MOBILIZING INVESTMENT THROUGH SOCIAL NETWORKS: EVIDENCE FROM A LAB EXPERIMENT IN THE FIELD

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(PRELIMINARY AND INCOMPLETE)

Abstract. Social networks are central to the operation of village economies in developing countries. In the absence of strong formal institutions, social networks often play a significant role in contract enforcement and in determining the scope of co-investment in productive projects. Social norms and rules of thumb may dictate how friends vs. strangers decide to share an economic surplus or how popular vs. socially isolated individuals sustain cooperation with others. We shed light on the effects of network characteristics on investment decisions through framed a field experiment. Our laboratory protocol builds on a basic two party trust game with a sender and receiver. In some treatments, we introduce third party monitors or punishers that may or may not be identifiable by the other two participants. We find that the social network interacts with the play of the game in economically meaningful ways. First, social proximity goes a long way toward solving the investment problem. Both senders and receivers in socially close pairs make larger transfers to each other. However, we also find evidence that adding third party punishers can crowd out some of the gains from altruism. Second, while on average, third party punishment actually decreases the size of investments made by the sender, very central punishers are efficiency enhancing. Moving from a socially peripheral judge to a socially central judge increases sender transfers by 25%. Third, demographic characteristics such as caste and elite status affect player strategies. Elites benefit from higher partner transfers as do high caste individuals in some specifications. However, these socially privileged individuals do not use their status to increase total surplus when they play the role of the sender in our games. Our results suggest that local network characteristics can help to overcome barriers to joint investment. If our findings are representative, then they also suggest that high caste individuals and named leaders may not be the best individuals to serve in the role of judges or mediators.

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1. Introduction

Sociologists and economists alike have repeatedly demonstrated the importance of social relations in a variety of human interactions. Given that social interactions do matter, how can organizations, namely firms or governments, harness existing social hierarchies to obtain efficient outcomes? In this paper, we identify social relationships within a society that permit maximal levels of cooperation. Specifically, by studying the behavior of pairs of participants in a simple sender-receiver investment game, which may or may not have a third-party judge, we shed light on how social networks reflect the propensity for individuals to cooperate with peers and affect the ability of an enforcer to sustain efficient outcomes.

The question of institutional and contract design is particularly important in developing countries. Without strong formal contracting institutions, social structures (networks) are frequently used to mediate economic and political interactions. This is especially true in rural settings where social hierarchies are particularly salient. Common examples of network-based economic relationships include social collateral in microfinance and ROSCAs, informal risk sharing arrangements and increased prevalence of family firms. While these particular arrangements have been studied at length, (see Feigenberg et al. (2010), Kinnan and Townsend (2010), and Bertrand and Schoar (2006) for recent analyses of each) less is understood about the optimal contract structure given network characteristics as inputs. For example, does decreasing social distance between parties improve efficiency? For which types of relationships can monitoring yield better outcomes? Which members of society serve as monitors with the lowest costs and highest realized outputs?

We play modified investment games as in Berg et al. (1995) and Charness et al. (2008) with experimental subjects from 35 South Indian villages. Instead of anonymizing participants, we reveal the identities of the relevant players in each game before transfer and punishment decisions are made. In addition to the two player sender-receiver investment game, we also introduce identifiable third party judges who can levy costly punishments on the receivers. In order to separate the mechanisms through which judges affect experimental outcomes, we also include experimental treatments with anonymous judges and with identifiable monitors who cannot punish. We combine the experimental results with household survey responses and village network data to determine how investment behavior is mediated by both demographic and network characteristics.

We distinguish between three categories of villager characteristics: symmetric network (social distance between players); asymmetric network (relative centrality measures such as degree and eigenvector centrality); and demographic (leadership status, caste, and wealth). Symmetric network characteristics convey the closeness of the bond between individuals. This may manifest itself in greater cooperation between players who are playing an investment game. However, these bonds could also backfire with the judge exhibiting cronyism towards close friends. Asymmetric network characteristics capture how important an individual is relative to his or her partner in a network sense. This network importance may proxy for social capital, allowing us to study the impact of a power hierarchy on economic outcomes. Moreover, theory shows that the centrality of a node reflects its importance in information transmission; nodes with higher centrality tend to both acquire more and propagate more information. Finally, we are also able to study three categories of demographic characteristics: caste and whether an individual is a village leader.

We find that receivers internalize the presence of the judge and transfer more to the sender. Senders do not make use of the receiver behavior by sending more; instead they transfer slightly less to the receiver in the presence of a judge. However, the senders' play leave them weakly better off in payoff terms in treatments with third-party presence as compared to environments with only the sender and receiver.

Network characteristics affect contracting outcomes in ways that we hypothesize. Social proximity is a very strong force for efficiency. Receivers and senders in socially close pairs both make larger transfers, and maximal transfers are also more likely. However, there is evidence that in some cases, adding third parties may crowd out social closeness. Socially distant people, however, may be helped by the addition of third party punishment.

Asymmetric network characteristics play the biggest role in games with third parties. We find that central individuals make the best judges by encouraging senders to make larger transfers, thus increasing the overall size of the surplus. We also find suggestive evidence that central individuals work to maintain their good reputations. Central receivers return especially large amounts of money to senders when somebody else is watching.

Our demographic characteristics of caste and elite status capture a different dimension of power within a network. We define elites as *gram panchayat* members, self-help group officials, *anganwadi* teachers, doctors, school headmasters, or owners of the main village shop. Both high caste individuals and elites are afforded special status in their communities and appear to use this status to increase personal payoffs in the experiments. However, these individuals do not tend to use their status to increase the overall economic surplus. Furthermore, high caste judges may team up with high caste senders or receivers to intimidate the third party. Such low caste senders and receivers make higher transfers. These results may be indicative of caste collusion.

The results of our games take a step towards understanding how a community might enlist its own social fabric to overcome a lack of formal institutions. To our knowledge, no previous study has used high quality network data to analyze the play of investment games with third parties. Moreover, rural India is the type of setting where network effects should matter most for economic outcomes.

Relevant Literature. Our baseline game builds from the literature started by the Berg et al. (1995) investment game. While game theory would predict zero transfers for anonymous partners, the authors find that senders make positive transfers and some receivers do fully reciprocate them. However, senders who transfer tend to lose money on average. Charness et al. (2008) add a role for third party punishment and find that senders transfer more and receivers reciprocate to a greater degree than in the case without the threat of punishment. Initial transfers are 60% higher when a judge is present, significantly increasing total payoffs.

While most experimental games are played with anonymous interactions, a smaller subset of the social preferences literature examines how the outcomes of experimental games change as the social ties between agents are strengthened within the experiment. Several papers including Hoffman et al. (1996), Bohnet and Frey (1999), Burnham (2003), and Charness and Gneezy (2008) randomly give dictators fairness priming, information prompts, pictures of the receiver, or allow the dictator to see the receiver and find that allocations made by the dictator to the receiver increase. Bohnet and Frey (1999) also add a treatment where both players visually identify each other and find that dictators are far more likely to split the surplus according to the "fair" 50-50 allocation rule. While these papers give importance evidence that social distance affects experimental outcomes, they fall short of being able to explain how realistic social dynamics interact with each participant's strategic behavior.

Recently, researchers have begun to combine experimental games with existing network structures. Goeree et al. (2010) use surveys to elicit complete peer networks among middle school students at a girls school. They then run dictator games where the students are able to identify each other and find that dictator offers can largely be explained by inverse social distance. Participants offer larger shares to closer friends. In a clever experimental design using networks of Harvard students and online dictator games,Leider et al. (2009) also find social distance effects and are able to disentangle different motivations for observed altruistic behavior. They separate baseline altruism toward strangers, directed altruism toward friends, and transfers to friends motivated by future interactions. Directed altruism increases transfers by 52% relative to strangers, while motivations of future interactions increase transfers to friends by an extra 24%. Understanding the strength of reciprocity versus directed altruism for extrapolating laboratory results to more realistic contexts.

The closest paper to our analysis is Glaeser et al. (2000), where the authors play the investment game with Harvard students and also elicit network and individual participant characteristics. Three of their findings are particularly relevant. First, senders in the investment game transfer larger sums to the receiver as social distance decreases. Second, senders send lower amounts to receivers of different races, and lastly, senders with more social status (parental education, proxies for wealth, volunteer organization membership, network degree) are returned larger amounts by the receiver and earn higher payoffs.

Moving beyond social distance, the literature on network theory has developed a rich language to characterize the importance of an individual in the social structure. Measures of centrality such as degree, eigenvector centrality, and betweenness centrality capture the importance of a node in the network. Degree is the number of neighbors it has, eigenvector centrality is a recursively defined measure which defines the centrality of a node as proportional to the sum of its neighbors' centralities, and betweenness centrality computes the share of shortest paths between all pairs of nodes that pass through the node whose centrality we are measuring. The centrality measures typically reflects a node's importance in transmission; more important nodes may be able to better punish others through reputational or social capital channels. Jackson, 2008 provides an excellent discussion of the concepts. Empirical network papers employing eigenvector centrality and betweenness centrality include Hochberg et al., 2007, Banerjee et al. (2011), and Schechter et al., 2011.

Finally, there has been some work to identify how social structures in developing countries affect experimental contracting outcomes. Fehr et al. (2008) and Hoff et al. (2009) investigate how castes in India mediate outcomes of binary choice dictator games as well as a simplified version of the Charness et al. (2008) investment games. They find a lower willingness for low caste individuals to punish norm violations than high caste individuals even within low caste groups, potentially implying collective action problems among disadvantaged populations. The authors also find that high caste individuals exhibit spiteful preferences and are more likely to punish cooperation in investment games in order to increase advantageous inequality. Many researchers have studied the causes and implications of elite capture by local leaders. Rajasekhar et al. (2011) examine the extent of the threat of elite capture by local politicians in the Indian state where we run our experiments. Fritzen (2007) finds high degrees of elite capture in community driven development programs in Indonesia. These findings highlight the great potential for social structures, caste and leadership to interact with economic development.

While previous work has begun to investigate the role of networks in joint investment decisions, we contribute to the literature in several ways. Unlike the networks of students often used in experimental work, we have the benefit of analyzing village networks which include almost half of all prime age residents. This allows us to construct network statistics, such as eigenvector centrality, that are predicted by network theory to play a role in social interactions. Furthermore, in contrast to other studies, our three person games include a role for authority to interact with economic decisions and capture more nuanced interactions between players. Finally, since rural village networks mediate most economic transactions in developing countries, it is crucial to understand barriers to joint investment in exactly these types of settings.

Structure of the Paper. The remainder of the paper is organized as follows. In section 2, we describe the experimental subjects, network and survey data sources and the experimental design. Section 3 discusses the framework. In section 4 we present the results. Section 5 concludes.

2. Data and Experimental Design

2.1. **Setting.** Our experiment was conducted in 45 villages[1] in villages in Karnataka, India which range from a 1.5 to 3 hour's drive from Bangalore. We chose these villages as we had access to village census demographics as well as unique social network data set, previously collected in part by the authors. The data is described in detail in Banerjee et al. (2011) and Jackson et al. (2010).

The graph represents social connections between individuals in a village with twelve dimensions of possible links, including relatives, friends, creditors, debtors, advisors, and religious company. We work with an undirected and unweighted network, taking the union across these dimensions, following Banerjee et al. (2011) and Chandrasekhar et al. (2011). As such, we have extremely detailed data on social linkages, not only between our experimental participants but also about the embedding of the individuals in the social fabric at large.

Moreover, the survey data includes information about caste and elite status. In the cultural context of southern Karnataka, a local leader or elite is someone who is a *gram panchayat* member, self-help group official, *anganwadi* teacher, doctor, school headmaster, or the owner of the main village shop.

2.2. **Experiment.** We conducted our experiment between April and August 2011. Each participant played 7 total rounds of four experimental treatments. Players were randomly assigned one of three roles in each round: sender (S) with endowment Rs. 60, receiver (R) with endowment Rs. 60, and judge (J) with endowment Rs. 100. A total of 14 surveyors moderated the experiments, each overseeing only one group of participants at a time.

