Information Networks and Conservation Auctions: Evidence from Laboratory Experiments

by

Daiwei Zhang

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Department of Resource Economics and Environmental Sociology

University of Alberta

Abstract

Conservation auctions have become a popular mechanism for gathering information about farmers' willingness to accept (WTA) compensation for the adoption of beneficial management practices (BMPs), allowing governments and environmental authorities to foster the adoption of these practices. In real life, farmers that participate in such auctions may not only know their own adoption costs but also those of other socially connected participants (e.g. neighbors). However, there is very limited literature on how information networks influence farmers' behaviors in conservation auction. This thesis tries to answer this question by conducting laboratory experiments containing multiple bidding rounds.

We find that: i) learning exists in multiple bidding rounds auction and may lead to efficiency loss; ii) networks in general may decrease auction efficiency as low-cost participants who are more likely to win try to increase bids when information about other participants' costs is available; iii) specific network structures, such as regular lattice and Erdos-Renyi, help reduce information rents gained by participants; iv) participants are only influenced by connections within two degrees of separation; and v) auction efficiency is expected to increase in auctions with information networks in which high-cost participants are highly connected and low-cost participants are isolated. These findings provide guidelines and suggestions for conservation auction design and policy decisions.

Preface

This thesis is an original work by Daiwei Zhang. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Generating Agri-Environmental Improvements: Integrating Social Networks into Conservation Auctions ", ID Pro00050471, approved on September 3, 2014.

Dedication

I would like to dedicate this thesis to my grandmother. Thank you for your continuous love and support, for always praying for me, for making my life full of joy and happiness.

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Chapter 1

Introduction

1.1 Background

As the impacts of human activities on the environment are increasing, it is important for scholars and policy makers to make an effort to understand and develop mechanisms to mitigate these negative impacts. In agricultural management, farmers can engage in environmentally friendly farming practices as a way to help preserve ecological environments. These beneficial management practices (BMPs) can help farmers to maintain agricultural production while minimizing environmental damage. BMPs contribute to a farm's overall sustainability by improving soil, water, air quality as well as wildlife habitats (Alberta Agriculture, Food and Rural Development, 2004). Some examples of BMPs include, but are not limited to, establishing vegetation along stream banks, constructing manure tanks or fences along waterways, and implementing reduced tillage (Boxall et al., 2013).

Given that BMPs help to improve agricultural sustainability on farmlands and surrounding communities, various government programs have been developed to promote BMP adoption. In Canada, the Environmental Farm Plan (EFP) program provided farmers with an opportunity to voluntarily participate in identifying both environmental benefits and potential risks on their farmlands. However, BMPs often come with high adoption costs when compared to traditional practices. For instance, farmers may need to face upfront construction costs and ongoing maintenance costs, therefore, observed adoption rates of BMPs tend to be significantly low due to this increase in costs (Boxall et al., 2013). Under this circumstance, government programs with financial incentives and technical support have been implemented alongside voluntary programs. The National Farm Stewardship Program (NFSP) in Canada offered cost-sharing incentives and technical assistance to farmers who implement BMPs to address environmental risks on their farmlands. Even so, according to Boxall et al. (2013), both payments and percentages of cost share offered were too low to provide sufficient incentives to boost BMPs adoption to significant levels. Therefore, information on farmers' willingness to accept (WTA) compensation is crucial when framing these programs and policies.

1.2 Conservation Auctions

In recent years, conservation auctions have become a popular approach for governments to collect WTA information and could facilitate the implementation of BMPs. These auctions encourage economic agents (farmers or landowners) to reveal their true and private preferences about the value of environmental goods and services (Cason et al., 2003). In other words, it helps government to minimize public expenditures and achieve desirable conservation outcomes at the same time (Banerjee et al., 2009). Conservation auctions are reverse auctions where there are multiple sellers (bidders) and just one buyer (auctioneer). In the auction, farmers submit a bid stating how much they are willing to accept as financial compensation for adopting BMPs. Typically, the government is the buyer and sets a limited budget for the auction. After all bids are submitted, they are ranked from low to high according to a measure of dollars per environmental benefit. Bids are then accepted from the lowest to the highest until the budget is exhausted. As a result, there can be multiple winners in a conservation auction.

One example of conservation auctions is the US Department of Agriculture's Conservation Reserve Program (CRP). The CRP offered farmers 10-15 year contracts to divert land from crop production and thus increase the provision of environmental goods and services (Cason et al., 2003). It employed a sealed bid discriminatory-price auction in which winners receive financial compensation in the amount of their bids.[1] Farmers were engaged in a cost-sharing program for establishing trees or grass covers on their farmlands as well as an annual payment determined by their bids (Claassen et al., 2008). In Canada, a conservation auction was used to promote wetlands restoration in the Assiniboine River Watershed of east-central Saskatchewan (see Hill et al., 2011). Similar to the CRP, the auction involved a sealed bid discriminatory-price mechanism and offered landowners 12-year term agreements to maintain restored wetlands for conservation easements. Another application of real world conservation auctions are the BushTender trials operated by the Australian government to promote conservation of native vegetation on private lands (Stoneham, 2003). In the United Kingdom, programs such as the Conservation Stewardship Scheme and the Nitrate Sensitive Areas Scheme applied reverse auctions to determine how much to compensate landowners who were willing to take environmental actions on their lands and who proposed the best quality land management plans (Cason and Gangadharan, 2004).

1.3 Information Networks

Recent analyses of economic systems suggest the existence of complex connections between economic agents and, as a result, their behaviors can be greatly influenced by their networks of relationships – or social networks (Wichmann, 2015). Social networks are often defined by a finite number of individuals (or actors) and a set of links among them through which information, goods, and services may flow (Maertens and Barrett,

[1] This contrasts with uniform-price auctions where all winners receive the same payment.

2013). The literature is rife with evidence about the importance of social connections and many researchers have incorporated the impacts of social networks into their studies (see Jackson (2008) for a review). In the area of agricultural technology and farming practice adoption, the effects of networks are likely to operate through the exchange of information among farmers. For example, Conley and Udry (2001) examined the impact of network learning in the progress of agricultural innovations and found that farmers were heavily influenced by the information they received from their connections. They find that the process of information exchange was complex and could not be explained by simple statistics. Foster and Rosenzweig (1995) find that farmers with neighbors that have experience with high-yielding seed varieties have higher profitability and rates of adoption. Moreover, Ward and Pede (2014) and Krishnan and Patnam (2014) find that neighbors are more important than extension services in influencing landowner behavior.

This thesis explores the premise that farmers have not only information about their own adoption costs, but also information about the adoption costs of other farmers they are connected with in the information network. Farmers can receive this information through communications or they can estimate costs based on type of crops and livestock, size of farmlands as well as quality of soil and water. This exchange of cost information defines information sharing networks. This work is interested in exploring how such networks can influence the performance of conservation auctions. We hypothesize that farmers adjust their bidding decisions based on the knowledge of each other's adoption costs. For example, a farmer with a leading position in a community have more connections than farmers who are relatively isolated; therefore, he has higher chances of possessing more information. With each farmer's different position in a community and different levels of knowledge of cost information, it is reasonable to expect that the information network can affect auction efficiency.

1.4 Objective and Approach

The primary goal of this thesis is to understand how information sharing network among bidders affects bidding behavior in conservation auctions. In doing so, we wish to see how incorporating networks into conservation auctions can help increase auction efficiency and, as a result, improve auction design to achieve maximum financial and environmental benefits. We examine this question by conducting a set of laboratory experiments in which cost information is shared through different network structures. These network structures are generated using the following two random network formation models (Erdos-Renyi and Watts-Strogatz), a free-scale network model (Barabasi-Albert), and two regular network topologies: lattice and star.[2] Participants connected within the information network are able to see each other's BMP adoption costs. No other types of communications were allowed during the experiments. Participants are asked to submit bids reflecting their compensation requests to adopt new farming practices after learning their own costs and their connections' costs (if they have any).

1.5 Summary of Results

Our results suggest that information networks influence bidding behavior in several ways. First, information networks help to reduce information rent seeking behavior when adoption costs are high. When costs are at a relatively low level, participants with networks bid higher than participants without networks; however, when adoption costs increase, participants with networks reduce their bids to the point that their bids are lower than bids in auctions without networks. Second, different network structures have different impacts on auction behaviors. The regular lattice network and the Erdos-Renyi network are found to reduce participants' information rents while the Barabasi-Albert network leads to an increase in information rents for low-cost partici-

[2]Chapter 3 provides a detailed discussion of the models used to construct information networks.

pants. Third, the number of connections of each participant affects bidding behavior. Having one additional connection whose cost is lower than the participant's own cost reduces rent demanded, while having one additional connection with higher adoption cost leads to an increase in rent requests. Fourth, participants who have central positions in the information network and high adoption costs have significantly lower information rents compared to others. Finally, first degree connections and second degree connections[3] generate different impacts on bidding behaviors. When costs of a participant's first degree connection increase, he faces less competition and has a higher chance to have his bid accepted in the auction and as a result demands higher information rents. In contrast, an increase in the costs of second degree connections leads to a reduced information rent requests. This is because when the costs of second degree connections increase, their first degree connections increase their bids, and in response, the participant decreases his bid (or increases the bid by a smaller amount than his first degree connection) to increase the likelihood of winning the auction.

These results represent new insights to the conservation auction literature and they contribute to integrating social network analysis, an emerging field in economics, with a large environmental conservation literature. They also provide avenues for policy makers to understand how farmers with knowledge of each other's adoption cost may act in reverse auctions. For instance, auctions in which information networks connect high-cost participants tend to reduce information rent requests. These are the types of networks that enable efficiency gains.

1.6 Thesis Organization

The remaining chapters of this thesis are organized as follows. Chapter 2 provides a literature review that presents background information about conservation auctions,

[3] First degree connections are direct links between two participants. Second degree connections are links between first degree connections and others, e.g. friends of friends.

discusses previous experimental work about auction performance, and surveys a small literature of social networks associated with auctions. Chapter 3 describes the methods employed in this study, including a discussion of the experimental design, an explanation of the models used to generate information networks, and a summary of characteristics of the networks used in thesis. Chapter 4 presents the experimental data and regression results. Chapter 5 summarizes our study, discusses the implications of the experimental results, and indicates directions for future research.

Chapter 2

Literature Review

2.1 Background

Conservation auctions are widely used by governments and organizations as a mechanism to increase levels of environmental goods and services on private lands (Iftekhar et al., 2014). In Canada, researchers have implemented conservation auctions to discover individuals' willingness to accept (WTA) compensation for the adoption of environmentally friendly programs. For example, Hill et al. (2011) performed a reverse auction for wetland restoration in Saskatchewan to explore how conservation auctions perform in Canada. Farmers that resided in the watershed areas were selected as potential participants. The auction contained two rounds allowing the opportunity for participants to change their bids after the first round. Auction budget information was provided to participants as well as the information about an environmental benefit (EB) index that was used to rank their bids in terms of dollars per EB. Their results showed that although only a small proportion of eligible farmers participated in the auction, the value of the submitted bids exceeded the auction budget by a great amount. They also suggested that annual conservation programs may provide more incentives for landowners as opposed to the long-term (12-years) program employed in this auction.

Brown et al. (2011) implemented a single-round conservation auction using a uniform-price design to examine Canadian rural landowners' WTA for the implementation of environmental programs on their lands. As pointed out by Schilizzi and Latacz-Lohmann (2005), using uniform-price auctions may discourage high-cost landowners' participation due to the low probability of winning or risk-aversion associated with high uncertainty. To address this issue, they assessed a value to each targeted land before auction implementation and converted all bids to percentages of this land value. In order to prevent participants from bidding strategically, successful participants were paid the lowest rejected bid (which would be higher than their own bids), thus encouraging bidders to reveal their true WTA. Communication between participants was allowed before the auction but prohibited during the auction. Their results showed that bids are more likely to reflect true WTA for participants who had previous knowledge of relative opportunity costs.

There is also an important literature examining conservation auction efficiency around the world. Kirwan et al. (2005) estimated the cost-effectiveness of the bidding mechanism in the Conservation Reserve Program (CRP) in the US. They examined the relationship between farmers' proposed rents (bid minus cost) and their bid score, which was calculated based on environmental benefits index (EBI). They found that farmers' net benefit had increased throughout time, and these amounts may be essential to encourage farmers to enroll in CRP and reveal their WTA. They suggested that another cost-effective option to the CRP could be incorporating a Pigouvian tax or subsidy to minimize societal costs, although it may result in large wealth transfers between taxpayers and farmers.

Claassen et al. (2008) reviewed and analyzed several US agri-environmental programs in order to determine the level of environmental benefits generated. Based on previous programs' research and data, they claimed that, generally, conservation auctions helped to increase environmental cost-effectiveness. However, auction efficiency and actual environmental outcomes greatly depend on many factors, such as the level of auction competition, information on soil quality, location of land as well as program incentives and program targets.

Jack et al. (2009) studied how conservation auctions could help to estimate an ecosystem-service supply curve for controlling soil erosion issues on Indonesian coffee farms. They performed a uniform-price procurement auction in two villages, with 82 participants in total. Participants were first asked to submit their bids, then the auctioneer announced bidder-identification numbers of provisional winners. Participants had the opportunity to revise and resubmit bids in several rounds before a final allocation decision was made. They explained that this auction design would help participants to increase familiarity with auction mechanism and provide them with an opportunity for learning. Information on number of rounds in an auction was also given to participants. Their results showed that conservation auctions overcome many weaknesses in existing valuation methods. They revealed accurate ecosystem-service supply curves and thus assisted policymakers to implement environmental-friendly services and programs.

