Trust and the Strength of Ties in Online Social Networks: An Exploratory Field Experiment

Ravi Bapna
University of Minnesota
rbapna@umn.edu

Alok Gupta
University of Minnesota
gupta037@umn.edu

Sarah Rice
Texas A&M University
srice@mays.tamu.edu

Arun Sundararajan
New York University
arun@stern.nyu.edu

Abstract

We conduct an exploratory study using a customized Facebook application to understand how social ties are linked to economic measure of trust. We employ the Investment Game, a well-established economic game designed to generate a quantifiable trust measure. We consider the relationship between observed trust and three "revealed preference" tie strength measures: 1) the degree of interaction between friends on their walls; 2) embeddedness, a metric related to the number of mutual friends shared; and 3) being tagged together in a photograph, indicative of a physical-world interaction. We identify latent heterogeneity among our subjects, establishing that for users with a large number of Facebook friends, the only measure associated with trust is whether the dyad was tagged in a photo together. In contrast, for users that are more selective and have fewer Facebook friends, all three aforementioned tie strength measures correlate with trust. Our findings are preliminary evidence that traditional measures of dyadic-trust like embeddedness which are used widely in physical-world social networks may not always be effective predictors of digital trust, because not all online social ties are created equal. Methodologically, our study contributes to an emerging body of research that showcases how to leverage the large-scale online social graph to better understand fundamental constructs of economic behavior.

Keywords: Investment Game, trust, switching regression, field study

1. Introduction

"Put not your trust in money, but put your money in trust."

~Oliver Wendell Holmes Sr.

Online social networks like Facebook, Snapchat and Twitter consume an increasingly significant portion of our time and attention. A 2014 Facebook study[1] estimates 829 million daily active users in the past year. Approximately 2 million friend requests are made and 3 million messages are sent on the Facebook platform every 20 minutes. With an estimated user base of approximately 1.3 billion, 81.9% of whom are outside of the U.S.,[2] this collective mass of connected humanity is a fascinating reservoir of social and economic influence. However, a primitive underlying this conjectured "influence" is a notion that people trust the opinions, intentions or actions of individuals they are connected to. Metaphorically, one might consider questions like "Which of your Facebook friends would you trust enough to invite to engage in political activism, and which of them would you rely on merely for product recommendations, blog posts or news source tweets?" The conjectured gains from leveraging the information contained in online social networks rests on being able to understand how an individual might answer such questions about different people with whom they share online social ties. And after all, what we have labeled a "Facebook friendship" is in fact a set of varied human relationships, ranging from childhood kinship to professional ties to casual acquaintances struck up over a late-night bar conversation. The importance of understanding the economic information contained in online interaction trails is further amplified by the move we have witnessed over the last few years towards population-scale peer-to-peer interaction in what is commonly called the sharing economy (Sundararajan, 2016), where digital social profiles and interaction histories often form a critical basis for assessing the trustworthiness of a trading partner.

In this paper we conduct an exploratory study of connections represented in a large-scale online social network, where little is formally known about the nature or veracity of the actual friendship formation process. Our research aims to understand whether user interactions that occur naturally on the Facebook platform (and are thus measurable through the Facebook API) are linked to well-vetted economic measures of trust. Our broad question is: *What can help explain the variation of trust exhibited in online social networks?* Our research is exploratory because we rely on naturally occurring social tie measures that can now be observed at scale and with precision using the Facebook API. In this regard, we advance prior research by laying the foundations for scalable and reliable measurement of an important set of trust predictors. Our field design, however, does not permit us the luxury of causal

[1] http://newsroom.fb.com/company-info/
[2] http://www.statista.com/topics/751/facebook/

inference. Such inference might be identified, for example, by creating exogenous variation in the strength of social ties of real people, which is a very challenging research undertaking.