The baseline game (T1) is a two player investment game with no third party monitor or judge. The surveyors select two participants at random and assign them to roles of S and R. S can then make a transfer to R, which then triples in size. Finally, R decides how much of his or her wealth from the game to return to S. This transfer does not grow when sent by R. Ending balances are then recorded by the surveyors.

In the other three treatments, we add third parties who can punish, monitor, or do both. In T2, we add an anonymous, geographically absent judge, (J). Three players are

[1] Ongoing, currently at 28.

randomly selected and given roles of S, R, and J. S and R then make the same transfer decisions as in T1. Upon the completion of the transfers, J is informed about the transfers and has the option to spend his or her own resources to levy a monetary punishment on R. For every Rs. 1 spent by J, R loses Rs. 4. T3 is a version of T1 with a third party monitor. The only difference is that an extra person is randomly chosen as J. S, R, and J are all mutually able to identify and watch each other during all of the decisions. J doesn't take any actions, but simply watches the transfers take place between S and R. Finally, T4 is combines the punishing and monitoring of T2 and T3. Again, a known person J plays the role of the judge. He or she both watches the proceedings of the experiment and has the option to spend resources to punish R. The punishment takes the same 1 to 4 ratio.

Each participant played 7 total randomly ordered rounds of the experimental games, including 2 rounds each of T3 and T4. Half of participants played T1 once and T2 twice, while the other half played T1 twice and T2 once. Out of the seven total rounds played, participants were each given their ending values for one randomly chosen round out. Participants were also given a fixed participation fee of Rs. 20 in addition from their earnings from the game.

2.3. **Descriptive Statistics.** In each village, 24 individuals between the ages of 18 and 45 were randomly invited to participate in our experiment. All together 1080 individuals participated in the experiment.[2] The average age is 30 with a standard deviation of 8.2 years. 60% of the participants are female and the average education level is 8.26 with a standard deviation of 4.3.[3] About 60% of the participants are GM caste or OBC. Finally, 22% of households have a leader.

Turning to network characteristics, the average social proximity between pairs (the inverse of the social distance) in our experiment is 0.32.[4] The maximum social distance, when it is finite, is 7 and the minimum is 1. 97% of pairs are reachable (there exists a path through the network connecting the two). The average degree is 10.4 with a standard deviation of 6.8, indicating that there is substantial heterogeneity in an individual's number of connections.

3. Framework

3.1. **Network Characteristics.** Rural villages in developing economies often must look inward when designing and enforcing business relationships. Since trust and informal authority alone must sustain these interactions, the network positions of the contracting parties could greatly affect the scope of joint investment and other productive activities.

[2]Ongoing, currently 648.

[3]This means that on average, an individual had attended 8th standard.

[4]Appendix A contains a glossary formally describing the network statistics used.

An important question is how the network relationships between agents impacts economic outcomes. Moreover, it may be the case that agents choose members of society to serve as enforcers of contracting norms. As these parties themselves are embedded in the social network, it raises the question of which network characteristics effective judges possess. Given the innumerable ways in which networks may affect economic interactions, we conceptualize the network as providing two distinct mechanisms that might impact contracting results. A natural division is suggested by graph theory: symmetric and asymmetric characteristics.

Symmetric characteristics are defined over pairs of individuals in a network and capture the strength of the tie between them.[5] This could express itself through trust or information flow. Friendship is the most straightforward example. Close friends probably share greater trust and also pass information from person to person with a higher frequency. We parametrize friendship by inverse social distance (or social proximity). Let γ_{ij} denote the minimum path length between individuals i and j. Since friendship is decreasing in social distance, we define social proximity as γ_{ij}^{-1}. Social proximity is commonly used in the experimental networks literature (e.g., Goeree et al., 2010; Leider et al., 2009).

Another symmetric metric proposed by graph theory is the spectral partition, which aims to maximize information flow within each subset and maximize information flow across subsets.[6] If two individuals are on the same side of the partition, then information from one is more likely to pass to the other. The sets created by the spectral partition capture the fact that information traveling between individuals may take many different routes that might be of a slightly longer length.

We should expect that unregulated interactions between pairs of individuals should have more cooperative outcomes for those with high social proximity or those on the same side of the spectral partition. The addition of a third party may cause efficiency to either increase or decrease. While judges who are socially close to senders may mete out stricter punishments on receivers, they may also want to preserve their reputations as just judges and avoid behavior that may appear to be collusive. Determining which force prevails is an empirical question.

In contrast to symmetric characteristics, we define asymmetric characteristics as directed relationships between pairs of individuals. Central individuals in a network are especially good at aggregating and disseminating information and can be considered important relative to others in the network. Graph theory suggests three metrics to capture this phenomenon: degree, betweenness and eigenvector centrality. Degree is a simple measure of the number of links connecting any individual node. This could be the number of friends an individual has. Betweenness centrality measures how much information travels

[5]We call these network characteristics symmetric as $f_{ij} = f_{ji}$, as opposed to asymmetric network characteristics which are directed. For example, $f_{ij} = \frac{x_i}{x_j} = \frac{1}{f_{ji}}$.

[6]Formally, we are interested in a ratio cut of the graph, discussed in Appendix A.

through a given node and is calculated as the number or fraction of paths between all pairs of nodes in the network that pass through that individual. Finally, eigenvector centrality is a recursive notion of importance, where centrality is measured as a weighted sum of the importances of all network neighbors.

There are several reasons why centrality should matter in our experiments. First, when facing central individuals, peripheral individuals may fear reputational punishments and may be on their best behavior. Central individuals may either exercise their power and try to capture as much of the surplus as possible, or may try very hard to maintain their importance by acting in a fair manner. We expect centrality to be particularly important when considering the role of the monitor. Receivers might be especially keen to return large transfers to the sender, since punishment by a central judge has the potential to be the strongest.

Finally, we also consider how symmetric and asymmetric demographic characteristics interact with contracting between individuals. Caste has both symmetric and asymmetric connotations. Two individuals belonging to the same caste group may operate much like social proximity or the spectral partition metric. However, caste also has a power dimension. High caste individuals may be able to exercise power over low caste individuals. Moreover, holding a named leadership role in a village could also affect the power dynamic between parties. The experimental predictions are similar to those for centrality. However, named leaders or elites may be better at resource capture than network leaders.

3.2. **Norms.** Communal norms may dictate the behavior of how individuals make decisions in our experiments. There may be natural focal points for how players choose to divide resources among themselves. We focus on the behavior of the receiver conditional on sender behavior since his or her decisions face scrutiny by the judge.

In his behavioral economics survey paper, Rabin, 1998 discusses sharing norms prevalent in human behavior. First he notes that people do not seem to allocate resources to be globally welfare maximizing and tend to think very locally about the specific pie being divided. He also notes that the 50-50 split the pie norm is commonly observed in surveys and experiments. Another common resource division is the minimax norm, which equalizes welfare improvements, but not total welfare. He also notes that reference levels may also interact with perceptions of fairness.

Suppose that the sender transfers τ_S rupees to the receiver. The transfer grows by a factor of α before reaching the receiver. Finally the receiver transfers τ_R back to the sender. We posit five possible norms that receivers could be playing:

(1) Keep the Entire Transfer: $\tau_R = 0$
(2) Keep the Surplus: $\tau_R = \tau_S$
(3) Split the Transfer: $\tau_R = \frac{\alpha\tau_S}{2}$

(4) Share the Pie: $\tau_R = \frac{(\alpha+1)}{2}\tau_S$[7]
(5) Return the Full Surplus: $\tau_R = \alpha\tau_S$.

We chose the multiplier $\alpha = 3$ so that we could distinguish between all five cases. Thus, the norms as a fraction of the amount sent are (1) $\frac{\tau_R}{\tau_S} = 0$, (2) $\frac{\tau_R}{\tau_S} = 1$, (3) $\frac{\tau_R}{\tau_S} = \frac{\alpha}{2} = 1.5$, (4) $\frac{\tau_R}{\tau_S} = \frac{\alpha+1}{2} = 2$, (5) $\frac{\tau_R}{\tau_S} = \alpha = 3$. If each player always plays the same norm as a function of his opponent (and not the amount transferred), then we can separate between these 5 norms and test which norm is being played in equilibrium.[8]

Beyond simply identifying the norms played by receivers in the game, we can also examine how the chosen norms change as functions of either the presence of a punisher or monitor or the network relationships between players.

4. Results

4.1. **Pooled Equilibrium Play.** Before analyzing the differences in equilibrium play between the four treatment groups, it is helpful to first understand the overall pooled results observed in the experimental sessions. The data as of August 2011 include 1,894 total games. We are still running the experiment in more villages and plan to update the results in the fall. Figure 1 shows the distribution of initial transfers from S to R observed in all 1,894 games. Almost all transfers are made in increments of Rs. 5 or Rs. 10. The modal transfer is 20, with the mean occurring at Rs. 28.6. A zero transfer is only observed in 12 of the games. The efficient transfer of Rs. 60 is observed 130 times (~7% of games).

Moving to the receiver's response, figure 2 shows the pooled distribution of transfers from R to S as a fraction of the initial transfer from S to R. Note that most of the receivers transfer weakly less than the amount sent by the sender, leaving receivers with quantities at least as high as their initial endowments[9]. Only 6% of games ended with the receiver sending more back to the sender than was initially transferred. Also note that there are two transfer levels with notably high frequencies occurring at $\frac{\tau_R}{\alpha\tau_S} = \frac{1}{3}$ and $\frac{\tau_R}{\alpha\tau_S} = \frac{2}{3}$. These values correspond to norms 2 and 4, "keep the surplus" and "split the pie." The receivers seem to be likely to adhere to some notion of fairness as described in the norms of section 3.2. The mean level of $\frac{\tau_R}{\alpha\tau_S}$ is approximately 0.5. Note that while both S and R tend to gain relative to their initial endowments, approximately 25% of senders are worse off in monetary terms than if they had played the static Nash Equilibrium, $\tau_S = 0$.

Figure 3 provides a better illustration of R's average response to S. The graph plots a local linear approximation of the fraction of the transfer from S to R returned to S as a function the initial transfer from S to R. Surprisingly, very small initial transfers are

[7] Solving $60 - \tau_S + \tau_R = 60 + \alpha\tau_S - \tau_R$ yields the result.
[8] Notice that if $\alpha = 2$, then we would not be able to separate between (2) and (3).
[9] At least before the judges in treatments 2 and 4 decide whether or not to punish.

rewarded with large return transfers (statistically indistinguishable from sending everything back). However, as $\tau_S > 20$ the overall relationship between initial transfer and amount returned is increasing, indicating increasing returns from cooperation. It is possible that the super-game is leading to the observed behavior when $\tau_S < 20$. It is possible that in these cases, receivers owe money to the senders outside of the game and therefore reciprocate with large relative transfers. However, under this logic, all parties could be made better off by the sender making larger initial transfers. Potential barriers to this are discussed below.

The equilibrium punishments incurred by the judges in treatment 4 also can also teach us about the acceptable transfer norms in the participating villages. Figure 4 shows incurred punishments as a fraction of transfers returned from R to S. On the interval from 0 to 1, punishment is decreasing as a function of the fraction returned to the sender, as would be expected from a norm-enforcer. Returning nothing is associated with an average punishment cost of Rs 4, and an average punishment amount of Rs 16. This expected punishment declines dramatically as $\frac{\tau_R}{\alpha\tau_S}$ approaches 1. Above 1, punishment appears to be increasing, but is very noisy. In this range, punishment enforces an unfair outcome for receivers. In this range final payoffs for receivers are lower than the initial endowments of Rs 60.

4.2. **Treatment Level Effects.** Given the pooled results for all three types of players, we can now look at how these behaviors change across treatments. Since the game is most easily solved using backward induction, we begin with the behavior of the receivers in response to the different monitoring and punishment regimes. We subsequently study sender behavior, assuming that senders internalize receiver behavior distributions when taking their decisions.

