THE ROLE OF FINANCIAL INFORMATION, SOCIAL CAPITAL AND REPUTATION IN LENDER DECISIONS

by

Michael Shane Maier

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Business Administration
in the Graduate College of
The University of Iowa

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Thesis Supervisor: Professor Douglas V. DeJong

ABSTRACT

This Thesis contains three essays on the economic behavior of individuals. The first essay, co-authored with Andreas Blume and Douglas DeJong is an experimental investigation into the contribution of cognition in a strategic setting where the goal is to coordinate by choosing different courses of action. Specifically, we study whether cognitive limits affect the ability of agents to achieve dispersion outcomes and; further, how these limits affect the means by which dispersion outcomes are attained.

We find that in the self-play treatment when agents are allowed to play against themselves, dispersion outcomes are relatively easy to obtain; however, when paired with others, cognitive differences increase the difficulty in achieving a dispersion outcome. When we relax the cognitive constraints, the ability of participants to achieve dispersion outcomes increases to approximately the same level as those in the self-play treatment; further, the means by which dispersion outcomes are achieved does not differ from those in the self-play treatment.

In the second essay I investigate how noise impacts incentives provided by contracts that are structured with option-style payoffs. Existing theory suggest that one cannot commit to not renegotiate based on the receipt of a non-contractible signal; however, others suggest that in the presence of a noise in the non-contractible signal may not result in partners wanting to renegotiate since the initial contract may still provide incentives for subsequent periods.

Using an experimental economics approach I find that players who receive a perfect non-contractible signal do not put forth high effort in a subsequent period; however, the presence of noise in the signal may result in players continuing to put forth high effort in a subsequent period. A behavioral explanation is provided for these observations.

In the final essay for which this Thesis is named, I employ a field study methodology to investigate the incremental role that social capital plays in both individual lending decisions and outcomes. I find that lenders are more likely to choose borrowers who have social capital; however, social capital does not impact the interest rate that borrowers pay or the rate of default.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Michael Shane Maier

has been approved by the Examining Committee for the thesis requirement for the Doctor of Philosophy degree in Business Administration at the December 2009 graduation.

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CHAPTER 1

COGNITION AND SPATIAL DISPERSION GAMES

Introduction

In spatial dispersion games the agents' common goal is to choose distinct locations. Such games have been used to study congestion problems, habitat selection, and networking issues, (Alpem and Reyniers, 2002; Alpem and Gal 2003). More generally, dispersion incentives in location games appear in models of product differentiation, (Salop, 1979), and variants of the voting models of Hotelling (1929), Downs (1957) and Palfrey (1984). We experimentally investigate the role of cognition in such games and compare it with the role of cognition in spatial matching games, where the common goal of the agents is to choose the same location. In our setup cognition matters because agents may be differentially aware of the dispersion opportunities that are created by the history of the game. Once agents achieve dispersion in a repeated spatial dispersion game and if they can remember past choices, they have the option to maintain dispersion by simply maintaining their previous choices. When agents do not have a simple record of their own past choices there may be other ways of sustaining dispersion. Cognitive issues arise when agents do not have a simple record of their own past choices, but there is a procedure for inferring own past choices. Some agents may be aware of this procedure while other agents may be unaware of it.

Unawareness of this sort requires more than simple lack of knowledge. In addition to not knowing the procedure the agent must not know that he does not know the procedure, i.e., he must lack *negative introspection.* Unawareness seems commonplace in everyday life, and yet has only recently attracted attention in the literature. One likely reason is that unawareness does not easily fit into conventional models of information economics. Violations of negative introspection are not compatible with the standard partitional state space model of knowledge, Aumann (1976), as pointed out by Geanakoplos (1992). More recently, Dekel, Lipman and Rustichini (1998) have demonstrated that *any* standard state space model precludes unawareness. They suggest that one way to avoid this conundrum is to make a distinction between the agent's and the analyst's description of the state space, and to treat the state space as "representing the agent's view of possibilities." Recently, there have been a few proposals of models of knowledge that permit unawareness, (Li, 2003; Schipper, 2002). Furthermore, there have been suggestions that properly incorporating unawareness into our models may shed light on issues related to contractual incompleteness and no-trade theorems.

Our objective is more modest. We accept unawareness as a simple empirical phenomenon and ask what happens when agents differ in their awareness in a simple strategic setting, i.e., when there is interactive unawareness. Common-interest games are attractive for this purpose because they help us focus on the central issue of how unawareness affects players' strategic reasoning about others. We need not worry for example about how differential awareness interacts with signaling motives, bargaining motives, deception, threats, punishments, or other-regarding preferences. Location games with a spatial structure are appealing because agents may differ in how much of this structure and its possible uses they perceive.

For a formal model of interactive unawareness in our games we follow Bacharach (1993). He calls for a model of games in which "one specifies the way players conceive the situation and how this varies." He provides details of such a model of *variable universe games* for the case where the players' aim is to choose a common action, i.e., for matching games. In Bacharach's model, a player's perception is essentially given by a partition of the set of actions. Blume and Gneezy (2002) extend Bacharach's approach to permit a more general structure on the sets of actions than partitions, or collections of partitions. It permits the spatial (circular) structure that is used in Blume and Gneezy (2002), Blume, DeJong and Maier (2003) and that will be used in the present paper to address spatial dispersion games.

A basic version of the dispersion game (that we expand upon and fully develop later in the paper) consists of two players who are randomly paired together for a one-shot game. The two players simultaneously and independently choose one of three identical unlabeled sectors of a disc, as illustrated in Figure 1.1. One player sees a disc whose labels have the directional order indicated in Figure 1.1. The other player sees a disc with the directional order of the labels reversed, as in Figure 1.l. The locations are randomized at the beginning of the one-shot game and neither player sees the labels A, B, and C themselves. In a spatial dispersion game, the payoffs are one if both players choose different sectors, A and B, B and C, or C and A, and zero if they choose the same sector. A, B, or C. For a simple spatial matching game the payoffs are just the reverse.

Blume and Gneezy (2002) have experimentally demonstrated that there are differences in awareness in spatial matching games. Blume and Gneezy consider one-shot spatial matching games in which players simultaneously choose a single sector from a disc with five sectors. All sectors are identical in size and shape, three are white, and two are black. They compare two scenarios, one in which a single individual plays against him- or herself, and one in which two distinct players play against each other. In either case, given the symmetry constraints imposed by the task, there is a unique optimal way to play the game. Success is only guaranteed if both choices correspond to the midpoint of the odd distance between the two black sectors. Cognitive differences can be shown to exist by having players play against themselves. When playing against themselves, players who are aware of the guaranteed success strategy will use it, while others will be attracted to the obvious alternative, to choose one of the black sectors. Blume and Gneezy find that a significant percentage of participants do not solve the game when playing against themselves.

In the matching games of Blume and Gneezy (2002), cognitive differences prevent players from coordinating on the unique optimal solution. Cognitive differences are likely to play a different role in dispersion games. Even though in both kinds of games agents have a common objective, the structure of equilibria is different. Unlike in matching games, in dispersion games typically none of the equilibria are strict: As long as there are more locations than agents, an agent can always switch to an unused location and still maintain dispersion. Also, while the matching games of Blume and Gneezy (2002) have a unique optimal solution, there are multiple ways in which dispersion can be achieved in our games. This makes the questions of whether any equilibrium is attained and, if so, which one will be selected important.

The present paper has agents interact repeatedly in spatial dispersion games. Repeated interaction in spatial matching games with a circular structure has been investigated by Blume, DeJong and Maier (2003). There, players are randomly paired each period. The stage game played in each period consists of two rounds. In the first round of the stage game two players simultaneously and independently choose one of n identical sectors of a disc, where n is odd. In the second round, after observing first round choices, but without being able to distinguish one's own from one's partner's choice, both players choose again. In both rounds, payoffs are one if both players choose identical sectors and zero otherwise. Note that the second round induces essentially the same choice problem as the task in Blume and Gneezy (2002) and therefore has a unique optimal solution.

In the repeated spatial matching games of Blume, DeJong and Maier, learning can occur at two levels. At one level, in each period, agents can learn by labeling actions in the first round and using these labels in the second round." At the other level, agents can learn across periods about how to learn within a period. This type of learning, which we call *cognitive learning,* has to the best of our knowledge of the literature only been addressed in the Blume, DeJong and Maier (2003) paper. Initially, there may be agents who are unaware of the fact that the labels introduced by first-round choices can always be used to identify a unique distinct sector. Other agents may be aware of this possibility. In the course of the multi-period interaction, agents may *become aware* of this possibility, i.e., engage in *aha learning, (*Biihler, 1907, 1908; Kohler, 1925; Weber, 2003). The results from our matching games support coordination outcomes and we find evidence for cognitive learning. That is, in simple environments agents learn across periods to make better use within a period of labels created in that period. We observe transfer of cognitive learning from simple environments to more complicated environments.

As previously noted, the structures of the action space that agents may or may not be aware of have different uses in dispersion games than matching games. For example, the circular structure of the matching game of Blume, DeJong and Maier (2003) enables agents to identify a unique candidate for a common action. The same circular structure in a dispersion game generates a "coordination problem" characterized by multiple, non-strict equilibria. This difference in the possible use of structures suggests that the learning may also be different.

Our main finding in the present paper is that in spatial dispersion games, strategic interaction magnifies the role of cognitive constraints. Specifically, with cognitive constraints, pairs of agents fail to solve a dispersion problem that poses little or no problem for individual agents playing against themselves. When we remove the cognitive constraints in our design, pairs of agents solve the same problem just as well as individuals do. In addition, we find that when playing against themselves agents do not change the mode by which they solve the dispersion problem when our design removes the cognitive constraints.

Game and Experimental Design

We study a repeated dispersion game in which two players are randomly paired together and stay paired for twenty-one periods. In the first period, the two players simultaneously and independently choose one of three identical unlabeled sectors of a disc, as illustrated in Figure 1.1 . One player sees a disc whose labels have the directional order indicated in Figure 1.l. The other player sees a disc with the directional order of the labels reversed, as in Figure 1.l. Neither player sees the labels A, B, and C themselves. The payoffs are one if both players choose different sectors, A and B, B and C, or C and A, and zero if they choose the same sector, A, B, or C. At the end of period one, the two players are informed about the sectors that were chosen.

At the beginning of the second period, players observe the previous period's choices but without being able to distinguish one's own from one's partner's choice, for example see Figure 1.2 where the players achieved a dispersion outcome and where the discs with the first period choices have been randomly spun and presented to the players. Figure 1.2 and 1.2 respectively, at the beginning of period two. Both players then choose again. The payoffs are again one if both players choose different sectors and zero if they choose the same sector. At the end of period two, the two players are informed about the sectors that were chosen. Specifically they see the choices made in period 2, marked by red dots, on the background of the choices made in the previous period, marked by shaded sectors. Each of the subsequent periods follows the same sequence outlined for the second period.

We implement a two-by-two design. The first dimension is the information provided to players about their choices. The *relative-location information condition* is described above. In the theory for dispersion games, it is common practice to assume that agents know their present location and the location of other agents when taking their future choice of action. This describes the *precise-location information condition* and is illustrated in Figure 1.3, where the choice of one player is noted in dark shading and the other player's choice is lightly shaded.

The second dimension of the design is the pairing of the players. The first condition *is fixed pairing,* as described above. The second condition is *self pairing* where a player is paired with him or herself for the duration of the repeated spatial dispersion game. The purpose of this dimension is to separate the cognition problem from the coordination problem. Thus, there are four treatments in our design; fixed-pairing with relative and precise location information, and self-pairing with relative and precise information.

The experiment was conducted using a series of six cohorts; two cohorts or replications each for the two information treatments with fixed-pairing and one replication each for the two information treatments with self-pairing. A cohort consisted of twelve participants. Such a design provides the same number of pair observations in each of the four treatments. All participants were recruited from undergraduate (sophomore and above) and graduate classes at the University of Iowa. None of the participants had previously taken part in or otherwise gained experience with this series of treatments. Upon arrival, participants were seated at separate computer terminals and given a copy of the instructions. Before each replication, instructions were read aloud and participants individually filled out questionnaires confirming their knowledge and understanding of the instructions. We then went over the questionnaire orally and answered questions. Since these instructions were read aloud, we assume that the information contained in them was mutual knowledge.

Each cohort played a repeated spatial dispersion game for twenty-one periods from one of the four treatments in the design. Each period had the following structure. Prior to the beginning of the first period, participants were paired using a random-matching procedure or paired with themselves. In the first period, participants chose a sector from a symmetric disc with 3 identical sectors. At the beginning of the first period, the discs were randomly rotated, independently across participants or across the two computer screens used by a participant in the self-pairing treatments, to eliminate all possibilities for *a priori* coordination. Then, participants made their choices by using a mouse to click on their chosen sector. They were given an opportunity to either revise or confirm their choices. At the end of the period, when all participants had made and confirmed their choices, they were informed about which sectors were chosen in their match.

At the beginning of period two, each disc was randomly rotated and period-one choices were displayed in the new configurations. In the display for the relative information treatments no distinction was made between one's own choice and one's partner's choice, see Figure 1.2. This procedure ensured that in the second period, participants only had information about the configuration of choices. In the precise information treatments, each player's choice was indicated for both players and for the self-pairing treatments the choices made on each computer screen were indicated for the player, see Figure 1.3. In the second period, participants once more chose one of the three sectors from the same disc as before with the prior choices displayed as just described. At the end of the period, when all participants had made and confirmed their choices, they were informed about which sectors were chosen in their pair along with the relative (precise) locations of the previous period's choices. Each subsequent period through period twenty-one followed the same sequence detailed for period two.

Each replication lasted from one-half to one hour. Participants' earnings ranged from $7.50 to $15.75 plus a "show up" payment of $5.

Theory

A solution for our relative information fixed-pairing treatment, must acknowledge two fundamental characteristics of the game. These are the symmetries that are built into the game, and potential differences in players' abilities to recognize when these symmetries have been broken.

Our design ensures that in the first period of our game all three sectors are completely symmetric. Players could not guarantee dispersion even if we permitted them to talk before the game. The fact that we rotate the disc independently across players guarantees that players *de facto* randomize by assigning equal probabilities to all sectors in the first period.

In the second period, players observe which sectors were chosen in the first period. Consider the case where players achieved dispersion in the first period (the other case, in which their choices resulted in congestion, is analyzed analogously).

The fact that we spin the disc and that both players' choices are marked identically ensures that players cannot distinguish between their own choice and their partner's choice. Therefore, players are *de facto* precluded from guaranteeing dispersion in the second period by maintaining their first-period choices in the second period.

However, unlike in the first period, the absence of communication is a binding constraint here. If they could communicate, they could agree on one player playing the *odd sector,* the sector not chosen by either player in the first period, and the other player playing one of the first-period choices. In the absence of communication, the fact that players' positions are identical prevents them from coordinating on such asymmetric behavior. Therefore we look for equilibria where in the second period both players put the same probability on the odd sector.

Before the third period (and similarly for subsequent periods) smart players will remember whether in the second period they chose the odd sector, the sector to the left of the odd sector (as viewed from the center of the disc), or the sector to the right of the odd sector. Then, if they manage to achieve dispersion in the third period, they can achieve dispersion in every subsequent period by following the rule of choosing the same sector in relation to the odd sector as in the previous period.

A problem arises because not all players need be smart, in the sense of realizing the possibility of making left-right distinctions on the disc. Players who can only distinguish chosen and unchosen sectors can only guarantee future dispersion if the dispersion realized was such that one player in the previous period chose the odd, unchosen, sector and the other chose one of the two previously chosen sectors. We formalize this problem by allowing for different types of players, who are endowed with different languages, a coarse-language and a fine-language, in which they describe the choice set to themselves.

The distinction between coarse- and fine-language players is as follows. Coarse language players can only distinguish *chosen* and *unchosen* sectors in any period after the first period. Fine-language players can use the circular structure to enumerate all sectors after the first period. Further, fine-language players can commonly distinguish all sectors in a period after the second period. The reason is that for period three and after, fine-language players can describe each others' choices relative to the odd sector. Already, in period two, a fine-language player can for example choose "the sector to the left of the odd sector." At the beginning of period three, a fine-language player can also see his partner's period-two choice in reference to the odd sector of period one. As a result, fine-language players can maintain dispersion in period three and all subsequent periods.

Player symmetry requires that players use identical strategies. Accordingly, we will focus on equilibria in which players use identical strategies and in which they employ efficient symmetric continuation strategies.

Denote by V_D a player's continuation payoff after players have achieved sustainable dispersion (dispersion in period three or later for fine-language players, and chosen-unchosen dispersion for coarse-language players) and by V_O the continuation payoff otherwise. Denote by p and q the probabilities of each player choosing the odd sector before there is sustainable dispersion, either the sector not chosen if players chose different sectors or the sector chosen if players chose the same sector. Note that the probabilities assigned to the two remaining sectors have to equal $(1 - p)/2$ each for one player and $(1 - q)/2$ each for the other. Of course in a symmetric equilibrium p and q must be the same. Consider the two cases were all players are fine-language players, $\lambda = 1$, or all players are coarse-language players, $\lambda = 0$. Then the payoff from using probability q against probability p equals:

$$\pi(q, p) = pq[0 + V_O] + (p(1 - q) + q(1 - p))[1 + V_D]$$
$$+ (1 - p)(1 - q)\left[\frac{1}{2}[1 + \lambda V_D + (1 - \lambda)V_O] + \frac{1}{2}[0 + V_O]\right].$$

In equilibrium, the player choosing q must be indifferent among all q. Hence the derivative with respect to q must be zero.

$$\frac{\partial\pi(q, p)}{\partial q} = pV_O + (1 - 2p)[1 + V_D] - (1 - p)\left[\frac{1}{2}[1 + \lambda V_D + (1 - \lambda)V_O] + \frac{1}{2}V_O\right]$$
$$= 0.$$

Solving for p, we obtain

$$p = \frac{2V_D + 1 - 2V_O - \lambda[V_D - V_O]}{4V_D + 3 - 4V_O - \lambda[V_D - V_O]}.$$

Hence, if all players are fine-language players, $\lambda = 1$, then

$$p_f = \frac{1}{3}.$$

Fine-language players uniformly randomize across all three sectors through period two and continue to randomize in period three and subsequent periods until dispersion is achieved. Once dispersion is achieved, players coordinate by both choosing left or right of the odd sector or by selecting chosen and unchosen.

If all players are coarse-language players, $\lambda = 0$, then

$$p_c = \frac{2[V_D - V_O] + 1}{4[V_D - V_O] + 3}.$$

Note that p_c is increasing in V_D-V_O. *We* conclude that coarse-language players put more probability on the odd sector than fine-language players. After period one, coarse-language players randomize until they achieve the dispersion outcome of chosen and unchosen sectors. Observe that cognitive differences only matter in the repeated game with at least three periods.

More generally, we can consider the incomplete information game where a player is a fine-language player with probability μ and a coarse-language player with probability 1-μ. Coarse-language players being unaware of their cognitive constraint attach no probability to other players being fine-language players. They play under the presumption that the other player is a coarse-language player with certainty. Therefore, in the incomplete information game, regardless of μ, coarse-language players use the strategy derived for the complete information game above in which all players are coarse-language players.

In contrast, fine-language players are aware of the fact that both types are present and accordingly have beliefs about the type of the player they are facing. Thus, in general, optimal behavior of fine-language players could depend on their beliefs and potentially require complicated updating of beliefs. Fortunately, in the present context, the previously noted strategy for fine-language players, derived above under the assumption that it is common knowledge that all players are fine-language players, remains optimal for *any* belief β by fine-language players that their partner is a fine-language player. To see this, simply note that this strategy is optimal against both fine-language players and coarse-language players. The optimality against fine-language players is immediate.

The optimality against coarse-language players follows from the following facts: (1) against a coarse-language player one cannot do better than a coarse-language player; (2) in periods in which a coarse-language player randomizes, *any* form of randomization, including playing the odd sector with probability P_f or repeating an action that led to dispersion the last period is optimal; and (3), trying to maintain dispersion by repeating last period's action is optimal in periods where a coarse-language partner is doing the same.

In the precise information fixed-pairing treatment, all players are fine-language players unless they ignore the information given to them. They can all distinguish among the sector they chose, the sector chosen by the player they are paired with, and the odd sector. All players uniformly randomize until a dispersion outcome is achieved. Once achieved, the dispersion outcome is played for the remainder of the game, both play left or right of the odd sector. As long as there are coarse-language players here, the probability of picking the odd sector is greater than or equal to one-third and the dispersion outcome can also be achieved by the chosen and unchosen selection.

In the self-pairing treatments, relative and precise information, all players uniformly randomize in period one. In period two, all players should achieve a dispersion outcome because there is no coordination problem after the first period. Fine-language players have the option of choosing to the left or right of the odd sector; coarse-language players can only coordinate by focusing on chosen and unchosen sectors.

Results

Dispersion Outcomes

We first present the proportion of dispersion outcomes achieved by period for the four treatments, fixed-pairing with precise and relative information and self-pairing with precise and relative information. Figure 1.4. First, note that the self-pairing precise information treatment reaches full coordination first. Second, the proportion of dispersion outcomes for the fixed-pairing precise information and self-pairing precise and relative information treatments are indistinguishable. In these three treatments, all players are either fine-language players (fixed-pairing) or should not have a coordination problem when selecting a dispersion outcome (self-pairing). Third, while the self-pairing precise and relative information treatments do not reach coordination in period two, as predicted, the treatments are well on their way by period three. Finally, the proportion of dispersion outcomes in the fixed-pairing relative information treatment is indistinguishable from the expectation that behavior is random, .67. This result contrasts sharply with the result in Blume and Gneezy (2002), where relative information increased coordination relative to precise information.

Individual Player Choices

Regarding individual player choices, our theory suggests that for fixed-pairing, prior to achieving a dispersion outcome, the probability of selecting the Odd sector is higher in the relative information treatment ($p > 1/3$) than in the precise information treatment ($p = 1/3$). Unfortunately, there are very few observations here, sixteen in period two to be exact, too few for any meaningful analysis across the two treatments. However, aggregating across the two treatments, $p > 1/3$, which is the prediction from theory in the presence of coarse-language players in both treatments.