Instead, we leverage a new aspect of today's digital environment, namely that social interactions often take place on technology platforms that offer interfaces (APIs) to the outside world that can be used to construct profiles upon which trust assessments are made. Our design is just one of many ways to refine the vast amount of social networking data available online in order to answer specific research questions. For instance, we can compute real-time, dynamic and revealed-preference style strength of tie measures between pairs of individuals by observing their online interactions, such as posting on each-others walls and jointly appearing in photographs. In contrast, prior work has relied on relatively costly declared-preference type surveys of friendship networks to elicit social ties (e.g, Mobius and Szeidl 2007). These approaches are often static and do not capture the variety[3] of micro-level data that we can obtain from the Facebook API.

We believe that understanding linkages between cleanly observed tie-strength measures and trust is an important research objective. While pro-social behavior has been widely documented (Mobius and Szeidl 2007) and its underlying drivers such as directed altruism and reciprocity separated out (Leider et al. 2010, Rosenblat and Mobius 2009), the underlying primitives of the technology enabled size, scale and reach of today's online social networks is not well understood. Moreover, this type of network represents potential for the deployment of social capital to act as the lubricant that reduces social and economic frictions. Consider as a motivating example the California based peer-to-peer car rental platform Getaround, the peer-to-peer short-term accommodation platform Airbnb, or the city-to-city ridesharing platform BlaBlaCar. These are just three of a multitude of sharing economy businesses that require or strongly encourage a Facebook ID from potential users, employing digitized social capital as a gateway to economic activity. As we have transitioned from low-stakes peer-to-peer exchange like shipping boxes exchanged on eBay to opening up our spare bedrooms, lending our automobiles and taking long-distance road trip with semi-anonymous peers, our dependence on online social profiles to facilitate peer-to-peer exchange has naturally expanded. The global economy is on the cusp of organizing, at scale, economic activity that is built upon measures of trust revealed through naturally occurring interactions in online social networks. Our research will provide useful input into the design of the computational trust systems that are the new digital institutions powering the peer-to-peer sharing platforms of the sharing economy.

[3] IBM's view is that big-data is not just about volume, but as much about variety, velocity and veracity.

Our research proceeds as follows. First, we operationalize a usable measure of trust in economic exchange. Next we determine the association between this trust measure and strength of ties measures that we collect from the Facebook pages of consenting subjects. Our measure of trust is derived from an economic game rooted in the experimental economics literature (e.g., Kagel and Roth 1997). It employs decisions involving monetary transfers to examine whether, and to what extent, trust is exhibited between two transacting parties. By coupling this trust measure with social "strength of ties" measures, our work builds upon Leider et al. (2010), in its deployment of non-anonymous versions of what were traditionally anonymous games (Berg et al. 1995) to link social distance and trust in an online context. An innovation of our paper is the custom Facebook application we develop specifically to play this game amongst "friends", thereby generating a quantified trust measure.[4] We test the association between this trust measure and three measures of social ties that have been validated by prior research. This allows us to determine empirically whether each of these measures is associated with trust in online social networks, and to what extent.

We also formally shed new light on the intuitive notion that measures of friendship and tie formation on Facebook may function differently online versus the way they do in the physical world.[5] The ease of "friending" someone online leads us to look for latent-heterogeneity among how trusting users are of their friends, and specifically whether this varies with the number of Facebook friends they have. Establishing how much variation might exist in the linkage between (a) the dynamic and behavioral strength of tie measures that can be captured from such networks, and (b) levels of trust between friends is essential if we want to tap the true potential of the reservoir of economic and social capital contained in population-scale online networks, and thus, this is the (natural) focus of our research.

Our study is modeled along the lines of Rosenblat and Mobius (2009) and comprises three stages, as depicted in Figure 1 below. The first stage establishes the positive effect of social capital on trust, consistent with theoretical expectations. By comparing anonymous pairings, where subjects do not know the identity of the person they are paired with, with non-anonymous trust levels, we establish the methodological validity of our Facebook based protocol (Rosenblat and Mobius 2009; Leider et al. 2010). The second stage of our design addresses our research question directly by focusing only on those pairs where identities are known, incorporating three strength of ties measures derived from the interaction data we collect through the Facebook API. Specifically these measures are: 1) the number of

