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Social Structure, Non-market Valuation, and Bargaining

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I am submitting herewith a dissertation written by Bruno Moreira Wichmann entitled "Social Structure, Non-market Valuation, and Bargaining." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

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Social Structure, Non-market Valuation, and Bargaining

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DEDICATION

This dissertation is dedicated to my loving wife, Marna Wichmann, who always believed in me and sacrificed so much to make my dreams come true.

Xuxu, we did it!

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Abstract

This dissertation consists of three chapters that explore the effects of social utility on non-market values and bargaining.

Chapter 1 considers the role of social networks in the valuation of public goods. In the model individuals derive utility from both their own direct enjoyment of the public good as well as from the enjoyment of those in their social network. We find that the network increases an individual's valuation for the public good when members of her network have a higher weighted average valuation than she does. The network increases aggregate valuation when it assigns higher importance, that is, greater total weight, to individuals with higher private values for the public good. The model provides a theoretical foundation for the idea of opinion leaders who have disproportionate influence over their communities. The model can also guide future empirical studies by enabling a more structural approach to non-market valuation in a socially-connected group.

Chapter 2 shows that yes/no responses of dichotomous choice Contingent Valuation (CV) surveys are not independent when social networks influence non-market values. The empirical CV literature has yet to attempt estimation of non-market values explicitly accommodating network effects. We investigate the statistical properties of estimates of mean willingness to pay obtained through standard approaches that ignore social networks. Monte Carlo experiments, with different types of simulated and real world social networks, indicate that failure to account for network effects leads to underestimation of non-market values.

Chapter 3 reports results of an experiment designed to explore the trade-offs between added surplus and lost bargaining power in long-term contracting. Participants played a sequential bargaining game whereby the first mover (the procurer) selects whether to be the recipient in a single-shot dictator game or a twice-repeated ultimatum game. We find that, in general, participants prefer to retain the bargaining power of the ultimatum games as opposed to engage in a dictator game played over a bigger endowment. This result suggests that diminished bargaining power can be a serious detriment to realizing long-term gains from trade.

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Chapter 1

Social Networks and Non-market Valuation

1.1 Introduction

For the most part, the theoretical public good valuation literature considers decision-makers in social isolation. There are two reasons why social structure might impact valuation. One is that individuals may be altruistic and care about public goods that benefit their friends even if they do not benefit themselves.[1] For example, the presence of a park might not generate any private utility for the indivudal, but if the park gives her friends utility and she values those friends' utility, she might have positive willingness to pay for the park due to social utility.[2] A second reason is that people might use the public good in groups.[3] For example, someone might like going to a park, but not alone, so to get enjoyment from the park her friends must also like the park. She gets utility from going to the park with friends, but might also get

[1]This is consistent with the finding of directed altruism by Leider et al. (2009). In their field experiment subjects allocate 52% more to close friends than to strangers in dictator games.

[2]As private utility we mean the direct (or own) utility that one receives from consuming a public good in social isolation, i.e. ignoring social effects. Social utility is the overall (or total) utility from the public good, which includes one's private utility and (possibly) the social utility from friends.

[3]For instance, Morey and Kritzberg (2010) provide evidence that the presence of a companion changes the willingness to pay for biking trails.

utility from going with friends' friends, and so on. Whichever the channel, altruism or joint use, the utility that one gets from the public good may be affected by friends' utility. Furthermore, friends may behave in the same way and the utility of friends of friends may affect friends' utility. This leads to network effects.

The purpose of this paper is to construct a model of public good valuation that can accommodate both of these network effects. As argued by Jackson (2009, pg. 491), "Many economic interactions are embedded in networks of relationships and the structure of the network plays an important role in governing the outcome." As a result, network models have been developed to explain a wide range of economic phenomena.[4] Our primary result links aggregate willingness-to-pay to network centrality. In particular, societies are willing to pay more in aggregate for a public good when that public good provides more benefit to people more central to the society. A straightforward implication is that public projects that pass the cost-benefit test and ultimately receive funding tend to favor more central agents.

To capture network interactions we use the sociometric approach in which the interaction patterns of agents are captured through the rows of a matrix (see DeGroot (1974) and DeMarzo et al. (2003)). The matrix-based approach proves well-suited for the problem of computing individuals' valuations for a public good when their valuations depend on those of others in their social network.[5] We assume that each individual has her own private value of the public good, and this private value is the one that would pertain if the public good were consumed in social isolation. Each individual's social value of the public good may depend on how much others in her social network enjoy it, though, and so the individual's social value of the public

[4]Network models have been used to explain labor market outcomes (see Calvó-Armengol and Jackson (2004, 2007)), risk sharing (see Fafchamps and Lund (2003) and Bramoullé and Kranton (2007b)), and opinion formation (see DeGroot (1974), Friedkin and Johnsen (1990), DeMarzo et al. (2003), and Neilson and Winter (2008)).

[5]As discussed by Wasserman and Faust (1994, chap. 3), the graph-theoretic approach, common in the work of Jackson and others (e.g. Jackson and Watts (2002), Jackson (2005), Jackson and Rogers (2007)), proves to be beneficial for modeling networks with multiple relations. The sociometric notation is, however, a simple way to model directed networks in which links between agents have different strength.

good may differ from her private value. We show that all network effects, including feedback effects, can be captured by a single weighting matrix so that each individual's social value is a weighted average of the population private values. In particular, each individual's centrality to the network is captured by the relevant column sum of the resulting weighting matrix. We refer to this column sum as an agent's *importance*.

The thought exercise pursued in the paper involves a comparison between the valuations assigned to a public good when individuals are socially isolated and the valuations assigned when society has a network structure, holding the original vector of private valuations constant across the two settings. The paper concentrates on when, and how, the network structure impacts the social value of the public good. For individual valuation of a public good the requirement for a network effect is very weak: the individual's social value of the public good differs from her private value if she cares about at least one agent with a different private value than her own. In other words, the structure of the network almost always impacts an individual's valuation for a public good. The paper also identifies when the aggregate social value of the public good depends on the network, and this occurs if agents in the population are not uniformly important. If more important agents have higher private values of the public good, the population's aggregate social valuation is higher.

The paper provides an economic foundation to a widely-used idea in the other social sciences, that of an opinion leader whose position in a community makes him or her instrumental in affecting social change. This idea has been used, among other places, in such diverse areas as agricultural development (Monge et al. (2008)), corporate training programs (Lam and Schaubroeck (2000)), and microfinance diffusion (Banerjee et al. (2011)). Opinion leadership is clearly tied to the idea of network centrality (see Katz (1953) and Friedkin (1991)). However, the model in this paper ties opinion leadership directly to an influence on others' willingness to pay for a public good. The results show that this leadership is easily identified with the agents whose columns have the largest sums in the social weighting matrix.

The results have important implications for policy analysis. When the network matters, sampling values from the population provides the right information for performing a cost-benefit analysis for that population, but that same sample cannot be used as the basis for cost-benefit analysis for a similar public project benefiting a different population. In other words, even when two populations are very similar, e.g. they have similar distributions of relevant socio-economic characteristics, benefit transfer cannot be done without placing restrictions about the shape of the social networks. Because of the network, one population might find it worthwhile to provide the public good while the other does not.[6]

The paper adds to the economics literature linking social preferences and public good provision. A group of papers concentrates on whether social values should be considered in cost-benefit analyses of public projects.[7] Flores (2002) and Bergstrom (2006) demonstrate that there are cases where welfare-improving public good projects would be rejected if cost-benefit analysis were based only on private values as opposed to social values. Therefore, with social preferences, a public project may be Pareto-enhancing even if the cost of the project exceeds the sum of all agents' private values.

Our contribution to this literature involves the use of a social network structure to explore the differences between the private and social welfare generated by public good provision. In doing so, our framework is similar to that of Bergstrom (1999) and Bramoullé (2001) in which a weighting matrix distinguishes private values from social values. The paper differs from the prior literature in the manner in which others' utility impact own utility. Bergstrom (1999) looks at a system of benevolent utility functions in which social connections automatically add to an individual's utility. Bramoullé (2001)'s treatment also involves adding friends' social utility to an individual's utility, however, he allows for individuals to be envious toward other agents and, in this case, other agents' social utilities are subtracted from own

[6]This result is in line with experimental evidence that social preferences are stronger towards socially connected agents. For instance, Leider et al. (2009) distinguish baseline altruism towards strangers from directed altruism that favors friends.

[7]See Bergstrom (2006) for a review of theoretical work.

utility. Our paper uses a different utility structure so that social connections neither automatically add or automatically subtract welfare, thereby disentangling the effects of social preferences and network structure.

The paper contrasts with the literature on local public goods in networks. In these papers the public good has the same value to everyone, but individuals only obtain access to the public good when they are connected directly to someone who provides it. Bramoullé and Kranton (2007a) present the first model of such public goods. They show that there always exists an equilibrium in which some agents free ride, and that in some cases the most efficient equilibrium entails provision by the central agent in the network. Their model concentrates on provision, which is made interesting by the localness of the public good, while ours concentrates on valuation for global public goods in the presence of networks.[8]

The joint-use interpretation of our model provides a theoretical foundation for the empirical recreation-site choice literature. Using a choice experiment, Morey and Kritzberg (2010) demonstrate that the presence of a companion can significantly change the value of mountain bike trails. They take their large estimates of the effect of a companion on the value of trails as evidence that real world site-choice data may be influenced by social interactions. Commensurate with these findings, other empirical papers find significant effects of party size on recreational values (see Kaoru et al. (1995) and Massey et al. (2006)). Along the same lines, Timmins and Murdock (2007) find evidence that some congestion can be desirable. Specifically, they estimate the value of a large recreational fishing site in Wisconsin (Lake Winnebago) accounting for congestion effects, and conclude that ignoring congestion leads to an understatement of the lake's value by more than 50%. Although these papers do not account for social networks explicitly, they provide some empirical support for our

[8]More recent research stemming from Bramoullé and Kranton (2007a) develops different network models of public goods. Newton (2010) analyzes the effect of coalitional behavior on local public goods provision. O'Dea (2010) examines the relationship between local public good provision and social network formation. Cho (2010) studies endogenous formation of networks for local public goods in sequential bargaining games. Chih (2010) incorporates interactive costs and social perception of free-rider behavior in a model of local public goods and network formation.

results by showing that social interactions affect valuation. Our results also inform this literature by suggesting that the strength of social ties to the companions, and not just the number of companions, affect valuation.

The remainder of the paper is organized as follows. Section 1.2 presents the model. Section 1.3 analyzes social network effects on an individual's utility and willingness to pay for public projects. Section 1.4 investigates social network effects on welfare and aggregate non-market valuation. Section 1.5 concludes.

1.2 The Model

A population consists of $n \geq 2$ agents indexed by $i = 1, ..., n$. Agents obtain utility from the consumption of a private good x and a public good g. Utility is assumed to be quasilinear. Agent i's overall utility is

$$V_i(x_i, g) = x_i + v_i(g), \tag{1.1}$$

where $v_i(g)$ is agent i's social utility from the public good.

The public good g is exogenously provided to the entire population, without congestion, such that every agent can benefit from its consumption. There are two channels through which the provision of g can affect i's social utility $v_i(g)$. First, agent i obtains *private* utility $u_i(g)$ from the consumption of g. This is the component of social utility that is obtained from own consumption of g and is independent of social effects. Second, agent i may care about the enjoyment of her friends and, as a result, may obtain *social* utility.[9]

Friendships are represented by a social network. Formally, let agent j be a *friend* of agent i if j is directly connected to i.[10] The social network is represented by the (possibly asymmetric) row stochastic matrix $\mathbf{A}$, with dimensions $n \times n$. An element

[9] As discussed in section 1.1, altruism or group consumption are two possible reasons for the influence of friends on an individual's social utility.

[10] In the network literature, connected agents are often referred to as neighbors.

a_{ij} is positive if j is a friend of i, and zero otherwise.[11] The diagonal of $\mathbf{A}$ is equal to zero reflecting the fact that an agent is not a friend of herself.

Social utility received from friends is assumed to be a weighted average of friends' public good utility v, with weights determined by the rows of $\mathbf{A}$.[12] Formally, agent i's social utility from the public good is defined as

$$v_i(g) = (1 - \lambda_i)u_i(g) + \lambda_i \sum_j a_{ij} v_j(g), \tag{1.2}$$

where $\lambda_i \in [0, 1)$ is a parameter that reflects the extent to which social utility of friends is relevant to agent i.

The term $(1 - \lambda_i)$ is the weight that agent i places on her own private enjoyment $u_i(g)$. Hence, the parameter λ_i is intuitively denoted as i's degree of social interaction in the consumption of g. Agent i is said to be *socially isolated* if i's social utility from the public good is not influenced by the social utility of friends. Thus, when λ_i=0, agent i's social utility $v_i(g)$ is equal to i's private utility $u_i(g)$. Social isolation shuts down the social channel through which the provision of g affects i's utility and the model simplifies to a standard utility model without network effects.

Let $\mathbf{v} = \big(v_1(g), ..., v_n(g)\big)'$ denote the social utility profile of all agents. Using matrix notation, $\mathbf{v}$ can be written as

$$\mathbf{v} = (\mathbf{I} - \mathbf{\Lambda})\mathbf{u} + \mathbf{\Lambda}\mathbf{A}\mathbf{v}, \tag{1.3}$$

where $\mathbf{I}$ is the identity matrix, $\mathbf{\Lambda}$ is a diagonal matrix with λ_i in the i-th row, and $\mathbf{u} = \big(u_1(g), ..., u_n(g)\big)'$ is the population's private utility profile. Bergstrom (1999) and Bramoullé (2001) study systems of utility functions using a similar framework: $\mathbf{v} = \mathbf{u} + \mathbf{A}\mathbf{v}$. In Bergstrom (1999)'s treatment agents are benevolent, thus, $\mathbf{A}$ is a

[11] A row stochastic matrix is a square matrix of nonnegative real numbers, with each row summing to 1. Therefore, we implicitly assume that every agent has at least one friend.

[12] From i's perspective, the intensity of the friendship between i and j is captured by a_{ij}. The element a_{ij} captures j's influence on i's social utility. The same friendship may have different intensity from j's perspective such that a_{ij} may be different from a_{ji}.

nonnegative matrix. In Bramoullé (2001)'s formulation entries of $\mathbf{A}$ are either positive (if there is an altruistic social connection) or negative (if the social connection is envious). Either way, adding a friend (or enemy) to an agent's network automatically increases (decreases) that agent's utility. While this might be realistic, it prohibits disentangling the impact of a change in size of a network from a change in its shape. In equation (1.2) adding a friend for agent i requires reconfiguring the i-th row of $\mathbf{A}$, retaining the requirement that the row sum to one. Consequently adding a friend does not automatically add to utility.[13]

The network component of (1.3) captures the social utility obtained by straight links to friends' social utility. The influence of friends' social utility on own social utility is determined by the matrix $\mathbf{\Lambda A}$. Borrowing Bramoullé's terminology we refer to $\mathbf{\Lambda A}$ as the *primary network*. Rearranging (1.3) yields

$$\mathbf{v} = (\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}(\mathbf{I} - \mathbf{\Lambda})\mathbf{u}. \tag{1.4}$$

To simplify notation make $\mathbf{W} = (\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}(\mathbf{I} - \mathbf{\Lambda})$. Again, borrowing Bramoullé's terminology, we refer to $\mathbf{W}$ as the *induced network*. Elements of $\mathbf{W}$ correspond to circuitous links between agents emerging from links in the primary network. Links in the induced network account for the impact of friends of i's friends on i's social utility, plus the impact of friends of friends of i's friends on i's social utility, and so on. Mathematically, this arises from the Neumann series approximation $(\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}$ $= \Big(\mathbf{I} + (\mathbf{\Lambda A}) + (\mathbf{\Lambda A})^{\mathbf{2}} + (\mathbf{\Lambda A})^{\mathbf{3}} + ...\Big)\Big(\mathbf{I} - \mathbf{\Lambda}\Big)$.[14] More intuitively, consider the three-person population with

$$\mathbf{\Lambda} = \begin{pmatrix} 0.8 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.2 \end{pmatrix}, \quad \text{and} \quad \mathbf{A} = \begin{pmatrix} 0 & 0.5 & 0.5 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

Then

[13] A second difference in our model is that network effects influence only one type of good (public good) but not the other type of good (private good).

[14] See Meyer (2000).

$$\mathbf{W} = \begin{pmatrix} 0.28 & 0.28 & 0.44 \\ 0.14 & 0.64 & 0.22 \\ 0.06 & 0.06 & 0.88 \end{pmatrix}.$$

From the matrix $\mathbf{A}$ we see that agent 1 is friends with agents 2 and 3 (because a_{12} and a_{13} are both positive) but agents 2 and 3 are not friends with each other (because $a_{23} = a_{32} = 0$). Nevertheless, because agent 2 cares about agent 1's utility which in turn depends on agent 3's utility, in the end agent 2 places weight on agent 3's utility and $w_{23} = 0.22 > 0$. The same reasoning explains why $w_{32} > 0$ even though $a_{32} = 0$. The rationale for $w_{23} > w_{32}$ is that $\lambda_2 > \lambda_3$, so that agent 2 places more weight on others' well-being than agent 3 does.

It follows from (1.4) that agent i's social utility can be expressed as a function of the elements of the private utility profile $\mathbf{u}$. The following expression represents the social utility function of agent i and corresponds to the i-th row of system (1.4),

$$v_i(g) = \sum_j w_{ij} u_j(g), \tag{1.5}$$

where w_{ij} is an element of the square matrix $\mathbf{W}$. Lemma 1.1 formally describes i's social utility function.

Lemma 1.1. *Agent i's social utility is a convex combination of the private utilities of all agents, i.e. for all i and j, $w_{ij} \in [0, 1]$ and $\sum_j w_{ij} = 1$.*

Proof. All proofs are found in the Appendix. $\square$

Lemma 1.1 establishes that agent i's social utility of the public good really is a weighted average of the private utilities of the agents in the economy, that is, that the weights in (1.5) are all nonnegative and sum to one. In addition, it implies that the primary network $\mathbf{\Lambda A}$ contains all of the information needed to determine how much weight agent i places on j's private utility of g, accounting for all possible induced interactions among all agents.

Agent i's overall utility function is obtained by plugging (1.5) into (1.1):

$$V_i(x_i, g) = x_i + \sum_j w_{ij} u_j(g). \tag{1.6}$$

We use equation (1.6) to define agent i's willingness to pay for an increase in the provision of the public good accommodating possible network effects. Normalizing the price of the private good, the compensating welfare measure associated with a discrete public project that yields an increase in g from g^0 to g^1 is defined by C_i that solves

$$V_i(m_i, g^0) = V_i(m_i - C_i, g^1) \tag{1.7}$$

where m_i represents agent i's income. Two compensating measures are defined. The first is agent i's willingness to pay under network interaction. It is defined by $C_i^{network}$ that solves

$$m_i + \sum_j w_{ij} u_j(g^0) = m_i - C_i^{network} + \sum_j w_{ij} u_j(g^1)$$

or just,

$$C_i^{network} = v_i(g^1) - v_i(g^0). \tag{1.8}$$

The second is the traditional compensating welfare measure that only accounts for private willingness to pay, that is, the measure that pertains if agent i is socially isolated ($\lambda_i = 0$). With social isolation, the social utility v_i simplifies to u_i (see equation (1.2)), and therefore private willingness to pay is defined as follows

$$C_i^{private} = u_i(g^1) - u_i(g^0). \tag{1.9}$$

Combining equations (1.5), (1.8), and (1.9) yields a relationship between the vectors $\mathbf{C}^{network}$ and $\mathbf{C}^{private}$:

$$\mathbf{C}^{network} = \mathbf{W}\mathbf{C}^{private}. \tag{1.10}$$

The same induced network $\mathbf{W}$ determines both social utility and willingness to pay under network interaction.

We can also use equation (1.6) to identify a single agent's impact on society. The amount $w_{1j}u_j$ measures j's contribution to agent 1's social utility, $w_{2j}u_j$ measures j's contribution to agent 2's social utility, and so on. Agent j's total contribution is then $\sum_i w_{ij}u_j(g)$. This motivates the following definition.

Definition 1.1. *Agent j's importance is defined as $\delta_j = \sum_i w_{ij}$.*

Since $\mathbf{W}$ is a row normalized matrix, agent importance is the sum of the elements of the j-th column of the induced network and can be intuitively thought as a measure of the "popularity" of agent j. This measure of importance is closely related to a number of measures of network centrality (see Friedkin (1991) and Opsahl et al. (2010)). The next lemma further characterizes agent importance.