Paired Player Choices

Paired choices of players are presented in Table 1.1 for the four treatments and as a basis for comparison, the expectation that behavior is random. The relationship between paired choices in period t and outcomes in period t - 1 is presented by treatment for periods two to twenty-one. Paired choices in period t are broken down by whether the paired choices are Odd/Not Odd or Both Not Odd with the Dispersed outcome in period t, or whether the paired choices are Other combinations that all imply the Matched outcome in period t. Outcomes are broken down by Dispersed and Matched in period t - 1. For comparison purposes, outcomes are also presented under the expectation that behavior is random between paired choices in period t and outcomes in period t - 1 is presented for periods two to twenty-one. Table 1.1 also presents the outcomes, Dispersed and Matched, for the paired choices for period t. Paired choices in period t are broken down by whether the choices are Odd/Not Odd or Both Not Odd with the Dispersed outcome in period t, or whether the paired choices are Other combinations that all imply the Matched outcome in period *t.* Outcomes in period *t* - 1 are broken down by Dispersed and Matched.

In the fixed-pairing precise information treatment, all players should be fine-language players and therefore should have access to playing left or right of the odd sector. How successful were the players in achieving a dispersed outcome and in coordinating their Not Odd choices, both choose Left or both Right, to achieve a dispersed outcome? From Table 1.1, out of a possible 240 outcomes, 210 are dispersed. For the 210 dispersed outcomes, 156 choices in period *t* were Both Not Odd (which implies both chose Left or both Right) and 54 were Odd/Not Odd (which from our theory implies chosen and unchosen).

Figure 1.4 suggests a difficult coordination problem in the fixed pair relative information treatment. Table 1.1 documents this problem. For the 165 dispersed outcomes achieved in period *t - 1,* players failed to capitalize on this success 52 times in period *t.* Further, for the successes achieved in period *t,* sometimes players coordinated on Odd/Not Odd, 69, and sometimes Both Not Odd, 44. A similar conclusion holds for the analysis of the 75 matched outcomes in period *t - 1.* Given either a dispersed or matched outcome in period *t - 1,* players face the coordination task in period *t* of choosing over Odd/Not Odd or Not Odd (with Not Odd presenting a secondary coordination problem of how to coordinate over the two sectors). Player choices are consistent with the expectation that behavior is random.

In the self-pairing treatments, players do not face such a coordination problem. A player can decide him or herself between Odd/Not Odd and Not Odd (both Right or both Left), regardless of the prior period's outcome. Players were very successful at achieving a dispersion outcome, but it is difficult to distinguish between coarse and fine-language players. The results implied by Figure 1.4 and shown in Table 1.1 (the two information treatments are combined in Table 1.1 because of their similar play) document that the number of matched outcomes is lowest in the self-pairing treatments despite the large number of Odd choices by players. Some players coordinated in period *t* by choosing Right or Left of the Odd sector on both screens, 82 out of 480.

However, most players coordinated by Odd/Not Odd, 350 out of 480. This choice, Odd/Not Odd (or from theory, chosen and unchosen) appears to be the "least costly" way to coordinate rather than a statement about coarse and fine-language players.

Frequency of Paired Choices by Period

We next consider how many times player pairs chose a particular set of choices in each period. Figure 1.5 presents the results for the fixed-pairing precise information treatment. The graph documents the frequency of the paired choices made. Both Not Odd, Odd/Not Odd and Other. To read this graph, note that for Both Not Odd, eight such paired choices were made in period two and thirteen such choices were made in period twenty-one with the frequencies of Both Not Odd choices similarly graphed for the periods in between. The graph documents not only the high frequency of the Both Not Odd choice and its sustainability but also the demise of the Other category of paired choices.

Figure 1.6 describes the frequency of paired choices in the fixed-pairing relative information treatment. Again, the figure documents the coordination problem in this treatment. All three paired choices, Both Not Odd, Odd/Not Odd and Other, were chosen throughout the treatment.

The self-pairing treatments of precise and relative information are presented in Figure 1.7; the two information treatments are again combined because of their similar play. The graph documents the high frequency and sustainability of the paired choice of Odd/Not Odd (from theory, chosen and unchosen). The Both Not Odd choice occurs with less frequency but is sustained throughout the treatments. The Other category of choices tends to die off over the treatments.

Summary

Spatial dispersion games are characterized by multiple, non-strict equilibria. It is an open question whether players can select and attain an equilibrium in a spatial dispersion game. If equilibrium can be achieved, how long will it take and what are its characteristics. A natural question to also ask is whether the insights from matching games extend to dispersion games?

Our principal finding is that in spatial dispersion games, strategic interaction magnifies the role of cognitive constraints when compared to matching games. Players in the fixed-pairing relative information treatment had a difficult time coordinating their actions in order to achieve a dispersion outcome. This result contrasts with the result in Blume and Gneezy (2002), where in matching games relative information increased coordination compared to precise information, and Blume, DeJong and Maier (2003), where three sector matching games with relative information achieved a high level of coordination.

With these cognitive constraints in the fixed-pairing relative information treatment, pairs of agents failed to solve the dispersion problem that posed little or no problem for individual agents. In the self-pairing treatments, players were very successful in achieving dispersion outcomes. While some players coordinated by choosing right or left of the odd sector on both screens, most players coordinated by selecting the "least costly" way to coordinate, selecting the odd and not odd sectors. Thus, in both information treatments with self-pairing, we find that the mode used by individual agents to solve the dispersion problem is the same, odd and not odd.

When we remove the cognitive constraints in our design, pairs of agents solve the same problem just as well as individuals do. The frequency of dispersion outcomes in the fixed-pairing precise information treatment is comparable to both self-pairing treatments. However, the dispersion outcomes were different. Consistent with theory, players essentially coordinated by both players choosing left or right of odd in the fixed-pairing precise information treatment. In the self-pairing treatments, the majority of players picked the least costly way to coordinate, selecting the odd and not odd sectors.

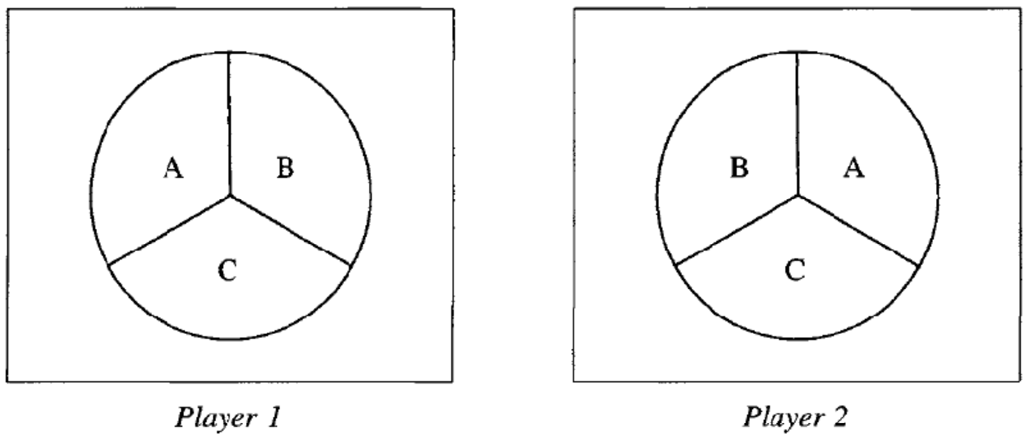

Figure 1.1 Circle Orientation Prior to Player Choices

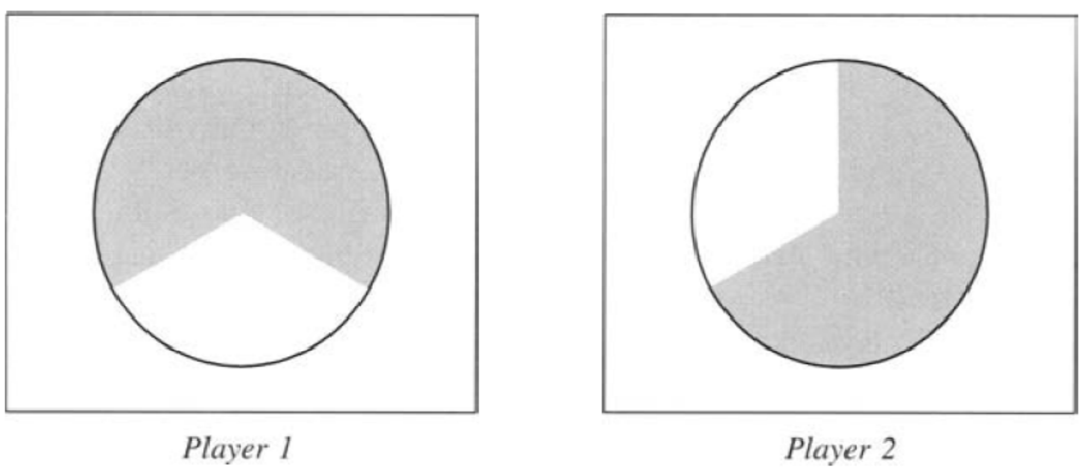

Figure 1.2 Circle Orientation After Initial Player Choices

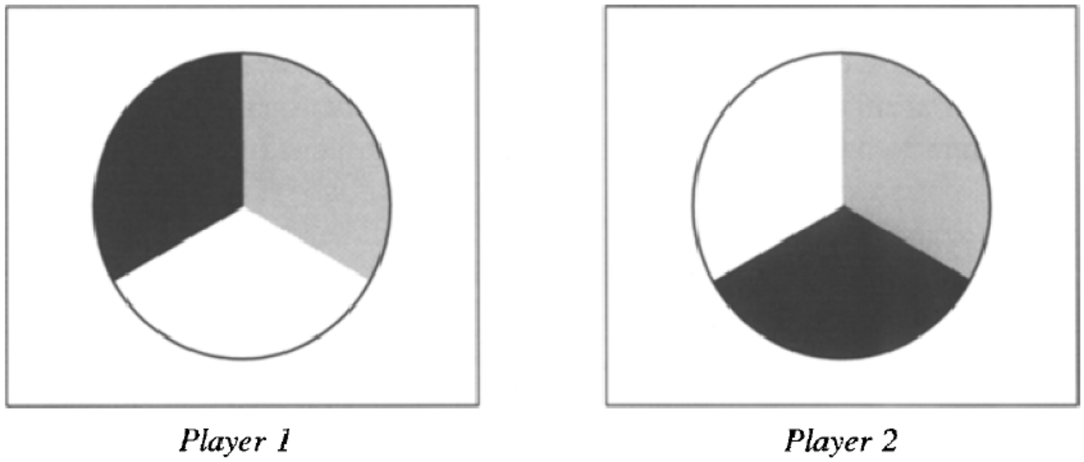

Figure 1.3 Circle Orientation After Second Player Choices

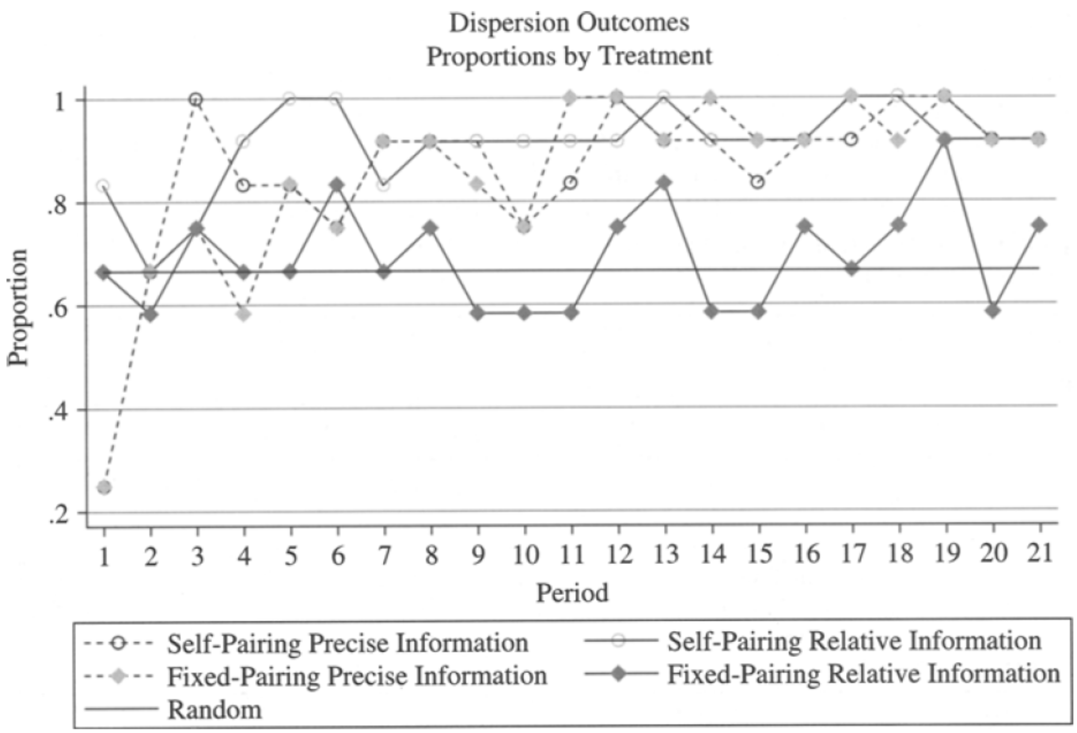

Figure 1.4 Dispersion Outcomes Proportions by Treatment

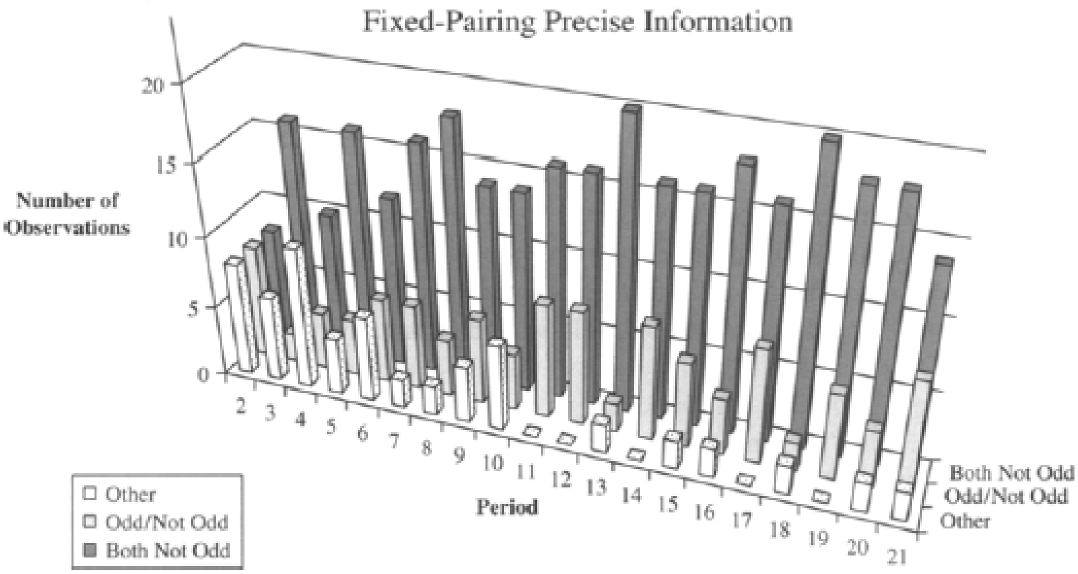

Figure 1.5 Fixed Pairing Precise Information Outcomes

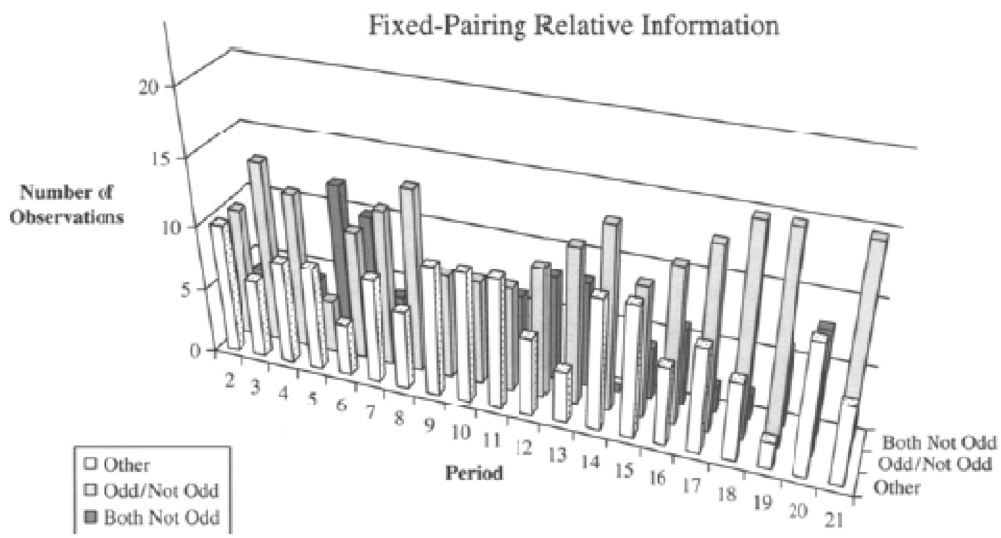

Figure 1.6 Fixed Pairing Relative Information

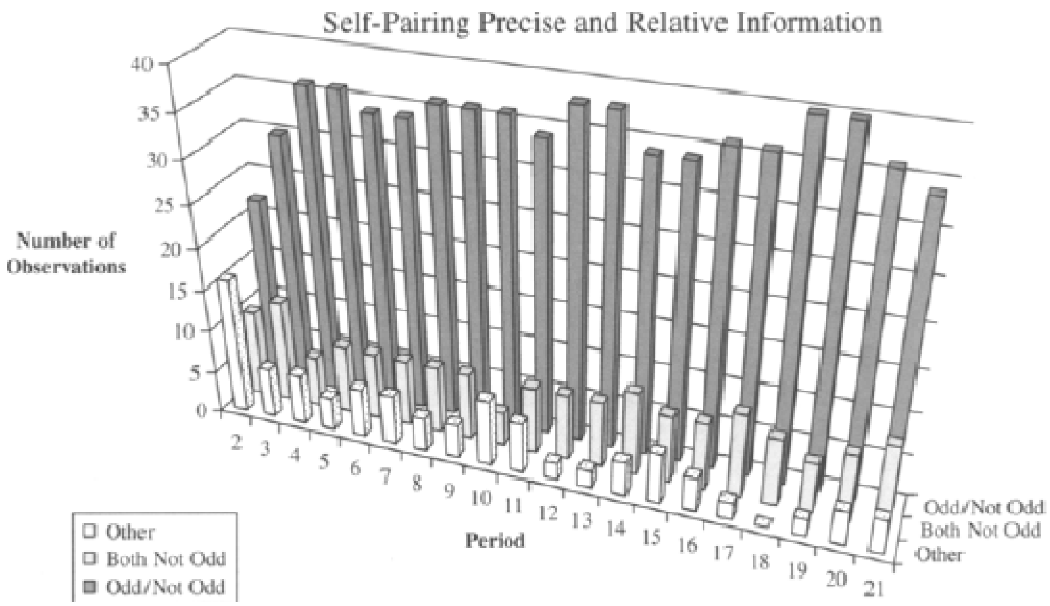

Figure 1.7 Self-Pairing Precise and Relative Information

Table 1.1 Experiment Outcomes

Treatment	*Choices Period t:*	*Paired Choices*			
		Dispersed		*Matched*	*Total*
		Odd/ Not Odd	*Both Not Odd*	*Other*	
	Outcome Period t − 1:				
Fixed-Pair					
Precise					
	Dispersed	39	150	13	202
	Matched	15	6	17	38
		54	156	30	240
Relative					
	Dispersed	69	44	52	165
	Matched	44	9	22	75
		113	53	74	240
Random		107	53	80	240
Self-Pair					
	Dispersed	323	71	36	430
	Matched	27	11	12	50
		350	82	48	480
Random		214	106	160	480

CHAPTER 2

RENEGOTIATE OR NOT: AN EXPERIMENT

Introduction

This paper investigates the value of information quality in a multi-period contract setting. In general, noise in performance measures is thought to be undesirable in contracting since it represents greater risk to the agent for which she must be compensated; therefore, performance evaluation should place more emphasis on measures which have less noise (Banker and Datar, 1989). Yet, in multi-period settings with non-linear compensation contracts, information may not always be helpful. When payoffs to an agent are contingent upon some event occurring, the agent may find it beneficial to reduce investment if they receive information indicating a payoff will not occur, even though the principal would prefer the agent put forth full effort or investment. In such a case, reviewing the contract and possibly resetting the benchmark or hurdle that must be met in order for the agent to receive payment provides a potential solution to this problem. Unfortunately, an agent who knows a contract may be reset might find it advantageous to reduce effort or investment in an early period. This has been dubbed the "ratchet effect" (Indjejikian and Nanda, 1999).

This paper contributes to the literature on contracting by experimentally examining agent responses to information quality in a modification of the Acharya, John and Sundaram (2000) (henceforth AJS) model. In AJS, the authors present a two-period agency model in which the principal provides a non-linear incentive contract to an effort-averse agent in the form of call-options on the firm's equity. The agent then makes an initial effort decision. After the decision has been implemented, interim information regarding the state of the world is obtained. If information indicating a poor outcome will occur, the principal decides whether to reset the strike price of the call options in order to encourage high effort in the subsequent period. If the principal does reset the strike price, incentives are restored; however, there is a potential cost to this action imposed by the "negative feedback effect" which impacts incentives in period one. AJS demonstrate that, in general, allowing for some resetting is nearly almost always optimal. In AJS, interim information received is a perfect indicator of the underlying state of the world.

The present work modifies the AJS framework to incorporate a feature included in Hermalin and Katz (1991) where non-contractible interim information quality is allowed to be less than perfect. When information quality is reduced, agents contemplating an effort or investment allocation decision for period two must now consider their action choice in period one in addition to the interim information received. There are two resulting implications: First, if investment in period one is high, the agent places less emphasis on information indicating a poor final outcome is likely and become more inclined to choose high investment in the second period. Second, knowledge that period one investment will be incorporated into the period two decision serves to diminish the "negative feedback" or "ratchet" effect, thus improving period one incentives.

Two research questions are then experimentally investigated. First, should a principal choose a contract that allows resetting of the performance hurdle considering the potential of the ratchet effect? Second, how does information quality affect agent incentives in these contracts? While there is a strong theoretical basis both for and against the ratchet effect, experimental evidence that agents actually do adjust their performance due to the ratchet effect is limited at best and results are usually inconclusive (e.g., Chaudhuri, 1998).