[4] We use the terms "friendship" and "friends" as they are commonly used when referring to Facebook connections in the cultural dialog. Simply put, a "friendship" denotes a connection between two individuals on Facebook.
[5] http://www.huffingtonpost.com/kari-henley/are-facebook-friends-real_b_180204.html

shared wall posts, 2) the number of photos in which the dyad is mutually tagged, and 3) a normalized measure of the number of common friends shared between the dyad, which, following the literature, we label "*embeddedness*".[6] In the third stage of the research design,we estimate an empirical model using the trust measures gathered in Stage 1 as the dependent variable, and test its association with the strength of ties measures gathered in Stage 2. Of particular interest is whether the strength of tie measures provide explanatory power about observed trust.

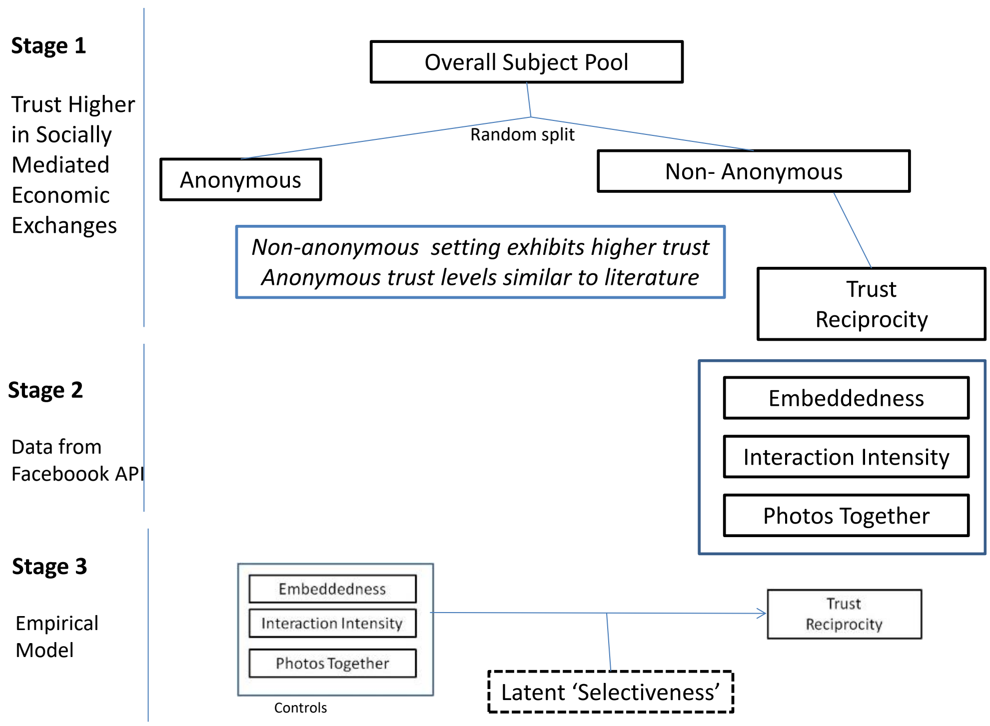

Figure 1: Research Schema – We use the Investment Game in Stage 1 to obtain the Trust Measure, Strength of Tie Measures are matched in Stage 2, and an Empirical Model is developed in Stage 3 to Link Strength of Ties Obtained from Facebook to Trust

Our approach advances prior network based studies because it leverages an exogenously created (and "real") social network as the basis for inferring social ties. Thus, we avoid potential issues of generalizability that arise from using artificially created networks. For example, prior work in this area has commonly built artificial social networks in a laboratory or in similarly stylized online settings

[6] At the request of an anonymous reviewer we define this measure as: $Embeddedness_{s,r}$ = (*number of common friends*)$_{s,r}$/*total number of friends*$_{s,r}$; however, we also run our tests using $Embeddedness_{s,r}$ = (*number of common friends*)$_{s,r}$/*min* (k_s -1, k_j -1) where k_s and k_r are the network degree of the Sender and Receiver respectively. This second variation of the embeddedness measure takes into account the fact that embeddedness is a dyadic function, where both the Sender and the Receiver can impact the number of mutual friends independent of the other. Results for this second measure are are not presented for brevity's sake, however results hold for both specifications.