Lemma 1.2. *Every agent in the network has positive importance, i.e. $\delta_i > 0$ for all i.*

The maximum value of δ_j approaches n and the minimum approaches 0. Consequently, every agent has at least a little importance to society and no single agent is a dictator. Average agent importance is 1.

1.3 Networks and Individual Valuation

This section analyzes the relationship between agent i's social and private utility. We explore differences between the traditional utility model in social isolation and our network model by studying how the shape of the social network affects non-market values. We begin by defining network neutrality.

Definition 1.2. *A network is neutral if, for the entire population, social utility is equal to private utility, i.e. for every private utility profile $(u_1, ..., u_n)$ we have $v_i = u_i$ $\forall i$.*

Under network neutrality, the social structure imposed by the system of interdependent utilities (1.4) is irrelevant. Stated differently, there are no network externalities as agents' overall utilities are not affected by network interactions. Identification of situations that lead to network neutrality becomes important because doing so also identifies situations where the network does matter, and Proposition 1.1 presents conditions that lead to network neutrality.[15]

Proposition 1.1. (Network neutrality). *Network neutrality holds if and only if all agents are socially isolated* (*i.e.* $\lambda_i = 0\ \forall i$).

Mathematically, network neutrality holds if and only if the primary network $\mathbf{\Lambda A}$ is a matrix of zeros. If this is the case, the induced network does not contain any (direct or indirect) connections between agents. In fact, $\mathbf{W}$ is the identity matrix.[16] Network effects are expected to be small if there are weak primary networks with little social interaction in the consumption of the public good. For example, one would be hard pressed to argue that λs are high when the public good in question is a sewer system. Of course altruism is always a possible reason for the existence of social preferences. However, it is probably safe to assume that a population's average λ for a park (possibly a jointly consumed public good) is higher than the average λ for a sewer system (a public good that is consumed individually). It may be the case that social networks are neutral if the public good is a sewer system. Importantly, though, Proposition 1.1 implies that when some agents care about friends' utility (so that $\lambda_i > 0$ for some agents) the shape of the network matters for social utility.

[15]The network could also be irrelevant if all individuals have identical private tastes, that is, if $u_i(g) = u_j(g)\ \forall i, j$. The irrelevance of the network then follows because every agent's social utility is a weighted average of the private utilities, which in turn are all equal. It is also possible, but extremely unlikely, that for some particular value of g the vectors of social and private values end up being identical. In real world applications, with large social networks, a combination of values in $\mathbf{\Lambda A}$ such that $v_i = u_i\ \forall i$ is essentially impossible.

[16]Proposition 1.1 indicates that if $\mathbf{\Lambda}$ is a matrix of zeros, then the induced network is equal to the identity matrix ($\mathbf{W} = \mathbf{I}$). There is no mathematical condition that imposed on $\mathbf{A}$ would lead to network neutrality. In fact, mathematically, if $\mathbf{A} = \mathbf{I}$ then $\mathbf{W} = \mathbf{I}$, regardless of $\mathbf{\Lambda}$. However, this is ruled out by the model construction as the diagonal of $\mathbf{A}$ has zeros reflecting the fact that agent i is not a friend of herself.

Proposition 1.1 implies that the network matters more when agents are more socially connected (so that λs are high), and it also follows from the structure of the model that, relative to a world of social isolation, network effects can significantly change individuals' well-being in environments in which agents have large disparities in private utilities. On the flip side, network effects are expected to be small if the population is homogeneous. For instance, consider a group of peasants of a small village in a developing country. Assume they are a very homogeneous group that obtains natural resources from a watershed. Despite the fact that there may be strong social utility associated with the consumption of the watershed (i.e. λs are not zero), one could imagine the private utilities from the watershed as being the same for every peasant. In this case, any random peasant is a perfect representative agent and the welfare generated by the watershed can be perfectly assessed by the welfare of a single peasant. This is a case in which the social network is neutral for a specific public good, but not in general.

The following corollary formalizes the obvious implication that when a network has no impact on individuals' social utility levels, that is, when network neutrality holds, it also has no impact on individual willingness to pay. It does so by comparing the network compensating measure $C_i^{network}$ to the private measure $C_i^{private}$.

Corollary 1.1. (Individual valuation neutrality). *If network neutrality holds, the willingness to pay measure $C_i^{network}$ is equal to the private measure $C_i^{private}$.*

If the social network is not neutral, it may have a significant effect on non-market values. A natural next step is to examine how the social network affects social utility. We now study the setting in which agents have heterogeneous private utilities and are not socially isolated. When network neutrality fails, the utility of g is determined by the social utility v, and it is different from the private utility u. The next proposition characterizes how the shape of the social network affects social utility and establishes the conditions in which the network generates a positive externality such that the social utility v_i is greater than the private utility u_i.

Proposition 1.2. (Network effects on utility). *In non-neutral networks (i.e. $w_{ii} \neq 1$), the network benefits agent i, i.e. $v_i(g) > u_i(g)$, if and only if*

$$u_i(g) < \frac{\sum_{j \neq i} w_{ij} u_j(g)}{\sum_{j \neq i} w_{ij}}. \tag{1.11}$$

The left-hand side of expression (1.11) is individual i's own private utility, and the right-hand side is the weighted average of her network's private utilities. If her network values the public good more than she does, on average, her social utility from the public good exceeds her private utility. Conversely, if she values it more than her network does, on average, the impact of the network is to reduce her social utility. So, for example, if i likes the beach more than any of her friends do, i receives lower social utility from going to the beach than she would if she were socially isolated.

As a consequence of proposition 1.2, willingness to pay under network interaction ($C_i^{network}$) is expected to be different from private willingness to pay in social isolation ($C_i^{private}$). Corollary 1.2 describes the circumstances in which the network generates higher valuations than those generated under social isolation.

Corollary 1.2. (Network effects on individual valuation). *In non-neutral networks (i.e. $w_{ii} \neq 1$), $C_i^{network} \geq C_i^{private}$ if and only if $\left(u_i(g^1) - u_i(g^0)\right) \leq \frac{\sum_{j \neq i} w_{ij}[u_j(g^1) - u_j(g^0)]}{\sum_{j \neq i} w_{ij}}$.*

Corollary 1.2 demonstrates that for agents with small private willingness to pay the network generates higher valuations than the ones in social isolation. In a social network environment, low private valuation agents are willing to pay more for an increment in g because they benefit from the gains of higher private valuation friends. To see this, consider the following example. The induced network is given by

$$\mathbf{W} = \begin{pmatrix} 0.5 & 0.1 & 0.4 \\ 0.2 & 0.6 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{pmatrix},$$

and the three individuals in the society differ in how much they value the change in the public good from g^0 to g^1. Let

$$\mathbf{u}(g^1) - \mathbf{u}(g^0) = \begin{pmatrix} 10 \\ 5 \\ 2 \end{pmatrix},$$

so that agent 1 has the highest private utility gain from the policy change and agent 3 has the smallest. Restricting attention to agent 3, note that

$$\frac{\sum_{j\neq i} w_{ij}(u_j(g^1)-u_j(g^0))}{\sum_{j\neq i} w_{ij}} = \frac{0.3(u_1(g^1)-u_1(g^0))+0.3(u_2(g^1)-u_2(g^0))}{0.6} = 7.5$$

which is larger than agent 3's private value of the change, $(u_3(g^1) - u_3(g^0)) = 2$. According to the corollary, agent 3's social value of the change should exceed her private value, and this is indeed the case as can be observed when one computes the social values

$$\mathbf{W}(\mathbf{u}(g^1) - \mathbf{u}(g^0)) = \begin{pmatrix} 6.3 \\ 5.4 \\ 5.3 \end{pmatrix}.$$

The example highlights the importance of recognizing networks to study non-market values that are influenced by social interactions between agents. When eliciting valuations from a population, subjects naturally report their true values, which are their social values. Part of the variation in these values arises from heterogeneous private values, which may be correlated with individual characteristics. The variation in elicited values is also affected by the shape of the network, though, and so studies that ignore the nature of the network may be misspecified.

1.4 Networks and Aggregate Valuation

This section investigates economic welfare generated by the provision of a public good. It considers non-neutral networks in which at least one agent is not socially isolated ($\exists\lambda_i$ s.t. $\lambda_i > 0$) and at least two agents have different private utility functions ($\exists\{u_i, u_j\}$ s.t. $u_i \neq u_j$ for $i \neq j$). The following definitions of welfare are discussed.

Definition 1.3.

A. *Social network welfare is defined as* $\sum_i v_i$

B. *Social isolation welfare is defined as* $\sum_i u_i$

C. *Welfare neutrality is defined by* $\sum_i v_i = \sum_i u_i$

In non-neutral networks, v_i is typically different from u_i.[17] However, this may or may not have welfare implications. In some cases, network neutrality fails but welfare is unchanged such that the social network welfare is equal to the social isolation welfare. Hence, the existence of social network effects on the provision of public goods does not necessarily affect the population's welfare but may nevertheless reorganize the distribution of social utility. Agent importance (δ, defined in section 1.2) is a fundamental concept for our network welfare analysis. The following proposition characterizes welfare neutrality.

Proposition 1.3. (Welfare neutrality). *If every agent in the network has the same importance, then the social network welfare is equal to the social isolation welfare.*

It is important to acknowledge that the social network may have relevant individual welfare implications even in the environments covered by Proposition 1.3. The proposition states that there are populations in which the aggregate welfare generated by the provision of g is unaffected by the social structure. Under welfare neutrality, the social network acts as a smoothing operator, re-distributing utility among agents and decreasing well-being concentration. The following example provides an illustration.

Consider two separate populations of size $n = 3$ with identical private utility profies for the public good but different networks. In both cases the private utility

[17] Recall that according to definition 1.2, network neutrality implies that $v_i = u_i \ \forall i$. Throughout this work, we refer to non-neutral networks as the counterpart of the neutral networks presented in definition 1.2. Thus, we use the term "neutral networks" to refer to definition 1.2, and not to welfare neutrality as in definition 1.3C.

profile is $\mathbf{u} = (5, 10, 15)'$, for social isolation welfare, or aggregate private utility, of 30. The two different social structures are given by the induced network matrices

$$\mathbf{W_1} = \begin{pmatrix} 0.5 & 0.1 & 0.4 \\ 0.2 & 0.6 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{pmatrix}, \quad \text{and} \quad \mathbf{W_2} = \begin{pmatrix} 0.5 & 0.3 & 0.2 \\ 0 & 0.6 & 0.4 \\ 0.5 & 0.1 & 0.4 \end{pmatrix}.$$

Both populations are welfare neutral because in each of them every column sums to one. For the private utility profile $\mathbf{u}$ given above, the resulting social utility profiles are $\mathbf{v_1} = (9.5, 10.0, 10.5)'$ and $\mathbf{v_2} = (8.5, 12.0, 9.5)'$. Both of these have the same social network welfare, or aggregate social utility, of 30. This demonstrates welfare neutrality. Network neutrality does not hold, however, as can be seen by the fact that in both populations agent 1's social utility exceeds her private utility, and in both cases agent 3's private utility exceeds her social utility. Furthermore, even though the presence of welfare neutral network effects does not change the average utility of the group, it changes the distribution of utilities in a variety of ways. Network $\mathbf{W_1}$ preserves the median utility level at 10, but network $\mathbf{W_2}$ reduces the median to 9.5. This second network also changes the ordering of who gains the most utility, with agent 3 having the highest private utility level but agent 2 having the highest social utility level. Finally, the second network obviously generates a larger standard deviation of social utility than the first network, and both of these standard deviations are smaller than in the private utility profile.

The following definitions are used to discuss the aggregate value of public projects.

Definition 1.4.

A. *Aggregate network value is defined as* $C^{network} = \sum_i C_i^{network}$

B. *Aggregate private value is defined as* $C^{private} = \sum_i C_i^{private}$

C. *Aggregate valuation neutrality is defined by* $C^{network} = C^{private}$

As a consequence of proposition 1.3, valuation of public projects is independent of social structure when the population has a social network that is welfare neutral. The next corollary formalizes this result.

Corollary 1.3. (Aggregate valuation neutrality). *If welfare neutrality holds, then* $C^{network} = C^{private}$.

Corollary 1.3 provides sufficient conditions for aggregate valuation neutrality. It implies that in networks in which agents have the same importance, i.e. $\delta_1 = ... = \delta_n = 1$, the aggregate value of a public good can be measured by either $C^{network}$ or $C^{private}$. Aggregate valuation neutrality does not require individual valuation neutrality. In fact, in non-neutral networks, $C_i^{network}$ is typically different from $C_i^{private}$ even when $C^{network}$ is equivalent to $C^{private}$. Therefore, standard non-market valuation measures can be used if: i) welfare neutrality holds, *and* ii) the objective is to obtain a measure of aggregate willingness to pay *or* mean willingness to pay *and not* median willingness to pay. This can be highlighted with an example similar to the one above. Let

$$\mathbf{W} = \begin{pmatrix} 0.5 & 0.3 & 0.2 \\ 0 & 0.6 & 0.4 \\ 0.5 & 0.1 & 0.4 \end{pmatrix}.$$

This is the same as induced network $\mathbf{W_2}$ in the previous example. Let $\mathbf{u}(g^1) - \mathbf{u}(g^0) = (4, 12, 16)'$. Then $\mathbf{v}(g^1) - \mathbf{v}(g^0) = (8.8, 13.6, 9.6)'$. The aggregate network value and the aggregate private value are equal at 32, but every agent's valuation changes. Importantly, the median social valuation of 9.6 is lower than the median private valuation of 12, demonstrating that welfare neutral networks can change the quantiles of the valuation distribution even though they do not change the mean valuation.

The preceding results highlight when a network does or does not impact welfare, but they do not address how the network impacts aggregate welfare and aggregate valuation. To this end, we define welfare-increasing social networks as follows.

Definition 1.5. *A social network is welfare-increasing if* $\sum_i v_i > \sum_i u_i$.

To facilitate welfare comparisons, it is useful to write the social network welfare as a weighted sum of the private utilities of all agents with weights determined by the importance of agents as defined in Section 2:

$$\sum_j \delta_j u_j,$$

where δ_j is agent j's importance as presented in Definition 1.1, i.e. $\delta_j = \sum_i w_{ij}$. Index agents by increasing values of private utility such that agent 1 is the lowest private utility agent and agent n is the highest private utility agent. Hence, $\mathbf{u} = (u_1, ..., u_n)'$ is a sorted private utility profile such that $u_1 \leq u_2 \leq ... \leq u_n$. It is now easy to see that social network welfare increases as the importance of high private utility agents increases and, as a consequence, the importance of low private utility agents decreases. To formalize this intuition, define the *distribution of importance* as the vector $(\delta_1/n, ..., \delta_n/n)$. This is a distribution because, recalling that $0 < \delta_i < n$ for each i, every element in the distribution of importance lies between zero and one. With this in mind, the next proposition formalizes the idea that the network increases social welfare by shifting improtance to agents with higher private values of the public good.

Proposition 1.4. (Welfare-increasing networks). *For all sorted private utility profiles* $\mathbf{u}$*, if the distribution of importance of a network* $\mathbf{W}$ *first order stochastically dominates (FOSD) that of the social isolation case, then* $\mathbf{W}$ *is a welfare-increasing network.*

Under social isolation, the induced network $\mathbf{W}$ is equal to the identity matrix. As a result, every agent in the network has the same importance $\delta = 1$. Thus, if the network's distribution of importance FOSD the (social isolation) uniform distribution of importance, then the provision of a public good in the network will generate welfare greater than the sum of the private values. Proposition 1.4 has important implications as the welfare generated by the provision of a public good can be enhanced or diminished by social networks with the outcome depending on the distribution of importance.

One implication is that public goods policy should target high importance individuals. This view provides new insights to questions like "Should the government fund fine arts?". A traditional approach to this problem would consider the potentially high costs associated with benefits to a select group of individuals with significant high utility from fine arts. However, if these individuals are important (or popular) individuals in the social network, the positive externalities generated from these policies may justify such public investments.

Accordingly, Proposition 1.4 provides structure to the idea of opinion leadership, that is, the existence of agents who can facilitate change. For a given population governed by a given network, projects valued more highly by agents with higher importance tend to be the projects valued by the entire population. In extreme cases, efforts to undertake projects valued highly by the single individual with the greatest importance tend to be more successful than those valued negatively by that same individual. Thus, opinion leadership and importance are linked in our framework. This is consonant with the conclusions from Flores (2002) and Bergstrom (2006), highlighting the fact that social utility can play an important role in cost-benefit analysis. A public project may be Pareto improving even though the sum of private values is not large enough to justify the public investments. That Pareto improvement comes from the high private values of highly important agents, or opinion leaders.[18]

If the social network is capable of generating striking changes in social welfare, it is important to understand which types of network are more desirable. This is formalized in the next proposition that facilitates comparisons of networks focusing on social welfare.

Proposition 1.5. (Network welfare comparisons). *For all sorted private utility profiles* $\mathbf{u}$*, if the distribution of importance of a network* $\mathbf{W}$ *FOSD that of another network* $\mathbf{W'}$*, then* $\mathbf{W}$ *generates greater social network welfare than* $\mathbf{W'}$*.*

According to Proposition 1.5, a network that favors high private utility agents generates greater social network welfare than one that favors low private utility agents. The following example stresses the relevance of this result. Consider two

[18]These ideas in turn provide an intuitive rationale why, for example, the United Nations might name a Hollywood actress such as Angelina Jolie as a Goodwill Ambassador. Refer to http://www.unhcr.org/pages/49c3646c56.html. Accessed on October 26, 2011.

geographically separated populations of same size, with separated social networks but with identical private utility profile $\mathbf{u}$. Assume that a central planner has the resources to implement a public project in one of the two populations. In which population should the project be implemented? If the cost of implementation is the same in both populations, private benefit-cost analysis would indicate that the central planner should be indifferent between the two options. Social benefit-cost analysis leads to a different conclusion. Considering definition 1.3A of social network welfare, if the two populations have different social networks, the project should be implemented in the network that places more weight on agents with higher private utility. Corollary 1.4 considers network effects on aggregate valuation.

Corollary 1.4. (Network effects on aggregate valuation). *$C^{network} \geq C^{private}$ if and only if $\sum_i \left(\delta_i - 1\right)\left[(u_i(g^1) - u_i(g^0)\right] \geq 0$.*

The corollary indicates that a social network has positive effects on aggregate valuation when the weighted sum of private willingness to pay is positive, with the weights determined by deviations from the mean importance. Intuitively, the more the distribution of importance favors agents with high private valuation, the greater is the aggregate network valuation. This result has important implications.

For example, suppose the public project is one that targets the improvement of attributes of a beach frequented by n residents of a certain neighborhood. Suppose *few* residents are surfers. As committed surfers, they love to be at the beach and have high private willingness to pay for an increase in beach quality. Now suppose that these few surfers have several friends and, as a result, are very popular residents of this neighborhood. Moreover, assume that this is a high enough combination of popularity and private valuation such that corollary 1.4 holds. The consequence is that these few surfer residents may be responsible for a significant boost in the value of the public project making $C^{network} > C^{private}$. Now imagine that the surfers leave the neighborhood. Clearly, if high valuation agents are not considered, the aggregate value of the public project decreases. However, because of the network structure, the aggregate value may drop further. Shocks in the network can make second-order valuation effects (network effects) larger than first-order effects. As a consequence, the condition in corollary 1.4 may be no longer satisfied in a neighborhood without surfers. The example emphasizes how sensitive aggregate valuation can be to changes in social structure.

1.5 Conclusion

Directed altruism towards friends or joint consumption of public goods with friends are possibly two important reasons to consider social structure in non-market valuation approaches. The paper builds a network model for analyzing provisions of public goods accounting for the presence of social utility operating through social connections. The model assumes that individuals' private values are the ones that pertain in the absence of social network effects while social values weight own private utility and social utilities of friends. This framework allows us to study the effects of the shape of the connections on non-market values, holding constant the effect of network size.

Current research on public goods in networks study environments in which links are used to share non-excludable goods, i.e. local public goods. Differently, the focus of our research is not to study incentives problems related to the production of local public goods. Instead, we present a valuation model in social networks. The model delivers two measures of willingness to pay for an increase in the provision of public goods: willingness to pay under network interaction, a measure that accounts for the influence of connected friends and feedback effects; and standard willingness to pay in social isolation, a special case of the model that arises when the network structure is neutral.

