.7	10.4%	94.8%	189.0	181.0	86.0%	90.2%
Bilateral Inter-Firm	-	11.3	11.3%	90.8%	183.4	173.4	82.5%	88.7%
	Yes	11.2	8.0%	88.5%	185.9	178.0	84.7%	93.6%
Multilateral Inter-Firm	-	11.4	10.2%	88.3%	182.3	152.1	81.4%	90.0%
	Yes	11.2	5.2%	83.5%	178.7	157.7	84.4%	98.7%
Overall Average	**-**	**11.2**	**10.7%**	**91.3%**	**185.6**	**168.4**	**83.58%**	**89.5%**
	Yes	***11.0***	***7.8%***	***88.9%***	***184.6***	***172.2***	***85.0%***	***94.3%***

Banded (shaded) rows are the mean values from sessions when the diminishing marginal rate of BMP adoptions was incorporated into the bid ranking process, and non-banded (white) rows are the mean values from sessions ignoring the subadditivity during the auction.

The opposite pattern was observed for the Environmental Efficiency (EE) changes. Introducing the subadditivity into the bidding significantly increased the EE for both inter-firm treatments, but not for the intra-firm one. EE increased from 82.5% to 84.7% (P=0.026) and from 81.4% to 84.4% (p=0.0043) in the bilateral and the multilateral inter-firm treatments, respectively. At the same time, it only slightly increased for the intra-firm sessions from 85.4% to 86.0% and the improvement was not statistically significant (p=0.465).

Consequently, the Cost Efficiency (CE) also presented a similar trend. CE increased by 4.9% from 88.7% to 93.6% in the bilateral (p=0.0000) and by 8.7% from 90.0% to 98.7 (p=0.000) in the multilateral intra-firm treatments. The CE only changed by 0.9% in case of intra-firm and the change was not statistically significant (p=0.1296). While the EE did not significantly increase in case of the intra-firm treatment, its level was higher than inter-firm treatments both with and without incorporating the subadditivity into the biding process. In case of the intra-firm treatment, each of the 12 subjects had 2 BMPs, and the available budget was doubled to match this. Consequently, the intra-firm treatment had the same budget scarcity as the other treatments; but this doubling created a thicker market and a smoother supply curve. Since BMP adoptions are indivisible, a smoother market allowed utilizing the budget to a greater extent, leading to higher abatement levels and consequently higher EE. On average, 94.8% of the available budget was spent in case of the intra-firm treatment. At the same time, the budget was only utilized at an average of 90.8% in case of bilateral and 88.3% in case of multilateral inter-firm. Introducing the externality further reduced the budget utilization for both inter-firm treatments, but not for the intra-firm treatment.

Overall, introducing the underlying spatial interdependency into the bid ranking process improved auction performance; however, the magnitude of the improvement varied depending on the subadditivity setting. The bilateral and the multilateral inter-firm treatments differed in the magnitude of the potential subadditivity. As the potential subadditivity doubled (from 10% to 20%), the potential cost savings also almost doubled as well. While the bilateral inter-firm and the intra-firm treatments had the exact same amount of potential subadditivity (10%), introducing this into the bid ranking brought quite different results. When the subadditivity was between the bidder's own BMPs, there was slight reduction in participation suggesting subjects considered both BMPs' chance of winning. They may have decided not to bid with one of the BMPs in order to not reduce the chance of winning with their other one. At the same time, if the subadditivity was between different bidders, they did not change their participation pattern to accommodate their peers.

The auction performance changed over time within sessions and exhibited a distinct pattern. Figure 3.7 to Figure 3.9 show the rent extraction over time in the three subadditivity treatments. The dark bars represent the average amount of rent extracted when the diminishing marginal rate was not incorporated into bidding. The light bars show the average information rent amount if it was introduced into the bidding. The rent extraction amount shows an upward trend within each block for both the light and the dark bars, which means that rent seeking activity increased over time as the participants learnt their cost effectiveness through repetition and they used it to their advantage. The deterioration of repeated discriminatory auctions over time is consistent with the literature (Cason, Gangadharan, and Duke 2003; Cummings, Holt and Laury*.* 2004; Latacz-Lohmann and Schilizzi 2007; Boxall et al. 2017) and was found in the previous chapter as well. Since all the auctions employed discriminatory pricing, this trend was expected.

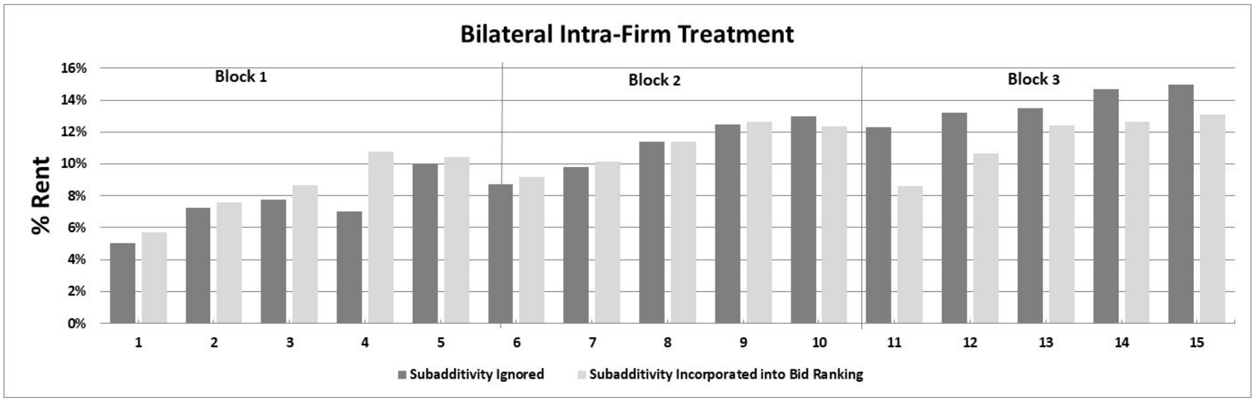

Figure 3.7. Average Percentage of Information Rent Extracted,
Intra-Firm Treatment

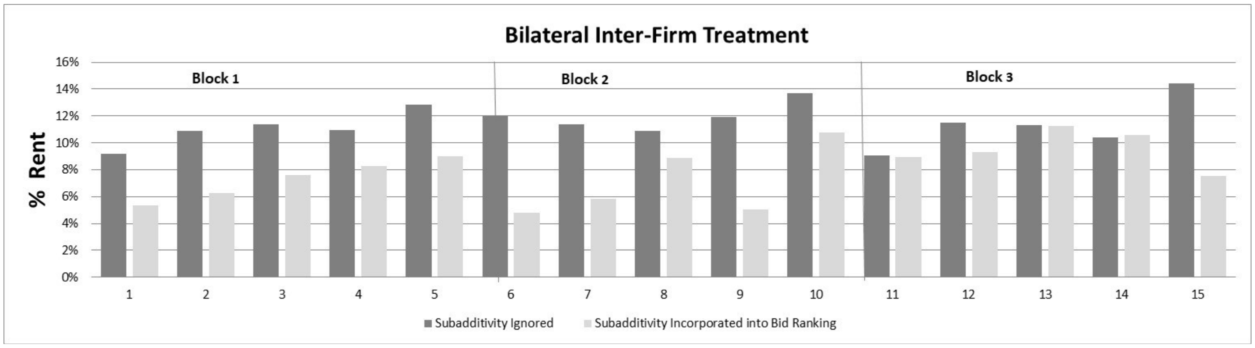

Figure 3.8. Average Percentage of Information Rent Extracted,
Bilateral Inter-Firm Treatment

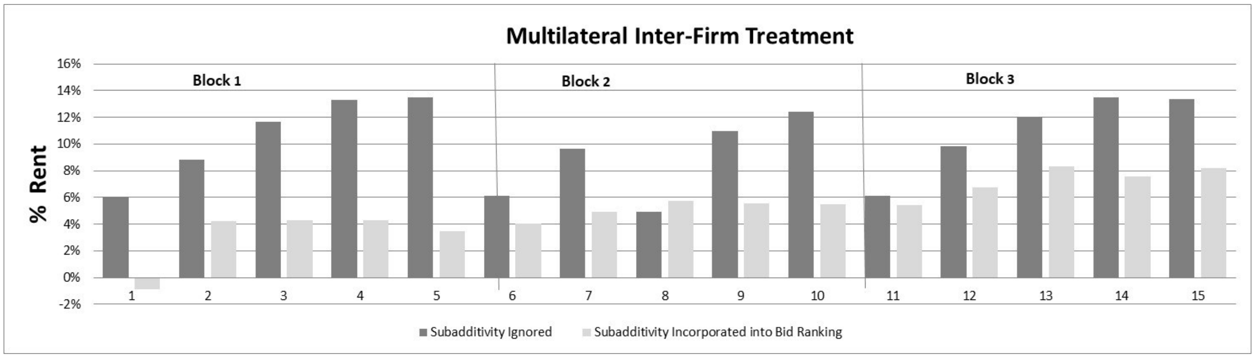

Figure 3.9. Average Percentage of Information Rent Extracted,
Multilateral Inter-Firm Treatment

However, as the figures show, the relationship of dark and light bars differs among the subadditivity treatments. On both inter-firm figures (Figure 3.8 and Figure 3.9), the dark bars are considerably higher than the light bars and they seem to be increasing faster. This means that incorporating the diminishing marginal rate into the bid ranking successfully reduced rent seeking in general, and it seems to have lessened the deterioration of the auction performance over time as well. This effect seems to increase as the magnitude of the diminishing rate increases, as the difference between the dark and light bars is larger in case of the multilateral than in case of the bilateral inter-firm treatment. On the other hand, the intra-firm figure does not show the same trend. In fact, the dark bars seem to be lower in the first block than the light bars, they have similar magnitude in the second block, and the dark bars are only becoming larger than the light ones in the last block. This means introducing the diminishing marginal rate into the bidding may not have had a direct immediate benefit, but was beneficial over time, potentially slightly reducing the learning effect.

3.5.3 Individual Bidding Behavior Analysis

3.5.3.1 Irrational Bids

During the experiment, there were a few unusual bid submissions among the high-cost producers in the last few repetitions after they likely realized that they could not win with the given BMP. In these instances, instead of refraining from participation they submitted a bid equal to the maximum allowed, which was beyond any reasonable expectation (=1000). This happened with all 4 high cost producers at least once (producer # 28, 32, 36, 43) and it also happened with producer #103, which had the highest cost among the mid-cost producers. This almost always happened when communication was allowed but the subadditivity was not incorporated into the bidding process. It occurred in one of the sessions that included the subadditivity into the bid ranking, but only in one group where all group members had higher cost and none of them were winning. It happened 18 times in total (16 communication and 2 silent sessions). Voice recordings show that participants submitting such bids were aware that they have high-cost BMP and instead of refraining from participation they decided to submit such bids just for fun.

> Player A: *"… no matter how much we do, we are not going to get it unless we go negative"*
>
> Player B: *"I'm not going to participate for that one, actually might as well bid, just for fun. Let's bid a thousand."*

In the experiments, submitting a bid had no cost or extra time commitment to the participants, which allowed them to submit these irrational bids without any consequences. While this is an interesting phenomenon about human behavior in the laboratory, it is unlikely to ever happen in an actual conservation auction as submitting a bid in an actual conservation auction takes time, effort and is potentially associated with some transaction costs (travel, postage etc). Since these excessive bids would skew the results, they have been omitted from the econometric analysis. Generally excluding these observations did not change the magnitude or the significance of the any other regressors in either equation. However, including these observations would have skewed the learning associated with the high and the mid-cost group.

3.5.3.2 Regression Result of the Bidding Behaviour

The individual bidding behaviour model focused on two performance measures: 1) participation and 2) percentage of the markup that the individuals asked for on top of their actual abatement cost, which is referred to as "markup". These two variables were estimated together with a selection model clustered to the individual bidder level as described in section 3.4.2. The econometric analysis was carried out using Stata software utilizing the selection model, which provides results of maximum likelihood estimation using Heckman's two-step model (Heckman 1979) as the starting point. The selection model was executed separately on each of the three subadditivity treatments: bilateral intra-firm, bilateral and multilateral inter-firm treatment.

While testing for the selection models is not available in Stata at this point, the participation and the markup models by themselves had no signs of autocorrelation. However, they suffered from heteroskedasticity. Because the selection models were clustered at the individual level, the model used the robust Huber/White/Sandwich estimations to correct the standard errors.

The results reinforce the appropriateness of using a selection model, as the inverse hyperbolic tangent of ρ[29] ("athrho") was highly significant in all models. The ρ values were over 0.9 in all three treatments, and the Wald-test rejected the hypothesis that ρ equals zero. Hence, the error terms of participation and markup equations were not independent, and estimating them separately would result in selection bias. The results shown in Table 3.4 display the marginal effects for the participation equation at the base case. The actual regression coefficients can be found in the Appendix (

Table 3.6.).[30]

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[29] The rho is the correlation coefficient between the error terms of the participation and the markup equation (P=corr(u1,u2)).

[30] The model excluded the 18 observations, which were identified as irrational bids as they are discussed in section 3.5.1. Including those observations would not change the general result to a great extent. However, it would change the significance of the level of the learning effect of the high-cost bidders.

Table 3.4. Marginal Effects using the Heckman Selection Model for Individual Bidding Behavior

	% of Markup				Probability of Participation (%)		
	Intra-Firm	Inter-Firm			Intra-Firm	Inter-Firm	
		Bilateral	Multilateral			Bilateral	Multilateral
Learning By Cost-Type:				**Learning By Cost-Type:**			
Low-Cost	9.71***	7.24***	7.16***	**Low-cost**	1.21	0.54	-3.11
	(0.88)	(1.90)	(1.29)		(1.65)	(1.63)	(3.20)
Mid-Cost	-2.78***	-4.96***	-2.83*	**Mid-Cost**	-7.68***	-8.6***	-11.01***
	(1.02)	(1.75)	(1.23)		(2.15)	(2.03)	(0.41)
High-Cost	-9.23***	-9.59***	-7.68***	**High-Cost**	-21.73***	-6.6**	-15.86***
	(1.86)	(3.30)	(2.00)		(3.57)	(3.49)	(5.37)
Dummy for Communication	-2.83**	0.75	2.28	**Dummy for Communication**	0.13	0.86	2.25
	(1.41)	(1.78)	(1.71)		(1.94)	(2.46)	(2.29)
Dummy for Subadditivity used in Bidding	0.31	-4.05**	-3.97**	**Dummy for Subadditivity Used in Bidding**	-2.17	-1.08	-3.42
	(1.43)	(1.85)	(1.68)		(2.05)	(2.71)	(2.65)
BMP Size (centered)	-0.14***	-0.25***	-0.26***	**Social Tie**	-6.65**	-1.70***	-2.28**
	(0.03)	(0.06)	(0.05)		(3.56)	(0.65)	(0.98)
				Bidder's Age (centered)	-0.31**	-0.26***	-0.13***
					(0.15)	(0.05)	(0.00)
Constant	9.95***	11.95***	8.70***				
	(1.60)	(2.74)	(1.64)	**P(Yi=1|X=0)** [a]	92.81***	88.07***	94.30***
Athrho[c]	1.528***	1.917***	1.732***	**Rho**[b]	0.9101	0.9576	0.9393
	(0.3837)	(0.2283)	(0.3219)	**p-value**[a]	0.0001	0.0000	0.0000
				Chi2	266.2	106.62	114.97
Lambda[d]	0.1676***	0.2545***	0.2438***	**N_cens**[e]	270	93	85
	(0.0428)	(0.0673)	(0.0850)	**N**[f]	2873	1437	1432

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level.
Marginal effects; Standard errors in parentheses

a) P-value for the independent equations hypothesis (H0: ρ =0)

b) The correlation coefficient between the error terms of the equations ($\rho = \mathrm{co}\,rr(u_1, u_2)$).

c) The inverse hyperbolic tangent of ρ ($athrho = \frac{1}{2}\left(\frac{1+\rho}{1-\upsilon}\right)$).

d) The inverse mills ratio ($\lambda=\rho*\sigma$, where σ is the available variance of the markup equation ($u_1 \sim$)

e) Number of observations where pmarkup is not observed because bid was not submitted.

f) The number of observations used in the model, excluding the 18 observations that are identified as “irrational”.

3.5.3.3 The Base Case

The constant terms in the markup equation represent the percentage of markup asked on top of the actual cost in the base case with all treatment variables being zero. The base case refers to an average age (25 years) bidder's behaviour with an average size BMP (31 kg phosphorus abated) in a single shot auction where there is no communication among the bidders and the underlying diminished marginal rate of return is ignored during the auction process. Moreover, it assumes zero social ties toward the other bidders, meaning all other bidders are complete strangers. The marginal effects reported for the participation equation are calculated at this base case.

The constants for the markup equation are generally low in all treatments reinforcing the cost effectiveness of conservation auctions even if there is a diminishing marginal rate in the BMP adoptions. The markup at the base case is highest in the bilateral inter-firm (11.95%), followed by the intra-firm (9.95%), which is closely followed by the multilateral inter-firm (8.70%) treatments.

For the participation equations, in place of the constant, the probability of submitting a bid in the base case is provided. The order of the participation rate among the three treatments is the reverse compared to the order of the constant for the markup equation: is highest in the multilateral inter-firm (94.3%), followed by the intra-firm (92.82%), and lowest in the bilateral inter-firm (88.07%) treatments. However, the calculated probabilities, as well as the order, would slightly change if the marginal effect would be calculated at a different point (e.g. at the mean instead of the base case). Nevertheless, the probability of the participation is very high initially (generally around 90%).

3.5.3.4 Learning Effect by Cost-Type

Bidding theory underpinning discriminatory auction tells us that high-cost producers are less likely to submit a bid than low-cost producers, and to shade their bid to a lesser degree once they know their cost position (Latacz-Lohmann and Van der Hamsvoort 1997). This theory has been confirmed in the laboratory in previous studies (Schilizzi and Latacz-Lohmann 2012, 2013). The experimental results also replicated this pattern, and the high-cost producers' participation rate was significantly lower than low-cost producers' regardless of the scope of the subadditivity.

In order to capture the differences in behaviours over time between the low-, the mid- and the high-cost type bidders, the model included three time-related variables as described in 3.4.2. All three learning effect variables were highly significant in the markup equation in all three subadditivity treatments. The learning effects of the participation equations were also highly significant for the mid- and the high-cost producers, but not among the low-cost producers.

The low-cost group's learning coefficient was positive and significant at the 1% significance level in all three markup equations. The coefficient was the highest for the intra-firm equation, and the low-cost bidders increased their markup request by 9.71% after the first repetition. They increased by another half of this amount after the second repetition and the effect slowly diminished with each repetition. Given that the constant was 9.95% for this equation, it means that the low-cost producers almost doubled their rent seeking activity after they learnt that their first bid had been successful. The low-cost group's learning coefficients in the two inter-firm treatments were almost identical and lower than in the intra-firm treatments: 7.24% and 7.16% for the bilateral and for the multilateral inter-firm treatments, respectively. The low-cost group's learning coefficient was not significant in any of the participation equations; therefore, the low-cost group participation did not change over the experiment in any of the subadditivity treatments.

The mid-and high-cost bidders' learning patterns were quite different compared to their low-cost counterparts. All the coefficients related to the mid and high-cost groups' learning were statistically significant and negative in all markup and participation equations. Hence, mid and high-cost bidders were decreasing both their rent seeking activity and their participation level over time. In the case of intra-firm, the mid-cost bidders reduced their rent seeking activity by 2.78%, and the high-cost ones reduced rent seeking three times faster by 9.23% after one repetition. Given that the constant was 9.95% for this treatment, this means that the high cost-producers quickly realized their cost disadvantage, and they dropped rent seeking activity almost completely. The same pattern can be observed in both intra-firm treatments. For bilateral inter-firm treatment, the mid-cost producers' rent seeking dropped by 4.96% and the high-cost producers' dropped by 9.59% after one repetition. For the multilateral inter-firm treatment, the mid-cost producers reduced rent seeking activity by 2.83% and high-cost producers reduced by 7.68% after one repetition. Since the constant was slightly lower in the multilateral inter-firm equation, again, this means that the high-cost producers' rent seeking activity quickly disappeared.

The mid-and high-cost bidders' participation was dropping even faster than their rent seeking behaviour. While low-cost bidders kept their participation level high during the entire experiment, the mid- and high-cost bidders started refraining from participation over time. In the case of the intra-firm treatment, the mid-cost bidders' participation rate dropped by 7.68% by the second round, another half of this by the 3rd and so on. The high-cost bidder's dropping out rate was even higher, and their participation rate dropped by 21.73% by the second repetition in this treatment. While the trend was similar for both inter-firm treatments, the magnitude of the decrease in participation rate was not as excessive. In the case of the bilateral inter-firm, by the second round the mid-cost bidders' participation rate decreased by 8.6% and the high-cost bidders' decreased by 6.6%. In the case of the multilateral inter-firm treatment, the mid-cost bidders' participation decreased by 11.01% and the high-cost ones reduced by 15.86% by the second round.

3.5.3.5 Incorporating Subadditivity into Bid Ranking

As is predicted based on the overall performance levels, incorporating the diminishing marginal rate of return into the bidding did not make any statistical difference for the intra-firm treatment. Neither bidders' participation rate nor their rent seeking activity changed over auction repetitions. However, if the negative subadditivity was present between firms, incorporating it changed the rent seeking activity in both inter-firm treatments. On the other hand, incorporating the subadditivity into the bid ranking reduced rent seeking activity in both inter-firm treatments with an almost identical amount. The amount of markup participants asked on top of their cost decreased by 4.05% and 3.97% for the bilateral and the multilateral inter-firm treatment, respectively. On the other hand, incorporating it into bidding did not statistically change the participation rate in either inter-firm treatment.

3.5.3.6 Communication

Allowing communication among bidders did not have a statistically significant effect on participation level in any of the treatments. Communication also did not make any difference in the amount of the markup that bidders asked for in any of the two inter-firm treatments. Communication was only significant in the intra-firm treatment, and reduced the asked markup by 2.83%.

3.5.3.7 BMP Size

The coefficient corresponding to the size of the BMP was significant and negative in all markup equations. Therefore, the larger producers asked for proportionally less markup than smaller producers. The coefficients were almost identical in the two inter-firm treatments. For each additional kilogram of phosphorus abatement, bidders asked on average 0.25% less markup for the bilateral, and 0.26% for the multilateral inter-firm treatment, respectively. For the intra-firm treatment, bidders asked on average 0.14% less markup for each additional kg. Originally, the BMP size variable was also included in the participation equations, but was not significant; hence, to simplify the equations it was excluded from the final model.

3.5.3.8 Socio-Economic Characteristics

While various socio-economic characteristics had been collected[31], only the bidder's age and the social ties among bidders remained in the final model as none of the other explored measures showed statistical significance. These two measurements were only included in the participation equations as they were not significant in the markup equation. Moreover, including additional variables in the selection model led to feasibility and convergence problems during the maximum likelihood iterations.

Bidder's age was statistically significant and negative in all three participation equations; hence, older people were less likely to submit a bid. The magnitude of the drop in participation rate was similar in the bilateral treatments, and on average bidders' participation rate decreased by 0.31% and 0.26% for each additional year in the bilateral intra and inter-firm treatments, respectively. The decline in participation rate due to age was slower in the multilateral inter-firm treatment (0.13% for an additional year). However, the participation rate decrease in the multilateral inter-firm case was much faster in general in this model than it was the bilateral inter-firm one.

The social tie was highly significant and negative in all participation equations. Hence, the more the participants knew their group-mates, the less likely they were to participate. The magnitude of the coefficients were similar in the inter-firm treatments and 1 unit increase in the social tie measurement lead to 1.7% and 2.28% drop in participation in the bilateral and the multilateral inter-firm treatments, respectively. The magnitude drop was much more prominent in the intra-firm treatment, and 1 unit increase in social tie lead to a 6.65% decrease in participation. In case of inter-firm treatments, the social tie measure was the average social tie that an individual had toward their group-mates. On the other hand, for the intra-firm treatments, the social tie measure was the average social tie that an individual had toward everyone in the session.

3.6 Discussion

The focus of this chapter was to analyze how potential diminishing marginal benefit of BMP adoptions would affect conservation auction performance. If regulatory agencies ignore potential relationships between BMP adoptions, perceived auction performance can be inflated. The actual achieved abatement across all winners was considerably lower than it would have been just simply adding up the individual abatement potentials. For example, in

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[31] The subjects were asked their age, gender, working status, education level, working or study fields and their social ties with their fellow participants.

the case of the multilateral inter-firm treatment, it may have appeared that the auction resulted in 182.3kg of phosphorus reduction, but the auction actually only led to an average of 152.1kg abatement due to the subadditivity. Incorporating the value interdependency into the bid ranking resulted in improved auction performance for both types of inter-firm treatments. Rent extraction decreased by 3.3% for the bilateral and 5% for the multilateral intra-firm treatments, respectively. Incorporating the subadditivity into the bidding also increased the actual abatement quantity by 2.2% for the bilateral and almost 3% for the multilateral treatment, respectively. As integrating the subadditivity into the auction resulted in both reduced rent seeking and increased abatement quantity, therefore the cost efficiency further improved and increased by 4.9% for the bilateral and 8.7% for the multilateral externality treatments.

Hence, it can be concluded that if there is diminishing marginal rate of the environmental outcomes between producers' adoption of BMPs, the auction is more effective if this subadditivity is incorporated into the auction. The higher the magnitude of the interdependency, or if it is more widespread, higher levels of improvement can be achieved by incorporating it into the bid ranking process. However, informing the bidders about this spatial relationship toward their neighbours can lead to reduced participation as producers may not bid in order to not worsen their neighbours' chance of winning. While regression analysis did not show overall statistical support for this behaviour, voice recordings indicated that it occurred in certain cases where bidders knew each other. A potential further extension of this study could explore the possibility of incorporating the subadditivity into the bid ranking, but without explicitly pointing this out to the participants.

However, if the diminishing marginal rate was present between a producers' own two BMPs, incorporating it into the bidding process did not lead to any statistically significant difference in any of the performance measures. Hence, incorporating the subadditivity into the bid ranking the way it was implemented here was not effective when the diminishing marginal rate was present between a producer's own two BMPs.

Potential further extensions could investigate the intra-firm case, allowing producers to submit package bids for both BMPs together. This type of joint bidding has rarely been studied in the conservation auction context, and has been pointed out as an issue worth further exploration (Latacz-Lohmann and Schilizzi 2005). To our knowledge, the only study exploring any type of bundle bidding in conservation auction allowed bidders to submit bids for the full, the half, and the quarter of the size of their BMP (Boxall et al. 2017). As Boxall and colleagues used BMP cost and abatement values from the same study area, the result of a joint bidding for two BMPs at the same time could be directly comparable with their results.

While the main focus of this study was investigating the effects of the underlying dependencies between BMPs on conservation auctions, the analysis produced various other results that have not been shown in the literature. Besides analyzing the overall auction performance, the individual bidding behaviour was analyzed and not just in terms of rent seeking, but considering the participation decision as well. Using a Heckman selection model, the participation and the bid formulation decisions were analyzed together. Our results provide statistical evidence that these decisions are interdependent, and analyzing them separately can lead to selection bias.

Another unique characteristic of analysing the individual bidding behaviour was to explore bidders' learning patterns by cost type. While learning effects are well-documented in the literature (Cason, Gangadharan, and Duke 2003a; Cason and Gangadharan 2004, 2005; Boxall et al. 2017, Wichmann et al. 2017), learning has not been separated out by cost before. Separating the learning by cost type would allow researchers to analyze the unique learning patterns of the low- and high-cost bidders separately. Bidding theory tells us that low-cost bidders rent-seek more than high-cost bidders (Latacz-Lohmann and Van der Hamsvoort 1997), which has been confirmed in the laboratory (Latacz-Lohmann and Van der Hamsvoort 1998) and in the field (Stoneham, Chaudhri and Strappazzon 2003). However, our finding shows that the low-cost bidders only bid differently if they are aware of their cost advantage. During the inter-firm sessions when participants had one BMP, initially low-cost bidders' behaviours were not significantly different from the other bidders neither in participation nor in terms of rent seeking amount. Voice recording shows that subjects even discussed that initially they did not know how their costs compared: *"Everyone always participates in the first one to see where they sit".*

However, over time, as participants learned how their costs compared to others, they changed their bidding and participation behaviour accordingly. Initially, rent seeking was in the 9-12% range on average, but the low-cost bidders doubled their rent seeking after the first round in all treatments and kept increasing it at a diminishing rate. At the same time, mid-cost producers decreased their rent seeking by about half after the first round and kept decreasing over time. They also lowered their participation rate by 8% in the bilateral and 11% in the multilateral treatments, respectively.

The high-cost bidders behaved similarly to the mid-cost bidders, but their behavior changed faster with a larger magnitude, and by the 3rd round their rent seeking activity was minimal. This trend was even more prominent in the case of the intra-firm treatment as each bidder had two BMPs to submit bids for, potentially belonging to different cost categories. This allowed bidders in the intra-firm treatment to obtain more information about the expected upper bid cap, and as a response they adjusted their participation rate more drastically. In the intra-firm treatment over 20% of the high-cost BMPs had not submitted bids after the first repetition.

Communication among bidders could potentially increase their information in regard to cost advantage or disadvantage and lead to declining auction performance. However, our study did not produce strong evidence that this had taken place. While voice recordings show that information exchange about participants' bids and costs had taken place frequently, it did not significantly affect the overall performance. One of the potential reasons is that information exchange was not always present even if communication was allowed. The magnitude of information exchange varied to a great extent between sessions. Moreover, such information exchange often only took place between group members, representing direct neighbours. Neighbours often had similar cost levels due to similar farm characteristics; hence information exchange potentially did not improve bidders' knowledge about their cost advantage in regard to the total bidders' pool.

In addition to the learning and the treatment variables, the only characteristic that showed statistical significance in individual bidding behavior was the size of the BMP. The larger the BMP was, the lesser amount of payment participants asked in proportion to their cost. A recent field auction study found that larger producers more likely win conservation contracts and it suspected that economics of scale allows larger farmers to reduce adoption costs (Leimona and Carrasco 2017). However, our findings offer an alternative explanation. On multi-unit auctions, where the bidders' size varies, bids are ranked on a per unit basis. During an auction, bidders balance the net-payout with the acceptance possibility (Latacz-Lohmann and Van der Hamsvoort 1997). When bids are ranked on a per unit basis, the probability of acceptance of a given bid per unit is independent of the size of the BMP. However, a larger producer's net-payout is larger with the exact same bid (per unit) than a small producer's even if their cost per unit is identical. Hence, a large producer's optimal bid is lower where there is a higher chance for their bid to be accepted.

There were two other variables (age and social tie) that played a role in participation and both factors reduced participation. Older participants were less likely to submit a bid; and their dropout rate was higher for the bilateral than it was for the multilateral treatments. Participants who knew their fellow bidders also were less likely to submit a bid, and the effect was almost three times bigger in the intra-firm sessions than it was in the inter-firm sessions. However, the difference in magnitude could be the result of the social tie variable construction between inter- and intra-firm treatments.

However, the negative coefficients could be a sign of bidders accommodating each other and refraining from participation in order to not decrease their group-mates' chance of winning. Interacting the social tie and age variables with the dummy variable regarding the subadditivity could further verify this theory. However, including such interaction terms did not lead to this conclusion and caused collinearity problems, and therefore were not included in the final model.

An alternative explanation is that this behavior difference is related to information. In the case of the intra-firm treatment, each participant was assigned to two BMPs as opposed to the inter-firm treatments, where participants only had one BMP to bid with. It is possible that older people are more susceptible to react to information by refraining from participation. Also, the higher level of social tie could have led to higher levels of communication and more learning among participants, which in turn could have led to more bidders refraining from participation as they realized their cost disadvantages. Again, interaction between the social tie and the communication dummy variable could verify this, but this caused collinearity problems and was not included in the final model. While the model did not provide statistical evidence for either of these explanations, there is some evidence to this reasoning in the voice recordings.

3.6.1 Extension of Conservation Auction Bidding Theory

Bidding theory in conservation auction, as established by Latacz-Lohmann and Van der Hamsvoort (1997), is based on utility maximizing producers. Bidders form an expectation about the potential upper bid cap ($\bar{\beta}$) and will submit a bid (*b*), which is somewhere between the bidders' own cost (*c*) and the upper bid cap. The amount of rent (*b*-*c*) the bidders ask for on the top of their cost optimally depends on the uncertainty of the cost and the bidders' risk aversion. Wichmann et al. (2017) extended the bidding theory and formulated the participation condition as follows:

$$U(b-c) * prob(b < \bar{\beta}) \geq 0 \tag{3.13}$$

If there is no uncertainty in regard to the cost, the left-hand side is always non-negative unless submitting a bid below cost. If we assume a strictly positive left-hand side of the equation required for participation, bidders then would submit a bid if their cost was lower than the expected bid cap

($c < \bar{\beta}$). This would imply that participants would lower their bid right to their cost, and stop participating after they did not win with a bid equal to their cost. However, this is not what was observed in the present laboratory experiments. In our experiments, on average, participants asked for $7 experimental dollars for rent in the round preceding the round they did not participate in. Ding et al. (2005) studied the emotional response of winning and losing in a reverse auction and found that losing in the auction causes frustration. Based on participants' response, bidding and losing is worse than not bidding.

While submitting a bid in the laboratory doesn't require significant extra time commitments or costs, formulating a bid still requires some effort. A multi-attribute utility function that is used in principal-agent models can be applied to this problem. Bidders' utility functions have two arguments ($U(\pi,e)$): the first argument is their profit and the second argument is the effort that is required to formulate the bid. Utility monotone increases in profit ($\frac{\partial U(\pi,e)}{\partial \pi} > 0$) and decreases in effort

($\frac{\partial U(\pi,e)}{\partial e} < 0$). As a result, earning zero profit without bidding is better than expressing an effort (e>0) and not winning: $U(0,0) > U(0,\varepsilon)$.

Moreover, in the case of multi-unit auctions, cost, bid and the bid cap are considered on a per unit basis. Hence, the potential profit of the bid submission needs to be multiplied by the quantity (q). The participation condition can be rewritten as follows:

$$U(q(b-c),e) * p(b) + U(0,e) * (1-p(b)) > U(0,0) \tag{3.14}$$

If we center the utility function assuming U(0,0)=0, the second term on the left-hand side is negative, and the equation becomes the following:

$$U(q(b-c),e) * p(b) + U(0,e) * (1-p(b)) > 0 \tag{3.15}$$

Consequently, in order to bid, the probability of winning has to be large enough to compensate the winners for the potential disutility of losing. Moreover, the higher the effort required to formulate a bid, the probability of submitting a bid decreases for two reasons. First, the utility from the same amount of payment decreases ($U(\pi,e_{high}) < U(\pi,e_{low})$), and the disutility of exerting the effort without return, e.g. losing also increases ($U(0,e_{high}) < U(0,e_{low})$). Hence, even if the probability of winning is not changing, there will be less participation and for a higher amount if submitting a bid is complicated.

This extension of the bidding theory explains why subjects in the laboratory do not lower the bids to their cost level before they stop participating. Moreover, it also provides an additional explanation as to why the participation rate was lower and was dropping faster in the intra-firm treatments. During the intra-firm treatments, participants had two BMPs; hence, understanding auction process, the screens, and the payment structure was more complicated, and bid submission required more effort. Therefore, participants reached the point earlier where exerting the effort was not worth the risk of losing. It also could be the reason older people were less likely to bid as they might value their effort more, hence need more compensation to exert the same effort.

In an actual field conservation auction, farmers often need to exert considerable effort in order to formulate and submit a bid. Therefore, it is not surprising that many actual conservation auction attempts experience very low participation rates in Canada (Brown et al. 2011; Hill et al. 2011). The previous chapter showed that low participation rates can especially degrade auction performance if the cost heterogeneity is high. This chapter illustrated exactly how learning effects lower participation rates over time. Even a slightly more complicated auction design with somewhat more learning opportunities (due to having 2 BMPs) significantly increased the participation dropout rate. Hence, it is crucial to organise conservation auctions in such a way that the formulating and submitting bids should require minimal effort. For example, offering online bid submission could reduce required effort. Moreover, making auction processes simple and easily understandable is essential.

3.7 Appendix

3.7.1.1 Proof

Proposition 1 *In multi-unit conservation auction optimal bid level has a reciprocal relationship to the quantity of abatement for risk averse bidders, if the bids are ranked on a per unit basis.*

Lets denote *b* as the bid per unit, *c* as the cost per unit, *q* as the quantity of the abatement, and $\overline{\beta}$ as the expected upper bid cap per unit, $F(b) = Prob(b > \overline{\beta})$ and $F'(b) = f(b)$. The agent has a well-behaved concave utility function: *U*>0, *U'*<0, and *U''*<0.

The agent maximizes its expected utility of:

$$U(q(b-c)) * (1-F(b)$$

The first order condition is:

$$q*U'(q(b^*-c))(1-F(b))-U(q(b^*-c)) * f(b) = 0$$

This can be rearranged as follows:

$$\frac{qU'(q(b^*-c))}{U(q({}^*b-c))} \le \frac{f(b)}{1-F(b)}$$

If q=1, this becomes the original formula presented by Wichmann et al. (2017):

$$\frac{U'(b^*-c)}{U(b^*-c)} = \frac{f(b^*)}{1-F(b^*)}$$

If q increases by ε and $\alpha = \varepsilon * (b-c)$, this becomes:

$$\underbrace{\frac{U'(\cdot+\alpha)}{U(\cdot+\alpha)}}_{<\frac{U'(\cdot)}{U(\cdot)}} + \underbrace{\frac{\varepsilon U'(\cdot+\alpha)}{U(\cdot+\alpha)}}_{<0} = \frac{f(b^{**})}{1-F(b^{**})} < \frac{f(b^*)}{1-F(b^*)}$$

Because the second derivate is negative, the U'/U is decreasing in profit, hence the first term on the left-hand size is smaller than it was when q=1. The second term on the left-hand side is negative (U'<0), therefore the left-hand side decreases as the quantity of abatement increases. Hence, the optimal bid is decreasing as the quantity increases: b**< b*.

Table 3.5. Descriptive Statistics, Wetland Restoration BMP

Unit	EBI	Cost	UnitCost	EBICost		Unit	EBI	Cost	UnitCost	EBICost
0.3	0.6	$642	$715.4	$118.2	**Min**	1.2	3.5	$1,370	$715.4	$216.8
99.2	261.0	$82,431	$2,420.7	$1,596.7	**Max**	36.6	82.7	$41,753	$1,655.5	$588.0
13.3	38.1	$12,826	$1,094.1	$430.7	**Mean**	15.0	41.8	$14,577	$1,069.1	$353.2
17.6	44.8	$14,931	$307.1	$298.2	**Std**	12.0	26.3	$11,716	$237.5	$129.0
ALL PRODUCERS						**DRAW**				

Table 3.6. Individual Bidding Behaviors, Heckman Model, Raw Coefficients for Participation Equation

Dependent variable: Participation	Intra-firm	Inter-firm	
		Bilateral	Multilateral
Learning by Cost Type			
Low-cost	0.9789	0.0295	-0.1968
	-(0.8084)	-(0.0961)	-(0.1640)
Mid-Cost	-1.3182*	-0.3361***	-0.2692***
	-(0.7952)	-(0.1088)	-(0.0984)
High-Cost	-1.6611**	-0.2792*	-0.3893**
	-(0.7863)	-(0.1598)	-(0.1540)
Dummy for Communication	0.0078	0.0334	0.1012
	-(0.1175)	-(0.0946)	-(0.0986)
Dummy for Subadditivity Used in Bidding	-0.1313	-0.0421	-0.1541
	-(0.1221)	-(0.1038)	-(0.1365)
Social Tie	-0.4015**	-0.0663**	-0.1029**
	-(0.1983)	-(0.0309)	-(0.0476)
Bidder's Age (centered)	-0.0190*	-0.0101***	-0.0058***
	-(0.0101)	-(0.0030)	-(0.0037)
P(Yi=1|X=0) [a]	1.4622***	1.1786***	1.5809***

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level;
Standard errors in parentheses

a) The probability of participation at the base case when all variables are zero.