On a more applied level, while AJS find that allowing for potential resetting of a contract is usually optimal and the principal cannot commit to not renegotiate (Christensen, Feltham and Sabac, 2003, 2005), some believe that restricting the use of repricing is a good corporate governance mechanism. For example, corporate-governance guidelines from CALPERS recommend companies include provisions in stock option plans that effectively preclude resetting[1]. Chen (2004) finds that some companies do adopt these recommendations.

How agents actually respond to information quality is an empirical question. While it is possible that agents incorporate information rationally, evidence from experiments in decision making suggest that bounded subadditivity (Tversky and Wakker, 1995) may affect agents such that their behaviour deviates from the predictions of a conventional Bayesian updating model. By having less than perfect information, an agent may underweight information and put forth high investment as noise in non-contractible information shifts the potential for a payoff from impossibility to possibility.

While the theoretical literature identifies tensions associated with multi-period agency, contracts with non-linear payment schedules are difficult to analyze using the standard analytical framework (Lambert, 2007). Empirical research related to the ratchet effect and contract incentives is difficult to interpret in an archival setting due to limited market proxies and issues of control (e.g., Carter and Lynch, 2001, 2003, 2004; Indjejikian and Nanda, 2003b; Chen, 2004). In contrast, the laboratory environment provides a setting where resetting can be prohibited and resulting agent behaviour observed without such complications. By using tools available to experimental economics, this paper exploits the comparative advantage of the laboratory and addresses how noise impacts incentive issues by providing a well controlled environment (Libby, Bloomfield and Nelson, 2002).

I find that participants behave consistent with model predictions in conditions with perfect information; however, when noise is present, agents continue to invest at a high level; as a result contract incentives may improve with a small amount of noise. A contract with less than perfect interim information which precludes contract resetting

[1] http://www.calpers-governance.org/principles/domestic/us/page07.asp

performs nearly as well as a contract without feedback and dominates contracts with perfect information.

The paper proceeds as follows: Section II provides the related literature and corresponding motivation, Section III presents the AJS model and extension, Section IV considers the experimental design and hypothesis development, Section V outlines the experimental procedure, Section VI considers the results while Section VII concludes.

Related Literature and Motivation

Agency contracts, incentives and renegotiation are extensively studied in the literature[2]. The general conclusion suggests that if negative interim information is observed, incentives provided by a contract may induce the manager to abandon a project even when the principal would prefer that the project continue. In such cases it is assumed renegotiation will occur (Fudenberg and Tirole, 1990). Yet the potential for renegotiation can induce the agent to take low effort actions in the early period. This lack of commitment can result in what has been termed the "ratchet effect" (Indjejikaian and Nanda, 1999) or the "negative feedback effect" (AJS).

Due to availability of data, empirical tests of contract resetting are usually limited to capital market settings. For example, Chen (2004) looks at the effect of repricing stock options on incentives for executives. Carter and Lynch (2001, 2004) consider executive performance and employee turnover after stock option repricing events.

Existing theoretical and empirical research recognizes the value of information quality in contracting; yet it is not always clear that agents respond to noise in signals as theory would suggest (Prendergast, 1999). Others view noise as having potential benefits for contracting. Cremer (1995) presents a multi-period model in which the principal may

[2] Contract structure, commitment and renegotiation are surveyed in Tirole (1999). Prendergast (1999) surveys the literature related to incentives in firms. Lambert (2001, 2007) reviews agency models and issues from an accounting perspective. Core, Guay and Larcker (2003) review the literature on equity compensation and incentives.

actually prefer less efficient information to prevent the possibility of firing a "good agent". Demski and Frimor (1999) demonstrate that the optimal contract in a two period setting will involve some "garbling" of a performance measure. More recently, Prendergast (2002) suggests noise in contracts may be positive by encouraging delegation in organizations. Arya and Glover (2003) show that coarser information sets can enhance the value of the abandonment option for the principal. One of the few empirical papers to specifically consider the impact of information quality on contract incentives is Indjejikian and Nanda (2003b) who find that target bonuses are inversely related to the noise of the accounting measure (defined as the volatility in return on equity).

The present setting recognizes tensions associated with two additional models in the renegotiation literature. Fudenberg and Tirole's (1990) model implies that renegotiation of a contract based on a signal which may be uninformative is harmful to economic welfare since renegotiation reduces commitment to the original contract and the agent; therefore, reduces effort. In contrast, the modified model considered here includes a non-contractible signal which is correlated with the first period action of the agent and is; therefore, informative. In contrast, Hermalin and Katz (1991) demonstrate that contracts with renegotiation based upon a non-contractible signal are not necessarily more costly for the principal to implement and; therefore, renegotiation does not reduce the principal's welfare. Unlike Hermalin and Katz; however, agents in the present setting are risk-neutral and therefore the "insurance" benefit provided to the agent by renegotiation is minimal.

The behavioral literature suggests that agents do not always correctly incorporate information into their decision making process. In particular, bounded subadditivity (a component of Cumulative Prospect Theory) is proposed by Tversky and Wakker (1995) to explain violations of the standard economic decision making model with risk. Under the predictions of bounded subadditivity, an agent reacts to a small increase in probability more strongly at the ends of a probability distribution, or as Tversky and Fox (2000) state

"An event has greater impact when it turns impossibility into possibility, or possibility into certainty, than when it merely makes a possibility more or less likely".

In the setting presented in this paper, receiving perfect information indicating a likely poor outcome after period one indicates there is no possible payoff if the contract hurdle price is not reset and; therefore, the agent will provide a minimum level of investment in period two. The introduction of noise alters the game slightly in that receipt of negative information does not preclude a payoff. Noise; therefore, turns impossibility into possibility. Subadditivity in option pricing settings has been tested by Fox, Rogers and Tversky (1996) and Miller and Shapira (2004). Yet to the author's knowledge, no experimental research has investigated the effects of information quality on incentives in a two-period contract with non-linear payoffs.

AJS Model Description and Extension

I first provide a summary of a simplified discrete version of the AJS model (adopting notation, see Table 2.1, used in the present paper) and then consider how the present model departs from theirs. In AJS, a principal employs a risk-neutral and investment-averse agent for two periods with a liquidating cash flow paid at the end of period two. The final cash flow will have one of the following values: O_{HH}, O_{HL}, O_{LH}, and O_{LL}, where $O_{HH} > O_{HL} = O_{LH} > O_{LL}$. The probabilities of realizing one of these cash flows are dependent on the investment made by the manager in each of two periods with higher investment corresponding to a higher probability of a high cash flow.

In period one the agent make an investment decision $i_1 \epsilon \{A_1, B_1\}$ and then observes public information $s \epsilon \{S_H, S_L\}$ regarding the terminal cash flows. Information S_H will be observed with probability $p(i_1)$ and S_L with probability $1 - p(i_1)$. After observing information, the agent makes a second investment decision $i_2 \epsilon \{A_2, B_2\}$. If S_H is observed, the terminal cash flow will be O_{HH} with probability $p(i_2)$ or O_{HL} with probability $1 - p(i_2)$; otherwise, if S_L is observed, the terminal cash flow will be O_{LH} with probability $p(i_2)$ or O_{LL} with probability $1 - p(i_2)$.

Investment in either period results in a cost or disutility of investment for the agent of c(i) where the cost of A_1 (A_2) greater than the cost of B_1 (B_2). The principal provides the manager with compensation in the form of a call option on firm equity. Each call option has a strike price x. Wages for the manager are therefore determined by deducting the strike price from the cash flow for a particular outcome. In the event the strike price is greater than the cash flow, the option pays nothing. Wages are; therefore, defined as follows for each outcome: $w_{HH} = \max(O_{HH} – x,0)$, $w_{HL}= \max(O_{HL} – x, 0)$, $w_{LH} = \max(O_{LH} – x, 0)$, $w_{LL}= \max(O_{LL} – x, 0)$ where $O_{HH} > x > O_{HL} = O_{LH} > O_{LL}$. The agent chooses each action in order to maximize compensation net of action costs. It is assumed that the agent remains employed for both periods. After observing S_H, the agent chooses action i_2 to maximize continuation utility (U_H) which AJS define as follows:

$$U_H(i_2) = p(i_2) * w_{HH} + (1-p(i_2)) * w_{HL} - c(i_2) \qquad \text{(eq. 2.1)}$$

If S_L information is received, then the agent faces the following continuation utility (U_L)and chooses investment accordingly:

$$U_L(i_2) = p(i_2) * w_{LH} + (1-p(i_2)) * w_{LL} - c(i_2) \qquad \text{(eq. 2.2)}$$

With a fixed strike price, w_{LH} and w_{LL} are both equal to zero since $x > O_{LH} > O_{LL}$. Therefore the agent simply maximizes utility by reducing investment as low as possible in order to minimize the cost or disutility of investment $c(i_2)$. In order to restore incentives to the agent, the principal may reduce the strike price to a level where the expected payoffs from w_{LH} and w_{LL} outweigh the cost.

In period one the agent attempts to maximize first period utility by choosing action i_1. Period one utility is defined in Equation 2.3.

$$U(i_1, U_H(i_2),U_L(i_2)) = p(i_1) * U_H(i_2) + (1-p(i_1)) * U_L(i_2) - c(i_1) \qquad \text{(eq. 2.3)}$$

In AJS, the decision of the principal to reset the strike (hurdle) price is endogenous to the model. To aid in the experimental implementation of the present setting, the reset decision is exogenously specified to ensure that agents are not reacting to any uncertainty regarding the actions of the principal[3]. Therefore, only two contract regimes are considered: commitment and resetting. Otherwise, the model incorporates the main assumptions of AJS and extends it by adding a quality parameter (q) to the interim information received (see Figure 2.2). In AJS, the quality of information received is perfect ($q = 1$); therefore, receiving information S_L eliminates the possibility of realizing cash flows O_{HH} or O_{HL}. In contrast, if the information contains some noise ($q < 1$), then observing S_L does not necessarily preclude the potential for O_{HH} or O_{HL} to be realized. The agent must therefore incorporate knowledge of her action in period one using Bayes rule to determine potential outcomes.

Control over production of information is a critical component in many two period models. If the agent privately observes information and then reports to the principal, a potential for "garbling" or information rationing exists (Demski and Frimor, 1999; Christensen, Demski and Frimor, 2002). While garbling and information rationing are indeed valid concerns in many settings, the main interest of this paper is how an agent responds to information which may include noise. For this reason, information in this paper is produced by a third party whose incentives are orthogonal to those of both the agent and the principal. Also, following Hermalin and Katz, I assume that contracts are written contingent on the final outcome only.

The adapted AJS model and timeline are presented in Figures 2.1 and 2.2. A risk-neutral agent makes an investment decision on behalf of a principal. At time 1, the agent is presented with the opportunity to choose one of two investment levels $i_1 \epsilon \{A_1, B_1\}$ each of which has a personal cost $c(i_1)$ to the agent and has a $p(i_1)$ probability of a "high" or successful intermediate state. Investment level A_1 is more costly to the agent than

[3] The role of the principal is not played by participants in the experiment. Participants take on the role of the agent in which they are presented with one of seven contracts.

level B_1 ($c(A_1) > c(B_1)$); however, level A_1 yields a higher probability of a high interim state $p(A_1) > p(B_1)$. The agent is also given a fixed wage R from which costs are deducted[4]. Notation and parameter values are provided in Table 2.1.

The agent chooses i_1 to maximize her expected utility in Equation 2.4 where $U_H(i_2)$ and $U_L(i_2)$ denote the continuation utility at t = 2 contingent upon observation of either positive information (S_H) or negative information (S_L) respectively.

$$U(i_1, U_H(i_2), U_L(i_2)) = p(i_1) * U_H(i_2) + (1-p(i_1)) * U_L(i_2) + R - c(i_1) \quad \text{(eq. 2.4)}$$

Once investment i_1 has been chosen, nature determines the true intermediate state from the Period 1 action. Let O_H denote a "high" intermediate state from action i_1, and O_L denote a "low" intermediate state. A third party then views the true interim state and provides non-contractible information, $s \in \{S_H, S_L\}$ based upon their observation. The information has a level of quality, $q \in (0.5,1]$ which is known by both the principal and agent. With probability q, information s will represent the true intermediate state and with probability 1-q the information will be incorrect. For the experiment three values of q are considered: one where information is perfect (q = 1) and two where information contains noise (q = 0.75 and q = 0.9) referred to as "high noise" and "low noise" respectively.

After the agent observes information at t = 2, she must choose an investment level $i_2 \in \{A_2, B_2\}$. As in Period 1, the investment level i_2 has an associated cost $c(i_2)$ to the agent and has a $p(i_2)$ probability of a "high" or successful outcome. Level A_2 is more costly to the manager than level B_2 ($c(A_2) > c(B_2)$); however, level A_2 yields a higher probability of a high final state $p(A_2) > p(B_2)$ occurring. To make this choice, the agent incorporates the information to maximize expected utility. If $s = S_H$, information is

4 The fixed wage is included to aid in the experimental implementation. AJS omit the fixed wage to allow for simplicity in their analysis, although they state that their model would allow for such compensation mechanisms.

positive and the agent chooses i_2 to maximize expected conditional continuation utility $U_H(i_2)$ where w_{HH}, w_{HL}, w_{LH} and w_{LL} are the final variable wages previously discussed. The potential for noise necessitates the addition of conditional probabilities to the AJS model. I define $p(O_H|i_1,S_H)$ and $p(O_L|i_1,S_H))$ as the posterior Bayesian probabilities that the true interim state is high or low respectively given information S_H and the agent has chosen i_1 at $t = 1$.

$$U_H(i_2) = p(O_H|i_1,S_H) * p(i_2) * w_{HH} + p(O_H|i_1,S_H)) * (1-p(i_2)) * w_{HL} + p(O_L|i_1,S_H)) * p(i_2) * w_{LH} + p(O_L|i_1,S_H)) * (1-p(i_2)) * w_{LL} + R - c(i_2) \quad \text{(eq. 2.5)}$$

If the agent observes S_L, she chooses i_2 as to maximize continuation utility U_L where again $p(O_H|i_1,S_L)$ and $p(O_L|i_1,S_L))$ are the posterior probabilities that the true interim state is high or low given S_L and the agents investment at $t = 1$.

$$U_L(i_2) = p(O_H|i_1,S_L) * p(i_2) * w_{HH} + p(O_H|i_1,S_L)) * (1-p(i_2)) * w_{HL} + p(O_L|i_1,S_L)) * p(i_2) * w_{LH} + p(O_L|i_1,S_L)) * (1-p(i_2)) * w_{LL} + R - c(i_2) \quad \text{(eq. 2.6)}$$

As in AJS, at $t = 3$ nature determines the final outcome which is a final liquidating cash flow $v \in \{O_{HH}, O_{HL}, O_{LH}, O_{LL}\}$. The agent receives $w \in \{w_{HH}, w_{HL}, w_{LH}, w_{LL}\}$ structured as a payment contingent upon realized liquidating cash flow. Table 2.1 defines the parameter notation.

The following section uses the above framework to describe the experimental design and develop the related hypothesis. In each subsection backward induction is used to first consider the wage structure and associated conditional continuation utilities $U_H(i_2)$ and $U_L(i_2)$. Continuation utilities are subsequently incorporated into the initial utility $U(i_1, U_H(i_2),U_L(i_2))$ to deduce optimal Period 1 choices[5].

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[5] All utilities have been rounded to the nearest 5 unit increment.

Experimental Design and Hypothesis Development

Experiment Design

The experiment uses a 3X2 between-subjects design in which participants make investment decisions in multiple two-period contract games. The experiment considers a two-period contract along two dimensions. The first dimension: contract commitment versus resetting. The second dimension: information quality. Under commitment, an agent understands that the principal commits to not reset the contract hurdle price should S_L be observed. Under resetting, the principal always lowers the hurdle price if S_L is observed in order to encourage the agent to undertake high investment in the second period.

With regard to the quality dimension, perfect information implies that interim information observed has a correlation of one with the interim state of the world. With noise the correlation falls below one. The experiment investigates whether noise improves the *ex post* efficiency of both contracts with commitment and resetting. Because noise may increase incentives in this environment, the expected value from continuing high investment may be sufficiently high even with S_L information as to outweigh the incremental cost of such investment. This feature of the model allows noise to serve as a potential substitute for resetting, although how agents actually respond information quality is an empirical question.

Table 2.2 highlights the parameters used for each treatment. Table 2.3 lays out the experiment design and associated hypothesis predictions that arise with a rational agent using Bayesian updating to incorporate information. Manipulation across the treatments is done via either 1) the hurdle price 2) information noise. A description of each treatment and related hypothesis is presented below.

The remainder of this section primarily concerns four contracts: Commitment without Noise, Resetting without Noise, Commitment with Noise, and Resetting with Noise. A fifth contract (No Feedback) with no information will be highlighted as a benchmark. The only elements changing in each contract are 1) the level of noise and/or 2) ability to reset. Otherwise, the model structure and parameters remain the same throughout. Contracts with perfect information (q=1) will be considered first, followed by treatments that introduce noise. As shown in Table 2.1, for this experiment $O_{HH} = 300$, $O_{HL} = 190$, $O_{LH} = 190$, and $O_{LL} = 0$.

Commitment without Noise (Treatment 2)

In this instance the principal commits to not reset the hurdle price, x, regardless of information received and the agent is aware of this commitment. The agent also is aware that information received at the end of Period 1 is perfect (q=1). Setting the hurdle price to x = 200, the resulting wage can be immediately inferred from the AJS results using backward induction. Specifically, the following terminal wage structure applies:

$$w_{HH} = \max(O_{HH} – x, 0) = \max(300 – 200, 0) = 100$$

$$w_{HL} = w_{LH} = \max(O_{HL} – x, 0) = \max(190 – 200, 0) = 0$$

$$w_{LL} = \max(O_{LL} – x, 0) = \max (190 – 200, 0) = 0$$

Since q=1, $p(O_H|i_1,S_H) = 1$, $p(O_H|i_1,S_L) = 0$, $p(O_L|i_1,S_L) = 1$ and $p(O_L|i_1,S_H) = 0$ in Equations 2.5 and 2.6. The associated continuation utilities for investments A_2 and B_2 using the experiment parameters (with R=50) are therefore:

$$U_H(A_2) = p(A_2) * w_{HH} + R - c(A_2) = 85$$

$$U_H(B_2) = p(B_2) * w_{HH} + R - c(B_2) = 45$$

$$U_L(A_2) = R - c(A_2) = 15$$

$$U_L(B_2) = R - c(B_2) = 25$$

If a S_L is observed at t = 2, action B_2 is more attractive to the agent since $c(B_2) < c(A_2)$. In the event that S_H is observed after Period 1, the agent will continue to invest at a high level $i_2 = A_2$.

Substituting these results into Equation 2.1, the initial utility for both A_1 and B_1 is:

$$U(A_1, U_H(A_2),U_L(B_2)) = p(A_1) * U_H(A_2) + (1-p(A_1)) * U_L(B_2) + R - c(A_1) = 80$$

$$U(B_1, U_H(A_2),U_L(B_2)) = p(B_1) * U_H(A_2) + (1-p(B_1)) * U_L(B_2) + R - c(B_1) = 60$$

Therefore the agent should prefer A_1 over B_1 in Period 1. During Period 2, the primary condition of interest is when S_L is observed after high investment in Period 1. In this case, the agent is facing a certainty of paying either 25 francs (if she chooses action B_2) or 35 francs (if action A_2). The agent should; therefore, prefer B_2.

This leads to the first hypothesis:

H1: With perfect information and commitment, participants will prefer the high investment action over low investment in Period 1; however, in period 2, if S_L is observed participants will prefer low investment.

Resetting without Noise (Treatment 3)

Consistent with prior literature and AJS, this contract is implemented as conditional resetting[6]. Conditional resetting implies that the hurdle price is adjusted only in the event that S_L is observed after Period 1. Let $x_r = 120$ represent the reset hurdle price and recall that $x = 200$. The following wage structure applies:

$$w_{HH} = \max(O_{HH} - x, 0) = \max(300 - 200, 0) = 100$$

$$w_{HL} = \max(O_{HL} - x, 0) = \max(190 - 200, 0) = 0$$

$$w_{LH} = \max(O_{LH} - x_r, 0) = \max(190 - 120, 0) = 70$$

$$w_{LL} = \max(O_{LL} - x_r, 0) = \max(0 - 120, 0) = 0$$

As in the prior case without noise, $p(O_H|i_1,S_H) = 1$, $p(O_H|i_1,S_L) = 0$, $p(O_L|i_1,S_L) = 1$ and $p(O_L|i_1,S_H) = 0$ in Equations 2.5 and 2.6. Continuation utilities following S_H are identical to the previous commitment case; however, if S_L is observed then:

$$U_L(A_2) = p(A_2) * w_{LH} + R - c(A_2) = 65$$

$$U_L(B_2) = p(B_2) * w_{LH} + R - c(B_2) = 40$$

Since $w_{LH} > 0$, resetting of the hurdle price provides an incentive in the second period to provide high investment relative to the commitment case regardless of the

[6] The literature also sometimes refers to conditional resetting as conditional renegotiation.

signal in period one. On the other hand, it is possible that if the hurdle price is reset, the agent finds it profitable undertake the B_1 action at t = 1 in order to increase the likelihood of obtaining the lower hurdle price in period two. This tendency of resetting to reduce period one investment is the ratchet effect.

The experiment parameters are designed so that Treatment 3 uses a reset hurdle of price $x_r = 120$. This results in the utility of the agent being the same in Period 1 regardless of which action is chosen. The following initial utilities apply:

$$U(A_1, U_H(A_2),U_L(A_2)) = p(A_1) * U_H(A_2) + (1-p(A_1)) * U_L(A_2) + R - c(A_1) = 95$$

$$U(B_1, U_H(A_2),U_L(B_2)) = p(B_1) * U_H(A_2) + (1-p(B_1)) * U_L(B_2) + R - c(B_1) = 95$$

This leads to the following hypotheses:

H2: With perfect information and resetting participants are indifferent between high and low investment in Period 1; however, participants will undertake high investment in Period 2.

Commitment with Noise (Treatments 4 and 6)

For Treatments 4 and 6, the hurdle price will not be reset. There is; however, noise present in the signal (q=0.75 or q=0.9) respectively. Because the principal commits to not reset the hurdle price, the wage structure is identical to the case with no noise and is thus omitted.