Iftekhar et al. (2014) studied the impact of different levels of competition on Australian conservation auction performance. Levels of competition were measured in terms of number of bidders and level of conservation targets, i.e. larger number of bidders and lower level of conservation targets represented higher levels of competition. Due to the larger number of scenarios in their work, they performed computational simulation experiments instead of laboratory experiments. In each simulated auction, participants were first asked to submit bids indicating their WTA. Next, the auctioneer provisionally selected winning bids which generated minimum procurement cost. Participants were then asked to revise their bids given this temporary result, and these steps continued until a certain number of rounds were reached in one auction. They found that higher levels of competition in a conservation auction help to reduce procurement costs and increase auction efficiency.

The majority of conservation auctions carried out so far employed a single bidding round. However, there is not a consensus in the literature regarding the issue of multiple bidding rounds. Some papers argue that multiple bidding rounds may lead to participants' behaving strategically (Cooper and Fang, 2008; Bernard, 2005), while others claim that it has the potential to increase auction efficiency (Cason and Gangadharan, 2004). Rolfe et al. (2009) implemented two field experiments and one real conservation auction in Australia to compare multiple bidding rounds with single bidding round auctions. First, in two field experiments, 12 and 9 landholders (respectively) were selected as participants to take part in 4 rounds and 3 rounds of auctions (respectively). Participants were asked to submit their bids based on opportunity costs which came from their knowledge of the land and their experiences of farm management. Their bids were ranked by environmental benefits per dollar, and after each round, the first 3 best bids were announced and participants with these bids received $20, $10 and $5 as prizes. Second, a real-life conservation auction was performed with 112 landholders targeted as potential participants. The auction budget was $350,000. It contained 3 bidding rounds which were held four weeks apart. Participants were provided with a map with the bid areas and their relative bid positions compared to other bids. The results of this auction indicated that relative bid prices dropped between rounds, creating potential efficiency gains. This indicated that efficiency was improved between rounds, which means more environmental benefit units were purchased with less money. Therefore, they claimed that using multiple bidding rounds can generate efficiency gains by reducing participants' bid values.

Schilizzi and Latacz-Lohmann (2012) evaluated the relative performance of uniform-price (UP) and discriminatory-price (DP) auctions using data from two Scottish fishing vessel decommissioning auctions in 2001 and 2003. Since the auctions were carried out using DP format, they first derived a DP cost curve by calibrating results from laboratory experiments conducted by Schilizzi and Latacz-Lohmann (2007). Then they used the DP cost curve to derive the UP cost curve for this analysis. By treating these two auctions independently, they found that the DP format outperformed the UP format in the 2001 auction, while the UP type showed better performance than the DP type in the 2003 auction. They concluded that the ambiguous results were affected by two factors: rent to cost ratio as well as bidder heterogeneity. They pointed out that an increase in similarity of bidders would lead to the loss of effectiveness of a DP auction.

2.2 Laboratory Experiments

Due to the limited availability of real conservation auction data, laboratory experiments are often employed by researchers to mimic field auction procedures and examine auction performance. Cason and Gangadharan (2004) conducted two laboratory experiments to examine how different auction designs would affect bidding behavior. The first experiment was aimed to investigate the relationship between information available to participants and their incentives to reveal their opportunity costs. This experiment consisted of 11 sessions with 5-10 periods in each session. Each session lasted about 2 hours and had 8 participants. In 6 sessions, participants were provided with information about the environmental benefits of the land use change they would sell if they decided to participate, while in other 5 sessions this information was not available. Multiple bidding rounds were used in this experiment. Participants had the opportunity to revise their bids after each round, and only the bids from final rounds were used to determine auction results. They found that, in general, providing environmental benefit information allowed participants to bid strategically and thus increase landowners' profits and reduced market performance. The second experiment focused on whether the pricing rule had an impact on participants' profits. 15 sessions of discriminative price auctions and 15 sessions of uniform price auctions were carried out with 36 periods in each session. In uniform price auctions, successful participants were paid with the first rejected bid. For this experiment, no information about environmental benefit was provided and a single bidding round was used. Overall, their results showed that discriminative price auction had an advantage in market performance measures, and that the uniform price auction performed better in providing incentives to reveal true opportunity costs.

Tisdell (2007) incorporated biophysical models into laboratory experiment to investigate the relative performance of three policy instruments in controlling sediment runoff in Australia. The three instruments were: i) a closed call auction, ii) a cap and trade market, and iii) command and control regulation. Three experimental sessions were carried out: one per policy instrument. Eleven university students were recruited as participants in each session. Participants were paid with a $10 show-up fee and additional earnings were based on their performance. The results suggested that the cap and trade market instrument performed better in terms of total program cost and production. Also, the first-price auction tended to result in participants' strategic behavior when compared to a second-price auction.

Schilizzi and Latacz-Lohmann (2007) investigated the performance of two conservation auction types: budget-constrained (BC) and target-constrained (TC) against the benchmark of an outcome-equivalent fixed-price payment. Two laboratory experiments were carried out in the University of Kiel and the University of Western Australia (Perth). The Kiel experiment recruited 88 first-year agricultural economics students that were placed either in the BC group or in the TC group. For the BC group, each session had 3 auction rounds and each round had a budget of €3900. Each participant had a unique opportunity cost which was randomly selected from a uniform distribution between €5 and €264. Participants not only had information about their own opportunity cost but also information about their position in the cost quartile. The opportunity cost was reshuffled between each round. After bids were ranked from low to high, winners were paid the difference between their bid and cost. For the TC group, the number of winners in the BC group was used as the experimental target while other settings remained the same. The Perth experimental design was almost identical to Kiel experiment, except for the number of participants that changed to 53, and the budget was changed to €2300. After comparing results to the fixed-price program, their research reached three main conclusions. First, both types of conservation auctions outperformed fixed-price program in a single round setting. Second, the repetition of auction rounds reduced its advantage to fixed-price program given the fact that participants learned from previous auction results. Third, the BC auction is more robust compared to the TC auction in repeated auction designs.

Kawasaki et al. (2012) conducted laboratory experiments to compare the relative performance of DP and UP auctions in an imperfect monitoring environment. Ninety-six undergraduate economics students were recruited as participants in 6 sessions of experiments. Each session had 25 rounds, 16 participants and lasted for 90 minutes. As a target-constrained auction, participants were told that only 8 (out of a total of 16 participants) would be able to win the auction. Each participant was assigned with a unique cost which was randomly selected from a uniform distribution between \$233 and \$1167. Each participant was given an initial endowment of \$3000. Costs were reshuffled between rounds for the fairness of auctions and participants knew the distribution of costs. After bids were submitted, each participant was informed of the 8th bid and whether they had won the auction or not. Winners could choose to maintain compliance by paying their cost and they had 15% chance of getting audited. If a winner was audited and he did not pay the cost, he then would face a fine of \$3000. Their findings suggested that when the issue of noncompliance exists, DP auction are more likely to cause adverse selection. The UP auction design tended to perform better in terms of budgetary cost-effectiveness and auction efficiency.

Boxall et al. (2013) performed a budget-constrained reverse auction laboratory experiment to compare three bid-selection rules and two pricing rules. Opportunity costs of each participant was calculated using survey results from an actual agricultural watershed. The experiment consisted of 12 sessions with 12 participants and 16 periods in each session. The three bid-selection rules were: i) maximization of environmental benefit, ii) maximization of program coverage, and iii) maximization of participation. Two pricing rules were uniform-price and discriminatory-price. Their findings suggest that among these three bid-selection rules, maximization of participation generated the highest abatement costs and highest rent capture, while maximization of environmental benefit led to the lowest abatement costs and rent capture. In addition, their experimental results showed that uniform-price auction performed better than discriminatory-price auction in terms of cost efficiency.

Banerjee et al. (2015) conducted laboratory experiments to compare auctions with and without spatial information on program targets. Their experiments included 12 sessions with 6 participants in each session, and each session had 13 periods (including 1 practice period). All participants were sitting in a circle and their positions stayed the same throughout a session. This design allowed them to build reputations between adjacent participants and have the chance to learn as the auction proceeded. After participants submitted their bids, a score was calculated in order to choose the winners. There were two treatments employed in this experiment. One treatment was providing participants with their scores as well as the positions of winners at the end of each period, while this information was hidden in the other treatment. Their results indicated that revealing bidder's spatial information would increase participants' familiarity with the auction and thus lead to greater rent-seeking behavior. On the other hand, auction efficiency was not significantly affected by providing spatial information.

Fooks et al. (2016) performed laboratory experiments to find out the effect of different experimental mechanisms on conservation auctions. They proposed that a socially optimal outcome could be achieved when buyers (agencies) set up spatial targeting goals and sellers (farmers) receive network bonuses at the same time. Their experiment consisted of 10 sessions with 12 participants in each session. Participants were evenly divided into 3 groups which represented a geographic region of farms. Each participant was assigned 3 non-adjacent parcels in their region (each parcel represented a farm land), and they could choose to either retain or sell some or all of their parcels. Retained parcels received constant revenue while sold parcels, if accepted by buyer, received a contract payment. In this experiment, spatial targeting, as one treatment, had two mechanisms: i) buyer paid bonuses to winning parcels based on their spatial structure; ii) buyer assigned a value to each parcel based on a spatial targeting rule. Network bonuses varied between sessions. Their results showed that using the spatial targeting treatment alone led to an improved social and environmental welfare outcome; while using network bonuses treatment alone led to a reduced welfare outcome. Also, the effect of interacting spatial targeting and network bonuses on welfare outcomes was positive. Therefore, they concluded that by adding spatial targeting to a competitive auction with network bonuses could generate greater welfare results.

2.3 Social Networks and Auctions

We are not aware of any paper in the literature that examines network effects in reverse auctions. There are, however, a few papers that investigate network effects in non-reverse auctions. Dass et al. (2014b) examined the role that networks play among bidders in online auctions. They examined second price auctions for fine art where bidding had an ascending format, i.e. once a bid was submitted; the next submitted bid had to be greater than the previous bid. The auction had a predetermined duration and once the bidding window closed the highest bidder wins the item. They examined networks created from the interactions between bidding and counter-bidding (instead of bidders knowing each other in real life), i.e. a bidding network as opposed to a social network. In other words, they modeled the changing interactions of bids and counter-bids as a network. For example, if participant A submits a bid and B follows with a counter bid, then A and B are "connected". Network size increases as more bidders enter the auction, while its average degree centrality declines as auction progressed. Their results showed that network structures significantly contribute to bidders' behaviors and help to predict final sales prices better than simple economic indicators. They also claimed that network analysis helps to identify key bidder's behavior which would be beneficial for auction house managers to achieve higher final sales prices.

Magnan et al. (2015) implemented auctions to examine how learning through social networks influence the demand for an agricultural technology in India. Their research was designed in two stages. First, they performed an experimental auction to identify potential adopters and randomly selected participants to adopt. Next, a second auction (one year later) was used to estimate network effects on demand. They concluded that participants of the second auction that were connected to a benefiting adopter were willing to pay 50% more for the technology, while having a non-benefiting adopter had no effect. However, because the levels of technology benefits were different to each individual, network effects can be limited. Therefore, they suggested that policies should focus on improving connections between farmers and their information flows.

Chapter 3

Methods

We designed and implemented a laboratory experiment that allowed us to examine the effects of various types of networks that share adoption cost information on bidding behavior of participants. In comparison to costly field implementations, laboratory experiments provide researchers with a low-cost way to examine auction performance in a simple context-free environment (Plott, 1997). Instead of analyzing networks that already exist in participants and are potentially endogenous to bidding strategies, we impose several network structures on the cost information sharing relationships, which permits an econometric investigation of different dimensions of network effects on bids. This chapter presents the experimental design, discusses the types of network structures used, and describes the characteristics of each network used in our experiment.

3.1 Experimental Design

The experimental design adopted in this thesis imitates real conservation auctions.[4] Participants play the role of farmers (sellers of environmental quality) that bid for compensation to adopt costly BMPs, and the experimentalist plays the role of the

[4] The experimental instructions are available in Appendix A.

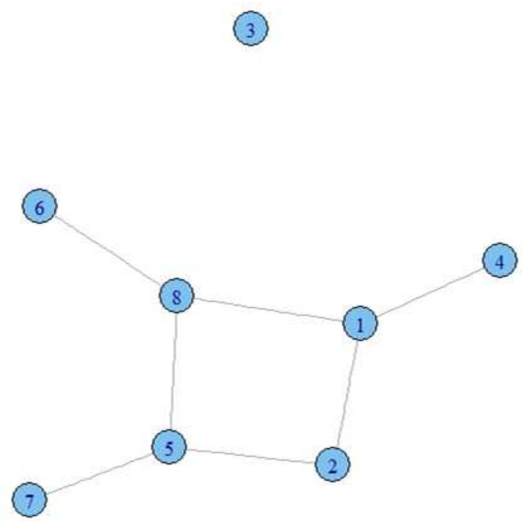
government or auctioneer (buyer of environmental quality). The experiment was implemented in the REES experimental laboratory, University of Alberta, using laptop computers with ZTREE economic experiment software (Fischbacher, 2007). University of Alberta students and staff were recruited as participants using the ORSEE online recruitment system (Greiner, 2015). Subjects registered in the system could only participate in one experimental session to minimize the effect of strategic bidding from learning.