Table 3.11. Individual Bidding Behaviors, Heckman Model, 18 Irrational Observation Included

	% of Markup				Probability of Participation (%)		
	Intra-Firm	Inter-Firm			Intra-Firm	Inter-Firm	
		Bilateral	Multilateral			Bilateral	Multilateral
Learning By Cost-Type:				**Learning By Cost-Type:**			
Low-Cost	9.84***	7.53***	7.38***	**Low-Cost**	0.48**	1.0	-0.49
	(0.88)	(1.98)	(1.40)		-(0.19)	(1.76)	-(0.34)
Mid-Cost	-1.05	-3.71	-2.34	**Mid-Cost**	-5.21**	-6.67***	-10.00**
	(0.74)	(2.17)	(1.75)		-(2.36)	-(2.64)	-(3.86)
High-Cost	1.45	-8.43*	0.18	**High-Cost**	-27.73***	-4.92	-6.84
	(4.68)	(3.47)	(7.59)		(4.38)	(3.64)	(6.29)
Dummy for Communication	0.02	-0.44	8.53	**Dummy for Communication**	0.46	0.01	4.93*
	(2.53)	(2.31)	(5.27)		(1.77)	(0.08)	(2.58)
Dummy for Subadditivity Used in Bidding	-1.90	-3.01	-11.14*	**Dummy for Subadditivity Used in Bidding**	-1.64	-0.15	-6.39**
	(2.44)	(2.27)	(5.67)		(1.75)	-(2.98)	(3.11)
BMP Size (centered)	-0.18***	-0.22***	-0.26***	**Social Tie**	-6.18**	-2.47**	-1.96**
	(0.05)	(0.06)	(0.07)		(3.22)	(0.65)	(0.99)
				Bidder's Age (centered)	-0.37**	-0.25***	-0.012**
					-(0.16)	-(0.05)	-(0.06)
Constant	9.94***	11.50***	8.11***				
	(1.64)	(2.80)	(2.02)	**P(Yi=1|X=0)** [a]	98.36***	85.49***	84.70***
Athrho[d]	-0.0239	2.0162***	2.3934***	**Rho**[b]	-0.0239	0.9652	0.9835
	-0.0178	-0.2094	-0.3083	**p-value**[c]	0.0000	0.0000	0.0000
				Chi2	172.2845	95.2507	85.415
Lambda[e]	-1.1099***	-1.2149***	-0.6142**	**N_cens**[f]	270	93	85
	-0.2559	-0.2216	-0.2936	**N**	2880	1440	1440

*** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level.
Marginal effects; Standard errors in parentheses

a) P-value for the independent equations hypothesis (H0: ρ =0)

b) The correlation coefficient between the error terms of the equations ($\rho = corr(u_1, u_2)$).

c) The inverse hyperbolic tangent of ρ ($athrho = \frac{1}{2}\left(\frac{1+\rho}{1-\upsilon}\right)$).

d) The inverse mills ratio ($\lambda = \rho * \sigma$, where σ is the available variance of the markup equation ($u_1 \sim$)

e) Number of observations where pmarkup is not observed because bid was not submitted. Optimal adoption pattern selection with interdependent BMPs

4 Optimal BMP Adoption Pattern Selection for Interdependent BMPs

4.1 Introduction

Beneficial Management Practices (BMPs) in agriculture are currently used to control non-point source pollution; but whether or not they are economically worthwhile to be applied depends on a variety of landscape characteristics. BMP cost-effectiveness is influenced by both the achievable pollution abatement amount of the given practice as well as their potential adoption and implementation cost. The traditional government policies that aim for a uniform pollution reduction or to encourage BMP adoption regardless of the landscape characteristics, tend to be inefficient and a waste of public dollars. The cost of the same overall water pollution abatement level using a uniform threshold policy can be threefold compared to a differentiated policy (Doole 2012).

This study presents a Mathematical Integer Programming (MIP) optimization model that maximizes the potential pollution reduction given a fixed government budget. The model is demonstrated with data from the South-Tobacco Creek Watershed Manitoba that were collected through the Watershed Evaluation of Beneficial Management Practices (WEBs). Similar studies often simplify either the cost side or the environmental side of the problem due to lack of data (Giri, Nejadhashemi and Woznicki 2012; Gitau, Veith and Gburek 2004; Gitau et al. 2006; Qi and Altinakar 2011, Zeferio, Cunha and Antunes 2012). Fortunately, our study area has been studied from both perspectives; hence, we have this unique opportunity to use actual phosphorus abatement estimates (Yang et al. 2008) along with spatially explicit cost estimates (Boxall et al. 2008; Packman 2010; Khakbazan et al. 2013) that include all costs related to the BMP adopted, including opportunity costs of the land.

In addition to considering spatial heterogeneity, this study is unique by allowing interdependencies among the BMPs. Implementing multiple BMP projects in close proximity can lead to a situation where their effectiveness decreases as there is diminishing marginal rate of return demonstrated by Perez-Pedini, Limbrunner and Vogel (2005). Disregarding these potential interdependencies between BMP projects implemented in close proximity may lead to an inflated total benefit calculation and reduced effectiveness of the program. This study explores how the optimal BMP project selection would change when there is diminishing marginal rate of multiple BMP adoptions.

This study analyzes the outcomes that the optimization model generates under various circumstances. The environmental goal explored here is to reduce nutrients from run-off from agricultural fields. However, depending on the details of how this goal is formulated into a measurable objective, the outcomes can vary dramatically. Moreover, depending on the magnitude of the underlying spatial interdependencies, the potential achievable abatement result can vary.

In addition to analyzing the optimal BMP selection result based on the goal formulation and various assumptions of the model, this study demonstrates how effective such optimization can be in actual conservation policies, and compares it to an alternative mechanism: a conservation auction. In a conservation auction that uses discriminatory pricing, producers submit the price they want to be paid for various Environmental Goods and Services they would provide. The government allocates the funds from the lowest cost-benefit ratio until the budget is exhausted. However, the agency can also select the projects to be funded by using an optimization model like the one presented in this study. While such programs are not widespread yet, the Baltimore County Land Preservation Program in the US used this technique, and it has been demonstrated that using the optimization resulted in considerable cost savings compared to other selection mechanisms, including ranking based on cost-benefit ratio (Messer et al. 2016). Moreover, if there is an underlying interdependency among the BMPs which is incorporated into the optimization model, it may further increase effectiveness over simple ranking.

One of the main concerns with regard to funding BMP adoption in conservation programs where the producers choose their own price is that the actual implementation cost of the BMP is unknown to the government agency. This information asymmetry allows producers to obtain information rents above their actual costs in such voluntary programs. Using the results from the previous chapter’s laboratory results, this study explores the effects of various levels of potential markup amounts that may be included in conservation contracts. The model also explores how such conservation programs are affected if the funding is split into sub-programs, or various payment and size restrictions are imposed on the participating agricultural producers and projects.

4.2 Literature Review

As water quality and quantity became more of an environmental concern and government policies started to form, studying the cost effectiveness of BMP implementations started to flourish in the late 90’s. Initially, most government programs only looked at one side of the problem, either the benefit or the cost side. *Benefit targeting* (BT) or *benefit ranking* is a method that simply ranks the projects based only on their environmental benefits. The US Fish and Wildlife Service (Babcock et al. 1997) use this approach in multiple large-scale environmental programs including national park selection. The other single sided view is *cost targeting* (CT) or *cost ranking*, where the projects are ranked based only on their cost, from the cheapest to the more expensive. Ferraro (2003) refers to this method as “bargain-shopping”, and states that this often maximizes acreage rather than actual environmental benefit. An alternative ranking approach, which is preferred by many economists, is cost-benefit targeting (CBT) or cost-benefit analysis (CBA), which ranks the projects based on cost-benefit ratios, and allocates the funds from the highest benefit per dollar until the budget is exhausted. There are a few recent studies that go a step further and compare the results of various ranking methods to a linear optimization (Duke, Dundas and Messer 2013; Messer et al. 2016). However, even these studies assume the benefits of BMP adoption are independent from each other.

Water quality issues arise from non-point source pollution with multiple spatially separated sources having water flowing between them; hence, there can be complex interdependencies between projects. As a result, optimization has been extensively used in project or site selection problems with regard to water quality issues. Initially, most studies took a cost minimization approach where the objective was to minimize the economic cost of achieving a given exogenous target water quality or quantity standard (Elofsson 2003; Froschl, Pierrard and Schonback 2008; Gren, Elofsson and Jannke 1997; Hanley et al. 1998; Khanna et al. 2003; Veith, Wolfe and Heatwole 2003, 2004; Yang and Weersink 2004; Yang et al. 2003; Yang, Khanna and Farnsworth 2005; Zylicz, 2003). As environmental policy objectives changed, the focus of these studies moved toward a benefit maximization approach where the objective was to maximize the environmental benefit given a fixed government budget (Ancev, Lifran and Tan 2008; Azzaino, Conrad and Ferraro 2002). This study follows the latter optimization approach. Regardless of which of the two approaches is used, studies generally rank BMP projects based on average cost per unit effectiveness (Balana, Vinten and Slee 2011).

As this literature emerged from water research initiated by hydrologists, soil, water and other earth scientists, focus was on the details of the most accurate modelling of the environmental benefit and very simple approaches for the cost side of the problem were employed. There are studies using a benefit targeting approach that ignore the cost side completely and focus on identifying the locations that yield the most environmental benefit regardless of cost (Giri, Nejadhashemi and Woznicki 2012; Zeferio, Cunha and Antunes 2012).

Much of the BMP optimization research focuses on structural BMPs like retention ponds, parallel terraces, and field strips, where the majority of the cost is from building and maintaining actual structures. Often, studies only include these direct costs and completely ignore the indirect or opportunity costs that arise by the foregone revenue of the land (Arabi et al. 2006; Perez-Pedini, Limbrunner and Vogel 2005; Hsieh and Yang 2007; Hsieh et al. 2010; Qi et al. 2008; Zhen, Yu and Lin 2004; Zhen et al. 2012; Karamouz, Nazif and

Hosseinpour 2011; Karamouz et al. 2010; Kaini, Artita and Nicklow 2012; Panagopolus, Makropoulos and Mimikou 2011).

Studies that focus on non-structural BMPs, such as changing crop rotations, include opportunity costs, but in a very simplified way as spatially explicit cost estimates are often unavailable. Most common approaches in the literature assume a fixed cost per hectare opportunity cost of each BMP, regardless of the location *(*Gitau, Veith and Gburek 2004; Gitau et al. 2006; Qi and Altinakar 2011). Others use a single net return parameter value per hectare that is associated with each type of rotation, regardless of field location (Srivastava et al. 2002, 2003). There are studies that take into consideration the full production cost from fuel, fertilizer, fixed cost etc, but do not distinguish cost among fields (Maringateli, Chaubey and Popp 2009; Maringateli et al. 2008, 2011).

Some studies may include cost differentiation based on the location, but are based on the soil and conservation manuals and not on actual field estimation in their study areas (Kao and Chen 2003). Others may include cost variation for different fields, but their production costs are calculated based on historical data, and are assumed to remain the same regardless of the management practice (Veith, Wolfe and Heatwole 2003, 2004).

As large-scale optimizations are computationally intensive, most of these earlier studies focused on how to overcome the computational limitations by introducing heuristics and different ways to shorten the computational time. Moreover, these studies were mainly published by hydrologists or soil scientists; hence their focus was to model the actual hydrological aspect of environmental abatement and include overly simplified economics. As a result of the imposed assumptions, their results were not really driven by the economic diversity and profitability of the land.

Initially, many optimization studies that emerged from the economic literature tried to assess the cost side by using representative farm models. Van Wenum, Wossink and Renkama (2004) used a representative crop farm from the Netherlands in an integer programming model setting for improving wildlife scores. Engle and Valderrama (2004) used a representative shrimp farm from Honduras in a linear programming model with an objective to reduce total phosphorus and nitrogen as well as biological oxygen demands in the water body. When a group of researchers and policymakers from the EU Water Framework Directive (WFD) reviewed this topic, they found that most studies use this representative farm type modelling, which fails to capture the actual spatial heterogeneity of real world farmers (Balana, Vinten and Slee 2011).

Yang et al. (2003) was the first study that addressed actual land heterogeneity from an economic cost perspective. The research was undertaken as a part of the CRP program in the

US aiming for 20% sediment reduction via cropland retirement. Since the entire future agricultural revenue stream had to be sacrificed, the profitability of the actual lands was the major driving force in their optimization. The authors computed quasi rents for each land parcel based on land topology variables such as soil type, slope, and proximity of water. In order to highlight this degree of richness on the cost side, they simplified the hydrology side by dividing the landscape into 3-parcel flow channels based on water movement patterns. The authors assumed that sediment reduction due to a land parcel was only dependent on the weather and the land topology and land activity within the flow channel. They pre-generated the potential sediment reduction estimates for each flow channel using a hydrological non-point source pollution (NPS) model. This pre-generated data was used in a linear integer programming model implemented with GAMS. Later, the authors used the same technique with different target levels and landscapes (Yang, Khanna and Farnsworth 2005). After the successful application on land retirement, they used this method on BMP optimization in multiple Canadian watersheds in Ontario. The model has been applied to riparian buffer strips (Yang and Weersink 2004) and conservation tillage (Yang, Khanna and Farnsworth 2005; De Laporte, Weersink and Yang. 2010).

As conservation auctions became popular and frequently used in government programs, especially in Australia, other conservation contracting arrangements started to emerge where producers "name their price". Agencies started to use optimization models to select the funded BMPs as opposed to the simple ranking used in conservation auctions. Most models employed mixed integer programming models, more specifically binary models, where the decision variable is a vector of the potential BMP selections. These models account for multiple BMP projects even on the same land parcel and they often use GAMS for implementation (Hajkovicz et al. 2007; Lowell et al. 2007; Crossman et al. 2010; Bryan et al. 2011; Doole 2012; Qui and Dosskey 2012). This present study follows these basic principles as well.

The majority of the optimization models assume that both the costs and the benefits of the BMP projects are independent from each other. One of our contributions is allowing environmental spillover effects between the BMP projects. There are only a handful of models in the literature that allow any kind of inter-dependency. Aulong, Bouzit and Dorflinger (2009) modelled a small dam location selection problem in Lebanon and allowed interdependencies both on the cost and the benefit side. However, their problem was very small as they only had 13 potential BMP projects. Because of the size of their problem, they were able to assess the actual cost and benefit of each potential combination individually using experts in the field. Since the complexity of these types of models grows with the number of projects by a factorial (O(n!)), this approach is not feasible for large or even medium-sized problems. In order to include dependencies either on the cost or on the benefit side, some simplification is required. One of the solutions is to divide the landscape into smaller units and only allow BMP project interdependency within the subunits. Yang et al. (2003) followed this approach by dividing the landscape into flow channels containing 3 land parcels. Another potential simplification is allowing interaction between BMPs on the same land parcel, but not between neighbouring parcels (Rabotyagov, Jha and Campbell 2010). This present study also follows this approach and accounts for interdependencies between BMPs located on the same or partially overlapping fields[32]. However, the model employed here uses a flexible approach by implementing the interdependency using a pre-generated matrix that contains the interdependency ratio between any two BMP projects regardless of their location. This approach can be used to model various levels of simplification depending on how this dependency matrix is constructed. The only limitation is that it assumes that spillover between any two BMPs is independent of the implementation of any other BMPs.

4.3 Optimization Model

There are two types of optimization models: cost minimizing and target maximizing. Cost minimizing models have a fixed exogenously determined environmental target and aim to minimize the cost that achieves this target. Target maximizing models start from the opposite direction and have a fixed budget and maximize the environmental benefit achievable from the given budget. This present study follows the latter approach, because it is simply more practical when it comes to conservation programs as government agencies usually have a fixed budget to start with.

In order to formulate the mathematical model, we need to assume functional forms for the cost and the environmental benefit of the BMP projects. For the sake of simplicity, a Leontief model is used. The conservation contract cost of a BMP on a given field or farm is assumed fixed and independent of the adoption of any other BMP anywhere in the study area. For example, the cost of a conservation contract for a Run-off Holding Pond BMP on a given farm is independent of the cost of any other BMP implemented by anyone else in the watershed, including the same farmer's other BMP adopted. This assumption may not hold in every BMP adoption combination. For example, restoring a wetland and converting the same field to forage are not independent because the opportunity cost of not having crop on the

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[32] Some BMPs are spatially limited to a single field. For example, a Forage BMP represents the establishment of perennial cover of a given field, and it is assumed that the entire field is converted to forage. However, some other types of BMPs, for example Riparian Area Management are spatially overlapping multiple fields, but typically do not fully include any field.

wetland area could be accounted for twice. However, wetland areas are usually quite small, so ignoring these will not really change the cost estimates significantly. Moreover, there could be large fixed costs associated with BMP adoptions; for example, if a farmer fences a riparian area, they may need to install an alternative waterer for their livestock, which has a large fixed cost. When a wetland is restored and fenced off in a field where cattle may graze, the producers also incur the cost of installing an alternative water supply. If a producer has restorable wetland and riparian areas on the same field, they incur this large expense only once, hence there is considerable amount of cost reduction possible between these two BMP projects. However, at the time when the farmers submit their price requests they cannot know if more than one of their BMPs will be funded. Hence, it can be assumed that they formulate their price request as if only one of their BMPs were selected. This type of positive synergy on the cost side is often explored by package bidding techniques (Holt et al. 2007) and can be a further extension of this study, but is not included here.

The total environmental benefit across the study region is simply the sum of the individual benefits of implementing the selected BMP adoption projects adjusted by the potential dependencies between the projects. The underlying interdependence between projects is extremely complex and related to various geographic characteristics of the land such as slope, soil type, crop selection (W. Yang, personal communication, 2012 July). For example, two neighbouring fields may or may not have water flow running between them depending on the slope of the landscape and may or may not drain into the same sub-catchment area. If there is water flow between the fields, there is a potentially diminishing rate of return in BMP adoption. If there is no water flow between the fields, BMP adoption in one has no effect on the other despite the fact that they are neighbours geographically. Ideally, we would obtain an exact value estimate from the hydrology model for each and every project combination. However, even with our relatively small study area, the potential number of BMP adoption projects is almost 600. In order to obtain estimates of all combinations of the projects, the hydrology model should be run $\frac{N!}{2}$ times, which is approximately 250 million estimates. This is an unrealistic data requirement and for simplicity we assume that each pair of BMPs adopted is independent from the rest. Consequently, the magnitude of the problem becomes N^2, which is approximately 350,000 values.

4.3.1 The Mathematical Model

BMP adoption can be viewed as a binary choice where a certain BMP project is either implemented on a given location or not. If both the cost and the environmental benefit of the BMP's are fixed, a Mixed-Integer Programming (MIP) model can be used with a binary choice variable vector, which is called X. Each and every potential BMP adoption project has a binary variable associated with it in this vector. This means that x_i equals 1 if the i^{th} project is selected for adoption by the social planner, and 0 otherwise. If the conservation contract is allocated via a conservation auction, this binary value represents acceptance or rejection of the bids. The number of BMP adoption projects is represented by the scalar N, which is 593 in this study area. Details of these projects, including the associated cost and environmental benefits, are included in the study area description (see section 4.4). The objective of the model is to maximize the environmental benefit of the adopted BMPs given fixed government budget(s). The conceptual optimization model can be formulated as:

$$\begin{gathered} maximize\ EB(X) \\ Subject\ to: \\ Cost(X) \leq budget \\ where \\ EB(X)\ is\ the\ total\ enviornmental\ benefit\ of\ the\ adopted\ BMPs \end{gathered}$$

If the environmental benefits of BMPs adopted are independent from each other, the environmental benefit function is linear and the total benefit of any two sets of BMPs is equal to the sum of the environmental benefit of the two sets: $EB(X^A + X^B) = EB(X^A) + EB(X^B)$. However, our model relaxes the independency constraint and assumes the BMPs are interdependent, and that there is a declining marginal benefit between BMPs located on the same or overlapping fields, potentially weakening each other's environmental effect. Functions where the combined value of two sets is lower than the sum of the value of the individual sets are called subadditive functions ($EB(X^A + X^B) < EB(X^A) + EB(X^B)$). Functions with this property are considered exhibiting diminishing marginal value.[33]

As similar studies assume independent environmental values, they model the environmental benefit function with a vector. The presented model in this study also starts with this approach. The environmental benefit is represented by the E vector, and an element (e_i) represents the environmental benefit achieved if only the i^{th} project gets adopted in the watershed and nothing else. If the abatement values were independent from each other, the objective function would be simply EX , the sum of the abatement of the projects that get

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[33] Functions when the opposite is true and the total value of the combined sets is larger than the sum of the values of the individual sets are called superadditive functions, and usually present in situation when there is an economics of scope effect ($EB(X^A + X^B) > EB(X^A) + EB(X^B)$)

selected for adoption. However, we assume there is a diminishing marginal benefit of multiple BMP adoptions, and our environmental benefit is subadditive. Hence, the objective function becomes EX minus the interdependencies between the adopted BMPs.

The negative spillover between any two BMPs is assumed to be independent from any other BMP adoption, and hence the interdependent relationships can be represented by an NxN matrix. As the model considers pair-wise interactions between any two BMPs, the model is quadratic, and it becomes a Mixed Integer Quadratic Programming (MIQP) model.

In order to facilitate sensitivity analysis, the interdependencies are represented by two parameters: an *s* scalar, and a *D* matrix. The *s* scaling parameter is a number between 0 and 1, and represents the proportional rate that overlapping fields are affecting each other. If the parameter is zero, there are no interdependencies among the BMPs and the environmental benefit of each BMP is independent from any other BMP adoption. In order to explore the effect of various levels of diminishing rate , sensitivity analysis was run on varying levels of this scaling factor between 0 and 30%. However, beside the scenarios that focus on this scaling, the base assumption was that the scaling factor is 10% based on personal communication with the hydrologist team that provided the estimation of the environmental values (Yang, personal communication 2012).

The *D* matrix elements represent the pair-wise subadditivity factor between any two BMP projects. If the two projects (*i*, j) are located on fields that do not have any potential interdependency, this value is zero ($d_{ij} = 0$). A positive value ($d_{ij} > 0$) suggests that there is a diminishing marginal rate between the BMPs and they are worsening each other. A negative value in the matrix ($d_{ij} < 0$) would represent BMPs that enhance each other. It is assumed that all the values in the D matrix are non-negative ($d_{ij} \geq 0$) for two reasons: a) here the interdependency represents diminishing marginal rate of return, and b) most quadratic solvers require the interaction matrix to be positive semi-definite, which would be violated by negative values.

Using the variables described above, the added environmental benefit of implementing a project is equal to its stand alone environmental value minus potential reduction caused by other projects that are implemented at the same time. Thus:

$$e_i - s\sum_{j=1}^{N} d_{ij} x_j \, . \qquad (4.1)$$

The costs of the BMP projects are assumed to be fixed, and represented by the *C* vector (Nx1). The elements of the *C* vector represent the amounts of compensation the regulator needs to pay to the producers in the form of conservation contracts to induce adoption of the given BMP projects. This is the cost the regulator incurs, but the actual implementation cost may differ from this. Various scenarios were explored based on what was included in the cost, which are described in detail in Section 4.5. Although implementing some projects may have net monetary benefits to the producers, the values in this vector are assumed to be non-negative ($c_i \geq 0 \; \forall i \in [1..N]$).

The potentially achievable environmental benefit is limited by the available budget(s). There can be multiple (M) programs that provide financial assistance for producers with each of their own budget represented by the BD (Mx1) vector. When the budgets of the different programs are pooled together, the budget constraint simply states that the total cost of the implemented projects cannot exceed the total available budget by all programs. However, these programs may be administered separately by different agencies and their budget cannot be combined. Hence, an alternative set of budget constraint is explored. The alternative budget constraints are formulated with the help of a *T* (NxM) binary selector matrix; the elements of this matrix represent which projects belong to which BMP type[34]. If the budget is separated, the cost of the implementation of the projects that belong to a given program cannot exceed the budget of that particular program.

In addition to the budget constraint, there can be additional constraints in the model due to some exogenous restrictions. The $A(NxL)$ matrix represents technical parameters of any additional constraints in the model, and the $b(Lx1)$ vector represents the right-hand side of these constraints. There could be physical constraints of the land (slope, soil type, etc) or any exogenous restrictions. For example, in this particular case, certain funding programs imposed restrictions on total payment and size restriction on producers. Various restrictions were explored by different scenarios, and the detailed description, including the mathematical formulation, can be found in Section 4.5. To solve the problem, the Cplex solver integrated into MATLAB was used.

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[34] The underlying assumption is that each project belongs to exactly one program.($\sum_{k=1}^{M} t_{ik} = 1 \; \forall i \in [1..N]$)

Mathematical Programming Model:

$$max\sum_{i=1}^{N} e_i x_i - s\sum_{i=1}^{N}\sum_{j=1}^{N} d_{ij} x_j x_i \qquad \text{(4.2) Objective}$$

Subject to:

$$\sum_{i=1}^{N} c_i x_i \le \sum_{j=1}^{M} BD_j \quad or \quad \sum_{i=1}^{M} t_{ij} c_i x_i \le BD_j \;\; \forall j \in [1..M] \qquad \text{(4.3a) Budget Constraints}$$

$$\sum_{i=1}^{N} a_{ik} x_i = b_k \;\; \forall k \in \{1..L\} \qquad \text{(4.3b) Optional Additional Constraints}$$

$$x_i \ge 0 \;\; \forall i \in \{1..N\} \;\; binary \qquad \text{(4.3c) Non-negativity Constraints}$$

$$t_{ij} = \begin{cases} 1 & if\ i^{th}\ BMP\ is\ j^{th}\ \ type \\ 0 & otherwise \end{cases}$$

Where the variables and parameters are the following:

N	*scalar*		*Number of BMP adoption projects*
$X(N \times 1)$	*row vector*	$\begin{bmatrix} x_1 & \dots \end{bmatrix}$	*Model binary choice variable*
$C(1 \times N)$	*column vector*	$\begin{bmatrix} c \\ \vdots \\ c_N \end{bmatrix}$	*Cost of each BMP project*
$E(1 \times N)$	*column vector*	$\begin{bmatrix} e \\ \vdots \\ e_N \end{bmatrix}$	*Environmental benefit values for each BMP*
s	*scalar*		*Externality scaling parameter*
$D(M \times N)$	*matrix*	$\begin{bmatrix} d & \cdots & \\ \vdots & \ddots & \vdots \\ d_{N1} & \cdots & \end{bmatrix}$	*air-wise externality factors between projects*
M	*scalar*		*Number of funding programs*
$BD(1 \times M)$	*column vector*	$\begin{bmatrix} B \\ \vdots \\ B_M \end{bmatrix}$	*The budget for each funding program*
$T(M \times N)$	*matrix*	$\begin{bmatrix} t & \cdots & \\ \vdots & \ddots & \vdots \\ t_{N1} & \cdots & \end{bmatrix}$	*lector matrix identifying which type the project belongs to*
L	*scalar*		*Number of additional external constraints*
$b(1 \times L)$	*column vector*	$\begin{bmatrix} e \\ \vdots \\ e_M \end{bmatrix}$	*Right hand side parameters for the additional constraints*
$A(L \times N)$	*matrix*	$\begin{bmatrix} a & \cdots & \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & \end{bmatrix}$	*nical parameters for additional constraints*

4.4 Data

This study utilizes the cost and environmental benefit values of different BMP adoptions, which are estimated based on the data collected from the South Tobacco Creek (STC) Watershed in Manitoba within the framework of the WEBS project. The study area is a 74 km^2 (206 ha) watershed located near Miami, Manitoba, Canada, approximately 150 km from Winnipeg. The watershed contains 33 producers[35], of which 16 had livestock in the base year, 2010. The main environmental concern in this particular watershed is nutrient runoff from the agricultural fields, which travels through the South Tobacco Creek, enters the Red River, and ends up in Lake Winnipeg, contributing to the lake's eutrophication process and causing water quality problems. This study focuses on the following five BMPs: Holding Pond, Riparian Area Management, tillage management (Zero Till), perennial cover (Forage), and Wetland Restoration (see detailed description in Table 4.1). There were additional types of potential BMPs identified by AAFC (2011) to improve water quality in this watershed, such as small dam and winter bale grazing. However, they were not included in this study due to lack of data availability.

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[35] In 2004 there were 36 producers in the watershed, but 3 producers had exited the business by 2010, and all their fields transferred to other producers; generally the immediate neighbour took over the fields.

Table 4.1. List of the Studied BMPs

BMP name	Description
Forage	Forage refers to the practice of converting cropland to forage production providing a permanent vegetation cover through the year to improve soil structure and water holding capacity.
Holding Pond	Holding Pond or retention basin is an excavated area that is built to retain runoff from livestock containment sites to reduce surface water pollution.
Riparian area	Riparian vegetation management in the given watershed involves fencing off stream banks to prevent cattle to deposit waste directly into the waterways.
Wetland restoration	Wetland restoration involves re-establishing previously drained wetlands that act as a nutrient sink.
Zero Till	Zero Tillage involves using alternative tillage equipment for soil preparation that minimizes disturbance and allows maintaining residual crop cover through the year to reduce soil erosion.

4.4.1 Environmental Benefit

Although several environmental benefits can arise from the adoption of these BMPs, such as increased biodiversity and reduced greenhouse gas emission, only water quality improvements are considered here. The values were obtained using the SWAT hydrological model, developed by Yang et al. (2008), which estimates water flow, sediment and nutrient runoff implications of different land management practices in the study area. The abatement values were calculated based on the landscape conditions in 2010, such as livestock and herd size in the given year (W. Yang, personal communication, January 2012). The used values represent the yearly abatement amount that can be achieved by each BMP project, assuming all other BMP’s status is as it was in the base year.

Table 4.2. BMPs Total Phosphorus Abatement (kg) Values, Summary

BMP	Total # BMP	#BMP Reduces TP	Total TP (kg) (All Projects)	Minimum[a] TP (kg)	Average[a] TP (kg)	Maximum[a] TP (kg)
Forage	320	313	1,122	-0.5[b]	3.5	41.5
Holding Pond	14	14	35	0.3	2.5	14.3
Riparian	6	6	9	0.0	1.6	3.3
Wetland	222	222	489	0.1	2.2	23.8
Zero Till	31	0	-1,231	-245.5[b]	-39.7[b]	-1.0[b]
Grand Total	**593**	**555**	**424[c]**	**-245.5[b]**	**0.7**	**41.5**

a) Total Phosphorus reduced by BMP project per year at the watershed outlet given in kg.

b) Negative value means that a BMP project increases the Total phosphorus loading

c) The total refers to the amount of abatement achieved when all BMP projects are adopted in the watershed. The maximum achievable is higher than this, as some of the BMPs actually increase this pollutant.

Each project has three main pollutant values associated with it: total phosphorus (TP), total nitrogen (TN) and sediment (SED). TP and TN values are given in kilograms per year abatement, and the SED values are given in metric ton per year abatement at the outlet of the watershed. Summary statistics of the BMPs' environmental benefits are in Table 4.2 to Table 4.4.

Table 4.3. BMPs Nitrogen Abatement Values (kg), Summary

BMP	Total #BMP	#BMP Reduces	Total TN(kg) (All Projects)	Minimum[a] TN (kg)	Average [a] TN (kg)	Maximum[a] TN (kg)
Forage	320	314	10,646.8	-7.3[b]	33.3	244.8
Holding Pond	14	14	265.9	2.1	19.0	108.9
Riparian	6	6	67.9	0.3	11.3	24.8
Wetland	222	222	2,851.7	0.7	12.8	118.2
Zero Till	31	31	8,753.7	9.4	282.4	1,525.3
Grand Total	**593**	**587**	**22,585.9[c]**	**-7.3 [b]**	**38.1**	**1,525.3**

a) Total Nitrogen reduced by BMP project per year at the watershed outlet given in kg.

b) Negative value means that a BMP project increases the total nitrogen loading.

c) The total refers to the amount of abatement achieved when all BMP projects are adopted in the watershed. The maximum achievable is higher than this, as some of the BMPs actually increase this pollutant.

Table 4.4. BMPs Sediment Abatement Values (metric tons), Summary

BMP	#BMP	#BMP Reduces	Total Sediment (ton) (All Projects)	Minimum[a] SED (ton)	Average[a] SED (ton)	Maximum [a] SED (ton)
Forage	320	305	1,783.9	-5.3[b]	5.6	77.7
Holding Pond	14	14	45.5	0.4	3.2	18.6
Riparian	6	6	8.9	0.0	1.5	3.9
Wetland	222	222	488.5	0.1	2.2	23.8
Zero Till	31	31	1,153.9	1.3	37.2	208.7
Grand Total	**593**	**578**	**3,480[c]**	**-5.3[b]**	**5.9**	**208.7**

a) Sediment reduction by BMP project per year at the watershed outlet given in metric ton.

b) Negative value means that a BMP project increases sediment loading.

c) The total refers to the amount of abatement achieved when all BMP projects are adopted in the watershed. The maximum achievable is higher than this, as some of the BMPs actually increase this pollutant.

It is noteworthy that the Zero Till BMP shows a very distinct pattern and all projects would actually increase phosphorus pollution in the study area. Moreover, the additional phosphorus deposition caused by the changed tillage practices is quite high, with an average of 40 kg a year with a maximum of 245 kg a year. While zero or conservational tillage practices can be exceptionally beneficial in rainfall runoff dominated climates, in colder climates with snowmelt dominated runoff, conservational tillage actually increases phosphorus leaching into the water body. This has been reported for both Manitoba (Li et al. 2011; Liu et al. 2014) and South Saskatchewan (Mekonnen, Mazurek and Putz 2017). At the same time, Zero Till BMPs are especially efficient in reducing nitrogen pollution even in such a climate. On average, Zero Till projects could abate over 280 kg of nitrogen at the watershed outlet, which is almost ten times higher than the average of any other BMP type.

4.4.1.1 Modelling the Diminishing Rate of Return

The estimated abatement values for each BMP are calculated based on the assumption that all other BMPs are in the current starting state (W. Yang, personal communication, January 2012). However, if a producer implements multiple BMPs on the exact same field, such as establishing forage on a field where there is also wetland restoration, the total abatement of the BMP adoption may not be equal to the sum of the individual abatement values. While in some cases, like biodiversity, multiple BMP adoptions can enhance each other, here the focus is water quality where there is a diminishing marginal rate of return for each additional BMP adoption. Our mathematical model imposes a restriction that the interdependency between any two BMPs is independent from any other BMP implementation. As the study area had 593 projects, there are over 350,000 potential BMP pairs (593x593). Estimating the exact relationship between each pair-wise combination of BMP adoptions would be extremely computationally intensive, and would require running a hydrologic simulation for each pair.

As the diminishing effect dissipates over distance (Perez-Pedini, Limbrunner and Vogel 2005), for simplicity it is assumed that spatial dependency only matters between those BMPs that are located on the same or overlapping fields. Imposing this restriction means that every element in the *D* matrix that doesn't represent BMP pairs with overlapping fields is zero. Using the GIS map of the watershed, the location of each BMP was identified with a total number of overlaps between BMPs at 1600 (see Table 4.5). As the *D* matrix is assumed to be symmetric, this means that there are only 3200 values in the *D* matrix that need to be calculated.

The smaller the BMP project is geographically, the fewer interdependencies it can have. Given the nature of the BMPs, projects cannot be located on fields overlapping with other projects of the same type. As there are 5 types of BMPs considered, projects that are limited physically to a single field, such as Forage Conversion, wetland, and Holding Pond can only have up to 4 interdependencies. However, as shown in the table, there are Holding Pond and Forage BMPs which don't have any interdependencies, and on average these types of BMPs have slightly less than 2 interdependencies. On average, Wetland BMPs also have 2 interdependencies, and each of them has at least one overlapping BMP. As riparian areas can overlap multiple fields, they interact with up to 10 other BMP projects. On average, a riparian area interacts with 6 other projects, and each of them interacts with at least 3 others. Zero Till adoption is not field based, but it is assumed that producers adopt this practice on their entire farm. In this watershed there are small farms with a single field and there are large operations with multiple dozens of fields. As a result, the number of interactions of Zero Till projects varies to a great extent with an average of 18 interactions per project. Each Zero Till project has at least 2 interdependencies, and the largest farm has 77.

Table 4.5. Summary Statistics, Number of Overlapping Fields by BMP Type, STC Watershed, Manitoba

BMP Types	Minimum	Maximum	Average	Total
Forage	0	4	1.7	540
Holding Pond	0	4	1.8	25
Riparian	3	10	5.8	35
Wetland	1	4	2.0	445
Zero Till	2	77	17.9	555
Grand Total	**0**	**77**	**2.7**	**1600**

4.4.1.2 Dependency Matrix Calculation

After identifying the pairs that have potential interaction, the magnitude of the interaction was calculated based on their abatement levels and the size of the overlaps. In the mathematical model, if only two projects *(i,j)* get implemented at the same time ($X_i = X_j = 1$) the objective function will be the sum of their environmental values minus their dependency score multiplied by the *s* scaling factor: $E = e_i + e_j - s*(d_{ij} + d_{ji})$. Based on that, if the projects are <u>not</u> located on the same or overlapping fields, there is no interdependency between them, and the corresponding elements of the D matrix are zeros ($d_{ij} = d_{ji} \equiv 0$). This means that the objective function will be simply the sum of their individual abatements ($E = e_i + e_j$).

If the two projects are located on the same field, and none of them extends beyond this one field, they have one to one connection. For example, let the ith and jth projects represent wetland restoration and Forage Conversion BMP on the exact same field. In this case, the corresponding element of the D matrix is set to be the average of their environmental values:

$d_{ij} = d_{ji} \equiv \frac{(e_i + e_j)}{2}$. Consequently, the objective function becomes the sum of their total values adjusted with the scaling factor:

$$\begin{aligned} E &= e_i + e_j - s*(\frac{(e_i + e_j)}{2} + \frac{(e_i + e_j)}{2}) \\ &= (1-s)*(e_i + e_j) \end{aligned} \tag{4.4}$$

However, some BMP projects expand onto more than one field, and two projects may not have a one to one connection. For example, let's assume project i is a riparian area, which overlaps two fields, and each of those can be converted to forage (project *j,* and *k*). In such cases, the D matrix dependency scores are set to be proportionate to the size of the overlap. Let's assume in this example the two field sizes are in 4:6 ratio. In this case:

$$d_{ij} = d_{ji} \equiv \frac{(e_i + e_j * 0.4)}{2} \quad \text{and} \quad d_{ik} = d_{ki} \equiv \frac{(e_i + e_k * 0.6)}{2} \tag{4.5}$$

The underlying assumption of the diminishing rate of effectiveness assumes that both BMP implementations are beneficial. However, depending on what is our objective function and what are the e_j values, this might not be the case. As it has been described before, all Zero Till and some of the Forage projects are actually increasing total phosphorus pollution; hence their corresponding e_i values can be negative. If the D dependency matrix values are calculated as it is described above with negative values in the E matrix, the matrix will no longer be positive definite, which causes implementation problems. Moreover, the interpretation of the value is also problematic. If one project is detrimental ($e_j < 0$) to the objective, it is unclear what the overall outcome would be if both projects were to be implemented. For simplicity, it is assumed that in such case the values are independent, as there is no diminishing rate of return. Moreover, it doesn't matter from an optimization point of view, as optimally a project with a negative value won't be chosen for implementation. Hence, for simplicity those elements in the D matrix are assumed to be zero. Consequently, the elements of D dependency matrix were calculated as follows:

$$d_{ij} = \begin{cases} \frac{w_{ij}(e_i + e_j)}{2} & \text{if } e_i, e_j > 0, \text{ and } w_{ij} \text{ is the proportion of the fields overlapping} \\ 0 & \text{otherwise} \end{cases} \tag{4.6}$$

4.4.2 Cost and Budget

In addition to the environmental benefit, the cost of adoption of these BMPs was also studied and estimated in the WEBS project, and this present study utilizes the existing estimations. The cost of Forage Conversion, Zero Tillage and riparian area management in this watershed was estimated by Boxall et al. (2008) for the year 2004. Additional details of the cost construction were obtained via personal communication (M. Cutlac, July 2012). While the cost of the Holding Pond BMP was also estimated by Boxall et al. (2008), their calculation only accounted for the pond excavation cost. However, Khakbazan et al. (2013) extended the Holding Pond BMP calculation including fencing, annual maintenance and water removal costs; hence, their calculations were used as the basis for the Holding Pond BMP cost estimation. Wetland BMP cost calculation was adapted from Packman (2010). Adapting the methodology of these studies, the cost of each project was calculated for the 2010 conditions and given in 2010 dollars. Each BMP adoption cost accounts for immediate capital expenditures, and also includes the net present value of the foregone revenue for a 5-year period using a 10% discount factor. In the mathematical model, the C vector elements are simply the corresponding estimated total cost for each of the BMP projects when the social optimum is calculated. The cost calculations include only 5 years of foregone revenue, because the funding program that was active in the base year lasted for 5 years and the conservation contracts had no obligations toward the producers beyond the lifespan of the program. Hence, the assumption is that the producers put the land back into production the way it was before if that was more profitable. Specific details of the cost calculation can be found in the Appendix, and summary statistics of the costs can be found in Table 4.6.

On average, Holding Pond projects are one of the cheapest as even the most expensive pond is below $15,000; and this BMP also does not have significant cost variation. While Wetland Restoration projects are even cheaper on average ($4,500), their cost can go up to $55,000 per field. This is simply the result of the variation in the number and size of impacted wetlands to be restored on various fields. There are fields with a single 0.1 acre drained wetland, and there is a field with 55 drained wetlands with a total size of 22 acres if restored. Forage Conversion projects cost $8900 on average, but have large variability among the projects with a standard deviation of $13,400, with the highest cost for a project being almost $200,000. This is the result of the large variability in both field sizes and profitability of the land. The smallest field is 2.5 acres, while the largest is almost 500 acres. Despite the hundredfold variation in farm sizes, the cost variation of Zero Till projects is less than tenfold and varies between $15,000 and $100,000, with an average of $22,000. Riparian areas have the highest average cost ($47,000), due to the large capital cost of fencing and alternative waterer installation. As the majority of the cost occurs initially, the short time frame (5 yrs) puts this BMP type at a disadvantage compared to BMPs where the cost comes from lost revenue streams, such as forage.

Table 4.6. Summary Statistics, BMP Cost by BMP Type, STC Watershed, Manitoba

BMP Types	# of BMPs	Total Cost[b]	Average Cost[a]	Std Dev[a]	Highest Cost[a]
Holding Pond	14	$72,191	$5,156	$4,174	$14,468
Riparian	6	$280,255	$46,709	$19,554	$70,994
Forage	320	$2,835,400	$8,861	$13,356	$197,175
Zero Till	31	$468,586	$15,116	$21,912	$102,193
Wetland	222	$995,182	$4,483	$5,645	$54,494
Grand Total	**593**	**$4,651,614**	**$7,844**	**$12,610**	**$197,175**

a) These values are given on a per project basis, in 2010 dollars, assuming net present value of cost through 5 years using 10% interest rate.

b) Total cost is the cost of implementing every BMP of the given type.