Receiver Behavior. Table 2 shows how the receiver behavior changes with the addition of punishers or monitors. Columns 1-3 show the differences in transfers by game for the whole sample. There are three different measures of the receiver's behavior, all conditional on cubic polynomials of the initial transfer from S to R: the transfer level, the transfer as a fraction of the initial transfer, and an indicator for the receiver returning sums at least as generous as norms 4 or 5. In all subsequent regressions, the standard two player trust game (T1) will be the omitted category. While none of the regression coefficients is significant in columns 1 is significant, the coefficients on the receivers transfers are positive for all games with monitors or punishers.[10] Furthermore, receivers are significantly more likely to play a generous norm in T4, when a judge who can both monitor and punish is present.

[10]Removing the fixed effects yields significantly positive coefficients for games 2 and 4. We may have more power to detect there effects once we add more villages to the analysis sample.

Since figure 3 shows ultra generous behavior for very small levels of τ_S, we also consider receiver behavior by game separately for $\tau_S > 20$ and $\tau_S < 20$. As judges may enforce fairness, receivers may feel more comfortable returning less in response to a stingy initial transfer. In general we would expect receiver behavior to improve, but this may not be the case at the extreme. Columns 4-6 show the three regression specifications conditioning on $\tau_S > 20$. In all specifications, receivers in T2 return more money to the senders. The point estimates for T4 are approximately half of the magnitude of those in T2, but are statistically insignificant.[11]

Note that all of the treatment coefficients are negative in columns 7-9, where the initial transfer is restricted to low levels. In fact, receivers in treatment 4 actually send smaller transfers back to the senders than when there is no third party involvement. The results are compatible with the receiver commiserating with the third party judge and feeling more comfortable reacting to an unfair allocation by the sender. Under this interpretation, it makes sense that T4 has stronger negative effects than T2, since in T2, the identity of the punisher is obscured. It's also possible that third party enforcers do not understand the financial obligations between S and R outside of the experimental games. Perhaps third parties lessen the extra-game enforcement mechanisms.

The existence of a punisher seems to push receivers towards better behavior when the senders act in a reasonably fair manner. The threat of monetary punishment, not the monitor drives the results. Also, the results in columns 7-9 suggest that the third party may enforce conclusions of sender unfairness drawn by the receiver.

In the above exercises, as we only observe equilibrium receiver strategies, some caution is required in interpreting the receiver regression results. While we did randomize partners and treatment assignment, we did not randomize sender transfers. Though endogenous with respect to the sender's transfer, observed receiver play does shed light on the behavior of the different parties on the equilibrium path. We do control for functions of the initial transfer in all receiver specifications.

Sender Behavior and Total Payoffs. Since the receivers seem to play better under the threat of monetary punishment, we might expect senders to internalize this fact and in turn send larger initial transfers. However, this does not seem to be the case in the data. Table 5 presents the payoffs and initial sender transfers by treatment. The first column shows that the total payoff decreases by Rs. 8.99 when individuals play the game with an anonymous judge from another village, relative to the baseline trust game. We cannot reject that the game in which J can only observe, but not punish, has different total payoffs than the baseline. However, the game in which J is another member of the village and therefore can both monitor and punish decreases total payoffs by Rs. 12.52. The average punishment in T2 is 7.86, so most of the Rs 8.99 decrease comes from the

[11]Again, the T4 coefficients are significant when the specification is run without fixed effects.

punishments incurred by the punishers. In game 4, the average punishment level is 8.69 and can't explain the full decrease in payoffs. Columns 2 and 3 show the payoffs separated by S and R. The entire difference in total payoffs (column 1) across treatments is borne by R (column 3). The fourth column looks at how the transfers of S to R respond to treatments. None of the treatments have statistically distinguishable effects relative to the baseline except for the fourth treatment, where J can punish. In this case, we see that S actually transfers Rs. 2.56 less than the baseline to R. Finally, column 5 shows the same regression but using an indicator for the sender transferring more than Rs. 20 as the dependent variable. Again, the sender is about 7.78% less likely to send a generous initial transfer in T4 vs the two person investment game.

The sender's behavior in response to the third party monitor is quite puzzling. On average, senders seem to reduce transfers despite the receiver behaving better on average when a third party individual participates in some way. Also striking is the fact that senders hold their payoffs constant (column 2 shows insignificant positive effects) even though overall payoffs suffer. The receivers are squeezed by the sender and occasionally punished by the judge leaving them significantly worse off in T2 and T4.

There are several possible mechanisms that could be driving these patterns. First, it may be the case that senders target a specific final payoff, since their payoffs seem to be unaffected by the presence of the punisher. Alternatively, senders may have significant risk aversion or ambiguity aversion. Making larger transfers assumes greater receiver risk, potentially explaining low average sender transfers. Figure 5 shows distributions of payoffs faced by senders when transferring Rs. 20, Rs. 40, and Rs. 60. Finally, it may be the case that senders do not fully understand the game. However, we do not think that a failure of comprehension explains the results. In specification checks available by request, we confirm that players do not learn over the rounds of the game and that education levels are uncorrelated with overall equilibrium play. Furthermore, anecdotal evidence supports player comprehension. Ultimately, we think that the ambiguity or risk aversion explanations best fit the data and qualitative evidence.

4.3. **Network Effects and Receiver Behavior.** Having discussed the level treatment effects, we now address the central theme of our paper: how social networks affect the ability for participants in an investment game to cooperate, possibly in the presence of a third-party judge. This will allow us to we shed light on the capacity of individuals to sustain cooperative behavior with their peers and assess whether judges with certain network properties are better able to enforce efficient outcomes. As before we begin by studying receiver behavior and then turn to sender behavior.

Symmetric Network Characteristics. We begin with an examination of symmetric network characteristics and receiver behavior. Recall that symmetric characteristics parametrize friendship or network closeness. Table 4 describes receiver behavior at varying levels of social proximity. Columns 1-3 use the transfer from R to S as the dependent variable, while columns 4-6 run the same specifications, but with an indicator for R playing a generous norm as the dependent variable. Columns 1 and 4 regress the receiver transfer variable on the standard treatment fixed effects and the social proximity variable. The receiver transfers Rs. 10.56 more to the receiver conditional on the initial transfer as the sender and receiver go from perfect strangers to direct friends with social distance 1. Similarly, friends are 32 percentage points more likely to play a generous norm than strangers. Columns 2 and 5 show the differences the in effects of social proximity between games with punishment (T2 and T4) and games without punishment (T1 and T3). Receivers who are socially close when there is no punishment threat send Rs. 13.01 more back to receivers and play a generous norm 32.7 percentage points more often. However, when there is a punisher, the effects of social proximity are smaller. Friends moving from games without punishers to games with punishers actually transfer less. While the coefficient on the interaction between punishment and social proximity (-5.434) is not significantly different from 0 in the transfer levels regression, the coefficient is significantly negative (-20%) in the generous norm regression. These negative coefficients are evidence of crowd out of the social motive. When there is a third party punisher, friendship has a weaker effect on receiver behavior. Columns 3 and 6 restrict the sample to games with identifiable monitors or punishers (T3 and T4) and includes the social proximities of S with J as well as R with J. Note that the coefficients on judge/sender and judge/receiver friendships are all small and insignificant. Friendship is powerful in sustaining cooperation between senders and receivers, but doesn't matter much with respect to monitors or punishers.

While average transfer from receivers to senders are higher among friends, it's also true that social proximity lowers sender risk when making the initial transfer. Figure 6 plots the empirical cdfs of sender payoffs for two separate initial sender transfer levels, Rs 10 (dashed lines) and Rs 60 (solid lines). Fixing the initial sender's transfer, any difference in final sender payoffs is a result of the receiver's transfer back to the sender. At each of initial transfer levels, we separate sender receiver relationships between high (red) and low (blue) social proximity. For both initial transfer levels, the red lines are generally to the right of the blue lines, indicating higher receiver transfers across the receiver distribution. For the Rs 60 initial transfers, the high social proximity cdf first order stochastically dominates the low social proximity cdf. The picture strongly supports the idea that the receiver returns more to his or her friends across the distribution.

Asymmetric Network Characteristics. Asymmetric network relationships between players also interact with the investment games. Table 5 focuses on receiver transfers and one measure of network importance, betweenness centrality. We scale the centrality variable to be equal to the individual's quantile within the village. Thus, all of the coefficients on the centrality variables can be interpreted as the effect from moving from the least central to the most central individual in the village. Columns 1 and 4 of the regression table show the association of S and R centrality on measures of the receiver's return transfer. Note that none of the coefficients is significant. Columns 2 and 5 show the effects of S and R centrality separately for games without a third player in the room and games with either type of monitor. Again, the main effects of S and R centrality cannot be distinguished from 0. However, the receiver's centrality matters differentially when a third party is present. Moving from T1 or T2 to T3 or T4, a central receiver will return Rs 9.199 more and will play a generous norm with an increased frequency of 26.3 percentage points. This strong effect may be indicative of reputation building on the part of the receiver. Rather than risk being punished or sanctioned socially, the central receiver instead behaves in a much more generous fashion. Columns 3 and 6 restrict the sample to only the games with third party monitors or punishers. Note that the coefficients on judge centrality are not statistically distinguishable from 0. Again, under this sample restriction, we see that central receivers return Rs 6.8 more to the senders than socially isolated receivers. They are also 18.6 percentage points more likely to play a generous norm.

Demographic Characteristics. Table 6 shows receiver behavior as a function of the elite status of the participants. The only significant pattern is that receivers return more money to senders who are elites. Column 1 shows this relationship, with transfers increasing by Rs 2.672 to elite senders. The coefficient in the generous norm regression is also positive, (4.56%), but is not significant. It is possible that senders use their elite status to capture more of the surplus.

Table 7 focuses on caste and receiver behavior. Columns 1 and 4 show the relationship of sender and receiver caste on the receiver's transfers. None of the coefficients is significant and the signs in columns 1 and 3 are not the same. Columns 2 and 5 again split the effect between cases with and without known third parties. In T1 and T2, if both the sender and receiver are high caste, transfers are Rs 10.72 higher than when only one is high caste. We find that adding a judge increases the transfers by the receiver when the sender is of high caste and the receiver is not, while adding a judge crowds out receiver transfers when both are high caste. Finally, columns 3 and 6 add the judge's caste to the regressions and limit the data-set to only those games with a known judge. We find that low caste receivers send Rs 31.33 less to low caste senders when the judge is high caste. We also find evidence of collusion between high caste senders and judges. When the receiver is low caste and is assigned to play with two high caste individuals, the transfer increases by Rs 42.52. The effects seem to disappear when all players are high caste. These results show that identifiable judges may result in collusion or in reinforcement of unequal status structures.

4.4. **Network Effects and Sender Behavior.** Having examined the network effects on receiver behavior, we turn to the network effects on sender behavior.

Symmetric Network Characteristics. Again we begin by looking at symmetric network characteristics and sender behavior. Figure 7 and 8 show the payoffs of S and the total payoffs of S and R as a function of sender-receiver social proximity. Both show that outcomes are increasing in proximity. Table 8 describes the transfers made from S to R at varying levels of social proximity. Columns 1-5 present regressions of transfers from S to R on the social proximity of the participants. Columns 6-8 display regressions of the transfers on whether the participants were on the same side of the spectral partition. Column 1 provides suggestive evidence, pooled across all games, that an increase in the social proximity between S and R corresponds to an increased transfer from S to R, though the point estimate is not statistically significant at the 10% level. Column 2 shows a similar result when we add an interaction between social proximity and whether the game has a judge who can punish (T2 or T4). Column 3 shows adds an interaction between social proximity and whether the game has a known judge or monitor (T3 or T4). The sum of the two presented coefficients is significant at the 10% level, indicating that socially close pairs have higher transfers between S and R. When we control for the proximity between S and J as well as R and J, we confirm this result: S transfers Rs. 7.22 more to R if they are at distance one as opposed to being socially unconnected (column 4). We also find evidence for the fact that in T4 as opposed to T3, social proximity between S and J induces the sender to transfer less to the receiver (column 5). This appears to provide evidence for collusion between the sender and the judge. A sender-judge pair at social distance one has the sender transferring Rs. 14.39 less to the receiver than a sender-judge pair who are not socially connected.