Participants enrolled in sealed bids conservation auctions. To simplify the experimental design, we assumed participants have the same unit and type of farmland; therefore, bids submitted would be based on dollar amounts per unit. Each participant was assigned with a cost of adopting BMPs, and this cost is the amount they would need to pay to implement the BMP if they win in the auction. Participants are not allowed to submit bids below their opportunity costs as this would lead to experimental losses. Costs were randomly selected from a uniform distribution ranging from \$5 to \$30. A budget cap amount of \$85 was established for every experimental auction, but this budget was not revealed to participants. This value assured that approximately 60% of participants would win an auction if they bid their costs.

We utilized a discriminatory auction design in which bids were ranked from the lowest to the highest, and then are accepted from low to high until the budget would be exhausted. Winners received compensation equal to their bids and subsequently must pay their adoption costs. Participants played several auction rounds. The result of each auction were provided to participants at the end of each round. The computer screens displayed information about whether their bids were accepted or not as well as their total payoffs. Participants were not allowed to communicate before and during the experiment.

Incorporating networks into the design assumed that participants of some sessions were connected through a cost information network. In a network session, if two participants were connected based on a pre-selected (exogenous) network, they then shared each other's cost information. That is, the computer screen displayed not only a participants own adoption costs, but also the adoption costs of other individuals in the participant's network. This information was available to participants before they submitted their bids. For example, in the network below (Figure 3.1), Participant 1 is connected with Participants 2, 4 and 8; therefore the four of them can see each other's cost information when deciding to submit a bid. Participant 4 only sees the cost of Participant 1, while participant 2 sees the cost of 1 and 5. Participant 3 is isolated in this network, hence she does not know anyone's cost information except for her own.

Figure 3.1: Example of an information network



We conducted 19 sessions with 8 participants per session. Each session contained 4 practice rounds and 16 real rounds (4 blocks with 4 rounds in each block). Networks were used in 14 sessions, while the other 5 sessions were not associated with networks and served as control sessions for analysis. For the purpose of equity, adoption cost for each participant was reshuffled at the beginning of each block of 4 rounds to improve the chances that all subjects faced low cost and high cost situations at least once. Network structure changes once after 8 rounds (excluding practice rounds). The specific networks selected to share cost information and their properties are discussed in the next section.

Participants received a \$5 show-up fee for participating in the experiment. Additional earnings were available and were based on their auction performance. Their payoffs for each round were calculated as follows: if their bid was accepted in the auction, then their payoff equaled their bid amount minus their cost, and if their bid was not accepted then their payoff was \$0. At the end of the experiment, four rounds (one round from each block) were randomly selected for payment. Therefore, the total payment each participant received consisted of the \$5 participation fee plus the sum of the payoffs of the selected auctions.

3.2 Generating Experimental Networks

This thesis used three types of network formation models to generate cost information sharing networks. All networks had the same size of 8 nodes (or individuals). Links connecting these nodes were generated using the following network models: i) two models of random network formation (Erdos-Renyi and Watts-Strogatz); ii) one scale free model (Barabasi-Albert); and iii) two regular network structures (lattices and stars). These network models are discussed below.

Erdos-Renyi Model

The Erdos and Renyi (1959) model of network formation generates graphs where each pair of nodes are connected independently and with equal probability p. When p is close to 1, the model is more likely to generate graphs with several links. Wichmann (2015) points out that the Erdos-Renyi model trades off network density and intransitivity since probability p is associated with the expected density[5] and $1-p$ represents the expected intransitivity[6] of a network. For this study, we simulate networks with $p \in \{0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6\}$.

Watts-Strogatz Model

The Erdos-Renyi model has some limitations such as that it does not take local clustering and power law formation into account, which makes it less applicable to real-world situations. The Watts and Strogatz (1998) model is a small-world model[7] based on the Erdos-Renyi model and it tries to solve the two limitations mentioned above in a simple way. This model constructs a lattice network in which each node is connected to K neighbors, with half of K neighbors on each side. Then each link is rewired with a probability p. When p equals 0, the model forms a regular lattice network and when p equals 1, this model collapses to the Erdos-Renyi model. When holding K constant, changing probability p alters network intransitivity while keeping density constant (Wichmann, 2015). Our experiments used Watts-Strogatz networks generated from parameters $K \in \{2, 4\}$ and $p \in \{0.1, 0.2, 0.3, 0.4\}$.

Barabasi-Albert Model

The third model is the Barabási and Albert (1999) model. It incorporates two properties that are not included in the previous models: growth and preferential attachment. In real world situations, the number of nodes in a network tends to increase over time and nodes with more connections are more likely to receive new links. The

[5]Network density is defined as the ratio of the number of links and the number of possible links.

[6]Network intransitivity is the probability that adjacent nodes of a node are not connected. Hence, high intransitivity indicates low clustering in a network.

[7]Small-world models are networks that are highly clustered, yet have small path lengths (Watts and Strogatz, 1998). Path length is the distance between any two nodes in a network.

Barabasi-Albert model captures these characteristics using a power law distribution to generate scale-free networks. The probability of a new node to be connected to an old node is given by $P_i \sim k_i^{-\alpha}$, where k_i is the degree[8] of agent i in the current time step and α is known as the scaling parameter (Wichmann, 2015). As pointed out by Barabási and Albert (1999), scale free networks are widely observed throughout the World Wide Web (connections between website pages), academic citations, as well as interpersonal social relationships. Our experiment generates Barabasi-Albert networks with scaling parameter $\alpha \in \{1, 2, 2.5, 3, 6\}$.

Regular Lattice

A regular lattice is a special case of the Watts-Strogatz model. As mentioned above, when p equals 0, it forms a symmetric regular lattice shape allowing each node to have the same number of connections.

Star Model

The last network type is the star network. It forms a simple network where there is a central node which is connected to all other nodes. This structure applies to situations when there is a leader in the community who has influence on all other members of a group, while others have little communications among themselves.

[8]The degree of a node is the number of connections of the node.

3.3 Chosen Information Networks and Their Characteristics

The experiments reported in this thesis utilized 22 networks distributed as follows:

- 7 Erdos-Renyi networks
- 6 Watts-Strogatz networks
- 6 Barabasi-Albert networks
- 2 Regular Lattice networks
- 1 Star network

There are many measurements that can be used to describe and compare networks. Below we list and discuss eight types of network statistics commonly used in the literature: degree, density, transitivity, diameter, average path length, eigenvector, betweenness and closeness.

Degree

Degree is the most straightforward and perhaps the simplest concept of measuring a node's centrality (Freeman, 1978). As the most basic structural property, the degree of a node is simply the count of its adjacent links, and therefore its number of direct contacts (Csardi and Nepusz, 2006).

Density

Density of a network is the ratio of the number of links and the number of possible links (Csardi and Nepusz, 2006). The number of links is also defined as the degree of a node (see above); thus, density of a network can also be called the average degree of a network.

Transitivity

Transitivity measures the probability that adjacent nodes of a node are connected (Csardi and Nepusz, 2006). Sometimes it is also named as the clustering coefficient. High transitivity implies high clustering of nodes in a network.

Diameter

Diameter of a network is the length of the longest distance between any two nodes (Csardi and Nepusz, 2006).

Average path length

Average path length calculates the average distance between any two nodes in a network (Csardi and Nepusz, 2006).

Eigenvector Centrality

Eigenvector centrality is a measure of the influence of a node in a network. It assigns a score to every node based on a concept that nodes with high scores are the ones connected to many other nodes which are, again, connected to many others and so on (Csardi and Nepusz, 2006). The eigenvector score of node i is the i-th element of the eigenvector associated with the largest eigenvalue of the network matrix (see Jackson, 2008).

Betweenness Centrality

Betweenness centrality is defined by the number of *shortest paths* going through a node or a link (Csardi and Nepusz, 2006), where a shortest path between two nodes is a path with the minimal number of nodes. It estimates the importance of a node when connecting other nodes (Jackson, 2008).

Closeness Centrality

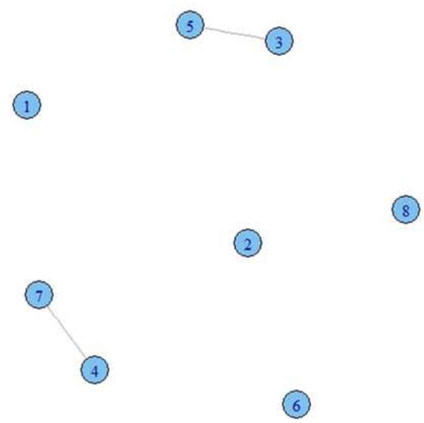
Closeness centrality calculates how many steps are required to access every other node from a given node (Csardi and Nepusz, 2006). It captures how easily a node can be reached by other nodes (Jackson, 2008).

Table 3.1 shows the network models and characteristics for each network employed in the experiment. Net 1 to Net 7 were created based on the Erdos-Renyi model with different probability values. As probability increases, the network's average degree, density and average closeness all increase. This is because higher probability generates more links between nodes. In network 1, p is as small as 0.05, and its transitivity value is not available because this network has no second degree connections, as illustrated in Figure 3.2. Net 8 to Net 13 are based on the Watts-Strogatz model with different K and p values. As previously discussed, when p increases while holding K constant, network transitivity changes (see Table 3.1). Net 14 to Net 19 were generated using the Barabasi-Albert model. Note that these networks have the same average degree, density and transitivity values, independent of values of the scaling parameter α. Transitivity values are equal to zero indicating that there is no chance that adjacent nodes of a node are connected in these networks. Net 20 and Net 21 give us two Regular Lattice networks. Net 20 has $K = 2$ and therefore forms a circle. As a result, it has transitivity equal to zero. Both networks have the same average eigenvector value which explains the influences of a node in these networks are the same. Net 22 has a star structure with only one central node connecting to every other node. It is noteworthy that this network has the same degree, density and transitivity values as the ones generated using the Barabasi-Albert model.

Table 3.1: Summary Statistics of Experimental Networks

Name	Model	Average degree	Density	Transitivity	Diameter	Average path length	Average Eigen-vector	Average Between-ness	Average Close-ness
Net 1	Erdos-Renyi ($p = 0.05$)	0.50	0.071	NA	1	1.000	0.500	0.000	0.019
Net 2	Erdos-Renyi ($p = 0.1$)	1.25	0.179	0.750	2	1.167	0.375	0.006	0.022
Net 3	Erdos-Renyi ($p = 0.2$)	1.75	0.250	0.000	4	2.000	0.621	0.125	0.047
Net 4	Erdos-Renyi ($p = 0.3$)	2.50	0.357	0.391	3	1.619	0.628	0.077	0.052
Net 5	Erdos-Renyi ($p = 0.4$)	3.00	0.429	0.120	3	1.607	0.740	0.101	0.089
Net 6	Erdos-Renyi ($p = 0.5$)	3.50	0.500	0.467	2	1.500	0.621	0.083	0.098
Net 7	Erdos-Renyi ($p = 0.6$)	4.25	0.607	0.619	2	1.393	0.808	0.065	0.105
Net 8	Watts-Strogatz ($K = 2, p = 0.1$)	2.00	0.286	0.000	5	2.286	0.662	0.214	0.064
Net 9	Watts-Strogatz ($K = 2, p = 0.2$)	2.00	0.286	0.667	3	1.538	0.434	0.042	0.029
Net 10	Watts-Strogatz ($K = 2, p = 0.3$)	2.00	0.286	0.429	2	1.500	0.464	0.048	0.037
Net 11	Watts-Strogatz ($K = 4, p = 0.1$)	4.00	0.571	0.429	2	1.429	0.834	0.071	0.100
Net 12	Watts-Strogatz ($K = 4, p = 0.3$)	4.00	0.571	0.509	3	1.500	0.701	0.083	0.098
Net 13	Watts-Strogatz ($K = 4, p = 0.4$)	2.00	0.286	0.400	2	1.467	0.546	0.042	0.037
Net 14	Barabasi-Albert ($\alpha = 1$)	1.75	0.250	0.000	4	2.214	0.520	0.202	0.068
Net 15	Barabasi-Albert ($\alpha = 2$)	1.75	0.250	0.000	5	2.429	0.598	0.238	0.062
Net 16	Barabasi-Albert ($\alpha = 2.5$)	1.75	0.250	0.000	4	2.214	0.520	0.202	0.068
Net 17	Barabasi-Albert ($\alpha = 2.5$)	1.75	0.250	0.000	4	2.321	0.587	0.220	0.064
Net 18	Barabasi-Albert ($\alpha = 3$)	1.75	0.250	0.000	4	2.214	0.467	0.202	0.068
Net 19	Barabasi-Albert ($\alpha = 6$)	1.75	0.250	0.000	4	2.286	0.498	0.214	0.066
Net 20	Regular Lattice($K = 2$)	2.00	0.286	0.000	4	2.286	1.000	0.214	0.063
Net 21	Regular Lattice($K = 4$)	4.00	0.571	0.500	2	1.429	1.000	0.071	0.100
Net 22	Star	1.75	0.250	0.000	2	1.750	0.456	0.125	0.085

Figure 3.2: Network 1



The discussion above highlights the variety of network topologies adopted in the experiment. These networks were randomly assigned to different sessions. Table 3.2 shows the distribution of networks among experimental sessions. A visual illustration of each network is available in Appendix B.