4.4.2.1 Budget

In 2010, producers were able to obtain financial assistance to implement selected BMPs under the Growing Forward Environmental Stewardship (GF) framework. The GF program, just like its predecessor, The National Farm Stewardship Program (NSFP), operated on a cost share basis. The program ran from 2008 to 2013, and was replaced by the Growing Forward 2 program, which again provided funding with a similar structure (see Boxall 2018). All three programs were operated in a way to reimburse a certain percentage of the direct cost of the BMPs up to a maximum amount (see Table 4.7). These programs only reimbursed producers for the direct initial capital expenses, but none of them considered the opportunity cost of land taken out of production. They also did not cover any annual repair, maintenance or any other indirect costs the producer could incur. While the percentage cost share and the maximum amounts increased over the 3 programs, the structure remained the same, and uptake remained low.

While these programs were funded by the federal government, they were implemented and administered by the provincial governments (Boxall 2018). Each province decided separately about the covered BMPs, the share percentages and the maximum amounts. In Manitoba, the Manitoba Agriculture, Food and Rural Initiatives (MAFRI) developed multiple programs providing financial assistance to implement BMPs. The main program was called the Environmental Farm Action Program (EFAP), and provided financial assistance for Riparian Management and Farm Yard Runoff Control (e.g. the Holding Pond BMP). EFAP covered 75%

of the initial establishment cost up to a maximum of $30,000 and $70,000, respectively. The second program implemented by MAFRI was the Manitoba Sustainable Agriculture Practices Program (MSAPP). MSAPP provided financial assistance to implement Reduced Tillage (Zero Till BMP), and establish perennial cover (Forage Conversion BMP). MSAPP provided 75% assistance for the tillage equipment modification, and the added fertiliser cost after seeding up to $30,000 per project. The program covered 75% of the initial equipment, seeding and fertilizer cost of establishing a perennial cover up to 40 acre per projects. The maximum payable amount per Forage Conversion project was $15,000 and the total amount payable to any given producer was limited to $100,000 in the MSAPP program. Moreover, the maximum payable amount per producer was maximized at $160,000 for all BMP projects including both EFAP and MSAPP programs.

Table 4.7. Government Programs Providing Financial Assistance for Producers to Adopt BMPs in Manitoba

		Length of the Contract	**Eligible Expenses**	**Non-Eligible Expenses**	**Cost %**	**Maximum Payment**
EFAP	Holding Pond	Only during the program	Actual Establishing of the pond only (Lining, Excavation)	Fencing Pumps Maintenance Opportunity Cost	75%	70K
	Riparian Area Management	Only during the program	Seeding Fencing Waterer	Maintenance Opportunity Cost	75%	30K
	Total EFAP					**160K**[d]
MSAPP	Forage	Only during the program	Seeding Labour Equipment use	Opportunity Cost	75%	15K
	Zero Till	Only during the program	Equipment Modification	Maintenance Opportunity Cost	75%	15K
	Total MSAPP					**100K**
	Wetland[a]	Perpetuity easement	N/A		$200/acre wetland + assessed land value[b]	

a) Wetland Restoration was not part of Growing Forward, but at the same time the Wetland Restoration Incentive Program (WRIP) was active and those are the values used in the table.

b) For the assessed land value, we used the assessed land value from the Manitoba land assessment

c) Calculated based on the Dufferin program which provided $40/acre tax credit for restored wetland

d) EFAP limit includes BMPs under both EFAP and MSAPP programs

While wetland restoration is one of the most beneficial BMPs when it comes to reducing phosphorus in the water, it was not funded by the GF program in Manitoba in the base year. However, financial assistance for wetland restoration was available to producers through the Wetland Restoration Incentive Program (WRIP). This program included a one-time payment of $200/acre wetland restored plus the assessed value of the land under the agreement (including existing, and restored wetlands and the surrounding grassland). In the base year the Dufferin Wetlands Program was also active. It offered a $40/acre tax credit for producers after restoring wetlands. Assuming 25.8% (15% federal + 10.8% Manitoba provincial) tax, this would realize a tax rebate of $10.3/acre wetland restored annually.

Using the programs' guidelines, the total amounts they would pay out were calculated, (assuming implementation of all the BMPs) and the budget was set to these amounts. As these programs were administered separately and in some case by different organizations, their budgets were potentially independent from each other. The budget calculations reflect this separation, and in the optimization, the budgets are divided into 3 separate programs: EFAP, MSAP, and WRIP or Wetland. The EFAP program's budget included the potential payment that could have been paid out to BMPs that fall under the EFAP program structure: the Holding Pond and the Riparian Area Management BMPs. The MSAPP program's budget included payments that could have been paid out for BMPs that fall under the MSAPP program: Forage Conversion and Zero Till. The WRIP or the Wetland program's budget includes the potential payment that could have been paid out by the WRIP program if all the wetlands were restored in the watershed, plus the potential value of the tax credit of the restoration. While this program's budget also included the tax credit, it is referred to as WRIP or the wetland program in this study. Based on the calculation, the EFAP program's budget is the smallest, at just under $150,000 (see Table 4.8.). The wetland program's budget is slightly over $230,000. The MSAPP program has a considerably higher budget than the other two programs, almost 1.5 million dollars. If the budgets of all 3 programs are pooled, the total funding available for all 5 BMPs would be $1.86 million.

Table 4.8. Budget Settings

BMP Types	# BMP	Cost	Budget[a]
Holding Pond	14 ponds	$72,191	$38,633
Riparian Mgt.	6 riparian areas	$280,255	$110,695
Total EFAP ($BD_{1)}$		$352,446	$149,328
Forage	320 fields	$2,835,400	$1,018,053
Zero Till	31 producers	$468,586	$465,000
Total MSAPP (BD_2)		$3,303,986	$1,483,053
Wetland (BD_3)	222 fields	$995,182	$233,597
Grand Total		**$4,651,614**	**$1,865,978**

a) The budget was calculated from all the cost that was eligible for financial assistance for the given BMP under the incentive programs in 2010.

4.5 Scenarios

In order to be able to assess the effectiveness of various government policies, a benchmark has to be set. The BMP adoption pattern resulting from this presented model is the social optimum. The social optimum itself is strongly dependent on the various assumptions that are imposed on the model. The first set of scenarios focuses on the implications of choosing an environmental objective. More specifically, how the social optimum generated by the model changes depending on the weights used in the environmental benefit index that are employed in the optimization. The second set of scenarios analyzes how the different levels of the underlying hydrological link affect the social optimum. Based on the results of the first two sets of scenarios, a base case is established with a specific set of weights used in the optimization and with a fixed assumption on the magnitude of the underlying BMP linkage. Further scenarios are compared to the social optimum produced in the base case.

Once we have the social optimum produced by the model, it will be compared to various alternative scenarios. The third set of scenarios focuses on the implications of various agri-environmental government programs restrictions, for example, splitting the programs, and therefore the available funding, into sub-programs or imposing payment or size caps regarding BMP adoption. The fourth set of scenarios investigates the effect of various types and levels of rent seeking activities.

The focus of the last set of scenarios is to compare the potential effectiveness of using optimization model instead of conservation auction in voluntary conservation programs.

4.5.1 Choosing an Objective

Excess phosphorus is identified as the main problem in excessive algae growth in Lake Winnipeg, which is where the water in the study area drains to (Daniel, Sharpley and Lemunyon 1998; Environment Canada 2011). Some studies go even further and suggest that phosphorus should be the sole goal of water quality improvement (Jeppesen et al. 2005). However, nitrogen is identified as the second main concern in this particular watershed. As it is the easiest to estimate, sediment loading reduction was traditionally a main objective in many programs; for example, the objective of the CRP in the US was to reduce sediment loading by 20%. It was also the sole focus of many optimization studies in Canadian study areas (Yang et al. 2003; Yang, Khanna and Farnsworth 2005; Yang and Weersink 2004;

Juttinen et al. 2012). As all three pollutants can be important, the environmental objective can be set up as the weighted average of the three abatement values:

$$\begin{aligned} E &= \alpha_1 * TP + \alpha_2 * TN + \alpha_3 * SED \\ &\alpha_1 + \alpha_2 + \alpha_3 = 1 \end{aligned} \tag{4.7}$$

Depending on the weights used (α_i), the relative importance of the various pollutants can be changed. As some BMP types can increase one pollutant and may reduce another, the environmental objective of the optimal BMP implementation can vary significantly based on the weight selection. In order to explore the possibilities, the first set of scenarios analyzed the optimum generated by the mathematical model depending on four different sets of weights used in the analysis.

The first scenario's optimization was based solely on phosphorus, using 100%/0%/0% weights for the TP/TN and SED respectively. There are several optimization studies, which focus on phosphorus (Kao and Chen 2003; Gitau et al 2006; Karamouz et al. 2010). Moreover, a metastudy analyzing the long-term effects of pollution reduction in 35 freshwater lakes concluded that reducing phosphorus level led to considerable water quality improvement even with minimal or no nitrogen level reduction (Jeppesen et al. 2005).

The second scenario used 60%/20%/20% weights for the three pollutants, and still gave phosphorus three times higher weight than the other two pollutants, emphasising its importance. To our knowledge, in studies that use weighted averages of these three pollutants, this ratio was the one with the highest phosphorus percentage (Qi and Altinakar 2011).

The third scenario used a relatively balanced approach with 45%/35%/20% for the TP, TN and SED pollutants, respectively. This particular combination index was chosen based on Boxall et al. (2008), and was quoted from Dr Jane Elliot who was the lead scientist of the WEBS project for the study area. Moreover, the majority of the optimization studies used similarly balanced weights on these pollutants. Some studies use perfectly balanced weights giving each pollutant equal importance (Srivastava 2002, 2003), others give slightly higher weight to phosphorus, but the EBI is similar to ours. During the GF Program, the EBI index used by the Manitoban government included a water quality portion (MAFRI 2010), where they simply counted how many nutrients are reduced by the given practice, which essentially also gave them an equal weight.

The final scenario's optimization was based solely on sediment loading as reducing sediments used to be the main focus of many earlier studies and government policies; and also, because it is the one easiest to measure out of the three pollutants. Some other studies used weights slightly skewed toward sediment, such as 30%/30%/40% used by Qi et al.

(2008), or 20%/40%/60% (Kaini, Artita and Nicklow 2011). Moreover, there are many studies, including multiple Canadian ones, which used sediment exclusively as the objective (Yang et al. 2003; Yang, Khanna and Farnsworth 2005; Yang and Weersink 2004; Qi and Altinakar 2011; Juttinen et al. 2012). One of the largest scale conservation auction programs, the CRP in the US, also uses sediment as the sole target.

These four scenarios represent the potential social optimum, and they are identical in all other respects, except for the used weights for the three pollutants in the objective function. These scenarios all incorporate the same level of diminishing rate between BMPs (10%). Moreover, each scenario used a pooled budget and was absent of any restrictions or rent seeking activities.

Table 4.9. Scenarios Exploring Various Environmental Objectives.

Scenario Name	Description	Environmental Goal
Phosphorus Only	Social optimum using Total Phosphorous abatement as a sole environmental objective	$\alpha_1 = 1,\ \alpha_2 = 0,\ \alpha_3 = 0$ $E = TP$
EBI with TP priority	Social optimum using an environmental index skewing heavily toward Total Phosphorous	$\alpha_1 = 0.6,\ \alpha_2 = 0.2,\ \alpha_3 = 0.2$ $E = 0.6 * TP + 0.2 * TN + 0.2 * SED$
Balanced EBI	Social optimum using a relatively balanced environmental index	$\alpha_1 = 0.45,\ \alpha_2 = 0.35,\ \alpha_3 = 0.2$ $E = 0.45 * TP + 0.35 * TN + 0.2 * SED$
Sediment Only	Social optimum using total Sediment abatement as the sole environmental objective	$\alpha_1 = 0,\ \alpha_2 = 0,\ \alpha_3 = 1$ $E = SED$

4.5.2 Ignoring the Interdependencies

The actual underlying hydrological links between BMP adoption can be quite complex and obtaining information that is necessary to address these potential linkages can be time-consuming and costly. To simplify these linkages, the assumption was imposed that the diminishing rate is proportionate to the overlapping fields' abatement represented by the scaling parameter (*s*) in the mathematical model. This allowed us to easily scale the underlying interdependency setting based on this parameter. In order to explore the effect of various levels of diminishing rates, the second set of scenarios focused on varying the magnitudes of the interdependencies from 0% to 30% with 5% increments.

This range is aligned with the few studies that considered diminishing marginal rate in BMP adoption. Srivastava et al. (2002, 2003) used proportional parameter to model diminishing rate of an additional BMP adoption, and ran sensitivity analysis with 1%, 10%

and 20% values. However, beside these scenarios that focused on this scaling, the base assumption through this study was that the scaling factor is 10%, an approximate average assessed value based on the SWAT model results (Yang 2012 personal communication).

At each level of diminishing rates, two scenarios were analyzed. The first scenario at each level, is the most efficient conservation option (the social optimum) resulting from the mathematical optimization that incorporated the diminishing marginal rate into the model. However, setting up and solving the mathematical model presented here takes considerable amount of time and effort even with the imposed simplification. In order to calculate the spatial dependencies, GIS locations of the BMPs had to be assessed for potential overlaps. Moreover, introducing the interdependencies led to a quadratic mathematical model (MIQP), which requires considerable computation power. The second scenario at each externality level uses an alternative objective in the optimization model that ignores the externality. Without the interdependencies, the optimization model remains linear (MIP), which can be solved with a wide variety of software, and more importantly spatial overlaps of the BMPs do not need to be assessed. Analysing the result of each of these two scenarios at various externality levels allow us to assess the trade-off between extra effort required to address the externality and the resulting additional environmental abatement. A summary of the two scenarios can be found in Table 4.10.

Table 4.10. BMP Selection Methods Analyzed by Various Levels of Diminishing Rates

Description	Model Type	Objective function	Required Data
Optimization incorporating the diminishing marginal rate	MIQP	$\max \sum_{i=1}^{N} e_i x_i - s \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} x_j x_i$	Cost (C) and abatement(E) Exact GIS identification and assessment required to estimate the D matrix
Optimization, ignoring the spatial dependencies	MIP	$\max \sum_{i=1}^{N} e_i x_i$	Cost (C) and abatement(E)

4.5.3 Government Restrictions

The third set of scenarios are analysing the effect of various restrictions and limitations that are often in place in environmental programs. In our base year (2010) the GF program was active, so these scenarios are analyzing the effects of the various characteristics of that program.

It makes sense to pool all available agri-environmental funding into an overall budget, where the most cost-effective projects would receive financial assistance regardless of their type. This is aligned with the mindset of the Environmental Farm Stewardship Program. However, in practice, multiple programs are often established and administered separately. In our base year, the Wetland Restoration BMP was excluded from the GF program in Manitoba, and funding for this BMP was provided by a completely separate program, the WIRP. Moreover, even within the GF program, different BMPs belonged to different sub-programs. Some of the considered BMPs were covered by the EFAP and others fell under the MSAP. The first scenario in this category was set up to mimic the notion that the total available budget is separated into three sub-programs: EFAP, MSAPP and Wetland. This meant that in the optimization, instead of a single budget constraint, three separate budget constraints were included, one for each program. The second scenario illustrates how an even further separation of the budget would affect the program's result, and it assumes that each BMP has its own budget. A summary of the set up of the scenarios analyzed can be found in Table 4.11.

Most agri-environmental programs contain various restrictions with regard to the maximum payment and the potential size of land that can be used. These restrictions may be in place to increase the fairness among the producers. Or they may be in place to ensure that the program is not exceeding the budget that has been set aside for it, which can be very important in cost-share based programs such as the GF or GF2. The next three scenarios were set up to analyze the effect of these payment and size restrictions imposed on the BMP projects.

At the base year, when GF program was active, the total payment to any given producer could not exceed \$160,000 for the EFAP program and it could not exceed \$100,000 for the MSAPP Program. Moreover, the MSAPP program also specified that the combined MSAPP and EFAP projects together could not exceed the EFAP limit of \$160,000. The participation level of the large operations (for example producer #51 that has 50 fields) was considerably reduced by such restrictions. Moreover, there are both Forage and Zero Till BMP projects, with costs exceeding the MSAPP limit by themselves. Hence, imposing such restrictions would exclude those BMP projects from participation completely. Limiting the involvement of certain producers and excluding large BMP projects could easily distort the optimal BMP selection allocation. In order to be able to explore the magnitude of this distortion, we can add additional constraints to the mathematical model and compare the model results with and without these restrictions. The mathematical formulation of these restrictions requires linking the BMPs that belong to the same producer. For this purpose, a binary producer selector matrix (*P*) was introduced. The P matrix is an N x K matrix, where N is the total number of BMP projects (=593), and K is the number of producers in the watershed (=33). A matrix element is 1 if the given BMP project belongs to the given producer, otherwise 0. As each BMP project has to belong to exactly one producer the sum of each row in the matrix must be equal to 1.

$$\sum_{k=1}^{K} p_{ik} = 1 \ \ \forall i \in [1..626] \tag{4.8}$$

$$where:$$

$$P\begin{bmatrix} p_{11} & \cdots & \\ \vdots & \ddots & \vdots \\ p_{1K} & \cdots & \end{bmatrix} \quad \text{ucer selector Matrix (N=593,K=33)}$$

$$p_{ik} = \begin{cases} 1 & \text{if the i}^{\text{th}} \text{ BMP is located on the k}^{\text{th}} \text{ producer land} \\ 0 & otherwise \end{cases}$$

Since the payment restrictions are specific to given programs, the producer selector matrix needs to be interacted with the program type selector matrix (T), which was introduced in the mathematical model (section 4.3.1). The specification for the given data is the following:

$$t_{i1} + t_{i2} + t_{i3} = 1 \ \ \forall \ i \in [1..N=593] \tag{4.9}$$

$$where:$$

$$t_{i1} = \begin{cases} 1 & \textit{if the } i^{th} \textit{ BMP belongs to the EFAP program (Holding Pond or Ripariam Management)} \\ 0 & otherwise \end{cases}$$

$$t_{i2} = \begin{cases} 1 & \textit{if the } i^{th} \textit{ BMP belongs to the MSAPP program (Zero Till or Forage)} \\ 0 & otherwise \end{cases}$$

$$t_{i3} = \begin{cases} 1 & \textit{if the } i^{th} \textit{ BMP is Wetland Restoration} \\ 0 & otherwise \end{cases}$$

Using the type and program selector matrix, the two payment constraints can be formulated as follows:

$$\text{EFAPP constraint: } \sum_{i=N}^{N} t_{i1} * p_{ik} * x_i * c_i \le \$160{,}000 \ \forall k \in [1..K=33], \tag{4.10}$$

$$\text{MSAPP constraint: } \begin{cases} \sum_{i=N}^{N} t_{i2} * p_{ik} * x_i * c_i \le \$100{,}000 \ \forall k \in [1..K=33], \\ and \\ \sum_{i=N}^{N} (t_{i1} + t_{i2}) * p_{ik} * x_i * c_i \le \$160{,}000 \ \forall k \in [1..K=33], \end{cases} \tag{4.11}$$

In addition to the Payment restrictions, the MSAPP program also imposed a size restriction on Forage BMP, and maximized any individual project size at 40 acres. The implementation of this restriction does not involve any additional constraint formulation, but changes the cost (c_i) and the environmental benefit (e_i) values of the projects involved. Forage Conversion costs do not have any lump sum amount, and therefore were calculated on a cost per acre basis multiplied by the acreage of the entire field. Hence, when the size is maximized at 40 acres, the per acre costs are simply multiplied by the 40 acres instead of the actual field sizes. The environmental benefit estimates presume that the entire field is converted to forage, so they also need to be adjusted when that is not the case. As there is no data available that tells exactly how these values would change with such size restrictions, the environmental values are assumed to be proportionate to the size of the field, and they are reduced by the same proportion if the size of the project was reduced. In the scenarios in order to be able to analyze the individual effect of these payment restrictions, all other characteristics of the optimization were identical to the social optimum case. The summary of the set up of these scenarios can be found in Table 4.11.

Since these restrictions were all in place at the base year, the last scenario was set up to show what the combined effect of the various government restrictions was. This scenario used separate budgets for each of the three programs (EFAP, MSAP, WRIP), and imposed all the government restrictions at the same time. It included the payment restrictions imposed by both the EFAP and MSAPP programs, and it also included the MSAPP size restriction.

Table 4.11. Scenarios Analyzing Government Restrictions

Scenarios	Budget	Benefit (E) and Cost (C) Matrix	Additional Constraint(s)
Social Optimum	Pooled Budget: $\sum_{i=1}^{N} c_i x_i \le \sum_{j=1}^{M} BD_j$	Original E, C	-
Budget Separated by Programs	Budget Separated by Programs: MSAP, EFAP, WETLAND. M=3 $\sum_{i=1}^{M} t_{ij} c_i x_i \le BD_j \ \forall j \in [1..M]$	Original E, C	-
Budget Separated by Individual BMPs	Budget Separated by Individual BMPs, M=5 $\sum_{i=1}^{M} t_{ij} c_i x_i \le BD_j \ \forall j \in [1..M]$	Original E, C	-
EFAP Payment restriction	Pooled	Original E, C	Maximum payment for EFAP program is 100K (Equation 4.10)
MSAPP Payment restriction	Pooled	Original E, C	Maximum payment for MSAPP program is 160K (Equation 4.11)
MSAPP Size Restriction	Pooled	E, and C values reduced for Forage projects that were originally larger than 40 ha	-
Combined Restrictions	Budget Separated by Programs : MSAP, EFAP, WETLAND. M=3 $\sum_{i=1}^{M} t_{ij} c_i x_i \le BD_j \ \forall j \in [1..M]$	E, and C values reduced for Forage projects that were originally larger than 40 ha	Max EFAP is 160K, Max MSAPP 100K (Equation 4.10 and 4.11)

4.5.4 Rent Seeking

Ideally, the government would pay the exact amount of the adoption cost to the producers. This is a naïve and unrealistic goal in most incentive-based policies. Since policy makers are facing an asymmetric information problem where the producers have more accurate information about their costs, the producers are able to extract information rent above their actual adoption costs (Latacz-Lohmann and Van der Hamsvoort 1997). Agri-environmental programs, such as the NFSP, GF or GF2, often cover only direct capital costs that can be clearly proven to the agency. However, most BMP adoptions also cause various indirect costs such as missing out on future revenue of the land that no longer can be used, or they may lead to increased input requirements, such as higher amounts of fertilizer or pesticides. Since producers still have to endure a proportion of the direct costs and the all the indirect costs, adoption rate of these kinds of cost-share programs are low unless the BMP adoption has private benefit to the producers (Sparling and Brethour 2007).

In order to induce a rational agent to adopt a costly BMP, the full cost of adoption has to be covered. Since the extent of these costs is only known to the producers, various voluntary programs can be set up when the producers name their own price for the conservation contract. Based on the received price request, the government can choose a subset of producers that they provide funding for at the price they asked. The government agency can select the BMPs by ranking the received requests based on cost-benefit ratio, which is essentially a first price or discriminatory pricing conservation auction. Such conservation auctions have been used by conservation programs worldwide such as the Conservation Reserve Program (CRP) in the US, various Australian programs such as BushTender, EcoTender, the Auction for Landscape Recovery (ALR) program and the Western Australian Conservation Auction program (Latacz-Lohmann and Schilizzi 2005). However, alternatively the BMPs can be selected using a binary integer programming model, such as outlined in this study. Such model (excluding the interdependency) was employed in the Land Preservation Program in Baltimore County, Maryland (Messer et al. 2016).

However, regardless of the selection method used, the received price request can be inflated and contain information rent above the actual cost. The fourth set of scenarios was used to explore the implications of such rent seeking activities. Since there are very few applications using mathematical programming models in BMP adoption, there is no information about the potential magnitude of the information rent in such conservation programs. However, conservation auctions using discriminatory pricing only differ from such programs in that instead of selecting the BMPs with an optimization model, they select the BMPs by simply ranking them on a cost/benefit ratio. Hence, we can make the assumption that magnitude of the rent seeking would be the same in an optimization based voluntary program as it would be in a discriminatory auction. As information rents exist because the actual cost of service is only known to the landowner, it is not something that can be observed easily in a real world auction situation. However, auctions have been studied extensively in laboratory settings, and have been proven to produce results similar to the real world (List 2001). Hence, we can approximate the size of the information rent based on experimental auction results of the previous chapter.

In scenarios where rent seeking is included in the optimization, the conservation contract cost (C matrix) includes a markup above the actual implementation cost, which is assumed to be proportionate to the cost. The previous chapter’s individual markup equations are used as a benchmark for the magnitude of the rent seeking activities, and four potential rent scenarios were considered (see Table 4.12). Two options were considered with two levels of information in each. Option A used the intra-firm model result, and Option B used the average of results of the two inter-firm models from the previous chapter. Two rent seeking levels were considered for each option depending on the assumed level of information the producers had about their cost advantage/disadvantage prior to the program: low and high.

In the case of low information, the producers are assumed to have no previous information on how their costs compare to others, hence the magnitude was set based on the previous chapter's bidding behaviour with no learning or communication effects ($\beta_1 = \beta_2 = \beta_3 = \beta_4$ in equation 3.10). In the low information scenarios, each producer's cost was multiplied by 1.1 and 1.06 in Option A and B, respectively.

In the case of high information, the producers are assumed to know that they have a cost advantage or disadvantage compared to others. As a result, low-cost producers learn to inflate their cost more. So mid-cost producers ask for less markup than low-cost ones, and high-cost producers ask for even less. In these scenarios, the information producers have is assumed to be equivalent with the learning effect of two rounds of auction in the previous chapter's experiments. In the high information scenarios, each producer's cost was adjusted based on their cost–type. Low-cost producers' cost was multiplied by 1.2 or 1.135 for Option A and B; mid-cost producers' cost was multiplied by 1.07 or 1.02 for Option A and B; high-cost producers' cost was multiplied by 1.01 or 1.001 for Option A and B. The summary of the rent level use in these rent seeking scenarios can be found in Table 4.12.

Table 4.12. Percentage of Markup Asked in the Rent Seeking Scenarios

Rent Seeking Level	Rent Seeking Scenarios	
	Option A	*Option B*
Low Information (No learning)	10% for everyone	6% for everyone
High Information (Assume learning equivalent of information gained after 2 experimental rounds)	Low cost 20% Medium cost: 7%: High cost :1 %	Low cost :13.5% Medium cost: 2% High cost =0.1 %

4.5.5 Optimization vs. Conservation Auction Performance

While the previously described scenarios focused on the effects of various assumptions and characteristics on the optimization model itself, the last set of scenarios compared the effectiveness of the optimization model to a potential conservation auction. Beside the social optimum, four scenarios resulting from the mathematical optimization model (OPT), and three scenarios resulting from a conservation auction (CA) were considered.

As described in the previous section (4.5.4), a voluntary program where the landowners state their price gives them the opportunity to inflate their costs and include information rent into their price regardless of the selection process used (optimization vs. simple ranking of an auction). Therefore, rent was included in all the analyzed scenarios, except the benchmark social optimum. All seven scenarios (OPT 0-3, CA 1-3) used the rent seeking structure from the High Information Option A rent seeking scenario, with the assumption that low-, medium-, and high-cost producers add an extra 20%, 7%, and 1% markup on top of their actual costs, respectively.

Table 4.13. Scenarios Comparing Optimization Models to Conservation Auction

Scenario Name	BMP Selection Method	Inter-dependency incorporated	Restrictions	Rent[a]	Budget
Social Optimum	Optimization	Yes	-	-	Pooled
OPT0	Optimization	Yes	-	High Information	Pooled
OPT1	Optimization	-	-	High Information	Pooled
CA1	Conservation Auction	-	-	High Information	Pooled
OPT2	Optimization	-	-	High Information	Separated by Programs
CA2	Conservation Auction	-	-	High Information	Separated by Programs
OPT3	Optimization	-	MSAPP Payment EFAPP Payment and Size	High Information	Separated by Programs
CA3	Conservation Auction	-	MSAPP Payment EFAPP Payment and Size Restriction	High Information	Separated by Programs

a) High Information B rent scenario assumes that low-cost producers ask for 20%, medium-cost ones ask for 7%, and high-cost ones ask for 1% extra on top of their actual abatement cost

The first optimization scenario (OPT0) didn’t include any other restriction or modification. It incorporated the underlying spatial interdependencies into the optimization, used a single pooled budget and was absent of any other restrictions. This scenario represents the result that could be achieved on an actual conservation program if the agency would assess the specific location and would select the funded BMPs based on the MIQP model described here.

The next two scenarios (OPT1 and CA1) still used a pooled budget and were also absent of any restrictions, but ignored the underlying hydrological link among BMPs. OPT1 represents the result that could be achieved if the agency didn't assess the potential spatial linkage, and selected the funded BMPs based on a simple MIP optimization model. CA1 represents the result that could be achieved if a single conservation auction were held using discriminatory pricing.

The following two scenarios (OPT2 and CA2) ignored the underlying hydrological link, used separate budgets for the three programs (EFAP, MSAP, WRIP), but were still absent of any restrictions. The last two scenarios (OPT3 and CA3) used separate budgets for the three programs (EFAP, MSAP, WRIP), imposed all the program restrictions at the same time, and ignored the potential underlying hydrological link between the BMPs. A summary of these scenarios can be found in Table 4.13.

4.6 Results

The goal of this study was to determine the socially optimal BMP adoption pattern and the maximum achievable abatement levels in the study area, under various imposed scenarios in order to assess the cost effectiveness of potential government policies. The analyzed scenarios were divided into 5 categories. The first 4 sets of scenarios explored how the result of the mathematical model changes depending on various characteristics of the model such as changing objective, ignoring the interdependencies, including rent into the cost, and imposing various external restrictions. The last set of scenarios compared the optimization model's result with a conservation auction that featured a simple cost-benefit ranking and ignored the underlying hydrological connection between BMPs.

4.6.1 Importance of Choosing Environmental Objectives

The first set of scenarios addresses the implications of how we choose the measurable environmental objective that we are optimizing for. The environmental goal was set up as a weighted combination of three pollutants: Total Phosphorus (TP), Total Nitrogen (TN), and Sediment (SED). Four scenarios were examined based on the weights used for the pollutants. The first scenario optimized solely based on phosphorus level and used 100%/0%/0% for the TP/TN/SED ratio. The second scenario optimized based on all three pollutants heavily prioritizing phosphorus and used 60%/20%/20% for the TP/TN/SED ratio. The third scenario optimized for all three pollutants giving a slight priority to phosphorus and used 45% /35%/20 weights for the TP/TN/SED ratio. The fourth scenario optimized solely based on sediment level and used 0%/0%/100% for the TP/TN/SED ratio.

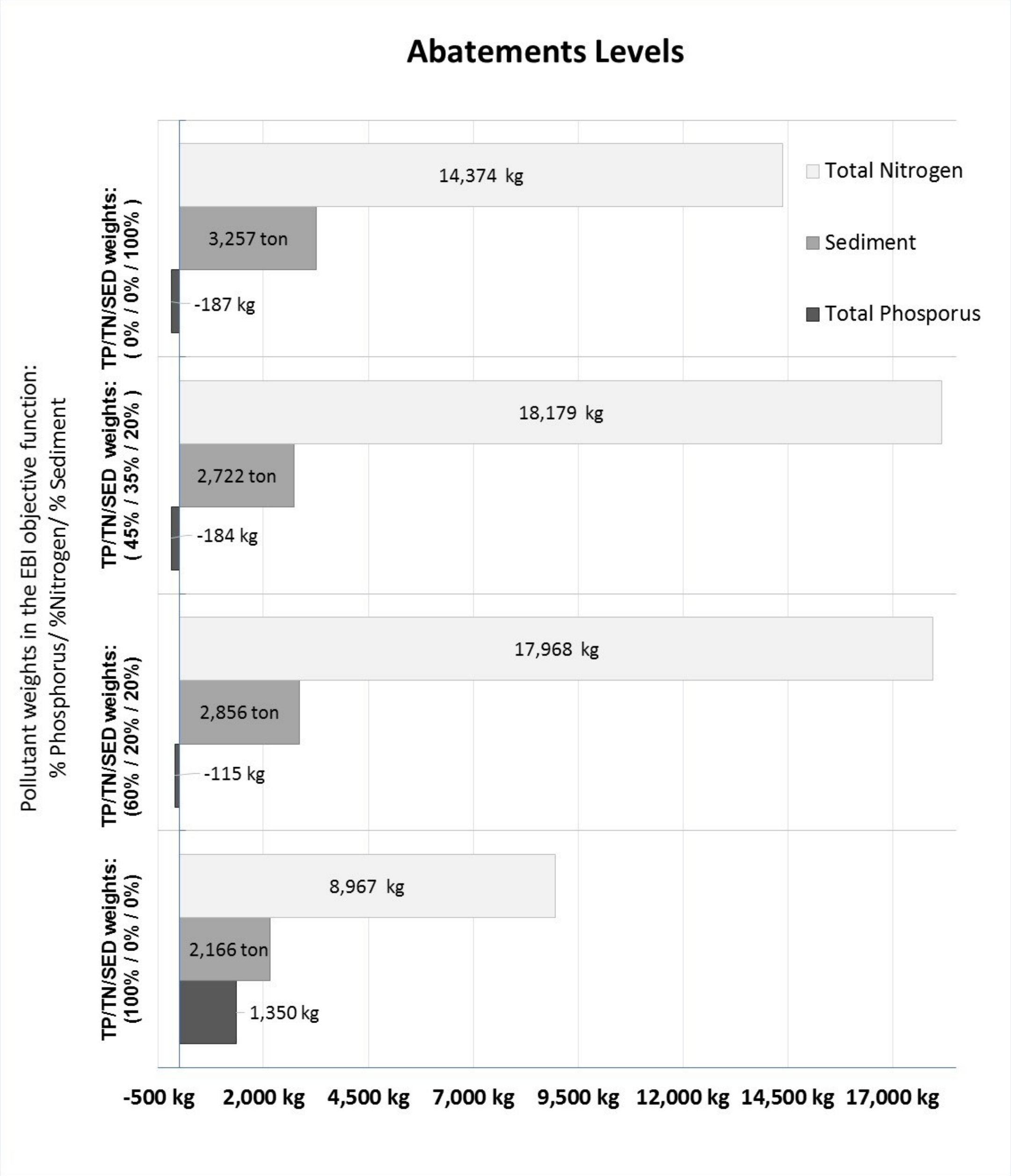

Figure 4.1. Abatement Values by Weights Used in the Objective Function

The results show that, in this particular watershed, choosing anything other than optimizing solely based on total phosphorus (TP) abatement would lead to a situation where the phosphorus loading increases in the water body. This situation is strongly driven by the fact that the Zero Till BMP is exceptionally great for achieving high levels of nitrogen and sediment abatement, but actually significantly increases phosphorus loading in the water in this particular watershed. This increase occurs because the watershed is located in the Canadian Prairies where the runoff is snowmelt driven (Li et al. 2011, Liu et al. 2014; Tiessen et al. 2010).

If the BMPs adopted are selected by solely optimizing for reducing sediment loading, phosphorus loading would increase by 187 kg per year (see Figure 4.1). If the BMPs adopted are selected based on a relatively balanced environmental index, phosphorus pollution would go up by almost the same amount (184 kg) per year. Even If the optimization uses an environmental index that heavily prioritizes TP (with a 60% weight), the abated phosphorus would still increase by 115 kg instead of decreasing. Since the first and foremost priority is to reduce phosphorus in the water body, these scenarios are simply not aligned with the environmental objectives of the province.

The optimization shows that by using the budget, which is about 1.85 million Canadian dollars, we can reduce the total phosphorus at the watershed outlet by 1350 kg a year, assuming there is a 10% diminishing rate among overlapping fields. At the same time, these BMP adoptions also reduce the total nitrogen by almost 9,000 kg a year, as well as reducing sediment loading by almost 2,200 metric ton a year. Dr Jane Elliot, who was the lead scientist of the WEBS project at the time of the data collection, stated that ideally each kg of phosphorus abated should come with at least 5 kg of nitrogen and 150 kg of sediment abatement (Boxall et al. 2008). This requirement is more than satisfied and not just in this case, but in all scenarios that are discussed throughout this study.

In the alternative scenarios, which do not use phosphorus as the single objective, we reach significantly higher levels of abatement for nitrogen and sediment. In scenarios where the weight used for nitrogen is not zero, we could reach around 18,200 kg of nitrogen abatement annually, which is twice as much as in the Phosphorus-only scenario. In these scenarios, the sediment abatement is also around 30% higher than it was in the Phosphorus-only scenario. When sediment is used as the sole objective, sediment abatement further increases, and we could reach over 3,250 metric tons abatement per year, which is 50% more than it is in the Phosphorus-only scenario. However, the additional nitrogen and sediment abatement would come at the expense of losing all potential phosphorus abatement and in fact would worsen the phosphorus pollution. After spending $1.85 M, increasing phosphorus loading at the watershed outlet, and eventually in Lake Winnipeg, is not aligned with the public interest. Therefore, the environmental objective was set to optimizing solely based on phosphorus level in all other scenarios. The result of the first scenario represents the social optimum in all other scenarios, and is used as a benchmark to evaluate the effectiveness of the other scenarios. Additional details about the results of these scenarios can be found in the Appendix (Table 4.17 -Table 4.20).

4.6.2 The Social Cost of Ignoring the Diminishing Marginal Rate of BMP Adoptions

This study assumes that there is a diminishing marginal rate between BMPs adopted at the same location. The magnitude of this decrease is assumed to be a fixed proportion of the BMPs abatement. Scenarios were run from 0% to 30% with 5% increments as a sensitivity analysis, and their result is shown in Figure 4.2. Two scenarios were run for each of the seven potential levels: a) optimization, incorporating the diminishing marginal rate between BMPs (Figure 4.2, dark bar), b) optimization, ignoring this subadditivity (Figure 4.2 , light bar).

If there is no actual hydrological link between these BMPs (subadditivity level =0%), we can achieve a maximum of 1409 kg of total phosphorus abatement per year at the watershed outlet in the study area. However, if there is actually a diminishing rate between any of the BMPs, we cannot achieve this amount of abatement, even if the implemented BMPs are chosen optimally. If there is a 5% diminishing rate between completely overlapping BMPs, we can optimally achieve 1374 kg of phosphorus abatement annually if this hydrological link is incorporated into the optimization. If this linkage is not taken into consideration and the implemented BMPs are selected by ignoring the interdependencies, we lose 7 kg of abatement and achieve 1367 kg (-0.5% loss).

Without intensive hydrological analysis of the site, the magnitude of the actual diminishing rate is unknown to the regulator. However, this sensitivity analysis showed a distinct pattern between the relationships of the optimal abatement generation versus abatement generated when the interdependency was ignored. The efficiency loss of ignoring the interdependencies increased as the magnitude of the actual hydrological linkage increased. However, the relationship is not linear, and the program would proportionally miss out on a lesser amount as the rate of the diminishing return increases. If two overlapping BMPs reduced each others' effectiveness by as much as 30%, ignoring this dependency would lead to missing 135 kg of phosphorus (1159 kg vs. the possible 1295 kg) abatement. This is slightly less than 11% of the total achievable phosphorus abatement.

The above scenarios give an approximate idea of how the various interdependency levels affect the efficiency loss of ignoring the spatial relationship. For simplicity, the magnitude of the underlying hydrological linkl is assumed to be the same in the rest of the study (10%). In this chosen base case, where 10% spillover is assumed, the maximum phosphorus abatement possible is 1350 kg using total phosphorus (TP) as the sole objective. If the spillover is ignored, but otherwise the BMPs are optimally selected, we can achieve 1325 kg of total phosphorus abatement. Hence, in the study area, the cost of ignoring the potential hydrologic linkages and using simple cost/benefit ranking is 27 kg less abatement than the maximum possible in our base case. This is less than 2% of the maximum obtainable at this level of spatial interdependencies.

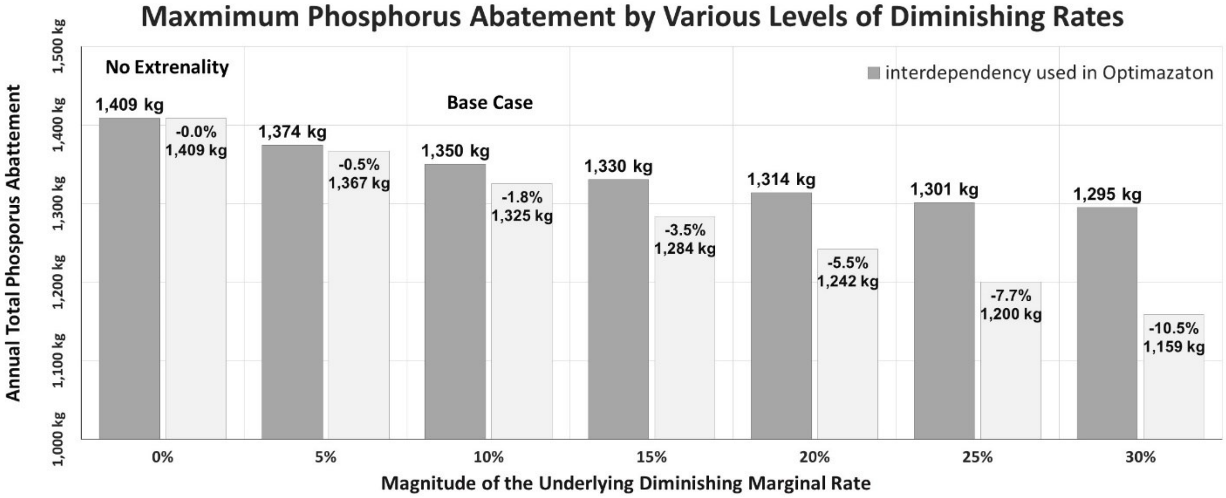

Figure 4.2. Maximum Achievable Phosphorus Abatement, by Underlying Externality Levels.