The remaining analysis now becomes slightly more complex as the continuation utilities are changed due to an increase in noise. Since $q < 1$, $p(O_H|i_1,S_H) < 1$, $p(O_H|i_1,S_L) > 0$, $p(O_L|i_1,S_L) < 1$ and $p(O_L|i_1,S_H) > 0$. Substituting into Equations 2.5 and 2.6 values for q=0.75 are shown:

$$U_H(A_2) = p(O_H|A_1,S_H) * p(A_2) * w_{HH} + R - c(A_2) = 75$$

$$U_H(B_2) = p(O_H|A_1,S_H) * p(B_2) * w_{HH} + R - c(B_2) = 45$$

This implies that if S_H is observed, the agent will prefer investment A_2 regardless of the first period choice[7]. On the other hand, if S_L is observed:

$$U_L(A_2) = p(O_H|A_1,S_L) * p(A_2) * w_{HH} + R - c(A_2) = 45$$

$$U_L(B_2) = p(O_H|B_1,S_L) * p(B_2) * w_{HH} + R - c(B_2) = 30$$

If the agent chooses A_1 in Period 1, then they should choose A_2 even if S_L is observed; however, if B_1 is chosen in Period 1, then they should prefer B_2 in Period 2.

The overall utility for period one is therefore:

$$U(A_1, U_H(A_2),U_L(A_2)) = p(A_1) * U_H(A_2) + (1-p(A_1)) * U_L(A_2) + R - c(A_1) = 80$$

$$U(B_1, U_H(A_2),U_L(A_2)) = p(B_1) * U_H(A_2) + (1-p(B_1)) * U_L(B_2) + R - c(B_1) = 55$$

The agent therefore prefers A_1 to B_1 in Period 1.

A moment to consider this result may be helpful. Recall that in the case with perfect information $U_L(i_2) = R - c(i_2)$. In the condition with noise $U_L(i_2) = p(O_H|i_1,S_L)*p(i_2) * w_{HH} + R - c(i_2)$. In the perfect information case the agent uniformly prefers the lower cost investment since there is no opportunity for a final payoff; however, with noise there is now the potential for the final payoff to outweigh the incremental cost of the action. This leads to Hypothesis 3 for Treatment 4.

H3 (Bayesian): With high noise (q=0.75) and commitment participants will prefer the high investment action over low investment in Period 1. When S_L is observed in Period 2 participants will prefer the high investment action over low investment conditional upon having chosen A_1.

To test the prediction of bounded subadditivity, a lower level of noise (q=0.9) is used in Treatment 6. In this "low noise" condition the parameters have been selected so $U_L(A_2) = U_L(B_2)$ if S_L and high investment was chosen in Period 1. Therefore, agents

[7] Note that all four continuation utility conditions must now be considered when q < 1. When q=1, $p(O_H|A_1,S_H) = p(O_H|B_1,S_H)$ which renders additional cases redundant. In the interest of space, dominated continuation utilities are omitted.

should be indifferent between taking a high investment action or a low investment action in Period 2 if S_L is received. Under the prediction of bounded subadditivity, agents will overestimate the expected payoff from the high investment action and therefore prefer to undertake high investment in Period 2. If this occurs Hypothesis 3′ will be rejected.

H3′ (Bounded Subadditivity): With low noise (q=0.9) and commitment participants will prefer the high investment action over low investment in Period 1. If participants are rational there will be no preference in Period 2 between high investment or low investment actions conditional upon having chosen A_1 and observing S_L.

These are the most complex cases considered. The agent now contends with two forces. First, the potential for resetting induces the ratchet effect in Period 1. Second, information noise enhances the attractiveness of the high investment choice in Period 2 which may increase the attractiveness of high investment in Period 1. Which effect dominates is an empirical question.

As in the prior resetting case without noise, the hurdle price will be adjusted should S_L be observed. Noise is also present (q=0.75 or q=0.9). The terminal wage structure if S_H is observed is identical to the case with commitment and is therefore omitted; however, if S_L is observed, then the following wage schedule is used for Treatment 5 (q=0.75):

$$w_{HH} = \max(O_{HH} - x_r, 0) = \max(300 - 120, 0) = 180$$

$$w_{HL} = w_{LH} = \max(O_{HL} - x_r, 0) = \max(190 - 120, 0) = 70$$

$$w_{LL} = \max(O_{LL} - x_r, 0) = \max(0 - 120, 0) = 0$$

Utilities for the case where S_L is observed are as follows:

$$U_L(A_2) = p(O_H|A_1,S_L) * p(A_2) * w_{HH} + p(O_H|A_1,S_L) * (1-p(A_2)) * w_{HL} + p(O_L|A_1,S_L) * p(A_2) * w_{LH} + R - c(A_2) = 110$$

$$U_L(B_2) = p(O_H|A_1,S_L) * p(B_2) * w_{HH} + p(O_H|A_1,S_L) * (1-p(B_2)) * w_{HL} + p(O_L|A_1,S_L) * p(B_2) * w_{LH} + R - c(B_2) = 75$$

Recall that if S_H occurs in the Commitment with Noise treatment then the agent should prefer A_2 over B_2 regardless of the choice in Period 1. Since continuation utilities are the same with resetting if S_H is observed, implications for the Commitment with Noise treatment also apply here. In the case where S_L occurs, resetting encourages the agent to undertake high investment in Period 2 regardless of the choice in Period 1. Using these values we can calculate the initial utility:

$U(A_1, U_H(A_2),U_L(A_2)) = p(A_1)* U_H(A_2) + (1-p(A_1))* U_L(A_2) + R - c(A_1) = 100$

$U(B_1, U_H(A_2),U_L(A_2)) = p(B_1)* U_H(A_2) + (1-p(B_1))* U_L(A_2) + R - c(B_1) = 90$

This implies the agent prefers A_1 to B_1.

H4 (Bayesian): With high noise (q=0.75) and resetting participants will prefer the high investment action over low investment action in Period 1; while rational participants will choose high investment in Period 2 conditional upon having chosen A_1 and observing S_L.

Treatment 7 (q=0.9) is included to investigate whether bounded subadditivity may influence Period 1 choices. To test this, the reset hurdle price used is $x_r = 105$. The following wage structure applies:

$w_{HH} = \max(O_{HH} – x_r, 0) = \max(300 - 105, 0) = 195$

$w_{HL} = w_{LH} = \max(O_{HL} – x_r, 0) = \max(190 - 105, 0) = 85$

$w_{LL} = \max(O_{LL} – x_r, 0) = \max(0 – 105, 0) = 0$

With this new hurdle price, Period 1 expected utilities are now equal which implies indifference for the agent in Period 1.

$U(A_1, U_H(A_2),U_L(A_2)) = p(A_1)* U_H(A_2) + (1-p(A_1))* U_L(A_2) + R - c(A_1) = 100$

$U(B_1, U_H(A_2),U_L(A_2)) = p(B_1)* U_H(A_2) + (1-p(B_1))* U_L(A_2) + R - c(B_1) = 100$

H4′ (Bounded Subadditivity): In the low noise (q=0.9) with resetting treatment participants will prefer high investment in Period 2. In Period 1, participants are indifferent between high and low investment if rational.

No Feedback (Treatment 1)

The case where no information is received is considered as a benchmark. Suppose there is no information. Under such circumstances, the situation is equivalent to agent making both investment choices in Period 1. The agent maximizes utility by choosing (A_1, A_2) since the expected utility of 80 dominates all other combinations[8]. This outcome is predicted by the following hypothesis:

H5: In the No Feedback treatment the participants prefer high investment over low investment in both periods.

Experiment Procedure

The experiment follows directly from the model and design presented in the preceding sections. The experiment is administered via computer terminal using a program written in Visual Basic[9]. Each treatment consists of 30 participants who take part in a 32 round "investment game" where each round is independent and identically-distributed and consists of two periods with each period consisting of an investment choice. Each treatment; therefore, has 960 rounds. 150 participants were randomly selected from a common subject-pool used for experimental economic experiments[10]. Subject-pool participants are primarily undergraduate students recruited on a voluntary basis. Prior to the experiment, instructions are read out loud to participants and a quiz administered to ensure mutual knowledge of the game structure.

At the beginning of each round in all treatments participants receive an R = 100 franc endowment and the right to sell an object at its "Purchase Price" if the "Redemption Value" of the object is greater than the purchase price at the end of the round. In Period

[8] One can easily verify that investment combinations (A_1, B_2), (B_1, A_2) and (B_1, B_2) all yield utility of 55.

[9] Source code (Visual Basic) and program are available from the author upon request.

[10] Note: Only the first five treatments have been completed. Once the proposed treatments to test for bounded subadditivity have been run, a total of 210 individuals will participate in this study.

1, participants are asked to choose one of two rows, referred to as "Row A" and "Row B". Each row contains two circles, one in Column X and the other in Column Y, see Figures 2.3, 2.4 and 2.5. A participant choosing Row A has a 70% chance of the computer choosing Column X and a 30% chance of Column Y being chosen. Participants choosing Row B observe Column X with 20% probability and Column Y with 80% probability. The participant incurs a cost of 35 francs if Row A is chosen while Row B costs 25 francs.

After the first period choice, the computer generates a random number from a uniform distribution between 1 and 100. If the random number is less than or equal to 70 (20) and the participant chose Row A (Row B), the computer selects Column X, otherwise Column Y is chosen. In terms of the preceding model, selection of Column X corresponds to a S_H being observed while Column Y corresponds to a S_L. For all treatments excluding Treatment 1 (No Feedback) the computer highlights the selected circle in Period 1. Participants then proceed to Period 2.

In Period 2, participants choose one of two circles, "Circle 1" and "Circle 2" respectively, see Figure 2.6. Seventy percent of Circle 1 is dark-shaded and 20 % of Circle 2 is dark shaded. The circles differ in their cost. Circle 1 costs 35 francs and Circle 2 costs 25 francs.

Once the participant has chosen a circle in Period 2, the computer generates two random numbers between 1 and 100 to determine the outcome. The first random number corresponds to the number the arrow points at on the circle selected by the computer in Period 1, the second corresponds to the number pointed at on the circle chosen in Period 2.

The contract is implemented as follows: if the arrows on both circles point to dark-shaded regions the final outcome is O_{HH}, the "Redemption Value" is 300 francs, and the "Purchase Price" corresponds to the hurdle price. If only one arrow points to a dark-shaded region while the second points to a light-shaded region the final outcome is either

O_{HL} or O_{LH} and the Redemption Value of the object is 190 francs. If neither of the arrows point to a dark-shaded region the final outcome is O_{LL}, and the Redemption Value of the object is 0 francs. Total profit for the round is:

Round Profit = Endowment – Cost of Period 1 Choice – Cost of Period 2 Choice + max(Redemption Value – Purchase Price, 0)

In treatments without noise, see Figure 2.3, information received by the agent leaves the participant without uncertainty as to the outcome from the circle selected in Period 1. Including noise, see Figures 2.4 (q=0.75) and 5 (q=0.90), the circle presents a participant with the posterior probability. For example, in Figure 2.4, if the agent selects Row A in Period 1 and the computer selects Column Y, then the posterior probability (when q=0.75) that the underlying interim state of the world is high (O_H) is 44% according to Bayes rule.

The following sections provide specific implementation details for the each treatment.

No Feedback

In Treatment 1 the participant makes both investment decisions without observing interim information. Participants are presented with the "No Noise" configuration, see Figure 2.3. Once both decisions are made, the computer randomly generates two random numbers between 1 and 100 according to the procedures outlined above. Payment is then determined according to the option structure with hurdle price x = 200.

Perfect Information Treatments

In the Perfect Information treatments no uncertainty exists in the outcome from the circle selected in Period 1, see Figure 2.3. Specifically, when S_H occurs (i.e., the computer selects Column X), then the probability of the arrow landing on a dark part of the circle selected in the first period is 1. If S_L occurs (computer selects Column Y), the arrow will land on a light area of the circle. The participant should take this additional information into account when making the Period 2 decision, choosing Circle 1 or 2.

Round Profit is as described previously, with the Purchase Price being set at 200 in the commitment treatment and 120 in the resetting treatment.

Noise Treatments

In Noise Treatments there is uncertainty in information, see Figures 2.4 and 2.5. Conditional on choosing Row A, when S_H is observed (i.e., the computer selects Column X), then the probability of the arrow landing on a dark part of the circle selected in the first period is 0.88 (0.95)[11]. On the other hand, when S_L occurs (computer selects Column Y), then the arrow will land on a dark area with only 0.44 (0.21) probability. Should the participant choose Row B, S_H will result in a shaded area of 0.43 (0.69) probability and the low signal with 0.08 (0.03) probability. The participant should take this additional information into account when making the Period 2 decision, choosing Circle 1 or 2.

Presentation of posterior probabilities is implemented in this way to avoid sequencing effects and to ensure that any non-equilibrium behavior is not due to the inability of a participant to correctly calculate and implement Bayesian probabilities. Again, round profit is calculated using a Purchase Price minus the Redemption Value as shown in Table 2.2.

Participants receive \$5 as a “show-up fee” and additional payments based upon the choices made. Final payments including the show-up fee ranged from \$15 to \$29.75 with an average payment of approximately \$22. Earnings based upon the decisions of the participant are in francs and converted into dollars at the end of the experiment at an exchange rate which provides an equivalent expected payoff in each treatment.

[11] Probabilities for the High Noise treatment (q=0.75) are shown outside of brackets while probabilities inside of the brackets indicate probabilities for the Low Noise treatment (q=0.9). All values are derived using Bayes Rule.

Results

No Feedback – Baseline Treatment

The No Feedback treatment provides the baseline for all treatments. Participants in this treatment behave as predicted and undertake high investment in both periods. Out of 960 observations, participants took the high action for Period 1 and Period 2, 873 and 863 times, respectively, see Tables 2.4 and 2.5. This corresponds to choosing the high action approximately 90% of the time in Treatment 1.

Since the model's prediction does not include an error term, strictly speaking the hypothesis that participants always choose high investment in both periods is rejected. In such instances the use of confidence intervals is informative as to which actions are preferred by participants. To construct confidence intervals, I first calculate a score for each participant for both Periods 1 and 2 by dividing the number of low investment choices by the total number of observed choices for the participant. This provides a score for both periods for each participant where 0 indicates all high investment choices and 1 indicates all low investment choices. The scores are then used to calculate confidence intervals. In the case the No Feedback Treatment the 99%, 95% and 90% confidence intervals are (0.00, 0.18), (0.02, 0.15) and (0.04, 0.14) shown in Table 2.7, the results suggest that participants choose high investment in the No Feedback treatment which is consistent with Hypothesis 5.

Hypothesis Results

Hypothesis 1 predicts that agents will choose high investment in Period 1 when faced with perfect information and a principal the commits to not reset the hurdle price. Table 2.4 data for Treatment 2 shows that out of the 960 observations, 780 (81%) of participant choices were for the high investment action. Confidence intervals for the first period actions are provided in Table 2.8 and are strongly suggestive that participants do prefer high investment actions with all three confidence intervals being much less than the value of 0.5[12] suggested by indifference.

The second part of Hypothesis 1 predicts that participants will choose the low investment action if they observe S_L since there is no possibility for additional payment. Table 2.5 indicates that 186 of 267 (70%) of second period choices[13] are for the low investment action. Corresponding 99%, 95% and 90% confidence intervals from Table 2.9 (0.47,0.93), (0.53,0.87) and (0.56, 0.84) show that the low action is somewhat preferred.

Hypothesis 2 predicts that agents will be indifferent in Period 1 when faced with perfect information and a principal who resets the hurdle price in the event of a S_L. Table 2.4 data for Treatment 3 shows that out of the 960 observations, 396 (41%) of participant choices were for the high investment action while 564 (59%) are for low investment. Under the indifference prediction, approximately 50% of the actions should be high investment and 50% low investment in Period 1.

The question of indifference in Treatment 3 is an aggregate phenomenon. It is expected that some participants may be attracted to either high investment or low investment actions on an individual level. Over the 32 rounds, some participants may also mix between the two choices. The 99%, 95% and 90% confidence intervals, (0.3, 0.88), (0.38, 0.8) and (0.41, 0.76), all contain the theoretical 0.5 low investment level suggested by indifference.

Part two of Hypothesis 2 predicts that participants will choose the high investment action if they observe S_L since the resetting of the hurdle price restores agent incentives.

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[12] Confidence intervals for Table 7 are constructed on an individual basis so that a score of 0 indicates that a subject takes all high actions and 1 all low actions. Indifference between the two choices would be suggested by the midpoint which is 0.5.

[13] Recall that the predictions are conditioned upon a participant having selected high investment in the first period.

Table 2.5 indicates that in the second period, participants choose the high investment action 116 times out of 129 (90%). Corresponding 99%, 95% and 90% confidence intervals support the inference participants prefer high investment (-0.08,0.39), (-0.02,0.33) and (0.02, 0.29). As predicted, a contract with perfect information that allows resetting does restore incentives upon receipt of S_L; however, the ratchet effect imposes a cost by encouraging lower investment in Period 1.

Hypothesis 3 (Bayesian) provides predictions for agent behaviour under commitment in the presence of information with noise. The hypothesis predicts that with high noise (Treatment 4) the agent will choose the high investment action in both periods. Table 2.4 shows that participants chose high investment 796 out of 928[14] (86%) actions. In Period 2, 161 out of 187 actions (86%) were high investment actions.

At this point it may be useful to compare the results of these four treatments. In the treatments with perfect information, commitment improves the performance of participants in Period 1 by encouraging high investment choices (81% in Treatment 2 vs. 41% for Treatment 3). This is a statistically significant difference as Table 2.9 shows (Fisher exact $p<0.000$).

Introducing noise improves performance in Period 1. While the difference in percentage terms may not seem that large between Treatments 3 (81%) and 4 (86%) the differences are statistically significant (Fisher exact $p=0.009$).

In Period 2 we see that resetting restores incentives lost when the participant observes S_L. This is indicated by the improvement in high investment choices from Treatment 2 to 3 (30% to 90%, $p<0.000$). Noise improves participant responses under commitment.

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[14] Observations for one subject were dropped due to the subject starting the task before full directions were given.

Hypothesis 4 (Bayesian) predicts agent behaviour when there is noise and the principal resets the contract. The high noise treatment (Treatment 5) predicts that the agent will choose the high investment action in both periods. Table 2.4 shows that in Period 1, participants made high investment choices 759 out of 960 times (79%). In Period 2, participants chose high investment 198 out of 217 times (91%).

Again a brief comparison between treatments may be useful to consider the results. In Period 1, Treatment 5 produced high investment choices significantly greater than Treatment 3 with perfect information as indicated in Table 2.10 ($p<0.000$). In Period 2, noise does not have an incremental benefit to restoring incentives beyond resetting as is indicated by comparing Treatments 5 with Treatment 3 (p-value 0.704).

Ex Post Contract Efficiency

An important question to be addressed is how close the different contracts come to achieving the outcome from the No Feedback contract. Efficiency metrics answer this question. There are two approaches to measuring efficiency; one is to compare actions of the participants in each round to the No Feedback (Treatment 1). The second method is to measure the principals realized payoff relative to the expected payoff if the agent were to choose high investment in both periods.

Using observed participant actions, Table 2.6 examines efficiency using two benchmarks. The first, Absolute Efficiency, is defined as the total number of rounds with high investment observations in both Period 1 and Period 2 divided by the total number of rounds. Relative Efficiency relaxes this definition slightly and uses the No Feedback, Treatment 1, efficiency as a benchmark. Using Absolute Efficiency, the observed efficiency of the No Feedback treatment is 86%. Treatments 2 and 3 (treatments with perfect information) are significantly less efficient at 60% and 39% respectively in absolute terms while in relative terms they are 70% and 45% efficient. As expected, Treatments 4 and 5 (treatments with high noise) have a higher Absolute Efficiency of 80% and 72%, respectively than their perfect information counterparts. They do still fall short of the No Feedback benchmark with Relative Efficiencies of 93% and 84% respectively; however, one fails to reject the null that Treatment 4 is statistically different from the No Feedback (p=0.267) while Treatment 5 is statistically different at a conventional alpha=0.05 level (p=0.038).

Table 2.7 considers an alternate measure of efficiency using the principal's realized payoff relative to the theoretical expected payoff of high investment by the agent in both periods. Overall the principal obtains 94% of the expected payoff in Treatment 1. Treatments 2 and 3 have lower levels of efficiency at 78% and 82% . The introduction of noise improves efficiency to 92% and 89% in Treatments 4 and 5.

Summary

Participants in this experiment behave largely as predicted. In treatments with perfect information participants are unwilling to invest at high levels after observing SL (Treatment 2) unless the contract hurdle price is lowered (Treatment 3). Participants also behave consistent with the ratchet effect in Treatment 3. Adding noise to interim information resolves both of these issues as demonstrated by observed actions in Treatments 4-5. Noise appears to restore incentives in Period 2 as well as offset the ratchet effect in Period 1.

Conclusion

This paper explores the value of information quality. While contracting theory provides predictions regarding agent responses to information quality, little is known about how agents actually respond to information. By extending the Acharya, John and Sundaram model to include variable information quality, the experiment in this paper demonstrates noise in information may have some beneficial aspects with regards to agent behaviour. With perfect information, agents tend to shirk in Period 2 if they receive unfavorable interim information. Resetting is a solution which restores incentives *ex post*; however, restoring incentives in this manner imposes a cost in the form of the ratchet effect in Period 1. When there is some noise in the interim information, high investment is exhibited in both periods.

There are some caveats to consider. First, in order to create setting that focuses on the basic decision making issues related to the applicable models, operationalization of the contracting setting is minimalist relative to natural contracting settings. The reader is also cautioned that this study uses student subjects rather than actual managers. This is done to enhance internal validity, which is a fundamental requirement of valid experimentation (Peecher and Solomon 2001).

There are additional avenues to extend the present work. How noise affects the actions of the principal is an open question. If principals also behave consistent with bounded subadditivity, they may have a tendency to reset a contract more often than would be predicted by the Acharya, John and Sundaram model. Also, in this experiment the decision to commit or reset the hurdle price is exogenously specified by the experimenter. An interesting extension would be to make this decision endogenous to the model. Such a design involves pairing participants together in a principal-agent setting and then allowing a participant playing the role of the principal to decide whether or not resetting occurs. Incorporating such a feature has further potential to study information quality issues related to long-term contracting as highlighted in Christensen, Feltham and Sabac (2005) and Sabac (working paper). An additional modification to the experiment would be to allow the agent to garble or ration information provided to the principal. Studies in this area would allow for further investigation of the strategic role that noise may play in voluntary disclosures.