By comparing these two measures, the paper demonstrates that non-market values can significantly be affected by social networks. For example, if the network is such that connections with high private utility agents are more intense, private willingness to pay understates the true value of non-market goods. However, if agents are equally "popular" in the social network, i.e. all agents receive the same amount of attention from their friends, the social structure may affect individual values but the overall welfare generated by the provision of the public good is the same of that generated in an environment of complete social isolation. We demonstrate that social welfare changes as a function of the distribution of popularity of agents in the network. When popular agents have high private valuation, the second-order (networks) effects have high impact on aggregate valuation.

The network model presented in this research can potentially guide empirical work. If the underlying consumption decisions involve considerations about the well-being of socially connected agents, conventional non-market valuation approaches may mislead econometric identification by not taking into account an important source of variation in the willingness to pay of agents: the social network. With network interaction, the value an individual attributes to a public good is a function of the values that friends attribute to the public good, and the value that friends attribute to the public good is a function of the individual's valuation. Manski (1993, 2000) refers to this as the *reflection problem*. If this is the case, the estimation of non-market values becomes even more challenging.[19]

Future empirical research should focus on the development of econometric models and survey techniques to facilitate estimation of non-market values accounting for the possible social network effects demonstrated in this paper. Future theoretical work should focus on generalizations of the analyzes developed in this research. These may include, for instance, the study of environments with multiple (substitute or complementary) public goods or the investigation of congestion effects.

[19]Readers interested in econometric identification of peer effects through social networks should refer to Bramoullé et al. (2009).

Chapter 2

Estimation of Non-market Values in the Presence of Social Network Effects: the Case of Advisory Referenda

2.1 Introduction

The ability to estimate non-market values has made economists a fundamental asset in formulating and analyzing public policies. It is common for policymakers to face choices that comprise trade-offs involving non-market goods. In such circumstances, the non-market valuation literature provides guidance to estimation of non-market values, which is essential to benefit-cost analyses.

Contingent valuation (CV) is often the only available approach to evaluate public projects. Using CV policymakers can study the provision of non-market goods in terms that are different from what is observed in revealed behavior data. Surveys allow researchers to create scenarios and obtain monetary values for different non-market goods, with different provision rules. This enables policymakers to design better projects, aiming at maximum welfare for a given budget constraint. As highlighted by Carson and Hanemann (2005, pg. 825), "much of the usefulness of conducting a CV study has nothing to do with explicitly obtaining an estimate of monetary value". They argue that CV data provide valuable information about the distribution of values of a public project, and how this distribution varies with variables such as demographics and characteristics of the project.

Under the simplest and most commonly used CV question format, the respondent is offered a binary choice between two alternatives. First, she can vote for maintaining the status quo policy. Second, she can vote in favor of an alternative policy at a specified cost. In addition to its simplicity, Carson and Groves (2007) demonstrate that under certain assumptions dichotomous-choice questions framed as referendum vote have desirable properties of incentive compatibility.[1]

Two frameworks provide the econometric foundation for dichotomous choice CV. Hanemann (1984) and Hanemann and Kanninen (1996) develop random utility models (RUM) based on differences in the indirect utility functions, comparing utility before and after the proposed policy.[2] Cameron and James (1987) and Cameron (1988) construct random willingness to pay (WTP) models based on differences in the expenditure function.[3] McConnell (1990) demonstrates that, under a reasonable set of assumptions, these frameworks are dual to one another.

The utility-theoretic interpretation of the yes/no responses in both RUM and WTP frameworks are constructed based on agents in social isolation. However, Chapter 1 develops a utility-based model in which the value of non-market goods can be affected by characteristics of the respondents' social network. If a respondent is altruistic and cares about non-market goods that benefit her friends, the utility of friends will influence the respondent's voting decision in a CV survey. Similarly,

[1] The literature early on recognizes advantages of the binary choice format. The Gibbard-Satterwaite theorem states that multinomial choice questions (i.e. the respondent is offered $k > 2$ alternatives) can not be incentive compatible without placing restrictions on the respondent's utility (see Gibbard (1973) and Satterthwaite (1975)).

[2] This approach is often referred to as the Hanemann's approach.

[3] This approach is often referred to as the Cameron's approach.

friends may also be altruistic and the utility of friends of friends may influence the voting behavior of the respondent's friends. This leads to network effects.[4]

The social structure of the population of interest can be an important determinant of the shape of the WTP distribution. With social network effects, a respondent's vote is influenced by her friends' votes. Her friends' votes, in turn, are influenced by the respondent's vote. This generates a reflection problem (see Manski (1993, 2000)). Therefore, an approach to recover non-market values from yes/no CV responses must be based on the estimation of a discrete choice model with network dependence. This issue has been, however, overlooked by the empirical non-market valuation literature.

This paper investigates the consequences of ignoring social network effects for dichotomous choice CV. We built on the work of Cameron and James (1987) to develop a random WTP model with social networks.[5] The model is directly related to the theory developed in Chapter 1. It can be easily shown that a standard WTP model utilized in Cameron-like approaches is a especial case of the more general network formulation developed in this paper. Our econometric specification is similar to a spatial autoregressive dependent variable model (SAL). The model is constructed by replacing the traditional weighting matrix of a spatial econometric model, usually assumed to be a distance matrix, by a row stochastic matrix that represents the social network.

The main result of the paper is that, in the presence of social network effects, standard dichotomous choice estimation approaches are inconsistent. Specifically, when utilities are influenced by social networks, the standard RUM and WTP models are misspecified. Hence, maximum likelihood estimation of the parameters of these models is inconsistent because estimation is based on a misspecified likelihood

[4]As discussed in Chapter 1, altruism is only one possible channel for the interdependence of respondents' utilities. Another reason might be joint consumption. If the utility of consuming a good in social isolation is different from the utility of consuming the same good with friends, joint consumption may also lead to network effects.

[5]Our econometric model builds on Cameron's expenditure difference formulation of dichotomous choice responses, however, the results can be extended to Hanemann's utility difference formulation.

function. The inconsistency arises from the heteroskedasticity induced by the network dependence in the discrete choice model.

If social networks are an important determinant of WTP, then estimation of non-market values is more challenging than is currently believed to be. A proper valuation approach must account for the heteroskedasticity induced by the network dependence. Moreover, for efficiency to be achieved, estimation must also use all the information contained in the non-diagonal variance-covariance structure of network models.[6]

The paper reports results of a Monte Carlo experiment designed to explore how the bias of standard approaches is influenced by characteristics of the social network and the intensity of the network effect. In an initial control simulation without network effects we find that the traditional mean WTP estimation is indeed consistent. Next, we find that when WTP is influenced by Erdos-Renyi networks, the performance of the standard estimation approach is negatively affected by the strength of the network effect, but is not influenced by the density of the network. We also find that, in networks with high correlation between respondents' importance (i.e. a measure of "popularity" of respondents) and private WTP, the estimation bias is very sensitive to strong network effects. Specifically, the coefficient of variation of of the distribution of traditional estimates of mean WTP is 308% in such an environment. Finally, the experiment shows that traditional mean WTP estimates are not reliable when the data is generated using real world social networks. We use data collected by Banerjee et al. (2011) of social networks in three rural villages of India to perform three Monte Carlo experiments. We find that, although the standard approach is theoretically inconsistent, it performs relatively well for simulations with villages 1 and 2. However, the distribution of estimated mean WTP shifts to the left when the network of village 3 generates the data. Network-level statistics are not able to explain this phenomenon. Further research is needed to formally identify the effects

[6]Refer to Fleming (2004) for a detailed discussion about spatial models with binary dependent variable. Refer to Bramoullé et al. (2009) for estimation of network models with continuous dependent variable.

of the characteristics of real world social networks on standard estimates of mean WTP.

Our results indicate that social networks place an additional layer of complexity to benefit transfer. With social network effects, the welfare generated by non-market goods provision takes place in the context of a particular social structure. A similar public project in a different location will probably be implemented in a very different social network. This type of difficulty is usually associated with revealed preference studies (because observed behavior is a function of the market structure) and should also be recognized in CV studies.

The remainder of the paper is organized as follows. Section 2.2 presents a network model of random willingness to pay. Section 2.3 discusses the consequences of ignoring social networks in dichotomous choice CV. Section 2.4 provides a Monte-Carlo investigation. Section 2.5 concludes.

2.2 A Stochastic Model of Willingness to Pay in Social Networks

There are n agents arranged in a social network. Let $\mathbf{A}$ be an $n \times n$ row stochastic matrix that represents the network. Diagonal elements of $\mathbf{A}$ are equal to zero while off-diagonal elements are either $a_{ij} \neq 0$, if agent i is influenced by agent j, or $a_{ij} = 0$ otherwise. An element a_{ij} (for $i \neq j$) is the weight of i's social connection to agent j. Notice that symmetry of $\mathbf{A}$ (typically assumed in spatial models) is not required, hence, $\mathbf{A}$ denotes a directed network.[7]

Agents have utility over a non-market good that is provided to the entire network. The goal is to evaluate a public project that yields a discrete increase in the provision

[7] In spatial models, the matrix $\mathbf{A}$ define the spatial lags of the left-hand side variable and it is typically assumed to be row stochastic and symmetric, e.g. a matrix of relative distances (see LeSage (1999)).

of this non-market good. Assume that the willingness to pay for the public project is given by

$$\mathbf{WTP}^* = \alpha\mathbf{i} + \mathbf{X}\gamma + \beta\mathbf{A}\,\mathbf{WTP}^* + \epsilon, \tag{2.1}$$

where $\mathbf{WTP}^*$ is an $n \times 1$ vector of unobserved willingness to pay, $\mathbf{i}$ is an $n \times 1$ vector of ones, $\mathbf{X}$ is an $n \times k$ matrix of k exogenous variables, and ϵ is an $n \times 1$ vector of i.i.d. normal errors, i.e. $\epsilon \overset{iid}{\sim} N(0, \sigma_\epsilon^2)$.[8] The i-th row of $\mathbf{A}\,\mathbf{WTP}^*$ is a weighted average of i's connected agents' willingness to pay. The intercept of the model is α. γ is a $k \times 1$ parameter vector that captures the effects of the agents' own characteristics $\mathbf{X}$ on $\mathbf{WTP}$. β is the network effect parameter that captures the effect of connected agents' $\mathbf{WTP}$ on own $\mathbf{WTP}$.

The random WTP model is closely related to the network model developed in Chapter 1. To see this, recall that the respondents' social utility profile under the status quo provision level of the public good (g^0) is

$$\mathbf{v}(g^0) = (\mathbf{I} - \mathbf{\Lambda})\mathbf{u}(g^0) + \mathbf{\Lambda}\mathbf{A}\mathbf{v}(g^0), \tag{2.2}$$

and the social utility profile under the policy provision level of the public good (g^1) is

$$\mathbf{v}(g^1) = (\mathbf{I} - \mathbf{\Lambda})\mathbf{u}(g^1) + \mathbf{\Lambda}\mathbf{A}\mathbf{v}(g^1). \tag{2.3}$$

Subtracting (2.2) from (2.3) we obtain

$$\mathbf{C}^{netwotk} = (\mathbf{I} - \mathbf{\Lambda})\mathbf{C}^{private} + \mathbf{\Lambda}\mathbf{A}\mathbf{C}^{network}.$$

The deterministic term $\alpha\mathbf{i} + \mathbf{X}\gamma$ in equation (2.1) corresponds to private WTP. The innovation of model (2.1) is the introduction of the network term $\beta\mathbf{A}\,\mathbf{WTP}^*$

[8] We assume strict exogeneity of $\mathbf{X}$, i.e. $\mathrm{E}(\epsilon|\mathbf{X}) = 0$.

that predicts the impact of connected agents on own valuation. A hypothesis test of the null $H_0 : \beta = 0$ is an empirical test of the existence of social network effects.[9]

Policymakers are interested in estimates of $\boldsymbol{\theta} = (\alpha, \gamma, \beta)$ to better design policy. Features of the public project are often included in $\mathbf{X}$ along with respondents' characteristics. With dichotomous choice CV, the econometrician does not observe WTP. Thus, estimates of $\boldsymbol{\theta}$ are obtained through observed voting behavior on "take-it-or-leave-it" survey questions. Assuming that the structural model (2.1) determines WTP, section 2.3 discusses the properties of estimates of $\boldsymbol{\theta}$ when estimation is guided by the standard WTP approach that does not account for social network effects.

2.3 Consequences of Ignoring Network Effects

The structural model (2.1) describes a respondent's latent WTP. Yes/no survey responses are, however, determined by the reduced form of model (2.1). The reduced form equation is

$$\mathbf{WTP}^* = (\mathbf{I} - \beta\mathbf{A})^{\mathbf{-1}}\alpha\mathbf{i} + (\mathbf{I} - \beta\mathbf{A})^{\mathbf{-1}}\mathbf{X}\gamma + \eta \tag{2.4}$$

where $\eta = (\mathbf{I} - \beta\mathbf{A})^{-1}\epsilon$. We make the standard assumption that $\mid \beta \mid < 1$, thus, the matrix ($\mathbf{I}$ - $\beta\mathbf{A}$) is invertible.[10]

The paper focuses on the expenditure difference formulation of dichotomous choice responses (Cameron's approach), however our results can be extended to the utility difference formulation (Hanemann's approach). In a dichotomous choice study we present respondent i with a "take-it-or-leave-it" offer to vote yes or no for the public

[9]Notice that the econometric model does not impose the restriction that $\alpha+\gamma+\beta = 1$. This cannot be done because $\mathbf{WTP}^*$ is measured in dollars and $\mathbf{X}$ is not. Hence, β should not be interpreted as the average degree of social interaction of the population (the parameter λ of Chapter 1). In fact, a situation in which β is negative is possible and represents environments in which friends negatively affect social WTP, possibly leading to a situation in which WTP in social isolation is greater than WTP under network interaction.

[10]If $\mid \beta \mid < 1$, then $(\mathbf{I} - \beta\mathbf{A})$ is a strictly diagonally dominant matrix and, by the Levy-Desplanques theorem, cannot be singular (see Taussky (1949), Theorem I).

project at cost t_i. Assuming that respondents truthfully answer the survey we observe the following data.

$$y_i = \begin{cases} 1 & \text{if} \quad WTP_i^* \geq t_i \\ 0 & \text{if} \quad WTP_i^* < t_i \end{cases}$$

The marginal probabilities are obtained as follows.

$$\begin{aligned} Prob\Big(y_i = 1|\mathbf{X}\Big) &= Prob\Big(\big[(\mathbf{I}-\beta\mathbf{A})^{-1}\alpha\mathbf{i}\big]_i + \big[(\mathbf{I}-\beta\mathbf{A})^{-1}\mathbf{X}\gamma\big]_i + \eta_i > t_i\Big) \\ &= Prob\Big(\eta_i > t_i - \big[(\mathbf{I}-\beta\mathbf{A})^{-1}\alpha\mathbf{i}\big]_i - \big[(\mathbf{I}-\beta\mathbf{A})^{-1}\mathbf{X}\gamma\big]_i\Big) \end{aligned} \tag{2.5}$$

The network effect introduces an interdependence in WTP_i^* and, as a result, the reduced form error η is distributed by a n-dimensional multivariate normal, with mean zero and variance-covariance matrix equal to

$$E(\eta\eta') = (\mathbf{I}-\beta\mathbf{A})^{-1}(\mathbf{I}-\beta\mathbf{A})^{-1\prime}\sigma_\epsilon^2. \tag{2.6}$$

Denote the i-th diagonal element of (2.6) as $\sigma_{\eta i}^2(\beta)$, and construct the standardized variable $z_i = \eta_i/\sigma_{\eta i}^2(\beta)$. We can re-write (2.5) as

$$Prob\Big(y_i = 1|\mathbf{X}\Big) = Prob\Big(z_i > \frac{t_i - \big[(\mathbf{I}-\beta\mathbf{A})^{-1}\alpha\mathbf{i}\big]_i - \big[(\mathbf{I}-\beta\mathbf{A})^{-1}\mathbf{X}\gamma\big]_i}{\sigma_{\eta i}^2(\beta)}\Big) \tag{2.7}$$

Equation (2.7) highlights the econometric challenge of the estimation of $\boldsymbol{\theta}$. With no network effects ($\beta = 0$) equation (2.7) simplifies to

$$Prob\Big(y_i = 1|\mathbf{X}\Big) = Prob\Big(z_i' > \frac{t_i - \big[\alpha\mathbf{i} - \mathbf{X}\gamma\big]_i}{\sigma_\epsilon^2}\Big), \tag{2.8}$$

where $z_i' = \epsilon_i/\sigma_\epsilon^2$ is the standard normal random variable. Equation (2.8) is the basis for estimation of WTP through standard maximum likelihood approaches. However, the procedure is based on the diagonal variance-covariance matrix $\sigma_\epsilon^2\mathbf{I}$.

With independent errors, the likelihood of observing the data is

$$\Pi_{i=1}^{n} \int_{-\infty}^{a_i} \phi(z_i) dz_i, \tag{2.9}$$

where ϕ is the standard normal pdf, and $a_i = [1 - 2y_i][t_i - (\alpha\mathbf{i} - \mathbf{X}\gamma)_i]/\sigma_\epsilon$.

The variance-covariance matrix of the model is described by (2.6) when there are network effects. The off-diagonal elements of $\mathrm{E}(\eta\eta')$ are not zero, errors are correlated and distributed according to a n-dimensional normal. The likelihood of observing the data is now

$$\int_{-\infty}^{a_1} ... \int_{-\infty}^{a_n} f(\mathbf{z}) d\mathbf{z}, \tag{2.10}$$

where f is the multivariate normal governing $\mathbf{z}$.[11]

In summary, the reduced form model that explains yes/no responses has a heteroskedastic error term. The heteroskedasticity is induced by the social network structure. This leads to the paper's proposition.

Proposition 2.1. *If respondents consider their social networks when valuing public projects (i.e. $\beta \neq 0$), then the standard approach for estimation of non-market values is inconsistent.*

Proof. Standard estimation uses optimization techniques to maximize the logarithm of the likelihood function (2.9). The log-likelihood function is

$$\mathcal{L} = \sum_{i=1}^{n} \Big\{ y_i \log\Big[1 - \Phi\Big((t_i - \big[\alpha\mathbf{i} - \mathbf{X}\gamma\big]_i)/\sigma_\epsilon\Big)\Big] + (1 - y_i)\log\Big[\Phi\Big((t_i - \big[\alpha\mathbf{i} - \mathbf{X}\gamma\big]_i)/\sigma_\epsilon\Big)\Big]\Big\},$$

where Φ is the standard normal cdf. However, with network effects, i.e. $\beta \neq 0$, the function $\mathcal{L}$ is misspecified and estimation must be based on (2.10), and not on (2.9). □

In words, the network structure introduces heteroskedasticity to the WTP model. Hence, standard approaches that ignore network effects are inappropriate for

[11]Refer to Fleming (2004) for additional details.

estimation of $\boldsymbol{\theta}$ because they are not robust to unspecified heteroskedasticity. Clearly, estimates of mean WTP are also inconsistent. Two facts make this an unsettling result. First, to the best of our knowledge, the CV literature has failed to attempt estimation of non-market values accounting for social network effects. Second, the norm of the profession is to perform CV using dichotomous choice data given the incentive compatibility properties of this elicitation mechanism.

The paper's proposition implies that estimation of non-market values based on dichotomous choice data must use techniques for estimating spatially dependent discrete choice models.[12] In general, these estimators can be divided in two major groups: heteroskedastic estimators, and full information estimators. Heteroskedastic estimators address the spatial (or network) dependence issue and provide consistent estimates of the parameters of the likelihood function. However, consistency relies on the assumption that the off-diagonal elements of the variance-covariance matrix are zero.

Full spatial information estimators account for the off-diagonal variance-covariance terms. These terms are usually not zero in real-world applications with complex social networks. This highlights a major practical difference between maximum likelihood estimation with and without networks. The variance structure of the network model does not allow the simplification of the multivariate normal into the product of univariate normal distributions. Valuation of the likelihood function is complex because involves integrating the joint distribution over n dimensions.