4.6.3 Social Cost and Government Program Restrictions

The focus of the scenarios analyzed in this section was assessing the effects of the various characteristics and limitations imposed in our base year (2010) on the GF program in Manitoba. All the presented scenarios assumed that the agency had full information, excluded any rent seeking activities, and accounted for the negative externality during the optimization.

The scenarios are compared based on the amount of total phosphorus abatement they achieved compared to the social optimum that represents 100% of the maximum achievable phosphorus abatement. In addition to the six analyzed scenarios, the graphical illustration of the results also includes the social optimum as a benchmark (Figure 4.3, first bar). Aside from the last one, the scenarios only differ from the social optimum in a single feature they represent in order to be able to isolate the effects of each of the restrictions being analyzed. The last scenario was set up to show the combined effects of the various government restrictions.

First, the effect of separating the budget is shown. The first scenario illustrates the effect of the total available funding being divided into 3 sub-programs: MSAP, EFAP, and Wetland as discussed in section 4.5.3. In such a case the program's effectiveness immediately drops by almost 8% (Figure 4.3, second bar). If the program's budgets were further separated into 5 individual BMPs, we would lose another 8% effectiveness, and could only achieve 84% of the maximum phosphorus abatement without accounting for any implementation difficulties (Figure 4.3; third bar).

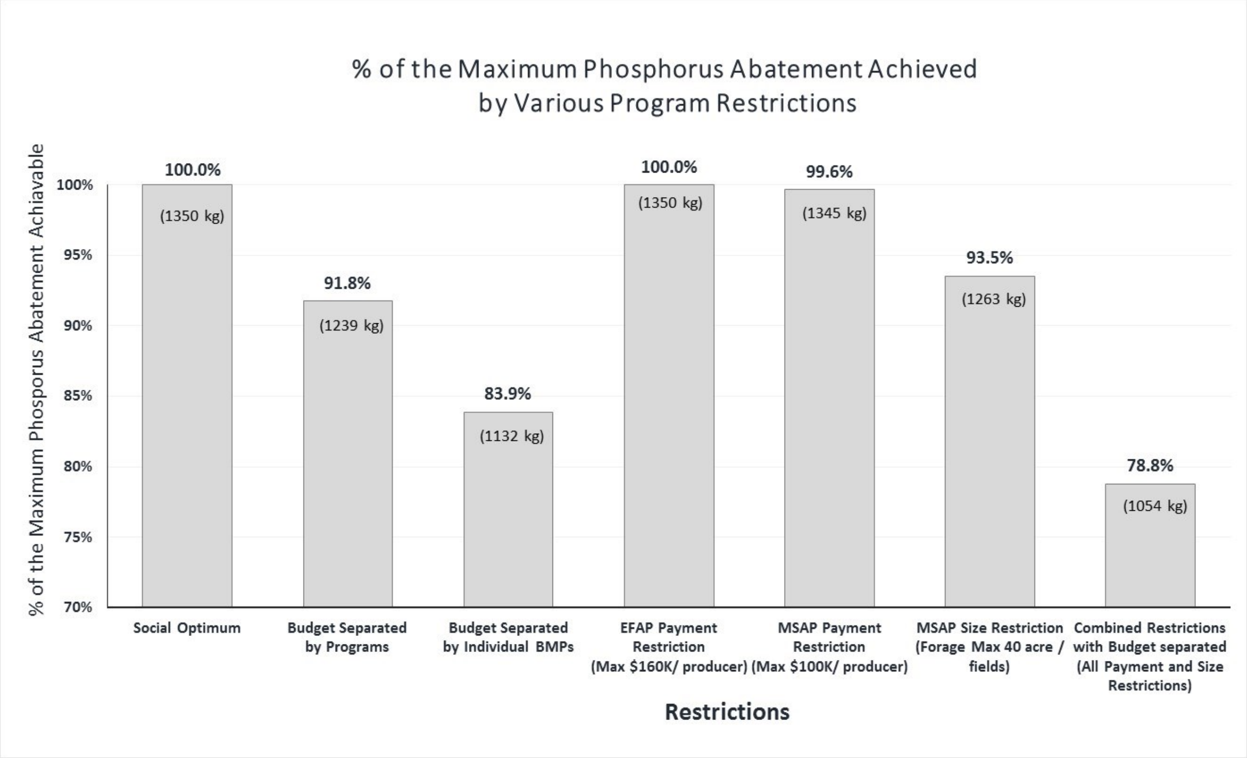

Figure 4.3. Maximum Achievable Phosphorus Abatement by Various Government Restrictions

Another typical restriction in agri-environmental programs is maximizing the payout to an individual producer. In our base year, the EFAP program capped the total payment to any single producer at $160,000 Canadian. In the study area, only a handful of BMPs belonged to this program, the Riparian Area Management BMP (6 projects) and Holding Pond BMP (14 projects). In this watershed, producers tend to only have a single one of these types of BMPs, and even the most expensive of those projects ($70K) was far below the payment cap. As a result, this restriction was not a limiting factor, and the constraint actually did not bind during the optimization. Hence, this restriction did not affect the optimally selected BMPs, and did not lead to any efficiency loss. Therefore, this scenario achieved the optimal 1,350kg of annual phosphorus abatement (=100%). This is not the case with the MSAPP program's payout restriction. In the base year, the MSAPP program's payout was capped at $100,000 to any single producer. Since there are some large producers in the study area's watershed, this restriction itself caused a 0.4% drop in the potential optimum.

In addition to the payment restrictions, there was also a size restriction imposed on some BMP projects, and Forage Conversion was limited to 40 acres on any given field. This size restriction itself led to a decrease in the maximum achievable phosphorus abatement level by 6.5% as it reduced the size of some very cost-effective projects. These payment and size restrictions may have been in place to reduce the size of the overall budget expenditure. However, it would have been more efficient to reduce the budget directly instead of reducing it through indirect size and payout limitations on certain BMPs as they caused significant drops in the maximum abatement effectiveness of the programs.

While the individual magnitudes of the efficiency loss caused by these restrictions may not seem that high, often these restrictions are imposed together. The last scenario showed exactly how much efficiency loss would occur if all the restrictions were imposed together. This scenario had quite a low performance and only reached 78.8% of the maximum phosphorus abatement achievable (Figure 4.3; last bar). It resulted in 1054 kg annual phosphorus abatement as opposed to the 1350kg that was achievable without these restrictions on the optimization.

The underlying mechanisms that led to these efficiency losses are discussed later when the optimization results are compared to potential conservation auction outcomes (section 4.6.5). The detailed results of the discussed scenarios can be found in the Appendix (Table 4.17 - Table 4.20).

4.6.4 Social Costs of Rent Seeking

We explored four rent seeking scenarios, two of which assume producers have no information about how their costs compare with others, and two scenarios where they have some information about their cost advantages or disadvantages. In the two low-information rent scenarios it is assumed that all producers ask 6% and 10% on top of their actual cost (shown as option A and B, respectively, in Figure 4.4). While this caused 5.7% or 9.1% of the total program payments respectively to be wasted on rent, the actual efficiency loss, in terms of not reaching as high abatement levels as it could, was of a much lesser magnitude. The low information scenarios still achieved 1,315 kg and 1,303 kg of phosphorus abatement, respectively. As the social optimum is 1,350 kg, this means 2.1% and 3.5% efficiency loss in terms of quantity abated.

The last two scenarios assumed that the producers knew if they had cost advantages or disadvantages compared to others in the watershed. In these scenarios, it was assumed that the low-cost producers asked proportionally more payment on the top of their actual abatement cost than the mid-cost producers, and the high-cost producers asked less. In the two scenarios, the low-cost producers, which had the most room to rent seek, included 13% and 20% extra in their bids on top of their actual costs, respectively. In these scenarios the achieved annual phosphorus abatement was 1,315 kg and 1,287 kg as opposed to the potentially achievable 1,350 kg. Hence, even in the highest rent seeking scenarios where many producers inflated their costs by 20%, the actual efficiency loss with regard to quantity was less than 5%. Additional details about the results of these scenarios can be found in the Appendix (Table 4.17 -Table 4.20).

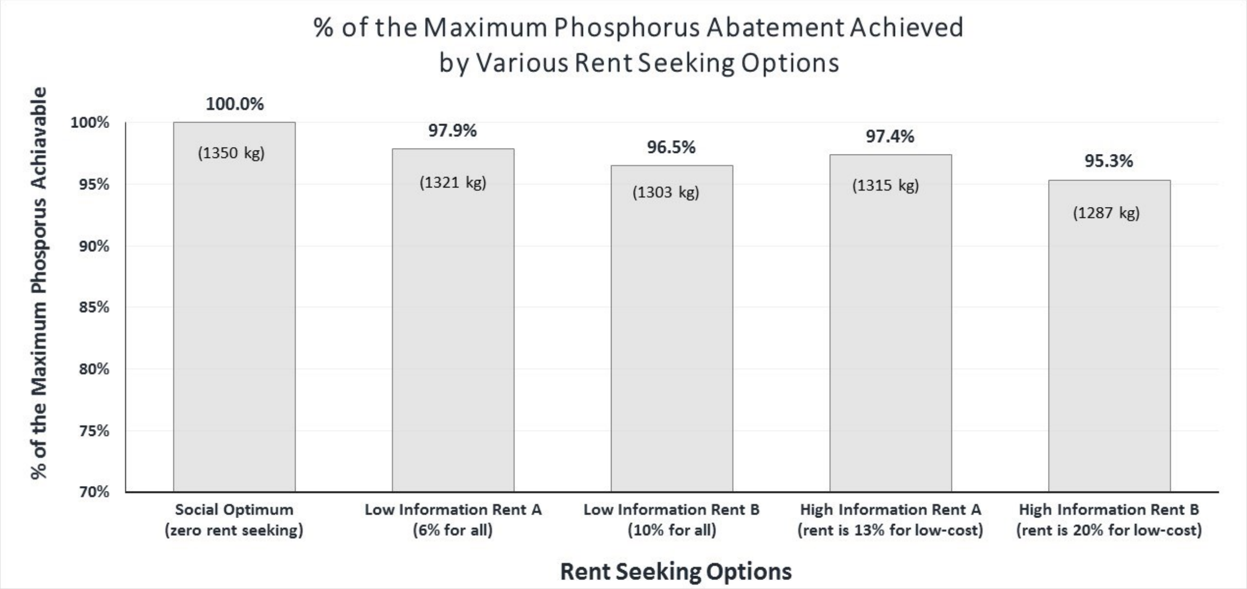

Figure 4.4. Maximum Achievable Phosphorus Abatement by Various Rent Seeking Options

4.6.5 Optimization vs. Conservation Auction Performance

While the previous scenarios focused on the various settings of the optimization model, these scenarios compared the social optimum to various potential conservation programs that would use either a mathematical programming model or a conservation auction to select the funded BMPs. The graphical illustrations compare the results of 8 scenarios: the social optimum, 4 scenarios representing conservation programs using optimization (OPT), and 3 scenarios using conservation auctions (CA) with similar settings.

The maximum achievable Phosphorus abatement was 1,350 kg (=100%) annually in this watershed as shown by the Social Optimum (Figure 4.5). Due to the rent seeking activity, this abatement level decreased by 4.7% from 1350 kg to 1285 even if the presented MIQP optimization model was used, accounting for the interdependencies among the BMPs (Figure 4.5, OPT0)

If the agency were to ignore the underlying hydrological connections and select the funded BMPs using a simpler MIP optimization, the effectiveness would be reduced by 1.7% and would lead to 1,263 kg of phosphorus abatement annually (Figure 4.5, OPT1). A potential conservation auction using simple ranking instead of optimization would result in the almost identical amount of abatement, and would lead to 93.3% of the maximum achievable level

(Figure 4.5, CA1). Hence, using an optimization instead of simply ranking would only improve abatement quantity by 4kg annually, unless we incorporate the diminishing marginal rate into the model.

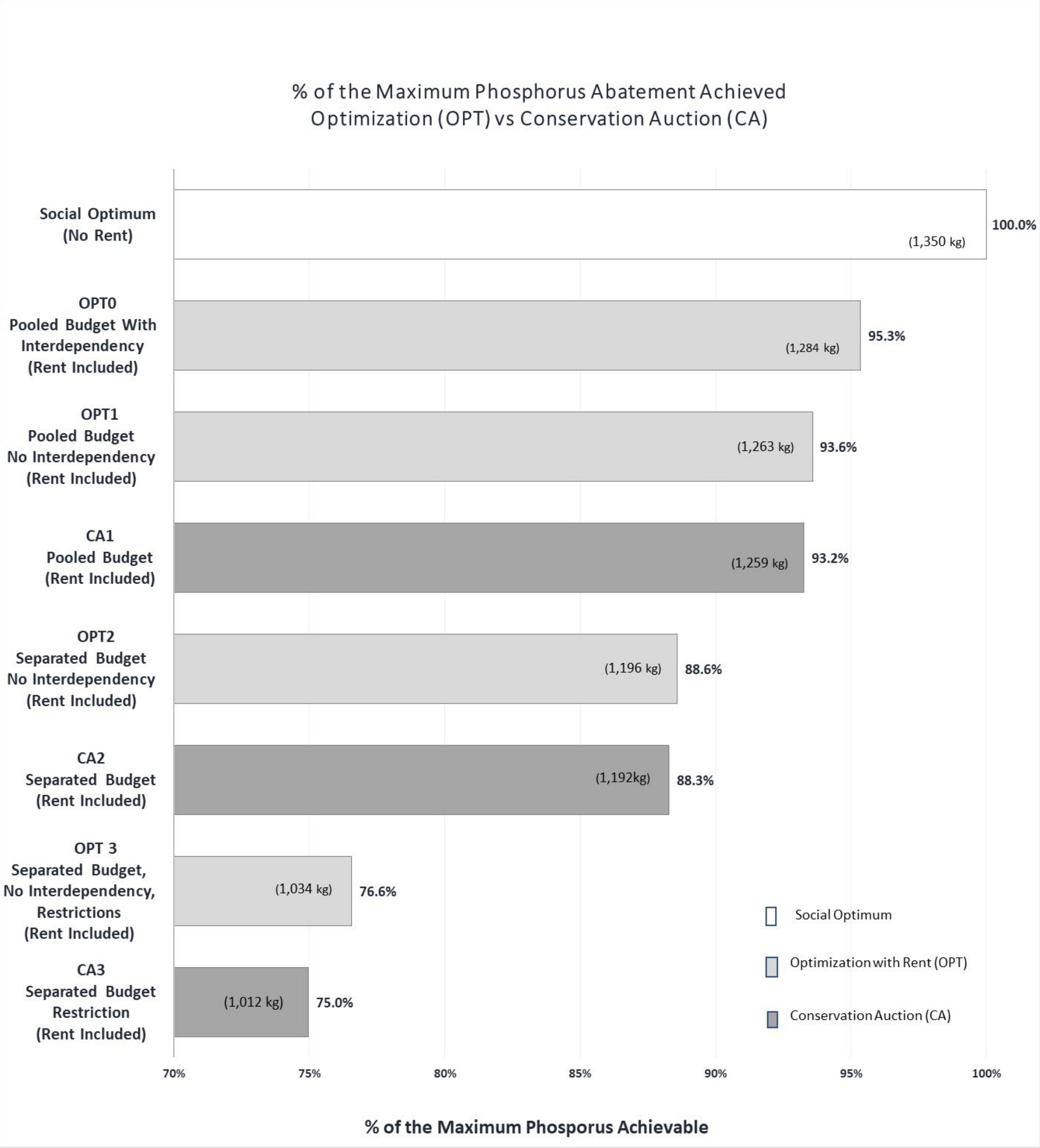

Figure 4.5. Maximum Achievable Phosphorus Abatement, Optimization vs. Conservation Auction

If the agency split the funding, the efficiency would drop by 5% and we could reach slightly over 88% of the maximum abatement achievable (Figure 4.5, OPT2, and CA2). Again, using optimization (OPT2) as opposed to the auction (CA2) would only provide 4 kg of phosphorus difference (1,296 kg vs. 1,292 kg). However, these were still superior compared to the scenarios where the agencies imposed various payout and size restrictions. When the available funding was not just separated into the three subprograms, but EFAP and MSAPP program payment and size restrictions were imposed, the efficiency dropped to 76.6% in case of optimization (Figure 4.5, OPT3), and to 75% in case of conservation auction (Figure 4.5, CA3).

We can also compare the efficiency of these scenarios in terms of cost. More specifically, we can compare the average costs of a kg of phosphorus abated in these scenarios. In this watershed, in the optimal case, the average cost of abating one kg of phosphorus annually would be $1,382 (Figure 4.6, Social Optimum). This is only achievable if we had full information about both the adoption costs and the underlying hydrological links and the social planner would optimize according to this information. However, the asymmetric information leads to rent seeking activities regardless of how we select the BMPs to be adopted. Even if the underlying spatial externalities were incorporated into an optimization, the price of a kg of phosphorus abatement would become $1450 (Figure 4.6, OPT0). If we ignored the interdependencies during the BMP selection, but still used the optimization model, the price would go up by another $27 (Figure 4.6, OPT1), and if a simple cost-benefit ranking was used, it would go up by $19 (Figure 4.6, CA1). If we split the funding by the 3 separate programs, the cost went up by an additional $67 in case of optimization (Figure 4.6, OPT2) and $43 in case of conservation auction (Figure 4.6, CA2).

However, the largest jump in the cost resulted from the various restrictions. Imposing the payment and size restrictions in the optimization model led to a $250 increase (Figure 4.6, OPT3), and in conservation auction led to an over $300 increase (Figure 4.6, CA3). Hence, we can conclude that despite rent seeking activity, a voluntary conservation program where agricultural producers name their own price can be very effective using either optimization or conservation auction as a selection mechanism, but only if no external restrictions are imposed.

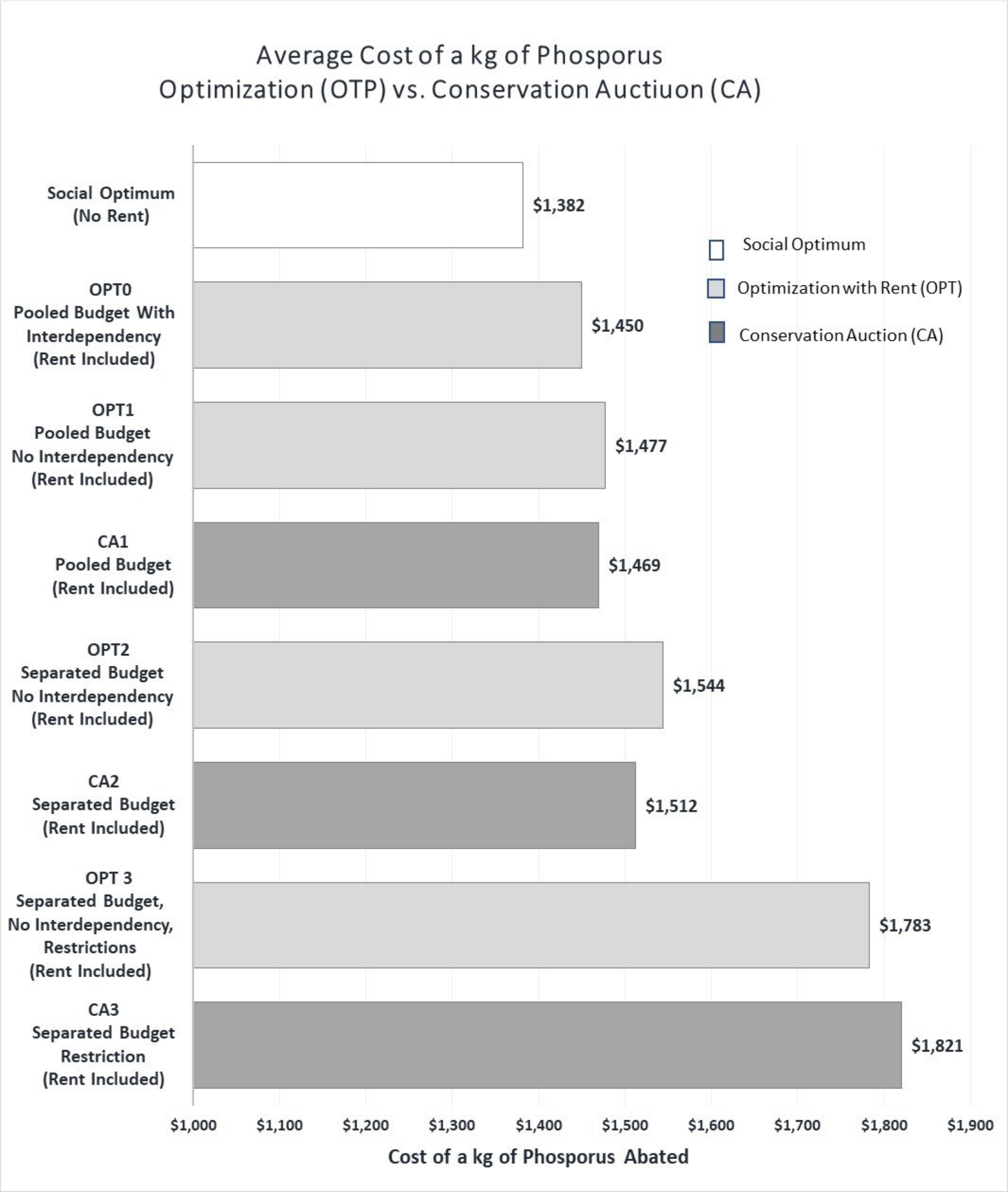

Figure 4.6. Average Cost of a kg of Phosphorus Abated, Optimization vs. Conservation Auction

4.6.5.1 The Cause of the Change in Efficiency

The above sections described how the achieved abatement level changes due to various characteristics and restrictions in an optimization based conservation program and in a conservation auction. The underlying mechanism that causes these distortions is that the funding doesn't go to those producers where it should be going. Optimally, the funding would go to the projects that could add environmental benefits in the most cost-efficient way. In this particular watershed, a total of 335 projects would receive funding with the given budget; of which 186 are low-cost and 149 medium-cost (Figure 4.7, Social Optimum).

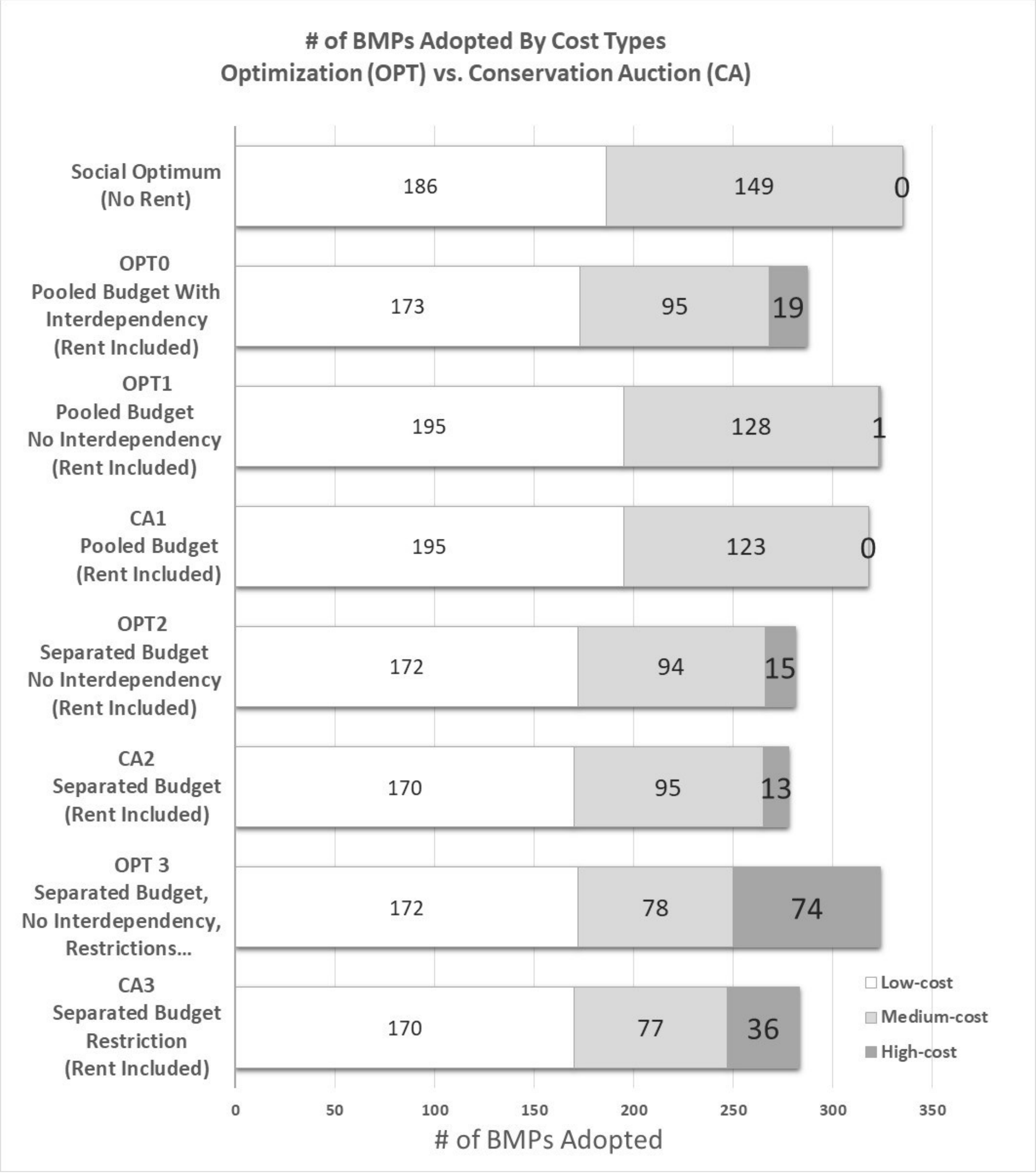

Figure 4.7. Number of BMPs Adopted by Cost Categories, Optimization vs. Conservation Auction

When rent is paid on the top of the actual cost, the same amount of money can fund only a smaller number of projects, hence the total number of projects was lower than the Social Optimum in all OPT and CA scenarios. However, the allocation of the low-, mid- and high-cost projects depends on the program considered. In the scenario with a single conservation auction with pooled budget (Figure 4.7; CA1), a total of 318 projects received funding, of which 195 were low-cost and 123 were medium-cost. When optimization was used without incorporating the interdependencies, the result was almost identical and again 195 low-cost, 128 medium-cost and 1 high-cost projects were funded (Figure 4.7; OPT1). The difference between these two scenarios is the result of the indivisibilities of the BMP adoption. In a conservation auction, the projects are simply ranked by cost-benefit ratio and the most cost-efficient projects are always selected first. At the cut-off point, when the project that is next in line by cost-benefit ratio is too expensive to be funded, the conservation auction can leave some money on the table. When the funding is allocated by optimization (which ignores the hydrological link), the leftover money is used to select some smaller expensive projects to be funded with it. This is the reason why the optimization scenarios have higher budget utilization rates than the corresponding conservation auction scenarios.

In order to achieve the highest abatement level, the underlying relationship between BMPs should have been taken into consideration. However, this can cause a situation where some the low-cost projects would not receive funding if they were located on a field with even more efficient projects. As a result, in the Social Optimum case only 186 out of the 195 low-cost projects would receive funding. When the cost included differentiated rent seeking, this effect got more prominent, reducing not only the number of funded low-cost projects (only 173 out of 195), but also causing some high–cost projects (17) to be funded (Figure 4.7; OPT1). Hence, while the cost-benefit ranking of the conservation auction may cause some efficiency loss in terms of abatement quantity, it actually improves the transparency and the perceived fairness of the program, as all the 195 low-cost projects would receive funding, and none of the high-cost ones.

While these scenarios (CA1, OPT1 and OPT0), had some minor differences, the main distortion resulted from separating the budget into sub-programs and imposing additional restrictions. In the scenarios where the budget was split into three sub-programs the number of the funded low- and mid-cost projects was reduced, and moreover, some of the high-cost projects received funding (Figure 4.7; CA2 and OPT2). The results in these two scenarios were almost identical. The number of low-cost projects that received funding was reduced from 195 to 170 in the case of OPT2 and to 170 in the CA2 scenario. The number of mid-cost projects that received funding was reduced from 128 to 94 in the OPT2 and from 123 to 95 in the CA2 scenarios, respectively. In the pooled budget scenarios neither OPT1 nor CA1 scenarios funded any high-cost projects, but 15 high-cost projects received funding in the OPT2 and 13 in the CA2 scenario as a result of the split budget. The slight difference between the OPT2 and the CA2 scenarios is the result of the indivisibility of the projects at the cut-off line as mentioned earlier. Since there were three programs in these scenarios with three budget cut-off points, the conservation auction left more money on the table. On the other hand, the optimization (OPT2) filled up this budget gap with smaller, not necessarily cost efficient, projects.

In the scenarios where the budget was not just separated into sub-programs, but the programs also imposed various restrictions there was a further shift from mid-cost to high-cost producers. The number of funded mid-cost projects was reduced to 77 in the auction (Figure 4.7; CA3), and to 78 in the optimization (Figure 4.7; OPT3), respectively. At the same time, the number of funded high-cost projects increased to 36 in the conservation auction (CA3), and to 74 in the optimization (OP3) respectively. Again, the reason of the difference between the conservation auction and the optimization model (CA3 vs. OPT3) is the indivisibility of the projects at the cut-off point.

Without knowing a priori, the actual abatement amounts, it is hard to decide where the funding should go. However, a general trend can be recognized in this study area. On average, Wetland Restorations are the most cost efficient at reducing phosphorus runoff: optimally 149 of the total of 222 wetland restoration projects would be funded, which is 67% of the wetland projects. Forage Conversion is often also very efficient in terms of phosphorus abatement in this watershed. Optimally about half (178 of the total 320 or 55%) of the eligible forage projects would receive funding. The Holding Pond BMP, which is a similarly efficient practice, would be funded optimally with a similar proportion (8 out of the 14 or 57%). Optimally, none of the Riparian Area Management or the Zero Till BMPs would receive funding (Figure 4.8, Social Optimum). While Riparian Area BMPs perform well in terms of benefit[36], they are very expensive due to the large capital cost of fencing and installation of alternative watering systems for livestock.

When rent was included in the cost of adoption, with the interdependencies still considered in the optimization, the adoption pattern remained very similar with slightly fewer projects getting funded. In the OPT0 scenario, 165 Forage Conversion, 134 Wetland Restoration, and 8 Holding Pond projects would receive funding. When the independencies was ignored during the BMP selection, there was a slight shift from Forage Conversion to Wetland Restoration both in the optimization (Figure 4.8; OPT1) and the conservation auction (Figure 4.8; CA1).

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[36] There is a Riparian Area BMP with phosphorus abatement level higher than the average Holding Pond BMP abatement level.

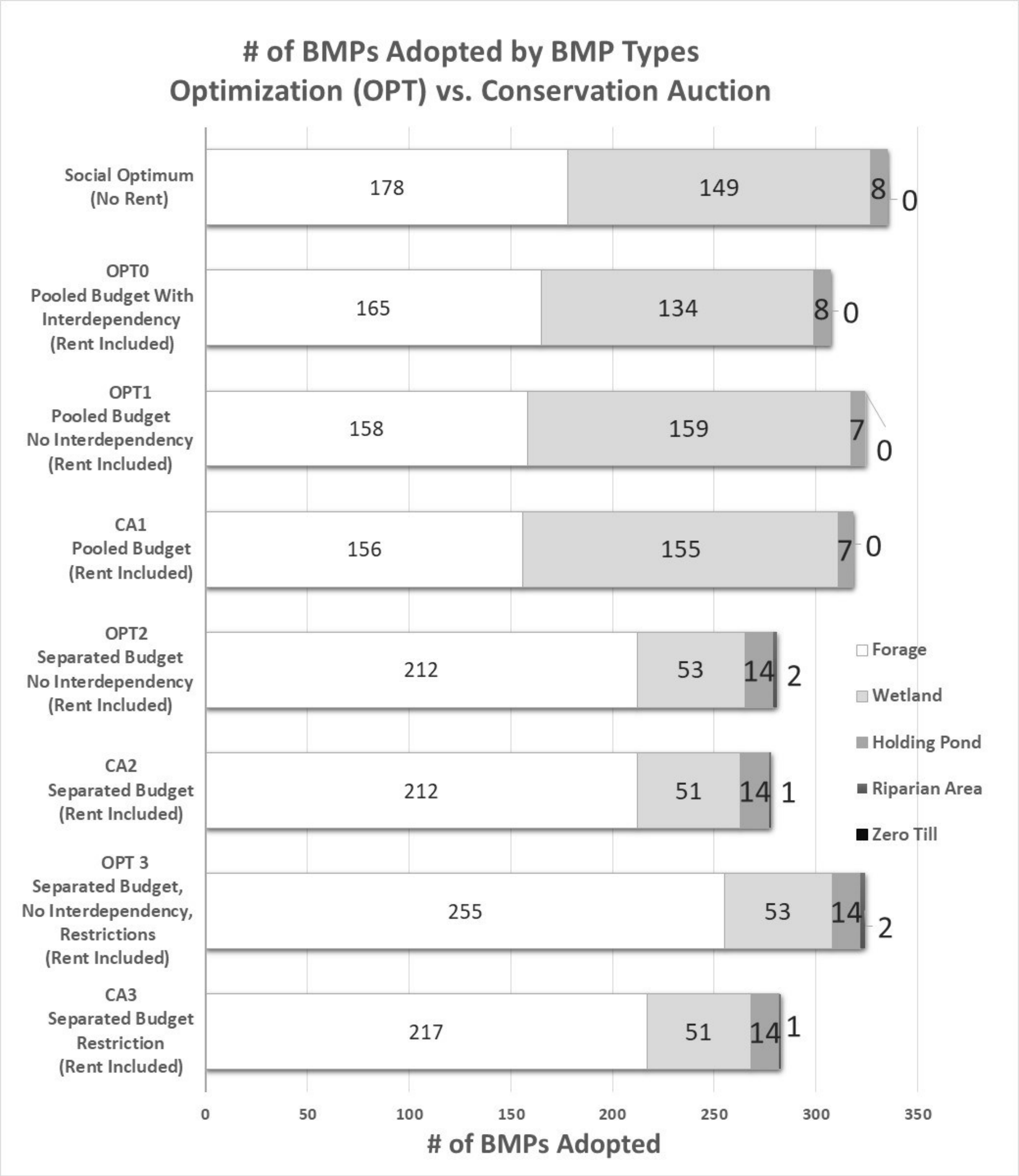

Figure 4.8. Number of BMPs Adopted by BMP Types, Optimization vs. Conservation Auction

When the budget was separated, funding unavoidably shifted away from the most efficient type of BMP, the Wetland Restoration, toward other, less efficient ones. With the separate Wetland Restoration budget, only about one third of the optimally selected wetland projects could receive funding, 53 in the optimization (Figure 4.8; OPT2) and 51 in the auction (Figure 4.8; CA2). While most of the money shifted from Wetland BMP toward the two second most efficient programs, Forage Conversion (212) and Holding Pond (14), a significant level of efficiency was still lost. Moreover, some of the previously not funded Riparian Area BMPs got selected, as the EFAP budget could only be used for two BMPs and all the projects in the other BMP (Holding Pond) in this sub-program were already funded.

When the various payment and size restrictions were imposed, operations with multiple cost-effective BMPs or with large cost-effective Forage Conversion BMPs did not receive the funding needed to improve their management practices. As discussed earlier (Section 4.6.3), the EFAP program's payment restriction did not bind, hence, there was no further distortion in the adoption patterns of the Holding Pond and Riparian Area BMPs. However, the payment and the size restrictions in the MSAPP program resulted in spreading out the funds from fewer large cost-efficient Forage BMPs toward many smaller less cost-efficient ones. As a result, the number of funded Forage Conversion projects further increased to 217 in the conservation auction scenario (Figure 4.8; CA3), and to 255 in the optimization scenario (Figure 4.8; OPT3).

4.7 Discussion/Conclusion

The purpose of this study was to show how the effectiveness of various BMP selection methods compares to each other, and to illustrate how much phosphorus can be abated in the study area with given funds. A mathematical programming model was presented that incorporated the notion of diminishing marginal rate of return of implementing multiple BMPs at the same location. Most spatial optimizations regarding BMP adoption emerged from hydrological studies, which were often simplified or neglected the financial part of the BMP selection. However, this present study shows that while the hydrological links among BMPs matter, the efficiency loss of ignoring these interdependencies is considerably less than the efficiency loss that occurs as a result of various restrictions imposed during the implementation of agri-environmental programs.

Since obtaining in-depth environmental assessments about the possible interdependencies can be very costly, the potential cost efficiency improvement that could result from incorporating this information into the selection process might not be worth it. In the study area, if there is a modest 10% spatial spillover between BMPs located on the same field, the efficiency improvement from incorporating this information into the optimization led to only 1.7% improvement in terms of abatement quantity. If instead of optimization a cost-benefit ranking is used, the cost efficiency loss is only 2.1%. This is similar in magnitude to what others have found in the literature. While using cost-benefit ranking over benefit-ranking leads to considerable efficiency improvements (Ferraro 2003; Duke, Dundas and Messer 2003; Messer et al. 2006; Kelly, Belcher and Khakbazan 2018), moving from cost-benefit analysis to optimization model improves the efficiency only marginally. Messer et al. (2016) found that cost-benefit ranking achieves 3.2% lesser environmental benefits than mixed integer optimization with a similar structure. However, they assumed independent parcels. As a sensitivity analysis, various levels of diminishing rates were explored in this present study, but even if the spatial interdependencies between any two overlapping BMP were as high as 30%, the cost efficiency improvement of incorporating this information into the optimization compared to a simple cost-benefit ranking was still less than 11% .

In order to achieve this cost efficiency improvement, ignoring the "cost" of setting up a mathematical model, a costly and time-consuming in-depth site analysis is required to assess potential interdependencies. Moreover, using an optimization model is not just an added cost, but also reduces the transparency of the program. A cost-benefit ranking method is easily understandable and completely transparent. Since projects with lower cost-benefit ratios get priority regardless of the effects of their neighbours, it could also be perceived as being fairer. Giving up the simplicity of cost-benefit ranking for a 2.1% efficiency improvement may not be desirable. However, this result is based on the assumption of homogeneous spillovers: a fixed proportion of diminishing rate between BMPs on the same field. While interdependencies between BMPs dissipate with distance (Perez-Pedini, Limbrunner and Vogel 2005), investigating the expansion of the spillover's scope to the next field could be worthwhile as it may change the magnitude of the efficiency loss. However, such expansion would require further spatial analysis of each BMP location in order to assess their neighbouring BMPs. An alternative way to model the diminishing marginal rate is to assume that each additional BMP adoption project has a diminishing rate regardless of their spatial location. Srivastra et al. (2002, 2003) used this approach by including a penalty coefficient into their objective function, and the penalty was simply the function of the number of BMPs adopted regardless of the BMPs' location.

While ignoring the spatial dependencies did not show cost efficiency loss to a large extent, changing the characteristics of funding programs did. The results showed that choosing the right objective is of the greatest importance in a government program. Often, agencies put significant effort into coming up with the formulation of the environmental benefit indices, but the results showed that anything other than focusing solely on the most important pollutant, phosphorus, could be a waste of public dollars. In the study area, all other EBI combinations led to increased phosphorus loading, despite the main priority being phosphorus reduction in the water system. Hence, if the environmental objective is improving water quality in lakes, instead of using EBI's, the sole focus should be reducing phosphorus levels. This result aligns with the most recent literature in soil science, which, based on 35 case studies, suggests focusing solely on phosphorus abatement as the limiting nutrient in the eutrophication process is phosphorus (Jeppesen et al. 2005). Our study suggests that spending 1.85 million Canadian dollars on funding the wrong BMPs in this watershed could actually worsen the water quality of Lake Winnipeg by increasing phosphorus run-off.

Without in-depth hydrological site assessments, the exact abatement level of individual BMPs cannot be determined. However, there is information about BMPS and abatement that could be considered in agri-environmental government policies. The effectiveness of the various BMPs changes by location (Kleinman et al. 2015). For example, while the Zero Tillage BMP can perform well in drier semiarid climates, in Manitoba where the run-off is snowmelt driven instead of rainfall driven, the practice increases phosphorus loss of the soil (Tiessen et al. 2010; Liu et al. 2014). Hence, when phosphorus abatement is the main priority, this BMP should not be funded or even encouraged. While changing fertilizer application practices along with the Zero Till BMP can mitigate this effect, there is no guarantee producers would follow that recommendation. While most of these agri-environmental programs, such as NSFP, GF, GF2, are mostly federally funded in Canada, their administration and execution is under provincial jurisdiction. Each province can choose which BMPs they provide funding for and to what extent. This gives the opportunity for each province to select BMPs that align with the given province's environmental objective and perform well in the given climate.