Further study may also consider the role precluding renegotiation in contracts plays in reputation formation. It is possible that by refusing to renegotiate, the principal develops a reputation for demanding high performance in the early period. Of course the decision to not renegotiate will incur a cost in the form of potential reduced output if a poor signal is observed. As this paper has shown, how agents respond to noise may help reduce this cost.

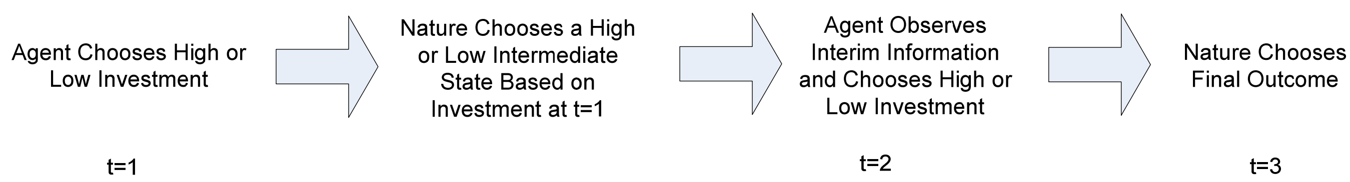
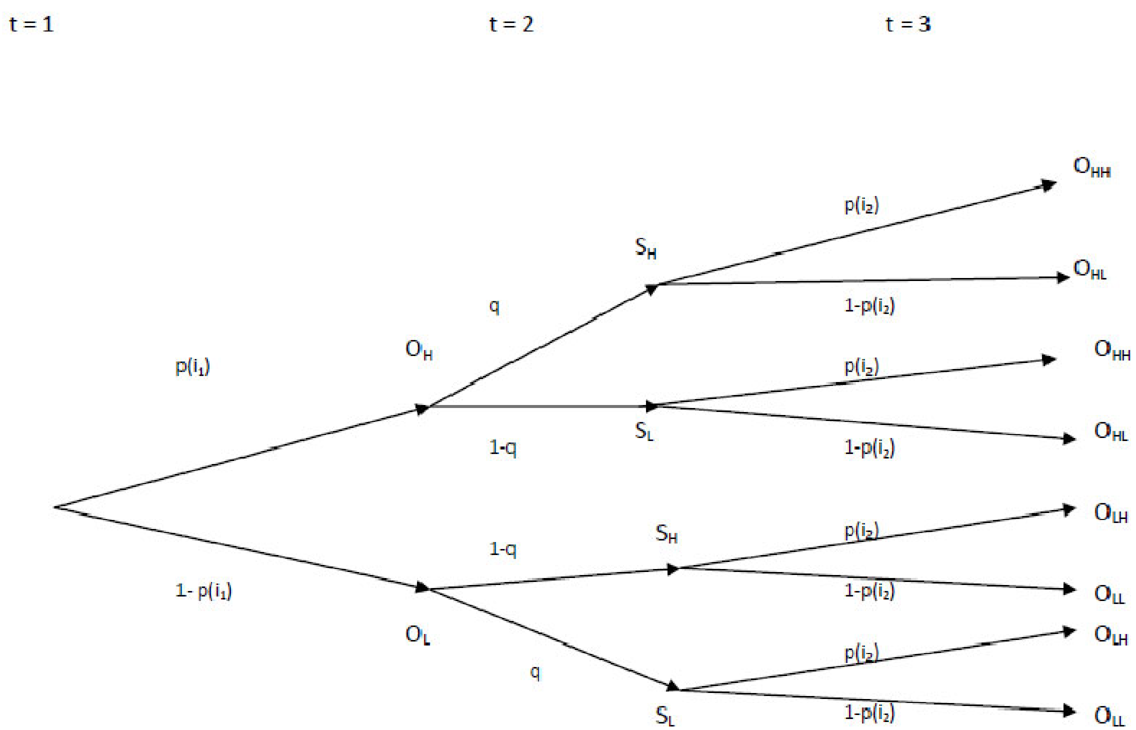


Figure 2.1 Timeline



$$U(i_1, U_H(i_2), U_L(i_2)) = p(i_1) * U_H(i_2) + 1\text{-}p(i_1) * U_L(i_2) + R - c(i)$$

$$U_H(i_2) = p(O_H|i_1,S_H) \ *p(i_2) * w_{HH} + p(O_H|i_1,S_H)) * (1\text{-}p(i_2)) * w_{HL} + p(O_L|i_1,S_H)) * p(i_2) * w_{LH} + p(O_L|i_1,S_H)) * (1\text{-}p(i_2)) * w_{LL} + R - c(i_2)$$

$$U_L(i_2) = p(O_H|i_1,S_L) \ *p(i_2) * w_{HH} + p(O_H|i_1,S_L)) * (1\text{-}p(i_2)) * w_{HL} + p(O_L|i_1,S_L)) * p(i_2) * w_{LH} + p(O_L|i_1,S_L)) * (1\text{-}p(i_2)) * w_{LL} + R - c(i_2)$$

Figure 2.2 Investing Game

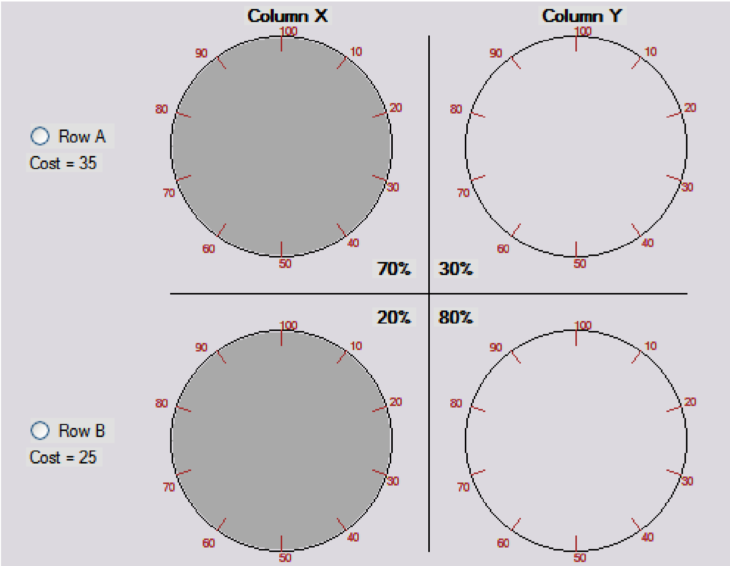


Figure 2.3 Period 1 Choice: No-Noise Configuration

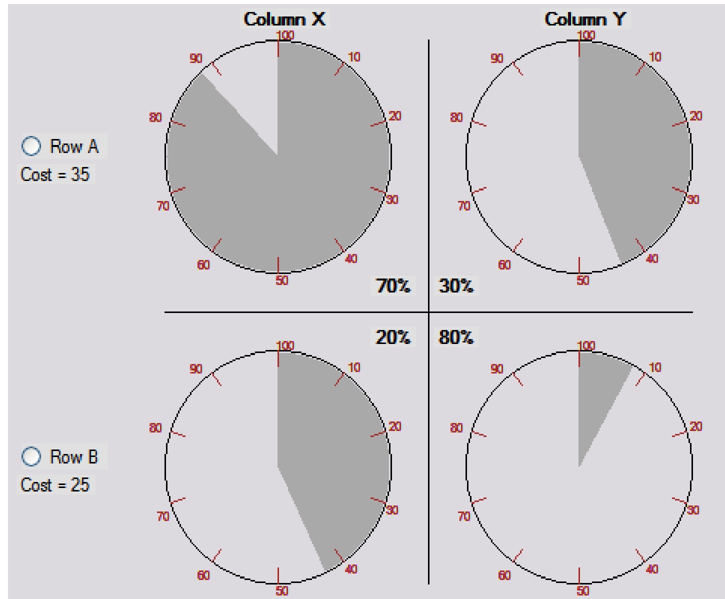


Figure 2.4 Period 1 Choice: High-Noise Configuration

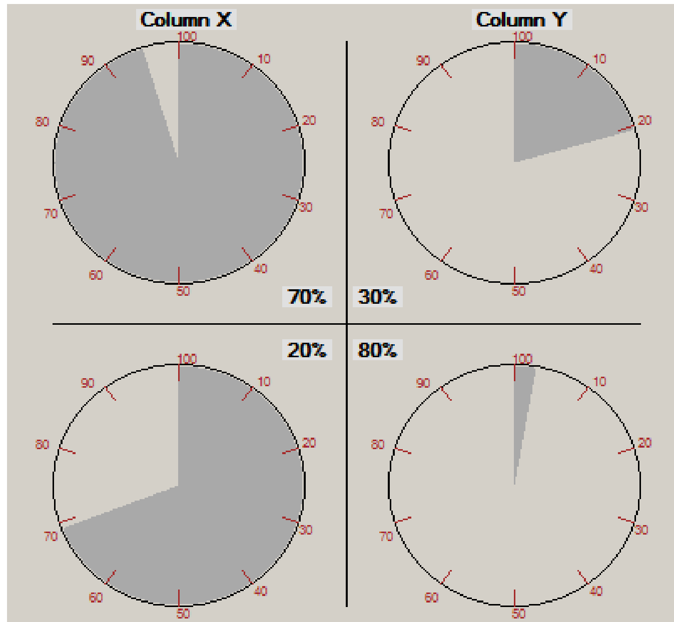


Figure 2.5 Period 1 Choice: Low-Noise Configuration

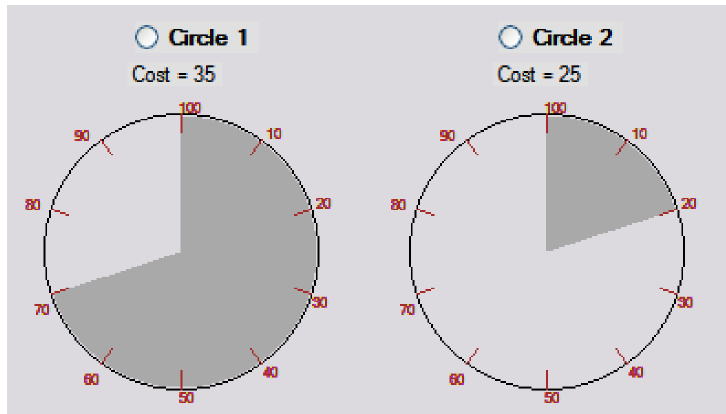


Figure 2.6 Period 2 Choice: All Configurations

Table 2.1 Model and Experiment Parameters

Parameter Description	Model Parameter	Experiment Parameter Value
Cashflow in State HH	O_{HH}	300
Cashflow in State HL or LH	O_{HL} or O_{LH}	190
Fixed Wage	R	50
Initial Hurdle Price	x	200
Reset Hurdle Price	x_r	120 or 105
Outcome Dependent Wage	w_{xx}	Varies
Period 1 Action Choice	i_1	Row A or Row B
Period 2 Action Choice	i_2	Circle 1 or Circle 2
High Investment in Period 1 (2)	A_1 (A_2)	Row A (Circle 1)
Low Investment in Period 1 (2)	B_1 (B_2)	Row B (Circle 2)
High (Low) Interim state	O_H (O_L)	-
Interim Information	s_H or s_L	Column X or Column Y
Information Quality	q	1, 0.9 or 0.75
Probability of High Outcome Given Action A	p(A)	0.7
Probabiltiy of Low Outcome Given Action A	1-p(A)	0.3
Probability of High Outcome Given Action B	p(B)	0.2
Probability of Low Outcome Given Action B	1-p(B)	0.8
Cost of High Investment	c(A)	35
Cost of Low Investment	c(B)	25

Table 2.2 Treatment Parameters

Treatment	Treat. Number	Investment Level	Cost	Probability of Success	Info. Quality (q)	Period 1 Strike Price	Period 2 Strike Price | S_L	Period 1 Exp. Value	Period 2 Exp. Value | S_L
No Feedback	1	A	35	0.7	-	200	-	80	-
		B	25	0.2	-	200	-	55	-
No Noise No Resetting	2	A	35	0.7	1	200	200	80	65
		B	25	0.2	1	200	200	60	75
No Noise with Resetting	3	A	35	0.7	1	200	120	95	115
		B	25	0.2	1	200	120	95	90
High Noise No Resetting	4	A	35	0.7	0.75	200	200	80	95
		B	25	0.2	0.75	200	200	55	85
High Noise with Resetting	5	A	35	0.7	0.75	200	120	100	155
		B	25	0.2	0.75	200	120	90	125
Low Noise No Resetting	6	A	35	0.7	0.9	200	200	80	80
		B	25	0.2	0.9	200	200	60	80
Low Noise with Resetting	7	A	35	0.7	0.9	200	105	100	145
		B	25	0.2	0.9	200	105	100	125

Note: This table provides a summary of experiment parameters for each treatment. Predicted actions for each treatment are highlighted in shaded cells.

Table 2.3 Experimental Design

	No Resetting	Resetting
No Feedback	Period 1: High Investment Period 2: High Investment	N/A
No Noise (q = 1)	Period 1: High Investment Period 2: Low Investment	Period 1: Indifferent Period 2: High Investment
High Noise (q = 0.75)	Period 1: High Investment Period 2: High Investment	Period 1: High Investment Period 2: High Investment
Low Noise (q = 0.9)	Period 1: High Investment Period 2: Indifferent	Period 1: Indifferent Period 2: High Investment

Table 2.4 Participant Choices – Period One

Treatment	1	%	2	%	3	%	4	%	5	%
High (Row A)	873	0.91	780	0.81	396	0.41	796	0.86	759	0.79
Low (Row B)	87	0.09	180	0.19	564	0.59	132	0.14	201	0.21

Note: This table provides the observed frequencies and relative percentages (expressed as a decimal) of participant choices in period one by treatment.

Table 2.5 Participant Choices – Period Two

Treatment	1	%	2	%	3	%	4	%	5	%
High (Circle 1)	863	0.90	81	0.30	116	0.90	161	0.86	198	0.91
Low (Circle 2)	97	0.10	186	0.70	13	0.10	26	0.14	19	0.09

Note: Table 2.5 Provides Second Period Choice Observations and percentages (expressed in decimal form) are conditional upon the individual having undertaken high investment in the first period and observing a low signal. Since no signal is observed in Treatment 1 the second period frequencies are unconditional.

Table 2.6 Outcome Efficiency Measures

Treatment	1		2		3		4		5	
	Row A	Row B	Row A	Row B	Row A	Row B	Row A	Row B	Row A	Row B
High (Circle 1)	825	39	575	59	375	555	738	55	696	171
Low (Circle 2)	48	48	205	121	21	9	58	77	63	30
Rel. % Efficiency (p-value)	N/A		70%		45%		93%		84%	
Abs. % Efficiency (p-value)	86%		60%		39%		80%		72%	

Note: Table 2.6 provides the number of rounds in which the specified behavior was observed and provides efficiency measures based on the percentage of optimal choices. Relative Efficiency is the Absolute Efficiency of a treatment divided by the Absolute Efficiency of the benchmark No Feedback treatment (Treatment 1). Absolute Efficiency is defined as the total of high, (Circle 1, Row A) choices divided by the total number of observations in that treatment. For example, Absolute Efficiency in Treatment 1 is calculated as 825/(825+39+48+48) = 0.86.

Table 2.7 Observed Payoffs by Treatment

	Frequency			Percentage			Efficiency
Market Price	0	190	300	0	190	300	
Treatment 1	125	424	411	13%	44%	43%	94%
2	267	338	356	28%	35%	37%	78%
3	165	536	259	17%	56%	27%	82%
4	142	387	399	15%	42%	43%	92%
5	150	441	369	16%	46%	38%	89%

Note: Table 2.7 provides the number of rounds in which the specified behavior was observed and provides efficiency measures based on the percentage of optimal choices. Relative Efficiency is the Absolute Efficiency of a treatment divided by the Absolute Efficiency of the benchmark No Feedback treatment (Treatment 1). Absolute Efficiency is defined as the total of high, (Circle 1, Row A) choices divided by the total number of observations in that treatment. For example, Absolute Efficiency in Treatment 1 is calculated as 825/(825+39+48+48) = 0.86.

Table 2.8 Confidence Intervals for Low Investment Choices - Period One

Confidence Interval	99%		95%		90%	
	Lower	Upper	Lower	Upper	Lower	Upper
Treatment 1	0.00	0.18	0.03	0.15	0.04	0.14
2	0.03	0.34	0.07	0.30	0.09	0.28
3	0.30	0.88	0.38	0.80	0.41	0.76
4	0.03	0.25	0.06	0.22	0.08	0.22
5	0.07	0.35	0.11	0.31	0.13	0.29

Note: Table 2.8 provides confidence intervals for the number of observed low investment choices in Period 1 for each treatment at the 99%, 95% and 90% levels respectively with 0 indicating all high investment choices and 32 indicating all low investment choices in Period 1.

Table 2.9 Confidence Intervals for Low Investment Choices - Period Two

Confidence Interval	99%		95%		90%	
	Lower	Upper	Lower	Upper	Lower	Upper
Treatment 2	0.47	0.93	0.53	0.87	0.56	0.84
3	-0.08	0.39	-0.02	0.33	0.02	0.29
4	0.04	0.30	0.07	0.26	0.09	0.24
5	-0.02	0.17	0.00	0.14	0.02	0.13

Note: Table 2.9 provides confidence intervals for the percentage (expressed as a decimal) of low investment choices in Period 2 conditional upon Period 1 high investment and observation of a low signal. For each treatment at the 99%, 95% and 90% levels respectively with 0 indicating all high conditional investment choices and 1 indicating all low conditional investment choices in Period 2.

Table 2.10 Hypothesis Tests for Differences in Treatments

Treatment	1	2	3	4	5
1	-	**< 0.000**	**< 0.000**	**0.001**	**< 0.000**
2	**< 0.000**	-	**< 0.000**	**0.009**	0.252
3	1.000	**< 0.000**	-	**< 0.000**	**< 0.000**
4	0.123	**< 0.000**	0.385	-	**0.000**
5	0.615	**< 0.000**	0.704	0.114	-

Note: Table 2.10 provides p-values for hypothesis tests that there is no difference in participant responses between individual treatments using Fisher's Exact Test. Period 1 p-values are provided in the upper diagonal while Period 2 p-values are provided in the lower diagonal. For example, the difference in participant choices in Period 1 for treatments 2 and 4 are statistically significant with a p-value of 0.009.

CHAPTER 3

THE ROLE OF FINANCIAL INFORMATION, SOCIAL CAPITAL AND REPUTATION IN LENDER DECISIONS

Introduction

This paper investigates how individuals interpret signals in a debt-contracting environment and whether those signals are reliable predictors of borrower behavior. In his paper, Akerlof (1970) demonstrates that markets where product quality is unknown may experience market failure. A proposed solution to this adverse selection problem is the use of reliable signals by which a seller may communicate quality. Examples of various signals used in debt-contracting are reputation (Kreps and Wilson, 1982) in the form of credit bureaus, the use of third parties to promote debt-issuance, such as underwriters and syndicates and the provision of financial information (Wittenberg-Moerman, 2008; Ball, Bushman and Vasvari, 2008). These signals allow a seller (borrower) to communicate quality and thereby reduce information asymmetries, thereby allowing a market to facilitate transactions. Effectively, signals in debt-contracting allow market participants to identify the probability that an agent is of a certain type and determine the price they are willing to pay for a series of future cash flows given the risk of default.

The present study provides evidence on the use of reputation, financial information and social signals used by individuals in debt-contracting. This is accomplished by examining which signals lenders in an online lending environment use to determine creditworthiness and how those signals correspond with borrower default behavior. I find that lenders place significant weight on the financial information signal (as measured by the Debt-to-Income ratio), reputational signals (as measured by a borrower's credit history and credit seeking behavior) and social capital (relationships with third-parties) when determining who should receive a loan and what interest rate to charge. When actual default behavior is considered, reputation and financial information signals are a significant predictors of future default; however, with the exception of groups that engage in monitoring, social capital fails to predict which borrowers will repay their loans.

The findings raise questions as to the incremental value of "social capital" in lending decisions beyond the institutional role of third-party affiliations in lending. Some commentators on the recent credit crisis have suggested that the traditional tools for risk assessment are inadequate and increased emphasis should be placed on the role of social capital in improving lending decisions (Statman, 2009). Sobel (2002) takes a critical view of social capital and believes that there is too much emphasis in the social capital literature on group membership as opposed to the economic role that the group plays in its environment.

The present setting is unique in that it allows the researcher to observe both sides of a market comprised of individual borrowers and lenders while controlling for social relationships between the borrower and endogenously created groups. Prior laboratory investigations on the role of financial information in individual debt-contracting decisions have focused on which specific elements of a financial report and/or ratios are important in lending or the impact of experience on lending, while a significant amount of field research on trust behavior in lending has taken place in developing world micro-lending environments where the group plays a significant role in enforcing loan repayment. In contrast, by incorporating elements from the socio-economic literature (Podolny, 1993; Conte and Paolucci, 2002; Ferrary, 2003; Olsen, 2008) the present study recognizes lending transactions may be a more complex process in which the decision maker may be swayed social considerations or "social capital" in addition to reputational records and financial measures. The setting also helps address the question as to what economic role financial reporting plays in society (Ball, 2008). This is accomplished by providing some evidence that 1) both simple financial reporting and monitoring institutions are predictive of future default behavior and; perhaps more importantly, 2) individual lenders use these institutions in their decision making even in this primitive lending environment.

The paper proceeds as follows: Section II provides a brief introduction to the Institutional History of the research setting. Section III reviews the Related Literature and Theories. Section IV provides the Hypothesis while Section V considers the Sample Selection and Research Design. Section VI provides the Results and Section VII concludes.

Institutional History

Operational History

This paper uses data obtained from an online lending website, Prosper Marketplace Incorporated (available at http://www.prosper.com, hereafter referred to as "Prosper"). Inspired by the micro-lending movement in developing nations and online lending websites such as kiva.org[15], Prosper officially started operations in April, 2006. The business model of Prosper is similar to eBay where buyers (lenders) and sellers (borrowers) are matched with each other while revenue is earned by Prosper in the form of fees. To date there have been over $178 million in loans originated with over 830,000 individual registered users.