Table 3.2: Distribution of Networks among Experimental Sessions

Session	Rounds 1-8	Rounds 9-16
1	Net 4	Net 4
2	Net 3	Net 2
3	Net 5	Net 6
4	No Network	No Network
5	No Network	No Network
6	No Network	No Network
7	Net 22	Net 21
8	Net 20	Net 22
9	Net 11	Net 12
10	Net 10	Net 8
11	No Network	No Network
12	Net 5	Net 22
13	Net 18	Net 14
14	Net 15	Net 16
15	Net 7	Net 1
16	Net 13	Net 9
17	Net 19	Net 17
18	No Network	No Network
19	Net 11	Net 16

Chapter 4

Results

This chapter presents the results of the experimental research. All econometric estimates reported in this section were obtained using data from real rounds, not the practice rounds. Since the participants submitted bids in several rounds, standard errors associated with parameter estimates are clustered at the participant level such that hypothesis tests are robust to unspecified heteroskedasticity and within-participant serial correlation.

4.1 Overview of Experimental Data

Subjects in the experiment received, on average, \$16.5 for participation (performance payoff plus fixed \$5 show-up fee). Sessions lasted for approximately 35 minutes. The preliminary analysis of the data revealed a few extremely high bids and we deemed these as outliers. It is well known that these extreme values can have a significant influence in econometric analyses (Osborne and Overbay, 2004). Therefore, in order for the results to represent the majority of participants, our analysis does not include bids that are higher than \$52.5 (this number represents a markup of 200% on average cost). These extreme bids are shown in Table 4.1.

Table 4.1: Outliers

Subject ID	Bid	Cost	Rent	Session	Period
31	80	22.3	57.7	4	4
35	55.6	22.8	32.8	5	1
82	60	22.7	37.3	11	2
82	60	22.6	37.4	11	5
115	100	25.7	74.3	15	3
115	1000	25.7	974.3	15	4
144	53	26.5	26.5	18	13
147	111	29.3	81.7	19	10
147	111	29.3	81.7	19	11
151	100	26.4	73.6	19	15
151	150	26.4	123.6	19	16

Table 4.2 shows summary statistics of bids, costs and information rents. The experiment collected 2421 observations from 19 sessions each with 8 participants, with 16 auctions rounds per session.[9] Costs were randomly selected from a uniform distribution in the range of \$5 to \$30 such that expected cost is \$17.5. The table shows that mean experimental cost is \$17.28, which is very close to the theoretical average. The mean bid in the experiment is \$21.71, so on average, the markup on cost is 25.64%. Average information rent sought by bidders in the experiment is therefore \$4.44 per bidder.

Table 4.2: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Bid	21.711	5.109	6	50
Cost	17.278	6.936	5	30
Rent	4.436	4.322	0	27.4

Figure 4.1 shows the distribution of all submitted bids in our experiment. The distribution of bids is relatively symmetric around its average of \$21.71. Figure 4.2 shows the right skewed distribution of information rents, which is not surprising as low cost participants have a higher probability of winning than high cost participants and as a result demand higher information rents.

[9] $2421 = (19 \times 8 \times 16) - 11$ outliers.

Figure 4.1: Bids Distribution

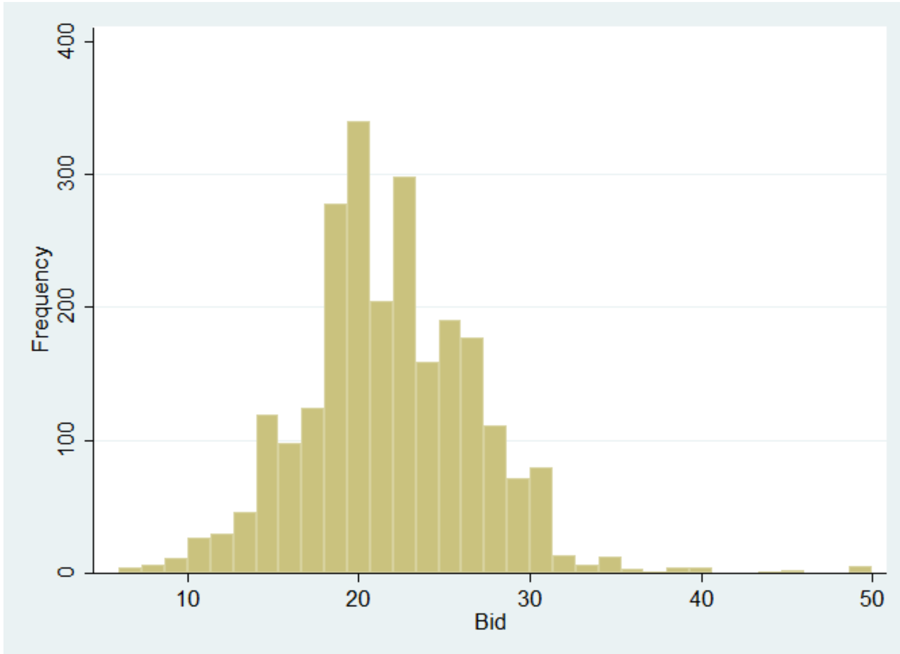
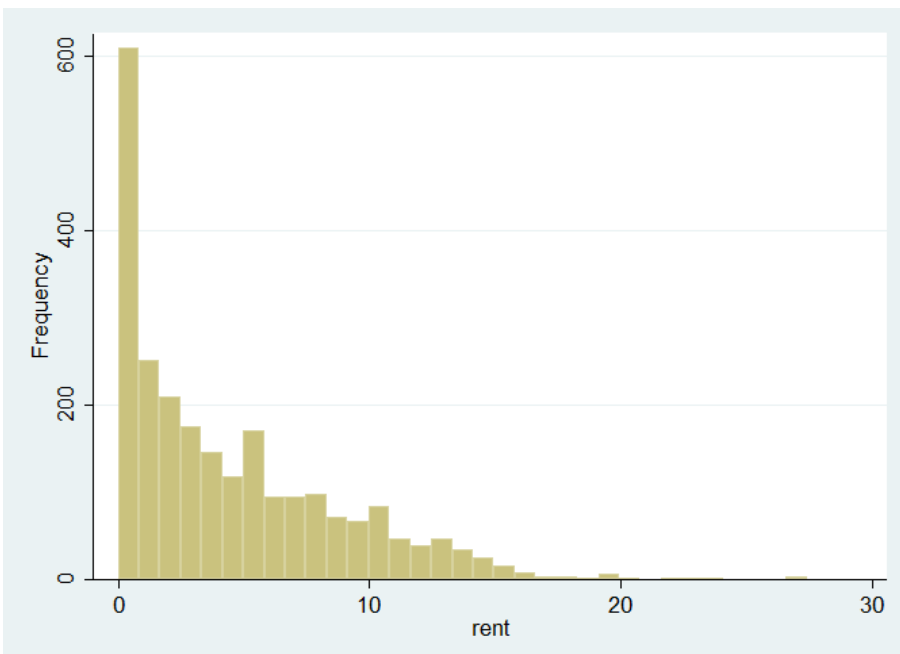


Figure 4.2: Rents Distribution



4.2 Demographics

Our first regression analysis of bidding behavior examines the relationship between participants' demographics and the demand for information rents. Table 4.3 shows a regression of expected rents[10] on age, gender, an indicator for being a student (base is staff) and dummy variables for agricultural and economics academic majors (for students). The estimation results indicate that we cannot reject the null of no effect of demographics on information rents.

Table 4.3: Effect of Demographics on Information Rents

	(1)	(2)	(3)
Age		-0.009	0.018
		(0.015)	(0.038)
Female		-0.115	-0.083
		(0.277)	(0.333)
Student		-0.172	
		(0.425)	
Agricultural major			0.143
			(0.375)
Economics major			0.427
			(0.385)
Constant	4.433***	4.861***	3.859***
	(0.139)	(0.697)	(1.028)
N	2421	2421	2071

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Learning

Our next set of regressions explore the possibility of learning effects in this experiment. Table 4.4 presents the results of three regressions of rents on period dummies; one

[10]Note that the data represents expected information rents as participants only receive these rents if they have their bids accepted.

using all observations, one using low cost observations (i.e. observations in the lower 25th quantile of the experiment's cost distribution), and a final regression that uses only data from high cost observations (i.e. observations in the top 25th quantile of the experiment's cost distribution). Overall, no statistically significant learning trend is found; however, we find interesting learning behavior when we separate observations into different cost groups. We find that low cost participants tend to increase their rent seeking behavior as they bid through each auction of the experiment. This indicates that low cost participants are learning about the experimental budget and the acceptance threshold and are seeking higher payoffs in each auction. On the other hand, high cost participants reduce their information rent demands in the initial periods of the experiment suggesting that, initially, they are trying to win the auction. However, the coefficient on the indicators of auctions 5-16 are not statistically different from those of the first auction, suggesting that high cost participants quickly learn that they have a low probability of winning the auction. Also, note that, as expected, baseline rents (as indicated by the constant) are lower for high cost participants ($1.44) than for low cost participants ($6.61).

Since our experimental design allows costs to change after each 4 periods, forming 4 blocks of 4 auctions in total, we also investigate learning using block indicators. We regress rents on four block dummy variables without a constant such that estimated block coefficients represent average rents of the 4 auctions in the corresponding blocks. Results are shown in Table 4.5. Overall, average rent is around $4.43, with rents tending to be higher in block 2. Low cost participants behave similarly to overall participants and have slightly higher rents in block 2. Average demand for rents from high cost observations equal $0.86 in the first block, and they hover around $1.38 in blocks 2-4.

Table 4.4: Learning in Different Periods

	Overall	Low cost	High cost
Period 2	0.163	1.181***	-0.762***
	(0.272)	(0.386)	(0.263)
Period 3	0.202	2.341***	-0.784**
	(0.289)	(0.564)	(0.336)
Period 4	0.224	2.254***	-0.793**
	(0.292)	(0.641)	(0.397)
Period 5	0.622	2.006*	0.459
	(0.458)	(1.075)	(0.516)
Period 6	0.596	2.510***	-0.214
	(0.486)	(0.930)	(0.404)
Period 7	0.700	3.290***	-0.338
	(0.485)	(0.899)	(0.583)
Period 8	0.706	3.121***	0.086
	(0.476)	(0.851)	(0.735)
Period 9	0.073	1.681	0.156
	(0.469)	(1.135)	(0.434)
Period 10	0.175	2.441**	-0.244
	(0.490)	(0.988)	(0.437)
Period 11	0.156	3.038***	-0.521
	(0.503)	(1.027)	(0.432)
Period 12	0.183	3.624***	-0.604
	(0.512)	(0.988)	(0.439)
Period 13	-0.453	0.870	0.189
	(0.441)	(0.980)	(0.689)
Period 14	-0.032	2.038*	0.429
	(0.475)	(1.040)	(0.816)
Period 15	0.026	2.948***	0.123
	(0.459)	(1.006)	(0.517)
Period 16	0.003	3.466***	-0.344
	(0.485)	(1.010)	(0.400)
Constant	4.223***	6.605***	1.444***
	(0.331)	(0.767)	(0.299)
N	2421	604	569

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.5: Learning in Different Blocks

	Overall	Low cost	High cost
Block 1	4.370***	8.049***	0.863***
	(0.308)	(0.617)	(0.141)
Block 2	4.879***	9.337***	1.442***
	(0.324)	(0.431)	(0.269)
Block 3	4.370***	9.301***	1.142***
	(0.328)	(0.602)	(0.254)
Block 4	4.109***	8.936***	1.546***
	(0.302)	(0.593)	(0.370)
N	2421	604	569

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Network Structure

Our key research question in this experiment is to learn about possible cost information sharing network effects on bidding behaviors in a reverse conservation auction. Figure 4.3 shows a scatter plot of bids and costs with two fitted lines, one representing bids in network treatments and the other for bids not in network treatments.[11] From the graph we can see that when cost is low, bids with networks tend to be higher than bids without networks. However, when cost increase, the two lines change positions and bids with networks are lower than bids without networks. The gap between the fitted bid lines and the cost line (or 45 degree line where bid equals cost) represents information rents. In general, expected information rents are high when costs are low, and decrease when costs are high. The graph shows that networks that share cost information can help reduce information rent seeking behavior when cost gets higher, but they actually increase bids when costs are low.

[11]The fitted lines represent smooth regression lines obtained from a regression of bids on a cost polynomial.