We find similar results for the spectral partition. When S and R are on the same side of the spectral partition, S transfers Rs. 7.94 more (column 6). In column 7 we add an interaction with a dummy for whether the game has a judge who can punish (T2 or T4). We find that the sender-receiver pairs who are on the same side of the partition have Rs. 5.66 higher transfers from S to R in games T2 and T4 as compared to T1 and T3.

Asymmetric Network Characteristics. Table 9 presents the relationship between sender transfers and asymmetric network statistics. Columns 1-4 present results for betweenness centrality and columns 5-8 present results for eigenvector centrality. As in Table 5, we scale the centrality variable to be equal to the individual's quantile within the village; all of the coefficients on the centrality variables can be interpreted as the effect from moving from the least central to the most central individual in the village. Columns 1 and 2 show that there is no significant association between the centrality quantiles of S, R, and interactions with whether the game has a known judge (T3 or T4). Figure 9 provides strong evidence that more central judges are associated with higher transfers from S to R: the most central judge induces S to transfer Rs. 3.63 more to R than the least central judge (column 3 of Table 9). Column 4 provides evidence that a large component of the judge effect enters through T4. Moreover, more central senders appear to send less to receivers in T4 as compared to T3 (column 5). Columns 5-8 display nearly identical results when we replace our measure of network importance by eigenvector centrality instead of betweenness centrality.

Demographic Characteristics. Table 10 presents results for sender behavior as a function of elite status of the participants. Senders who are elites send between Rs. 1.69 and Rs. 2.85 less than non-elites (columns 1 and 3). When the receiver is an elite or leader, S transfers Rs. 1.73 to 1.82 more to R (columns 1 and 3). Column 2 suggests that there seem to be no statistically detectable effects of sender and receiver elite status interacted with T3 or T4 and column 3 demonstrates that whether the judge is an elite does not affect sender transfers

The effect of caste composition on sender transfers are displayed in Table 11. None of the coefficients in column 1 are significant. Column 2 splits the effect between cases with and without known third parties. In T1 and T2, if both the sender and receiver are high caste, then transfers are Rs. 6.85 higher as compared to both being low caste. In T3 and T4 it appears that high caste senders transfer Rs. 9.576 less to low caste receivers. The difference between the treatments provides only suggestive, though not statistically significant, evidence that the presence of a known judge reduces a high caste sender's transfer. Column 3 suggests that a low caste sender fears collusion of a high caste judge and receiver and therefore sends Rs. 26.38 less. If the sender is high caste as well, the reduction in transfer is lower.

4.5. **Perfect Games.** Aside from sender and receiver transfers, we can also analyze specific payoff outcomes for both S and R. One natural set of outcomes is what we call the *perfect game*, where senders send their entire endowments, $\tau_S = 60$, and receivers return half of the total pie, $\tau_R = 120$. This sequence of transfers occurs in 3.27% of all games played. Table 12 shows some network determinants of this fully cooperative outcome. Column 1 shows the likelihood of a perfect game by treatment. Note that perfect games are less likely overall when there is a punisher. A punisher from afar (T2) lowers the probability of the perfect game by 0.78% (not statistically significant), while a combined punisher and monitor lowers the likelihood by 2.1%. Column 2 adds the social proximity between S and R to the regression. While going from far to close increases the overall likelihood of a perfect game by 5.85%, the coefficient is not statistically significant. Recall, that in the previous analysis, we find some evidence that punishers actually crowd out altruism on social proximity. We examine crowd-out effects in the perfect game outcomes in column 4. We find that without a punisher, close friends are 13.8% more likely to play a perfect game than strangers. However, all of these gains disappear when a punisher is added. The crowd-out of social proximity is large at 17.5%. Note that in the interacted specification, games with punishment actually have positive and significant coefficients.

These can be interpreted as the effects of adding a punisher when the sender and receiver do not know each other. Adding an anonymous punisher increases the likelihood of a perfect game by 5.23% and adding a known punisher increases the likelihood by 3.94%. This is solid evidence that punishment can help improve efficiency for perfect strangers. Also, the strong social proximity effects found above also are present in determining perfect game outcomes, but can easily be crowded out by adding third parties to the contracting process. Finally column 4 shows the effect of having a central judge on the likelihood of a perfect game outcome. Moving from the least central to the most central individual increases the chance of a perfect game by 2.83%. Again, if the right person is chosen, judges can have quite beneficial outcomes. These results show that when used correctly, the network can be a powerful too for increasing investment and for encouraging fair outcomes. However, either picking the wrong judge or meddling in places where bilateral contracting is already working can have detrimental effects.

5. Conclusion

We use laboratory experiments in the field to understand how different contracting environments affect the outcomes of joint investment opportunities. We use detailed network data to further analyze how the social network characteristics of participants interact with the contracting environments to shape final payoffs. Our games are played among individuals from rural Indian villages who can fully identify each other, thus making all past and future interactions between the participants relevant for how they play our games. We find that all three categories of network statistics, symmetric, asymmetric and demographic affect how the games are played in different ways.

Our results on symmetric network characteristics, such as social proximity and being on the same side of the spectral partition, confirm that individuals with close ties are better able to overcome weak institutions and attain more efficient levels of investment. The decreased ability for socially distant pairs to achieve comparable outcomes may severely limit the scope and size of economic organizations in places with weak institutions.

We find that adding a judge with punishment capabilities to a bilateral contracting environment can have mixed results. While the average effect decreases efficiency in our sample, we also find that if the right individual is chosen, a judge can be efficiency enhancing. Highly central judges do increase efficiency over the two party levels. We also find signs that judges may crowd out other social network effects. For example, judges crowd out social proximity in determining whether or not players play a perfect game, but act to increase the chances for a pair of strangers. Adding judges also allows for reputation motives on the part of S and R. We find that central individuals are more prone to reputational concerns. Also, the fact that we do not find sender-judge collusion among socially close individuals might indicate that motivations aside from maximizing monetary payouts in the game are at play.

Finally, the results on demographic characteristics indicate that elite capture can occur among leaders and high caste individuals. If these tasks are representative then maybe recognized leaders aren't necessarily the best equipped to moderate economic interactions. There may exist much better suited individuals.

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Figures

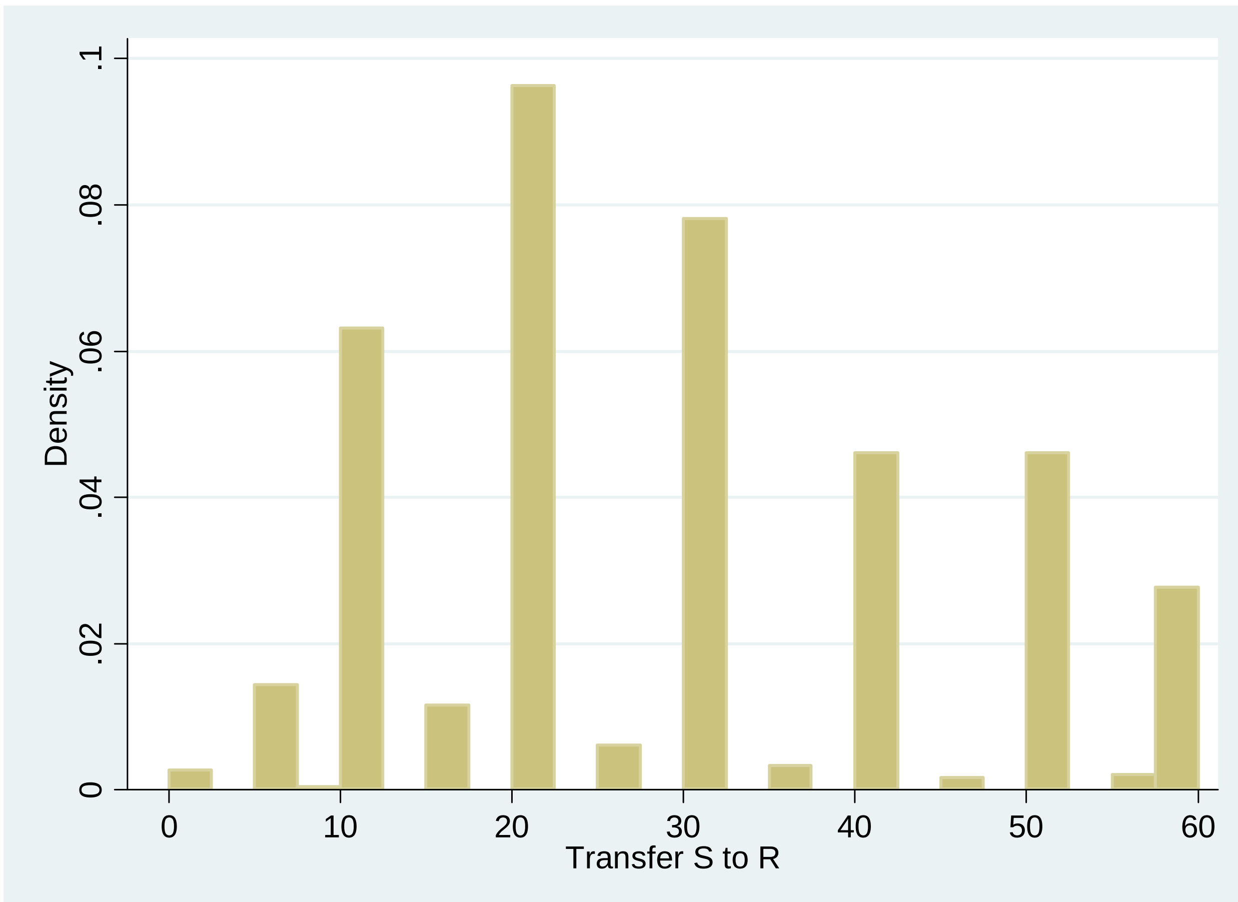

Figure 1. Distribution of transfers from sender.

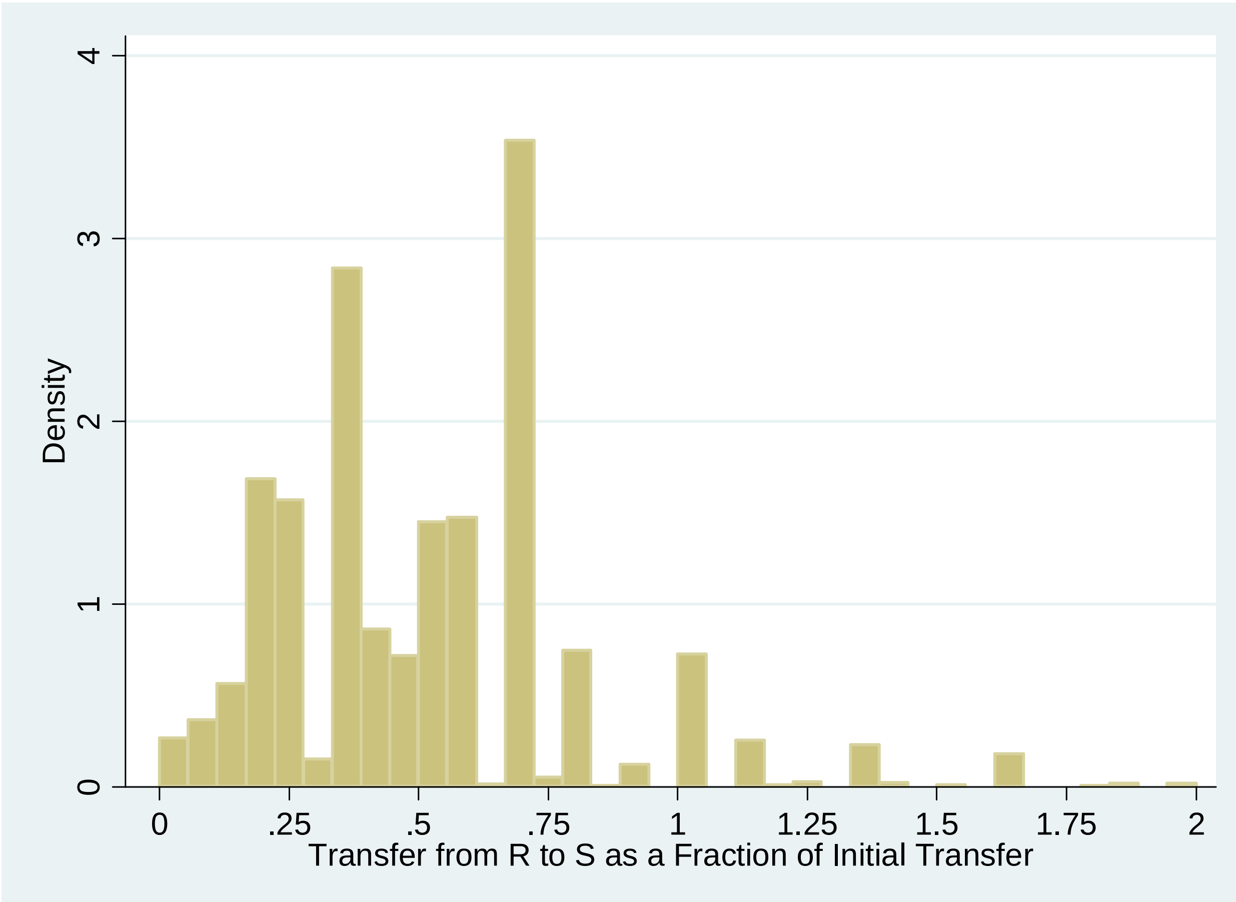

Figure 2. Distribution of transfers from receiver to sender as a fraction of the initial transfer.