Moreover, our study showed that not just choosing the wrong objective, but also imposing various restrictions to these programs can be detrimental when it comes to abatement quantity. In this study area, phosphorus loading at the watershed outlet can be reduced by over 1350 kg annually for 5 years with the given budget if the BMPs are optimally selected and we assume that the producers' costs of adopting the BMPs are completely reimbursed. However, even just splitting the total funding into 3 sub-programs with separate budgets, but otherwise still optimally selecting the BMPs reduces the maximum achievable amount by 8%. The more sub-programs are being created, the worse this abatement potential gets. If each of the 5 BMPs examined in this present study had their own sub-program and budget, we would lose another 8% in efficiency, and thus achieve 16% less than by pooling the programs and their budgets together. Many agri-environmental programs have a cap on how much funding a producer can receive in total, or they may impose a size limitation on the adopted BMPs. As the study area is located in Manitoba, and the data is from the year 2010, program restrictions that were used in Manitoba in the given year were explored. These restrictions together led to a 23% efficiency loss in terms of the maximum achievable abatement quantity. In monetary terms, this means that the combined effect of these restrictions, including budget splitting, increased the price of a kg of phosphorus abatement by over $300.

Most BMPs have both direct costs, such as establishing a retention pond, and indirect costs in the form of loss or reduced revenue associated with farming the land. As the indirect costs are only known to the producers, government programs often only provide funding to reimburse proven direct costs. Moreover, even these costs are often not fully covered, but only at a certain percentage and usually up to a maximum amount. As the producers have to endure the entire indirect cost, and the remaining direct cost, the uptake of these cost share programs can be low, unless there is a private benefit to the producer (MacKay and Hewitt 2005; Boxall et al. 2008). Covering the full cost would more likely lead to higher adoption rates, but as the indirect costs are only know to the producers, they can use asymmetric information for rent seeking.

Voluntary conservation programs, where producers name their own price could be an effective tool to overcome the information asymmetry problem in such situations. To assess the potential performance of such programs in this study area, the efficiency of these types of programs was estimated using the previous chapter’s results. Rent seeking was assumed to be differentiated based on cost-type, and low, medium and high cost producers were assumed to be asking 20%, 7% and 1% markup, respectively. Using these rent amounts two types of voluntary conservation programs were assessed: conservation auctions and mathematical optimization. Conservation auctions using discriminatory pricing select the funded BMPs by simply ranking them based on cost-benefit ratio. These types of conservation auctions gained popularity in the past two decades and are being applied worldwide. Alternatively, a mathematical optimization model, such as the one presented in this study, could also be used to select the funded BMPs for further efficiency improvements. A similar model has been recently used in the US (Messer et al. 2016).

The result showed that selecting the funded BMPs using an optimization model that considers the spatial interdependency among the BMPs resulted in a high abatement level that was within 5% of the social optimum despite the rent seeking. However, incorporating the diminishing rate into the optimization requires a complicated quadratic optimization and detailed spatial assessment of the potentially overlapping BMPs. Ignoring the underlying interdependencies and using a simpler linear optimization model for the BMP selection only reduced the efficiency by an additional 2%. However, a conservation auction using the same rent seeking structure resulted in almost identical abatement levels. The difference between the linear optimization and the simple ranking of the auction was only 4 kg of phosphorus abatement annually. Since the conservation auction is more transparent and can be perceived as being fairer, using an optimization model over an auction doesn’t have much appeal, unless there are underlying interdependencies between the BMPs, which are then incorporated into the optimization.

Rent seeking results in about $90 higher per kg phosphorus price than it would be socially optimal, both in the case of conservation auctions and optimization without incorporated interdependencies. However, splitting the funding into sub-programs and imposing various restrictions, the per kg phosphorus price further increases by over $300 for the optimization and $350 for the conservation auction. Hence, conservation auctions or optimization models used in similar voluntary programs have a great potential for allocating funds to the best performing BMPs, but only if restrictions are not limiting their effectiveness.

Unfortunately, agri-environmental government programs often have an activity based focus and success is measured based on the number of projects they fund instead of the actual environmental benefit the program achieves. Imposing payment and size restrictions, and offering funding for many types of BMPs regardless of their effectiveness, ultimately spreads the money and funds more projects. For example, in the study area, using the optimization on the arrived offers would lead to 165 forage projects to be selected for implementation, but changing the program structure and imposing payment and size restrictions would lead to 255 forage projects to be implemented instead. This may look like a success, but those projects would achieve much less in terms of actual environmental benefit than performance based programs, such as conservation auctions, could achieve. The ineffectiveness of measuring the result in terms of number of projects implemented has been pointed out before (Boxall, Weber and Perger 2013), and this study further reinforces this notion.

In the past decade, there has been tremendous effort and money spent on improving water quality in Lake Winnipeg without much actual environmental improvement. Between 2012 and 2017, the Growing Forward 2 program spent over $4 million dollars on funding EG&S and providing financial assistance to producers implementing BMPs (Growing Forward 2017). During the same timeframe, the Lake Winnipeg Basin Initiative also spent $4.4 million dollars on funding BMPs using various cost-share programs, including the WRIP examined here (Environmental Canada 2017). Unfortunately, the phosphorus loading in Lake Winnipeg was only reduced by 1% as a result and the water quality did not improve considerably (Environment Canada, 2017). This present study suggests that selecting BMP projects based on performance based measures can considerably improve pollution abatement. In order to improve the efficiency of these programs, instead of the quantity of the projects implemented, it is time to focus on quality and provide financial assistance to projects that perform best and provide the highest abatement potential for the limited funding available.

4.8 Appendix

4.8.1 Detailed BMP Cost Calculation

4.8.1.1 Opportunity Cost -Yield Model

Beside any direct cost, the cost of each BMP project included the net present value (NPV) of the opportunity costs of the foregone revenue of the land using a 10% discount rate given in 2010 dollars. These foregone revenue streams were calculated using Boxall et al. (2008) yield model. They estimated a yield and production cost equation for the 5 main crops (canola, barley, flax, oats, and wheat) as well as for pasture and forage using various site characteristics, management practices and weather variables. Based on the historical crop rotations, they projected the crop rotation for each field in the study area for 12 years: 2007 to 2018. Based on the individual fields' land characteristics, and the projected crop rotation, they estimated net revenue for each field for each year in their planning horizon. The detailed values of these net revenue forecasts were obtained via personal communication (M. Cutlac, July 2012). This present study assumes the contracts are 5 years long; hence, it used only Boxall et al. (2008) projected net revenue values from the year 2010 to 2014 and adjusted with the Manitoban Price index (Statistics Canada 2017) to convert the values into 2010 dollars. A summary statistic of these NPV values can be found in Table 4.14.

Table 4.14. Summary Statistics, Opportunity Cost by Fields, STC Watershed, Manitoba

Rotation Type	NPV the Net Revenue Stream for the 5-Year Duration ($2010)			
	Maximum $/acre	Minimum $ / acre	Average $/acre	StdDev $/acre
Crop rotation	$636	$171	$400	$44
Forage rotation	$662	$75	$356	$58
Pasture	$10	-$104	-$42	$8
Overall	**$662**	**-$104**	**$360**	**$52**

The net present value of the opportunity cost varied considerably based among the fields. Fields that were pasture were previously assumed to remain pasture permanently and they had the lowest opportunity costs. On average, pastures would generate a $42 / acre NPV loss to the farmers, but in some cases the loss was as high as $104/acre. Hence, using the field for something else actually would be beneficial in most cases. There were a few pasture fields that could have generated some income, but the highest net revenue would have been $10 / acre.

Crop fields had the highest opportunity cost on average with a $400 / acre NPV value for the program length of 5 years. While the magnitude of revenue depends on various land characteristics, cropping a land always generates positive NPV. Hence, giving up land that is in crop rotation always has significant opportunity cost and even the lowest NPV was $171 / acre. The highest opportunity cost was $636 / acre, which means that such a producer would not implement any BMP even if it would provide high environmental benefit, because it is just simply too expensive to do so.

Fields that previously alternated forage and crop rotation (labeled as forage rotation in the table) had the largest variation when it comes to opportunity cost. It is assumed that once a field is turned into forage, the producer would keep it for 7 years before turning it back to crop rotation. Fields that are in forage rotation normally generate some loss in the first couple of years until the cover is fully established and starts to generate income. Depending on where a given field was in their rotation at the base year, the opportunity cost varied considerably. Fields that were starting their forage rotation anyway had very low opportunity cost with $75 / acre being the lowest. However, fields that just finished their forage rotation prior to the base year, and would start their crop rotation, would incur the highest opportunity cost among all fields with a maximum of $662 / acre. This is the result that the prior forage rotation would provide, which is a yield boost for the upcoming crop rotation if the field were used as planned. For the structural BMPs (Holding Ponds, Wetland and Riparian areas), the opportunity cost related to the land was calculated by multiplying these $ / acre values with the size of the land that would be taken out of production by the BMPs. Since the wetland BMP is assumed to be field-based, the opportunity cost of the wetland was simply calculated as the size of the wetlands on the field multiplied by the $ / acre opportunity cost of the given field. The same calculation was held for Holding Ponds where the potential sites were on an active field. Some of the Holding Pond sites were planned on areas that were not used as an agricultural field, hence there was no opportunity cost associated with them. Some riparian area BMPs overlapped with multiple fields that may have had different opportunity costs associated with them. In such cases, a weighted average of the fields' opportunity costs was used. The used weights were the approximate size proportion of the riparian area located on the various fields based on visual inspection.

4.8.1.2 Holding Pond

In the STC watershed, there were 16 cattle yards (owned by 12 producers) in 2010, 2 of which already had the Holding Pond built during the WEBs project. Hence there were 14 eligible BMP projects to receive financial assistance to establish a new retention pond. The direct capital and the maintenance cost estimation used in this study was adapted from a previous study by Khakbazan et al. (2013), which estimated minimum and maximum Holding Pond cost for an earlier year in the watershed. The capital cost related to the retention pond included the cost of the excavation, the liner cost, the cost of establishing the pumping system, and fencing cost to protect members of the producer family from falling into the pond (Khakbazan et al. 2013). Their cost estimation used the provincial guidelines of recommend pond size per animal as a minimum of 19 and a maximum of 28 m^2 per animal. Their calculation assumed square sized pond using clay liner which is approximately 30% cheaper than plastic liner. Khakbazan et al. (2013) annual cost included pond maintenance and pumping cost, which was also proportionate to the herd size. This present study used a different base year, with different herd sizes; hence their cost formulas were recalculated to suit the situation here. Since their calculation provided a minimum and maximum value, a simple arithmetic average was used here. Moreover, all costs were adjusted using the Manitoban consumer price index (Statistics Canada 2017) to convert the values into 2010 dollars. Besides the direct capital, the pond maintenance and the pumping cost, this present study also included the opportunity cost of the land that would be taken up by the pond, which was described previously. In case of the Holding Pond BMP, the main cost driver was the initial capital cost, which accounted for 89.1% of the total cost on average. The NPV of the annual maintenance and pumping cost accounted for 10.8% of the total cost on average. The magnitude of opportunity cost of the land was dismissible with a 0.1% of the cost on average as the ponds' sites were generally selected to be built on pasture area or non-used land.

4.8.1.3 Riparian Management

In the STC watershed only 6 producers were identified as having riparian areas that could be eligible to receive financial assistance for riparian area management (Boxall et al. 2008). The cost of the BMP included the fencing cost and the waterer provided to the cattle with a 2% annual repair cost and the seed and restoration of the riparian area. This present study used the fencing cost calculation by Boxall et al. (2008), and adjusted the values with the Manitoban CPI (Statistic Canada 2017). Boxall et al. (2008) and Packman (2010) used two different calculation methods for the alternative waterer. In order to be consistent between

BMPs, the method used by Packman (2010) was used in all BMPs. This present study assumed building a waterer cost $4314, which is the price adjusted value used by Packman (2010), and can provide water for up to 150 cattle. The size of the herd grazing on the riparian areas was less than this in most cases. Hence we assumed a fixed capital cost of establishing a single waterer. There was one riparian area with a larger herd, in which case we assumed there would be two waterers built to provide sufficient water for the cattle. This present study also included the seeding cost of establishing the perennial cover over the riparian area by multiplying the size of the riparian area by $119 / acre seeding cost. The $ / acre cost was price adjusted from the forage seeding cost used by Boxall et al. (2008). The opportunity cost of the land was calculated as described above.

On average, the majority (60.8%) of the total cost of the Riparian area BMPs came from the initial capital cost of fencing, building the alternative water source for the cattle and seeding costs. However, the proportion varied considerably among BMPs. In some cases, this was as high as 93%, for example where the riparian area was located next to a pasture field with dismal amount of opportunity cost. However, when the area was located next to high value cropland, the capital cost was only 39.4% of the total cost. The opportunity cost of the land accounted for 34.8% of the total cost on average. There was a BMP where the NPV of the land was zero, but there was also one where the NPV of the lost revenue accounted for 57.4% of the total cost. The maintenance cost was below 5% in all riparian area BMPs and did not vary considerably.

4.8.1.4 Wetland Restoration Cost

In the STC watershed, there are 963 restorable wetlands (Packman 2010). Theoretically, each could be restored separately. However, cost efficiency suggests that wetland restoration would most likely occur on a field by field basis. Packman's cost estimates show that the majority of the restoration cost comes from machinery rental and labor; it makes more financial sense for producers to restore all wetlands on a given field and get compensated for multiple wetlands for the same cost. This means that the STC watershed has 222 potential wetland restoration projects, by 28 producers. This present study followed the cost calculation presented by Packman (2010), which included the restoration cost, potential fencing and waterer installation cost, nuisance cost and the opportunity cost of the land taken out of production. The restoration cost is assumed to be a fixed $162 per field and $365 per producer, which are values adjusted by the Manitoban CPI index from Packman (2010). The nuisance cost that a producer needs to drive around the wetland in the future was calculated simply by multiplying the machinery cost with a nuisance factor based on the number of wetlands and field size. For wetlands that are located on pastures, the producer needs to install fence to keep the livestock away; and if there is no alternative water source, the producer also needs to install a waterer. The fencing and waterer cost was calculated the same way as in the case of the riparian area BMPs, assuming circular wetlands. Both the fence and waterer are assumed to have a 2% yearly maintenance cost such as in the riparian area BMPs. The opportunity cost of the foregone revenue of the wetland was calculated as described in the previous section. Despite the short time horizon (5 yrs), the majority of the cost came from the lost cropping revenue of the land and the opportunity cost accounted for 68.1% of the total cost on average. Generally, the second biggest cost was the restoration cost, which accounted for 23.8% of the total cost on average. However, the relative magnitude of these two costs varied greatly among the projects. Wetland BMPs that are located on loss generating pasture fields had negative opportunity costs. On the other hand, on high value cropland fields, almost all the cost came from the lost revenue, and there was a field where the opportunity cost was 95.8% of the total cost. At the same time, projects where the field only had a couple of very small wetlands had the majority of the costs (85.2%) come from the restoration. Fencing and water installation cost accounted for only 6.6% of the total cost on average, because only 11 projects incurred this. However, for those projects that had this expense, it was the main cost driver since they were pasture fields without significant, or in some cases negative, opportunity cost. Moreover, these projects also incurred maintenance costs, which accounted for another 6-7% of their total cost. Nuisance cost accounted for less than 1% of the total cost in all projects.

4.8.1.5 Forage Cost

Generally, non-structural BMPs can be implemented separately on each field. Forage Conversion can be very expensive as the producers forgo the entire field’s crop revenue stream when converting it to perennial cover. As a result, this BMP is unlikely to be implemented on a larger than a field scale. The cost of Forage Conversion was calculated based on the Boxall et al. (2008) calculations. Based on various land characteristics, they predicted a forage yield, and a forage production cost; and as a result net revenue from forage was calculated for each field depending on how many years the field had already been foraged. As it has been mentioned before, forage is assumed to have a 7-year long cycle after which it needs to be re-established which results in restarting the cycle. Forage generates a considerable loss in the first year due to the seeding cost that only occurs at the beginning of the cycle. Moreover, the yield is lower initially until the cover is fully established; hence, the generated revenue is considerably lower than any alternative crop revenue would be in the first few years. The STC watershed had 353 fields in total, but it is assumed that only 320 forage BMPs could have participated in the program at the base year. Fields which started their 7-year long forage rotation the year before the base year would not be eligible for financial assistance because they would be in forage for the entire 5 year duration of the program. Moreover, the 22 pasture fields also would not be eligible for financial assistance.

The total cost of the forage BMP was calculated as the NPV of the opportunity cost of the field minus the net revenue of the forage and the value of the yield boost that the forage cycle provides for the crop in the following year. The average cost of Forage Conversion was \$212.4 / acre, but due to the cyclical nature of forage rotation, the cost of Forage Conversion significantly varied. There were fields where producers would have started a forage rotation anyway in the following year. On these fields, converting to forage only meant starting the forage rotation one year earlier than planned. As a result, the cost was minimal and even negative in some cases with -\$82.8 / acre being the lowest cost. On the other hand, the cost of conversion was extremely high on fields where the producer just started the crop rotation cycle after the forage rotation. These fields would miss out on crop revenues that were expected to be very high due to the yield boost from the previous forage rotation. The highest cost for Forage Conversion was \$701.8 / acre.

4.8.1.6 Zero Till

Although tillage practices could be chosen at the field level, due to the substantial machinery cost, producers most likely would choose to implement this BMP in their entire farm or not implement it anywhere. In the base year, there were 33 producers in the study area, but zero or conversional tillage was already practiced on 2 farms. These were the producers who received the required equipment during the WEBs project as they were the test sites. Hence, it is assumed that 31 Zero Till BMP projects would be eligible for financial assistance in the base year. This present study adapted the Boxall et al. (2008) Zero Till BMP cost calculation. Boxall et al. (2008) estimated the yield and production cost changes due to the alternative tillage practice for the 5 different crops, and their result can be found in Table 4.15. They calculated the net total cost as the change in yield multiplied by the historic average of the price of the given crop plus the change in production cost. This present study calculated Zero Tillage cost the same way, except used the historical average of the crop prices in the 10 years preceding the base year, from 2000 to 2009. Moreover, we adjusted the production cost changes using the Manitoban CPI (Statistic Canada 2017) to convert it into 2010 dollars. Similarly to Boxall et al. (2008), the net revenue changes were minimal in case of barley (\$0.2 / acre) production. In case of wheat production, Zero Till actually was beneficial increasing the net revenue by \$12.8 / acre. However, the net revenue was significantly reduced in case of the other 3 crops: with \$40.5, \$28.6 and \$54 / acre for oats, flax, and canola production, respectively. The NPV of each BMP was calculated by adding up the annual net revenue changes over program length of 5 years using Boxall et al. (2008) crop rotation projection and using a 10% interest rate.

Table 4.15. Net Revenue Changes due to Zero Till by Crop Type (Adapted from Boxall et al. 2008, pg 56)

Crop	Boxall et al. (2008) original calculation in $2004				Our calculation in $2010		
	Change in Yield Bu/ac	Price $2004/bu	Change in Production Costs $2004/ac	Change in Net Income $2004/ac	Price $2010/bu (Historical Price average)	Change in Production Costs $2004/ac	Change in Net Income $2010/ac
Wheat	4.76**	4.00	5.570**	13.47	$3.97	$6.171	$12.75
Barley	2.28	2.40	5.594	-0.12	$2.77	$6.198	$0.12
Oats	-20.42**	1.65	-8.544	-25.15	$2.45	-$9.466	-$40.50
Flax	-2.55	7.50	3.254	-22.38	$9.81	$3.605	-$28.65
Canola	-5.51**	7.50	10.669**	-51.99	$8.34	$11.820	-$57.72

Based on the calculation, adopting Zero Tillage BMP would be beneficial to one producer in the watershed, and would generate and extra $0.2 / acre revenue to this farmer. All other producers would incur significant cost with $111.6 / acre being the highest. The average cost of Zero Till BMP was $33.4 / acre. While this cost is lower on a per acre basis than some other type of BMPs, this BMP would be implemented on the entire farm, while other BMPs are only implemented on individual fields like forage, or just a small subset of a field like riparian area.

Table 4.16. Number of BMPs by Producer and by BMP Types, STC Watershed, Manitoba

	Producer ID	# of BMPs in Given BMP types					Total # of BMP
		Forage	Holding Pond	Riparian	Wetland	Zero Till	
1	1	1			1	1	3
2	4	9	1		5	1	16
3	9	1			1	1	3
4	16	3	1		2	1	7
5	17	1			1	1	3
6	18	4			2	1	7
7	20	8			1	1	10
8	21	10			8	1	19
9	22	1			1	1	3
10	24	7		1	8	1	17
11	25	4		1	4	1	10
12	26	7	1		3	1	12
13	28	16			12	1	29
14	29	1			1	1	3
15	30	2			1	1	4
16	32	4					4
17	33	19	1		14	1	35
18	34	14	1	1	13	1	30
19	36	4			4	1	9
20	39	7			4	1	12
21	41	18	3		10	1	32
22	43	4	1		3	1	9
23	44	25		1	17	1	44
24	47	35	1		27	1	64
25	49	38	1	1	21	1	62
26	50	2	1				3
27	51	45	1	1	30	1	78
28	54	1			1	1	3
29	56	9			8	1	18
30	62	9	1		7	1	18
31	101	9			9	1	19
32	103	1			2	1	4
33	104	1			1	1	3
	Total	**320**	**14**	**6**	**222**	**31**	**593**

4.9 Scenario Results

The tables below contain the detailed result of each of the scenarios discussed in this study. The first table (Table 4.17) contains the annual abatement quantities of each pollutant: total phosphorus, total nitrogen and sediment. If the BMPs were selected and payments were made according to the given scenario, the amount of each of the pollutants was reduced by these amounts for each of the 5 yrs of the program at the STC watershed outlet. The table also contains the main efficiency measurement, which shows the proportion of the total phosphorus abatement achieved by the given scenario compared to the maximum achievable (the social optimum) in the study area.

Table 4.17. Detailed Result, Annual Abatement Quantities by Scenarios

	Scenario Name	Efficiency (Percentage of the Social Optimum)	Annual Abatement Quantities at the watershed outlet		
			Total Phosphorus (kg)	Total Nitrogen (kg)	Sediment (ton)
	Social Optimum	*100.0%*	*1,350*	*8,967*	*2,166*
Varying Objective	TP/TN/SED weights: (60%/20%/20%)	-8.6%	-115	17,968	2,856
	TP/TN/SED weights: (45%/35%/20%)	-13.6%	-184	18,179	2,722
	TP/TN/SED weights: (0%/0%/100%)	-13.8%	-187	14,374	3,257
Program Restrictions	Budget Separated by Programs	91.8%	1,239	9,565	2,199
	Budget Separated by Individual BMPs	83.9%	1,132	7,576	1,946
	EFAP Payment restriction	100.0%	1,350	8,967	2,166
	MSAPP Payment restriction	99.6%	1,345	9,038	2,137
	MSAPP Size Restriction	93.5%	1,263	8,944	1,947
	Combined Restrictions	78.8%	1,064	8,636	1,834
Rent Seeking	Low Information Rent A (6% markup)	97.9%	1,321	8,678	2,114
	Low Information Rent B (10% markup)	96.5%	1,303	8,519	2,085
	High Information Rent A (markup varies)	97.4%	1,315	8,663	2,100
	High Information Rent B (markup varies)	95.3%	1,287	8,439	2,053
Optimization vs. Conservation Auction	OPT0: Optimization, Interdependency Included	95.3%	1,287	8,439	2,053
	OPT1: Optimization, Interdependency Ignored	93.6%	1,263	8,125	2,009
	CA1: Conservation Auction-Pooled Budget	93.2%	1,259	8,070	2,004
	OPT2: Optimization, Separated Budget	88.6%	1,196	9,018	2,126
	CA2:Conservation Auction - Separated Budget	88.3%	1,192	8,983	2,125
	OPT3: Restricted Optimization, Separated Budget	76.6%	1,034	8,422	1,791
	CA3:Restricted Conservation Auction, Separated Budget	75.0%	1,012	7,932	1,742

Table 4.18. Detailed Result, Abatement, and Total Cost for the 5-year Program Length by Scenarios

	Scenario Name	Total Cost ($2010)	Rent % (rent / total cost)	Abatement Cost for the 5 yrs period: Total Phosphorus ($/kg)	Total Nitrogen ($/kg)	Sediment ($/ton)
	Social Optimum	$1,865,935	0.0%	$1,382	$208	$861
Varying Objective	TP/TN/SED weights: (60%/20%/20%)	$1,865,953	0.0%	-$16,166	$104	$653
	TP/TN/SED weights: (45%/35%/20%)	$1,865,965	0.0%	-$10,166	$103	$685
	TP/TN/SED weights: (0%/0%/100%)	$1,865,966	0.0%	-$9,983	$130	$573
Program Restrictions	Budget Separated by Programs	$1,864,785	0.0%	$1,505	$195	$848
	Budget Separated by Individual BMPs	$1,371,315	0.0%	$1,211	$181	$705
	EFAP Payment restriction	$1,865,935	0.0%	$1,382	$208	$861
	MSAPP Payment restriction	$1,865,917	0.0%	$1,387	$206	$873
	MSAPP Size Restriction	$1,865,965	0.0%	$1,478	$209	$958
	Combined Restrictions	$1,801,547	0.0%	$1,694	$209	$982
Rent Seeking	High Information Rent B	$1,865,965	11.8%	$1,450	$221	$909
	High Information Rent A	$1,865,896	6.9%	$1,419	$215	$888
	Low Information Rent A	$1,865,960	5.7%	$1,412	$215	$882
	Low Information Rent B	$1,865,958	9.1%	$1,432	$219	$895
Optimization vs. Conservation Auction	OPT0: Optimization, Interdependency Included	$1,865,965	11.84%	$1,450	$221	$909
	OPT1: Optimization, Interdependency Ignored	$1,865,963	11.95%	$1,477	$230	$929
	CA1: Conservation Auction-Pooled Budget	$1,849,644	12.00%	$1,469	$229	$923
	OPT2: Optimization, Separated Budget	$1,847,092	7.18%	$1,544	$205	$869
	CA2:Conservation Auction - Separated Budget	$1,802,420	7.34%	$1,512	$201	$848
	OPT3: Restricted Optimization, Separated Budget	$1,842,774	6.26%	$1,783	$219	$1,029
	CA3:Restricted Conservation Auction, Separated Budget	$1,842,774	6.26%	$1,821	$232	$1,058

Table 4.19. Detailed Result, Number of BMPs Adopted by BMP Types and by Scenarios

	Scenario Name	Total # of BMPs Adopted	# of BMPs Adopted by BMP Types				
			Zero Till	Riparian Mgt	Holding Pond	Wetland	Forage
	Social Optimum	335	0	0	8	149	178
Varying Objective	TP/TN/SED weights: (60%/20%/20%)	289	29	0	6	60	194
	TP/TN/SED weights: (45%/35%/20%)	284	30	0	7	55	192
	TP/TN/SED weights: (0%/0%/100%)	253	30	0	7	44	172
Program Restrictions	Budget Separated by Programs	285	0	2	12	46	225
	Budget Separated by Individual BMPs	228	0	2	7	45	174
	EFAP Payment restriction	335	0	0	8	149	178
	MSAPP Payment restriction	348	0	0	9	161	178
	MSAPP Size Restriction	368	0	0	9	168	191
	Combined Restrictions	319	0	2	12	45	260
Rent Seeking	High Information Rent B	307	0	0	8	134	165
	High Information Rent A	320	0	0	8	141	171
	Low Information Rent A	323	0	0	8	142	173
	Low Information Rent B	313	0	0	7	138	168
Optimization vs. Conservation Auction	OPT0: Optimization, Interdependency Included	307	0	0	8	134	165
	OPT1: Optimization, Interdependency Ignored	324	0	0	7	159	158
	CA1: Conservation Auction-Pooled Budget	318	0	0	7	155	156
	OPT2: Optimization, Separated Budget	281	0	2	14	53	212
	CA2:Conservation Auction - Separated Budget	278	0	1	14	51	212
	OPT3: Restricted Optimization, Separated Budget	324	0	2	14	53	255
	CA3:Restricted Conservation Auction, Separated Budget	283	0	1	14	51	217

Table 4.20. Detailed Result, Number of BMPs Adopted by Cost Categories and by Scenarios

	Scenario Name	Total # of BMPs Adopted	# of BMPs Adopted by Cost Categories		
			Low Cost	Medium Cost	High Cost
	Social Optimum	335	186	149	0
Varying Objective	TP/TN/SED weights: (60%/20%/20%)	289	161	70	58
	TP/TN/SED weights: (45%/35%/20%)	284	152	68	64
	TP/TN/SED weights: (0%/0%/100%)	253	135	71	47
Program Restrictions	Budget Separated by Programs	285	163	95	27
	Budget Separated by Individual BMPs	228	164	61	3
	EFAP Payment restriction	335	186	149	0
	MSAPP Payment restriction	348	186	161	1
	MSAPP Size Restriction	368	189	177	2
	Combined Restrictions	319	162	83	74
Rent Seeking	High Information Rent B	307	181	126	0
	High Information Rent A	320	184	136	0
	Low Information Rent A	323	186	136	1
	Low Information Rent B	313	185	128	0
Optimization vs. Conservation Auction	OPT0: Pooled Budget, Interdependency Included, No Rent	307	173	95	19
	OPT1: Pooled Budget, Interdependency Ignored	324	195	128	1
	CA1: Pooled Budget	318	195	123	0
	OPT2: Separated Budget	281	172	94	15
	CA2: Conservation Auction, Separated Budget	278	170	95	13
	OPT3: Separated Budget, Restrictions	324	172	78	74
	CA3: Separated Budget, Restrictions	283	170	77	36

5 Conclusion

Improving water quality is one of the most important environmental objectives in most OECD countries (OECD, 2012). As the agriculture sector is often a significant source of water pollution, policy makers are developing various incentive programs to induce farmers to adopt various BMPs. As the environmental benefit that these BMPs would provide is a public benefit, and their implementation is a private cost, without financial compensation there is under-provision of these environmental services. As a result, various incentive programs had been set up worldwide that deliver financial assistance to producers implementing BMPs. In Canada, Agriculture Canada has been providing the largest, national-wide funding opportunities for BMP adoptions for the past fifteen years. The current program, called Growing Forward 2, continues the predecessors' (Growing Forward and National Farm Stewardship Program), funding structure, and as such it is set up on a cost share basis. Because these types of programs only provide partial subsidies of the direct costs, only BMPs that have private benefits, such as fuel tanks and watering systems, are getting adopted in large quantities (Sparling and Brethour 2007; Vukina et al 2008; Rollins, Simpson and Boxall 2018). At the same time, the BMPs that provide large public environmental benefits without private benefit, such as wetland restoration or grassland ecosystem conservation, experience very low adoption rates. Despite the fact that over time the public share of the subsidies and the compensation limit of these practices increased, the uptake of these BMPs that would provide the highest environmental benefit remained low. This suggests that new incentive policies need to be explored and instead of offering partial subsidy for a wide variety practices, funding efforts should be concentrated on practices that could deliver the most environmental benefit (Boxall 2018). Alternative methods, such as conservation auctions, or spatial targeting could be used to allocate the same amount of funds in a more effective way, achieving higher environmental benefit (Boxall 2018).

The main problem with the idea of fully compensating the producers for the incurred costs is that only the producers themselves know the full extent of their costs. This information asymmetry could potentially lead to overcompensation and allow producers to obtain payment above their true cost. Conservation auctions can be used as a cost revealing mechanism and it had been shown that they can outperform fixed payment schemes and improve cost efficiency in agri-environmental programs (Latacz-Lohmann and Van der Hamsvoort 1998). However, due to the information asymmetry, the effectiveness of the various types of conservation auctions cannot be directly studied in the field. Hence, conservation auctions are often studied in the laboratory, and the first two papers in this thesis utilized this method to analyze conservation auction effectiveness, using data from a small watershed in Manitoba.

Most previous laboratory studies on conservation auctions used hypothetical cost functions, often assuming that the size of the environmental benefit provided by producers is the same or they drew the cost and size from a uniform distribution (Cason, Gangadharan, and Duke 2003a; Cason and Gangadharan 2004, 2005). However, when a laboratory study (Boxall, Weber and Perger 2013) used cost functions that were estimated based on actual BMPs adopted in our study area, it showed results contradictory to the previous findings (Cason and Gangadharan 2004, 2005), despite using the same experimental setup. This led to the suspicion that various characteristics of the underlying supply function of BMP adoption, such as shape and cost variability, could be important factors in determining the cost effectiveness of conservations auctions.

The first paper in this thesis draws from this idea and investigates how cost variability levels among potential BMPs influences the performance of conservation auctions used to induce their adoption. The laboratory experiments presented in this paper used cost curves based on actual BMP adoption costs and environmental benefits collected from a small watershed in the Canadian Prairies. The result shows that magnitude of cost heterogeneity among the BMPs plays a fundamental role in auction performance. If the costs among the BMPs do not vary to a large degree, especially among the most cost-effective producers, a conservation auction can be a valuable tool to induce BMP adoption.

The uniform pricing mechanism resulted in better auction performance than discriminatory auctions if the cost heterogeneity is minimal. However, there is flipping point in cost heterogeneity levels when discriminatory auctions become favourable. The cost heterogeneity level associated with the flipping point changes with learning as it causes deterioration of discriminatory auctions' performance, but does not affect uniform auctions to a large degree. Consequently, uniform auctions are recommended if foreseeable learning effects would be present; either because the auction is planned to be repeated, or because information exchange is expected among bidders. However, if there is large cost heterogeneity among BMPs, conservation auctions can become ineffective and expensive. Examining the connections between cost heterogeneity and BMP types suggests that structural BMPs, in which the main cost driver is the land independent construction cost, tend to have low cost heterogeneity; hence, they are a prime candidate for conservation auctions. On the other hand, if a BMP cost is mainly driven by a foregone revenue stream, the BMP appears to have large cost heterogeneity because land profitability varies to a large degree due land characteristics, such as soil type, slope.

Another important matter arising from the experiments is the importance of sufficient bidder participation levels in a conservation auction. Low levels of bidder participation can hinder auction performance. While the usage of reverse (procurement) auctions has a long history in various service industries such as transportation and electricity, it is not a well-know concept among agricultural producers in Canada. This can result in a lack of interest from potential adoptees. Moreover, auction participation is not costless, and the associated time and cost can discourage producers from partaking in the auction. Hence, before implementing conservation auctions to induce BMP adoption, the potential market should be carefully evaluated ensuring that the BMPs considered do not have excessively high levels of cost heterogeneity, and that there are enough participants to hold a successful auction.

While conservation auctions could result in a much more cost-efficient solution than current cost-share programs, they still do not account for any spatial allocation among the potential adoption of BMPs. As the water flows from one field to another, the environmental benefits provided by the BMPs are spatially dependent and their effectiveness is contingent on other BMPs that may be adopted in the same area. Hydrologists have reported that the water quality improvements resulting from multiple BMP adoptions in close proximity exhibit a diminishing marginal rate (Perez-Pedini, Limbrunner and Vogel 2005). If such underlying dependency exists among the BMPs, ignoring it can lead to the perception of an inflated abatement amount. This leads to the objective of the second paper in this thesis, which investigated the effectiveness of conservation auctions incorporating the notion of diminishing rates of return between BMPs. This paper showed a potential method for incorporating this so called subadditivity into the bid ranking and winner selection process. The technique significantly improved the auction performance if the diminishing marginal rate was materialised between neighbouring farms. However, the method was ineffective if the diminishing rate was present between BMPs implemented on fields owned by the same producer.

The economic analysis of the bidding behaviours showed the importance of various details in similar analysis. The analysis utilized a selection model between auction participation and bid submission, which had not been done in analysing experimental conservation auction data before. The results showed that the two decisions are not independent; hence, analyzing bidding behaviour by itself can lead to biased estimates. The second technical detail was that learning effects are significantly different based on the potential bidder’s cost type. Hence, lumping together learning effects into a single cost-independent learning structure can lead to misleading estimates. Generally, conservation auctions are used to address information asymmetry with regard to the costs between producers and regulatory agencies. However, our study area has been extensively studied under the a government research program from both environmental and economic perspectives. This allowed us to investigate an alternative path that can be taken to induce BMP adoption: that of spatial targeting, which is presented in the third paper of this thesis. This paper presented a mathematical programming model that estimated the optimal BMP adoption pattern associated with a given budget in the study area. The model, similar to the second paper, included the notion of diminishing marginal return of the environmental benefit of BMP adoption, and assumed a subadditivity among the BMPs adopted on the same farm. If there were no information asymmetry, the social planner could run such model and engage in environmental contracts with the optimally selected farmers to achieve the desired BMP adoption pattern.

The benchmark given by the optimization was compared to various government incentive policies. The comparison resulted in multiple relevant policy implications. Firstly, the most important in an environmental policy is to be clear about the objective and BMPs selected for financial assistance should be based on the environmental objective. In Manitoba, the main priority with regard to water quality is to reduce phosphorus runoff, which is a key contributor in the Lake Winnipeg eutrophication process. Yet, the province keeps offering financial assistance for BMP types (such Zero Tillage) that are actually acting counter to this goal in some areas. The result also showed that various restrictions (splitting the available funding into sub-programs, limiting BMP size, and limiting maximum payments) can also significantly decrease policy effectiveness. Offering funding for a wide variety of BMPs combined with the various restrictions can lead to a situation where there are a large number of adopted BMPs that do not generate significant amounts of abatement. These restrictions can lead to the adoption of less cost-efficient BMPs, or in some cases, adoption of BMPs that are actually damaging to the environmental goal. In the past decade, millions of dollars had been spent on funding BMP adoption in Manitoba with the intent of reducing phosphorus levels in Lake Winnipeg with rather minimal results (Environment Canada 2017). Allocating available funds based on cost efficiency and the generated abatement level could be considerably higher. Information asymmetry with regard to the actual BMP adoption costs makes spatial targeting very difficult. Moreover, the compensation that a landowner would actually be willing to accept (WTA) to implement various BMPs may be higher than their true cost of adoption. In order to approximate the potential magnitude of these amounts, the bidding results from the previous papers were used as a benchmark. This allowed us to compare various aspects of spatial targeting to the use of conservation auctions in a similar setting. Our results show that pooling all potential funds into a single program that uses conservation auctions to allocate the funds could generate as much as 93% of the maximum achievable abatement in the study area with the given budget. Despite the potential rent seeking, conservation auctions can still produce higher abatement quantities than existing alternative programs. While spatial targeting using a mathematical optimization could further improve the effectiveness over the conservation auctions by 2%, it requires obtaining a much more in-depth environmental and hydrological assessment of a given landscape, which may not be feasible.

Limitations and Further Research

The results presented in this thesis showed that conservation auctions can be a cost effective tool in allocating public dollars in agri-environmental policies to induce BMP adoption. However, there are several limitations to our findings. The first paper showed that the BMPs with low heterogeneity are good candidates for conservation auctions, but excessive cost heterogeneity is detrimental to their effectiveness. In the studied watershed, structural BMPs, such as Holding Ponds and Wetland Restoration, exhibit low cost heterogeneity as their cost is quasi proportional to the size of the land and the environmental benefit they could provide. On the other hand, non-structural BMPs, such as Forage Conversion, exhibit large cost heterogeneity as their costs strongly depend on the productivity and the physical characteristics of the land, which varies to a larger degree. While this finding has direct policy implications, the question remains open whether this is a general trend. Since the examined BMPs were limited to a small geographic area, further examination of BMP cost curves from various areas is recommended in order to make general recommendations. During the WEBs program, environmental and economic implications of BMP adoptions were studied in eight other watersheds across Canada. Collaborating with the other research teams could be a starting point for estimating BMP cost functions from various locations that allow us to assess general trends in BMP cost heterogeneity.

There are also limitations in the findings due to restrictions in the scope of the experiments. The number of bidders can have a significant effect on the market prices in both discriminatory and uniform auction (Kagel, Harstad and Levin 1995). Since the experiments presented in this thesis all have the same number of bidders, the generalization of the results is dependent on this fixed bidder count.

Another experimental limitation of the study is that the cost curves used were not specifically designed to identify the differences between cost heterogeneity and market power. As a novelty, the experiments utilized BMP cost functions estimated using actual producer and agronomic data in the study area. While this has the advantage of showing the potential effectiveness of conservation auctions based on relevant data, it has the disadvantage that it may lead to identification problems. As a potential remedy, additional experimental sessions could be carried out using artificially designed cost curves that have identical cost heterogeneity to the 6 existing curves, but hold different market concentration features.

The second paper in this thesis explored conservation auction effectiveness when there is diminishing marginal benefit among BMP adoptions. The paper only found behavioural responses to the diminishing marginal rate introduced in the auction when the synergy was present between different bidders and not when it was present between different BMPs adopted by the same bidder. However, the result is conditional on the magnitude of subadditivity used in the experiment, which was 10%. It is possible that the level of subadditivity was not sufficient to induce behavioural response. However, it could suggest that an alternative path should be taken to explore situations where the diminishing marginal rate of the benefit is between BMPs of the same firm. In forward auctions, such situations are often remedied in package bidding. Such techniques are explored in conservation contexs using bilateral trading situations (Nemes, Plott and Stoneham 2008). However, it has not been studied in conservation or in any reverse auction situation, which could be a next step in further investigations.

Another potential limitation of the first two papers came from the nature of the methodology employed which is laboratory study. Laboratory auctions are generally assumed to be externally valid (Roe and Just 2009; Brookshire et al. 1987; List and Shogren 1998) and produce incentive comparable behaviour. However, the ultimate external validity for this particular auction structure would be to move to the next level and execute small-scale field auctions in a watershed.

The third paper in this thesis used a mixed integer optimization method to explore the ideal BMP adoption pattern in our study area that, given a fixed budget, would produce the highest phosphorus abatement amount at the watershed level. The main limitation of the study is that its result depends on imposed assumptions. The paper incorporated diminishing marginal rate of multiple BMP adoptions, which had been established in the hydrology literature (Perez-Pedini, Limbrunner and Vogel 2005). However, the magnitude of this diminishing rate is not well-known in the literature. This study used a fixed diminishing rate between any two BMPs that are located on the same or overlapping land. While the paper carried out sensitivity analysis of various levels of diminishing rate between 0-30%, the rate was assumed to be the same across all BMPs. If there is significant variation between the rates based on BMP types, this approach could be too restrictive. In order to assess the true extent of the potential variability in interdependencies, a more in-depth analysis of the hydrology literature is necessary.