Figure 4.3: Bids and Costs (with & without networks)

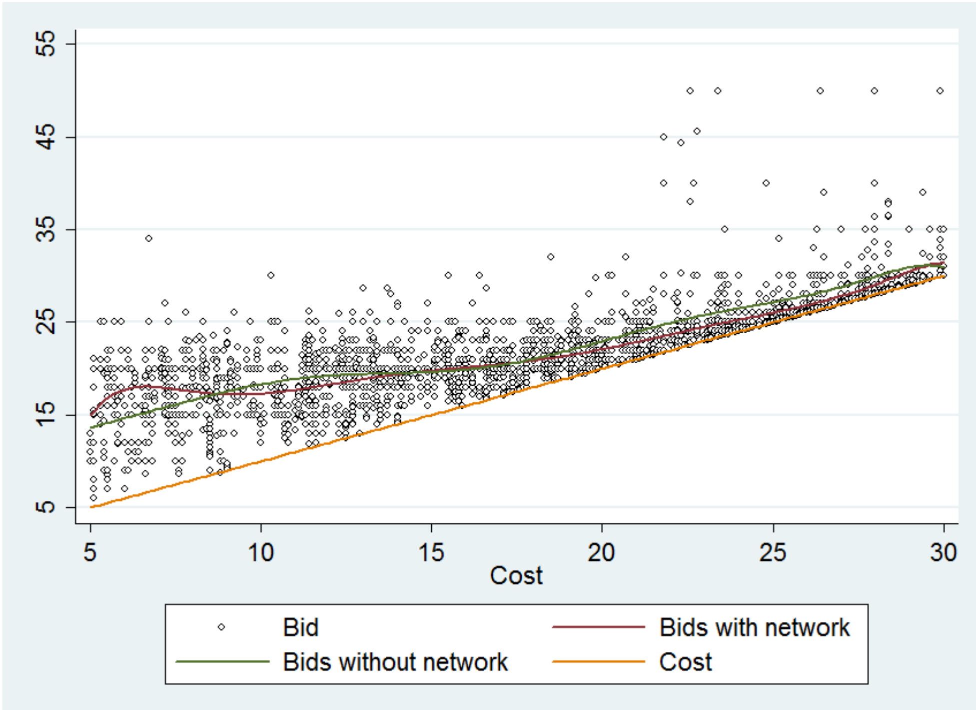


Table 4.6 shows the results of a regression of information rents on a network treatment indicator. As shown in the table, overall, the network effect is not statistically significant, and this result applies to participants with low or high costs. Therefore, pooling all experimental data together, we do not find statistical evidence that average bidding when some participants may have cost information about others is not different from behavior when information is not shared through networks. Nevertheless, the estimate of the network coefficient is positive for low cost observations and negative for high cost observations, confirming our intuition that low cost participants take advantage of network information and increase their bids; and that high cost participants decrease their bids to increase their probability of winning the auction when they learn the costs of others.

Table 4.6: The Effect of Networks on Rents

	Overall	Low cost	High cost
Network	-0.379	0.451	-0.683
	(0.363)	(0.696)	(0.419)
Constant	4.712***	8.587***	1.765***
	(0.333)	(0.605)	(0.400)
N	2421	604	569

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, we explore possible effects of different network structures on information rents. Table 4.7 shows the results of five models that regress rents on specific network indicators, restricting observations to data of the baseline sessions (no network) and the corresponding network session. We find that information rents in sessions with the regular lattice and Erdos-Renyi networks are statistically significantly lower than rents of the baseline sessions. Specifically, in the regular lattice network, participants' average rent is \$1.45 lower than rent without cost information sharing network and in the Erdos-Renyi networks, participants' average rent is \$0.81 lower than rent without a network. We do not find statistically significant effects of the other network structures (Star, Barabasi-Albert, and Watts-Strogatz) on bidding behavior. These results indicate that having cost information sharing networks in an auction can help reduce information rents; however, this reduction depends on network topology.

Table 4.7: The Effect of Network Type on Rents

	Regular Lattice	Star	Barabasi	Erdos	Watts
Network	-1.447**	-0.432	0.291	-0.814*	-0.159
	(0.636)	(0.760)	(0.438)	(0.422)	(0.453)
Constant	4.712***	4.712***	4.712***	4.712***	4.712***
	(0.335)	(0.334)	(0.334)	(0.334)	(0.334)
N	763	827	1079	1209	1083

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We investigate bid heterogeneities between low and high cost observations by estimating models reported in Table 4.7 using the corresponding low/high cost observations. Results are shown in Table 4.8 where separate estimates are obtained for each network structure. We find that the regular lattice structure reduces low-cost participants' rent by \$2.54 and this effect decreases to \$1.14 for high-cost participants. The Erdo-Renyi network reduces high-cost participants' rent by \$0.97. Interestingly, low-cost participants with Barabasi-Albert networks actually increase their rents by \$1.81 on average. These results are consistent with the fitted lines in Figure 4.3, where low-cost participants with a network have higher information rents than those participants without networks, and in contrast, high-cost participants with networks have lower information rents.

Table 4.8: The Effect of Each Network Type on Rents (low cost vs high cost)

	Regular Lattice		Star		Barabasi		Erdos		Watts	
	low cost	high cost	low cost	high cost	low cost	high cost	low cost	high cost	low cost	high cost
Network	-2.537**	-1.143**	0.413	-0.748	1.810**	-0.298	0.103	-0.970**	0.407	-0.615
	(1.093)	(0.460)	(1.301)	(0.463)	(0.881)	(0.493)	(0.835)	(0.424)	(0.794)	(0.508)
Constant	8.587***	1.765***	8.587***	1.765***	8.587***	1.765***	8.587***	1.765***	8.587***	1.765***
	(0.611)	(0.405)	(0.610)	(0.404)	(0.609)	(0.402)	(0.609)	(0.402)	(0.608)	(0.402)
N	188	167	208	187	272	255	268	265	260	251

Standard errors clustered at the participant level in parenthesis.

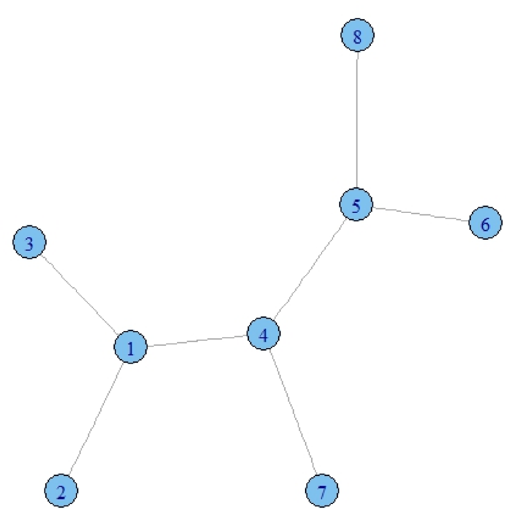
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Cost Effects through the Network

In a cost information sharing network participants' bidding behaviors may be affected by their connections' costs. We categorize participants relative to one another as 1st, 2nd, and 3rd degree connections. The 1st degree connections of subject i are all participants j directly connected to i (and therefore sharing cost information). A 2nd degree connection of participant i is another participant k that is directly connected to a participant j but not directly connected to i. Following the same logic, a 3rd degree connection is a participant s (different from j and k with respect to i), that is directly connected to a 2nd degree participant k.

Let us use network 17 (see Figure 4.4) to offer an example of these concepts. For Participant 1, her 1st degree connections are Participants 2, 3 and 4, since they are connected directly to 1. Her 2nd degree connections are Participants 5 and 7 as these two are directly connected to Participant 4, which is 1's 1st degree connection. Participants 6 and 8 are 1's 3rd degree connection because Participant 1 needs to go through 2 individuals (namely 4 and 5) to get to either 6 or 8.

Figure 4.4: Example of network: Network 17



In a conservation auction, participants are competing for information rents. We can obtain expectations about the signs of costs of connections on information rents by assuming that participants' rents are strategic substitutes (i.e., to undercut the competition, i decreases his bid in response to an increase of j's bid). When costs of a participant's 1st degree connections increase (i.e. 1st degree rents decrease), she faces less competition and has more room to obtain rents. As a result, we expect the average cost of 1st degree connections to have a positive impact on rents. On the other hand, when the average cost of a participant's 2nd degree connection increases, we expect her 1st degree connections to increase their bids. In response, she could either increase her bid at a lesser amount than her 1st degree connections to gain more profit, or she could decrease their bid to make sure she wins. Either way we expect a decrease in information rents. Hence the expected sign of the average cost of 2nd degree connections is negative.

Table 4.9 shows the relationship between participants' rents and their connections' costs. From Model 1 we can see that when the cost of 1st degree connections increases by \$1, participants increase their rents by 11 cents. When considering the effect of 2nd degree connections, Model 2 shows that when average cost of 1st degree connections increases by \$1, participants increase their rents by 21 cents, and when average cost of 2nd degree connections increases by \$1, participants will decrease their rents by 37 cents. Therefore, we can say that 2nd degree connections indirectly influence participants' behavior in an auction. Model 3 indicates that the cost of 3rd degree connections do not influence participants' bidding behavior.

We further explore the impacts of the costs of 1st degree connections on bidding behavior. We examine how information rents change in response to variation in the lowest and highest cost in a participant's network. Results are presented in Table 4.10. A \$1 increase in the lowest cost within participants' 1st degree connections increases information rents by 11 cents. Similarly, when the highest cost of the 1st degree connections increase by $1, rents grow by 9 cents. This result suggests that participants' behavior respond to changes in both the lowest and highest costs of members in their direct network. However, after controlling for average cost (Models 3 and 4), we cannot reject the null of no effect of extreme costs (highest and lowest) on rents.

Table 4.9: The Effect of Connections' Costs on Rents

	(1)	(2)	(3)
Average cost of 1st degree connections	0.106***	0.213***	0.093
	(0.029)	(0.028)	(0.077)
Average cost of 2nd degree connections		-0.368***	-0.382***
		(0.046)	(0.044)
Average cost of 3rd degree connections			0.142
			(0.090)
Constant	2.620***	6.949***	6.832***
	(0.465)	(0.939)	(0.945)
N	1786	1786	1786

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.10: The Effect of 1st Degree Connections on Rents (lowest cost vs. highest cost)

	(1)	(2)	(3)	(4)
Lowest cost of 1st degree connections	0.105***		0.013	
	(0.030)		(0.054)	
Highest cost of 1st degree connections		0.091***		-0.017
		(0.023)		(0.045)
Average cost of 1st degree connections			0.122**	0.151**
			(0.055)	(0.060)
Constant	2.956***	2.449***	2.105***	2.130***
	(0.383)	(0.433)	(0.474)	(0.471)
N	1698	1698	1698	1698

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.6 Number of Connections

Our previous results show that, in auctions where networks are used to share cost information, the average cost of 1st degree connections is an important determinant of information rents. Next, we are interested in understanding whether or not the number of connections a participant has plays a role in influencing auction behavior. Table 4.11 presents results of regression models of the effect of the total number of connections, the number of connections with lower cost, and the number of connections with higher cost on information rents. In Model 1, we do not find a statistically significant effect of the number of connections on rents. However, Model 2 estimates indicate that the number of connections with lower cost has an effect on rents. Specifically, on average, one additional connection with lower cost decreases rents by \$1.64. In addition, Model 3 shows that participants' rents increase, on average, by \$1.39 for each additional connection with higher cost. These effects increase after we control for the number of connections. By including number of connections as a right-hand variable in both regressions, as noted in Model 4 and 5, the marginal effect of a low cost connection increases (in absolute value) to -\$2.25 while the marginal effect of a high cost connection increases to \$2.25.

4.7 Network Centrality

A final test of the effect of cost information sharing networks on information rents comes from examining the effect of participants' relative position in the network on bidding behavior. Participants with more connections have an information advantage compared to participants who are isolated or have fewer connections. We rank partic-

Table 4.11: The Effect of Number of Connections on Rents

	(1)	(2)	(3)	(4)	(5)
Number of connections	-0.031			0.980***	-1.271***
	(0.146)			(0.119)	(0.134)
Number of connections with lower cost		-1.636***		-2.251***	
		(0.150)		(0.154)	
Number of connections with higher cost			1.394***		2.251***
			(0.122)		(0.154)
Constant	4.405***	6.257***	2.697***	4.678***	4.678***
	(0.362)	(0.263)	(0.185)	(0.300)	(0.300)
N	1786	1786	1786	1786	1786

Standard errors clustered at the participant level in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ipants in each auction based on their degree centrality to examine the effect of having a privileged network position on information rents. Degree centrality measures the number of connections a participant has as a proportion of the network size. As all sessions in our experiments had 8 participants, the most central participant is simply the participant that has the largest number of connections.

When pooling across all auctions with networks, the estimates shown in table 4.12 suggest that we cannot reject the null hypothesis of no difference in behavior between central and other participants of the auction. Model 2 compares participants who have low cost and are central in a network with participants who are not in central position and whose costs do not fall into the lower 25th quantile. It shows that on average, central participants with low costs demand $4.79 more in information rents from the auctioneer compared to others.

In contrast, Model 3 compares participants who have high cost and are central in a network with participants who are not in central position and whose costs do not fall into the upper 25th quantile. It reveals that on average, central participants with high costs earn $3.86 less in rents compared to others. Model 4 only focuses on participants who have low cost while Model 5 concentrates on high-cost participants solely. Although we do not find a statistically significant effect in the low-cost group, we do find as exhibited in Model 5, that on average, information rents of high-cost central participants are 48 cents lower than rents of other high-cost participants who are not central in a network. This result suggests that high-cost central participants are aware of their competitive disadvantage and reduce their bids to try to win the auction. Thus it implies that the auctioneer's budget is important in an auction, not just the information rents.

Table 4.12: The Effect of Network Centrality on Rents

	(1)	(2)	(3)	(4)	(5)
Most central participant(s)	-0.115			-0.419	-0.476**
	(0.401)			(0.705)	(0.230)
Most central participant(s) × Low cost		4.790***			
		(0.660)			
Most central participant(s) × High cost			-3.862***		
			(0.220)		
Constant	4.362***	3.958***	4.610***	9.167***	1.224***
	(0.178)	(0.154)	(0.163)	(0.374)	(0.172)
N	1786	1786	1786	456	430

Standard errors clustered at the participant level in parenthesis.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 5

Discussion

This final chapter summarizes the main findings of this research and provides a discussion of their policy implications as well as directions for future research.