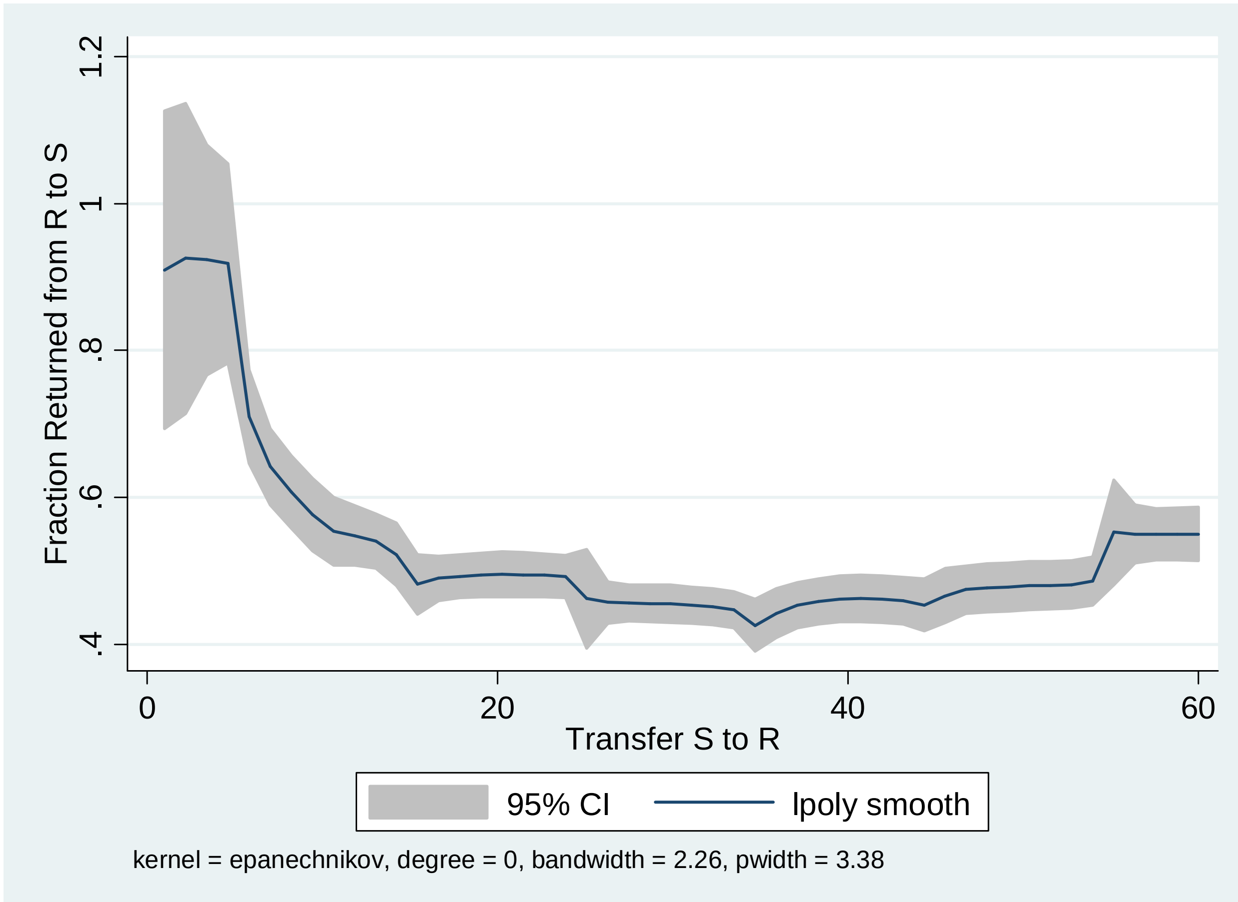

FIGURE 3. Fraction returned from R to S as a function of transfer S to R

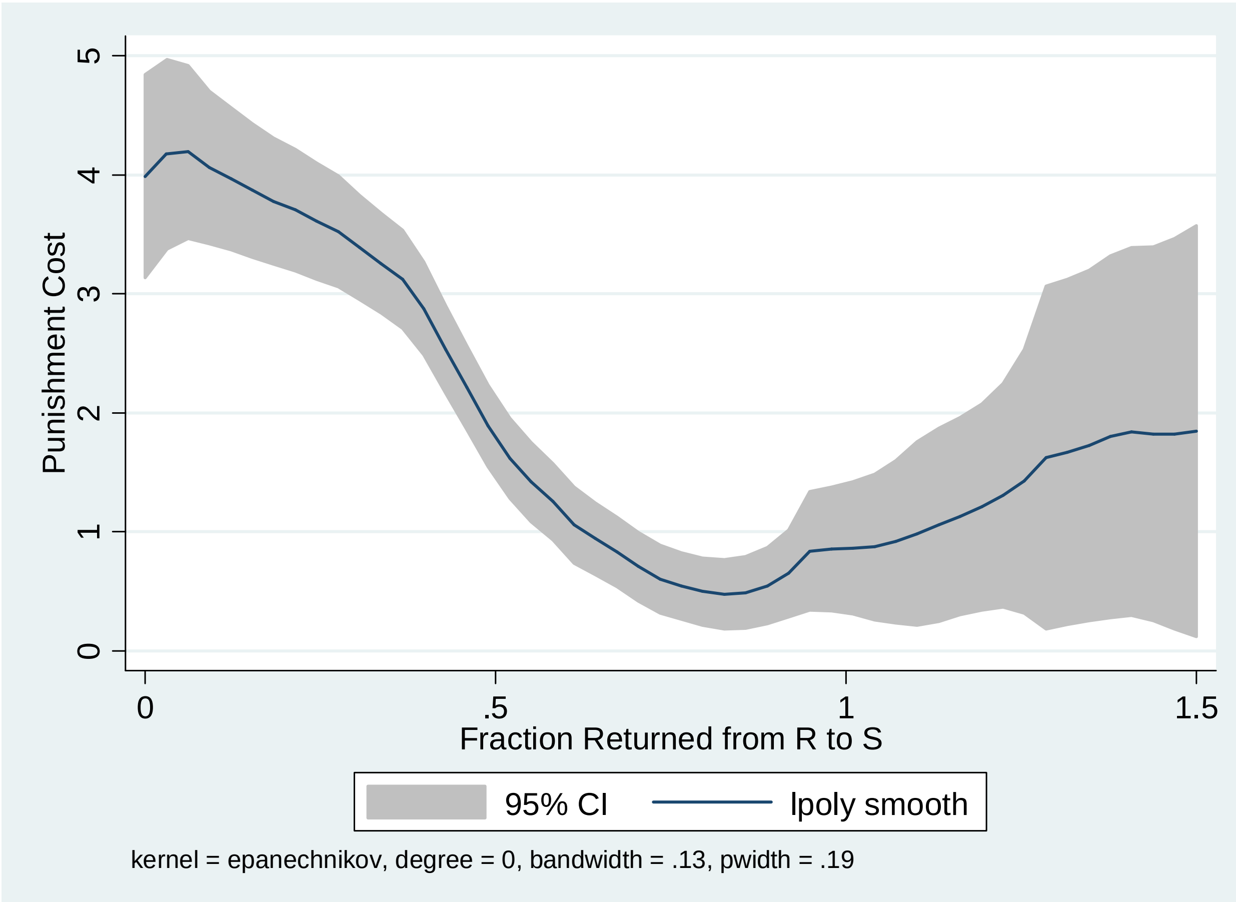

FIGURE 4. Punishment cost paid by J by fraction returned from R to S

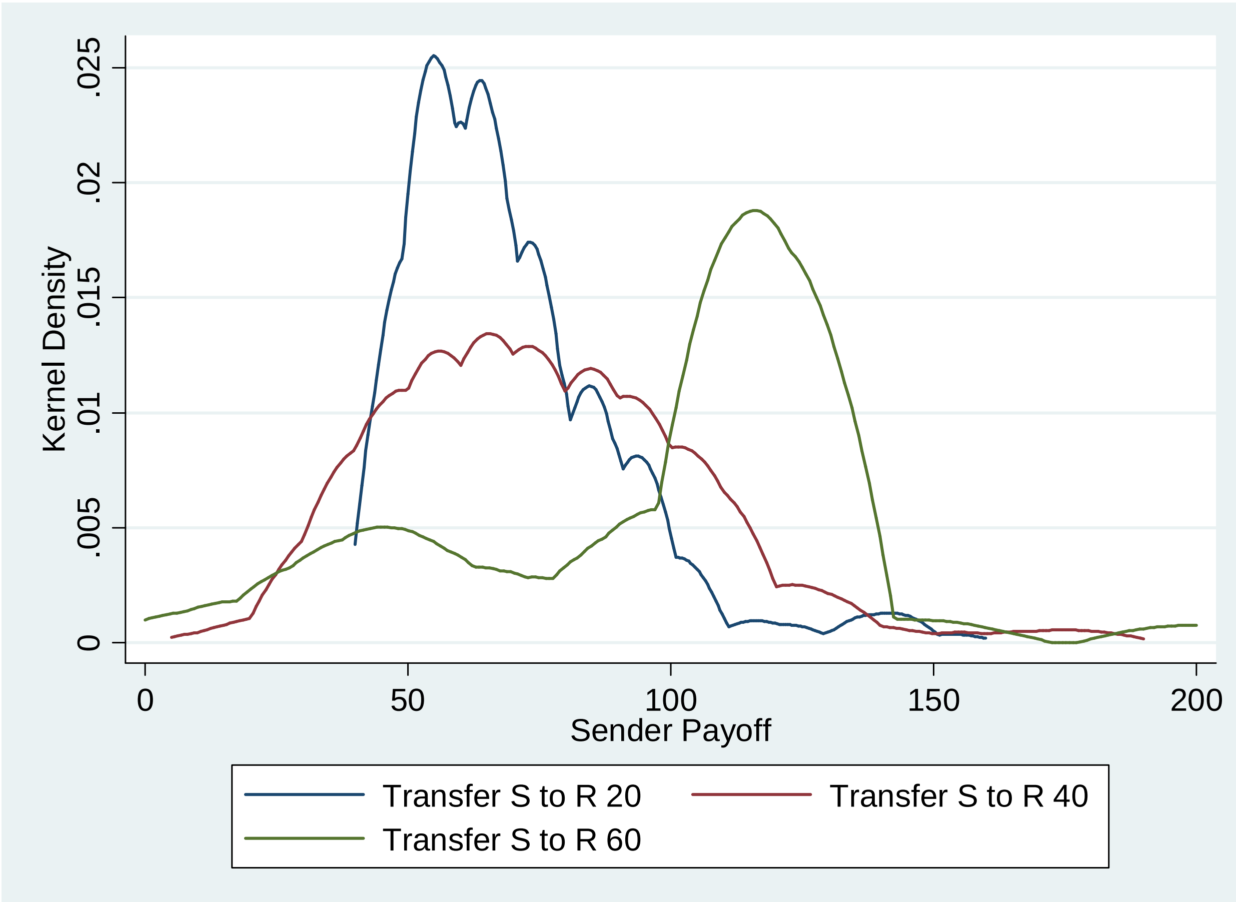

FIGURE 5. Densities of transfer R to S, by transfer S to R