Moreover, the study only assumed diminishing rates between BMPs that are located on the same or overlapping fields. While the diminishing rate of BMP adoption dissipates quickly with distance (Perez-Pedini, Limbrunner and Vogel 2005), restricting the spatial dependency to the same or overlapping field may be underestimating the extent of interdependencies. The next step would be to undertake further spatial assessment of the BMPs in the study area and establish the pairwise connection between BMPs located in spatially adjacent fields and integrate this information into the model.

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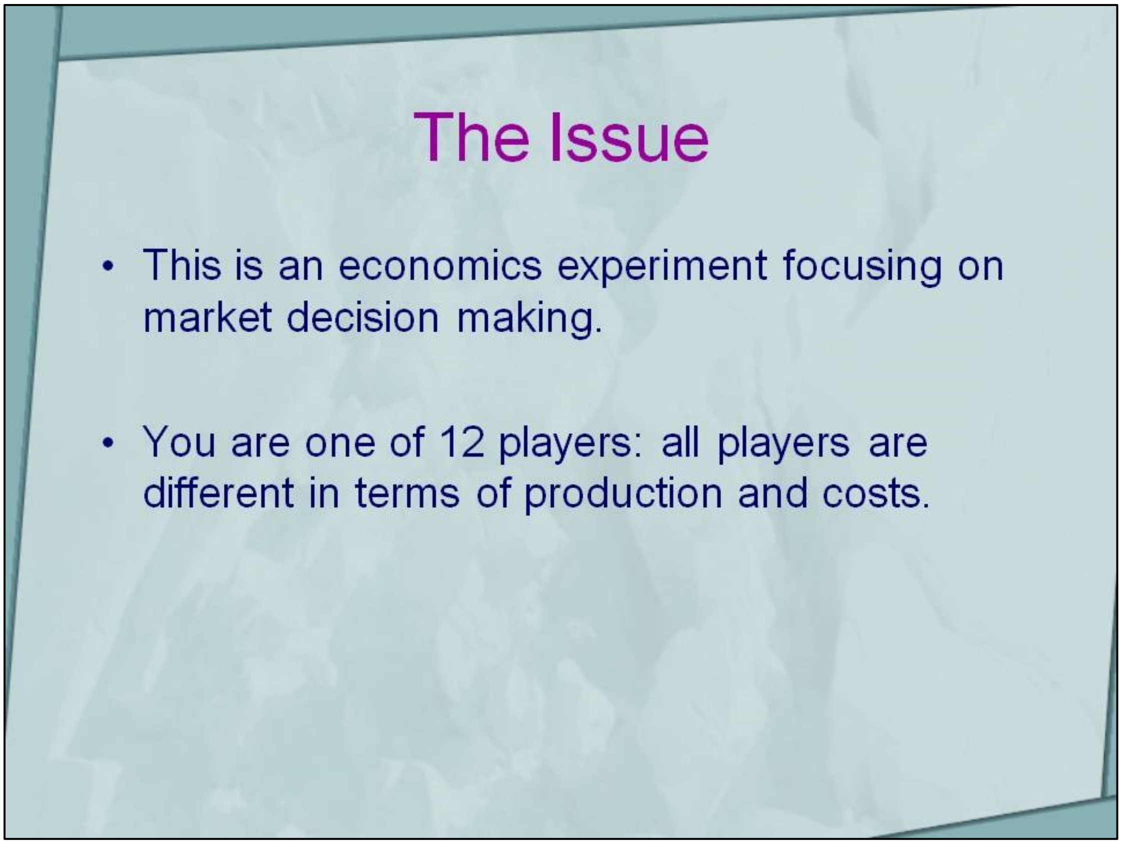
APPENDIX A: Experiment Instruction for 1st Paper

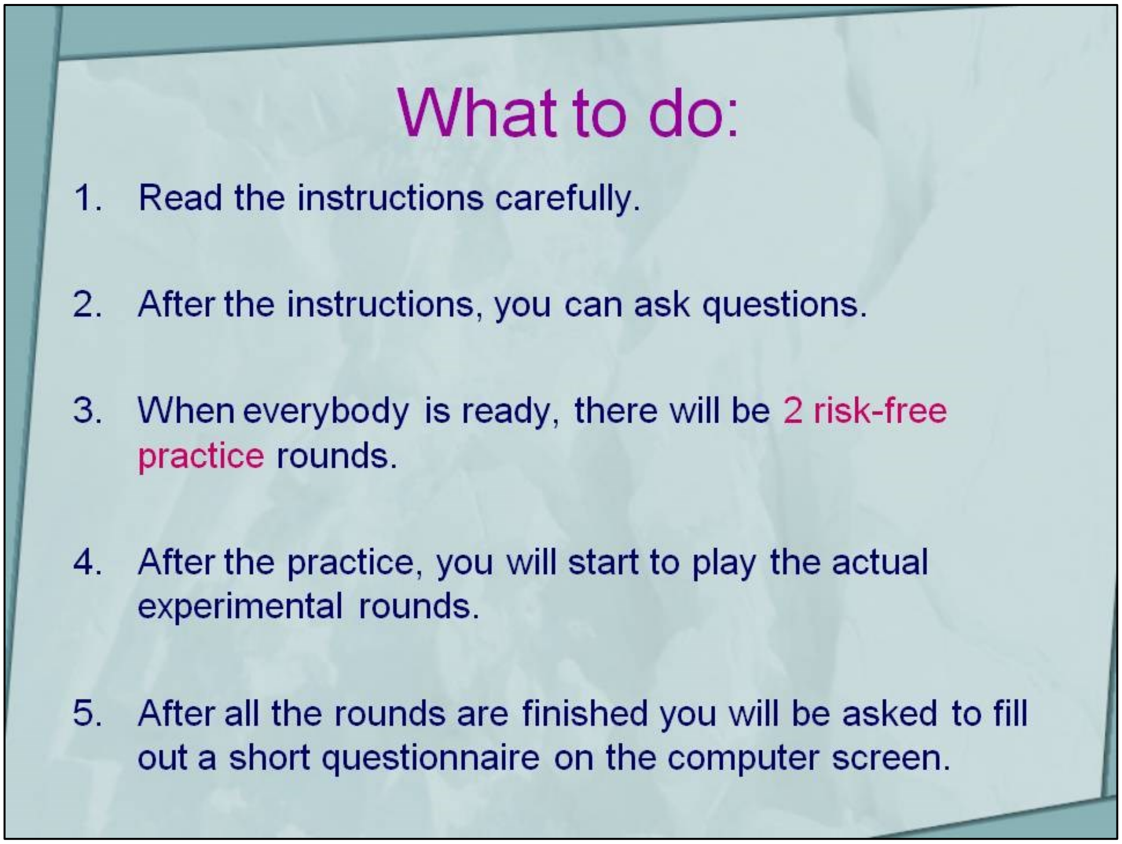
Welcome to
a Rural Economy
Department
Experimental Session

Instructions



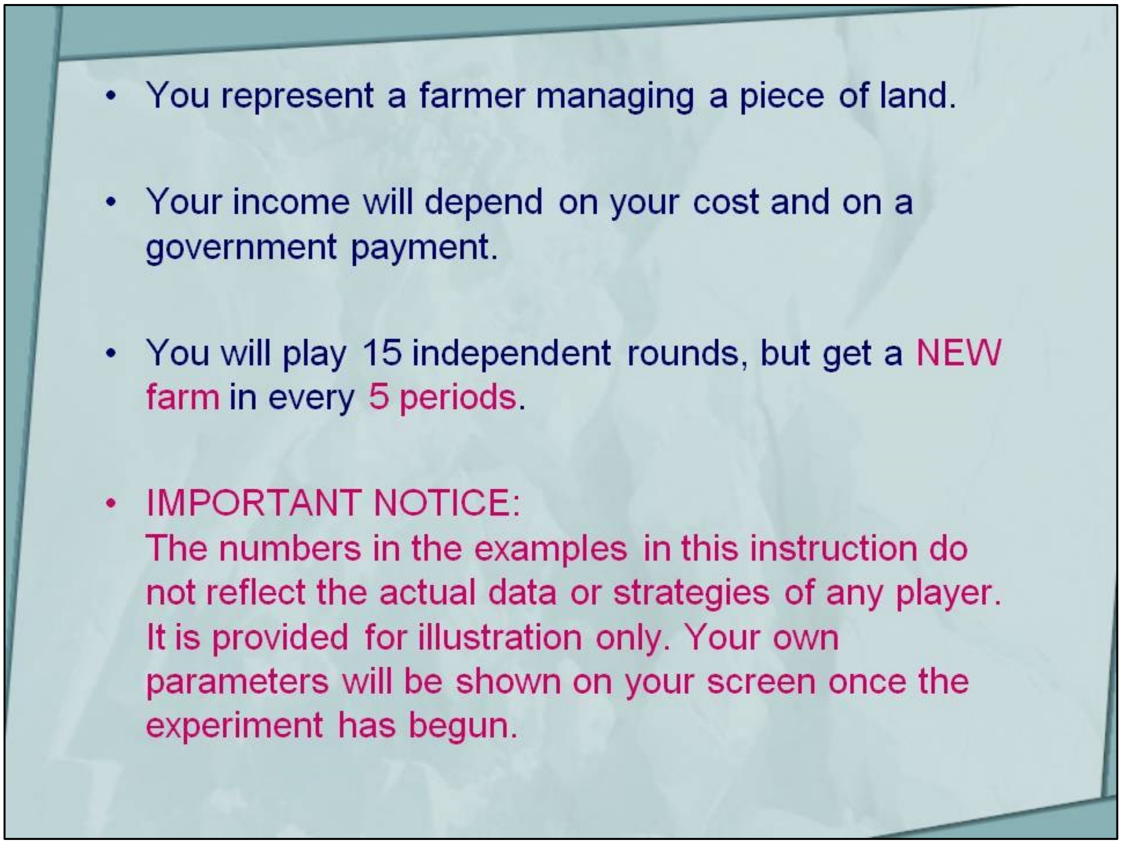
The Issue

- This is an economics experiment focusing on market decision making.
- You are one of 12 players: all players are different in terms of production and costs.

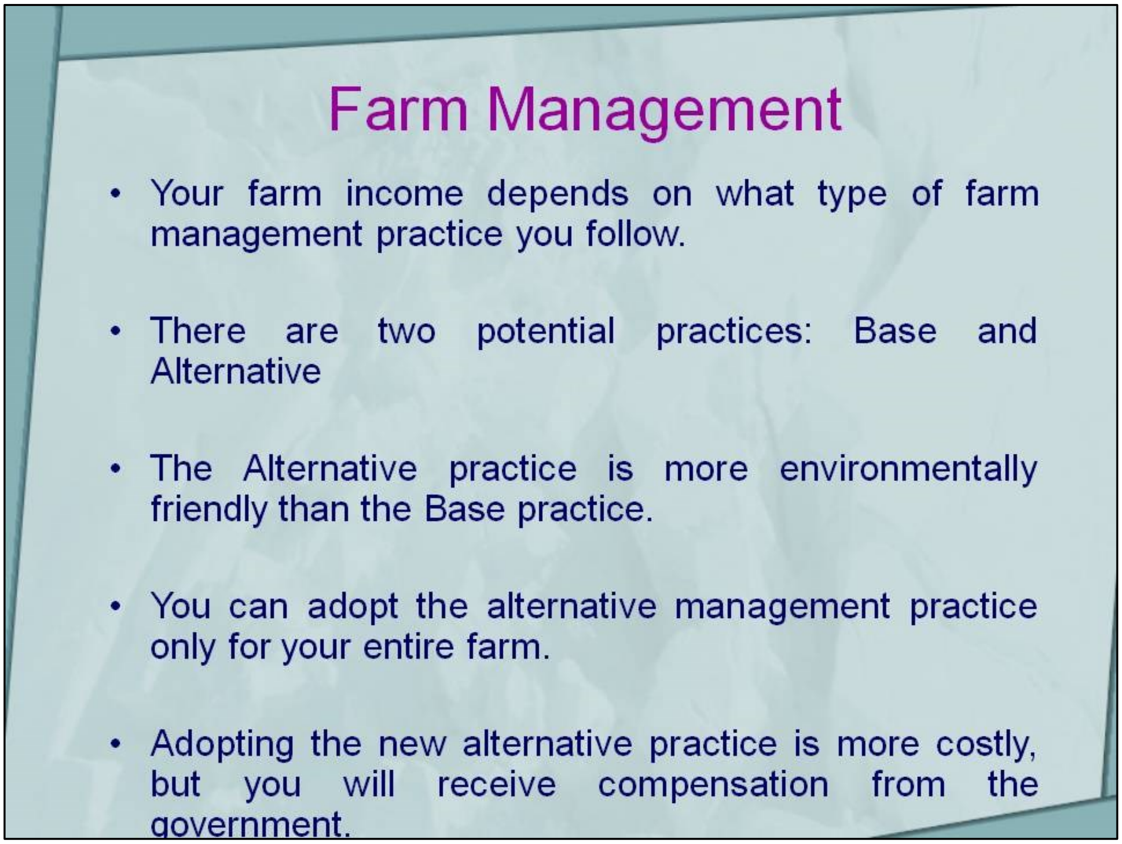


What to do:

1. Read the instructions carefully.
2. After the instructions, you can ask questions.
3. When everybody is ready, there will be 2 risk-free practice rounds.
4. After the practice, you will start to play the actual experimental rounds.
5. After all the rounds are finished you will be asked to fill out a short questionnaire on the computer screen.

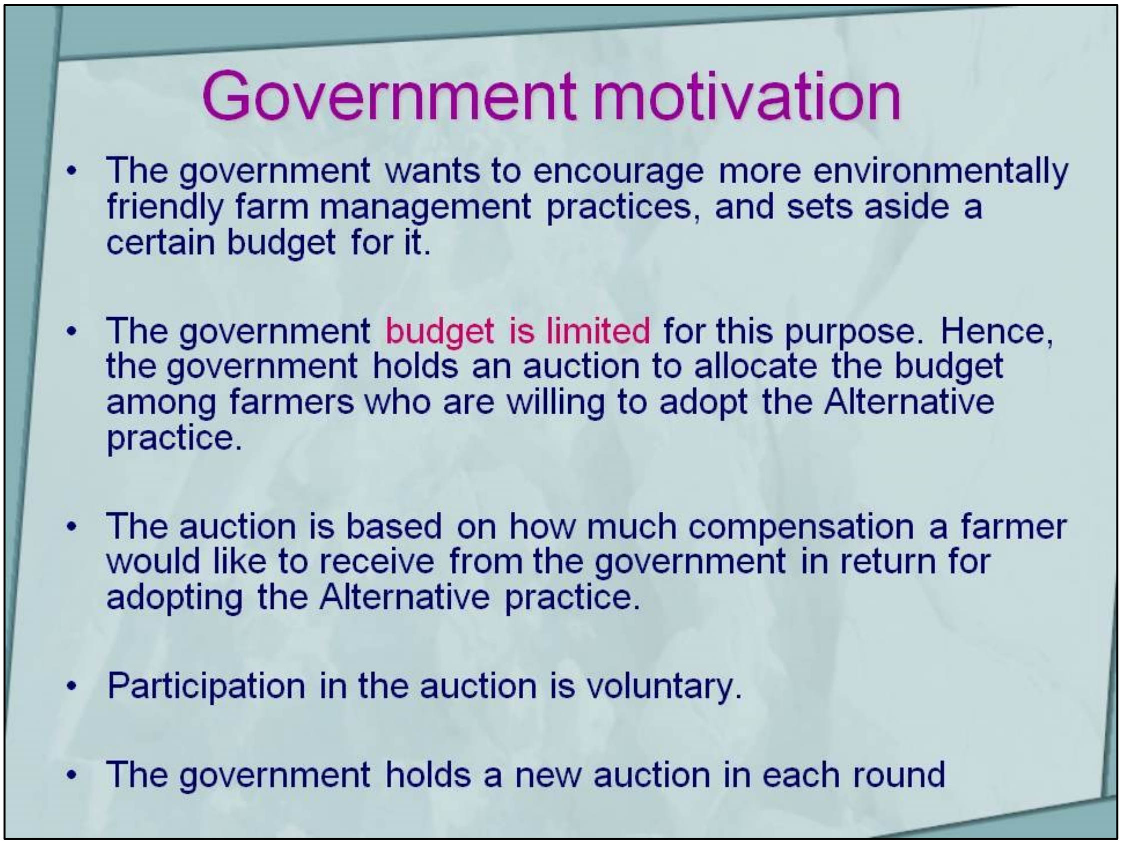


- You represent a farmer managing a piece of land.
- Your income will depend on your cost and on a government payment.
- You will play 15 independent rounds, but get a NEW farm in every 5 periods.
- IMPORTANT NOTICE:
  The numbers in the examples in this instruction do not reflect the actual data or strategies of any player. It is provided for illustration only. Your own parameters will be shown on your screen once the experiment has begun.



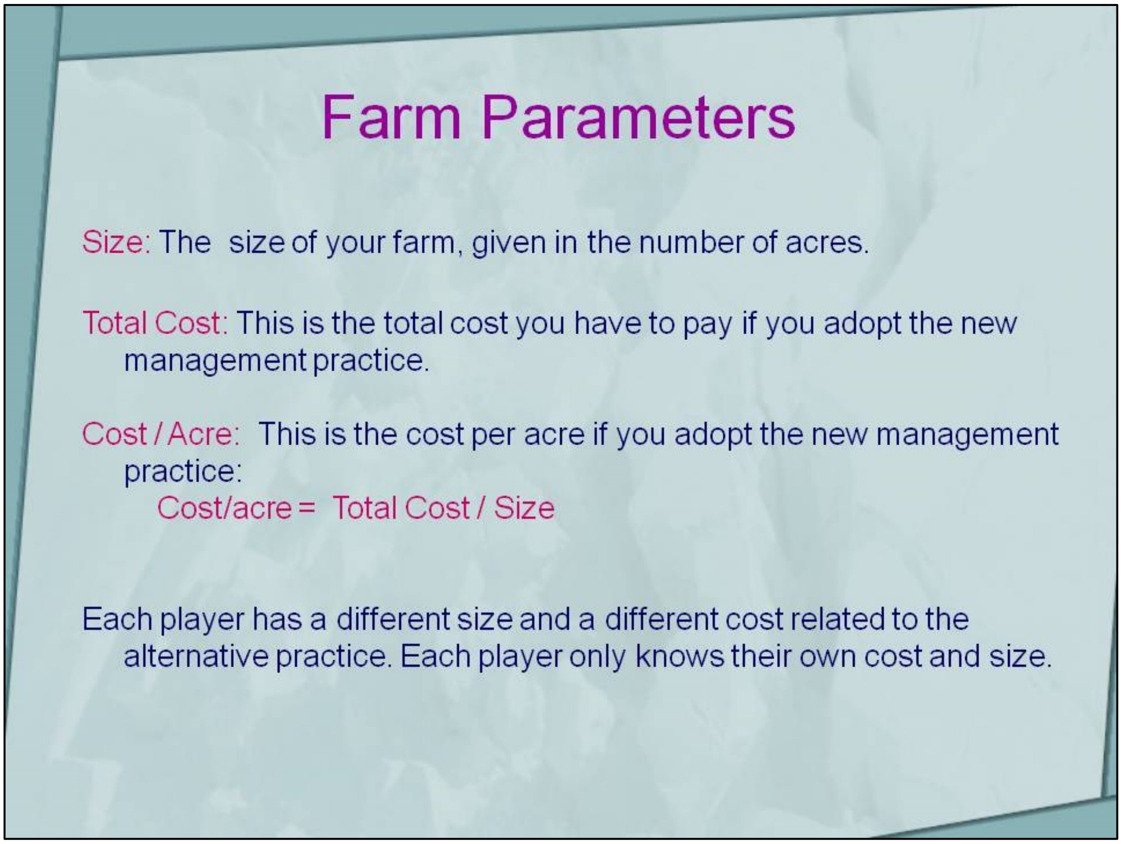
Farm Management

- Your farm income depends on what type of farm management practice you follow.
- There are two potential practices: Base and Alternative
- The Alternative practice is more environmentally friendly than the Base practice.
- You can adopt the alternative management practice only for your entire farm.
- Adopting the new alternative practice is more costly, but you will receive compensation from the government.



Government motivation

- The government wants to encourage more environmentally friendly farm management practices, and sets aside a certain budget for it.
- The government budget is limited for this purpose. Hence, the government holds an auction to allocate the budget among farmers who are willing to adopt the Alternative practice.
- The auction is based on how much compensation a farmer would like to receive from the government in return for adopting the Alternative practice.
- Participation in the auction is voluntary.
- The government holds a new auction in each round



Farm Parameters

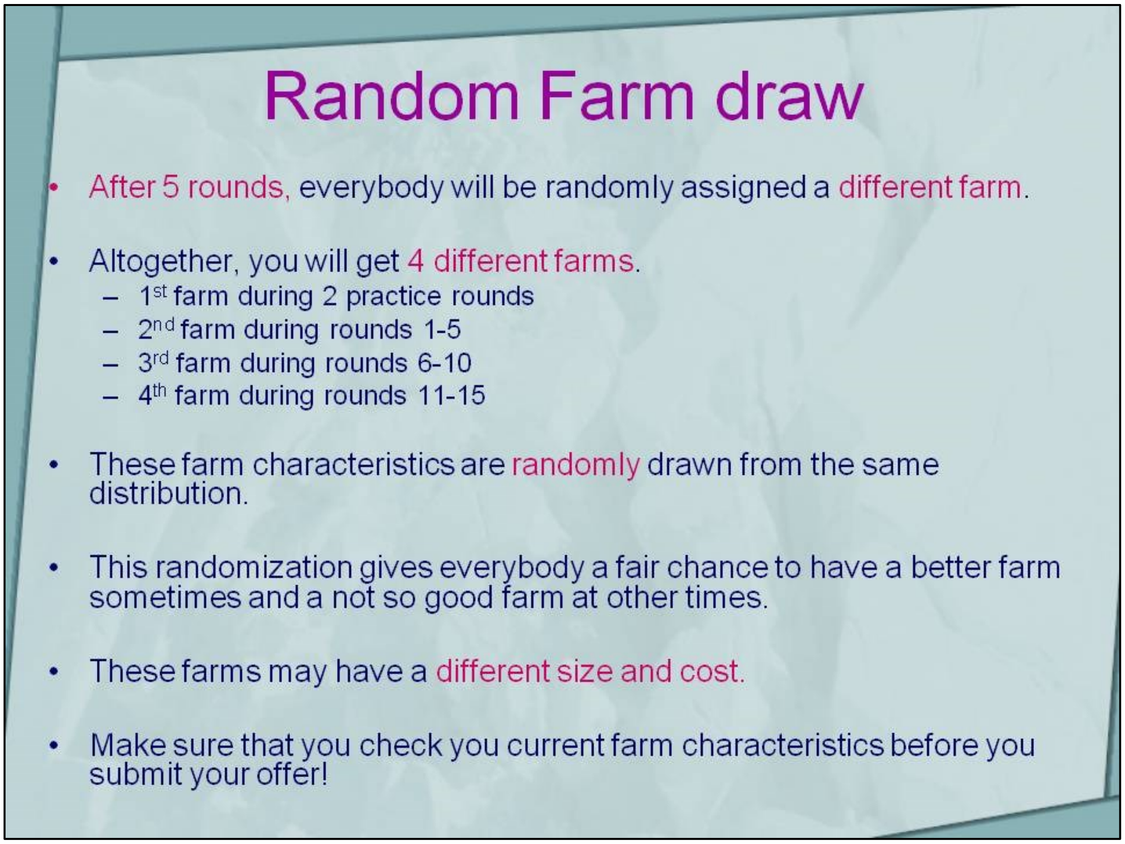
Size: The size of your farm, given in the number of acres.

Total Cost: This is the total cost you have to pay if you adopt the new management practice.

Cost / Acre: This is the cost per acre if you adopt the new management practice:

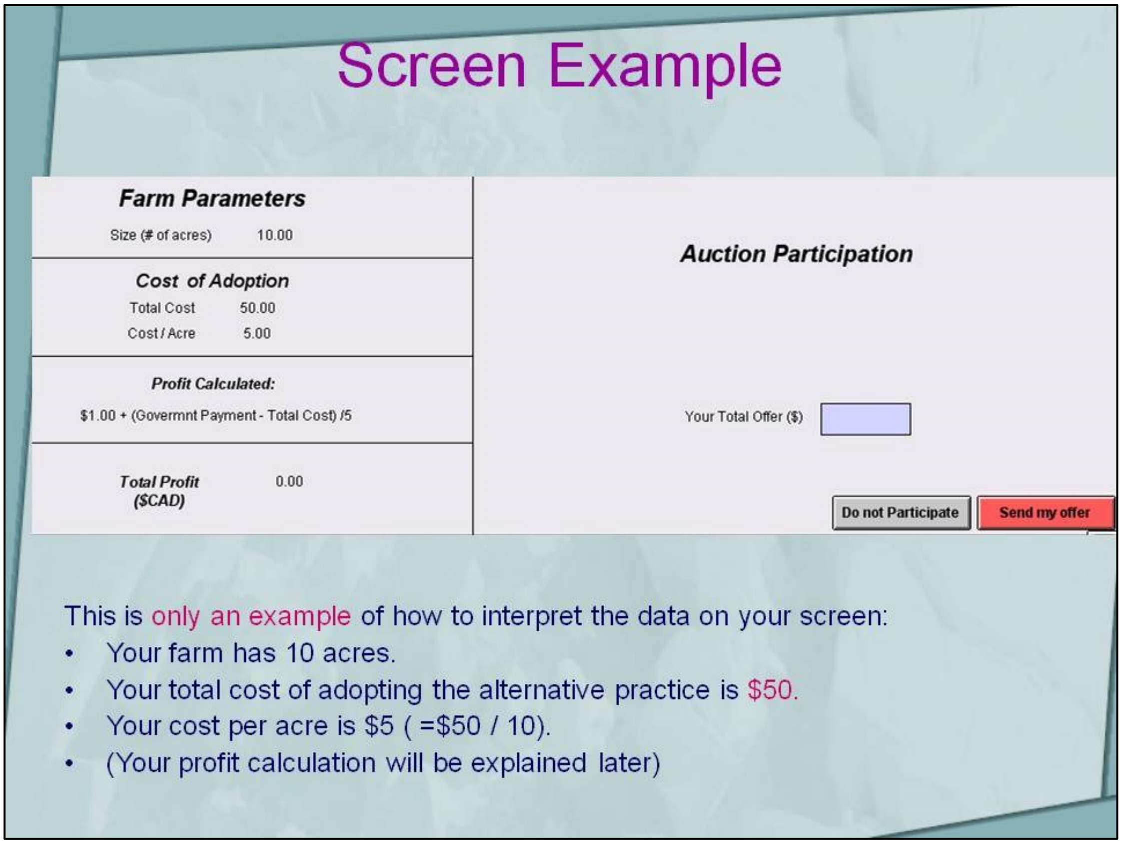
Cost/acre = Total Cost / Size

Each player has a different size and a different cost related to the alternative practice. Each player only knows their own cost and size.



Random Farm draw

- After 5 rounds, everybody will be randomly assigned a different farm.
- Altogether, you will get 4 different farms.
  - 1st farm during 2 practice rounds
  - 2nd farm during rounds 1-5
  - 3rd farm during rounds 6-10
  - 4th farm during rounds 11-15
- These farm characteristics are randomly drawn from the same distribution.
- This randomization gives everybody a fair chance to have a better farm sometimes and a not so good farm at other times.
- These farms may have a different size and cost.
- Make sure that you check you current farm characteristics before you submit your offer!



Screen Example

Farm Parameters

Size (# of acres) 10.00

Cost of Adoption

Total Cost 50.00

Cost / Acre 5.00

Profit Calculated:

$1.00 + (Govermnt Payment - Total Cost) /5

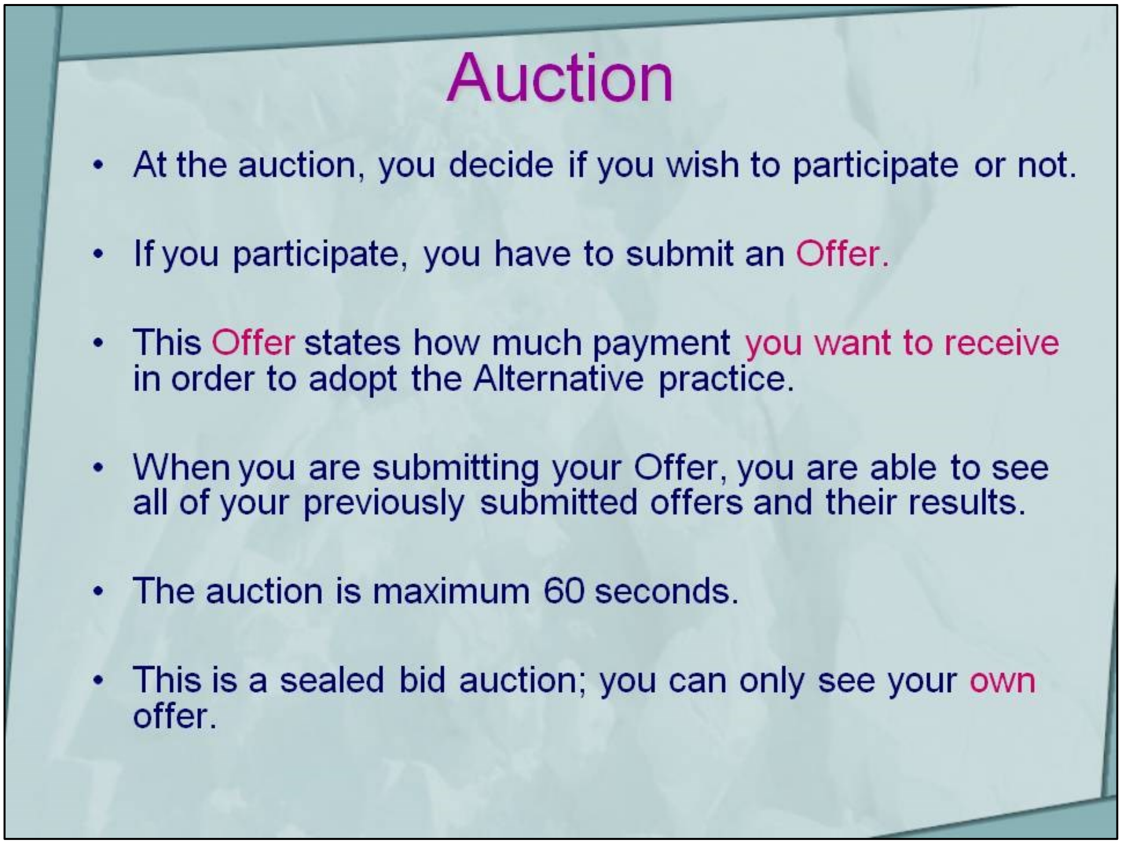
Total Profit ($CAD) 0.00

Auction Participation

Your Total Offer ($)

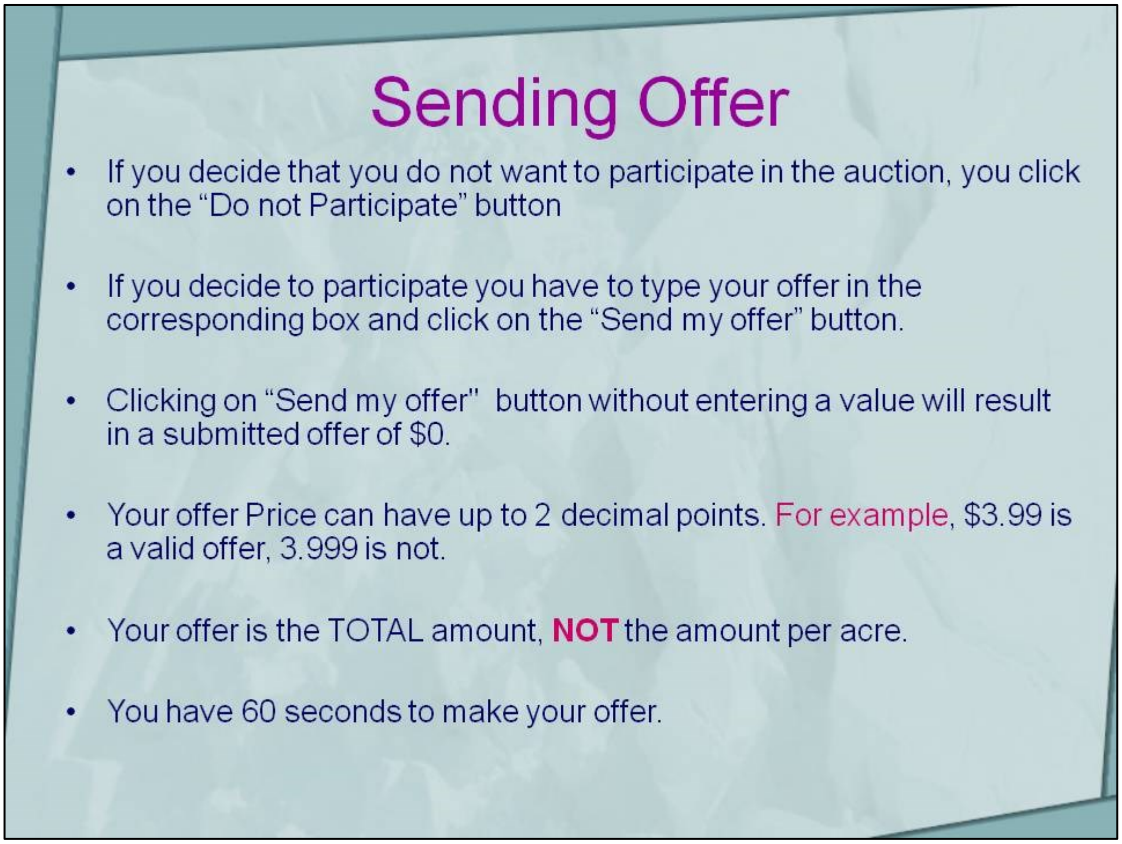
This is only an example of how to interpret the data on your screen:

- Your farm has 10 acres.
- Your total cost of adopting the alternative practice is $50.
- Your cost per acre is $5 (=$50 / 10).
- (Your profit calculation will be explained later)



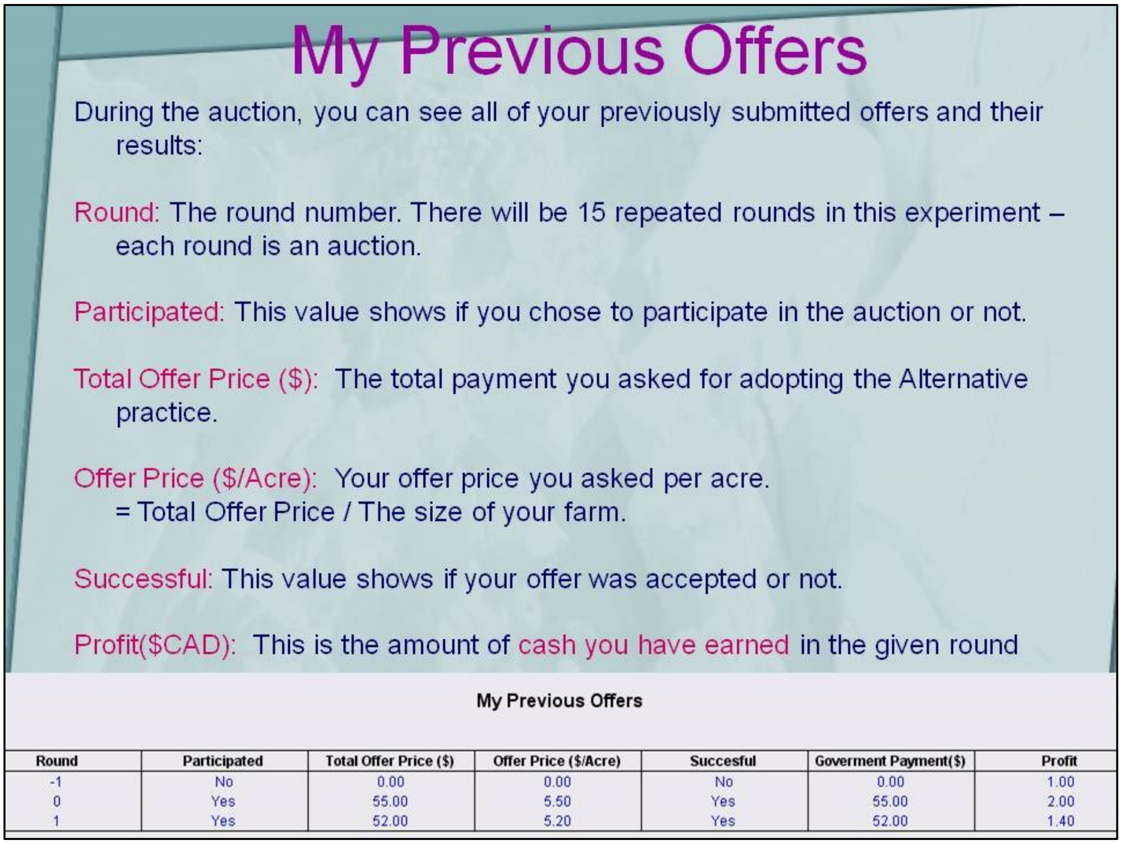
Auction

- At the auction, you decide if you wish to participate or not.
- If you participate, you have to submit an Offer.
- This Offer states how much payment you want to receive in order to adopt the Alternative practice.
- When you are submitting your Offer, you are able to see all of your previously submitted offers and their results.
- The auction is maximum 60 seconds.
- This is a sealed bid auction; you can only see your own offer.



Sending Offer

- If you decide that you do not want to participate in the auction, you click on the “Do not Participate” button
- If you decide to participate you have to type your offer in the corresponding box and click on the “Send my offer” button.
- Clicking on “Send my offer" button without entering a value will result in a submitted offer of $0.
- Your offer Price can have up to 2 decimal points. For example, $3.99 is a valid offer, 3.999 is not.
- Your offer is the TOTAL amount, **NOT** the amount per acre.
- You have 60 seconds to make your offer.



My Previous Offers

During the auction, you can see all of your previously submitted offers and their results:

Round: The round number. There will be 15 repeated rounds in this experiment – each round is an auction.

Participated: This value shows if you chose to participate in the auction or not.

Total Offer Price ($): The total payment you asked for adopting the Alternative practice.

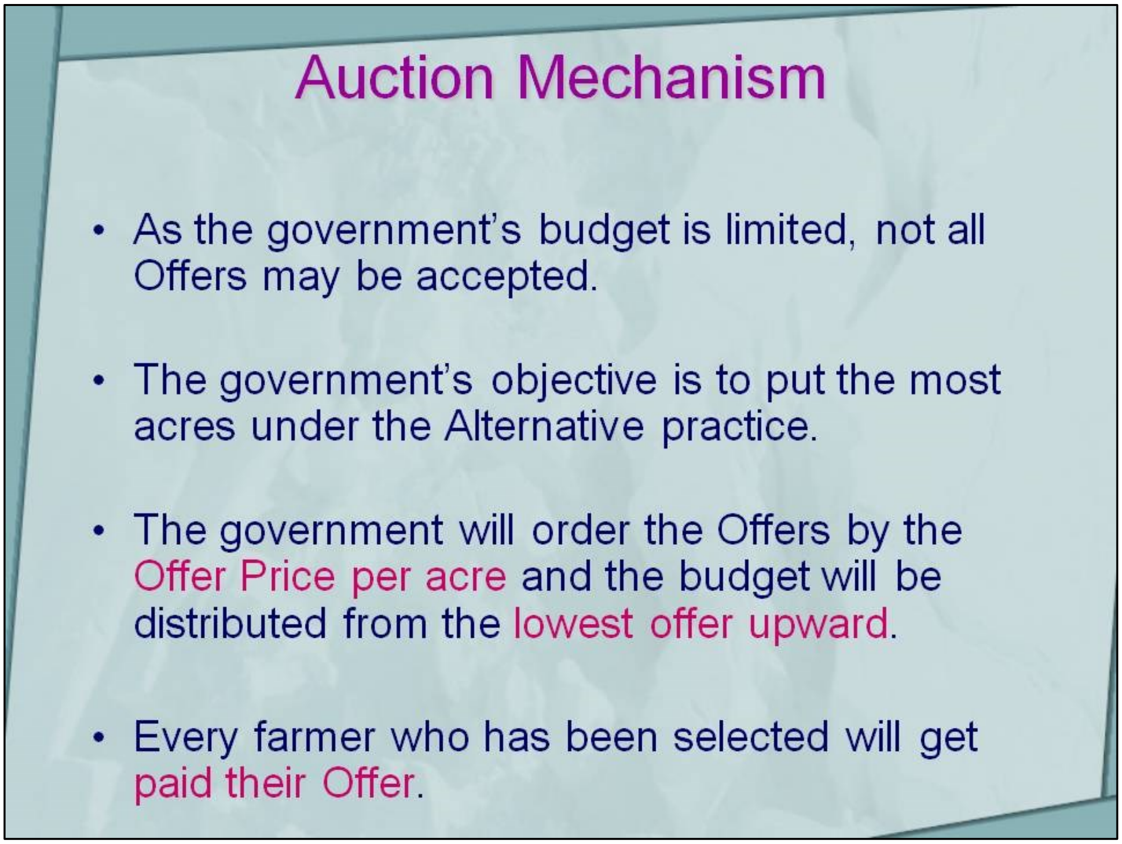
Offer Price ($/Acre): Your offer price you asked per acre.
= Total Offer Price / The size of your farm.