According to Proposition 2.1, standard estimation approaches deliver inconsistent estimates of mean WTP when non-market values are influenced by social networks. Since the dichotomous choice elicitation format has been so widely used, it is important to understand how the structure of a network influences traditional estimates. Next section investigates this question.

[12] Refer to LeSage (1999), Fleming (2004), and Franzese Jr and Hays (2008) for a discussion of the estimation challenges related to discrete choice models with spatial dependence.

2.4 Monte Carlo Experiments

The Monte Carlo experiments examine the random WTP model (2.1). Our goal is to explore the performance of standard estimation approaches when the social network term $\beta\mathbf{AY}^*$ is ignored. To do this, we estimate mean WTP using a maximum likelihood probit regression model as discussed by Cameron and James (1987). The dependent variable is a binary indicator for the yes/no response. The policy cost is included on the right hand side among the explanatory variables $\mathbf{X}$. The parameters of the latent WTP model are recovered from the probit estimates as demonstrated by Cameron and James (1987).

We expect that the standard estimation approach performs poorly when $\beta \neq 0$ and delivers inconsistent estimates of mean WTP (see proposition 2.1). Our Monte Carlo experiments aim to explore how the WTP bias reacts to changes in the strength of the network effect, β, and to changes of the type of network structure.

The setup of each Monte Carlo experiment is the following. We consider a population of size $n = 300$. We use the reduced form equation (2.4) to construct a vector of "true" WTP (i.e. a vector in which element i is the WTP of respondent i). Next, we generate 1000 Monte Carlo samples by re-sampling the error term (the Monte Carlo samples are replications of the "true" model). We use the standard approach to estimate mean WTP in each Monte Carlo sample. Specifically, for every replication $j = 1, ..., 1000$, each respondent $i = 1, ..., 300$ votes yes or no for the project at cost t_i. A "yes" response ($y_i = 1$) is observed if $WTP_i \geq t_i$, "no" ($y_i = 0$) is observed otherwise. The cost t_i faced by respondent i is randomly selected from the set of the deciles of the original "true" WTP distribution.

The variables of the right hand side of equation (2.4) are determined as follows. For simplicity, $\mathbf{X}$ is assumed to be a single variable. The explanatory variable is constructed to be orthogonal to the error term ϵ and the network matrix $\mathbf{A}$ as follows. Define $\tilde{\mathbf{X}}$ as a vector with elements increasing in equal increments from $\tilde{X}_1 = 0$ to

$\tilde{X}_n = 1$. The vector $\mathbf{X}$ is a scrambled version of the vector $\tilde{\mathbf{X}}$. The same vector $\mathbf{X}$ is used in every Monte Carlo sample.

The parameters values are fixed as follows.

$$\alpha = 2 \qquad\qquad \gamma = 4$$

This implies that the deterministic part of the unobserved WTP (i.e. $\alpha\mathbf{i}+\mathbf{X}\gamma$) ranges from \$2 to \$6. We explore four values for β. First we assume $\beta = 0$ representing no network effects. We expect the standard approach to perform very well in this model. Next we set β equal to 0.25, 0.50, and 0.75, representing environments of increasing social network effects.

Three types of networks are explored. First we study Erdos-Renyi networks in which links are i.i.d. and each pair of respondents is connected with fixed probability d. Second we explore networks with a strong correlation between private WTP and respondents' "popularity" (i.e. agent importance in Chapter 1). Finally, we investigate estimation of WTP using real-world social network data collected by Banerjee et al. (2011).

As a result, we perform 37 Monte Carlo experiments. The number of experiments is determined by the number of networks (eight in section 2.4.1, one in section 2.4.2, and three in section 2.4.3) and the number of βs (0, 0.25, 0.50, and 0.75). Hence, 37 vectors of "true" WTP are generated according to the reduced form equation (2.4).[13] The same vector of errors ϵ, with elements drawn independently from a standard normal distribution, is used to construct the "true" WTP vector of all experiments. Therefore, as previously described, we generate 1000 Monte Carlo samples for each one of the 37 experiments. The size of each sample is equal to $n = 300$. We construct these samples by re-drawing 1000 vectors ϵ. We use the same 1000 error vectors, together with the fixed vector $\mathbf{X}$, in all experiments. Hence, the differences between the experiments come exclusively from variations of β and $\mathbf{A}$.

[13] Number of experiments is equal to the number of networks (12) times the number of βs that are different from zero (3), plus the model with no network effect ($\beta = 0$).

To evaluate the performance of the standard approach we first compute the mean WTP Root-Mean-Square-Error (RMSE). For each Monte Carlo experiment, the RMSE is computed as

$$RMSE = \sqrt{\frac{\sum_{j=1}^{r}\left(\widehat{E[WTP]}_j - E[WTP]\right)^2}{r}},$$

where r is the number of Monte Carlo samples (or replications), $\widehat{E[WTP]}_j$ is the standard prediction about mean WTP in replication j, and E[WTP] is the "true" mean WTP. Specifically, the WTP prediction is given by

$$\widehat{E[WTP]}_j = \frac{\sum_{i=1}^{n}\widehat{WTP}_{ij}}{n},$$

where $\widehat{WTP}_{ij}$ is the estimate of WTP of respondent i in replication j.[14] The RMSE is measured in dollar units and can, therefore, be directly compared with the "true" mean WTP. The normalization RMSE/E[WTP] is particularly informative and measures the average bias of the standard approach in percentage terms. We refer to this value as the *coefficient of variation* of the distribution of estimated WTP.

Let us first evaluate the performance of the traditional estimator when $\beta = 0$. In this case, there is no network effect and the likelihood function is correctly specified. Figure B.1 presents the kernel density function of the $\widehat{E[WTP]}$ obtained through the $r = 1000$ trials. The vertical line denotes the "true" value of mean WTP. As expected, the standard estimator performs well and the coefficient of variation is only 0.0323, i.e. less than 5%. Bellow we examine situations in which $\beta \neq 0$.

[14] WTP_{ij} is obtained by plugging the estimates of $\boldsymbol{\theta}$ in equation (2.4) and taking the conditional expectation. Notice that even thought η has a complex variance structure, η is a mean zero error.

2.4.1 Erdos-Renyi Networks

Erdos-Renyi networks are a natural starting point for the simulations with $\beta \neq 0$. These networks assume that there is a fixed set of nodes (i.e. $n = 300$). Each link is formed with a given probability d, and the formation of links is independent. Let the network *density* be the ratio of actual number of links over the maximum possible number of links (i.e. the relative fraction of existing links). Clearly, the expected density of Erdos-Renyi networks is equal to the probability of connection d.

We perform 24 simulations using Erdos-Renyi networks.[15] We explore four low density networks (d equal to 0.025, 0.050, 0.075, and 0.1), and four high density networks (d equal to 0.2, 0.4, 0.6, and 0.8). Table B.1 presents the coefficient of variation of the empirical distribution of $E\widehat{[WTP]}$. Our simulations show that the coefficients of variation hover around 3% when there is a small network effect of $\beta = 0.25$. This result indicates that, when links are independently formed with fixed probability, the standard estimation approach, although theoretically inconsistent, performs remarkably well. In fact, the kernel densities displayed in the first column of Figures B.2 and B.3 (in the appendix) are similar to the density shown in Figure B.1, in which the data generating process has no network effects.

The performance of standard approach is, however, unsatisfactory when β increases to 0.50. The coefficients of variation are approximately 13%. Moreover, the kernel densities peak to the left of the true mean WTP suggesting that the standard approach underestimates mean WTP (see second column of Figures B.2 and B.3). The negative bias is also observed in the Monte Carlo samples with $\beta = 0.75$. In strong network effect conditions, the coefficients of variation are enormous, reaching 123% when $d = 0.6$. The network density seems to have no impact on the mean WTP bias for conditions with $\beta = 0.25$ and $\beta = 0.50$. There is significant fluctuation in the coefficients of variation of the different density simulations when $\beta = 0.75$. However, it is hard to identify a pattern between network density and these errors.

[15] We use 8 networks and 3 βs, totaling 24 simulations.

2.4.2 Matching Importance and Private WTP

In this section, the explanatory variable is constructed to be correlated with the column sums of the network matrix $\mathbf{A}$ as follows. The right hand side variable $\mathbf{X}$ equals $\tilde{\mathbf{X}}$, i.e. a $(n \times 1)$ vector with elements increasing in equal increments from 0 to 1. Links within columns of the network $\mathbf{A}$ are formed with independent probability. The probability of a link in the first column of $\mathbf{A}$ is equal to $X_1 = 0$, the probability of a link in the second column of $\mathbf{A}$ is equal to $X_2 = 0.0033$, the probability of a link in the third column of $\mathbf{A}$ is equal to $X_3 = 0.0066$, and so on. In the last column, the probability of a link is equal to $X_{300} = 1$. The expected density in this network is 0.5. Clearly, there is a strong positive correlation between $\mathbf{X}$ and the importance of respondents. Figure B.4 demonstrates this correlation.

Results again indicate that the performance of the standard approach is satisfactory when $\beta = 0.25$ (see Figure B.5). The distribution of estimated mean WTP is centered around the true value, and the coefficient of variation is again 3%. As in Erdos-Renyi networks, the performance suffers when β increases. The coefficient of variation increases to 8% when $\beta = 0.50$, and to an impressive 308% when $\beta = 0.75$. This result suggests that a strong correlation between respondents' importance and respondents' exogenous characteristics significantly affects the performance of standard approaches in environments with strong network effects.

2.4.3 A Real World Social Network

This section uses real network data collected by Banerjee et al. (2011) and made available by the authors online.[16] The data was obtained from a survey of social networks in rural villages of southern Karnataka, a state in India. Individuals were asked detailed questions about the relationships they had with others in the village. This information enables the construction of network graphs for each village.[17] This

[16]Data source: http://dvn.iq.harvard.edu/dvn/dv/jpal/faces/study/StudyPage.xhtml?globalId=hdl:1902.1/16559.

[17]Refer to Banerjee et al. (2011) for a detalied description of the data.

section uses data on the first three villages of the dataset. We denote these villages as Village 1 ($n_1 = 182$ respondents), Village 2 ($n_2 = 195$ respondents), and Village 3 ($n_3 = 292$ respondents). Table B.2 presents characteristics of these networks.[18]

Figures B.6, B.7, and B.8 confirm that the standard approach is able to deliver robust estimates in a model with small network effects. When $\beta = 0.25$, the coefficients of variation are below 5% for the Monte Carlo simulations of all three villages. In Village 1, the coefficients of variation are below 10% even when β is high. In Village 2, the coefficient of variation is a little above 10% for $\beta = 0.75$. In general, the kernel densities of both villages are centered and the performance of the traditional mean WTP estimator is relatively good. This is not the case with data from Village 3. The mode of the estimated mean WTP distributions for the models with $\beta = 0.5$ and $\beta = 0.75$ are located significantly to the left of the true mean WTP. The coefficient of variation for $\beta = 0.5$ is 14% and for $\beta = 0.75$ is 52%. This result demonstrate how unpredictable the theoretical bias of the standard estimator is when WTP is influenced by real world social networks. Drawing conclusions from the network measures of Table B.2, one would think that the bias increases with the size of the real world network, and decreases with their transitivity. We are, however, unable to draw firm conclusions from only three networks. Future work is needed to explore this issue. For instance, with more network data, identification of the sensitivity of the standard approach to the network can be accomplished with a regression of the coefficient of variation on characteristics of the networks.

[18] A *node* corresponds to a respondent. The *degree* of a node is the number of connections of the node. The *average path length* is the average distance between any two nodes in the network. The *betweenness* centrality captures how important a node is in terms of connecting other nodes. The *closeness* centrality tracks how easily a node can reach other nodes. The *density* is the average degree divided by $n-1$. The *transitivity* measures the probability that the adjacent nodes of a node are connected. The *diameter* of a network is the largest distance between any two nodes. Refer to Jackson (2008) for a detailed explanation of these network measures.

2.5 Conclusion

There is empirical evidence suggesting that social utility may be an important component of non-market values.[19] Social networks are natural channels for social preferences to operate through. However, current stated preference approaches to estimation of non-market values do not explicitly accommodate possible social network effects.

This paper builds a network model of random willingness to pay to discuss the consequences of ignoring social network effects in standard approaches for estimation of non-market values using dichotomous choice data. In our framework, the probability of yes/no response is governed by the reduced form equation of the WTP model with networks. The econometric challenge is that, with network effects, the error term of the reduced form model is not homoscedastic. In fact, the variance-covariance matrix of the reduced form model is not diagonal. The reduced form errors are not independent even when the error term of the structural model is homoscedastic and not correlated. This complex variance-covariance matrix structure is induced by the social network that correlates the WTP of a respondent to that of her friends.

We use Monte Carlo experiments to investigate the performance of standard approaches when the data generating process involves a network. We find that the density of Erdos-Renyi networks does not influence the bias of traditional estimates. Also, when respondents' importance is correlated with private WTP, estimates from the traditional approach that ignores the network structure have coefficients of variation that can reach 308% of the true WTP value. In addition, standard approaches are not reliable when the simulations use data collected by Banerjee et al. (2011) on social networks of three villages in rural India. Finally, in all simulations, the bias monotonically increases with the strength of the network effect.

[19] For instance, McConnell (1977) finds that lot of teenagers at a beach make it more attractive to other teenagers. Timmins and Murdock (2007) show that ignoring congestion leads to an understatement of more than 50% of the value of a recreation fishing site. Morey and Kritzberg (2010) use a choice experiment to demonstrate that the presence of a companion can significantly change the value of mountain bike trails.

With social network effects, the characteristics of the reduced form error term invalidate maximum likelihood estimation based on standard probit or logit models. This presents a great challenge for welfare analysis. Contingent valuation approaches are valuable because they provide rich information about the distribution of WTP. Clearly, a better understanding of the WTP variation allows policymakers to design better public projects. However, failure to account for network effects in the widely used probit models make it impossible to consistently estimate marginal effects. Future work should focus on the development of estimation approaches to overcome these difficulties, allowing researchers to rely on data from the mostly used CV elicitation format even when responses are influenced by social network effects.

Chapter 3

Added Surplus and Lost Bargaining Power in Long-term Contracting: An Experimental Investigation

3.1 Introduction

When a firm signs a long-term contract for a building or design project, two things happen. On the positive side, the long-term relationship allows the linked parties to make relationship-specific investments that can increase the joint surplus they share. On the negative side, the long-term contract changes the nature of the bargaining game the parties face over any subsequent increases in that surplus. This alteration in the bargaining game can account for why, once the contract is signed, any changes in the output are more expensive than they would have been before the contract was signed. The contract transfers bargaining power to the vendor, who then receives a disproportionate share of any additional surplus.

This trade-off between surplus gains and bargaining power loss is especially acute in military procurement, where large weapons systems require long development processes and frequent changes. Examples abound of projects with long delays and huge cost overruns, with final price tags often amounting to non-trivial multiples of the original estimates. The US Department of Defense recognizes the problems inherent in signing long-term contracts, and its regulations specifically state that before a multiyear procurement contract can be signed the military must show evidence that a multiyear contract will lead to substantial savings over a series of single-year contracts, that the requirements, funding, and design are all stable, and that the cost estimates are realistic.[1] In other words, the Department of Defense seeks to limit long-term contracts to situations in which the gains from increased surplus can be realized but where the loss of bargaining power will not come into play.

The purpose of this paper is to explore the trade-off between increased surplus and altered bargaining power in long-term contracts. We report results of an experiment designed to capture these two features of the contracting environment. The experiment involves two players. Player A takes the role of the procurer and player B takes the role of the vendor in a two-period procurement process. Player A initially makes a choice between a long-term contract or a sequence of two short-term contracts. At the time of player A's choice, both players know how much surplus will be generated under the short-term and long-term contracts. Under the short-term contract the players will bargain over two \$20 surplus amounts using ultimatum bargaining with player B making the offer. Under the long-term contract the players will bargain once over some other fixed and known amount, ranging from \$30 to \$50, using a dictator game with a restricted offer space and player B again making the offer. So, in choosing the long-term contract player A loses bargaining power by switching from being the receiver in two ultimatum games to being the receiver in a single dictator game, but also changes the surplus to be shared, in some treatments increasing it by \$10.

[1] See GAO (2009), available at www.gao.gov/assets/290/287947.pdf .

The paper investigates whether the changes in bargaining power lead to welfare losses in the sense that the procurer foregoes additional surplus in order to retain bargaining power. The results are striking. Three quarters of subjects give up the additional \$10 surplus (i.e. an increase of 25% of the surplus to be shared) when obtaining it requires moving to a standard, unconstrained dictator game. Even when the dictator offers are constrained so that the recipient is guaranteed at least \$10 from the \$50 dictator endowment, half of the subjects still opt for the greater bargaining power provided by the two \$20 ultimatum games. This result is especially notable when one considers that the ultimatum game offers only very weak bargaining power, as the standard game theoretic solution suggests that the receiver earns \$0 in both the ultimatum and the unconstrained dictator games.

The game as designed has a gift exchange component. To understand how, consider player A's choice between playing the dictator game or the two ultimatum games. Choosing the dictator game constitutes a gift to player B in that player A cedes the right to reject player B's offer, giving player B more freedom to take a larger share of the endowment. If player B is reciprocal, player B might make a higher offer to A in the dictator game than in the two ultimatum games. Moreover, if the dictator game is a gift from player A to player B, the size of the gift increases with the endowment received by player B, and decreases with the minimum allowable offer in the constrained dictator games. We find mixed evidence that reciprocity is organizing the data. Player A chooses the dictator game more often when the surplus grows from \$30 to \$50, however this may also be a reflect of efficiency preferences. Moreover, player A is more likely to choose the dictator game when the minimum-allowable offer is higher. These results suggest that the bargaining power obtained by player A through the constraint on player B's offer crowds-out any reciprocity motivation that player A might have. In fact, player A's average payoff is higher with the sequence of two ultimatum games demonstrating that possible reciprocity beliefs are misplaced.

The paper relates to an established literature on contracting structures and efficiency. Klein, Crawford, and Alchian (1978) and Williamson (1983) conclude that long-term contracts provide the incentive for more efficient relationship-specific investment by reducing the possibility of ex post opportunism behavior or the holdup problem. Crawford (1988) writes a model in which parties have perfect information and perfect foresight, however, short-term contracts must be voluntarily negotiated in the bargaining environments created by earlier contracts. Crawford shows that a sequence of short-term contracts distorts investment decisions only when the efficient investment plan involves mainly sunk-costs and the relationship plays a consumption-smoothing role, with a general tendency to underinvest. Fudenberg et al. (1990) develop a principal-agent model in which the agent is always at least as well informed as the principal. They find that the timing of the agent's information advantage is central for determining the value of long-term contracts. Long-term contracts are efficient if the principal and the agent have the same beliefs about future payoff. Hence, long-term contracts are beneficial only to avoid recontracting under asymmetric information. Rey and Salanie (1990) consider multi-period principal-agent relationships to show that a sequence of short-term contracts can be as efficient as long-term contracting when there is no asymmetric information at the recontracting dates. Anderson and Devereux (1991) study contract structures in a labor market in which a monopoly trade union supplies labor to an industry. They explore the trade-off between the wage precommitment of long-term contracts and the wage flexibility of short-term contracts. They find that long-term contracts are beneficial in industries with flexible techniques (i.e. high degree of complementarity between factors of production) and with relatively stable output prices. Theilen (2011) writes a principal-agent model relaxing the assumption that the contractor (principal) has all the bargaining power and that the contractee and subcontractee (agents) have none. He finds that a centralized structure is not always preferable to a decentralized structure.

More recently, the efficiency of contracts has also been studied in bargaining experiments. In an experimental paper, Cabrales et al. (2011) explore the effect of different degrees of bargaining power on the design and the selection of contracts in a hidden-information context. They find that when principals compete against each other to hire agents of unknown types, inefficiencies generated by the information asymmetries may disappear. However, when agents compete to be hired, efficiency improves dramatically. Cabrales and Charness (2011) analyze an experiment in which a principal offers one of three possible contract menus to a team of two agents of unknown type, with both agents' participation needed for production. They observe that rejection of contract menu offers depends on how discriminating the offers are, concluding that there is a trade-off between overall efficiency and the distribution of earnings in relation to the rejection payoffs.