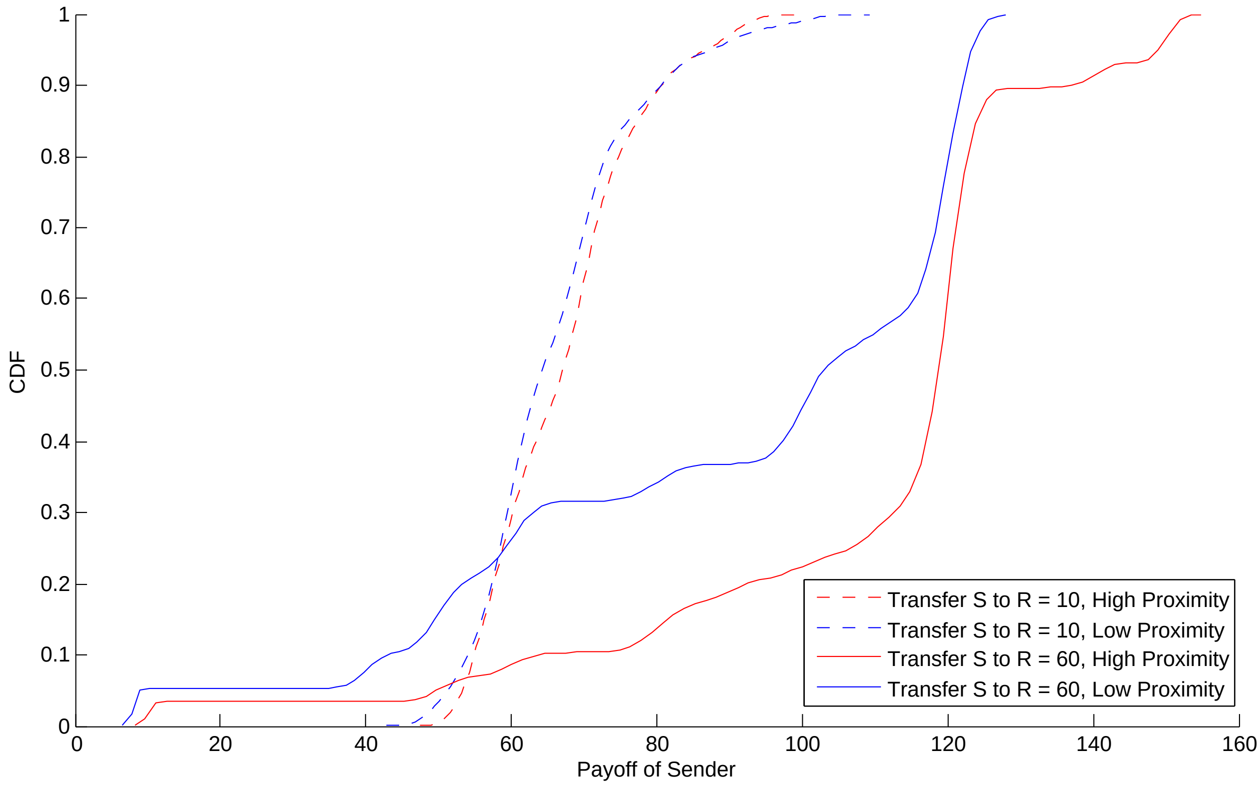

FIGURE 6. CDF of sender payoffs by transfer R to S and social proximity of S and R

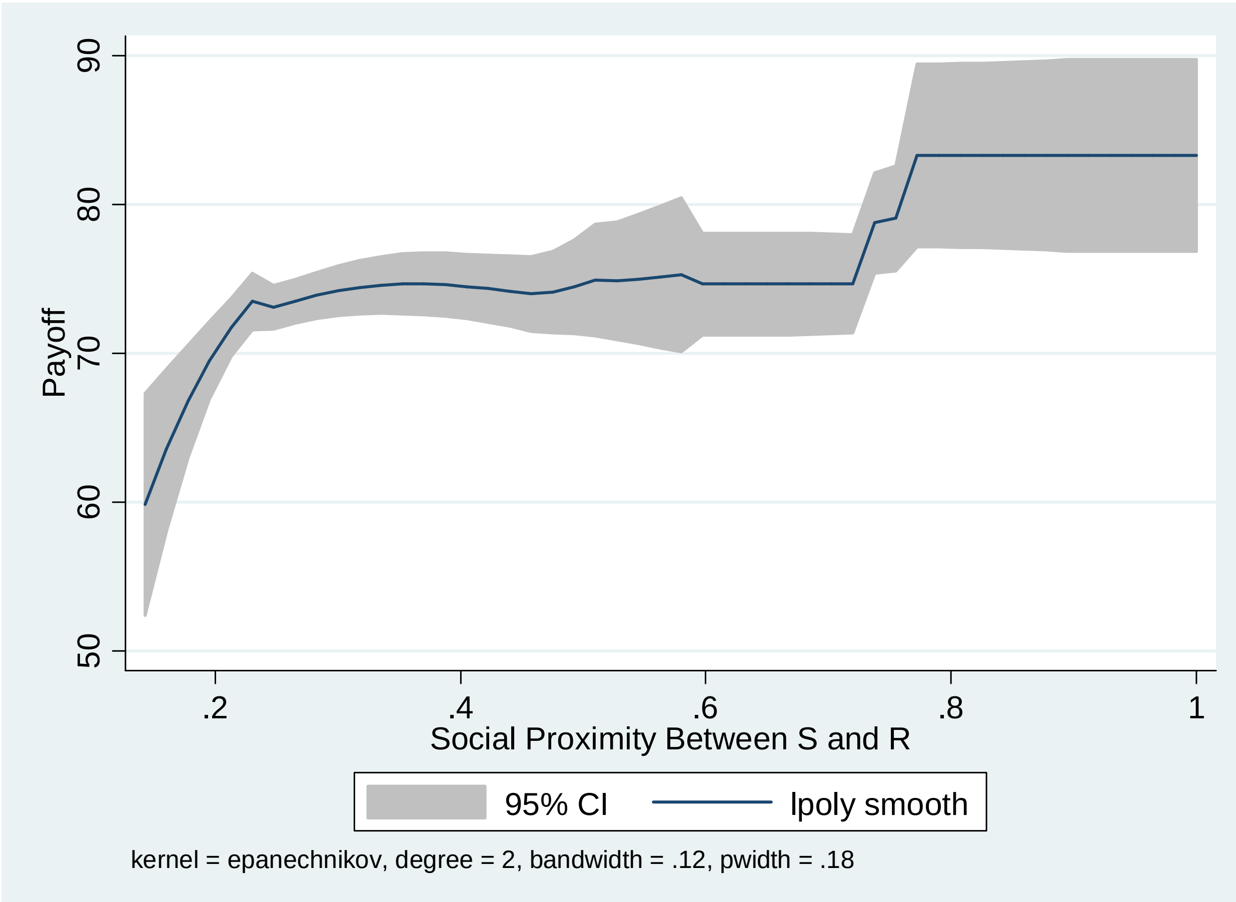

FIGURE 7. Payoff to S as a function of social proximity between S and R.

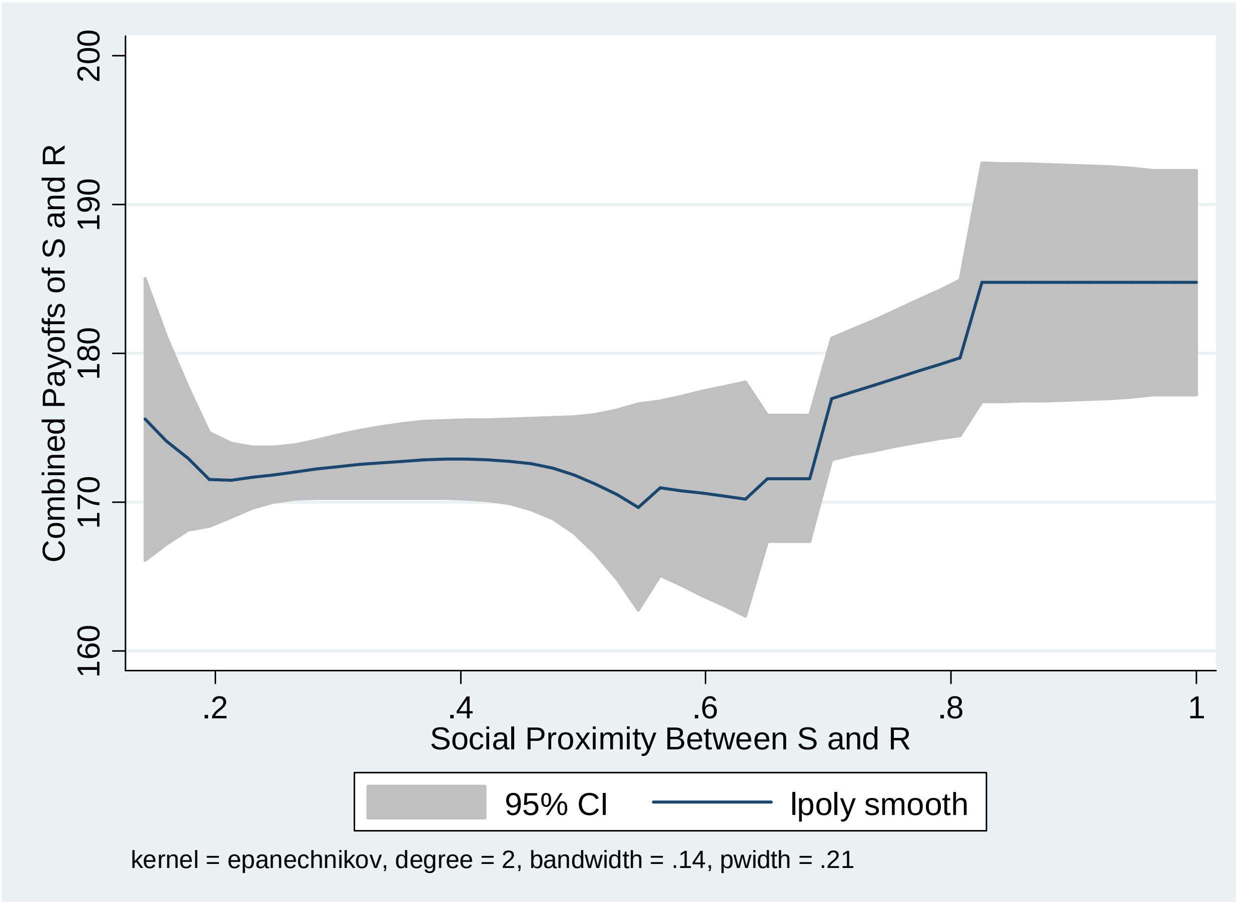

FIGURE 8. Total payoff of S and R as a function of social proximity between S and R.