(e.g., Suri and Watts 2010), which creates natural concerns about the robustness of the network as well as the true nature of what are being thought of as "social" ties. Using a pre-formed network that is exogenous to our study allows us to instead use actual social relationships as the basis for measuring social ties between individuals.

Our initial empirical analysis finds that for a typical user in our subject pool, the average number of wallposts shared by the dyad has a significant association with trust. Surprisingly, however (and again for the average user in our sample), other measures of social distance were not significantly associated with economic trust. Based on the conjecture that not all social ties are created equal, we next examine whether there is latent heterogeneity in the normative view Facebook users have of friendship. We do so by estimating a switching regression model, wherein the observations are endogenously partitioned into two regimes. Results from this latter analysis show that individuals with fewer total Facebook friends exhibit different associations between trust and social ties than those with more Facebook friends. Specifically, we find that for Facebook users with fewer listed friends (those that are arguably more selective in accepting friend requests), all three online social tie strength metrics are significantly and positively linked to trust. In contrast, for users with a larger number of friends (those that are perhaps less discriminating in what they consider a Facebook friendship), the only measure that empirically explains variation in observed trust is whether the dyad was tagged in the same photo.[7] This finding also suggests offline indicators of friendship might be the most robust measure of social distance for these types of users. To the best of our knowledge, ours is one of the first studies to rigorously investigate the nuanced nature of friendship in online social networks and link it to trust in an economic setting.

The following section discusses the background for this work, drawing on related literature. We then provide a brief description of the Investment Game and the specific measurements that proxy for the strength of social ties within pairs. Next we report our results and their implications, and conclude with a summary of limitations and conclusions.

2. Background

2.1 Trust and Trustworthiness

Some notion of trust as an important determinant of outcomes permeates a variety of academic disciplines, including economics (e.g., Dasgupta 1988), social psychology (e.g. Leqwicki and Bunker 1995; Lindskold 1978), and marketing (e.g. Anderson and Weitx 1989; Dwyer et al. 1987). Universally, trust

[7] We collect data from participant's Facebook wall during a three month period and identify any photo tags that occur during this window.

can be defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor" (Mayer et al. 1995). A particularly useful definition in the context of economic interaction comes from a 1990 book by the sociologist James Coleman, who defined trust as *a willingness to commit to a collaborative effort before you know how the other person will behave.* Trust has also been referred to as "an important lubricant of a social system" (Arrow 1974) and has been shown theoretically to be important in economic exchanges. In some cases trust has also been shown to reduce transaction costs by mitigating opportunistic behavior (Bromiley and Cummings 1995). There is precedent to viewing trust as something which ensues when an individual calculates the costs and/or rewards of cheating, and upon determining that it would not be in the best interest of one party to cheat, assumes that party can be trusted (Lindskold 1978; Akerlof 1970). Related work examines trust building within anonymous exchanges (Ho and Weigelt 2005) and the relationship between social ties and trust in knowledge transfer outcomes (Levin and Cross 2004). Work looking at the influence of technologically mediated exchange on trust and deception within distributed teams shows that in some cases mediation can lead to greater trust when compared to face-to-face communication (Burgoon 2003). Evolutionary models suggest that trust maximizes genetic fitness and therefore, is likely to eventually emerge in spite of self-interested motives. This suggests that trust can be viewed as a primitive to guide behavior in new situations (Berg et al. 1995).

Trust and trustworthiness play an important role in facilitating online economic exchange, as demonstrated when considering the dynamics within buyer and seller dyads (Rice 2012). For example, upon deciding to engage in an online economic transaction a buyer must move first and pay for the good before it is shipped. In other words, the buyer must initially trust that the seller will deliver the good as promised, and in doing so allocate payment to that seller before receipt of the good. If a seller's trustworthiness is deemed low it is less likely the buyer will trust that seller and either the exchange may not occur, or the seller's willingness to pay for the good will be lower to reflect the perceived riskiness of the transaction.