Finally, the paper contributes to a growing literature that studies contracting in the context of social preferences. MacLeod (2007) concludes that when the party with the bargaining power in a surplus-generating relationship has some taste for honesty, and reciprocates good behavior, parties can achieve close to the first best, with cooperation decreasing as we reach the end of the relationship. Von Siemens (2009) develops a model of ultimatum bargain in which the vendor's type varies in the level of fairness and is private information. He finds that investments may affect the procurer's beliefs about the vendor's type and hence the procurer's bargaining behavior, which can generate strong incentives to invest. Hart and Moore (2008) argue that contractual performance depends on whether the trading parties are able to realize the profits they believe themselves to be entitled to. If expected profits are not realized, they feel mistreated and engage in punishing behavior. This negative reciprocity leads to welfare losses. Fehr et al. (2011) provide an experimental test of Hart and Moore's theory. Their experiment is designed as follows. A buyer determines what type of contract to offer, a rigid or a flexible contract. In a second stage contracts are auctioned off in a competitive setting. The theory predicts that rigid contracts will ensure the delivery of high quality by the sellers. Fehr et al. find that sellers shirk less often when paid a low price if the buyer defers price determination to the market process rather than choosing a low price directly in a rigid contract. This finding supports the view of rigid contract prices as reference points. Similar experimental evidence is obtained by Charness (2004). His results show that reciprocity is lower when wage is determined by a third party. Reference point effects are also observed in an experiment by Erlei and Reinhold (2012). However, in contrast to Fehr et al. (2011) the magnitude of these effects is only small. Erlei and Reinhold introduce a new treatment in which contract types are exogenously determined by the experimenter. They find that negative reciprocity leads to more shading than Fehr et al. with respect to endogenously chosen rigid contracts. They argue that this happens because sellers punish buyers for choosing rigid contracts.

The reminder of the paper is organized as follows. Section 3.2 presents the theory and predictions. Section 3.3 describes the experimental design. Section 3.4 discusses the results. Section 3.5 investigates behavior through the lens of a theory of reciprocity. Section 3.6 concludes.

3.2 Theory and Predictions

Two players, A and B, are in a surplus-generating relationship that lasts for n periods. Player A chooses whether to govern the relationship with a single long-term contract or a series of short-term contracts. This choice impacts the relationship in two ways.

First, it changes the total amount of surplus to be shared over the n periods. Let V_L denote the total surplus generated when the contract governs all n periods, and let V_S denote the per-period surplus when the relationship is governed by single-period contracts. In general $nV_S \neq V_L$, and one could easily envision reasons why the inequality might go either way. If a long-term contract allows one party to make long-term relationship-specific investments but the series of short-term contracts does not, one would expect $nV_S < V_L$. On the other hand, if the long-term contract allows one or both of the players to shirk in their effort decisions, one would expect $nV_S > V_L$ because renegotiation of short-term contracts allows for punishment of this shirking.

The second change instituted by the long-term contract is that it alters the bargaining power of the two parties. To capture this, let α_S denote player A's share of the surplus under a short-term contract, and let α_L similarly denote player A's share under a long-term contract. Likewise, let β_S and β_L denote player B's short-term and long-term shares, respectively, with $\alpha_S + \beta_S = \alpha_L + \beta_L = 1$. Again, the change in bargaining power could go in either direction. One possibility is that when A chooses a long-term contract, that contract encourages player B to inflate his costs to capture more of the long-term surplus. In this case $\alpha_S > \alpha_L$. Of course, the long-term contract might instead allow player A to inflate her costs at B's expense, in which case $\alpha_S < \alpha_L$.[2]

The basic premise for the paper is that when player A chooses a long-term contract over a series of short-term ones, she institutes a trade-off between increased total surplus and reduced bargaining power, so that $nV_S < V_L$ but $\alpha_S > \alpha_L$. When player A chooses a long-term contract her payoff is $\alpha_L V_L$, and when she chooses a series of short-term contracts her total payoff is $n\alpha_S V_S$. Obviously, she chooses the long-term contract if and only if

$$\alpha_L V_L \geq n\alpha_S V_S.$$

In the experiment, the sequence of short term contracts is implemented using a sequence of two \$20 ultimatum games. Player A, who chooses between the two contracts, is the receiver in both ultimatum games, and player B is the proposer. The timing of the ultimatum games is as follows. Player B makes an offer $0 \leq x_1 \leq 20$ in the first ultimatum game, and player A chooses whether to accept or reject. If she rejects, both players receive payoffs of zero and the game ends. If she accepts, their payoffs are locked in and they move on to the second ultimatum game, with player

[2]Player A's effective bargaining power might also be impacted by any feelings of reciprocity that A's contract choice generates in player B. We explore this idea separately in Section 5.

B making an offer $0 \leq x_2 \leq 20$ and A accepting or rejecting. If A rejects they both receive their payoffs from the first game but nothing else, that is, A receives x_1 and B receives $20 - x_1$. If A accepts they both receive the agreed-upon payments from both ultimatum games, that is, A receives $x_1 + x_2$ and B receives $40 - x_1 - x_2$.

If players behave according to the standard theoretical paradigm with purely self-interested players and subgame perfection, A accepts any offer and B offers zero. For these selfish, backward-inducting players, then, the appropriate bargaining power levels are $\alpha_S = 0$ and $\beta_S = 1$. The ultimatum game is so widely used in the experimental literature, however, precisely because the selfish subgame perfect equilibrium prediction fails. In that literature offers tend to be around 40% of the surplus (see Camerer (2003) for a review), so a more likely level of bargaining power for short-term contracts has $\alpha_S = 0.4$ and $\beta_S = 0.6$.

The experiment implements the long-term contract scenario using a single *constrained dictator game* with player A acting as the receiver. This game is governed by two parameters: the total surplus to be shared (V_L) and the minimum allowable offer (m). Player B can choose any amount $m \leq x \leq V_L$ to give to player A. The payoffs are then x for player A and $V_L - x$ for player B.

In the standard theoretical paradigm with purely self-interested players, B gives the minimum allowable amount m to player A. The experimental literature contains many studies with dictator games in which m is zero, and the average amount given is about 20% of the surplus. If this continues to hold for the experiment used here, an empirically likely level of bargaining power for long-term contracts has $\alpha_L = \max\left\{0.2, \frac{m}{V_L}\right\}$.

Whether player A should opt for the long-term contract or the sequence of short-term contracts depends on both the size of the long-term surplus, V_L, and her beliefs about bargaining power. In keeping with previous notation, suppose that player A believes that she will receive a share $\hat{\alpha}_S$ of the ultimatum game surplus and a share $\hat{\alpha}_L$ of the dictator game surplus when there is no minimum offer constraint. She chooses the sequence of short-term contracts if and only if

$$40\hat{\alpha}_S \geq \max\{m, \hat{\alpha}_L V_L\}.$$

This consideration leads to our first two hypotheses.

Hypothesis 1. Increases in the size of the long-term contract surplus V_L make it more likely for player A to choose the long-term contract.

Hypothesis 2. Increases in the minimum allowable dictator offer m make it more likely that player A chooses the long-term contract.

A third hypothesis arises from thinking about likely values of $\hat{\alpha}_S$ and $\hat{\alpha}_L$. If beliefs are driven by standard game-theoretic constructs, both $\hat{\alpha}_S$ and $\hat{\alpha}_L$ are zero and player A chooses the long-term contract if and only if $m \geq 0$. On the other hand, if beliefs are consistent with laboratory behavior so that $\hat{\alpha}_S \approx 0.4$ and $\hat{\alpha}_L \approx 0.2$, then given that the ultimatum games have surpluses of \$20 each she should opt for the sequence of short-term contracts unless either $m \geq 16$ or $V_L \geq 80$. None of our experimental treatments have parameters this large, so under this rational expectations assumption she should always choose the short-term contract. This leads to our final hypothesis.

Hypothesis 3. Player A's average payoffs are higher with short-term contracts for all parameter values.

In the experiment we use three different values for the dictator-game surplus ($V_L = 30, 40, 50$) and we use three different values for the minimum allowable dictator offer ($m = 0, 2, 10$). If play in the ultimatum and dictator games is consistent with behavior in other experiments, so that the receiver averages 40% of the ultimatum game surplus and 20% of the dictator game surplus, then player A's expected payoffs from the sequence of short-term contracts should average \$16, and her average payoffs from the long-term contract should follow the pattern in Table C.1.

3.3 Experimental Design

A total of 268 subjects were recruited from the undergraduate student body at the University of Tennessee-Knoxville in the fall of 2010. The experiment was conducted in 12 sessions in the UT Experimental Economics Laboratory. The laboratory consisted of 24 networked computer workstations in separate cubicles. The experiment was implemented on the computers using custom-made software programmed in Java.[3] All experimental sessions lasted around 1 hour and participants' average earnings were $17.62.

Participants played four different types of games.[4] A game requires two players, A and B. At the start of the experiment, subjects were randomly assigned to the role of either player A or B, and remained in the assigned role throughout the experiment. In each game, participants were randomly matched with a different player of the opposite type. It was carefully explained that neither player will ever learn with whom they were paired.

In each game, player A moves first by selecting one of two options. First, player A can be a recipient in a sequence of two ultimatum games. This option represents A's preference for a sequence of two short-term contracts. Alternatively, player A can be a recipient in one dictator game. This option represents A's preference for the long-term contract.

The two ultimatum games are played as described in the preceding section. The rules of the dictator game define our treatments. Dictator games differ in two dimensions: i) the endowment of the game, and ii) restrictions on player B's action space. In our baseline treatment the endowment of the dictator game is $40 and no restrictions are placed on B's offers, i.e. the minimum allowable offer m is zero. Hence, our baseline treatment involves a standard dictator game over $40. We refer to this treatment as No-40, where the notation "No" indicates that no restrictions are placed on B's offer and the "40" indicates the size of the surplus.

[3]Screen shots are available in the Appendix.
[4]This paper, however, focuses on three games.

Treatments No-30 and No-50 are identical to the baseline treatment except that the endowments are \$30 and \$50, respectively. These treatments capture the fact that long-term contracts may have lower or greater surplus when compared to a sequence of short-term contracts. Our next treatments involve a small increase in player A's bargaining power in the dictator game by restricting B's minimum allowable offer to \$2, i.e. $m = 2$. Three treatments involve this restriction: Low-30, Low-40, and Low-50. The increase in bargaining power is "low" because, according to the empirical belief $\hat{\alpha}_L = 0.2$, the restriction $m = 2$ does not bind (see Table C.1).

Completing the experimental design are three discrete dictator treatments: High-30, High-40, and High-50. In these treatments, dictator games are again played over \$30, \$40, and \$50, however, B's offer is restricted to be either \$10 or half of the total endowment, i.e. \$15, \$20, or \$25, respectively. These are our high bargaining power treatments in which A is guaranteed a minimum of \$10 in the dictator game, i.e. $m = 10$. In all treatments, player B's splitting choices are restricted to whole numbers.

Each subject played three games holding the dictator game constant at either \$30, \$40, or \$50, but varying the bargaining power between no bargaining power ($m = 0$), low bargaining power ($m = 2$), and high bargaining power ($m = 10$). The order of the games was randomized. Table C.2 shows how the 397 observations are distributed throughout the treatment cells.[5]

3.4 Results

We begin by presenting player A's behavior on the first choice. Overall, 26% of the subjects choose the dictator game. Figure C.1 shows A's first choice broken down by the endowment of the dictator game. Pooling across all game types, an increase of the endowment of the dictator game leads to an increase of the share of subjects

[5]Five observations were lost due to technical problems in the computer recording processes.

choosing the dictator game. However, this increase is not statistically significant from treatment 30 to treatment 40.[6]

Figure C.2 shows A's first choice broken down by the amount of bargaining power that A holds in the dictator game. Pooling across endowments, an increase of A's bargaining power in the dictator game leads to an increase of the share of subjects choosing the dictator game. However, this increase is not statistically significant from treatment No to treatment Low.[7]

Figure C.3 shows, for each treatment cell, the proportion of subjects that choose the dictator game. Holding constant the action space for the dictator game, an increase of the endowment of the dictator game leads to an increase of the share of subjects choosing the dictator game. However, the only statistically significant difference in proportions is the one between treatment High-40 and treatment High-50.[8]

We obtain evidence in support of Hypothesis 1. We observe the following relationship between player A's first choice and the surplus to be shared in the dictator game.

Result 1. Holding B's action space constant, the probability that player A chooses the dictator game increases as the endowment of the dictator game increases from \$30 to \$50.

Holding constant the endowment of the dictator game, we find the puzzling pattern that dictator game choice frequency rises with the amount of bargaining power for

[6]Two-sided tests on the equality of proportions: H_0: Prop(30) = Prop(50) with P-value = 0.0009, H_0: Prop(30) = Prop(40) with P-value = 0.1312, and H_0: Prop(40) = Prop(50) with P-value = 0.0722.

[7]Two-sided tests on the equality of proportions: H_0: Prop(No) = Prop(Low) with P-value = 0.8054, H_0: Prop(No) = Prop(High) with P-value = 0.0167, and H_0: Prop(Low) = Prop(High) with P-value = 0.0326.

[8]Figure C.3 makes it readily apparent that differences between No-40 and No-50 and differences between High-30 and High-40 cannot be statistically significant. For the remaining comparisons the two-sided tests on the equality of proportions are as follows: H_0: Prop(No-30) = Prop(No-40) with P-value = 0.2928, H_0: Prop(Low-30) = Prop(Low-40) with P-value = 0.1051, H_0: Prop(Low-40) = Prop(Low-50) with P-value = 0.3617, and H_0: Prop(High-40) = Prop(High-50) with P-value = 0.0433.

two surplus levels but not for the third. The share of subjects who choose the dictator game when the endowment is \$30 more than doubles from 11% in treatment Low-30 to 27% in treatment High-30. For the larger endowment of \$50, the share of subjects choosing the dictator game doubles from 25% in treatment No-50 to 49% in treatment High-50. In contrast, for the \$40 endowment we find no statistical evidence that the proportion of subjects choosing the dictator game varies according to the bargaining power.[9]

In general, we obtain evidence in support of Hypothesis 2. The following result describes A's behavior with respect to B's minimum allowable offer in the dictator game.

Result 2. Holding the endowment of the dictator game constant, the probability that player A chooses the dictator game increases as B's minimum allowable offer in the dictator game increases from \$0 to \$10.

Hypothesis 3 concerns player A's earnings across the two contract choices, and discussing those requires looking at player B's offers. Accordingly, we now to player B's offer in the dictator game. Table C.3 shows B's average offer in the dictator game in each treatment cell. Sample sizes are reported because we did not utilize the strategy method, and therefore the experiment only generated observations when player A actually chose the dictator game. The small sample sizes lead to low power statistical tests, but the following broad patterns emerge. First, on average offers amounted to 28% of the endowment, which is higher than the usual amount for laboratory dictator games. Part of this may be due to the constraints on the dictator offers, as offers in the no bargaining power treatments are 11%, 22%, and 22% of the \$30, \$40, and \$50 endowments, respectively. Second, moving down the columns shows that even though the offer limit m does not bind the average, a small increase in receiver bargaining power from $m = 0$ to $m = 2$ increases average offers by about

[9]Two sided tests on the equality of proportions. H_0: Prop(Low-30) = Prop(High-30) with P-value = 0.0525, H_0: Prop(Low-40) = Prop(High-40) with P-value = 0.7140, and H_0: Prop(No-50) = Prop(High-50) with P-value = 0.0197.

\$5 for the \$30 and \$40 endowments and by \$2.60 for the \$50 endowment.[10] Third, moving across the rows shows that offers increase when the endowment improves from \$30 to \$40.[11] Offers, however, do not increase when the endowment rises from \$40 to \$50.[12] Finally, with the single exception of the High-30 treatment, offers are at least as high as those predicted in Table C.1.

Table C.4 shows player B's average offers in the ultimatum games. These offers hover around 40% of the \$20 endowment, which is consistent with behavior observed in other laboratory ultimatum game experiments. Strikingly, there is no variation across treatments.

Table C.5 summarizes information about average payoff of player A. We find evidence in favor of Hypothesis 3. Player A is better off choosing the ultimatum games as opposed to the dictator game in six of the nine treatments (the exceptions are Low-50, High-40, and High-50). Because the experiment only generated data for dictator games when subjects actually chose the dictator games, statistical tests between the payoffs are impossible for some of the cells. Every time we have the power to reject the null that player A's average payoff is different between the ultimatum and dictator games, though, the two-sided t-test favors the ultimatum games (No-30, No-40, Low-30, and High-30). This leads to our next result.

Result 3. In general, player A's average payoff is higher with the sequence of two ultimatum games.

A major concern of this paper regards the trade-off implicit in the signing of long-term contracts. Entering into a long-term contract can increase the surplus to be

[10] Two sided t-tests. H_0: Mean(No-30) = Mean(Low-30) with P-value = 0.0821, H_0: Mean(No-40) = Mean(Low-40) with P-value = 0.2175, and H_0: Mean(No-50) = Mean(Low-50) with P-value = 0.5332.

[11] Two sided t-tests. H_0: Mean(No-30) = Mean(No-40) with P-value = 0.2304, H_0: Mean(Low-30) = Mean(Low-40) with P-value = 0.1572, and H_0: Mean(High-30) = Mean(High-40) with P-value = 0077.

[12] Two sided t-tests. H_0: Mean(No-40) = Mean(No-50) with P-value = 0.6194, H_0: Mean(Low-40) = Mean(Low-50) with P-value = 0.9769, and H_0: Mean(High-40) = Mean(High-50) with P-value =0.6916.

shared by the two parties, but at the cost of reducing the bargaining power of one of those parties. The game subjects faced allows player A to choose between a long-term contract and a short-term contract, and treatments vary according to the size of the surplus in the long-term contract and the amount of bargaining power retained by player A in the long-term contract.

The clearest trade-off between efficiency and bargaining power arises in the No-50 treatment, where player A has the choice between retaining some bargaining power through the two \$20 ultimatum games or giving up all bargaining power but participating in a \$50 dictator game. In this treatment, 75% of the subjects chose the bargaining power (see Figure C.3), foregoing the additional surplus, suggesting that diminished bargaining power can be a serious detriment to realizing long-term gains from trade. Similar patterns emerge for the other \$50 constrained dictator treatments, with 67% of player As in the Low-50 and 51% of the player As in the High-50 treatment also choosing to forego the additional surplus from the long-term contract.[13]

The treatment High-30 allows consideration of the same issue but in the opposite direction. In this case player A has significant bargaining power in the constrained dictator game, because player B's only possible offers are \$10 and \$15. The issue arises as to whether player A elects to guarantee a payoff of at least \$10 but at the expense of generating \$10 less surplus. 27% of player As made this choice.[14] This rate of surplus-avoidance is smaller than in the \$50 surplus cases, but the lower rate is consistent with the fact that, according to Table 5, player A earns an average of \$4.50 more playing the ultimatum games than the dictator game in this treatment.

[13] All of these proportions differ significantly from zero at the $P = 0.000$ level.
[14] This proportion differ significantly from zero at the $P = 0.000$ level.

3.5 Reciprocity

The results from section 3.4 show that when trading off bargaining power against added surplus to be shared, choices often favor bargaining power. The experimental design allows us to address additional issues that are interesting in their own light. Let us start by examining what beliefs player A holds when making the original choice. As noted in Section 3.2, if player A forms beliefs according to standard, self-interested game theory, player A should choose the dictator game 100% of the time in the Low and High bargaining treatments. Subjects clearly did not behave this way. If, instead, player A forms beliefs consistent with typical play in laboratory ultimatum and dictator experiments, she should choose the ultimatum games 100% of the time. The answer seems to be somewhere in between and may be driven by beliefs about reciprocity.

Reciprocity beliefs are possible because the game, as designed, has a gift exchange component. To see how, consider the No-40 treatment in which player A chooses between two \$20 ultimatum games and a standard \$40 dictator game. Choosing the dictator game constitutes a gift to player B in that player A cedes the right to reject player B's offer, giving player B more freedom to take a larger share. If player B is reciprocal, player B might give A a larger share of the \$40 in the dictator game than in the ultimatum games. The No-50 treatment has a bigger gift, in that choosing the dictator game not only cedes complete control to player B but also increases the size of B's endowment. By the same token, the Low-40 treatment has a smaller gift than the No-40 treatment because player A cedes less control to player B when choosing the constrained dictator game than when choosing the unconstrained dictator game. In general, the gift embodied in the dictator game choice is larger as one moves from left to right in a row of Table C.3 and as one moves from bottom to top in a column of Table C.3.