Prosper uses an auction mechanism to set the rate a borrower receives. The process is as follows: similar to eBay, a borrower posts a loan request for an amount between $1000 and $25,000 on the Prosper website with the maximum rate of interest she is willing to pay as well as the purpose of the loan (i.e., consolidate credit card debt, start a business, vacation etc.). Potential lenders then view the listing, along with a summary of the borrower's credit history obtained from Experian[16] as well as a credit

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[15] Kiva.org focuses on providing micro-loans to borrowers in developing nations.

[16] Experian is one of the three major credit bureaus in the United States along with TransUnion and Equifax.

grade (see Figures 3.1 and 3.2). Credit grades, which provide a summary indication of a borrower's reputation, range from AA (excellent credit) down to HR (High Risk)[17]. Potential lenders are also shown a financial measure called the "Debt-to-Income" (hereafter DTI) ratio. Lenders have the option to ask questions of potential borrowers to clarify the loan request, although there is no obligation of a borrower to respond to a question. All questions and responses may be viewed by other lenders.

If a lender feels the potential return from a loan is sufficient to compensate for the associated risk, the lender may place a bid (minimum $50 up to a maximum of the requested loan amount). The lender also states the minimum interest rate they are willing to accept[18]. To ensure all bids are legitimate (i.e., no "shill bidding"), Prosper requires that each lender transfer sufficient funds into their Prosper account prior to bidding on a loan. Once a lender bids on a loan, those funds are no longer available to the lender unless the listing is cancelled, expires or another bidder is willing to fund the loan at a lower interest rate.

Once a sufficient number of bids have been received to "fund" the loan, the interest rate begins to drop. A lender willing to provide the borrower with a better rate may "bump off" a lender with the highest minimum rate by bidding with a rate that is at least 0.05% less than the current rate. Once a funded listing expires, the final rate is the minimum rate that was needed to provide funds for the loan.

In order to better understand the auction process, consider a hypothetical listing for a borrower requesting $1000 with a maximum requested interest rate of 20% that has four bids of $200 each, three bids have a minimum interest rate of 15% while the fourth

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[17] Note by definition the credit grade is a reputation score since it provides a probability of default (see Figure 3.3).

[18] While other lenders can see who has bid on a loan as well as the order of bids, they cannot see the minimum interest rate of a particular bid. Only the current interest rate required to fund the loan is shown.

bid has a minimum rate of 20%. At this point the loan is not fully funded since there is only $800 worth of bids while the borrower has requested $1000. If the auction were to end at this point, the borrower would not receive the loan and all funds involved in the bidding process would be returned to the lenders respective accounts.

Now suppose a fifth lender posts a bid of $200 with a minimum rate of 19%. There are now sufficient bids to fund the loan ($1000); however, if the listing were to end at this point, the interest rate would be set at 20% since that is the minimum rate necessary to provide funds to the borrower. If a sixth lender arrives and bids $100 at 10%, then there are more funds than required to fund the loan ($1100 vs. $1000), to resolve this, the bidder(s) with the highest interest rate(s) have the amount of their bid reduced until the total amount provided by winning bids is equal to the amount of the loan request. In this instance, the bidder who placed the $200 bid at 20% would have their bid amount reduced to $100. Note that the rate that the borrower would pay (and all lenders receive) would still be 20% since that is the rate required to provide $1000 worth of funds.

Finally, consider a seventh bidder who places a $300 bid at 14%. Again, the lenders with the highest minimum rates are dropped until the supply of funds equals the amount of the loan request. In this case, the remaining $100 from the 20% bid would be dropped as well as the $200 bid at 19%. The interest rate on the loan now drops to 15% because that is the minimum rate required to fund the loan.

Following the close of the auction, funds are transferred to the borrower's bank account and Prosper services the loan, charging both the borrower and lender a servicing fee[19]. If sufficient bids are not received prior to the expiry of the listing, the listing is

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[19] Technically Prosper legally remains the lender and simply resells portions of each note to the winning bidders who are referred to as "lenders" throughout the website. In October, 2008 Prosper Marketplace ceased making new loans while it awaited approval from the United States Securities and Exchange Commission (SEC) to sell securities. On November 24, 2008, Prosper entered into an agreement with the SEC to cease further violations of securities laws and to pay a fine for selling securities without proper

cancelled and all funds are released to the lenders to bid on other loans. All loans are for a fixed three year term and are unsecured with no pre-payment penalty. Should a borrower default on a loan payment, the loan is assigned to a debt-collection agency. If a loan proves to be uncollectible, it may be sold to a junk-debt buyer for pennies on the dollar[20] or Prosper may pursue legal action against the borrower.

Borrower Affiliation with Third Parties

Upon inception, Prosper promoted "social lending". Prospers implementation of social lending relied on the concept of a group. According to Prosper, borrowers who are in a group are less likely to default on their obligations since they may have an attachment to the group and do not want to negatively impact the reputation of the group[21]. Each group on Prosper is started by a "Group Leader". To become a group leader, any registered user can simply apply to create a group. Prosper then reviews and typically approves the application.

After approval, the group leader decides what set of criteria (if any) will be used to qualify borrowers for membership in the group. For example, group leaders may

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registration. Further information is available at http://www.sec.gov/litigation/admin/2008/33-8984.pdf . The SEC approved the registration statement for Prosper in July of 2009, and lending subsequently resumed on July 13, 2009. It should be noted that the lending environment is much more restricted after registration with the SEC. Only lenders who reside in certain states and meet income and net worth qualification tests are permitted to participate in lending, in addition, only borrowers with credit scores of 640 or greater (equivalent to a C grade or better) are now permitted to post a listing.

20 The risk of default for high-risk borrowers is non-trivial on Prosper and some lenders have suffered large losses. One of the larger lenders on Prosper (known as "pensioner"), made 173 loans for a total of nearly $883,000 to primarily high-risk borrowers. Over $465 thousand worth of pensioner's loans have defaulted while another $98 thousand worth of loans are currently in "late" status. The defaulted loans have been sold off for a total of $17, 126, or approximately four cents on the dollar. Despite this loss, the expected rate of return on pensioner's portfolio is estimated to be -0.64%.

21 Prosper may have borrowed the group concept from the micro-loan movement in developing nations. In developing nations, many micro-loans are given to an individual who is a member of a group. If an individual does not pay back the loan, the group will not receive further credit until the loan is repaid. On Prosper there is no such sanction in place against the group other than having a defaulted loan reported to lenders.

restrict group membership based upon employment (e.g., Microsoft employees, teachers, police officers), education (e.g., Cornell, Penn State or Harvard alumni), religion, geographic region, sexual orientation or credit grade. In some instances criteria are non-exclusive and anyone can join. Once a member has joined the group, they are allowed to create their listing which includes recognition that they are part of a particular group. Typically, a group leader retains significant control over their group and personally reviews a listing before it is made public, while other groups may require no such review.

During the time period used in this study, group leaders receive compensation in two forms. The first form is a lump-sum finder's fee or "reward" that is paid by Prosper when the loan originates. The second form is a "group fee" which is an ongoing percentage of the loan principal charged to a borrower that can range from an annualized rate of 0-5%. The group fee effectively increases the rate that a borrower must pay on a successful listing. The group leader chooses what percentage they wish to charge borrowers and fees are disclosed prior to a borrower joining the group.

Although unintended by Prosper, some group leaders began providing verification services (commonly referred to as "vetting") for statements made in the loan listing[22]. For instance, a group leader may require an individual to submit W2's, paystubs or tax returns as proof of employment, others may require a copy of an individual's actual credit report to document any potential reasons for a poor credit grade. Some group leaders even go so far as to personally interview potential borrowers in their homes. In one case, a CPA from Michigan started a group to provide "verification services" to self-employed borrowers. A common custom arose where groups providing verification services provide a "vetting report" for potential lenders to view.

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[22] Prosper was concerned that there was a potential for identity theft by group leaders providing monitoring services. As a result they strongly discouraged the practice of vetting by group leaders.

Financial Information

The proxy for financial information used in this study is the debt-to-income (DTI) ratio. Because of the role DTI plays in this study, it is important to understand both how the ratio is constructed, as well as the sources of information used. Doing so will allow one to appreciate both the strengths and limitations of such a ratio in this setting.

DTI is constructed as follows: total monthly minimum debt payments divided by income. Monthly minimum debt payments are obtained from the most recent credit report and are simply the sum of all monthly minimum credit card and installment loan payments plus the monthly payment that would result from a successful Prosper loan listing. To provide that those owning a home rather than renting are treated equally, monthly minimum housing payments (i.e., mortgage payments) are excluded from the calculation of total debt-payments; therefore, monthly mortgage payments are not included in the calculation of DTI.

Since consumer credit reports do not include information on income, the denominator of the DTI ratio is monthly income as reported by the borrower to Prosper. Since monthly income is self-reported, this can create a potential problem for verifiability of information. To overcome this limitation, Prosper discourages potential borrowers from misreporting their income by requiring that any listed income be substantiated by tax forms from the prior tax year. Due to the volume of applications, Prosper does not verify these documents prior to a listing being posted. Instead, documentation of income is requested only after a loan has received sufficient bids to become funded. If documentation is not provided within ten business days of the close of the listing, then the loan is cancelled and funds are returned to lenders for bidding on another loan.

Ensuring that the DTI ratio is verifiable in this manner implies that it may not be timely for decision making purposes. For instance, consider an individual who earned \$12,000 while they were a student in the prior year, but has now graduated and is currently employed in a position that pays \$60,000 per year. If the individual has \$200 worth of monthly debt payments then their DTI as reported to lenders would be 20% ($200 / ($12,000 / 12)). In contrast, their "real" DTI ratio is actually 4% ($200 / ($60,000 / 12)).

Related Literature and Theory

Reputational Signals

Consistent with prior literature, I define reputation as the probability that an agent is of a certain type[23]. The majority of experimental economics reputation research deals primarily with how reputation is formed by a trustee (e.g., Camerer and Weigelt, 1988; Neral and Ochs, 1992). Recently, increased popularity of online auctions as well as data availability from such environments has led to heightened interest in the use of online auctions to study reputation. Studies of reputation to date primarily share the common characteristic of using data collected from eBay auctions of a particular homogenous good. (e.g., Resnick, Zeckauser et al., 2006; Houser and Wooders, 2006; Melnik and Alm, 2002). In general, reputation has been found to be important in facilitating economic transactions. Consistent with theory, buyers generally take a sellers reputation into account when purchasing and higher rated sellers obtain a price premium on the sale of their goods[24].

While the use of reputation in the present study is mainly as control variables, the reputation score used in this paper does offer two main advantages over prior studies which use eBay. First, there is a greater degree of heterogeneity in the reputation scores

[23] Camerer (2003) states that, "In modern game theory, a player's reputation is crisply defined as the probability that she has a certain privately observed type or will take a certain action."

[24] Jamal and Sunder (working paper) document that baseball card which are graded by reputable independent third-parties do obtain a price premium. Ganguly, Herbold and Peecher (2007) experimentally show that reputation can transfer from one existing assurance service to a new assurance service if the competencies required in the new service are similar. There is a stream of literature within the finance literature which looks at the effect of underwriter reputation on bond and IPO pricing (e.g., Beatty and Ritter, 1986; Carter and Manaster, 1990; Fang, 2005; Daniels and Vijayakumar, 2007).

of sellers (borrowers); further, the reputation score (credit grade) has previously been empirically shown to correspond with the probability of default.

Financial Information

Recent research into the use of financial information in lending decisions has largely focused on the role of accounting information in debt-contracting. As stated previously, Ball, Bushman and Vasvari (2008) associate the value of accounting information with the predictive ability of accounting numbers to identify future downgrades in credit ratings, and by implication future default risk. Wittenberg-Moerman (2008) looks at the secondary loan market to determine how firm and loan characteristics affect information asymmetry in lending relationships.

Laboratory investigations of the role of financial information in individual lending decisions have attempted to identify which informational items or signals are predominant in lender decisions. One general approach is exemplified by Abdel-Khalik and El-Sheshai (1980) who use the Brunswick lens model methodology to identify which accounting ratios individuals focus on when making a lending decision. More recent literature by Andersson (2004) and Liyanarachchi and Milne (2005) have investigated the role of experience in the use of accounting information in lending. Guiral-Contreras, Gonzalo-Angulo and Rodgers (2007) perform an experiment to investigate whether professional loan officers use a qualified audit report in their decision making process while Catasus and Grojer (2003) investigate the use of intangibles by in loan officer decisions. Kwok (2002) finds that loan officers ignore cash flow information as provided by the statement of cash flows and instead focus on accrual-based reports. By using the field-study approach, the current research avoids some of the issues inherent with the prior laboratory studies[25] and allows the researcher to identify the role of reputation, financial information and social capital simultaneously.

Social Signals and Social Capital

The principle that individuals may use social signals in evaluating the potential trading partners is well established in the literature on social capital; however, there is surprisingly little empirical evidence on the role or reliability of such signals in debt-contracting. Much of the difficulty in determining the role that social capital plays in economic transactions may simply be due to the lack of an agreed upon definition of social capital. Some authors suggest that social capital is defined simply as "membership in a group" (Bourdieu, 1986). Others take a more expansive view of social capital as being a "person's social characteristics - including social skills, charisma and the size of his Rolodex" (Glaeser, Laibson and Sacerdote, 2002). In contrast, Sobel (2002) takes a critical view of the social capital literature and argues that when actual outcomes from social interaction are analyzed social capital may actually be harmful to society at large, or that groups may coordinate on a bad equilibrium by encouraging risky behavior by their members. He goes to suggest that the value of social capital is dependent upon the institutional environment in which it operates. Environments with strong (weak) formal institutions will place a low (high) value on social capital.

Given the difficulty of defining social capital, it is perhaps not surprising that there are relatively few empirical studies attempting to disentangle social capital outcomes from other institutional characteristics of groups (i.e., monitoring and enforcement roles). One of the most innovative empirical studies on social capital to date has been work by Dean Karlan in his 2005 combination of experimental economics and field research in a Peruvian micro-lending environment. Perhaps a striking feature of this

[25] Bonner (2008) highlights both the advantages and limitations associated current judgement and decision making research in accounting.

work is how few of the proxies for social capital are actually significant predictors of actual default behavior. Individuals who are more "trusting" as measured by a prior administration of a trust game are actually less likely to repay their loans[26]. In fact the only reliable "social capital" indicator appears to be geographic proximity; this suggests that there may be other institutional environments or mechanisms, such as reputational concerns at work in these settings which may be confounded when measuring social capital outcomes.

There are a variety of potential explanations for how social capital may work. Podolny (1993) relies on the sociological notion of status to explain how certain economic actors in a market obtain a competitive advantage and therefore are able to become a low cost producer. Podolny provides evidence of how clients associating themselves with a "high status" underwriter in a lending syndicate obtain a lower rate of interest. Applying the status argument to the present setting, if an individual is granted a higher level of status by the community via joining a group or having a group leader lend to them then they will receive a lower rate of interest and therefore have a competitive advantage.

On the surface it may appear as though status and reputation is the same concept. The distinction being made here between status and reputation is that reputation is an objective evaluation of an agent's type based on prior history whereas status may be subjective, based upon a "community" assessment and is therefore a relative measure. To quote Podolny:

> *"If an actor is uncertain of the actual quality of the goods that confront her in the market, or if she is unwilling or unable to bear the search costs*

[26] Karlan attributes this to the possibility that individuals who behave in a more trusting manner in the trust game are actually exhibiting gambling behaviour and are therefore less likely to make wise business decisions when loaned funds for a business venture.

of investigating all the different products in the market, then the regard that other market participants have for a given producer is a fairly strong indicator of the quality of that producer's output."

More recently, Conte and Paolucci (2002) propose a model in which individuals use third-party relationships to transmit information on reputation. Under their formulation, if I am trying to judge whether another individual is trustworthy, I will consider the relationship that others have established with that individual. Essentially, if A does not know B, but C trusts B, then A may use C's judgment of B to determine whether to trust B.

In a similar vein, Ferrary (2003) perhaps comes closest to the present study in terms of research question. The focus of Ferrary's work is to study social influences on the lending environment. Ferrary uses a case study approach to document how lenders use "social capital" to augment the use of accounting (financial) information and reputation mechanisms. Ferrary states:

"One of the main findings of economic sociology is that social networks modify economic regulation because of the principle of solidarity that links their members and because the nature of the information that circulates in them changes the nature of the exchange. The mutual knowledge of the social network's members reduces the information asymmetry for trades made between these members."

He continues with:

"In economic trades, the social capital of an individual is constituted by the persons with whom he has trust relationships. The transitivity of this relationship…strengthens and maintains the social network by multiplying interpersonal relationships."

In addition to the socio-economic arguments, there are also existing economic based theories which may provide potential explanations for why affiliating with a third-party can reduce perceived risk in an economic transaction. Tirole's (1996) group reputation model posits that group reputation is simply an aggregate measure of the reputation of all members of the group. Group members who deviate from accepted behavior can lower the reputation of the group leading to lower economic rents for all members of the group. To avoid lower economic rents, the group will sanction or expel those who do not comply with group norms. As a result, membership in the group becomes a method to promote economic bonding. Note that because United States law governing debt collection at the time of this study does not permit group leaders to contact delinquent borrowers, it does not appear that the Tirole model will be applicable in the current setting since the enforcement mechanism envisioned in the model is not available on Prosper. While this may be seen as a limitation by some, it is a useful feature since any decrease in default behavior by group members can more easily be attributed directly to social capital rather than the enforcement role that groups play in many studies of micro-lending institutions.

As described previously, the spontaneous emergence of groups that engage in "vetting" of potential borrowers provides an interesting opportunity by which to research the role of groups in monitoring. Diamond (1991) proposes a model of "monitoring" in which a borrower wishing to obtain a loan has two options. The borrower can either go directly to the public debt market or can undergo monitoring via a bank loan. In Diamond's model, monitoring is an action performed prior to the loan being granted. Borrowing directly from a bank provides a lower interest rate than that provided by the public debt markets; however, monitoring imposes additional transactional costs upon the company. As a result, high and low quality borrowers issue debt directly via the debt markets since the monitoring costs may exceed the interest rate differential for these two groups. At best, borrowers with good reputations are able to cover the cost of monitoring and therefore monitoring simply serves as a screening mechanism. On the other hand, borrowers with extremely poor reputations choose to not undergo monitoring since there is a risk their negative private information will be exposed. There are real economic gains for medium quality borrowers and they prefer monitoring since the interest rate savings exceed monitoring costs. In the present study groups are identified if they play a monitoring role and thus can; therefore, provide a more direct test of the hypothesis that social capital enhances economic transactions.

Hypothesis Development

The setting used in this paper provides several convenient proxies that can be used to understand how lenders assess the incremental changes in default risk due to reputation, financial information and social capital and whether those expectations are actually realized in the future performance of borrowers. The first method of investigation is simply to look at which loans the market chooses to fund. This is done by evaluating which borrower characteristics are influential in lender decisions. The second measure is to compare interest rate differentials based upon these same factors. If a borrower characteristic is viewed as reducing default risk, then lenders should be willing to offer the borrower a reduced rate of interest. Finally, borrower characteristics will be evaluated with respect to how well they predict future defaults. Under this definition the value of a signal will be its ability to predict future default.

Social Signals

Affiliation with third-parties may provide the borrower with social capital and; therefore, indicate a lower risk of default. Three measures of social capital are considered. Consistent with Bordieu (1986) the first proxy is group membership. If simply joining a group provides a signal of reduced risk, then lenders will be more likely to lend to a member of a group and will be willing to lend at a lower rate of interest. Further, if group membership is a valuable signal, then group members will default at a lower rate than non-group members. Stated formally:

H_{1a}: If social capital indicates lower risk, then members of groups are more likely to receive a loan than non-members and will be provided with a lower rate of interest. Members of a group are less likely to default than non-group members.

In many cases it is very easy to join a group, and it is unlikely that membership alone indicates a significant level of trust on the part of the group leader. On the other hand, if a group leader places a winning bid and lends funds out of their own pocket, then lenders may view this more favorably than if the group leader does not participate in the loan. The amount of a group leader's bid may also indicate that the borrower is less likely to default and therefore provides an indication of reduced information asymmetry (Ball, Bushman and Vasvari, 2008).

H_{1b}: If lenders view group leader bids as indicating lower risk, then borrowers with a group leader bid will be more likely to receive a loan with a lower rate of interest. Loans with group leader bids default are less likely to default than loans with no group leader bids.

To evaluate the role that monitoring (Diamond, 1991) may play in this environment and to distinguish it from social capital; I also identify groups that require borrowers to undergo monitoring prior to joining their group or posting a listing. Since monitoring generates additional verified information beyond that provided by Prosper and reduces information asymmetry, it is anticipated that borrowers who undergo monitoring will be more likely to obtain a loan. Further, monitoring may also reduce the risk of default; therefore resulting in a lower rate of interest; however, Diamond predicts that interest rate gains from monitoring are only available for medium quality borrowers. Monitoring for borrowers with good reputations simply acts as a screening device, while extremely poor reputation borrowers choose to avoid monitoring in order to avoid revealing negative information. Under the monitoring hypothesis, medium quality borrowers who undergo monitoring are provided with lower interest rates, while those with high credit grades do not receive significantly lower rates. While the Diamond model suggests that low quality borrowers do not benefit from monitoring, the sample may be censored since Prosper's requirement of a minimum credit score of 520 limits the pool of borrowers by excluding those with extremely low reputations.

H_{1c}: If monitoring reduces information asymmetry, then borrowers in groups that monitor will be more likely to receive a loan with a lower rate of interest. As the credit grade increases, the impact of monitoring on the interest rate provided by lenders decreases. Monitoring also reduces the likelihood of default.

Financial Information Signals

Financial information is seen as important since it may be used to predict future default behavior. Due to a lack of a financial buffer, borrowers with high levels of minimum debt payments relative to their income may be less likely to repay their debt in a timely manner if they experience an adverse change in circumstance that affects future cash flow, such as large unexpected expenses, disability or job loss. As discussed previously, because of limitations in how DTI is defined in this setting, it is not clear *ex ante* that DTI will be a significant predictor of future default or whether lenders will use the ratio in assessing risk; however, if DTI is interpreted by lenders as providing information regarding risk, then borrowers with high DTI ratios will be less likely to receive loans. The rate of interest will also rise as DTI increases.