Successful: This value shows if your offer was accepted or not.

Profit($CAD): This is the amount of cash you have earned in the given round

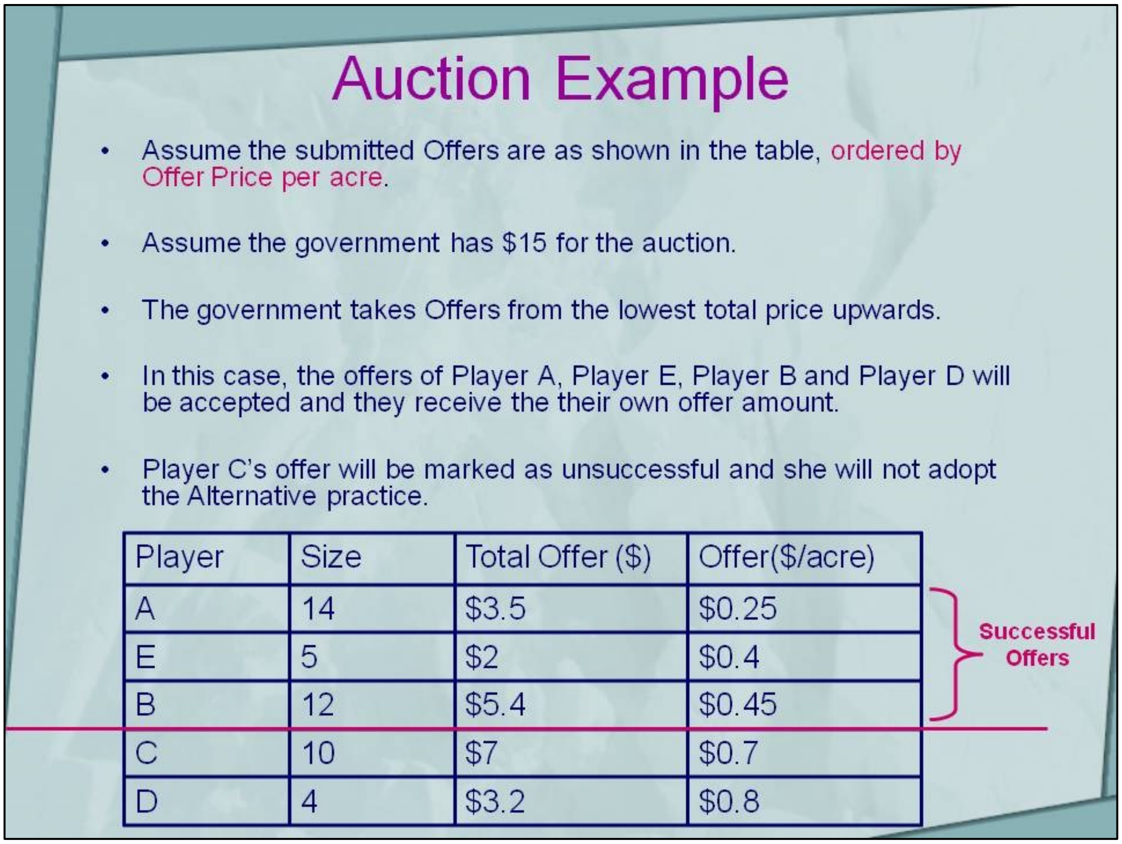
My Previous Offers

Round	Participated	Total Offer Price ($)	Offer Price ($/Acre)	Succesful	Goverment Payment($)	Profit
-1	No	0.00	0.00	No	0.00	1.00
0	Yes	55.00	5.50	Yes	55.00	2.00
1	Yes	52.00	5.20	Yes	52.00	1.40



Auction Mechanism

- As the government's budget is limited, not all Offers may be accepted.
- The government's objective is to put the most acres under the Alternative practice.
- The government will order the Offers by the Offer Price per acre and the budget will be distributed from the lowest offer upward.
- Every farmer who has been selected will get paid their Offer.

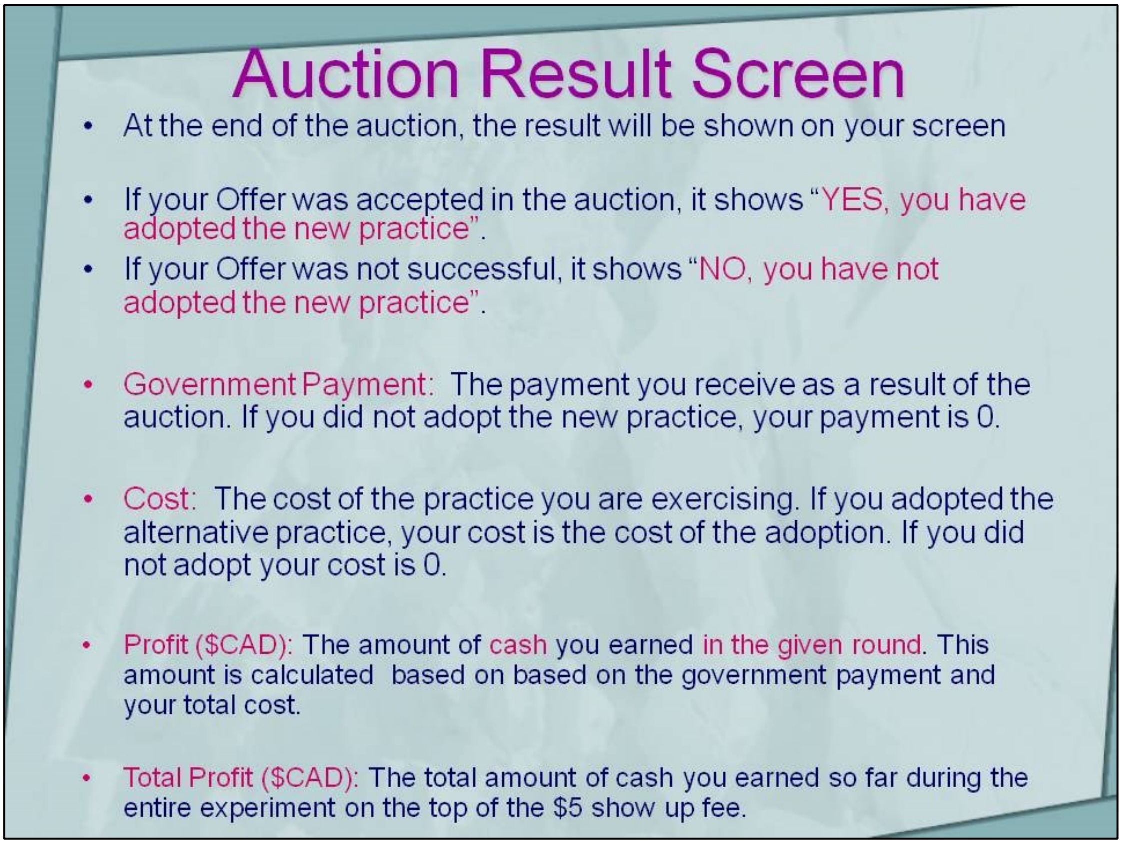


Auction Example

- Assume the submitted Offers are as shown in the table, ordered by Offer Price per acre.
- Assume the government has $15 for the auction.
- The government takes Offers from the lowest total price upwards.
- In this case, the offers of Player A, Player E, Player B and Player D will be accepted and they receive the their own offer amount.
- Player C's offer will be marked as unsuccessful and she will not adopt the Alternative practice.

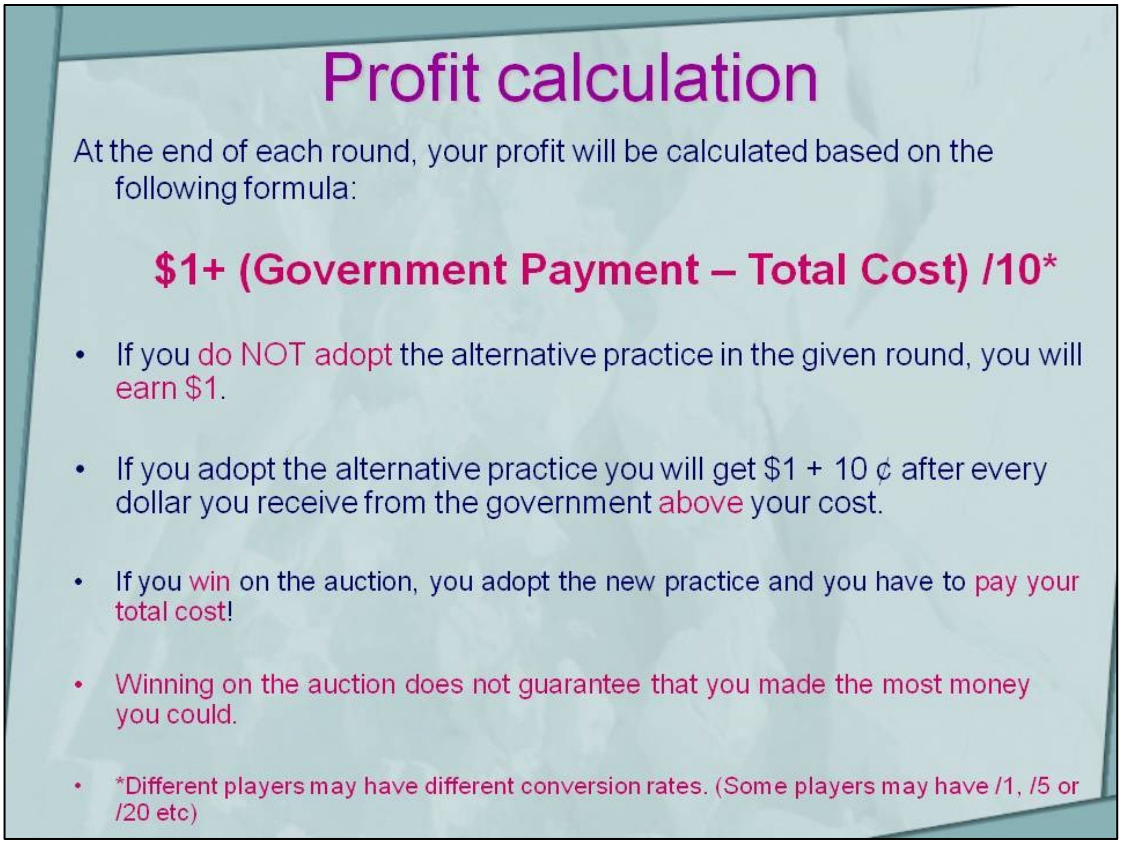
Player	Size	Total Offer ($)	Offer($/acre)
A	14	$3.5	$0.25
E	5	$2	$0.4
B	12	$5.4	$0.45
C	10	$7	$0.7
D	4	$3.2	$0.8

Successful Offers



Auction Result Screen

- At the end of the auction, the result will be shown on your screen
- If your Offer was accepted in the auction, it shows "YES, you have adopted the new practice".
- If your Offer was not successful, it shows "NO, you have not adopted the new practice".
- Government Payment: The payment you receive as a result of the auction. If you did not adopt the new practice, your payment is 0.
- Cost: The cost of the practice you are exercising. If you adopted the alternative practice, your cost is the cost of the adoption. If you did not adopt your cost is 0.
- Profit ($CAD): The amount of cash you earned in the given round. This amount is calculated based on based on the government payment and your total cost.
- Total Profit ($CAD): The total amount of cash you earned so far during the entire experiment on the top of the $5 show up fee.

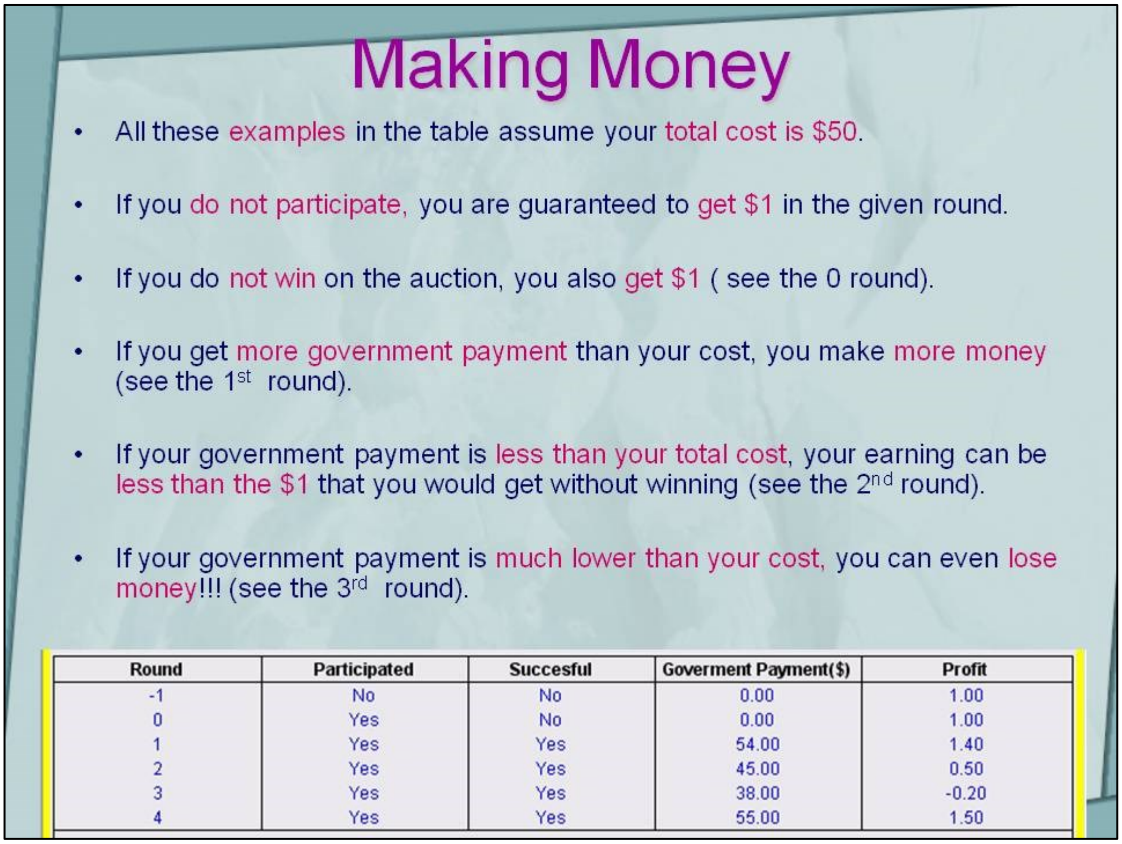


Profit calculation

At the end of each round, your profit will be calculated based on the following formula:

$1+ (Government Payment – Total Cost) /10*

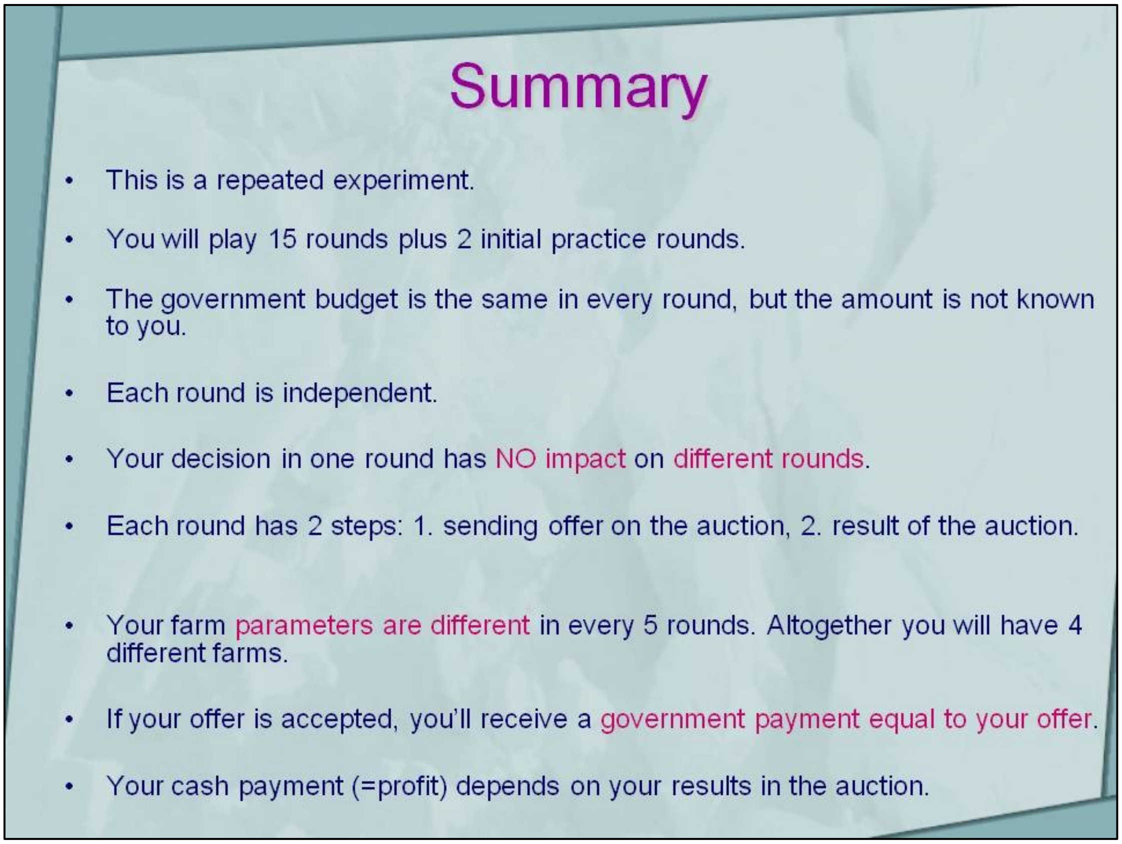
- If you do NOT adopt the alternative practice in the given round, you will earn $1.
- If you adopt the alternative practice you will get $1 + 10 ¢ after every dollar you receive from the government above your cost.
- If you win on the auction, you adopt the new practice and you have to pay your total cost!
- Winning on the auction does not guarantee that you made the most money you could.
- *Different players may have different conversion rates. (Some players may have /1, /5 or /20 etc)



Making Money

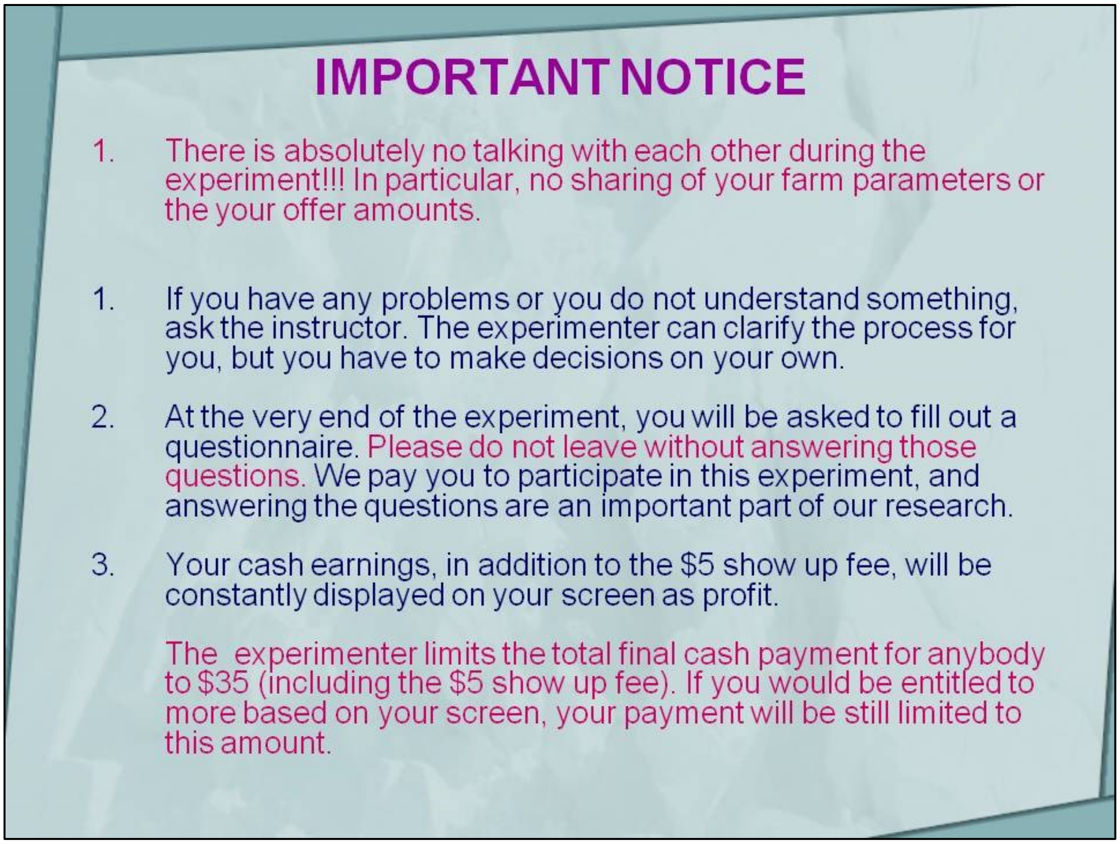
- All these examples in the table assume your total cost is $50.
- If you do not participate, you are guaranteed to get $1 in the given round.
- If you do not win on the auction, you also get $1 (see the 0 round).
- If you get more government payment than your cost, you make more money (see the 1st round).
- If your government payment is less than your total cost, your earning can be less than the $1 that you would get without winning (see the 2nd round).
- If your government payment is much lower than your cost, you can even lose money!!! (see the 3rd round).

Round	Participated	Succesful	Goverment Payment($)	Profit
-1	No	No	0.00	1.00
0	Yes	No	0.00	1.00
1	Yes	Yes	54.00	1.40
2	Yes	Yes	45.00	0.50
3	Yes	Yes	38.00	-0.20
4	Yes	Yes	55.00	1.50



Summary

- This is a repeated experiment.
- You will play 15 rounds plus 2 initial practice rounds.
- The government budget is the same in every round, but the amount is not known to you.
- Each round is independent.
- Your decision in one round has NO impact on different rounds.
- Each round has 2 steps: 1. sending offer on the auction, 2. result of the auction.
- Your farm parameters are different in every 5 rounds. Altogether you will have 4 different farms.
- If your offer is accepted, you'll receive a government payment equal to your offer.
- Your cash payment (=profit) depends on your results in the auction.



IMPORTANT NOTICE

1. There is absolutely no talking with each other during the experiment!!! In particular, no sharing of your farm parameters or the your offer amounts.

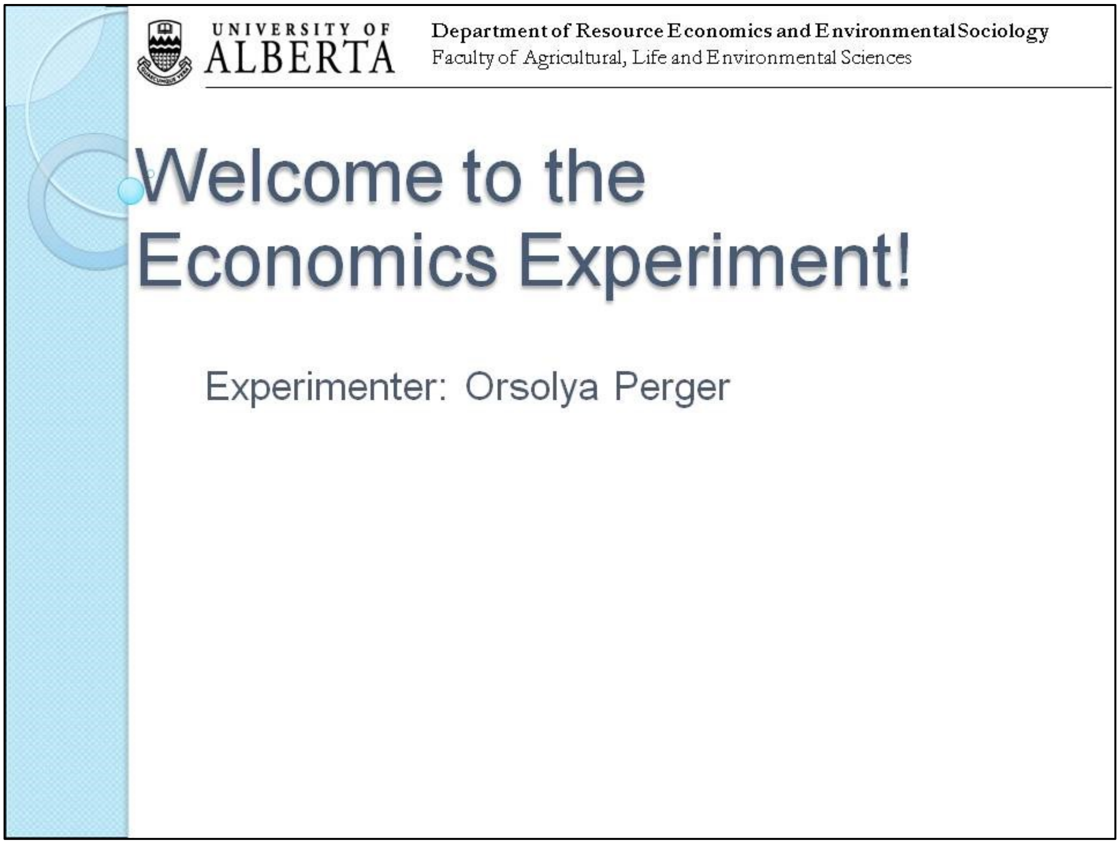
1. If you have any problems or you do not understand something, ask the instructor. The experimenter can clarify the process for you, but you have to make decisions on your own.

2. At the very end of the experiment, you will be asked to fill out a questionnaire. Please do not leave without answering those questions. We pay you to participate in this experiment, and answering the questions are an important part of our research.

3. Your cash earnings, in addition to the $5 show up fee, will be constantly displayed on your screen as profit.

   The experimenter limits the total final cash payment for anybody to $35 (including the $5 show up fee). If you would be entitled to more based on your screen, your payment will be still limited to this amount.

APPENDIX B: Experiment Instruction for 2nd Paper

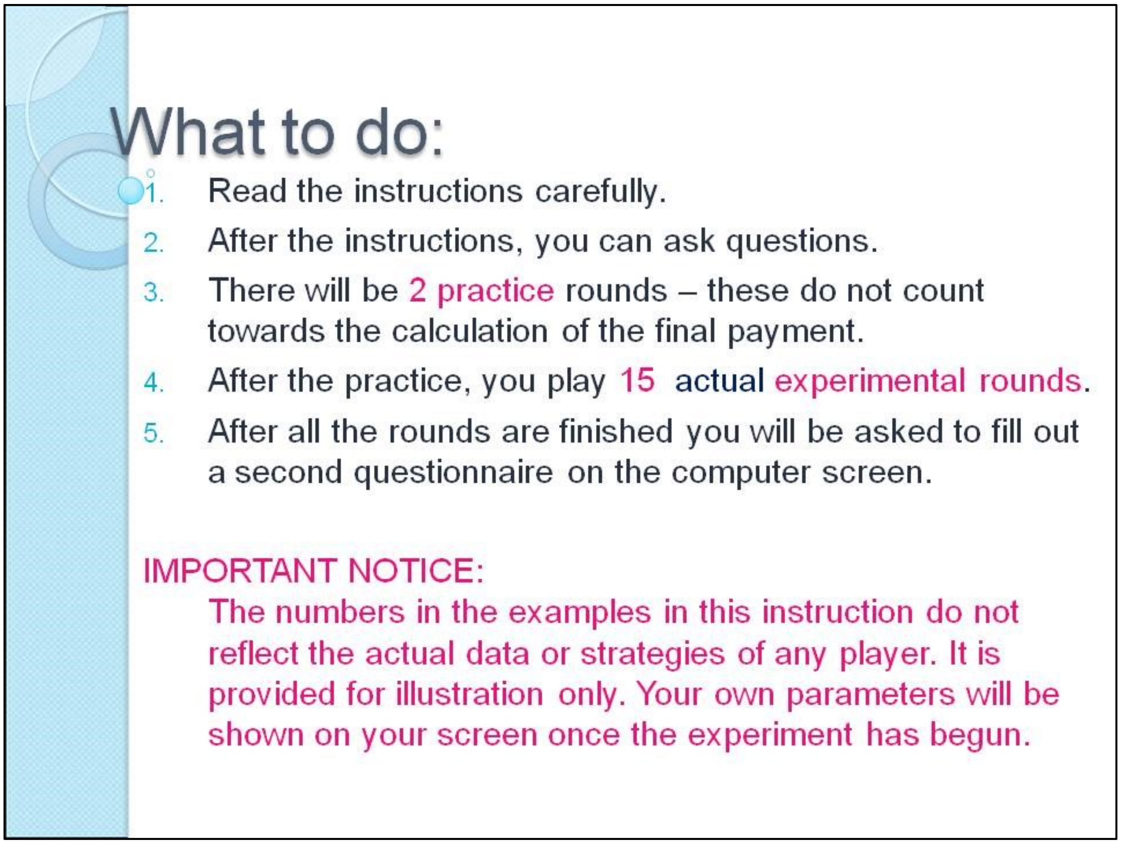


UNIVERSITY OF ALBERTA

Department of Resource Economics and Environmental Sociology
Faculty of Agricultural, Life and Environmental Sciences

Welcome to the Economics Experiment!

Experimenter: Orsolya Perger

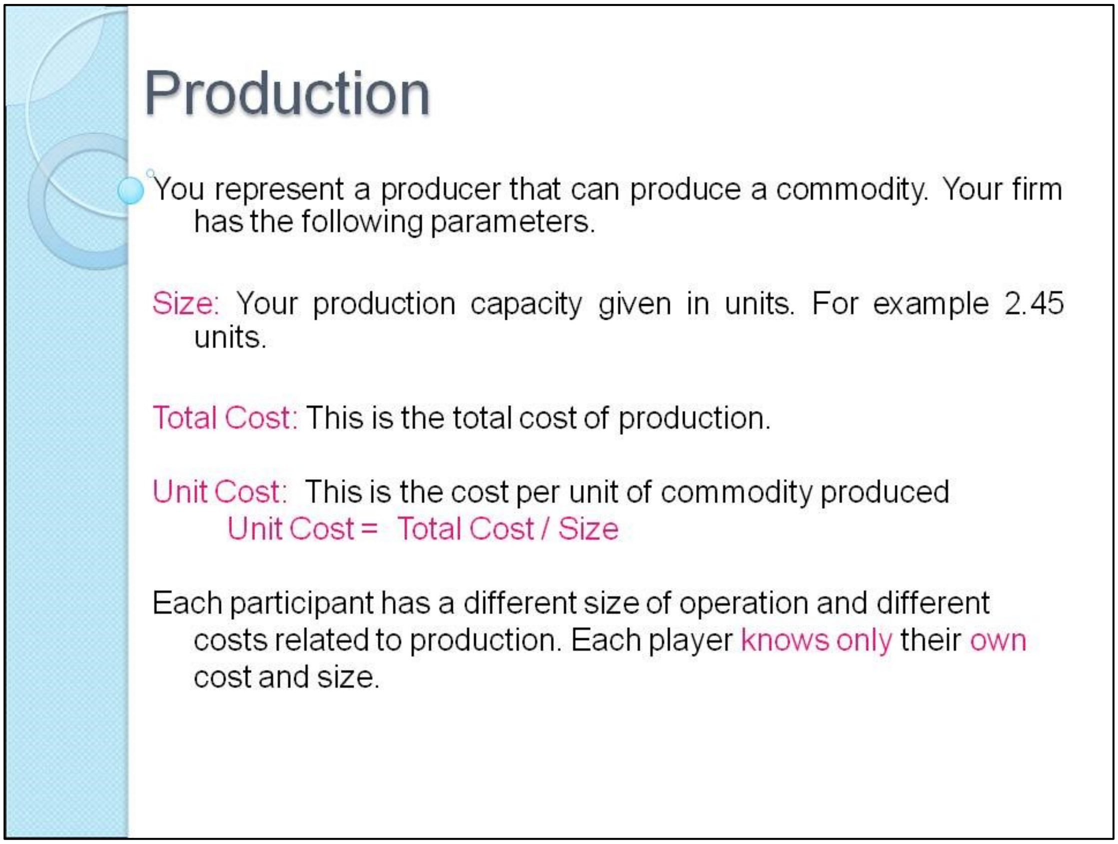


What to do:

1. Read the instructions carefully.
2. After the instructions, you can ask questions.
3. There will be 2 practice rounds – these do not count towards the calculation of the final payment.
4. After the practice, you play 15 actual experimental rounds.
5. After all the rounds are finished you will be asked to fill out a second questionnaire on the computer screen.

IMPORTANT NOTICE:

The numbers in the examples in this instruction do not reflect the actual data or strategies of any player. It is provided for illustration only. Your own parameters will be shown on your screen once the experiment has begun.



Production

- You represent a producer that can produce a commodity. Your firm has the following parameters.

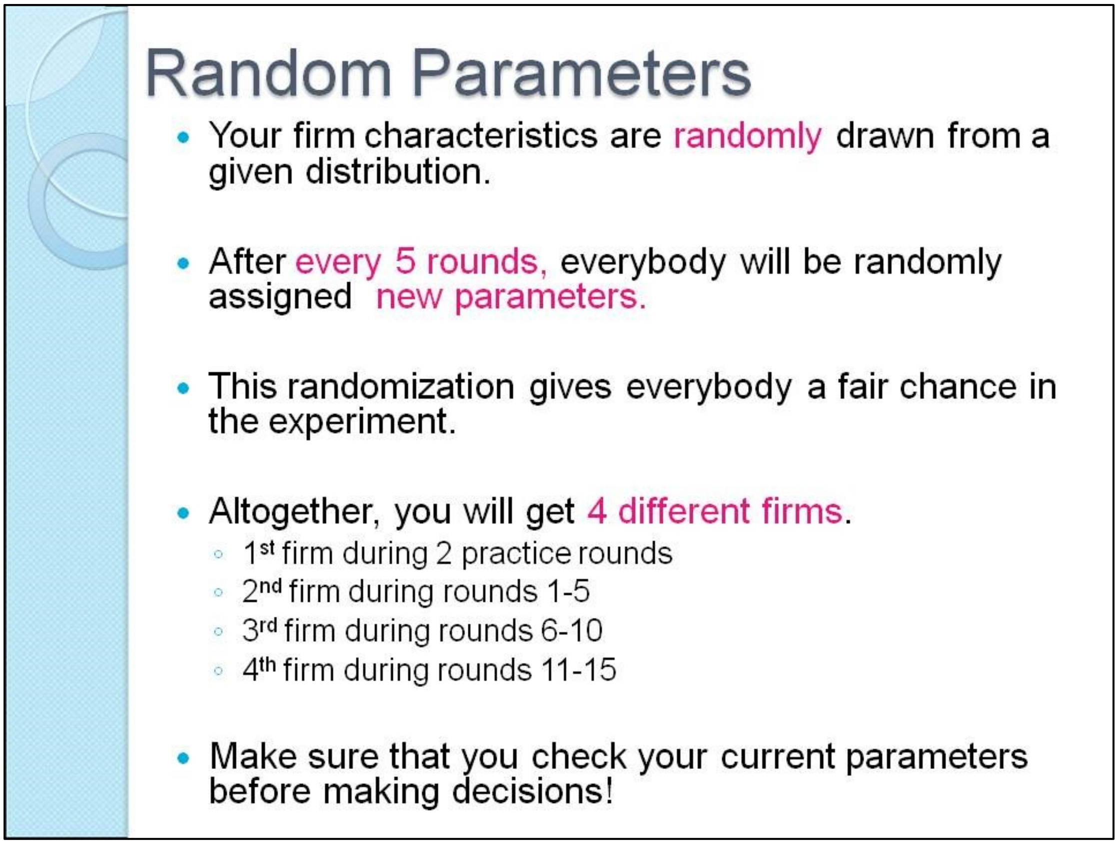
Size: Your production capacity given in units. For example 2.45 units.

Total Cost: This is the total cost of production.

Unit Cost: This is the cost per unit of commodity produced

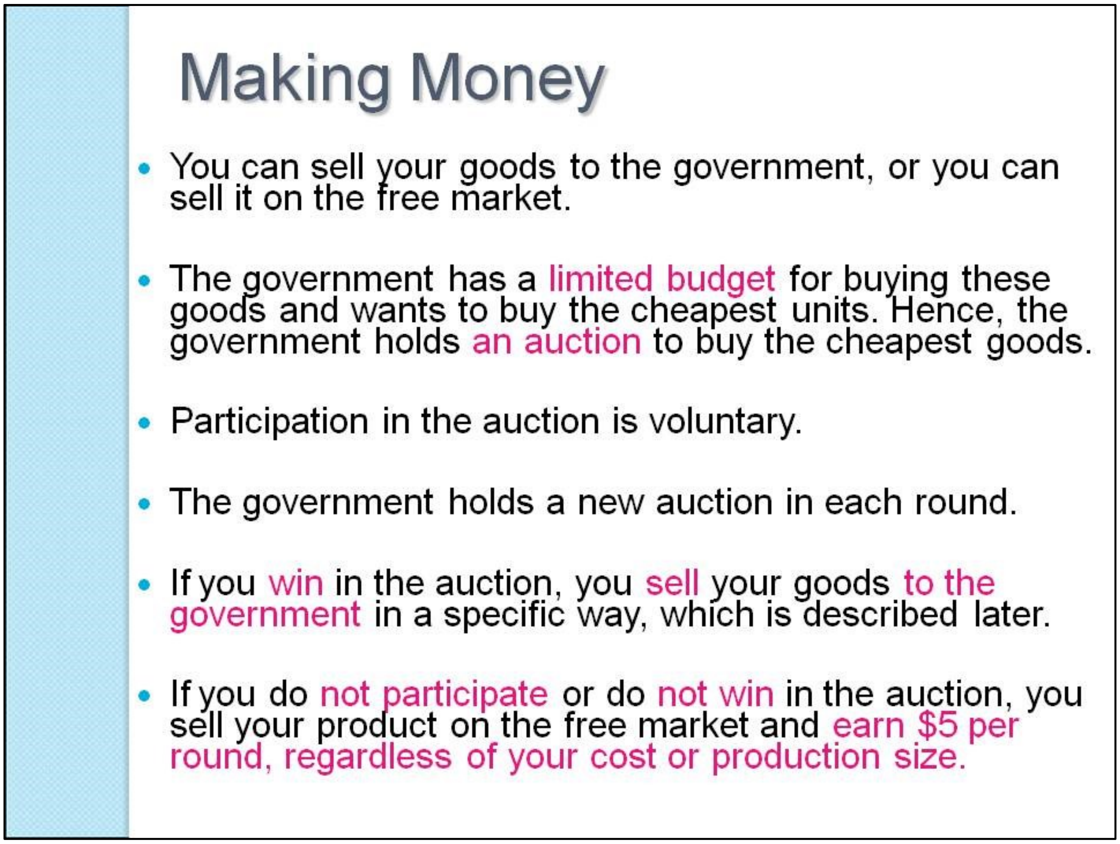
Unit Cost = Total Cost / Size

Each participant has a different size of operation and different costs related to production. Each player knows only their own cost and size.



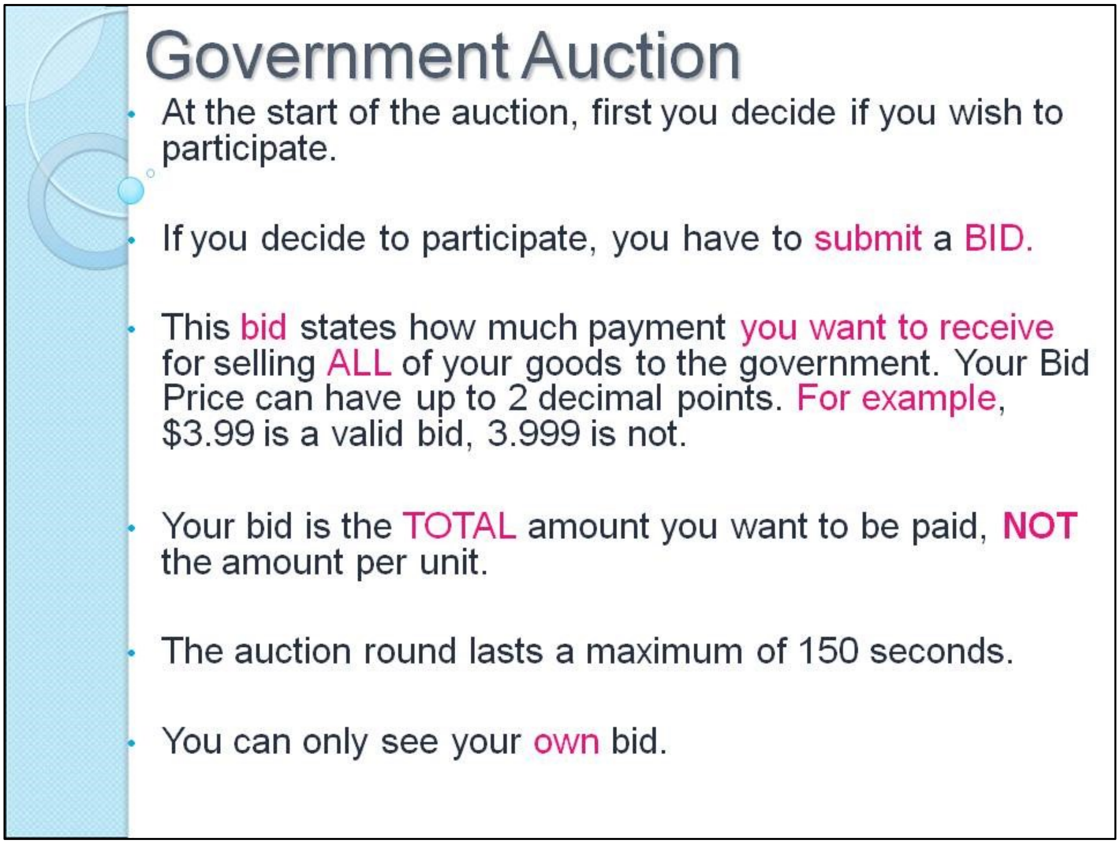
Random Parameters

- Your firm characteristics are randomly drawn from a given distribution.
- After every 5 rounds, everybody will be randomly assigned new parameters.
- This randomization gives everybody a fair chance in the experiment.
- Altogether, you will get 4 different firms.
    - 1st firm during 2 practice rounds
    - 2nd firm during rounds 1-5
    - 3rd firm during rounds 6-10
    - 4th firm during rounds 11-15
- Make sure that you check your current parameters before making decisions!