It is possible to adapt the model of Section 2 to account for reciprocity. Because Table 4 shows that ultimatum offers do not seem to vary with the treatment, we restrict attention to the effects of player B's reciprocity on dictator offers only. Let $\hat{\alpha}_L(m, V_L)$ denote player A's beliefs about the share player B will offer in a dictator game with minimum offer m and surplus V_L. The size of A's gift to B decreases in m and if smaller gifts lead to less reciprocity, $\hat{\alpha}_L$ is decreasing in m. Similarly, the size of A's gift to B increases in V_L and if larger gifts lead to greater reciprocity, $\hat{\alpha}_L$ is increasing in V_L. Player A chooses the sequence of short-term contracts if and only if

$$40\hat{\alpha}_S \geq \max\{m, \hat{\alpha}_L(m, V_L)V_L\}.$$

This analysis provides an additional motive for player A to choose the long-term contract: she might believe that her returns from giving gifts will exceed her returns from retaining bargaining power.

The function $\hat{\alpha}_L(m, V_L)$ is reminiscent of the emotional state function posited by Cox et al. (2007). In their model a player's emotional state determines the marginal rate of substitution between own payoff and others' payoff, and the emotional state depends on both the size of the gift and the players' reletive social status. They provide empirical evidence that supports their theory and find that other-regarding preferences may indeed depend on reciprocity. The function $\hat{\alpha}_L(m, V_L)$ can be thought of as a reduced-form representation where player A believes the size of the gift impacts player B's emotional state which in turn affects B's dictator offer to A.

The gift exchange theory predicts that as the size of the dictator-game surplus increases, the size of the gift entailed by choosing the dictator game increases, and so subjects should choose the dictator game with higher frequency. This behavior generates exactly the same pattern as Hypothesis 1. The gift exchange theory also predicts that as the minimum-allowable offer increases, the size of the dictator game "gift" shrinks, and so subjects should choose the dictator game with lower frequency. This patter runs exactly opposite of Hypothesis 2. Since the model of Section 2 was built entirely on the idea of perceived bargaining power, looking at how contract choices compare as the minimum-allowable offer changes provides a test of the gift-exchange model against the bargaining power model.

Figure 1 shows that player A chooses the dictator game more often when the surplus grows, a result consistent with both models. Figure 2 shows that player A's contract choices are more consistent with the bargaining power model than the reciprocity-based one, with subjects more likely to choose the dictator game when the minimum-allowable offer is higher. Figure 3 breaks this down by surplus size, and the only statistically significant changes in behavior have player A taking the dictator game more frequently, not less frequently, when the minimum-allowable offer increases. This is evidence that, if reciprocity plays any role in contract choice, it is crowded-out by the demand for bargaining power. In fact, when the change in bargaining power is large (from Low to High), the change in behavior is also large and in the direction predicted by the bargaining power model. The frequency of dictator game choices increases from 23% in Low to 35% in High.

Despite this, there is evidence that reciprocity plays some role in behavior, and this can be found from player B's allocations in the dictator game. As Table C.3 shows, offers are much smaller in the No-30 treatment than in any of the other treatments, and about half of the standard 20% benchmark. Choosing the dictator game in this treatment is a negative gift because it reduces the surplus, and it leads to negative reciprocity. As for the other treatments, offers do increase weakly as one moves from left to right in the first two rows of Table C.3, but we are hesitant to overplay this because the increase could also simply reflect the larger endowment player B has available to share. In our High discrete offer space treatment, in which B can offer either \$10 or half of the endowment, we observe that players offer the fair split only 8% of the time in treatment High-30. That proportion grows to 27% in treatment High-50.[15] It must be said that, again, this might be an endowment effect as opposed to evidence of reciprocity.

Another test of reciprocity would come from looking at the columns of Table C.3, with reciprocity predicting higher offers with movements up a column. Giving up the

[15]The fair split accounts for 50% of offers in treatment High-40. Thus, the proportion of type B players choosing to be fair does not monotonically increase with the endowment of the dictator game (the gift).

bargaining power associated with the right of refusal in the two ultimatum games constitutes a larger gift when the alternative is an unconstrained dictator game than when there is a minimum allowable offer. The evidence in Table C.3 shows that offers increase with movements down the column, not movements up the column as reciprocity predicts. This is not a clean test, however, because movements down the column restrict the offers the dictator can actually make. Nevertheless, this provides further evidence suggesting that bargaining power may, in fact, crowd-out reciprocity.

If one takes the gift exchange argument seriously, then one should also find an effect in the ultimatum game offers. This time, though, if choosing the dictator game is a positive gift then choosing the ultimatum game is a negative gift, and so gift exchange would suggest lower offers as one moves to the right along a row in Table C.4 and higher offers as one moves down a column. Once again the reciprocity pattern does not seem to fit the data in Table C.4. For instance, the large negative gift entailed in choosing the dictator game in No-30 does not correspond to a large positive gift from choosing the ultimatum game instead. The lack of response in the ultimatum offers may simply be driven by the fact that A can reject low offers, in which case this provides further evidence that bargaining power crowds out reciprocity.

A final opportunity for identifying if player A believes in reciprocity comes from A's rejection behavior in the ultimatum games. To see how this works, compare two treatments, No-40 and High-40. In the baseline game No-40 player A's initial choice involves either two \$20 ultimatum games or a single, unconstrained \$40 dictator game. In High-40 the unconstrained dictator game is replaced by a constrained one in which B can only offer \$10 or \$20. Choosing the dictator game in No-40 is more of a gift to player B than choosing the dictator game in High-40. Conversely, choosing the ultimatum games in High-40 is more of a gift than choosing the ultimatum games in No-40. If player A believes that choosing the ultimatum games in High-40 is, in fact, a gift to player B, then she would expect B to reciprocate with higher offers in those games. If she receives a low offer, she would be more likely to reject than if she had not given a gift, so we would expect to see higher ultimatum game rejection rates, conditional on the offer level, in High-40 than in No-40.

Table C.6 shows the marginal effects from Probit regressions on A's ultimatum game rejection decisions with P-values in parentheses. Column (1) conditions only on the amount being offered, and column (2) controls for the second ultimatum game. The results show that A is less likely to reject a higher offer, as expected, and also more likely to reject in the second round than in the first. Column (3) controls for A's initial gift of giving up the high bargaining power in the High-30, High-40, and High-50 treatments by using treatment dummy variables. This coefficient is positive, which is in line with a hypothesis that player A believes that choosing the ultimatum games constitutes a gift, but it is not statistically significant. Column (4) adds a dummy for the No-50 treatment, which represents the most negative "gift" player A can give to player B. Choosing the dictator game in No-50 gives B complete freedom to allocate the largest surplus available with no constraints whatsoever, while choosing the ultimatum games instead both reduces the surplus and gives A bargaining power. If A recognizes the ultimatum game as a negative "gift," she would follow up by being more lenient in rejecting offers and one would expect a negative coefficient on the No-50 dummy. The coefficient is negative, but far from significant. The addition of the No-50 dummy almost makes the High Bargaining treatment coefficient statistically significant, providing the closest evidence from this analysis that player A believes in a gift exchange paradigm.

The intriguing appeal of the gift exchange argument is that it provides an explanation for why subjects might choose the dictator game and lower bargaining power in the first place. If they think that player B will view the dictator game as a gift and then reciprocate, they might believe that their payoffs will be higher in the dictator game than in the sequence of ultimatum games. Table C.5 shows that these beliefs are misplaced, however, and that player A ultimately earns more on average by choosing the ultimatum games.

3.6 Conclusion

This paper reports results of a bargaining experiment in which the first mover (the procurer) selects whether to be the recipient in a single-shot dictator game or in a sequence of two $20 ultimatum games. The second mover takes the role of the vendor. Our treatments modify the dictator game in two dimensions. First we vary the endowment received by the vendor in the dictator game to amounts that are lower ($30), equal ($40), or higher ($50) than the total endowment of the ultimatum games. Second we vary the minimum-allowable offer in the dictator game from $0 to $2, and then to $10.

The game design allow us to study a procurer's decision between offering a vendor a long-term contract (implemented through the dictator game) or a sequence of short-term contracts (implemented through the ultimatum games), exploring the trade-off between added surplus and lost bargaining power in long-term relationships. We find that 75% of the participants prefer to retain the bargaining power provided by the accept/reject decision in the sequence of ultimatum games as opposed to engage in a unconstrained dictator game played over the bigger endowment of $50. Moreover, even when the dictator's offer is restricted to a minimum of $10, the share of subjects selecting the dictator game over $50 increases to only 49%, a striking result considering that backward-inducting game theory predicts that the procurer would receive $0 in the sequence of ultimatum games. This result suggests that diminished bargaining power can be a serious detriment to realizing long-term gains from trade.

We also explore behavior through the lens of a theory of reciprocity. This is possible because the experiment, as designed, has a gift exchange component. The dictator game can be viewed as a gift from the procurer to the vendor because the procurer forgoes the right to reject the vendor's offer. The size of the gift is positively correlated with the endowment of the dictator game. The gift, however, decreases with the minimum-allowable offer imposed to the vendor in the dictator game. If the procurer has reciprocity beliefs, she may choose the dictator game more often when it constitutes a bigger gift in hope that the vendor reciprocates by offering a high share of the endowment.

Reciprocity can be an important aspect of contracting. As argued by MacLeod (2007), surplus-generating relationships are more efficient when the party with the bargaining power has some taste for honesty, and reciprocates good behavior. In our experiment, however, we find mixed evidence of reciprocity beliefs. Although participants choose the dictator game more often when its endowment increases, they select the dictator game more often when the minimum allowable offer increases (i.e. decreasing the gift). Also, the procurer's average payoff is higher with the sequence of two ultimatum games. These results suggest that feelings of reciprocity are crowed-out by a preference for bargaining power. Hence, in our experiment, reciprocity is not able to prevent efficiency losses.

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Appendix

Appendix A

Appendix

A.1 Social Networks and Non-market Valuation

Lemma 1.1. *Agent i's social utility is a convex combination of the private utilities of all agents, i.e. for all i and j, $w_{ij} \in [0,1]$ and $\sum_j w_{ij} = 1$.*

Proof. First notice that $(\mathbf{I} - \mathbf{\Lambda A})$ is a strictly diagonally dominant matrix and, by the Levy-Desplanques theorem, cannot be singular (see Taussky (1949), Theorem I). Hence $\mathbf{W}$ always exists. $(\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}$ is a nonnegative matrix. To see this, note that the matrix $(\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}$ can be written as the Neumann series $(\mathbf{I} + (\mathbf{\Lambda A}) + (\mathbf{\Lambda A})^{\mathbf{2}} + (\mathbf{\Lambda A})^{\mathbf{3}} + ...)$, i.e. a sum of nonnegative matrices. Since $(\mathbf{I} - \mathbf{\Lambda})$ is also a nonnegative matrix, $\mathbf{W} = (\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}(\mathbf{I} - \mathbf{\Lambda})$ is a nonnegative matrix. To prove lemma 1.1 it must be demonstrated that $\mathbf{t}$, the row sum vector of the matrix $\mathbf{W}$, is a vector whose entries are all 1. The row sum vector of a matrix can be obtain by pos-multiplying the matrix by a column vector $\mathbf{i}$ whose entries are all 1. Thus, $\mathbf{t}$ can be written as

$$\mathbf{t} = (\mathbf{I} - \mathbf{\Lambda A})^{-\mathbf{1}}(\mathbf{I} - \mathbf{\Lambda})\mathbf{i} \tag{A.1}$$

By construction, $(\mathbf{I}-\mathbf{\Lambda A})$ and $(\mathbf{I}-\mathbf{\Lambda})$ have the same row sum column vector $\mathbf{r}$, with the i-th entry equal to $1-\lambda_i$. As a consequence,

$$(\mathbf{I}-\mathbf{\Lambda A})\mathbf{i}=\mathbf{r} \tag{A.2}$$

$$(\mathbf{I}-\mathbf{\Lambda})\mathbf{i}=\mathbf{r} \tag{A.3}$$

Plugging (A.3) into (A.1) yields to

$$\mathbf{t}=(\mathbf{I}-\mathbf{\Lambda A})^{-\mathbf{1}}\mathbf{r}$$

According to (A.2), $\mathbf{i}=(\mathbf{I}-\mathbf{\Lambda A})^{-\mathbf{1}}\mathbf{r}$. Thus, $\mathbf{t}=\mathbf{i}$. □

Lemma 1.2. *Every agent in the network has positive importance, i.e.* $\delta_i>0$ *for all* i.

Proof. Rewrite $\mathbf{W}=(\mathbf{I}-\mathbf{\Lambda A})^{-\mathbf{1}}(\mathbf{I}-\mathbf{\Lambda})$ as $\mathbf{W}=\mathbf{XY}$. Notice that an element of $\mathbf{W}$ can be written as $w_{ii}=x_{i1}y_{1i}+x_{i2}y_{2i}+...+x_{ii}y_{ii}+...+x_{in}y_{ni}$, where x_{ij} and y_{ij} are elements of $\mathbf{X}$ and $\mathbf{Y}$, respectively. Elements of the diagonal of $\mathbf{X}$ are greater or equal to 1, i.e. $x_{ii}\geq 1$. To see this, recall that $\mathbf{X}$ can be written as the Neumann series $(\mathbf{I}+(\mathbf{\Lambda A})+(\mathbf{\Lambda A})^{\mathbf{2}}+(\mathbf{\Lambda A})^{\mathbf{3}}+...)$, which is a sum of the identity matrix with nonnegative matrices. $\mathbf{Y}$ is a diagonal matrix with $0<y_{ii}\leq 1$. To see this, recall that $\mathbf{\Lambda}$ is a diagonal matrix with elements $0\leq\lambda_i<1$. Therefore, since $\mathbf{X}$ and $\mathbf{Y}$ are nonnegative matrices, and $x_{ii}y_{ii}>0$, it follows that $w_{ii}>0$ for all i, thus $\delta_j=\sum_i w_{ij}>0$. □

Proposition 1.1. *Network neutrality holds if and only if all agents are socially isolated (i.e.* $\lambda_i = 0\ \forall i$*).*

Proof. According to equation (1.2), $v_i = (1-\lambda_i)u_i + \lambda_i \sum_j a_{ij} v_j$. If $\lambda_i = 0$, then $v_i = u_i$. This establishes the "if" part. For the other direction, suppose on the contrary that $\lambda_i > 0$ for some i. Without loss of generality, suppose that $i = 1$. Set $u_1 = 0$ and $u_2 = ... = u_n = \bar{u} \neq 0$. Then $v_1 = \lambda_1 \sum_{j \neq 1} a_{1j} \bar{u} = \lambda_1 \bar{u} > 0$, which provides a contradiction. □

Corollary 1.1. *If network neutrality holds, the willingness to pay measure* $C_i^{network}$ *is equal to the private measure* $C_i^{private}$.

Proof. $C_i^{network} = \sum_j w_{ij} u_j(g^1) - \sum_j w_{ij} u_j(g^0)$ (see equation (1.8)), or just $C_i^{network} = v_i(g^1) - v_i(g^0)$. If the network is neutral, $v_i(g) = u_i(g)$. It follows that $C_i^{network} = u_i(g^1) - u_i(g^0) = C_i^{private}$ (see equation (1.9)). □

Proposition 1.2. *In non-neutral networks (i.e.* $w_{ii} \neq 1$*), the network benefits agent i, i.e.* $v_i(g) > u_i(g)$*, if and only if*

$$u_i(g) < \frac{\sum_{j \neq i} w_{ij} u_j(g)}{\sum_{j \neq i} w_{ij}}.$$

Proof. $v_i(g) > u_i(g) \iff \sum_j w_{ij} u_j(g) > u_i(g) \iff w_{ii} u_i(g) + \sum_{j \neq i} w_{ij} u_j(g) > u_i(g)$ $\iff \sum_{j \neq i} w_{ij} u_j(g) > (1 - w_{ii}) u_i(g) \iff \frac{\sum_{j \neq i} w_{ij} u_j(g)}{\sum_{j \neq i} w_{ij}} > u_i(g)$.

According to lemma 1.1, $\sum_{j \neq i} w_{ij} = (1 - w_{ii})$. Thus, for $w_{ii} \neq 1$, $\sum_{j \neq i} w_{ij} > 0$. □

Corollary 1.2. *In non-neutral networks (i.e.* $w_{ii} \neq 1$*),* $C_i^{network} \geq C_i^{private}$ *if and only if* $\left(u_i(g^1) - u_i(g^0)\right) \leq \frac{\sum_{j \neq i} w_{ij} [u_j(g^1) - u_j(g^0)]}{\sum_{j \neq i} w_{ij}}$.

Proof. $C_i^{network} > C_i^{private} \iff v_i(g^1) - v_i(g^0) > u_i(g^1) - u_i(g^0) \iff \sum_j w_{ij}u_j(g^1) - \sum_j w_{ij}u_j(g^0) > u_i(g^1) - u_i(g^0) \iff (1-w_{ii})u_i(g^1) - (1-w_{ii})u_i(g^0) < \sum_{j\neq i} w_{ij}u_j(g^1) - \sum_{j\neq i} w_{ij}u_j(g^0) \iff \big(u_i(g^1) - u_i(g^0)\big) < \frac{\sum_{j\neq i} w_{ij}(u_j(g^1)-u_j(g^0))}{\sum_{j\neq i} w_{ij}}$.

According to lemma 1.1, $\sum_{j\neq i} w_{ij} = (1 - w_{ii})$. Thus, for $w_{ii} \neq 1$, $\sum_{j\neq i} w_{ij} > 0$. □

Proposition 1.3. *If every agent in the network has the same importance, then the social network welfare is equal to the social isolation welfare.*

Proof. $\sum_i v_i = u_1 \sum_j w_{j1} + u_2 \sum_j w_{j2} + ... + u_n \sum_j w_{jn} = \sum_i \sum_j w_{ji}u_i$. When agents have the same importance, the columns of the induced network sum to one, i.e., $\sum_j w_{ji} = 1$. To see this, note that since the rows of $\mathbf{W}$ sum to 1, i.e. $\sum_j w_{ij} = 1$ (see lemma 1.1), the sum of all entries in $\mathbf{W}$ is equal to $\sum_i \sum_j w_{ij} = n$. If all agents have the same importance, the importance of a single agent is obtained by dividing n evenly among the n columns of $\mathbf{W}$. If this is the case, the column sum vector of $\mathbf{W}$ is a vector of ones. Hence, equality of agents' importance implies $\sum_j w_{ji} = 1$. Therefore, $\sum_i v_i = \sum_i \sum_j w_{ji}u_i = \sum_i u_i$. □

Corollary 1.3. *If welfare neutrality holds, then* $C^{network} = C^{private}$.

Proof. $C^{network} = \sum_i C_i^{network} = \sum_i v_i(g^1) - \sum_i v_i(g^0)$. If welfare neutrality holds, $\sum_i v_i(g) = \sum_i u_i(g)$. Then, $C^{network} = \sum_i u_i(g^1) - \sum_i u_i(g^0) = C^{private}$. □

Proposition 1.4. *For all sorted private utility profiles* $\mathbf{u}$*, if the distribution of importance of a network* $\mathbf{W}$ *first order stochastically dominates (FOSD) that of the social isolation case, then* $\mathbf{W}$ *is a welfare-increasing network.*

Proof. See proposition 1.5 with **W'** equal to the identity matrix. □

Proposition 1.5. *For all sorted private utility profiles* $\mathbf{u}$*, if the distribution of importance of a network* $\mathbf{W}$ *FOSD that of another network* **W'***, then* $\mathbf{W}$ *generates greater social network welfare than* **W'***.*

Proof. It will be shown that, for all sorted private utility profile, if distribution of importance of a network $\mathbf{W}$ FOSD that of another network **W'**, then $\mathbf{W}$ generates greater social network welfare than **W'**. Hence, it must be demonstrated that, $\sum_{i=1}^{k} \delta_i \leq \sum_{i=1}^{k} \delta_i'$ implies $\sum_{i=1}^{n} \delta_i u_i \geq \sum_{i=1}^{n} \delta_i' u_i$, for all sorted private utility profile $\mathbf{u}$.