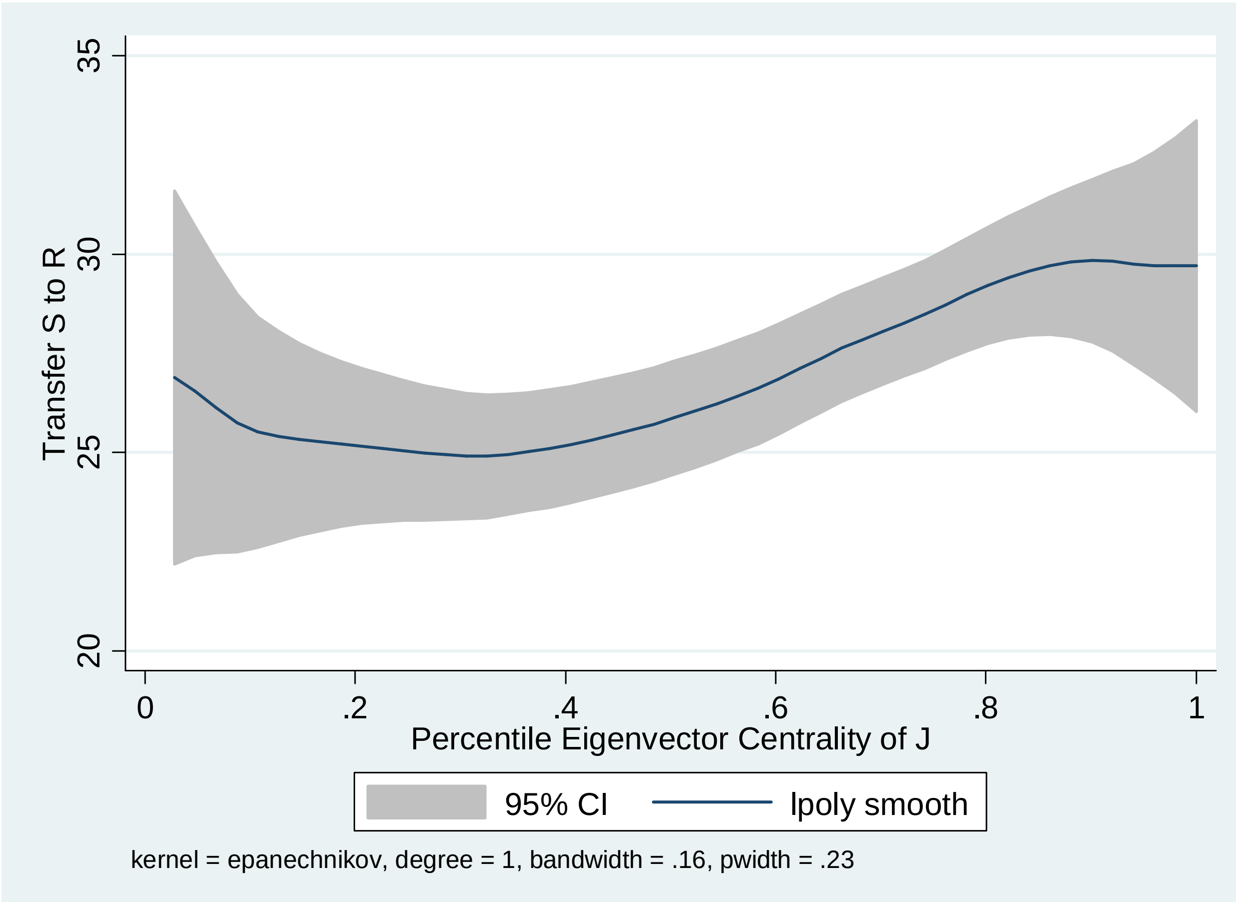

FIGURE 9. Transfer from S to R as a function of the percentile of the eigenvector centrality of J.

Tables

Table 1. Summary Statistics

	Mean	Std. Dev
Age	30.02	8.20
Female	0.60	0.49
Education	8.26	4.30
High Caste	0.60	0.49
HH has a Leader	0.22	0.41
Average Proximity b/w Pairs	0.32	0.17
Average Reachability b/w Pairs	0.97	0.17
Average Degree	10.42	6.79
Average Eigenvector Centrality	0.02	0.03
Average Betweenness Centrality	0.01	0.01

Table 2. Receiver Behavior and Third Party Enforcement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample			Initial Transfer > Rs 20			Initial Transfer < Rs 20		
	Transfer R to S	Fraction R to S	Generous Norm	Transfer R to S	Fraction R to S	Generous Norm	Transfer R to S	Fraction R to S	Generous Norm
Game w/ Punishment from Afar	2.559	-0.0221	0.0271	5.072*	0.121*	0.0814**	-1.745	-0.404	-0.0162
	(1.531)	(0.0597)	(0.0312)	(2.574)	(0.0626)	(0.0376)	(2.774)	(0.259)	(0.0635)
Game w/ Monitoring	0.264	-0.0483	0.0260	-0.762	-0.0223	0.0195	-0.879	-0.261	-0.000686
	(1.655)	(0.0682)	(0.0396)	(2.612)	(0.0684)	(0.0477)	(1.856)	(0.246)	(0.0702)
Game w/ Monitoring and Punishment	2.556	0.0334	0.0584*	2.637	0.0691	0.0403	-3.475*	-0.454*	-0.0225
	(1.678)	(0.0779)	(0.0331)	(2.485)	(0.0664)	(0.0372)	(1.767)	(0.266)	(0.0747)
Transfer S to R Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1732	1721	1735	900	900	902	408	397	409
R-squared	0.540	0.160	0.215	0.437	0.195	0.271	0.318	0.375	0.416

Standard Errors are Clustered at the Room Level

Table 3. Main Effects

VARIABLES	(1) Total Payoffs	(2) Payoff S	(3) Payoff R	(4) Transfer S to R	(5) Transfer S to R >Rs 20
Game w/ Punishment from Afar	-8.985***	1.298	-10.61***	-0.657	-0.0253
	(2.852)	(1.798)	(2.103)	(1.247)	(0.0344)
Game w/ Monitoring	0.157	0.125	-1.093	-0.302	-0.0402
	(3.210)	(1.658)	(2.754)	(1.546)	(0.0432)
Game w/ Monitoring and Punishment	-12.52***	0.969	-14.97***	-2.562*	-0.0778*
	(2.973)	(1.763)	(2.433)	(1.397)	(0.0446)
Observations	1892	1890	1885	1891	1892
R-squared	0.252	0.155	0.106	0.244	0.178

*** p<0.01, ** p<0.05, * p<0.1

Standard Errors are Clustered at the Room Level

Table 4. Receiver's Transfers and Symmetric Network Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Transfer R to S	Transfer R to S	Transfer R to S	Generous Norm	Generous Norm	Generous Norm
Social Proximity Between S and R	10.56***	13.01**	12.62**	0.238***	0.327***	0.246**
	(3.959)	(4.889)	(6.293)	(0.0754)	(0.0731)	(0.108)
Social Proximity S R * Game Has a Punisher		-5.434			-0.200*	
		(5.940)			(0.114)	
Social Proximity Between S and J			-1.053			-0.0711
			(5.708)			(0.108)
Social Proximity Between R and J			0.0193			-0.0692
			(6.135)			(0.0950)
Game w/ Punishment from Afar	2.721*	4.522*		0.0306	0.0968**	
	(1.551)	(2.515)		(0.0320)	(0.0455)	
Game w/ Monitoring	0.463	0.486	-2.111	0.0303	0.0311	-0.0282
	(1.648)	(1.641)	(1.936)	(0.0396)	(0.0394)	(0.0362)
Game w/ Monitoring and Punishment	2.694	4.523*		0.0609*	0.128***	
	(1.678)	(2.394)		(0.0335)	(0.0470)	
Transfer S to R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1732	1732	778	1735	1735	778
R-squared	0.542	0.542	0.564	0.221	0.222	0.312

Standard Errors are Clustered at the Room Level

Table 5. Receiver's Transfers and Asymmetric Network Characteristics

	(1) Transfer R to S	(2) Transfer R to S	(3) Transfer R to S	(4) Generous Norm	(5) Generous Norm	(6) Generous Norm
Betweenness Quantile of S	-0.530	-0.181	-2.479	0.0182	-0.0175	0.0185
	(2.227)	(3.232)	(3.407)	(0.0346)	(0.0524)	(0.0559)
Betweenness Quantile of R	0.994	-3.467	6.800*	0.0357	-0.0893	0.186**
	(3.140)	(3.766)	(3.594)	(0.0595)	(0.0668)	(0.0751)
Betweenness Quantile of J			-3.209			-0.0475
			(3.706)			(0.0687)
Betweenness Quantile of S * Game Has J (Known)		-0.505			0.0875	
		(4.323)			(0.0719)	
Betweenness Quantile of R * Game Has J (Known)		9.199**			0.263***	
		(3.925)			(0.0702)	
Game w/ Punishment from Afar	2.576*	2.537		0.0273	0.0263	
	(1.539)	(1.539)		(0.0313)	(0.0311)	
Game w/ Monitoring	0.319	-5.002	-2.246	0.0268	-0.186**	-0.0338
	(1.625)	(3.848)	(1.874)	(0.0397)	(0.0699)	(0.0344)
Game w/ Monitoring and Punishment	2.612	-2.776		0.0587*	-0.156**	
	(1.649)	(3.764)		(0.0328)	(0.0663)	
Transfer S to R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1732	1732	793	1735	1735	793
R-squared	0.540	0.541	0.558	0.215	0.221	0.317

Standard Errors are Clustered at the Room Level

Table 6. Receiver's Transfers and Elite Status

	(1) Transfer R to S	(2) Transfer R to S	(3) Transfer R to S	(4) Generous Norm	(5) Generous Norm	(6) Generous Norm
Sender's HH has Leader	2.672*	3.026	1.341	0.0456	0.0359	0.0396
	(1.546)	(2.180)	(1.692)	(0.0290)	(0.0383)	(0.0376)
Receiver's HH has Leader	-0.721	-1.013	-1.107	-0.0300	-0.0372	-0.0162
	(1.757)	(2.291)	(2.045)	(0.0368)	(0.0474)	(0.0425)
Judge's HH has Leader			0.646			-0.00616
			(2.609)			(0.0469)
S HH Has Leader * Game Has J (Known)		-0.717			0.0211	
		(2.748)			(0.0508)	
R HH Has Leader * Game Has J (Known)		0.582			0.0168	
		(2.641)			(0.0543)	
Transfer S to R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1732	1732	808	1735	1735	808
R-squared	0.541	0.541	0.552	0.217	0.217	0.298

Standard Errors are Clustered at the Room Level

Table 7. Receiver's Transfers and Caste

	(1) Transfer R to S	(2) Transfer R to S	(3) Transfer R to S	(4) Generous Norm	(5) Generous Norm	(6) Generous Norm
Sender is High Caste	-0.458	-4.934	-21.33	0.0326	-0.0763	-0.166
	(4.133)	(5.123)	(13.37)	(0.0877)	(0.105)	(0.180)
Receiver is High Caste	1.435	-0.807	5.585	0.100	0.0252	0.220
	(4.655)	(4.755)	(20.21)	(0.0783)	(0.103)	(0.239)
High Caste S and R	3.853	10.72*	-16.89	-0.0783	0.0124	-0.325
	(5.631)	(5.707)	(20.99)	(0.106)	(0.133)	(0.378)
Judge is High Caste			-31.33*			-0.291
			(15.60)			(0.248)
High Caste S and J			42.52**			0.315
			(17.43)			(0.292)
High Caste R and J			8.761			0.0623
			(24.57)			(0.329)
High Caste S, R and J			-11.57			-0.177
			(27.35)			(0.398)
High Caste S * Game Has J (Known)		8.812*			0.234**	
		(5.199)			(0.113)	
High Caste R * Game Has J (Known)		4.885			0.165	
		(6.172)			(0.117)	
High Caste S and R * Game Has J (Known)		-13.93			-0.201	
		(9.214)			(0.178)	
Transfer S to R Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	527	527	128	527	527	128
R-squared	0.609	0.612	0.821	0.288	0.295	0.608