5.1 Summary and Implications

First, our results show that demographics and the students' majors do not affect rent seeking behavior. To the extent that these experimental findings are translated to the real world, these results suggest that auction design should not be influenced by the farmers' experience or academic background. However, we should be cautious about transferring results from experiments involving a body of students with low levels of variation in various demographic characteristics to the real world.

Second, we find that there is significant learning for low-cost participants as they increase their rent-seeking demands throughout the experiment. High-cost participants quickly learn that they are not competitive and reduce their compensation demands in the initial rounds. This result suggests that auctions implemented in multiple rounds may suffer efficiency losses as low-cost participants learn their relative cost position in the bidder pool and demand higher levels of compensation. On one hand, high-cost participants are not likely to participate, however, low-cost participants tend to bid high in these settings. Therefore, the design of sequential auctions should consider the issue of self-selection where highly rent-seeking participants select themselves into an auction leading to undesirable environmental outcomes.

Learning in repeated auctions is a phenomenon that has been widely reported in the literature. For instance, Shoemaker (1989) found that in the US Conservation Reverse Program, farmers had the potential to learn the bid caps and gain economic rents through repeated auction periods. This then led to a reduction in economic efficiency and less desirable environmental outcomes. Bernard (2005) developed an experiment that conducted repeated second-price auctions to find the impact of learning. The author claimed that repeated auction trials could result in participants' loss of valuable information, especially on products they were unfamiliar with. Cooper and Fang (2008) also found evidence of learning in second-price auction experiments, where participants learned through sequential auction rounds to avoid overbidding.

Third, we find qualitative evidence that cost information sharing networks in general increase rent requests of low-cost bidders and decrease rent requests of high-cost bidders. This finding suggests that networks may decrease the efficiency of the auction as participants that are likely to win (low-cost participants) increase bids, and only participants that are likely to lose decrease bids. Normally, conservation auctions have higher operation costs than other programs promoting BMPs (Boxall et al., 2013). Our results indicate that in order to keep auction implementation expenses at a low rate, and conditioned on adoption costs, it may be beneficial to implement auctions in economies with thin networks, as the more likely network effect is a decrease in efficiency due to an increase in the size of bids from low-cost participants.

To further explore the relationship between information sharing networks and bidding behavior, the thesis also explores the effects of different information network structures. Our fourth finding is that behavior is different in auctions where cost information is shared through a regular lattice network. In these auctions, average rent requests are \$1.45 lower than the rents in the baseline auctions where there are no information networks. This effect represents a 33% reduction of mean compensation demanded. Surprisingly, this negative effect is stronger for low-cost participants (-\$2.54) than for high-cost participants (-\$1.14). This is an interesting demonstration that the efficiency of real-world auctions may depend on the structure of information networks. This result indicates that conservation auctions may be more efficient in environments in which bidders share cost information through a regular lattice network. This is an interesting finding as this network structure is similar to one in which the exchange information operates through spatially connected farms. This would be the case, for example, of in rural settlements where farmlands are located along a road, or a circular rural settlement where lands form a central space and each farmland has a similar number of adjacent neighbors.

In addition to the regular lattice network, we also find that cost information sharing in Erdos-Renyi networks induces a negative impact on average rent requests, especially for high-cost participants. In these auctions, participants' average rent requests are \$0.81 lower compared to rents in auctions where information networks do not exist. This is an intriguing result as the Erdos-Renyi network structure is expected to be very different from that of a regular lattice network. One network is completely random and link formation is independent (Erdos-Renyi) while the other is structurally symmetrical (Lattice). It is a puzzle to us why only such extreme models are able to affect bidding and further research is needed to shed some light on this issue.

Fifth, we examine how cost effects propagate through the information network. Our results indicate that only first and second degree connections impose a significant effect on participants' rent requests, and the cost effect of third degree connections is not statistically significant. This result suggests that despite the possibility of very complex pathways through which cost information may directly or indirectly navigate a network, only information within two degrees of separation matters for bidding behavior. This finding of "localized effects" is in line with results in the literature. For example, Krishnan and Patnam (2014) argues that farmers are more likely to be influenced by their neighbors than extension agents in regards to technology adoption. In the simulation study of Wichmann (2015), the author concludes that focusing on the subset of agents within two-order of distance from the target agent is sufficient to provide information necessary for network study and analysis, despite the existence of complex network structures.

Our sixth finding is that the number of connections of a bidder affects her information rent request. For every additional connection with lower cost, the average information rent demanded decreases by \$1.64. For every additional connection with higher cost, these rents increase by \$1.40. Participants increase their rent requests when they know they are more likely to win. Therefore, to decrease auction spending, it is beneficial to have participants connected to as many lower-cost neighbors as possible. In other words, when choosing where to implement an auction, policy makers should favor information networks in which high-cost participants are highly connected, and low-cost participants are more isolated.

Finally, we find that participants who are central in a network and have high adoption cost have significantly lower information rents when compared to others. These central high-cost participants decrease rent requests by \$3.86. On the other hand, central and low-cost participants increase rent requests by \$4.79. This result has a similar implication to our previous results. Conditioned on adoption costs, conservation auctions are expected to be more efficient when central participants are the ones with higher costs.

In summary, the results above show new sources of variation of bids in conservation auctions and provide guidance for researchers to further evaluate the environmental performance of these market instruments. These results should be of interest to organizations and agencies worldwide who are involved in the design and implementation of conservation auctions. Examples of such actors in Canada are organizations such as Ducks Unlimited, Alberta Land Institute, as well as provincial governments, as these entities have been engaged, for example, in the implementation of conservation auctions promoting wetland restorations (Brown et al., 2011; Hill et al., 2011). These results can also benefit the managers of environmental programs overseas. These programs include the US Conservation Reserve Program, the Australian BushTender Trail and the UK Conservation Stewardship Scheme (Cason et al., 2003; Stoneham, 2003; Cason and Gangadharan, 2004; Claassen et al., 2008).

Our results also suggest that where conservation auctions are contemplated that the auctioning agency have some understanding of the size and structure of information sharing networks that characterize the relationships among residents within the area of interest. In our experiment we imposed network structures exogenously and really do not have an idea of which structure we employed is a likely match to those in the real world. This points to a need for research on information sharing networks in rural farming communities in which policy makers desire changes in land management behaviour to generate significant environmental improvements.

5.2 Limitations and Further Research

This research faces several limitations. First, as our results are based on experiments, external validity may be a concern as noted above. Debates around the generalizability of experimental findings are common in social science disciplines.[12] These debates are especially acute in economics (perhaps the most "quantitative" social discipline). Roe and Just (2009) present an interesting discussion about internal and external validity in economics. They view the use of field data and laboratory experiments as the most

[12] For example, refer to Lynch (1982) and Winer (1999) for a discussion of external validity of experiments in consumer research and marketing, Berkowitz and Donnerstein (1982) for a discussion in the field of psychology, Johnson (1998) in anthropology, to name a few.

common approaches to empirical research and argue that these two methods fall on opposite ends of a spectrum of research approaches, with the interior of this spectrum being characterized by intermediary approaches such as natural and field experiments. Movements towards the interior spectrum tend to ease tensions between internal and external validity, but also lead to limitations (e.g less research control and reduced replicability). For this work, the other end of the spectrum (field data) was not a viable methodological alternative for two main reasons: i) data availability (we are not aware of field data on conservation auctions paired with network information); ii) econometric identification (field data would be problematic as real-world networks are likely endogenous to farmers' behaviors such as bidding). There is, however, evidence in the literature that the issue of external validity of experimental work may not be very problematic in auction settings. Boxall et al. (2008) argue that producers and students act in a similar manner in experimental conservation auctions. Previous experimental work in the literature suggest that experimental auctions tend to be externally valid (Brookshire et al., 1987; List and Shogren, 1998). Nevertheless, as an alternative approach, one could pursue an analysis of networks and bidding using an approach at the interior of the research spectrum (e.g. a randomized control trial). This was, however, not a feasible option due to several constraints that thesis project faces (e.g. time and budgetary constraints).

Second, this thesis examines one particular channel through which networks can influence conservation auctions: strategic behavior in a non-cooperative setting where BMP adoption cost information is shared through a network. There are other ways that social networks could affect the efficiency of conservation auctions. For example, in several cases, it is reasonable to expect farmers participating in an auction to be socially connected, perhaps because their farms are located in the same geographical region being targeted for BMP adoption. In these cases, farmers may cooperate and agree on collusive strategies to extract more rents from the auctioneer. The role of social networks as a collusion facilitator should the focus of future research.

Third, and finally, our experimental design abstracts away from three aspects of the bidding process. One is that participants are not allowed to submit bids below their costs. In real life, however, farmers may have “green” motivations and, as a result, this biding strategy could arise as a rational one. If these preferences are “contagious” and may travel through social networks, it would be possible for central actors with green bidding behavior to significantly influence auction performance. A second limitation of the experiments of this thesis is that participants cannot opt out of the auction and must submit bids in all cases. In the real world, participation rates in conservation auctions are often low and may be related to characteristics of social networks. Third, the experiment independently assigns BMP adoption costs to participants. In reality, there might be a correlation between costs of farmers connected in an information network. For instance, if information flows between geographically adjacent farms, adoption costs of these areas may be similar as they are located in the same region and therefore face similar weather and soil characteristics. These are questions that should also be the focus of future research.

Bibliography

Alberta Agriculture, Food and Rural Development (2004). *Beneficial Management Practices: Environmental Manual for Crop Producers in Alberta*. Alberta Agriculture, Food and Rural Development.

Banerjee, S., A. M. Kwasnica, and J. S. Shortle (2015). Information and auction performance: A laboratory study of conservation auctions for spatially contiguous land management. *Environmental and Resource Economics 61*(3), 409 – 431.

Banerjee, S., J. S. Shortle, A. M. Kwasnica, et al. (2009). The agglomeration vickrey auction for the promotion of spatially contiguous habitat management: theoretical foundations and numerical illustrations. *Proceedings of the annual meeting of the agricultural and applied economics association, Agricultural and Applied Economics Association, Milwaukee*.

Barabási, A.-L. and R. Albert (1999). Emergence of scaling in random networks. *science 286*(5439), 509–512.

Berkowitz, L. and E. Donnerstein (1982). External validity is more than skin deep: Some answers to criticisms of laboratory experiments. *American Psychologist 37*(3), 245.

Bernard, J. C. (2005). Evidence of affiliation of values in a repeated trial auction experiment. *Applied Economics Letters 12*(11), 687 – 691.

Boxall, P. C., O. Perger, and M. Weber (2013). Reverse auctions for agri-environmental improvements: Bid-selection rules and pricing for beneficial management practice adoption. *Canadian Public Policy 39*(Supplement 2), S23–S36.

Boxall, P. C., M. Weber, O. Perger, M. Cutlac, and A. Samarawickrema (2008). Results from the farm behaviour component of the integrated economic-hydrologic model for the watershed evaluation of beneficial management practices program. Technical report, University of Alberta, Department of Resource Economics and Environmental Sociology.

Brookshire, D. S., D. L. Coursey, and W. D. Schulze (1987). The external validity of experimental economics techniques: analysis of demand behavior. *Economic Inquiry 25*(2), 239.

Brown, L. K., E. Troutt, C. Edwards, B. Gray, and W. Hu (2011). A uniform price auction for conservation easements in the canadian prairies. *Environmental and Resource Economics 50*(1), 49–60.

Cason, T. N. and L. Gangadharan (2004). Auction design for voluntary conservation programs. *American Journal of Agricultural Economics 86*(5), 1211–1217.

Cason, T. N., L. Gangadharan, and C. Duke (2003). A laboratory study of auctions for reducing non-point source pollution. *Journal of Environmental Economics and Management 46*(3), 446 – 471.

Claassen, R., A. Cattaneo, and R. Johansson (2008). Cost-effective design of agri-environmental payment programs: U.s. experience in theory and practice. *Ecological Economics 65*(4), 737 – 752.

Conley, T. and C. Udry (2001). Social learning through networks: The adoption of new agricultural technologies in ghana. *American Journal of Agricultural Economics 83*(3), 668 – 673.

Cooper, D. J. and H. Fang (2008). Understanding overbidding in second price auctions: An experimental study. *Economic Journal 118*(532), 1572 – 1595.

Csardi, G. and T. Nepusz (2006). The igraph software package for complex network research. *InterJournal Complex Systems*, 1695.

Dass, M., S. K. Reddy, and D. Iacobucci (2014a). A network bidder behavior model in online auctions: A case of fine art auctions. *Journal of Retailing 90*(4), 445–462.

Dass, M., S. K. Reddy, and D. Iacobucci (2014b). Social networks among auction bidders: The role of key bidders and structural properties on auction prices. *Social Networks 37*, 14–28.

Erdos, P. and A. Renyi (1959). On random graphs. *Publicationes Mathematicae 6*(290-297), 5.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental economics 10*(2), 171–178.

Fooks, J. R., N. Higgins, K. D. Messer, J. M. Duke, D. Hellerstein, and L. Lynch (2016). Conserving spatially explicit benefits in ecosystem service markets: Experimental tests of network bonuses and spatial targeting. *American Journal of Agricultural Economics 98*(2), 468 – 488.