$\mathbf{W}$ generates greater social network welfare than **W'** when

$$\sum_i \delta_i u_i > \sum_i \delta_i' u_i \tag{A.4}$$

(see proof of Proposition 1.3). Construct $p_i = \delta_i/n$ and re-write (A.4) as

$$\sum_i p_i u_i > \sum_i p_i' u_i. \tag{A.5}$$

Since $\mathbf{p} = (p_1, ..., p_n)$ represents a probability vector, $U_i = \sum_i p_i u_i$ is a expected utility function. Let $P(k) = \sum_{i=1}^{k} p_i$ be the cdf that governs the probability vector $\mathbf{p}$. If $P(k)$ *FOSD* $P'(k)$, i.e. $\sum_{i=1}^{k} p_i \leq \sum_{i=1}^{k} p_i'$ for all k, then the expected utility under P is greater than the expected utility under P', $U_i > U_i'$, as in (A.5).

□

Corollary 1.4. $C^{network} \geq C^{private}$ *if and only if* $\sum_i \big(\delta_i - 1\big)\big[(u_i(g^1) - u_i(g^0)\big] \geq 0$.

Proof. $C^{network} \geq C^{private} \iff \sum_i C_i^{network} \geq \sum_i C_i^{private} \iff \sum_i v_i(g^1) - \sum_i v_i(g^0) \geq \sum_i u_i(g^1) - \sum_i u_i(g^0) \iff \sum_i \delta_i u_i(g^1) - \sum_i u_i(g^1) - \sum_i \delta_i u_i(g^0) + \sum_i u_i(g^0) \geq 0 \iff \sum_i \big(\delta_i - 1\big)\big((u_i(g^1) - u_i(g^0)\big) \geq 0.$ □

Appendix B

Appendix

B.1 Estimation of Non-market Values in the Presence of Social Network Effects: the Case of Advisory Referenda

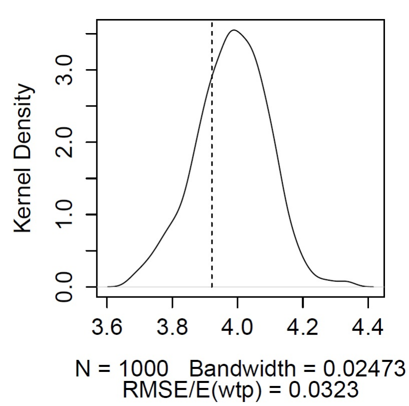

Figure B.1: Kernel Estimates for MC Trials with No Network Effect

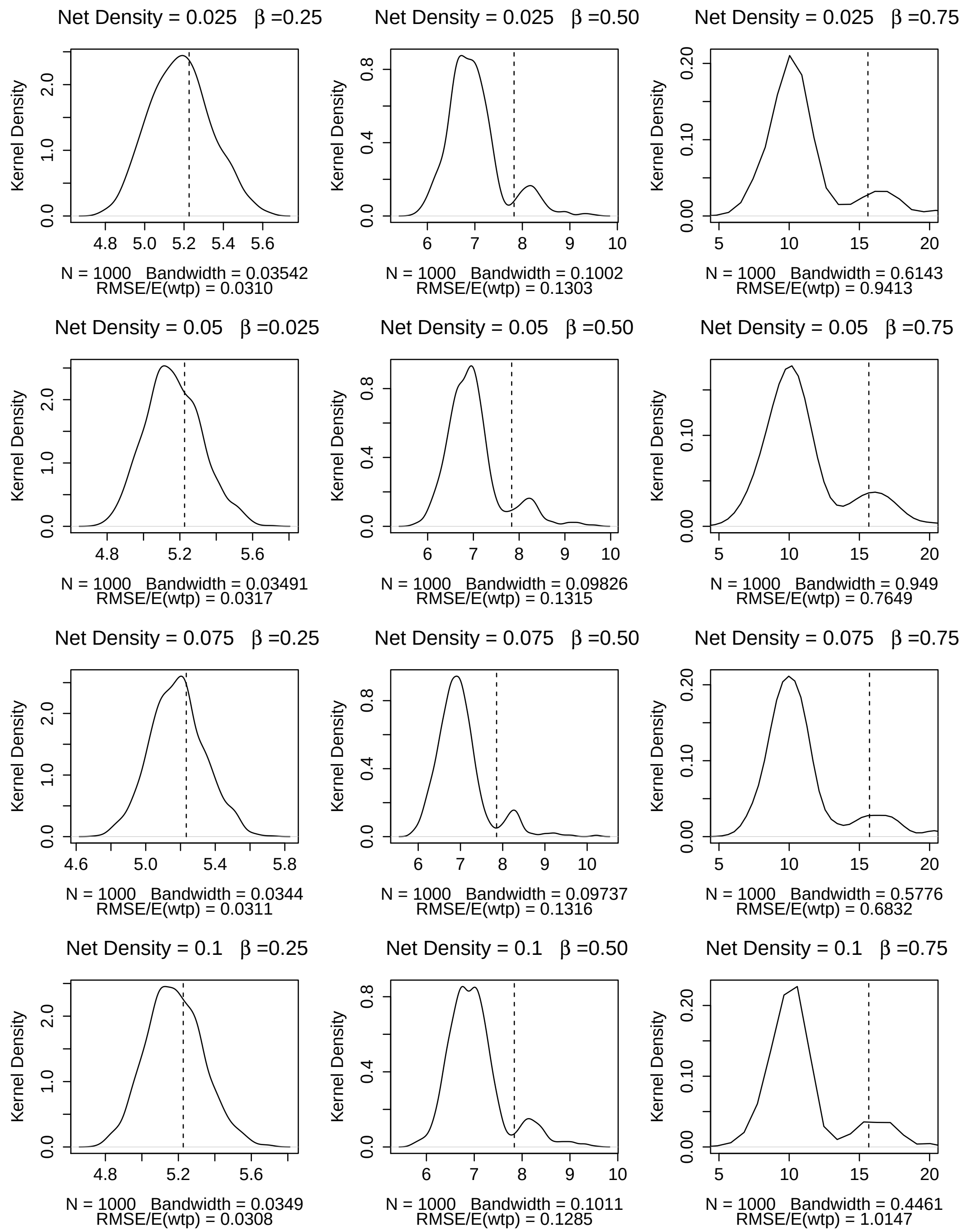

Figure B.2: Kernel Estimates for MC trials with Low Density Erdos-Renyi Networks

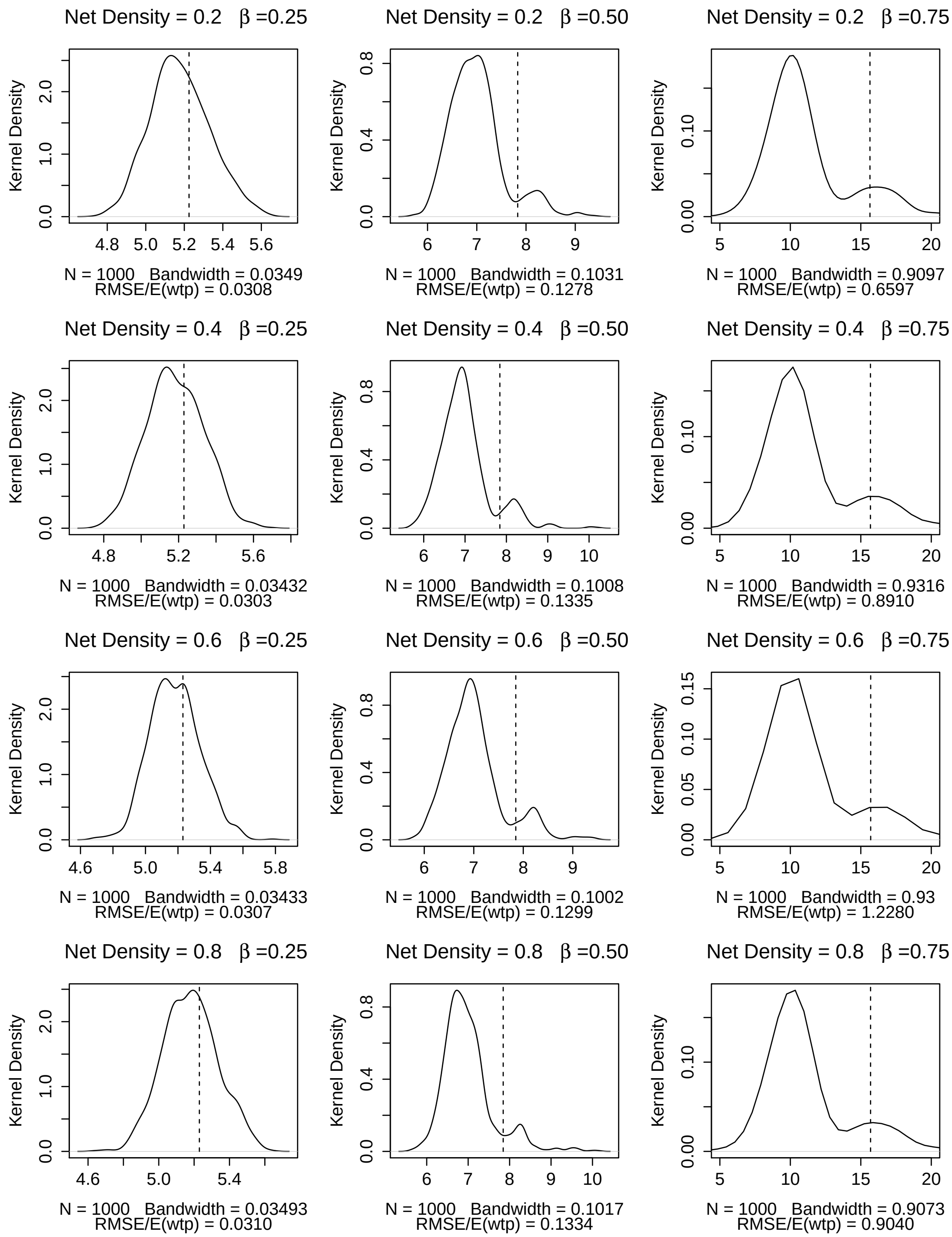

Figure B.3: Kernel Estimates for MC trials with High Density Erdos-Renyi Networks

Table B.1: Coefficient of Variation for Erdos-Renyi Simulations (1000 draws).

	Network Effect β		
d	0.25	0.50	0.75
0.025	0.0310	0.1303	0.9413
0.050	0.0317	0.1315	0.7649
0.075	0.0311	0.1316	0.6832
0.10	0.0308	0.1285	1.0147
0.20	0.0308	0.1278	0.6597
0.40	0.0303	0.1335	0.8910
0.60	0.0307	0.1299	1.2280
0.80	0.0310	0.1334	0.9040

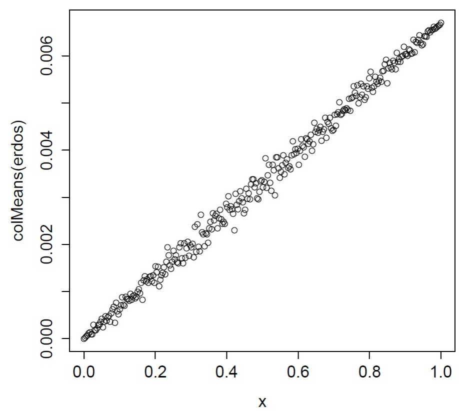

Figure B.4: Correlation Between Importance and **X**

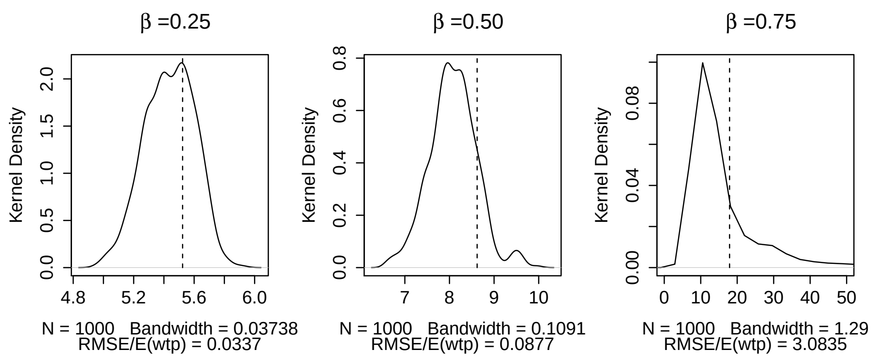

Figure B.5: Kernel Estimates for MC trials with Network Importance Matching **X**

Table B.2: Real World Networks

	Village 1	Village 2	Village 3
Number of nodes	182	195	292
Average degree	19.08	17.73	17.73
Average path length	2.5734	2.9540	2.8130
Average betweenness	0.0162	0.0169	0.0108
Average closeness	0.0006	0.0002	0.0001
Density	0.0524	0.0355	0.0304
Transitivity	0.1751	0.1777	0.1285
Diameter	5	6	6

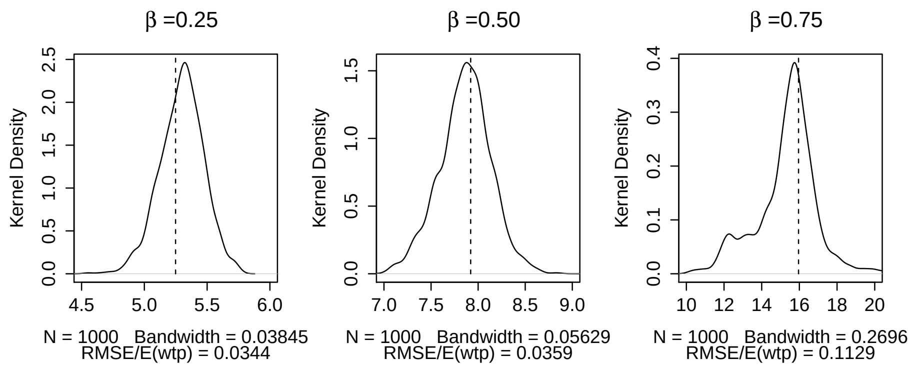

Figure B.6: Kernel Estimates for MC trials - Banerjee et al. - Village 1

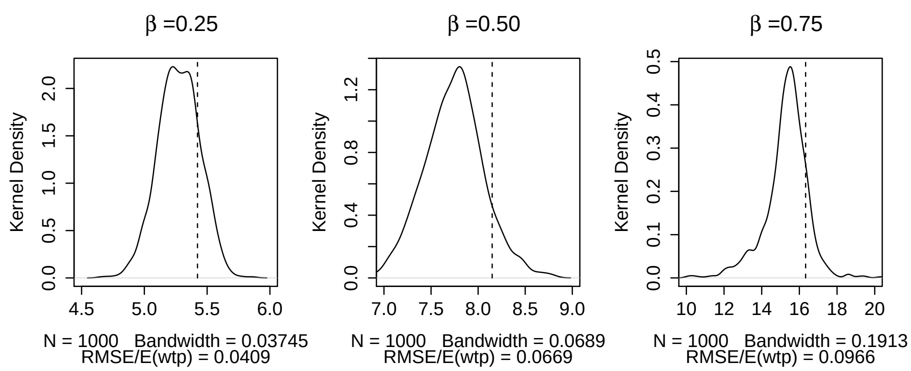

Figure B.7: Kernel Estimates for MC trials - Banerjee et al. - Village 2

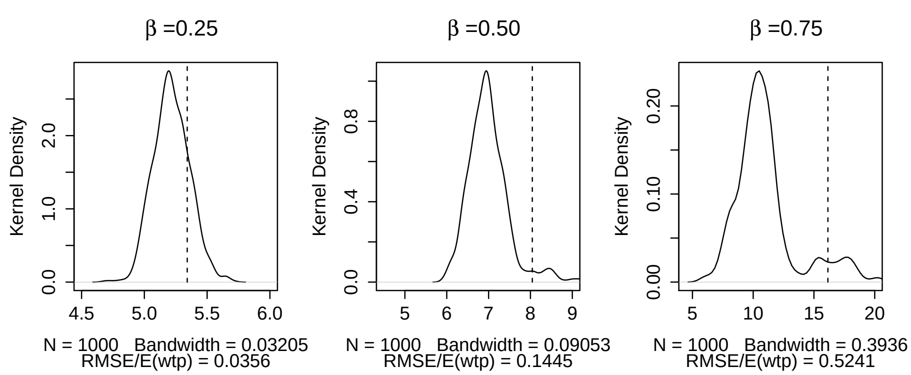

Figure B.8: Kernel Estimates for MC trials - Banerjee et al. - Village 3

Appendix C

Appendix

C.1 Added Surplus and Lost Bargaining Power in Long-term Contracting: An Experimental Investigation

Table C.1: Expected player A payoffs from long-term contract, $\hat{\alpha}_L = 0.2$

	V_L		
	30	40	50
$m = 0$	6	8	10
$m = 2$	6	8	10
$m = 10$	10	10	10

Table C.2: Number of observations in each treatment cell.

		30	40	50	All
No	($m = 0$)	45	45	44	134
Low	($m = 2$)	45	41	45	131
High	($m = 10$)	44	43	45	132
All		134	129	134	397

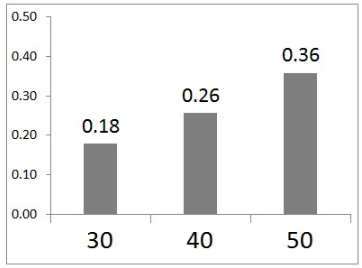

Figure C.1: A's first choice and endowments

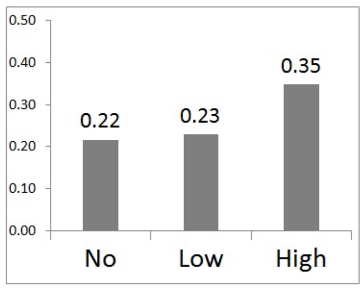

Figure C.2: A's first choice and bargaining power

Figure C.3: A's first choice, endowments, and bargaining power

Table C.3: B's average offer in the dictator game

	30	40	50
No ($m = 0$)	3.43	8.64	11.00
	$n = 7$	$n = 11$	$n = 11$
Low ($m = 2$)	8.60	13.50	13.60
	$n = 5$	$n = 10$	$n = 15$
High ($m = 10$)	10.42	15.00	14.09
	$n = 12$	$n = 12$	$n = 22$

Table C.4: B's average offer in the ultimatum games

	first ultimatum			second ultimatum		
	30	40	50	30	40	50
No ($m = 0$)	8.71	8.50	8.39	7.64	8.07	7.47
Low ($m = 2$)	8.05	7.90	8.00	7.57	8.21	7.85
High ($m = 10$)	8.41	8.52	8.39	7.90	7.43	8.11

Table C.5: Player A's payoff

	Ultimatum			Dictator		
	30	40	50	30	40	50
No ($m = 0$)	15.24	14.15	14.42	3.43***	8.64**	11.00
Low ($m = 2$)	14.10	13.94	13.30	8.60*	13.50	13.60
High ($m = 10$)	14.91	13.35	13.17	10.42**	15.00	14.09

T-tests. H_0: Mean(Ultimatum)= Mean(Dictator)

*** P-value $\leq$ 0.01, ** P-value $\leq$ 0.05, * P-value $\leq$ 0.10

Table C.6: A's rejection - Probit regressions

Dep. Variable: Rejection=1	(1)	(2)	(3)	(4)
Offer	-0.049	-0.046	-0.046	-0.046
	(0.000)	(0.000)	(0.000)	(0.000)
Second Ultimatum		0.034	0.033	0.033
		(0.043)	(0.043)	(0.046)
High Bargaining			0.033	0.031
			(0.117)	(0.103)
No-50				-0.011
				(0.590)
Predicted Prob. of Rejection	0.067	0.063	0.060	0.060
N	555	555	555	555

Probit regression with a constant.
Coefficients represent marginal effects.
P-value in parenthesis.

C.2 Instructions

Thank you for participating in this experiment.

This is an experiment in individual decision-making. The instructions are simple, and if you follow them 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 depend partly on your decisions and partly on the decisions of the player with whom you are matched.

It is important that you strictly follow the rules of this experiment. 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 a monitor will come over to your desk and answer it in private.

Description of the Task

You will be participating in a simple experiment in which you will play 4 games. A game requires 2 players, one of whom will be called Red Player and the other Blue Player. At the start of the experiment, the computer will randomly assign you the role of either Red Player or Blue Player. You will remain in your assigned role throughout the experiment.

In each game, you will be randomly matched with a different Player of the opposite type. That is, if you are a Blue Player you will be matched with a different Red Player for each game. Please note that neither you, nor the person with whom you are matched, will ever learn with whom they were paired.