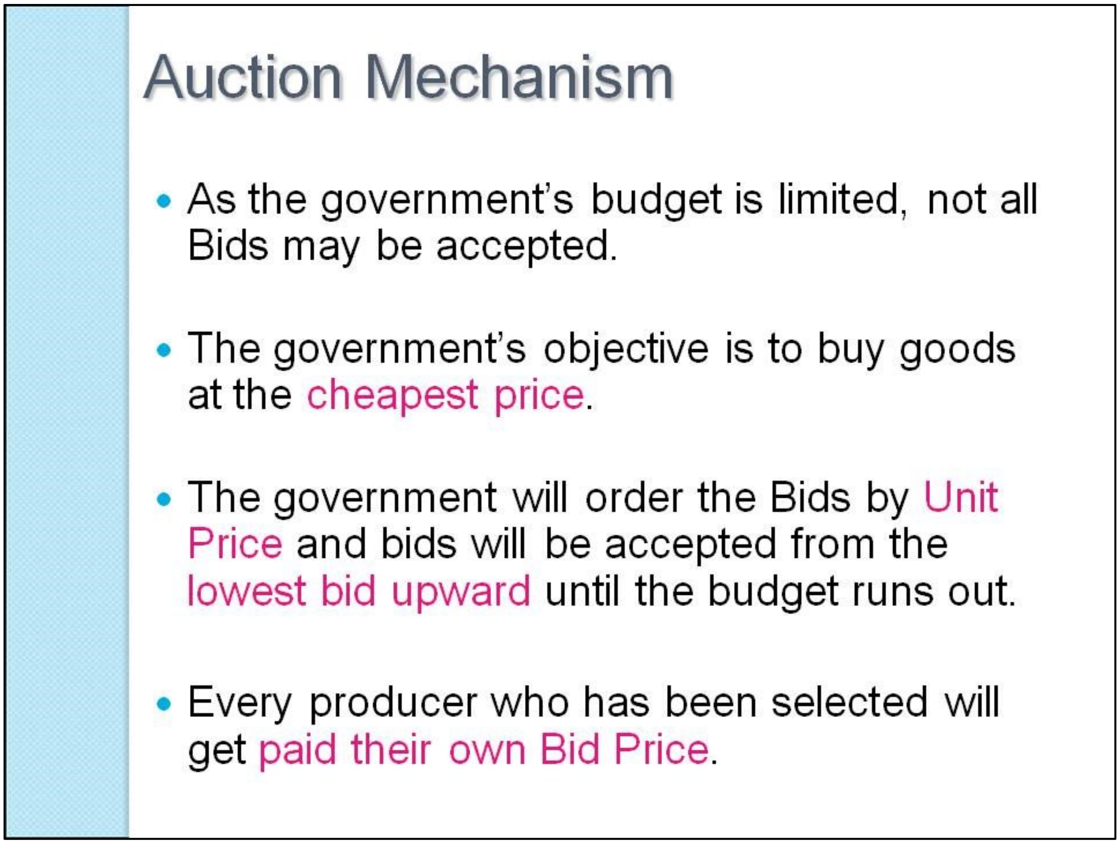
Making Money

- You can sell your goods to the government, or you can sell it on the free market.
- The government has a limited budget for buying these goods and wants to buy the cheapest units. Hence, the government holds an auction to buy the cheapest goods.
- Participation in the auction is voluntary.
- The government holds a new auction in each round.
- If you win in the auction, you sell your goods to the government in a specific way, which is described later.
- If you do not participate or do not win in the auction, you sell your product on the free market and earn $5 per round, regardless of your cost or production size.



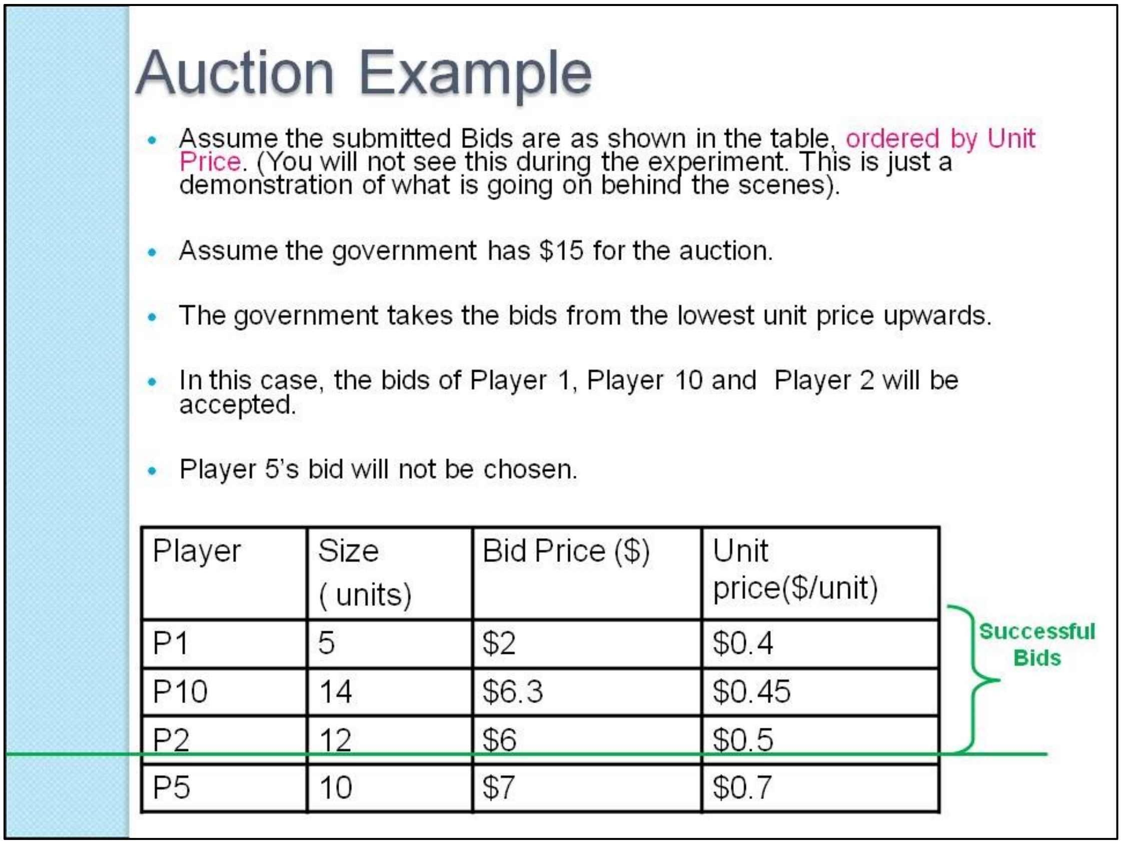
Government Auction

- At the start of the auction, first you decide if you wish to participate.
- If you decide to participate, you have to submit a BID.
- This bid states how much payment you want to receive for selling ALL of your goods to the government. Your Bid Price can have up to 2 decimal points. For example, $3.99 is a valid bid, 3.999 is not.
- Your bid is the TOTAL amount you want to be paid, **NOT** the amount per unit.
- The auction round lasts a maximum of 150 seconds.
- You can only see your own bid.



Auction Mechanism

- As the government's budget is limited, not all Bids may be accepted.
- The government's objective is to buy goods at the cheapest price.
- The government will order the Bids by Unit Price and bids will be accepted from the lowest bid upward until the budget runs out.
- Every producer who has been selected will get paid their own Bid Price.

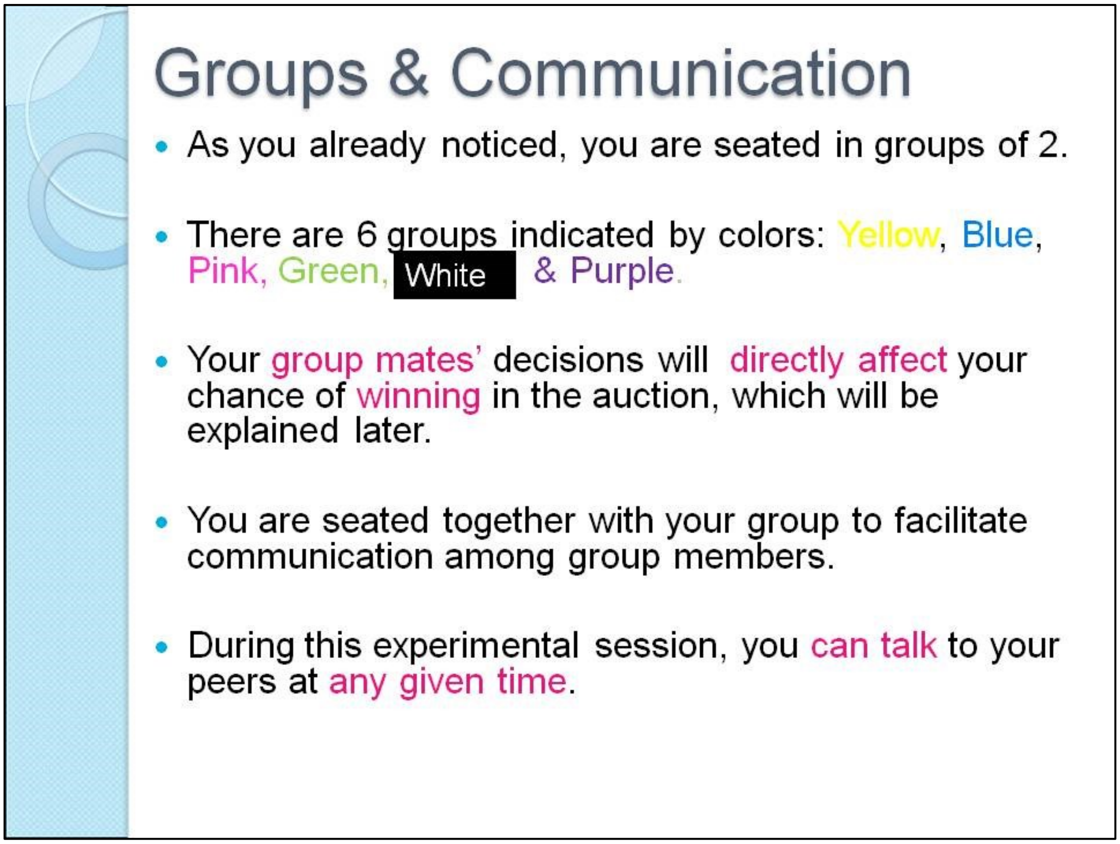


Auction Example

- Assume the submitted Bids are as shown in the table, ordered by Unit Price. (You will not see this during the experiment. This is just a demonstration of what is going on behind the scenes).
- Assume the government has $15 for the auction.
- The government takes the bids from the lowest unit price upwards.
- In this case, the bids of Player 1, Player 10 and Player 2 will be accepted.
- Player 5's bid will not be chosen.

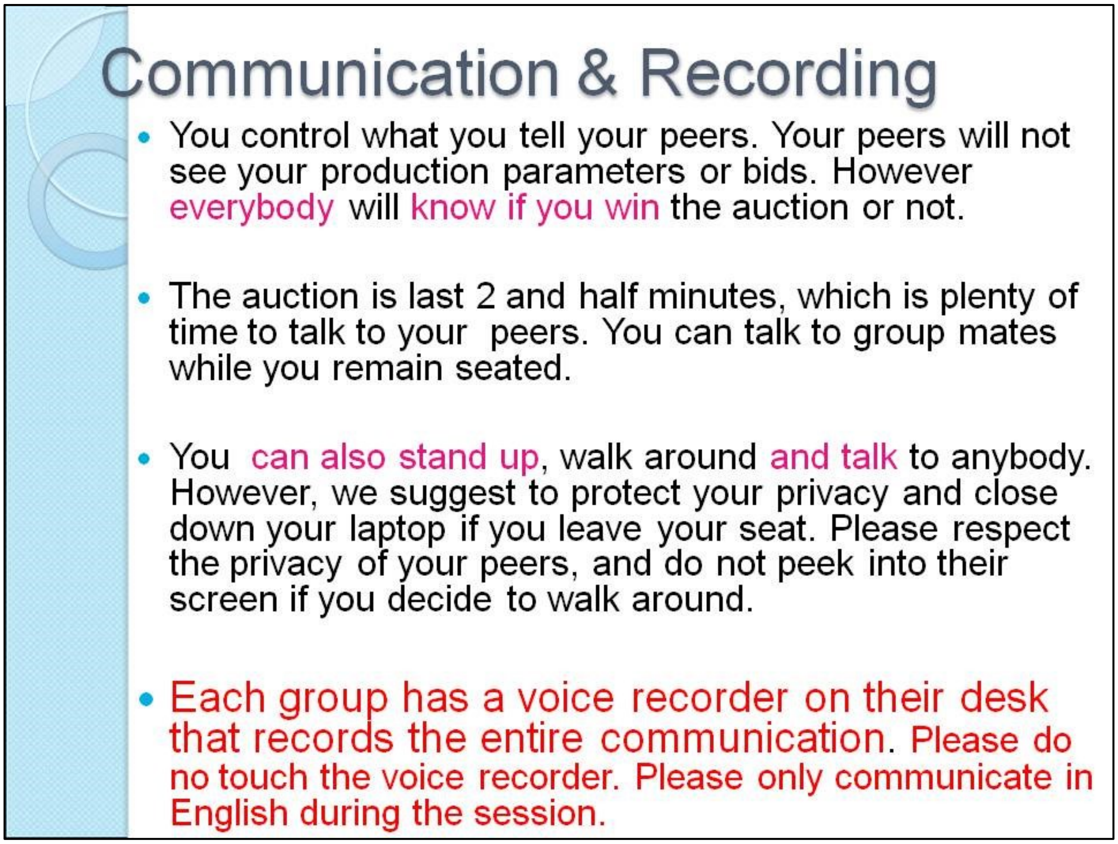
Player	Size (units)	Bid Price ($)	Unit price($/unit)
P1	5	$2	$0.4
P10	14	$6.3	$0.45
P2	12	$6	$0.5
P5	10	$7	$0.7

Successful Bids



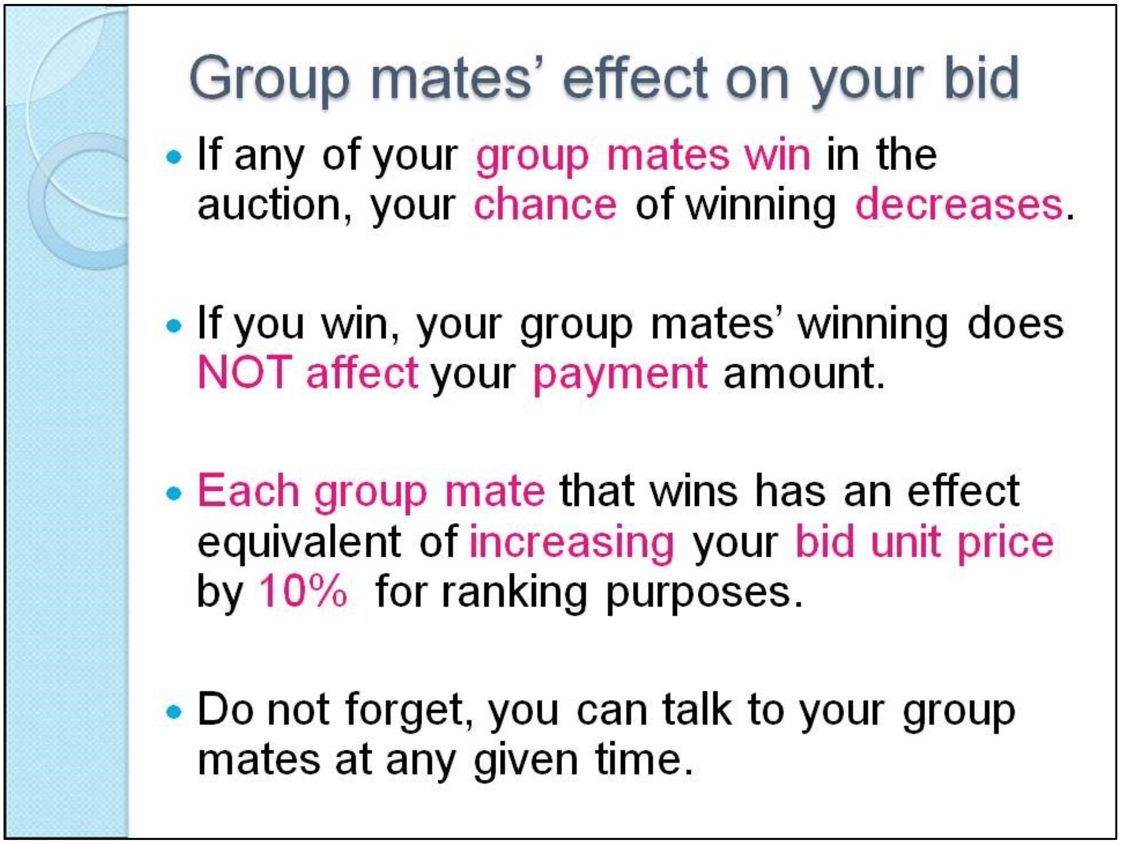
Groups & Communication

- As you already noticed, you are seated in groups of 2.
- There are 6 groups indicated by colors: Yellow, Blue, Pink, Green, White & Purple.
- Your group mates' decisions will directly affect your chance of winning in the auction, which will be explained later.
- You are seated together with your group to facilitate communication among group members.
- During this experimental session, you can talk to your peers at any given time.



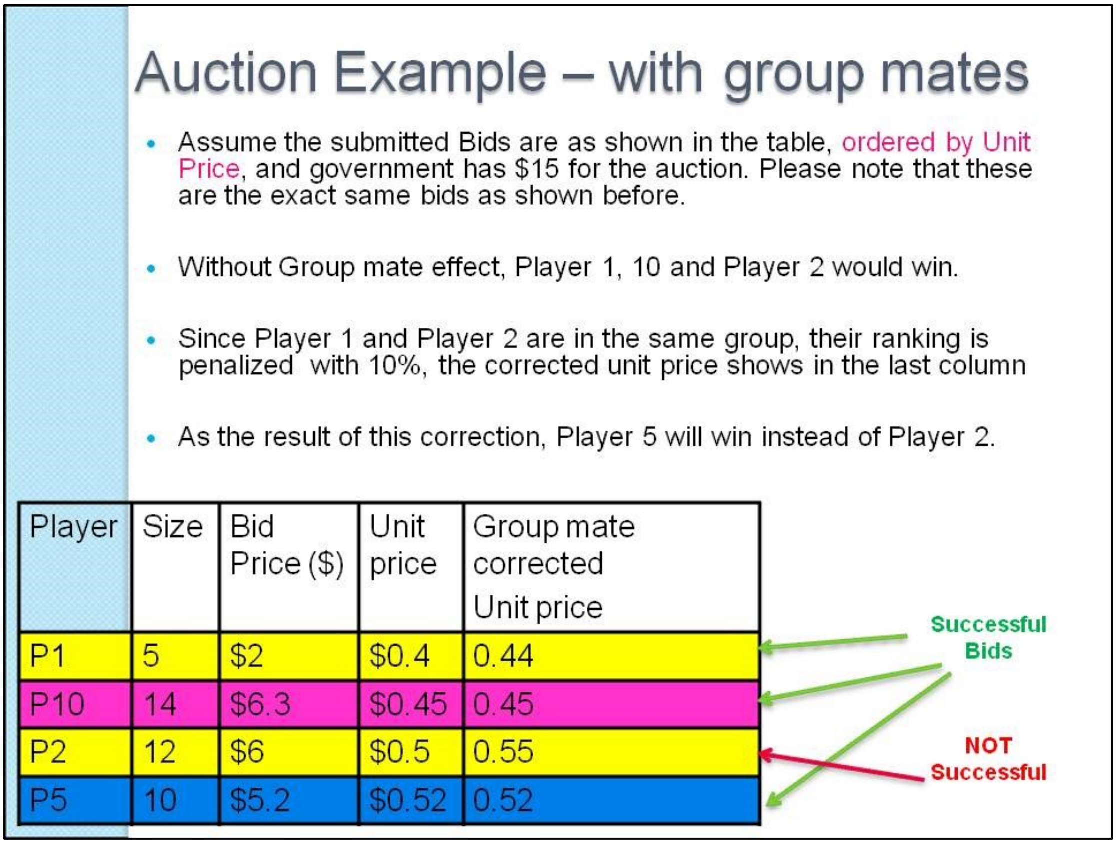
Communication & Recording

- You control what you tell your peers. Your peers will not see your production parameters or bids. However everybody will know if you win the auction or not.
- The auction is last 2 and half minutes, which is plenty of time to talk to your peers. You can talk to group mates while you remain seated.
- You can also stand up, walk around and talk to anybody. However, we suggest to protect your privacy and close down your laptop if you leave your seat. Please respect the privacy of your peers, and do not peek into their screen if you decide to walk around.
- Each group has a voice recorder on their desk that records the entire communication. Please do no touch the voice recorder. Please only communicate in English during the session.



Group mates' effect on your bid

- If any of your group mates win in the auction, your chance of winning decreases.
- If you win, your group mates' winning does NOT affect your payment amount.
- Each group mate that wins has an effect equivalent of increasing your bid unit price by 10% for ranking purposes.
- Do not forget, you can talk to your group mates at any given time.



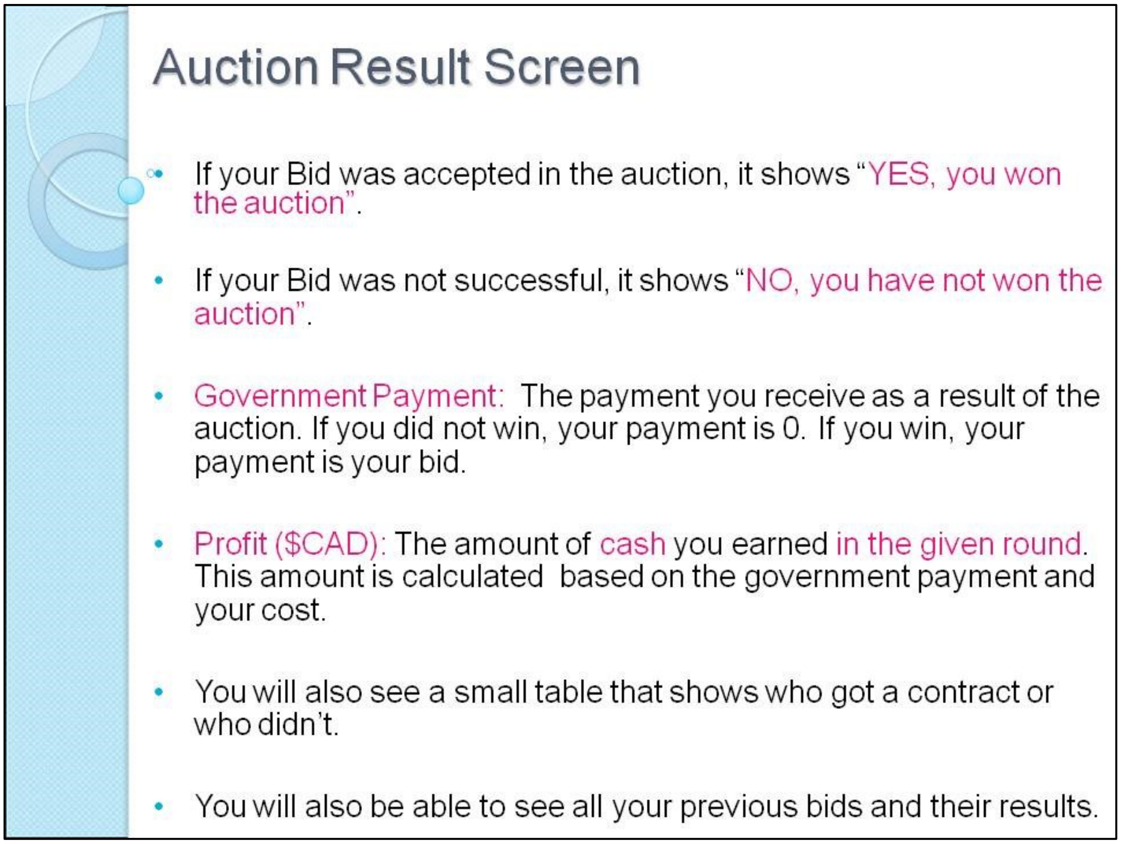
Auction Example – with group mates

- Assume the submitted Bids are as shown in the table, ordered by Unit Price, and government has $15 for the auction. Please note that these are the exact same bids as shown before.
- Without Group mate effect, Player 1, 10 and Player 2 would win.
- Since Player 1 and Player 2 are in the same group, their ranking is penalized with 10%, the corrected unit price shows in the last column
- As the result of this correction, Player 5 will win instead of Player 2.

Player	Size	Bid Price ($)	Unit price	Group mate corrected Unit price
P1	5	$2	$0.4	0.44
P10	14	$6.3	$0.45	0.45
P2	12	$6	$0.5	0.55
P5	10	$5.2	$0.52	0.52

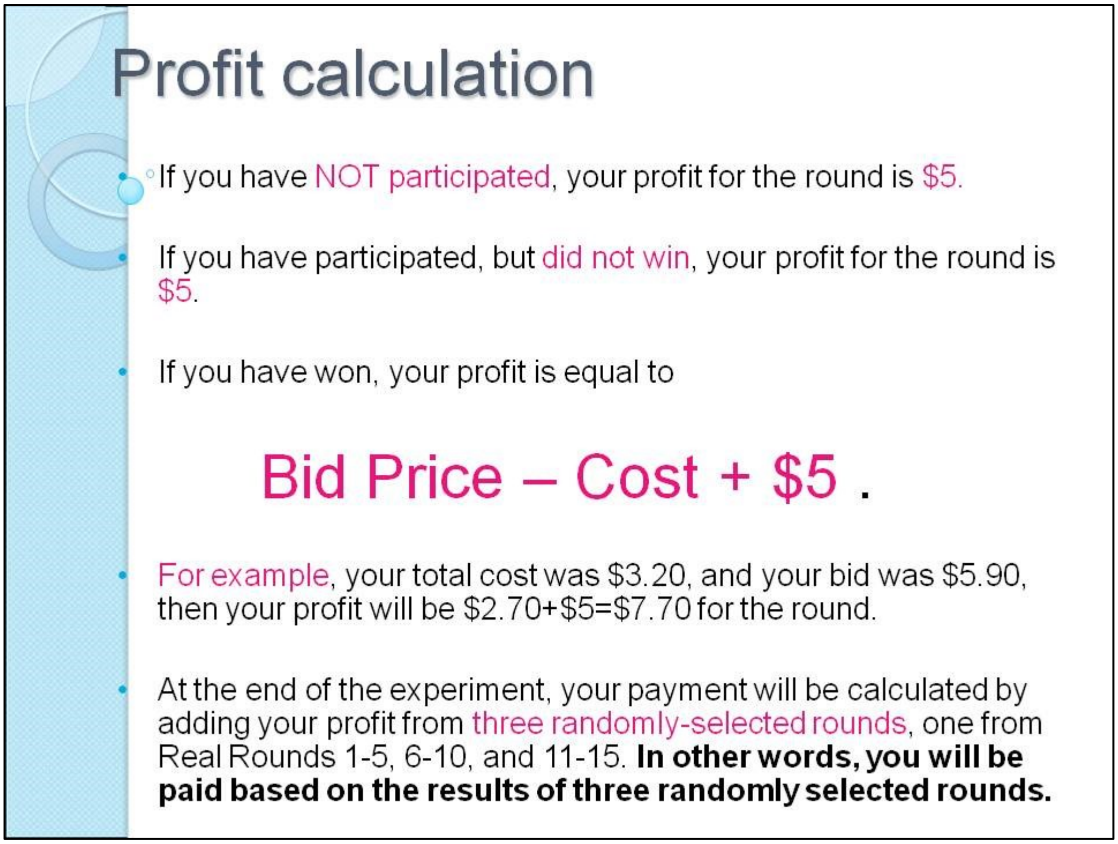
Successful Bids

NOT Successful



Auction Result Screen

- If your Bid was accepted in the auction, it shows "YES, you won the auction".
- If your Bid was not successful, it shows "NO, you have not won the auction".
- Government Payment: The payment you receive as a result of the auction. If you did not win, your payment is 0. If you win, your payment is your bid.
- Profit ($CAD): The amount of cash you earned in the given round. This amount is calculated based on the government payment and your cost.
- You will also see a small table that shows who got a contract or who didn't.
- You will also be able to see all your previous bids and their results.

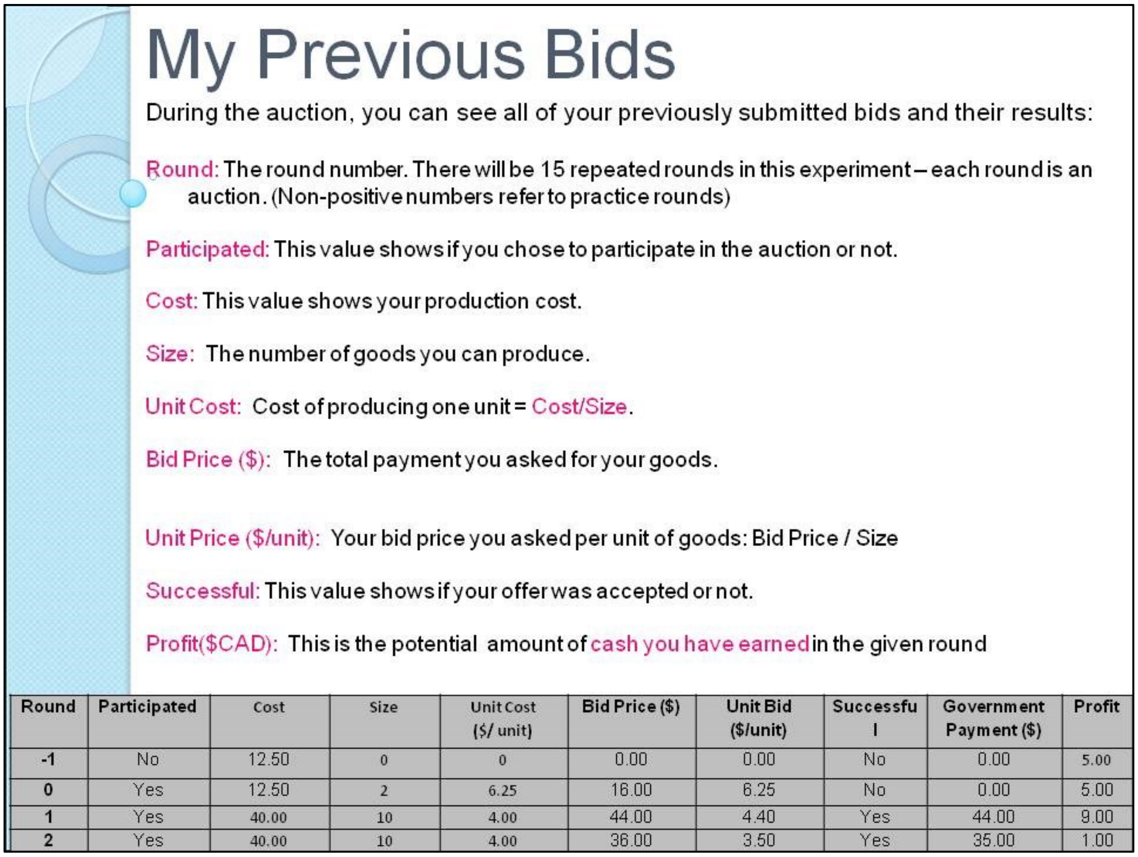


Profit calculation

- If you have NOT participated, your profit for the round is $5.
- If you have participated, but did not win, your profit for the round is $5.
- If you have won, your profit is equal to

Bid Price – Cost + $5 .

- For example, your total cost was $3.20, and your bid was $5.90, then your profit will be $2.70+$5=$7.70 for the round.
- At the end of the experiment, your payment will be calculated by adding your profit from three randomly-selected rounds, one from Real Rounds 1-5, 6-10, and 11-15. **In other words, you will be paid based on the results of three randomly selected rounds.**



My Previous Bids

During the auction, you can see all of your previously submitted bids and their results:

Round: The round number. There will be 15 repeated rounds in this experiment – each round is an auction. (Non-positive numbers refer to practice rounds)

Participated: This value shows if you chose to participate in the auction or not.

Cost: This value shows your production cost.

Size: The number of goods you can produce.

Unit Cost: Cost of producing one unit = Cost/Size.

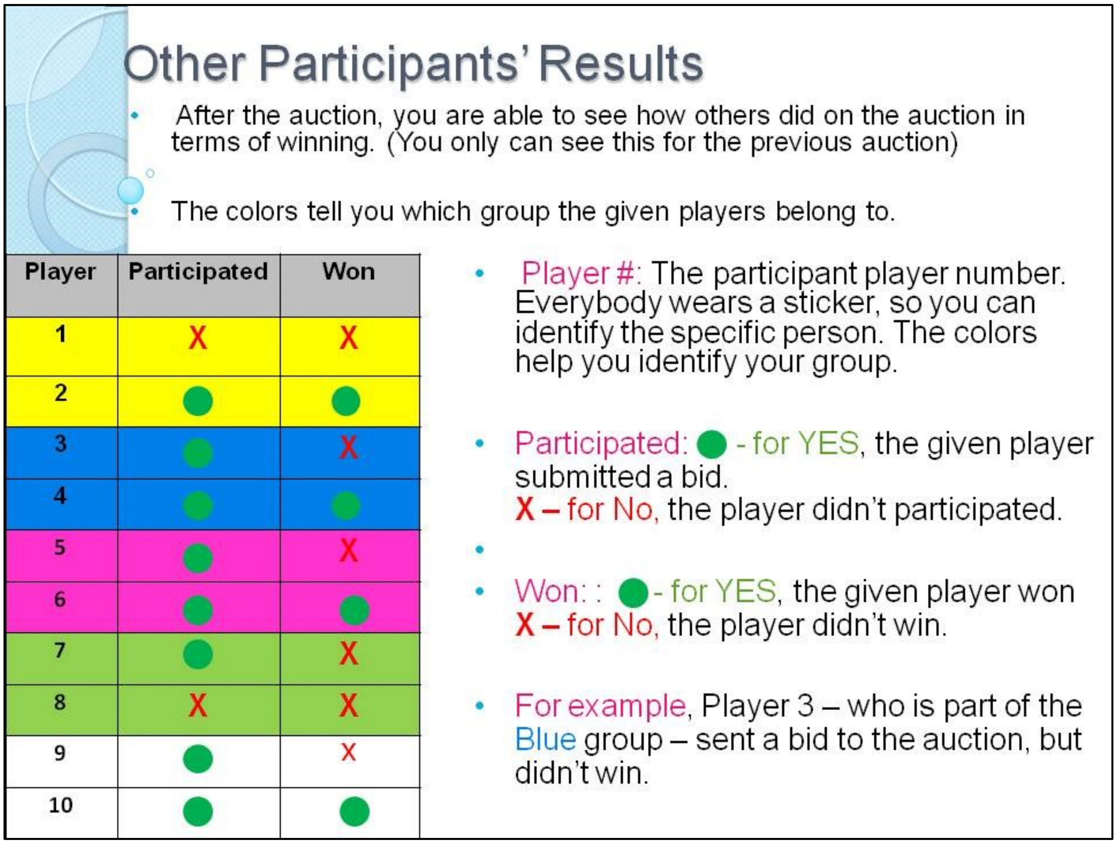
Bid Price ($): The total payment you asked for your goods.

Unit Price ($/unit): Your bid price you asked per unit of goods: Bid Price / Size

Successful: This value shows if your offer was accepted or not.

Profit($CAD): This is the potential amount of cash you have earned in the given round

Round	Participated	Cost	Size	Unit Cost ($/ unit)	Bid Price ($)	Unit Bid ($/unit)	Successfu l	Government Payment ($)	Profit
-1	No	12.50	0	0	0.00	0.00	No	0.00	5.00
0	Yes	12.50	2	6.25	16.00	6.25	No	0.00	5.00
1	Yes	40.00	10	4.00	44.00	4.40	Yes	44.00	9.00
2	Yes	40.00	10	4.00	36.00	3.50	Yes	35.00	1.00

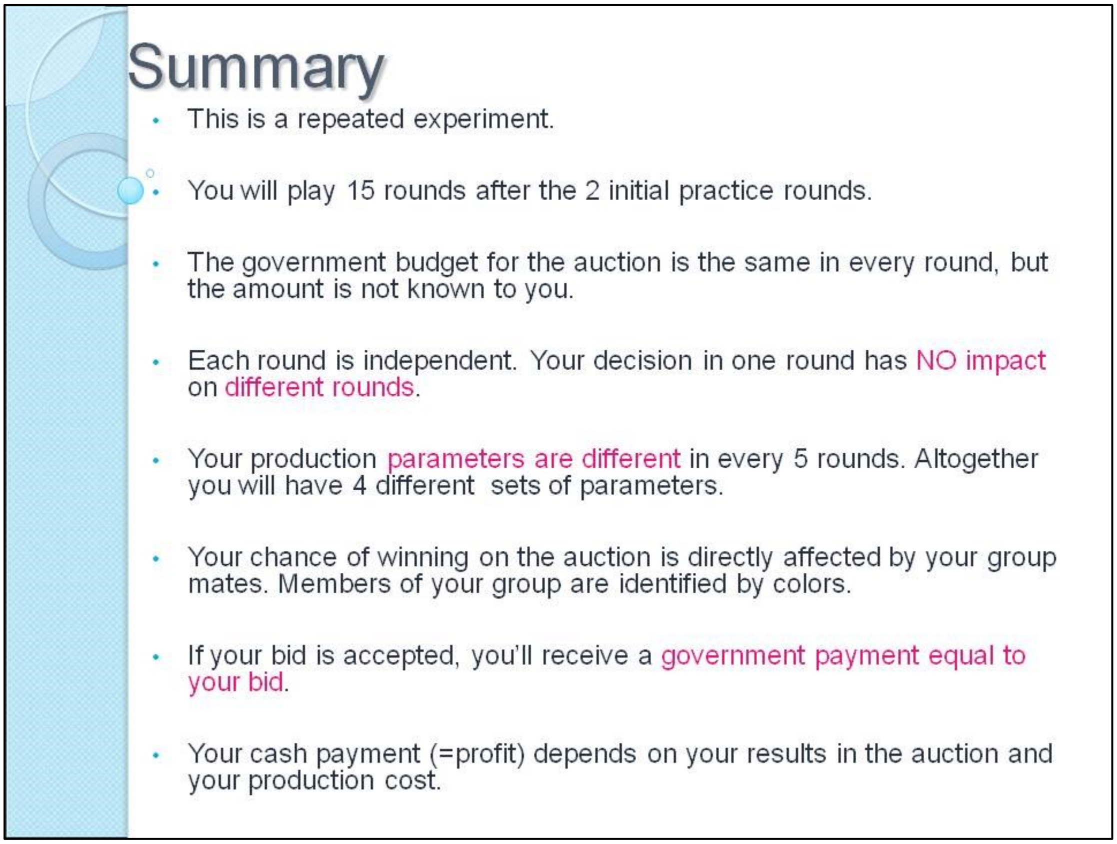


Other Participants' Results

- After the auction, you are able to see how others did on the auction in terms of winning. (You only can see this for the previous auction)
- The colors tell you which group the given players belong to.

Player	Participated	Won
1	X	X
2	●	●
3	●	X
4	●	●
5	●	X
6	●	●
7	●	X
8	X	X
9	●	X
10	●	●

- Player #: The participant player number. Everybody wears a sticker, so you can identify the specific person. The colors help you identify your group.
- Participated: ● - for YES, the given player submitted a bid.
  X – for No, the player didn't participated.
-
- Won: : ● - for YES, the given player won
  X – for No, the player didn't win.
- For example, Player 3 – who is part of the Blue group – sent a bid to the auction, but didn't win.



Summary

- This is a repeated experiment.
- You will play 15 rounds after the 2 initial practice rounds.
- The government budget for the auction is the same in every round, but the amount is not known to you.
- Each round is independent. Your decision in one round has NO impact on different rounds.
- Your production parameters are different in every 5 rounds. Altogether you will have 4 different sets of parameters.
- Your chance of winning on the auction is directly affected by your group mates. Members of your group are identified by colors.
- If your bid is accepted, you'll receive a government payment equal to your bid.
- Your cash payment (=profit) depends on your results in the auction and your production cost.