Foster, A. D. and M. R. Rosenzweig (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy 103*(6), 1176–1209.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks 1*(3), 215–239.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association 1*(1), 114–125.

Hill, M. R., D. G. McMaster, T. Harrison, A. Hershmiller, and T. Plews (2011). A reverse auction for wetland restoration in the assiniboine river watershed, saskatchewan. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 59*(2), 245–258.

Iftekhar, M., A. Hailu, and R. Lindner (2014). Does it pay to increase competition in combinatorial conservation auctions? *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 62*(3), 411–433.

Jack, B. K., B. Leimona, and P. J. Ferraro (2009). A revealed preference approach to estimating supply curves for ecosystem services: Use of auctions to set payments for soil erosion control in indonesia. *Conservation Biology 23*(2), 359 – 367.

Jackson, M. O. (2008). *Social and economic networks.* Princeton university press Princeton.

Johnson, J. C. (1998). Research design and research strategies. *Handbook of methods in cultural anthropology 1*, 131–171.

Kawasaki, K., T. Fujie, K. Koito, N. Inoue, and H. Sasaki (2012). Conservation auctions and compliance: Theory and evidence from laboratory experiments. *Environmental and Resource Economics 52*(2), 157–179.

Kirwan, B., R. N. Lubowski, and M. J. Roberts (2005). How cost-effective are land retirement auctions? estimating the difference between payments and willingness to accept in the conservation reserve program. *American Journal of Agricultural Economics 87*(5), 1239 – 1247.

Krishnan, P. and M. Patnam (2014). Neighbors and extension agents in ethiopia: Who matters more for technology adoption?. *American Journal of Agricultural Economics 96*(1), 308 – 327.

List, J. A. and J. F. Shogren (1998). Calibration of the difference between actual and hypothetical valuations in a field experiment. *Journal of Economic Behavior & Organization 37*(2), 193–205.

List, J. A. and J. F. Shogren (1999). Price information and bidding behavior in repeated second-price auctions. *American Journal of Agricultural Economics 81*(4), 942 – 949.

Lynch, J. G. (1982). On the external validity of experiments in consumer research. *Journal of consumer Research 9*(3), 225–239.

Maertens, A. and C. B. Barrett (2013). Measuring social networks' effects on agricultural technology adoption. *American Journal of Agricultural Economics 95*(2), 353 – 359.

Magnan, N., D. J. Spielman, T. J. Lybbert, and K. Gulati (2015). Leveling with friends: Social networks and indian farmers demand for a technology with heterogeneous benefits. *Journal of Development Economics*.

Osborne, J. W. and A. Overbay (2004). The power of outliers (and why researchers should always check for them). *Practical Assessment, Research & Evaluation 9*, 1.

Pant, K. P. (2015). Uniform-price reverse auction for estimating the costs of reducing open-field burning of rice residue in nepal. *Environmental and Resource Economics 62*(3), 567 – 581.

Plott, C. R. (1997). Laboratory experimental testbeds: Application to the pcs auction. *Journal of Economics and Management Strategy 6*(3), 605 – 638.

Porter, D., S. Rassenti, W. Shobe, V. Smith, and A. Winn (2009). The design, testing and implementation of virginia's nox allowance auction. *Journal of Economic Behavior and Organization 69*(2), 190 – 200.

Roe, B. E. and D. R. Just (2009). Internal and external validity in economics research: Tradeoffs between experiments, field experiments, natural experiments, and field data. *American Journal of Agricultural Economics 91*(5), 1266–1271.

Rolfe, J., J. Windle, and J. McCosker (2009). Testing and implementing the use of multiple bidding rounds in conservation auctions: a case study application. *Canadian Journal of Agricultural Economics/Revue Canadienne d'Agroeconomie 57*(3), 287–303.

Schilizzi, S. and U. Latacz-Lohmann (2005). Auctions for conservation contracts: a review of the theoretical and empirical literature. *Scottish Executive Environment and Rural Affairs Department*.

Schilizzi, S. and U. Latacz-Lohmann (2007). Assessing the performance of conservation auctions: an experimental study. *Land Economics 83*(4), 497–515.

Schilizzi, S. and U. Latacz-Lohmann (2012). Evaluating conservation auctions with unknown bidder costs: the scottish fishing vessel decommissioning program. *Land Economics 88*(4), 658–673.

Shoemaker, R. (1989). Agricultural land values and rents under the conservation reserve program. *Land Economics 65*(2), 131.

Stoneham, G. (2003). Auctions for conservation contracts: An empirical examination of victoria's bushtender trial. *Australian Journal of Agricultural and Resource Economics 47*(4), 477 – 500.

Tisdell, J. (2007). Bringing biophysical models into the economic laboratory: An experimental analysis of sediment trading in australia. *Ecological Economics 60*(3), 584–595.

Valente, T. W., K. Coronges, C. Lakon, and E. Costenbader (2008). How correlated are network centrality measures? *Connections (Toronto, Ont.) 28*(1), 16.

Ward, P. S. and V. O. Pede (2014). Capturing Social Network Effects in Technology Adoption: The Spatial Diffusion of Hybrid Rice in Bangladesh. *Australian Journal of Agricultural and Resource Economics 58*.

Watts, D. J. and S. H. Strogatz (1998). Collective dynamics of small-worldnetworks. *nature 393*(6684), 440–442.

Wichmann, B. (2015). Agents of change and the approximation of network outcomes: a simulation study. *Networks and Spatial Economics 15*(1), 17–41.

Wilson, S. A. (2013). *Incorporating variable costs of adoption into conservation auctions.* Unpublished MSc. Thesis. Department of Resource Economics and Environmental Sociology. University of Alberta.

Winer, R. S. (1999). Experimentation in the 21st century: The importance of external validity. *Journal of the Academy of marketing Science 27*(3), 349–358.

Appendix A

Experimental Instructions

Thank you for participating in this experiment.

This is an experiment in individual decision-making. You will be asked to play a computer game and make decisions in several rounds. If you follow the instructions carefully and make good decisions, you will have the opportunity to earn a considerable amount of money. You will be paid for your participation in CASH at the end of the experiment. Your earnings for today's experiment will include a $5 show-up fee, and additional earnings will depend partly on your decisions and partly on the decisions of other players.

You cannot talk to other players during the experimental session. It is important that you strictly follow the rules. If you disobey the rules, you will be asked to leave the experiment. If you have a question at any time during the experiment, please raise your hand and we will come over to your desk and answer it in private.

Background

The government wants to encourage farmers to adopt new farming practices. The adoption of these practices is costly to farmers. The government has set aside a limited budget to pay farmers to adopt these practices. The government does not know farmers' adoption costs and has not decided how much to pay each farmer. Instead, farmers get to decide how much they would like to be paid to adopt the new practice. All farmers submit their requests for financial compensation to the government in an auction. After all requests are submitted the government will accept the best requests until the budget is exhausted. Going forward, we will refer to these requests as bids.

Procedure for Playing the Auction

In today's experiment you will play the role of a farmer. Different farmers have different adoption costs. At the beginning of an auction you will learn how much your cost of adopting the new practice is. After learning your cost you will be asked to submit your bid demanding compensation to adopt the new farming practice.

If your bid is successful, that is, if the government accepts your bid and you receive payment to adopt, you will have to pay your adoption cost. Therefore, the computer will not allow you to submit a bid lower than your adoption cost as this would not be beneficial to you.

How Bids Are Accepted?

An auction has 8 players. All players submit bids requesting dollar compensation to adopt the new farming practice. Once all bids are submitted, the computer will rank all 8 bids from lowest to highest to determine which players will receive payment. The bids will then be accepted from the lowest one upward until the auction budget is exhausted. Notice that according to this procedure more than one player may have bids accepted. At the end of an auction, the computer program will inform you whether your bid was successful or not.

The auction budget will remain the same throughout the experiment; however, no player will ever know the budget amount. Each player will only know whether their own bid is accepted or not. In addition, your bid is your private information and will not be revealed to other players.

The Auction Payoff

If your bid is accepted, you receive payment equal to your bid and you have to pay your adoption costs. Therefore, your dollar payoff is:

$$\text{Payoff} = \text{Your Bid - Your Adoption Cost.}$$

If your bid is not accepted, you do not receive payment and you do not have to pay your adoption cost. Therefore, your dollar payoff is:

$$\text{Payoff} = 0.$$

The computer will not allow you to submit a bid lower than your adoption cost as this would not be beneficial to you.

The Structure of the Session

The session is made up of 20 auctions. Initially, there will be 4 practice auctions. These auctions are for you to familiarize yourself with the software and the procedure for playing the auction. The practice auctions will not be counted in the determination of your experimental earnings.

After the practice auctions, you will play 16 real auctions that will determine your earnings for today's experiment. These 16 auctions are divided in 4 blocks of 4 auctions.

After the last auction ends, you will be asked to answer a short survey.

The Costs of Adoption

The computer will randomly assign a different adoption cost to each player. The adoption cost can be any amount between \$5 and \$30, with each amount between \$5 and \$30 being equally likely. You will see your adoption cost on the computer screen before you submit your bid. The costs of ALL players will change after every block of 4 auctions.

Information about the costs of OTHER players may or may not be available to you. At the beginning of the experiment the computer randomly decides who will learn the costs of others. If you learn the cost of other players they will also learn your cost. If you cannot see the cost a player on the computer screen, he/she will not be able to see yours. After the second block of auctions, the information available to you about the costs of other players may change. The computer will again randomly decide which players will learn the costs of others.

Notice that both adoption costs and information sharing are determined at random so that everyone has a fair chance to have bids accepted.

Your Experimental Earnings

Your earnings for today's experiment will be calculated based on 4 of the 16 real auctions. At the end of the experiment, the computer will randomly select four auctions for payment. In particular, it will select one auction from each auction block. Your final earnings will be the sum of the payoffs from these 4 randomly selected auctions plus the $5 show-up fee.

Therefore, even though you will make 20 bidding decisions (including 4 practice auctions), only 4 of these will end up affecting your earnings. You will not know in advance which auctions will be chosen for payment, but each auction has an equal chance of being selected. Therefore, it is in your best interest to try to do well in all auctions.

Before we begin, do you have any questions?

Good luck and thank you for your participation.

Appendix B

Illustrations of the Experimental Networks

Figure B.1: Network 1 (Erdos-Renyi)

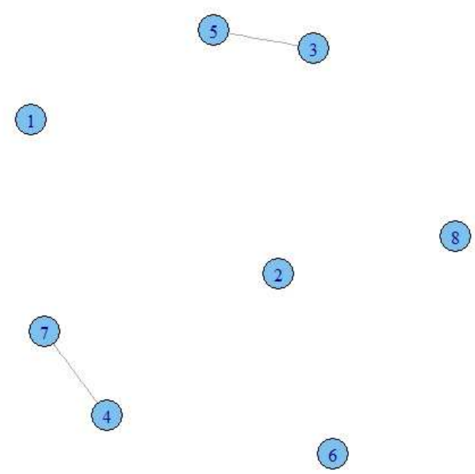


Figure B.2: Network 2 (Erdos-Renyi)

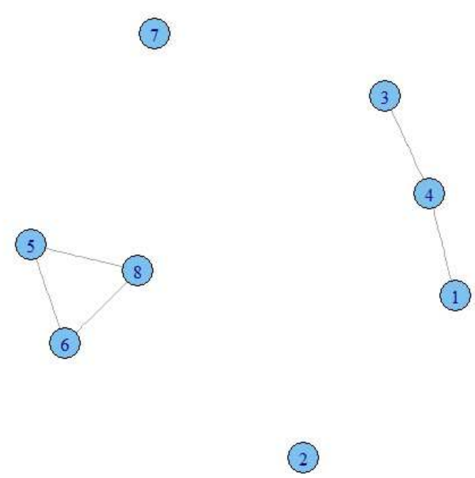


Figure B.3: Network 3 (Erdos-Renyi)

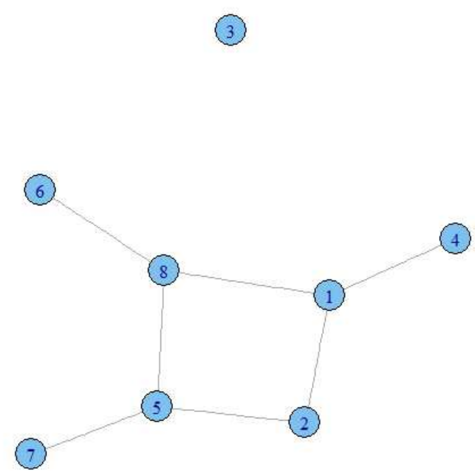


Figure B.4: Network 4 (Erdos-Renyi)

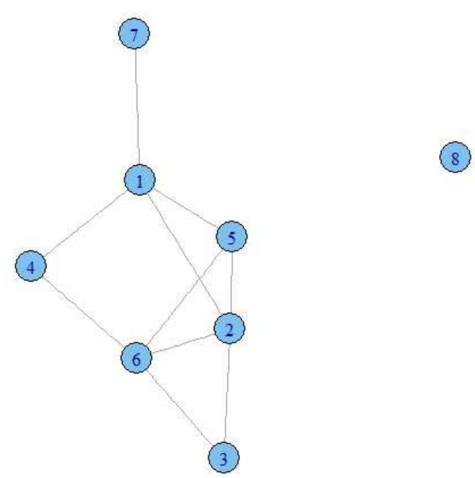


Figure B.5: Network 5 (Erdos-Renyi)