Prior empirical research examining differential trust[8] (Leider et al. 2010) has been restricted to highly specialized networks, or has been limited to revealing gender or ethnicity (Bohnet and Zeckhauser 2004; Eckel and Grossman 2006; Eckel and Wilson 2003; Fershtman and Gneezy 2001). Experimental work incorporating game theoretic design offers insights regarding factors that can impact individual levels of trust in economic exchanges, such as reputation and social history (e.g., Bolton et al. 2001).

[8] As opposed to measuring absolute trust between strangers.

Other work looking at the importance of trust formation (e.g., McKnight 1998), shows that early development of trust is critical to establishing functional organizational relationships. Our approach differs from this prior literature in that we do not focus on the formation of trust, rather we look at trust within established social ties in a large online social network, the dynamics and fundamental constructs of which are not yet fully understood.

2.2 The Strength of Social Ties

The concept of tie strength can be defined as the following: "The strength of a tie is a combination of the amount of time, the emotional intensity, the intimacy, and the reciprocal services which characterize the tie" (Granovetter 1973). Two types of ties are commonly referred to in the literature. One is a weak social tie, which is a link between two individuals who are not closely connected, such as casual acquaintances or co-workers who do not interact regularly. The other is a strong social tie, which refers to the connection between close friends who interact frequently. Studies on the effects of tie strength show both strong and weak ties have an impact on information dissemination (Granovetter 1973), job seeking (Granovetter 1974; Bridges and Villemez 1986), and income levels (Simon and Warner 1992; Gorcoran et al. 1980). Experimental work that investigates the formation of social ties using public good experiments shows that tie formation is contingent upon the success of the game. The aggregation of individual ties comprises a social network, and the importance of social network structure on the formation of trust has been touted in the social psychology literature. Additionally, work by Karlan et al. (2009) models a setting where social structures are used as collateral in procuring loans, showing that networks can build trust when agents use their connections as social collateral.

2.3 The Link between Trust and Social Ties

Our conceptualization of the connection between trust and social ties starts from Burt (1992) who shows that when two friends share a friend (or in the language of social networks, when there is triadic closure in the friendship) there is likely to be a greater level of trust between the dyad. There are a number of studies that have examined the question of social distance in the context of the trust game,[9] including Buchan et al. (2006) which finds that factors such as ethnicity and geographic proximity hold weight in explaining observed differences in trust. Specifically they show that other regarding preferences are influenced by the country of origin when the trust game is played against varying nationalities. Etang et al. (2011) play the investment game with participants in Cameroon, where some

[9] Trust Game and Investment Game are used interchangeably.

pairs are from the same village and others are from different villages. Similar to prior work, they find significantly more money is sent on average when players are from the same village. Related work by Buchan et al. (2002) shows that cooperation decreases as social distance increases, in part due to the interaction of culture and social identity and its effect on trust. Work by Binzel and Fehr (2013) compares the determinants of trusting a stranger to those of trusting a member of an individual's social network (i.e., a friend). They implement the trust game with a powerful within-subject design to find that trust is based on the estimated trustworthiness of the reciprocating party. However, what is most interesting about their finding is the first mover's assessment of the other's trustworthiness is no more accurate in the friend pairing than in the stranger pairing. The implication is that social networks may not be perfect substitutes for formal institutions, as they may not be able to resolve inefficiencies that arise from information asymmetries.