Standard Errors are Clustered at the Room Level

Table 8. Sender's Transfers and Symmetric Network Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R
Social Proximity Between S and R	4.046	5.123	3.075	7.222**	4.361				
	(2.935)	(4.229)	(3.992)	(2.890)	(3.659)				
Social Proximity S and R * Game 4					7.149				
					(5.415)				
Social Proximity Between S and J				-1.424	5.784				
				(3.215)	(4.709)				
Social Proximity S and J * Game 4					-14.39**				
					(5.518)				
Social Proximity Between R and J				-3.478	-3.366				
				(3.097)	(4.054)				
Social Proximity R and J * Game 4					-0.608				
					(5.365)				
Social Proximity * Game Has a Punisher		-2.406							
		(5.260)							
Social Proximity S and R * Game Has J (Known)			2.221						
			(4.111)						
S and R on Same Side of Spectral Partition						7.944***	5.194*	6.711**	7.082***
						(2.435)	(2.602)	(3.206)	(2.342)
S and R on Same Side * Game Has a Punisher							5.656***		
							(1.304)		
S and R on Same Side * Game Has J (Known)								2.550	
								(3.855)	
S and J on Same Side of Spectral Partition									-6.864***
									(2.021)
R and J on Same Side of Spectral Partition									1.095
									(1.482)
Observations	1735	1735	1735	793	793	1735	1735	1735	793
R-squared	0.186	0.186	0.186	0.239	0.245	0.189	0.190	0.189	0.241

Standard Errors are Clustered at the Room Level

Table 9. Sender's Transfers and Asymmetric Network Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Betweenness Centrality				Eigenvector Centrality			
	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R	Transfer S to R
Centrality Quantile of S	-0.759	-0.614	-2.005	1.562	-2.007	-2.725	-1.826	3.392
	(2.048)	(2.438)	(2.379)	(3.138)	(1.857)	(2.225)	(2.523)	(2.956)
Centrality Quantile of S * T4				-7.468*				-10.82***
				(4.174)				(3.662)
Centrality Quantile of R	-0.409	-1.237	0.272	1.626	-1.405	-1.086	-0.931	1.542
	(1.377)	(2.045)	(2.002)	(2.844)	(1.777)	(2.155)	(2.423)	(3.072)
Centrality Quantile of R * T4				-2.552				-4.876
				(3.560)				(3.834)
Centrality Quantile of J			3.630*	0.989			4.495**	3.449
			(2.140)	(2.414)			(2.049)	(2.423)
Centrality Quantile of J * T4				6.048*				2.453
				(3.533)				(3.526)
Centrality Quantile of S * Game Has J (Known)		-0.276				1.521		
		(2.495)				(2.761)		
Centrality Quantile of R * Game Has J (Known)		1.702				-0.634		
		(2.893)				(3.219)		
Observations	1735	1735	793	793	1735	1735	793	793
R-squared	0.243	0.243	0.351	0.357	0.244	0.244	0.352	0.362

Standard Errors are Clustered at the Room Level

Table 10. Sender's Transfers and Elite Status

	(1)	(2)	(3)
	Transfer S to R	Transfer S to R	Transfer S to R
Sender's HH has Leader	-1.688	-1.027	-2.846**
	(1.028)	(1.371)	(1.135)
Receiver's HH has Leader	1.734*	1.765	1.823*
	(0.941)	(1.252)	(1.049)
S HH Has Leader * Game Has J (Known)		-1.396	
		(1.595)	
R HH Has Leader * Game Has J (Known)		-0.151	
		(1.753)	
Judge's HH has Leader			0.884
			(1.641)
Observations	1735	1735	808
R-squared	0.246	0.247	0.346

Standard Errors are Clustered at the Room Level

Table 11. Sender's Transfers and Caste

	(1)	(2)	(3)
	Transfer S to R	Transfer S to R	Transfer S to R
Sender is High Caste	1.392	5.847*	-3.985
	(2.466)	(3.124)	(7.004)
Receiver is High Caste	1.965	5.447*	1.401
	(2.364)	(2.844)	(7.998)
High Caste S and R	0.107	-4.442	-4.019
	(3.060)	(4.278)	(12.73)
Judge is High Caste			12.55
			(12.95)
High Caste S and J			-14.52
			(12.59)
High Caste R and J			-26.38**
			(12.92)
High Caste S, R and J			29.04**
			(12.21)
High Caste S * Game Has J (Known)		-9.576*	
		(4.947)	
High Caste R * Game Has J (Known)		-7.756	
		(5.403)	
High Caste S and R * Game Has J (Known)		9.938	
		(7.111)	
Observations	527	527	128
R-squared	0.355	0.365	0.527

Standard Errors are Clustered at the Room Level

Table 12. Determinants of Perfect Games

	(1)	(2)	(3)	(4)
	Perfect Game	Perfect Game	Perfect Game	Perfect Game
Social Proximity Between S and R		0.0585	0.138*	
		(0.0435)	(0.0705)	
Social Proximity * Game Has a Punisher			-0.175**	
			(0.0681)	
Game w/ Punishment from Afar	-0.00776	-0.00406	0.0523**	
	(0.0121)	(0.0123)	(0.0243)	
Game w/ Monitoring	0.00367	0.00571	0.00625	0.0251
	(0.0128)	(0.0131)	(0.0133)	(0.0170)
Game w/ Monitoring and Punishment	-0.0210*	-0.0180	0.0394*	
	(0.0120)	(0.0120)	(0.0204)	
Judge's Ecen Quantile				0.0283*
				(0.0142)
Observations	1892	1786	1786	793
R-squared	0.125	0.112	0.119	0.167

Standard Errors are Clustered at the Room Level

Appendix A. Glossary of Network Statistics

In this section we briefly discuss the network statistics used in the paper. Jackson (2008) contains an excellent and extensive discussion of these concepts which the reader may refer to for a more detailed reading.

Path Length and Social Proximity. The *path length* between nodes i and j is the length of the shortest walk between the two nodes. Denoted $\gamma(i,j)$, it is defined as $\gamma(i,j) := \min_{k\in\mathbb{N}\cup\infty} \left[A^k\right]_{ij} > 0$. If there is no such walk, notice that $\gamma(i,j) = \infty$. The *social proximity* between i and j is defined as $\gamma(i,j)^{-1}$ and defines a measure of how close the two nodes are with 0 meaning that there is no path between them and 1 meaning that they share an edge. In figure 10, $\gamma(i,j) = 2$ and $\gamma(i,k) = \infty$.

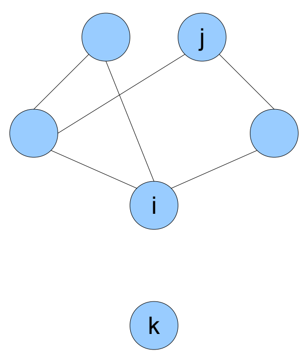

Figure 10. Path lengths i,j and i,k

Vertex characteristics. We discuss three basic notions of network importance from the graph theory literature: degree, betweenness centrality, and eigenvector centrality. The *degree* of node i is the number of links that the node has. In figure 11(a), i has degree 6 while in (b) i has degree 2. While this is an intuitive notion of graphical importance, it misses a key feature that a node's ability to propagate information through a graph depends not only on the sheer number of connections it has, but also how important those connections are. Figure 11(b) illustrates an example where it is clear that i is still a very important node, though a simple count of its friends does not carry that information. Both betweenness centrality and eigenvector centrality address this problem.

The *betweenness centrality* of i is defined as the share of all shortest paths between all other nodes $j, k \neq i$ which pass through i. This is a normalized measure which is useful when thinking about a propagative process traveling from node j to k as taking the shortest available path.

The *eigenvector centrality* of i is a recursive measure of network importance. Formally, it is defined as the ith component of the eigenvector corresponding to the maximal eigenvalue of the adjacency matrix representing the graph.[12] The intuition for its construction is that one may be interested in defining the importance of a node as proportional to the sum of all its network neighbors' importances. By definition the vector of these importances must be an eigenvector of the adjacency matrix and restricting the importance measure to be positive means that the vector of importances must be the first eigenvector. Intuitively, this measure captures how well information flows through a particular node in a transmission process. Relative to betweenness centrality, a much lower premium is placed on a node being on the exact shortest path between two other nodes. We can see this by comparing figure 11(b), where i has a high eigenvector centrality and high betweenness, to (c), where i still has a rather high eigenvector centrality but now has a 0 betweenness centrality since no shortest path passes through i.

[12] The adjacency matrix A of an undirected, unweighted graph G is a symmetric matrix of 0s and 1s which represents whether nodes i and j have an edge.

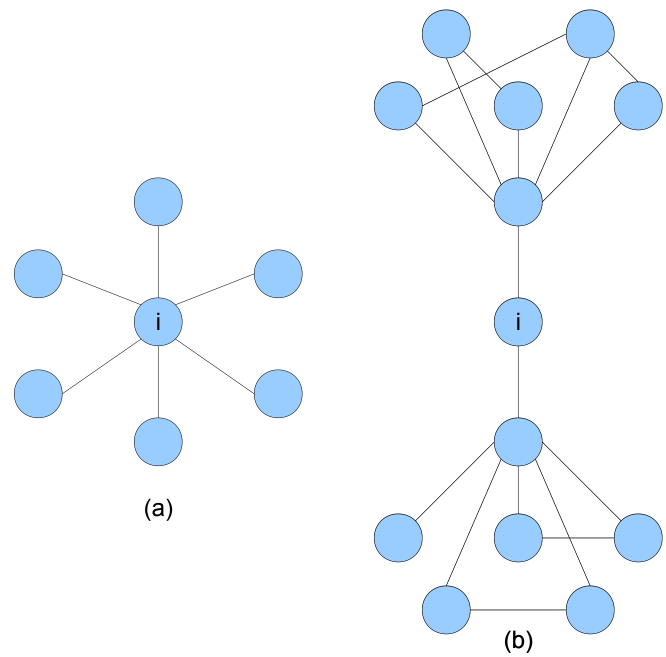

FIGURE 11. Centrality of node i

Spectral Partition. One exercise performed in graph theory is to partition the set of nodes into two groups such the information flow across the groups is low while the information flow within the groups is high. These partitions are of economic interest insofar we can think of information traveling from i to j not simply along the shortest path between the two nodes but through possibly many paths. The full flow process of information may carry important economic data. Network statistics which capture this feature, therefore, may be important to study.

There are numerous ways to partition the network including minimum cut, minimum-width bisections, and uniform sparsest cut. See Arora et al. (2004) for a recent discussion. The general result in this literature is that finding the cut is NP-hard. Consequently, approximation algorithms must be used.

We employ a simple approximation described as follows. Given a graph $G = (V, E)$, we partition V into disjoint sets U and W such that $\frac{\sum_{i \in U} \sum_{j \in W} A(G)_{ij}}{|U||W|}$ is minimized. Following a simple approximation motivated by Hagen and Kahng (1992), we compute the "side" of node i based on the sign of ξ_i where ξ_i is the eigenvector corresponding to the second smallest eigenvalue of the Laplacian of the graph G, defined as $L(G) = D - A$ where

$D = diag\{d_1, ..., d_n\}$ a diagonal matrix of degrees and A is the adjacency matrix. Figure 12 illustrates the intuition of the partition. We say nodes i and j are on the same side of the spectral partition if $sign(\xi_i) = sign(\xi_j)$.

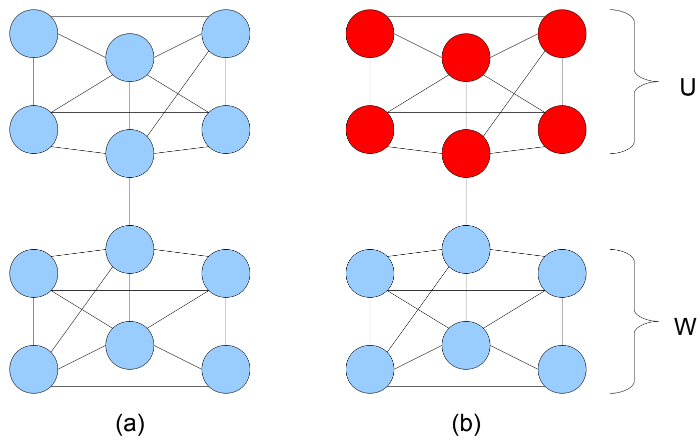

FIGURE 12. Spectral partition of V into U and W