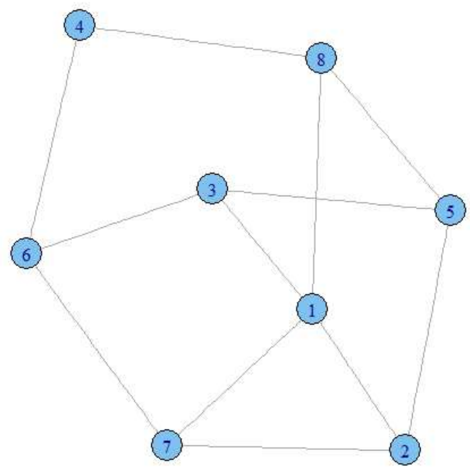


Figure B.6: Network 6 (Erdos-Renyi)

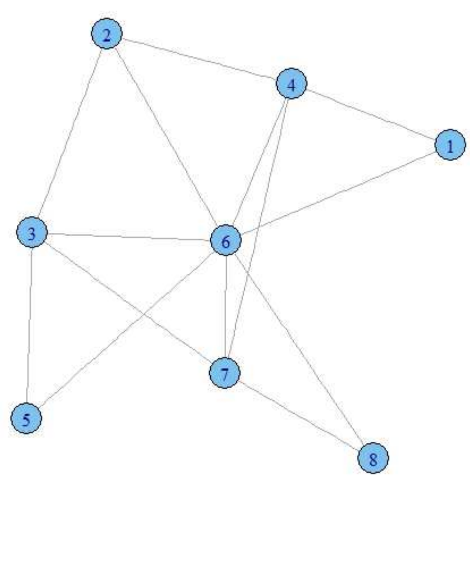


Figure B.7: Network 7 (Erdos-Renyi)

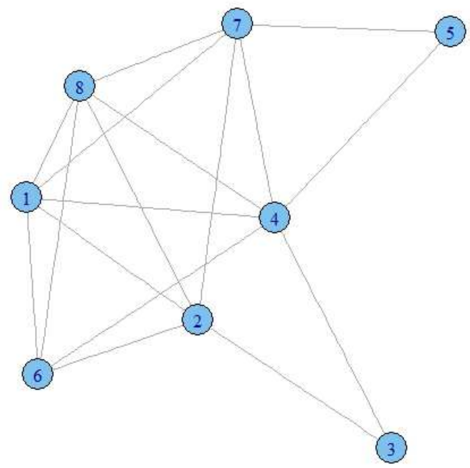


Figure B.8: Network 8 (Watts-Strogatz)

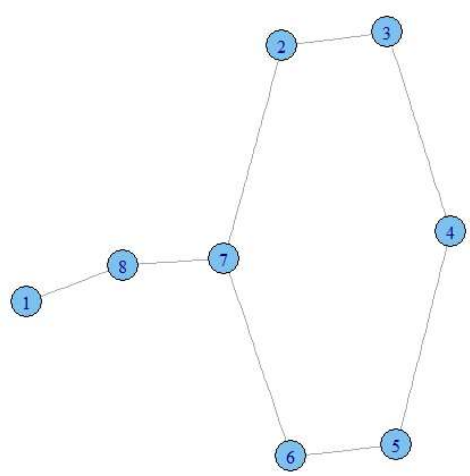


Figure B.9: Network 9 (Watts-Strogatz)

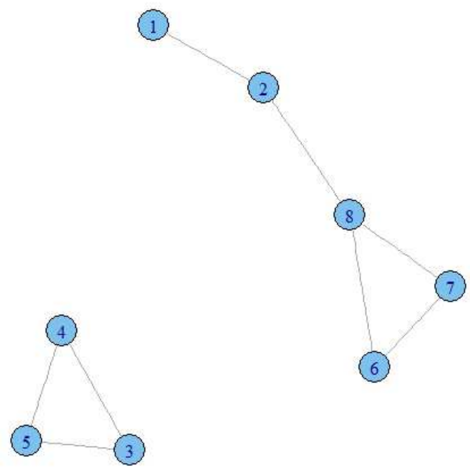


Figure B.10: Network 10 (Watts-Strogatz)

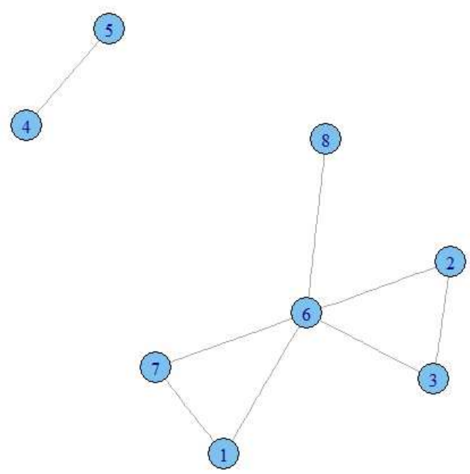


Figure B.11: Network 11 (Watts-Strogatz)

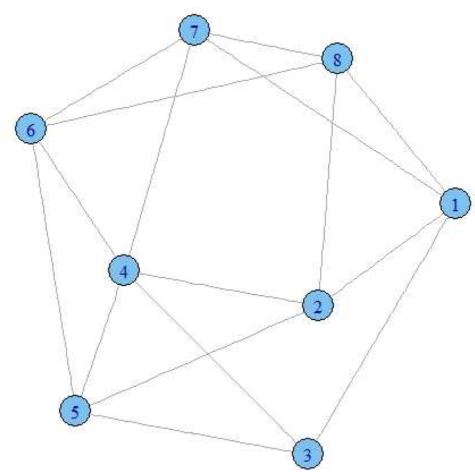


Figure B.12: Network 12 (Watts-Strogatz)

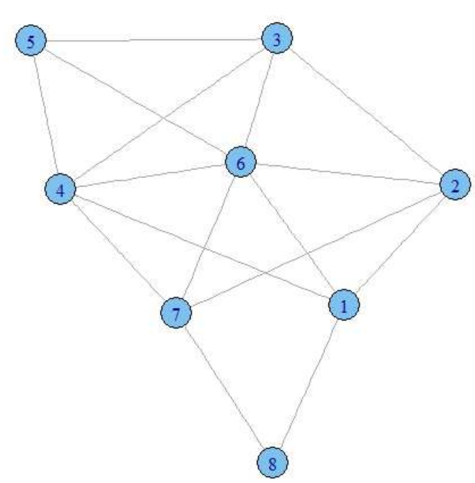


Figure B.13: Network 13 (Watts-Strogatz)

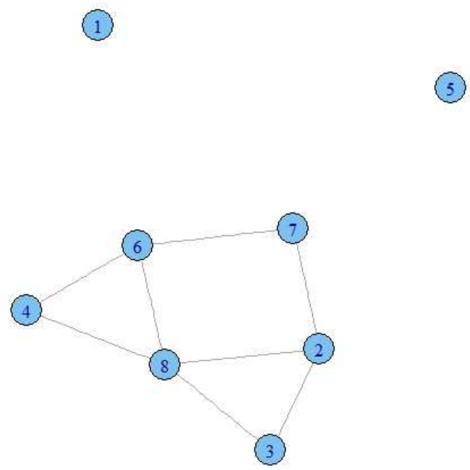


Figure B.14: Network 14 (Barabasi-Albert)

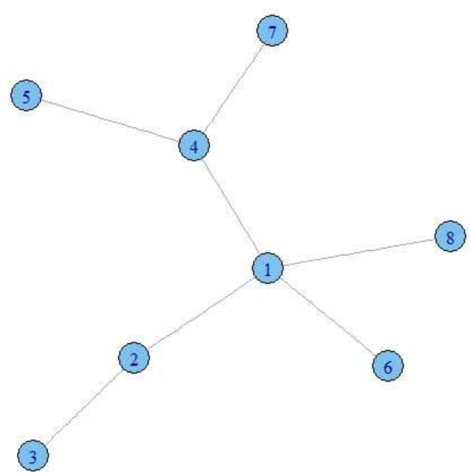


Figure B.15: Network 15 (Barabasi-Albert)

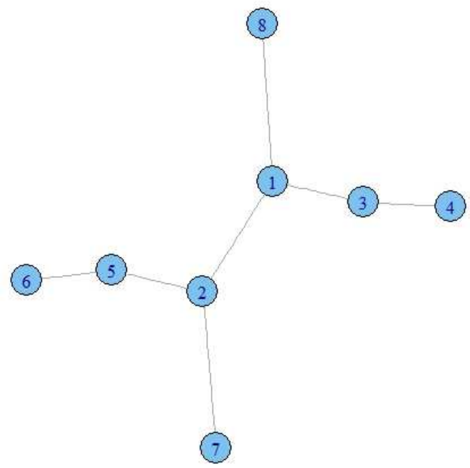


Figure B.16: Network 16 (Barabasi-Albert)

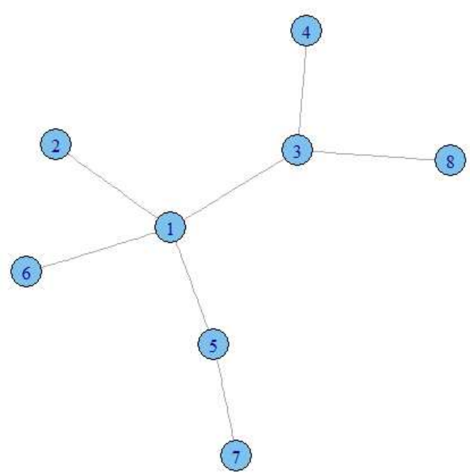


Figure B.17: Network 17 (Barabasi-Albert)

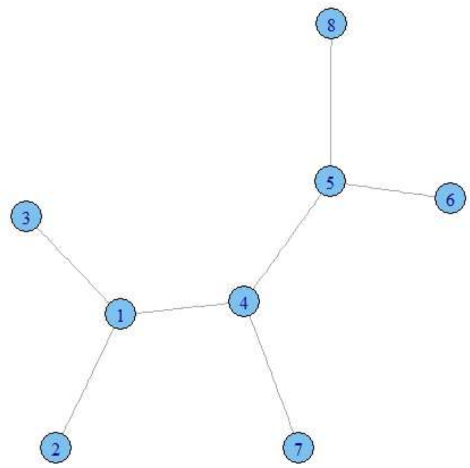


Figure B.18: Network 18 (Barabasi-Albert)

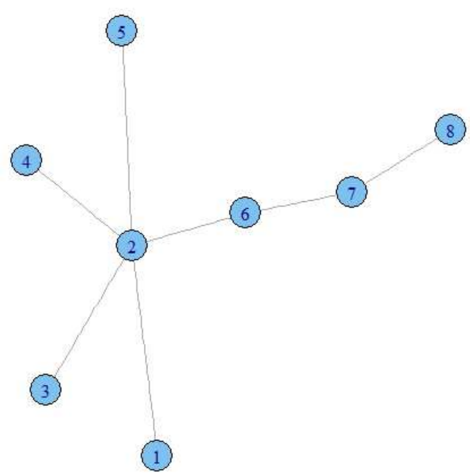


Figure B.19: Network 19 (Barabasi-Albert)

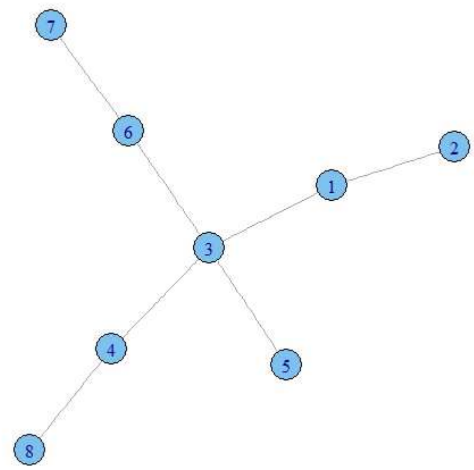


Figure B.20: Network 20 (Regular Lattice)

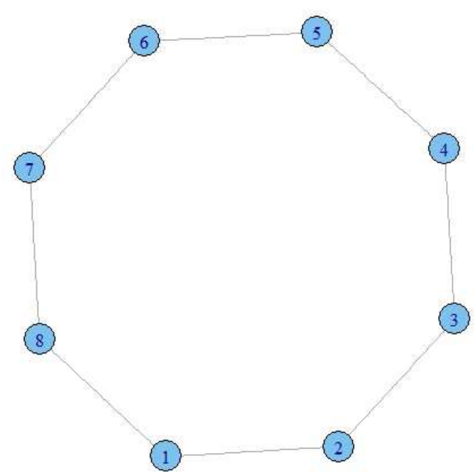


Figure B.21: Network 21 (Regular Lattice)

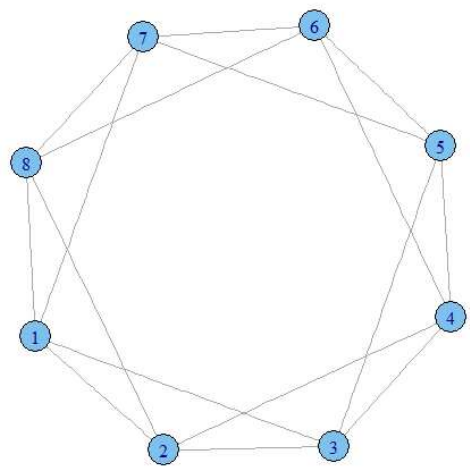


Figure B.22: Network 22 (Star)