H_2: If lenders consider DTI in lending decisions, then borrowers with high DTI ratios will be less likely to receive a loan. As DTI increases, borrowers must pay a higher rate of interest to compensate for increased default risk. Borrower default is increasing in DTI.

Reputation

Since Prosper provides a credit grade for all borrowers, and since the credit grade is known to predict expected default rates for borrowers, a borrower's credit grade will serve as the primary proxy for their reputation. As a borrower's reputation decreases, they will find it more difficult to obtain a loan. Those who do obtain a loan will most likely be required to pay an increased interest rate to compensate lender for the increased risk of default. While it has already been empirically shown by Experian that credit grades are linked to future default behavior, reputation will be included as a control. As well, the current sample will also be analyzed to determine the ability of reputation to predict future default.

> H_3: If lenders consider reputation in lending decisions, then borrowers with poor reputations will be less likely to receive a loan. As reputation decreases, borrowers must pay a higher rate of interest to compensate for increased default risk. Borrowers with poor reputations are more likely to default than borrowers with good reputations.

Sample Selection and Research Design

This study uses a field research approach to understand how lenders in an online lending environment use reputation, financial information and social capital in decision making[27]. Data is collected from Prosper Marketplace Incorporated directly using a publically available Application Programming Interface (API) provided by Prosper[28]. Listings between April 17, 2006 and September 12, 2007 are gathered[29]. Between these dates there are 96819 loan listings. 6006 listings are eliminated due to incomplete or missing credit information. These listings result in a total of 8642 loans being granted

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27 The use of field data has been used to study economic environments ranging from labor markets (Roth, 1984), individual stock trading behavior (Odean, 1998; Barber and Odean, 2000, 2006), online privacy (Jamal, Maier and Sunder, 2003, 2005) and even reputation in online outsourcing markets (Banker and Hwang, 2008).

28 The data is available at http://www.prosper.com/about/academics.aspx. Viewing of credit data requires registration with Prosper as a lender.

29 The dates have been chosen to provide consistency in the comparison of borrowers. Between February 13, 2006 (Prosper Launch Date) and April 17, 2006 lenders were only provided with limited credit history information consisting of the credit grade and debt-to-income ratio. Borrowers listing after April 17, 2006 have extended credit data displayed although it is not always available. On September 12th, 2007, Prosper changed their compensation method for group leaders by shifting to a referral reward system and eliminating group leader fees.

which have the necessary information for analysis[30]. Descriptive statistics for the sample by credit grade are provided in Tables 3.1 and 3.2.

The main research question of interest is how lenders perceive borrower characteristics when making a lending decisions. Within a particular credit grade, there are several factors that lenders may use to set the interest rate. Since a larger loan request entails larger monthly payments and requires a greater amount of lender funds it is likely that the interest rate will be correlated positively with the size (*AMOUNT*) of the loan request. Borrowers willing to pay a higher rate of interest may find it easier to obtain a loan; however, even with the auction mechanism used by Prosper, they do expose themselves to the risk that they may pay more than the average borrower with similar credit characteristics. To account for this, the variable *MAXRATE* is included and is simply the starting rate of interest for the auction.

Homeownership may be seen as a positive characteristic since the purchase of a home typically involves obtaining a mortgage which may include verification of income and other assets[31]. Homeownership is tracked via the *HO* indicator variable where 1 indicates homeownership. Another control factor considered is the Group Fee (*GLREWARD*) that the lender charges. Recall that the group fee is a fixed percentage of the outstanding principal that the group leader charges to the borrower. The group leader has full discretion as to the amount of the fee that they charge to the borrower (from 0 to 5 %).

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30 The author has made 27 loans on Prosper for a total of approximately $2200 with an average interest rate of over 15%. All loans and listings which involve the author have been excluded from the analysis; however, inclusion of these loans does not materially affect the results. Out of the 27 loans made, 8 have been repaid in full with 18 borrowers presently being current on their payments and 1 borrower being over 30 days late.

31 Glaeser, Laibson and Sacerdote (2002) suggest that homeownership is a form of social capital; however, in their model social capital from homeownership arises from the relative loss of mobility that homeownership imposes on individuals rather than the screening mechanism I am suggesting here.

Reputational Proxies

Since by definition a credit score is a prediction of future default, the credit grade is effectively a summary of the borrower's reputation where a lower credit grade is associated with a higher risk of default. While prior evidence of not paying debts or prior bankruptcy are considered by Prosper in addition to other factors[32] when determining the credit grade of an individual, it is possible lenders will be biased against those who have prior delinquencies, judgments or bankruptcies in their credit history. For example, if two borrowers both have credit grades of "C", but one borrower has prior delinquencies and the other has none, then it is reasonable to believe that lenders will systematically prefer the borrower with no prior delinquencies and view that borrower as less risky. Therefore, there may be an incremental impact on the rate lenders charge to those with these characteristics. The variables *DEL* and *PR* are borrower delinquencies[33] and public records[34] respectively.

Lenders may also be suspicious of recent credit seeking behavior. Many recent inquiries for a borrower's credit history may indicate a certain level of desperation on the part of a borrower; therefore, the number of inquiries (*INQ*) from the past six months is also considered.

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[32] Note that unlike corporate bond ratings, income is not considered when assigning a consumer credit score.

[33] An account is reported as delinquent to the credit bureau when a borrower falls at least 30 days behind on payments to an account. Once a delinquency has been noted it is not removed from the credit record for seven years even if the account is brought to current status. DEL is an indicator variable of 1 if there are one or more delinquencies reported and 0 otherwise.

[34] Public records in a credit report include but are not limited to items such as bankruptcy, divorce and court judgments. Lenders can see the number of public records, but are not told what the public records actually are.

Social Information Proxies

To investigate the potential social signaling roles that groups may play in this setting, I use the variable *INGROUP* to indicate whether the borrower is a member of a group. I also use the variable *MONITOR* to indicate whether a listing is sponsored by a "Monitoring Group". Monitoring groups have group leaders who undertake additional steps to create new information for the marketplace via verification of voluntary disclosures provided in a loan listing prior to approving the listing. Because of this verification step and the corresponding reduction in information asymmetry, lenders may perceive less risk for borrowers in such groups.

In order to determine whether a group is a monitoring group, I first obtain a copy of the "Group Page" from the Prosper website which describes the characteristics of the group including any stated criteria used by the group leader[35]. A search is then conducted in the Prosper forums archives site on both the group name and the user name of the group leader[36]. Results from this additional search are used to identify the nature of a particular group. Together, data gathered from the Group Page and forums are used to determine the group category.

In order to be considered a "Monitoring Group", there must be some indication that the group leader makes it standard practice to obtain additional information to verify statements made in the loan listing. Such data gathering exercises may include reviewing

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[35] Due to the number of groups on Prosper not all groups are studied to determine whether they are a monitoring/non-monitoring group. Within the Prosper system, there are over 4000 groups listed; however, a large majority of these groups do not undertake any significant activity during this period and have not generated a single listing or loan. To ensure that group leaders are actively pursuing the group concept, I exclude groups with fewer than 5 listings during the time period. This leaves 375 groups representing over 96% of the group listings on Prosper during the time period in question.

[36] Prosper previously hosted the forums on their own site; however, they eliminated the legacy forums in early 2008 and replaced them with heavily moderated forums after certain lenders with poor investment records began to use the forums to raise questions about the company's business practices and viability. The researcher has used these legacy forums which are available at http://www.prosperreport.com to assist in making group category determinations.

tax documents, pay stubs, phoning employers or in some cases even requiring an in-person meeting.

In addition to the *MONITOR* indicator variable, I also include two additional variables which may be of interest to lenders since they may indicate a trust relationship between the group leader and the borrower. The first is *GLBID*, an indicator variable set to 1 if the group leader places a bid on the listing; the second is *GLPCT* which is the total percentage of the loan that a group leader participates in. It is anticipated that lenders will view a group leader who bids on a listing as a positive signal and as a result both *GLBID* and *GLPCT* are expected to increase the probability of receiving a loan as well as resulting in a reduced interest rate.

Financial Information Proxy

The metric used to measure financial information is the DTI ratio. Borrowers who have large monthly obligations relative to their income may be more likely to default on their payments; the debt-to-income (*DTI)* provides a ratio of the approximate percentage of income (including the proposed loan) that debt payments will consume each month. As discussed previously, because of how the DTI ratio is constructed, *ex ante* it is not clear that a relationship between DTI and future default will exist. Recall that DTI excludes mortgage payments; therefore, individuals with very large mortgages will have a somewhat lower DTI than a metric which would include all minimum debt payments. Additionally, since Prosper requires that income reported be verifiable from the prior tax year, the DTI ratio may not be timely.

Model Specifications

To better understand what factors affect investor decisions, the following regression is estimated where *FUNDED* is a binary variable equal to 1 if the listing is funded and 0 if it expires, is terminated or otherwise withdrawn.

$$FUNDED = \alpha_1 + \beta_1 AMOUNT + \beta_2 DTI + \beta_3 DEL + \beta_4 PR + \beta_5 HO + \beta_6 INQ + \beta_7 INGROUP + \beta_8 MONITOR + \beta_9 GLPCT + \beta_{10} GLBID + \beta_{11} GLREWARD + \beta_{12} MAXRATE + \boldsymbol{\beta_{13} CREDITGRADE} + \varepsilon \qquad (eq. 3.1)$$

The same factors are then used to analyze the performance of borrowers by using borrower characteristics to predict default outcomes. Two definitions of $DEFAULT$ are considered. The first definition is when Prosper formally declares the loan to be in default status. This can occur because of bankruptcy, death or inability to collect. Because there is often a significant time lag (often more than one year from the date of first delinquency) between when a serious delinquency occurs and a formal default is declared, a second, less restrictive definition of default is also examined. Under the second definition, a loan is also considered to be in default once it is 90 or more days past due. The following logistic regression is estimated:

$$DEFAULT = \alpha_1 + \beta_1 AMOUNT + \beta_2 DTI + \beta_3 DEL + \beta_4 PR + \beta_5 HO + \beta_6 INQ + \beta_7 INGROUP + \beta_8 MONITOR + \beta_9 GLPCT + \beta_{10} GLBID + \beta_{11} GLREWARD + \beta_{12} MAXRATE + \boldsymbol{\beta_{13} CREDITGRADE} + \varepsilon \qquad (eq. 3.2)$$

The rate of interest lenders demand for funded loans is also used to assess how lenders perceive the risk of borrowers. Specifically, I estimate the following model:

$$RATE = \alpha_1 + \beta_1 AMOUNT + \beta_2 DTI + \beta_3 DEL + \beta_4 PR + \beta_5 HO + \beta_6 INQ + \beta_7 INGROUP + \beta_8 MONITOR + \beta_9 GLPCT + \beta_{10} GLBID + \beta_{11} GLREWARD + \beta_{12} MAXRATE + \boldsymbol{\beta_{13} CREDITGRADE} + \varepsilon \qquad (eq. 3.3)$$

Under this specification, if lenders perceive that a certain characteristic indicates a reduced (increased) level of default risk, then lenders will demand a lower (higher) rate of interest to compensate them. Finally, to better understand how interest rates are set and the role monitoring plays in this environment, I estimate the following regression for each credit grade:

$$RATE = \alpha_1 + \beta_1 AMOUNT + \beta_2 DTI + \beta_3 DEL + \beta_4 PR + \beta_5 HO + \beta_6 INQ + \beta_7 INGROUP + \beta_8 MONITOR + \beta_9 GLPCT + \beta_{10} GLBID + \beta_{11} GLREWARD + \beta_{12} MAXRATE + \varepsilon \quad \text{(eq. 3.4)}$$

Results

Lender Use of Signals

Table 3.3 provides the results of the logit model to identify which signals lenders use when choosing which borrowers to fund. Social factors are a large component of funding decisions. Belonging to a group makes it three times more likely that your loan will be funded. Belonging to a group that monitors increases the odds of obtaining a loan by an additional factor of 3.6 times. Surprisingly, one of the strongest predictors of being funded is for the borrower to obtain a significant bid from their group leader. For each additional percent that the group leader participates in the loan the likelihood of funding increases seventy five times.

Reputational signals also play a significant role. Those with higher credit grades generally find it easier to obtain a loan as is indicated by the declining odds ratio as credit quality decreases[37]. Also, those with few inquiries and no prior delinquencies find it significantly easier to obtain a loan. Homeowners find it slightly easier to obtain a loan.

Lenders also view financial information as a valuable signal in determining who should receive a loan (odds ratio 0.0274) indicating that lenders believe those with a low DTI are much less likely to default.

Borrower Performance

Table 3.3 also provides results from regressions run using data to predict default activity. Again, two definitions of default are used. The column "Default" uses an indicator variable set to 1 if a loan is placed into formal default by Prosper either by

[37] Note that since dummy variables are used to indicate credit grade, only dummies for A-HR are included in the regression. Borrowers with AA credit correspond to having all dummy variables A-HR equal to 0.

bankruptcy or non-collectability. The results provided in the column labeled "Late" included both loans that are in formal default as well as those that are ninety (90) or more days past due.

Under both definitions, the financial information proxy DTI is a strongly significant predictor of future late or default behavior with odds ratios of 1.9325 and 1.4951 respectively (both are significant with $p < 0.000$). Reputational signals are also fairly reliable with the odds of default nearly monotonically increasing as credit quality decreases. The value of prior delinquencies and public records along with inquiries is somewhat mixed. They are fairly strong indicators of future late activity (DEL odds ratio 1.675, $p < 0.000$; PR odds ratio 1.0881, $p = 0.002$) and prior delinquencies also predict future formal defaults; however, prior public records are not significant in predicting future default activity[38]. Recent credit seeking behavior is a red flag and is strongly significant for both late and formal default prediction.

In addition, it should be noted that borrowers who indicate a greater desperation for fund by accepting a high rate of interest are also more likely to be late or default (odds ratios of 164.59 for late and 389.43 for default only). Interestingly, borrowers who pay group fees to a group leader are much more likely to be late or default. While a positive correlation between a higher group leader fee and default behavior may seem counterintuitive in the sense that one would suspect "good" group leaders would be able to extract economic rents via higher group fees, this is not the case. One should recall from the funding logistic regression results that lenders are skeptical of borrowers who join a group with high fees and are much less likely to fund a loan if group fees are involved. The simplest explanation for this apparent paradox may be that group leaders with high fees simply attract borrowers who are desperate or intend to not repay their

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[38] This may be due to bankruptcy law provisions which do not allow a borrower to declare bankruptcy twice within a set period of time.

loan and therefore do not care how much they pay in group fees, lenders correctly identify the incentives facing these borrowers.

While lenders do use social signals in choosing which loans to fund, social capital is not predictive of future default. Being in a group (INGROUP), having a group leader bid on your loan (GLBID) and the group leader participation percentage (GLPCT) are all statistically insignificant. The only social signal that is predictive of future default is the MONITOR variable. Members of a group that monitors are 0.78 times as likely ($p = 0.008$) to be ninety or more days late or default as comparable individuals in groups that do not undergo monitoring, and 0.85 times as likely ($p = 0.099$) to formally default. This indicates that monitoring appears to work moderately well in preventing future defaults.

Lender Interest Rate Determination

Table 3.4 provides results for both lender and borrower interest rate regression results. Since the results are largely qualitatively similar for both regressions, discussion will place an emphasis on the lender rate results. As the coefficient on the financial information metric DTI suggests, lenders consider an increase in DTI to indicate heighted risk of default and therefore demand an increased premium in interest rate of almost 0.015% for each percentage point increase in DTI ($p < 0.000$).

Results also show that lenders perceive lower risk for individuals displaying some social signals but not others. Social capital (membership in group) does not provide borrowers with a lower rate of interest; however, borrowers who are part of a monitoring group receive a rate that is just over 1% lower on average than those in a non-monitoring group ($p < 0.000$). Remarkably, lenders consider percentage of participation of a group leader, not whether the group leader has bid on the loan or not in assessing risk. Lenders actually demand a statistically significant higher rate of interest if a group leader bids on a loan; however, as the group leader increases their participation in the loan as measured by the percentage retained, the perceived risk is reduced and borrowers are provided with a lower rate as is indicated by the coefficients on the GLBID and GLPCT variables.

Since by definition there is a mechanical relationship between the group leader fee and the interest rate paid by the borrower (i.e., Borrower Interest Rate = Lender Interest Rate + Group Leader Fee), the GLREWARD variable can be interpreted as to what percentage of the group fee is effectively paid by the lender and borrower respectively. Overall, approximately 2/3 of the group leader fee is paid by the lenders in the form of a reduced interest rate, while the remaining 1/3 is paid by the borrower.

The remaining variables of interest from Table 3.4 are all statistically significant in their predicted direction. Larger loans are perceived as carrying more risk, as are borrowers with prior delinquencies, public records and recent inquiries. Homeowners are also viewed as posing less risk.

Interest Rate Determination by Credit Grade - Monitoring

Hypothesis

The monitoring hypothesis based upon Diamond (1991) predicts that lenders are more likely to fund a loan with monitoring and that monitoring becomes more valuable as credit quality decreases. Table 3.5 provides results of the regression predicting the lender rate of interest for each credit grade. Results are somewhat consistent with Diamond in that monitoring becomes more valuable as a borrower's reputation decreases as indicated by the gradual decrease in the monitoring coefficient as credit quality decreases. For instance AA borrowers in a monitoring are provided an incremental rate reduction of 0.56% while those in the HR group receive a 1.34% reduction.

Results from Table 3.5 also point to two additional interesting observations. First, lenders seem to use the willingness of a borrower to pay group fees into account when setting the interest rate. In particular they seem to be suspicious of those with good reputations who are willing to pay group fees. Note that the GLREWARD coefficient is monotonically increasing as the credit grade improves from -0.8696 in the HR group to

0.4907 in the AA group. While there is not a monotonic relationship between interest rate and DTI, the positive coefficients on DTI indicate that financial information is also a significant predictor of the interest rate lenders demand for individuals in all credit grades.

Conclusion

This paper has used data from a peer-to-peer lending website to determine the role signals play in debt-contracting decisions by individual lenders. The data from Prosper provides an environment where a simultaneous examination can be made of how reputational, financial information and social capital are used by individuals in debt-contracting. Results show all three types of signals are used in varying degrees by lenders in both determining the selection of borrowers and the rate charged; however, when it comes to predicting future default behavior, social signals do not appear to provide significant predictive capability in this setting. In contrast, reputation, financial information and monitoring do provide lenders with a mechanism to predict future default.

The data raise several important questions and have some implications for potential future research. First, while the use of financial information and reputation by lenders seems to be correctly used; why do lenders use social signals to choose trading partners when their usefulness in predicting default is largely non-existent? Consistent with Sobel's (2002) arguments on social capital, perhaps the lack of an enforcement role for the group in this environment diminishes the institutional value of such social signals.

The lack of geographic proximity in this environment may also play a role. While the results do seem to directly contradict Ferrary, to his credit, he does state that proximity is a requisite condition for social capital to develop. It is not clear whether why this should be the case. Perhaps this reliance on geographic distance is the result of better information collection by lenders or those in close proximity are worried about their future reputation (indirect reciprocity) since they will have to interact with the market at a future date. Individual lenders who may be comfortable in using social cues in their personal "real world" interactions may not realize the importance of potential future market interaction when they transact with others in the virtual world of the internet. It also raises the question of why geography is so important to obtaining positive social capital outcomes in both Ferrary (2003) and Karlan (2005) among others.

Second, if social signals bias lenders towards providing loans when they should not be granted, then further study into the role of banking relationships, such as the Liberti and Mian (2009) study of lending hierarchies and information, may be valuable in establishing mechanisms to overcome such bias. It may be that lending mechanisms which do not rely on direct human social interaction may perform better than those who rely on personal interactions such as mortgage brokers and bank lending officers.

Third, it is not clear what role intuition and emotion may play in this context. A recent paper by Lipshitz and Shulimovitz (2007) shows that professional loan officers do use "gut-feelings" in their decision making process. To what degree these gut feelings are based upon social capital versus reputation and financial signals, and whether such intuition and emotions lead to better outcomes (i.e., lower borrower defaults) is an interesting question that may be pursued in the future.

Two additional research possibilities exist as extensions of this paper. The first research question would provide a specific test Podolny's status model. Podolony predicts that providing higher status to an individual (i.e., providing them with a better interest rate than their risk profile would suggest) can transform that individual into a better citizen (i.e., lower their default rate). An additional research stream would be to use Olsen's (2008) conjecture that home bias is the result of individuals trusting those who are close to them rather than better information. Since all lenders in this environment observe the same information (with the exception of listings by borrowers in monitoring groups), then there should be no home bias observed in this environment unless lenders trust borrowers who live close to themselves more than those living geographically further away.

There are some limitations to the current study. First, while there are some individual lenders who are professionally involved in the lending industry, a large number of lenders in this environment are not professionals and therefore the direct applicability to other lending environments may not hold; although this concern is somewhat mitigated by the auction mechanism which may correct for individual errors in judgment. Second, while the presence of a single financial metric (DTI) provides a relatively clean setting to determine the weight placed upon financial information by individuals, the DTI ratio is affected by the difference in timeliness between income and debt payment reporting.

Caution should also be noted when projecting the results for credit grades in this setting to corporate debt credit ratings. A key difference between corporate debt ratings and the personal credit scores in this environment is that corporate debt ratings make use of both income and debt payment information gained from financial statements, while personal credit scores do not consider the income of a borrower. While this is beneficial in the current setting since it reduces the correlation between the reputation score (credit grade) and DTI, care must be taken when discussing any implications for corporate credit ratings.

Finally, the models used cannot possibly capture all social signals used by lenders. There are a variety of other factors that may influence lender decisions which are not directly observable or measurable. For instance, some group leaders are much more aggressive in their promotion of group listings. There is also a great deal of "soft" information included in the loan listing and borrower question and answer sections which cannot be easily quantified or categorized. Further methods to classify this data may provide useful insights into how individuals make decisions in debt contracting.