The Blue Player will move first by selecting one of two branches, Branch A or Branch B. If the Blue Player selects Branch A, the Red Player will be provided an endowment and will propose a way to split this endowment with the Blue Player. The Blue Player will then decide whether to accept or reject the offer. If the Blue Player accepts the offer, the Red Player will be provided a new endowment and the decision problem will be repeated. If the Blue Player rejects the offer, the game will end.

If the Blue Player selects Branch B, the Red Player will be provided an endowment of money and will propose a way to split this endowment with the Blue Player. Once the Red Player decides how to split the endowment, the game will end.

The terminal brackets contain the payoff information. The game will end at one of the four terminal brackets. The top number in each bracket gives the formula for calculating the payoff in $'s for the Blue Player. The bottom number in each bracket gives the formula for calculating the payoff in $'s for the Red Player.

Procedure for Playing the Game

The Blue Player will move first by selecting one of two branches, Branch A or Branch B. The procedure for playing the game that follows from each of these branches is detailed below.

Branch A

If the Blue Player selects Branch A, the Red Player will receive an endowment of money $EA1 from the experimenters. Red Players will then have to decide how much of their endowment, if anything, to transfer to their Blue partner.

The Blue player then has to decide whether to Accept the offer of to Reject the offer.

If Blue accepts the offer:
- Blue gets the transfer
- Red gets their endowment (EA1) minus the transfer.

If Blue rejects the offer:
- Blue gets nothing
- Red gets nothing

If Blue rejects the offer, the game will end. If Blue accepts the offer, a second and final round will be played. At the start of the second round, the Red Player will receive a new endowment of money $EA2 from the experimenters. They will then have to decide how much of this new endowment, if anything, to transfer to their Blue partner.

The Blue Player then has to decide whether to Accept or Reject this second offer.

If Blue accepts the second offer:
- Blue gets the initial and second transfer.
- Red gets their initial endowments (EA1 and EA2) minus the initial and second transfers.

If Blue rejects the offer:
- Blue gets the initial transfer.

- Red gets their initial endowment (EA1) minus the initial transfer.

Regardless of the decision made, the game will end after the Blue Player accepts or rejects the second transfer. Please note that the payoffs of each round are independent. Therefore, actions in the second round do not affect the payoffs from the first round.

Branch B

If the Blue Player selects Branch B, the Red Player will be given an initial endowment of money $EB. The Red Player will then have to decide how much of their endowment, if anything, to transfer to their Blue partner. Once the Red Player determines a transfer amount, payoffs are realized as follows:

- Blue gets the transfer
- Red gets the initial endowment minus the transfer

This will be the end of the game.

Important Note

Red Player's splitting choices must be whole numbers. In some games, Red Player's choice will be restricted. Red's possible proposals could be restricted to two specific amounts or to a subset of whole numbers. These restrictions are always imposed by the experimenters.

Please, take some time now to study the structure of the game. This same basic procedure will be followed for each of the four games.

Final Payoffs

You will only be paid your earnings for one of the four games you will play during today's session. After all four games have been completed, we will randomly select one of the games by selecting an index card that is numbered from 1 to 4. The number on the card which is selected will determine which game will determine your earnings for today's session.

Even though you will make four decisions, only one of these will end up affecting your earnings. You will not know in advance which decision will hold, but each decision has an equal chance of being selected.

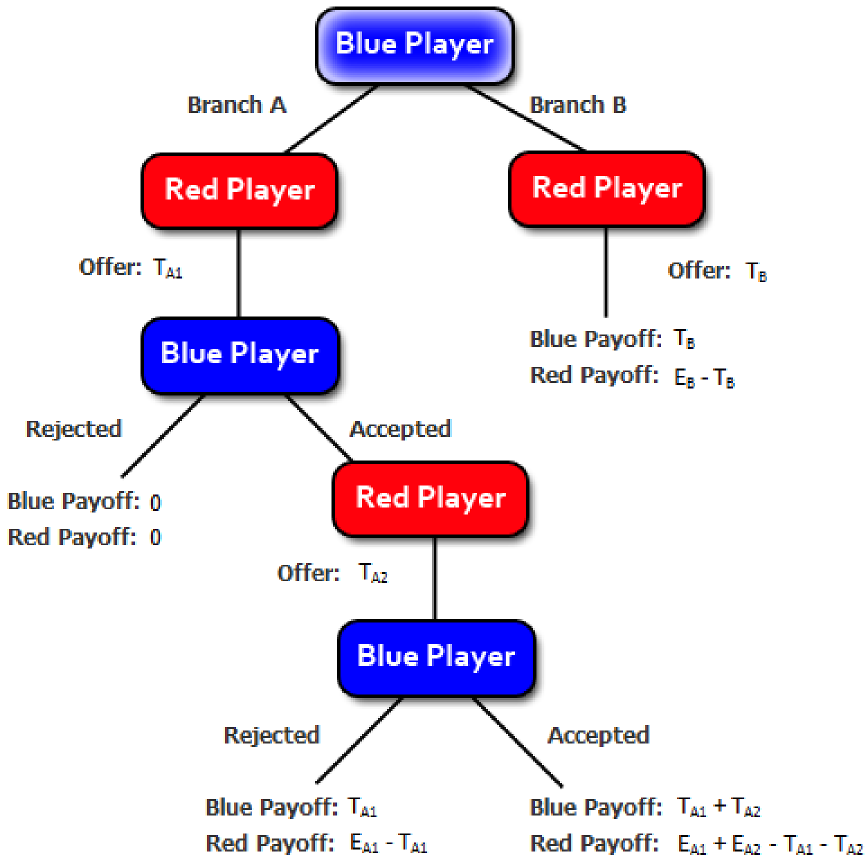

Figure C.4: Game Tree.

C.3 Screen Shots

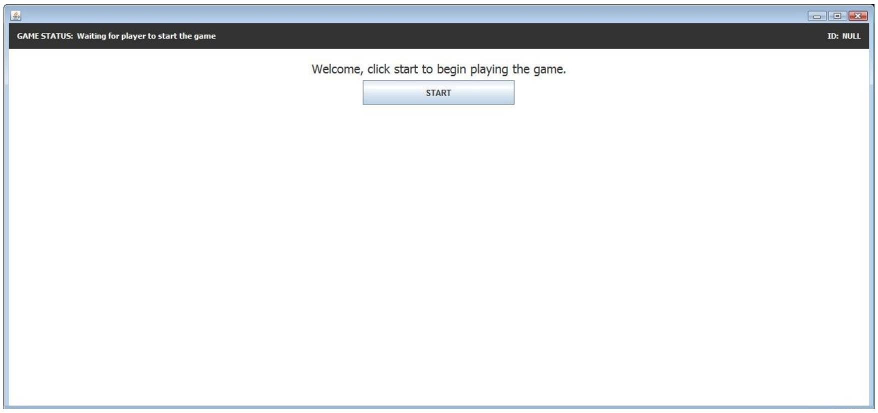

Figure C.5: Welcome screen.

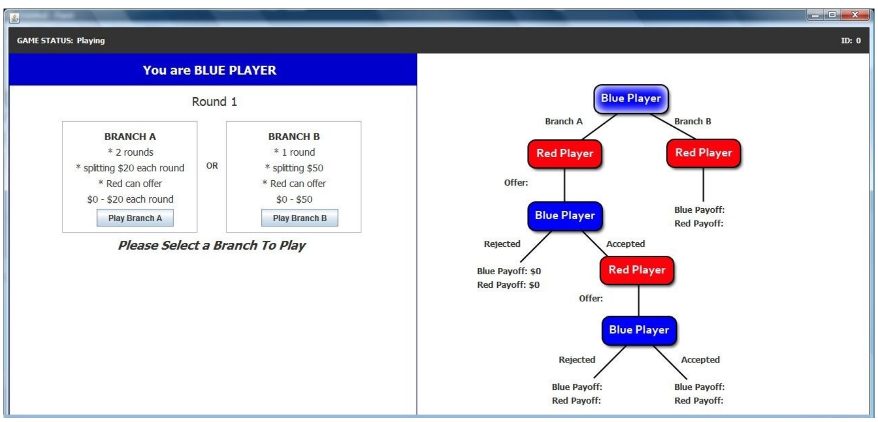

Figure C.6: Random assignment of player type - Player A (Blue). Player A's original choice (Treatment No-50).

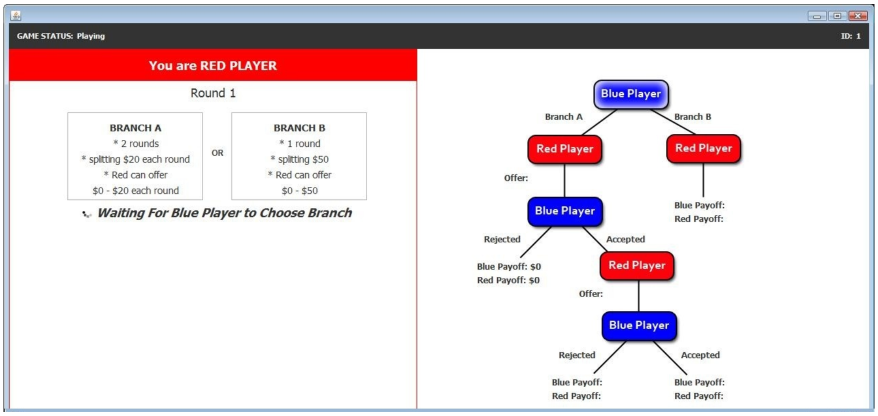

Figure C.7: Random assignment of player type - Player B (Red).

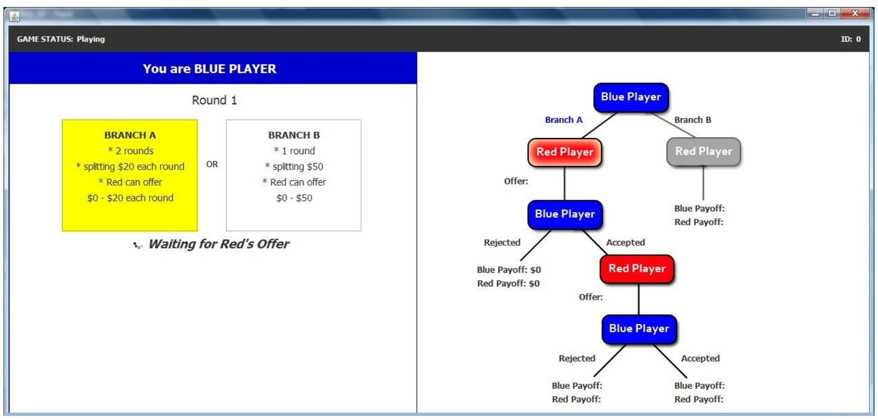

Figure C.8: Waiting screen - Player A.

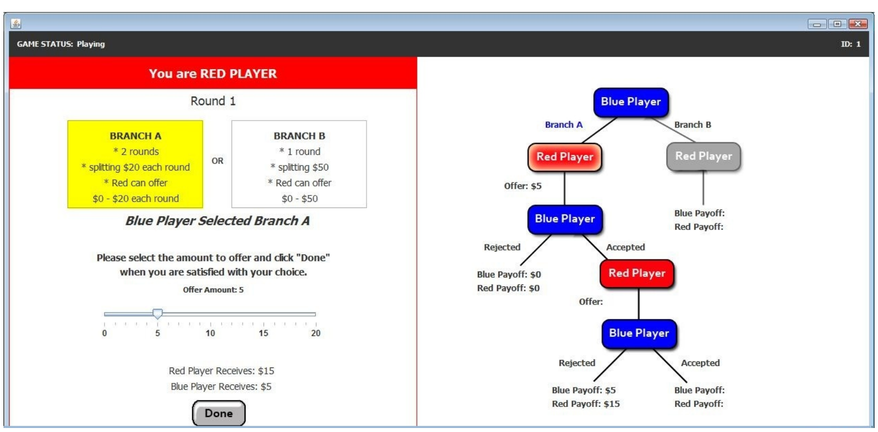

Figure C.9: Player B's offer in the first ultimatum game.

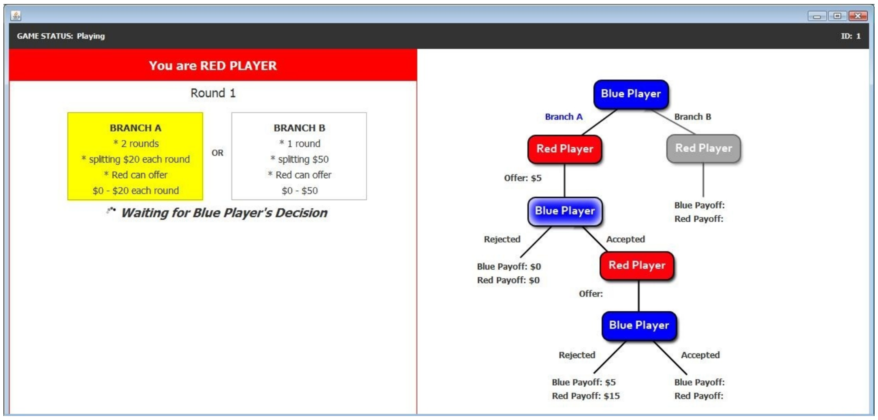

Figure C.10: Player B is waiting for A's first accept/reject decision.

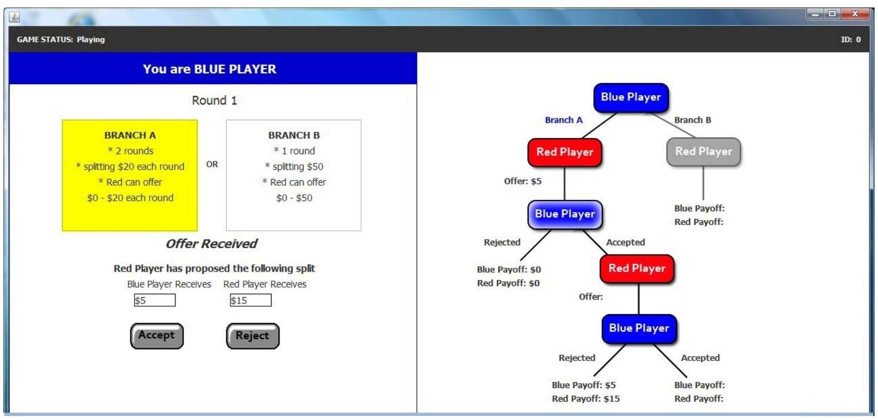

Figure C.11: Player A's first accept/reject decision in first ultimatum.

Figure C.12: Confirmation screen - Player A.

Figure C.13: Waiting screen - Player A

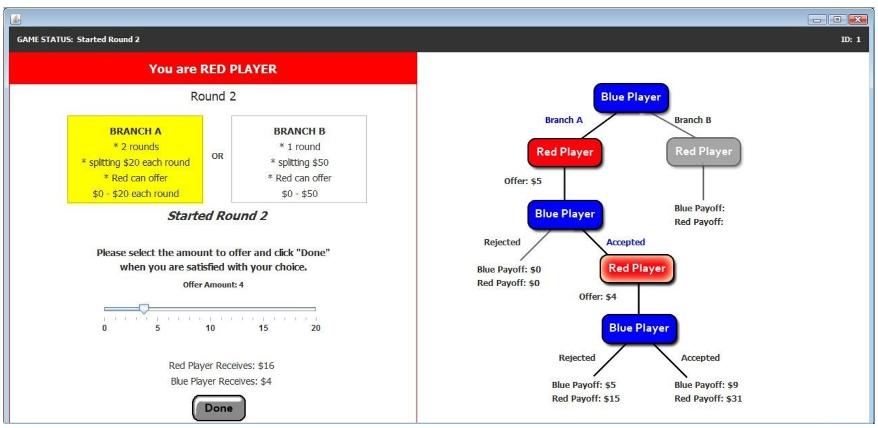

Figure C.14: Player B's offer in the second ultimatum game.

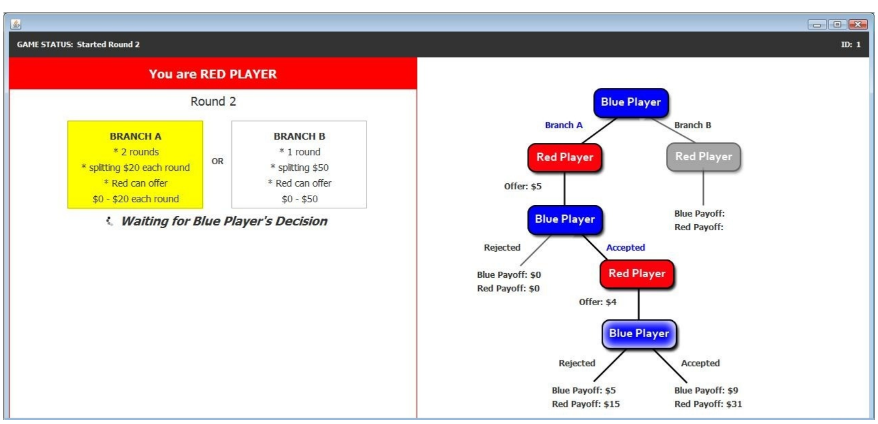

Figure C.15: Player B is waiting for A's second accept/reject decision.

Figure C.16: Player A's second accept/reject decision in first ultimatum.

Figure C.17: Confirmation screen - Player A.

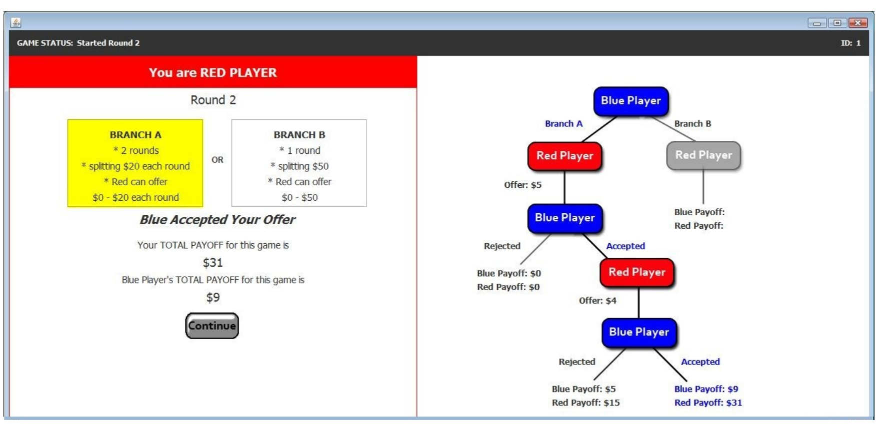

Figure C.18: Confirmation screen - Player B.

Figure C.19: Starting next treatment - Player A.

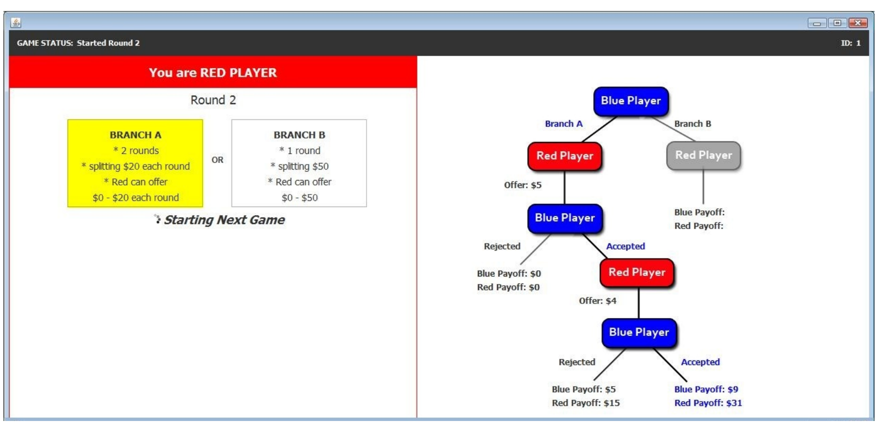

Figure C.20: Starting next treatment - Player B.

Vita

Bruno Moreira Wichmann was born in Fortaleza, Ceara, Brazil. He attended Colegio Batista Santos Dumont High School in Fortaleza. He received a Bachelor of Science and a Master of Science degrees in economics from the Federal University of Ceara. Bruno left Brazil to pursue graduate studies in economics in the United States. He obtained a Master of Arts and a Doctor of Philosophy degrees from the University of Tennessee, Knoxville. He has accepted a position as an Assistant Professor of Resource and Environmental Economics at the University of Alberta, Canada.