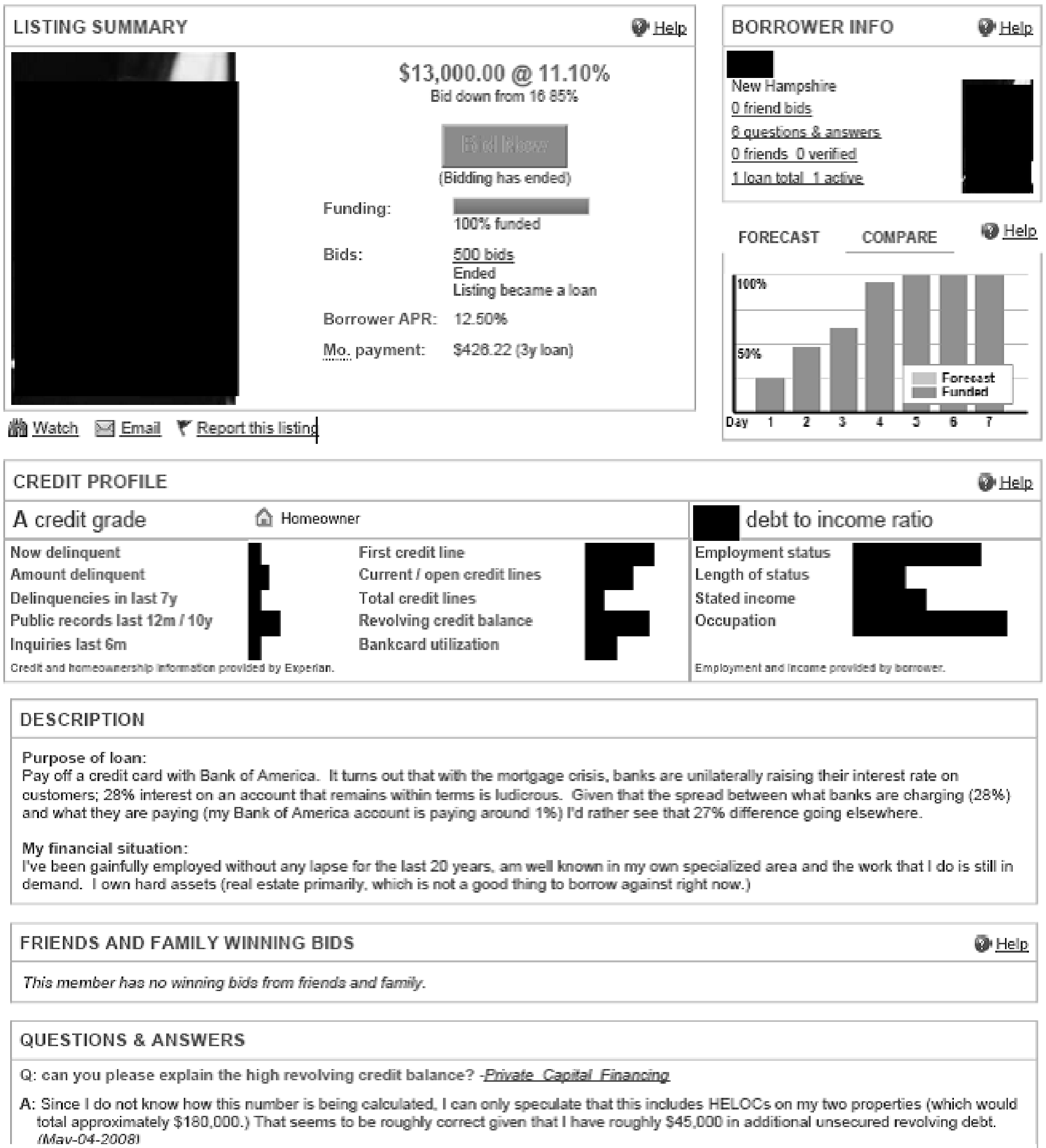

Figure 3.1 Sample Loan Listing – Data Censored For Privacy Purposes

Source: Prosper Marketplace, 2008

A Prosper credit grade is a letter grade that Prosper assigns you based on your credit score, for use solely in the Prosper marketplace. Prosper obtains your Experian Scorex PLUS℠ credit score from your credit report, and assigns one of seven credit grades.

Here is a table that shows the equivalent credit scores for Prosper credit grades:

Grade:	AA	A	B	C	D	E	HR
Score:	760 and up	720-759	680-719	640-679	600-639	560-599	520-559

Your credit grade is posted with your loan listing to help lenders plan their bids appropriately. Your numerical credit score is never displayed or disclosed to anyone.

Figure 3.2 Prosper Credit Grade Information

Source: Prosper Marketplace, 2008

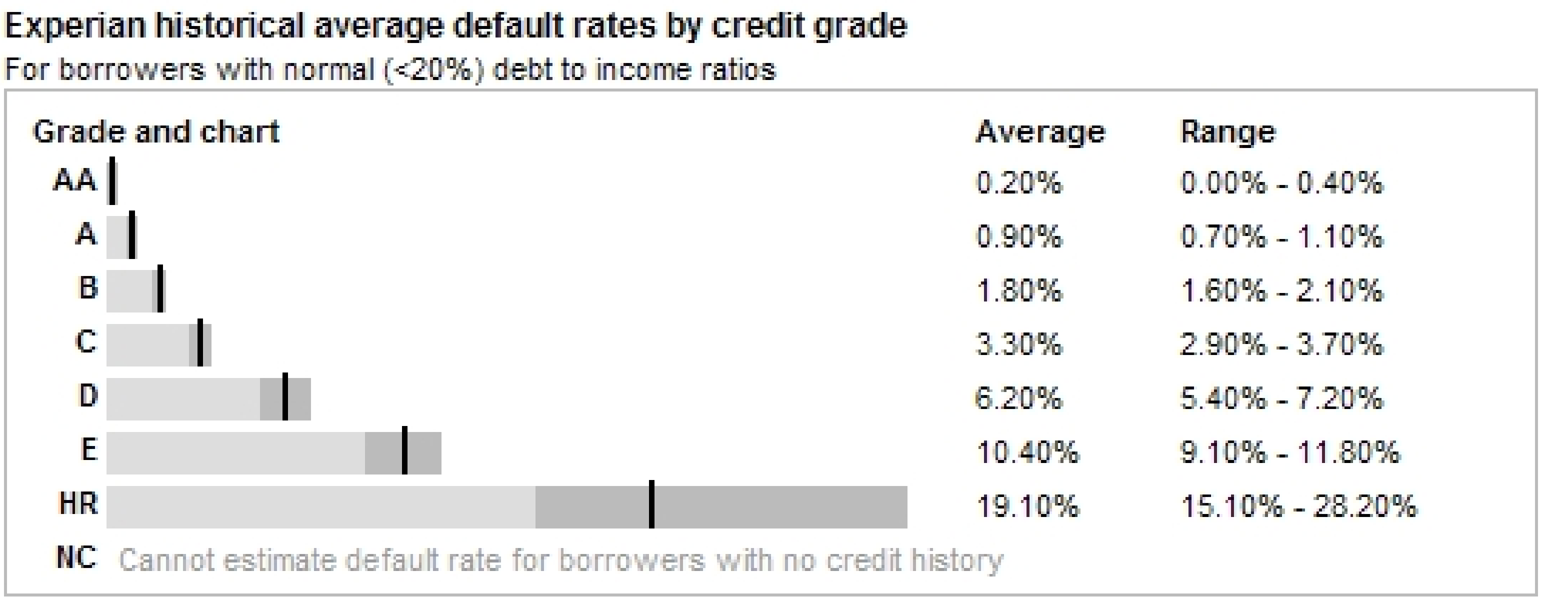

Figure 3.3 Experian Predicted Default Rates

Source: Prosper Marketplace, 2008.

Table 3.1 Sample Descriptive Statistics

Credit Grade	AMOUNT	DTI	DEL	PR	HO	INQ	MAXRATE	INGROUP	MONITOR	LNPCT	GLBID	GLREWARD	LENDERRATE	BORROWERRATE
AA														
Mean	10720.74	0.2561	0.1747	0.1073	0.6729	1.678	0.0989	0.3695	0.0400	0.0134	0.2826	0.002	0.0908	0.0918
St. Dev.	8504.16	0.2709	0.3798	0.4315	0.4692	2.459	0.0406	0.4827	0.1958	0.0641	0.4252	0.0028	0.0195	0.0201
Min.	1000	0	0	0	0	0	0	0	0	0	0	0	0	0
Max	25000	1	1	7	1	34		1	1	0.9954	1	0.01	0.242	0.247
A														
Mean	11722.01	0.3541	0.2372	0.1729	0.4694	2.129	0.1165	0.4422	0.0458	0.0091	0.2608	0.0026	0.1092	0.1106
St. Dev.	8218.72	0.25855	0.4254	0.4984	0.5000	0.291	0.0416	0.4421	0.2092	0.0372	0.4292	0.0028	0.0247	0.0252
Min.	1000	0	0	0	0	0	0	0	0	0	0	0	0.05	0.05
Max	25000	1	1	6	1	58	0.3392	1	1	0.5	1	0.01	0.267	0.267
B														
Mean	12191.96	0.3885	0.3075	0.2660	0.4736	2.908	0.1396	0.4723	0.0358	0.0072	0.2739	0.0061	0.1308	0.1337
St. Dev.	7843.89	0.2813	0.4615	0.6864	0.4993	4.010	0.0483	0.4993	0.186	0.0323	0.446	0.0058	0.0282	0.0292
Min.	1000	0.0075	0	0	0	0	0	0	0	0	0	0	0.05	0.05
Max	25000	1	1	16	1	52	0.3158	1	1	0.92	1	0.02	0.285	0.29
C														
Mean	10941.5	0.385	0.4669	0.4007	0.4718	3.472	0.1589	0.4747	0.0469	0.008	0.2771	0.0068	0.1553	0.1593
St. Dev.	7353.47	0.2779	0.4989	1.033	0.4992	4.218	0.0557	0.4993	0.2114	0.0335	0.4476	0.0062	0.029	0.0302
Min.	1000	0	0	0	0	0	0	0	0	0	0	0	0.03	0.03
Max	25000	1	1	34	1	63	0.35	1	1	0.9182	1	0.02	0.285	0.29

Table 3.1 Continued

D														
Mean	9310	0.394	0.5694	0.468	0.2996	3.619	0.1717	0.4641	0.0535	0.0122	0.3044	0.067	0.1848	0.189
St. Dev.	6846	0.2772	0.4952	1.275	0.4581	4.26	0.617	0.4987	0.225	0.0484	0.4602	0.0063	0.0355	0.036
Min.	1000	0	0	0	0	0	0	0	0	0	0	0	0	0
Max	25000	1	1	97	1	63	0.3575	1	1	1	1	0.03	0.29	0.29
E														
Mean	7308.14	0.3447	0.776	0.7898	0.2833	4.566	0.1847	0.4752	0.0423	0.01	0.227	0.0129	0.2182	0.2267
St. Dev.	5794.14	0.2581	0.417	0.1768	0.4506	4.938	0.071	0.4993	0.2012	0.0457	0.419	0.012	0.0396	0.0402
Min.	1000	0	0	0	0	0	0	0	0	0	0	0	0.0575	0.0575
Max	25000	1	1	95	1	56	0.5	1	1	1	1	0.05	0.35	0.35
HR														
Mean	6109.85	0.2989	0.9036	0.8443	0.1875	4.929	0.15831	0.4653	0.0319	0.0118	0.2095	0.0133	0.22	0.23076
St. Dev.	5117.71	0.2698	0.2951	1.398	0.3903	5.596	0.0736	0.4988	0.1758	0.0576	0.407	0.0125	0.0482	0.048
Min.	1000	0	0	0	0	0	0	0	0	0	0	0	0.0021	0.0021
Max	25000	1	1	32	1	127	0.4975	1	1	1	1	0.05	0.3575	0.3575

Note: AMOUNT is the amount of the requested loan (in thousands), MAXRATE is the maximum rate that a borrower is willing to accept expressed as a decimal. DTI is the Debt-to-Income ratio (as a percentage), DEL is an indicator variable with a value of 1 if a delinquency is reported to the credit bureau, 0 otherwise. PR is the number of public records reported to the credit bureau. HO is an indicator variable that equals 1 if the borrower is a homeowner and 0 otherwise. INQ is the number of inquiries in the past six months. GLREWARD is the percentage of the loan that the group leader charges in fees. GLPCT is the percentage of the loan that the group leader participates in. GLBID is an indicator variable equal to 1 if the group leader places a winning bid and 0 otherwise. MONITOR is an indicator equal to 1 if the listing is sponsored by a group that engages in monitoring and 0 otherwise. INGROUP is an indicator variable that equals 1 if the borrower is a member of a group and 0 otherwise.

Table 3.2 Number of Listings, Loans and Defaults by Credit Grade

Credit Grade	Listings	Loans	Defaults	Defaults + 90 Days Late
AA	3456	1151	76	107
A	3457	1014	145	205
B	5117	1230	239	317
C	8926	1550	397	531
D	12563	1527	399	542
E	16131	1019	382	492
HR	41163	1151	598	735
Total	90813	8642	2236	2929

Note: Table 3.2 provides the number of listing, loans and default ts by Credit Grade. Default is a loan that has been determined by Prosper to be uncollectible. The column "Defaults + 90 Days Late" includes both defaults and loans that have been at least 90 days overdue.

Table 3.3 Association Between Funding Probability, Defaults and Borrower Characteristics

Dependent Variable	Funded	Odds Ratio	Late	Odds Ratio	Default	Odds Ratio
DTI	**-3.595**	**0.0274**	**0.659**	**1.9325**	**0.402**	**1.4951**
INGROUP	**1.129**	**3.0939**	0.087	1.0905	0.107	1.1129
MONITOR	**1.283**	**3.6087**	**-0.248**	**0.7807**	***-0.160***	***0.8518***
GLPCT	**8.923**	**7503.0**	0.098	1.103	0.231	1.2594
GLBID	**-0.313**	**0.7314**	0.109	1.115	0.090	1.0943
GLREWARD	**-30.075**	**1.91e-12**	**9.392**	**11996.1**	**6.549**	**698.44**
AMOUNT	**-0.161**	**0.8510**	**0.070**	**1.0722**	**0.070**	**1.0726**
DEL	**-1.076**	**0.3410**	**0.516**	**1.6750**	**0.522**	**1.6853**
PR	**-0.113**	**0.8929**	**0.084**	**1.0881**	0.036	1.0363
HO	**0.290**	**1.3370**	***0.146***	***1.1575***	0.063	1.0646
INQ	**-0.013**	**0.9872**	**0.077**	**1.0796**	**0.065**	**1.0675**
MAXRATE	**30.495**	**1.75e+13**	**5.104**	**164.59**	**5.965**	**389.43**
A	**-0.194**	**0.8240**	**0.764**	**2.1456**	**0.637**	**1.8912**
B	**-1.018**	**0.3614**	**0.906**	**2.4747**	**0.831**	**2.2949**
C	**-2.407**	**0.0901**	**1.197**	**3.3113**	**1.067**	**2.9076**
D	**-3.709**	**0.0245**	**1.205**	**3.3377**	**0.981**	**2.6681**
E	**-5.541**	**0.0039**	**1.493**	**4.4540**	**1.286**	**3.6182**
HR	**-6.950**	**0.0010**	**2.113**	**8.2763**	**1.855**	**6.3893**
N	90813		8642		8642	
Log Likelihood	-16612		-4536		-4109	
Liklihood Ratio Test χ^2	23864		1804		1444	
Df	18		18		18	
p	0.0000		0.0000		0.0000	

Note: Table 3.3 provides results from the logistic regression from Equations 3.1 and 3.2. Bold indicates significance at the α=0.01 level. Bold with italics indicates significance at the α=0.1 level.

Table 3.4 Association Between Interest Rate and Borrower Characteristics

	Predicted Sign	LENDERRATE	BORROWERRATE
Intercept		**0.0271**	**0.0271**
DTI	+	**0.0146**	**0.0145**
INGROUP	-	-0.0009	-0.0009
MONITOR	-	**-0.0107**	**-0.0107**
GLPCT	-	**-0.0214**	**-0.0213**
GLBID	-	**0.0036**	**0.0036**
GLREWARD	?	**-0.6788**	**0.3217**
AMOUNT	+	**0.0009**	**0.0009**
DEL	+	**0.0069**	**0.0069**
PR	+	**0.0011**	**0.0011**
HO	-	**-0.0024**	**-0.0024**
INQ	+	**0.0033**	**0.0003**
MAXRATE	+	**0.4912**	**0.4917**
A	-	**0.0031**	**0.0031**
B	-	**0.0123**	**0.0123**
C	-	**0.0235**	**0.0234**
D	-	**0.0381**	**0.0381**
E	-	**0.0577**	**0.0576**
HR	-	**0.0628**	**0.0627**
n		8642	8642
Adj-R^2		0.8353	0.8505

Note: Table 3.4 provides results of the regression from Equation 3.3. Bold indicates significance at the α=0.01 level.

Table 3.5 Association of Interest Rate with Borrower Characteristics by Credit Grade

	Intercept	DTI	INGROUP	MONITOR	GLPCT	GLBID	GLREWARD	AMOUNT	DEL	PR	HO	INQ	MAXRATE
Predicted Sign		+	-	-	-	-	?	+	+	+	-	-	+
AA	**0.0624**	**0.0268**	-0.0069	**-0.0056**	**-0.0345**	-0.0012	**0.4907**	**0.0013**	**0.0045**	**0.0050**	**-0.0029**	**0.0007**	**0.1229**
A	**0.0581**	**0.0294**	-0.0017	-0.0034	***-0.0287***	-0.0003	-0.1229	**0.0015**	**0.0074**	0.0006	**-0.0033**	***0.0004***	**0.2240**
B	**0.0559**	**0.0303**	-0.0014	***-0.0056***	-0.0079	0.0016	**-0.4628**	**0.0014**	**0.0077**	***0.0017***	***-0.0028***	0.0002	**0.3398**
C	**0.0651**	**0.0205**	-0.0002	**-0.0138**	-0.0038	-0.0008	**-0.4930**	**0.0013**	**0.0080**	**0.0020**	**-0.0031**	0.0002	**0.3919**
D	**0.0608**	**0.0168**	***-0.0046***	**-0.0103**	**-0.0281**	**0.0065**	**-0.6030**	**0.0011**	**0.0088**	**0.0019**	***-0.0026***	***0.0004***	**0.5047**
E	**0.0358**	**0.0202**	-0.0031	**-0.0097**	0.0159	0.0016	**-0.6891**	**0.0015**	**0.0074**	0.0008	0.0017	0.0002	**0.6680**
HR	**0.0259**	**0.0126**	-0.0027	**-0.0134**	-0.0060	**0.0098**	**-0.8696**	***0.0012***	**0.0071**	0.0012	-0.0034	**0.0005**	**0.7397**

Note: The regression model is run for each credit grade AA through HR for Equation 3.4. LENDERRATE is the interest rate that a lender receives on a particular loan. AMOUNT is the amount of the requested loan (in thousands), DTI is the Debt-to-Income ratio (as a percentage), DEL is an indicator variable with a value of 1 if a delinquency is reported to the credit bureau, 0 otherwise, PR is the number of public records reported to the credit bureau. HO is an indicator variable that equals 1 if the borrower is a homeowner and 0 otherwise. INQ is the number of inquiries in the past six months. INGROUP is a dummy variable that equals 1 if the borrower is a member of a group and 0 otherwise. Bold indicates statistical significance at the $\alpha = 0.01$ level. Bold with italics indicates significance at the $\alpha=0.1$ level.

Table 3.6 Pearson Correlation Statistics

	AMOUNT	MAXRATE	DTI	DEL	PR	INQ	HO	GLREWARD	GLPCT	GLBID	MONITOR	INGROUP
AMOUNT	1	-0.0399	0.1859	-0.2398	-0.0924	0.0381	0.2357	-0.1118	-0.0794	0.0632	0.0076	0.0010
MAXRATE	0.0001	1	0.0246	0.1471	0.0621	0.1040	-0.0715	0.1965	0.0530	0.1578	0.0824	0.1913
DTI	0.0000	0.0000	1	-0.1289	-0.1031	0.0361	0.0318	-0.0496	-0.0171	0.0111	-0.0109	-0.0734
DEL	0.0000	0.0000	0.0000	1	0.1856	0.0688	-0.1127	0.1240	0.0000	-0.0416	-0.0221	0.0340
PR	0.0000	0.0000	0.0000	0.0000	1	0.0377	-0.0244	0.0617	0.0005	-0.0004	-0.0132	0.0307
INQ	0.0004	0.0000	0.0000	0.0000	0.0000	1	0.0720	0.0578	0.0032	0.0192	0.0086	0.0334
HO	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1	-0.0528	-0.0043	0.0257	0.0006	-0.0047
GLREWARD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1	0.1017	0.2547	0.0409	0.5548
GLPCT	0.0000	0.0000	0.0000	0.9889	0.8800	0.3301	0.1754	0.0000	1	0.4082	0.0838	0.1550
GLBID	0.0000	0.0000	0.0004	0.0000	0.9121	0.0000	0.0000	0.0000	0.0000	1	0.1379	0.3795
MONITOR	0.4686	0.0000	0.0006	0.0006	0.0001	0.0094	0.8405	0.0000	0.0000	0.0000	1	0.1464
INGROUP	0.9271	0.0000	0.0000	0.0000	0.0000	0.0000	0.1364	0.0000	0.0000	0.0000	0.0000	1

Note: Table 3.6 provides the correlations and statistical significance of relationships between the independent variables. The top diagonal of the matrix is the correlation, while the bottom diagonal provides the p-value. AMOUNT is the amount of the requested loan (in thousands), MAXRATE is the maximum rate that a borrower is willing to accept expressed as a decimal. DTI is the Debt-to-Income ratio (as a percentage), DEL is an indicator variable with a value of 1 if a delinquency is reported to the credit bureau, 0 otherwise. PR is the number of public records reported to the credit bureau. HO is an indicator variable that equals 1 if the borrower is a homeowner and 0 otherwise. INQ is the number of inquiries in the past six months. GLREWARD is the percentage of the loan that the group leader charges in fees. GLPCT is the percentage of the loan that the group leader participates in. GLBID is an indicator variable equal to 1 if the group leader places a winning bid and 0 otherwise. MONITOR is an indicator equal to 1 if the listing is sponsored by a group that engages in monitoring and 0 otherwise. INGROUP is an indicator variable that equals 1 if the borrower is a member of a group and 0 otherwise.

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