Recent studies on the effects of social structure on other regarding behavior in an offline setting include work by Leider et al. (2010) and Rosenblat and Mobius (2009), in which each map a friendship network using a combination of surveys and truth-telling inducing tasks to evaluate strength of ties between individuals. Trust is measured as a function of self-reported social distance and the authors find that friends exhibit higher levels of trust than non-friend pairings. Work by Glaeser et al. (2000) uses two different experiments, a trust game and a risk game, along with a survey, to identify individual and situational predictors of trust. Of important relevance to our paper is their finding that increasing social proximity increases both trust and trustworthiness. Specifically they find the degree of social connections between sender and receiver, and the duration of their friendship, all predict trust and trustworthiness in the trust game. Interestingly, they find risk profiles may not have any bearing on the amount sent in this exchange. Other experimental work investigating the effects of social ties on trust and altruism does so by first creating a network in the laboratory, and then testing behavioral effects on those same networks (Di Cagno and Sciubba 2008). Methodologically our work differs from these earlier studies in that we do not contrive an artificial network in a laboratory, or rely on self-reported measures regarding friend relations. Moreover, we aim to test whether these results hold when tested in an online social network where tie formation and social interactions likely differ from more traditional offline settings.

3. Methodology

3.1 Research Design and Procedures

To address our research question we developed a Facebook app to play the well-established Investment Game and generate a quantifiable measure of trust. The game is played in pairs, where one person is the Sender and the other person is the Receiver. The game begins with the Sender (first mover) receiving an endowment, which in our study is $10. The Sender is then asked how much of this endowment he/she would like to send the Receiver (second mover). Any amount sent is tripled, thereby increasing the overall pie, and upon receipt of the Sender's allocation the Receiver decides how much to return. This single shot game concludes after the Sender learns of the Receiver's return choice, and payoffs are reported to both players. Players are paid by depositing money into their designated PayPal account or by mailed check.[10] The game is depicted in Figure 2.

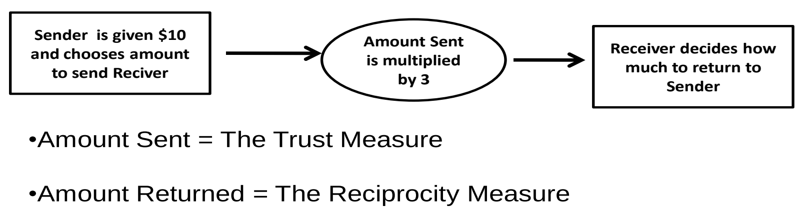

Figure 2: Schematic of the Investment Game

The sub-game perfect equilibrium for a single shot Investment Game played between anonymous players is one where Receivers expropriate the entire amount invested by Senders, and so Senders opt not to invest. However, when players know each other the resultant accountability changes this equilibrium prediction, as social concerns become a rational input that may drive non-pecuniary preferences. In the investment game the first mover is the *trustor*, so in our setting the Sender must trust that the Receiver will return an amount deemed worthy of play. As such, the trust metric in the Investment Game is the monetary amount sent by the Sender to the Receiver. The other metric is the measure of reciprocity exhibited by the Receiver, which is the amount he or she returns to the Sender. Typically this analysis is secondary and relatively straight forward, as it tends to be overwhelmingly driven by the amount invested by the Sender. Our results of the Receiver analysis are consistent with these prior findings[11] and are shown in the Appendix.

Subjects were recruited to play our game via a hybrid online-offline snowball sampling method. An initial email was sent to class lists where instructor permission was granted among a variety of upper

[10]Sender payoffs: $10 – (amount sent) + (amount returned); Receiver payoffs: 3x (amount sent) – (amount returned)

[11] We point out that within the methodology of experimental economics the goal is to explain behavior in the aggregate rather than among individual subsets of the population. Therefore, while studies such as McKnight (2002) parse trust into multiple psychometric dimensions that could vary by individual, our randomized design allows us to interpret results as mean behavior of the population (Croson 2005).

level undergraduate and MBA level classes. Out of approximately 600 emails initially sent, 190 people signed up for our Facebook API and became part of the subject pool. The initial subject pool was also given a feature to invite their friends via Facebook. Each individual was given $5 as payment for signing up. The basic requirement was that non-anonymous pairings be known "friends" on Facebook, in order to ensure there was an existing social tie to analyze. We also required that the exchange was completed within twenty four hours. In these non-anonymous games each player knew the identity of their partner, and each was included on the other's friend list.[12] When subjects were selected to play the game they were sent an email providing instructions as to how to proceed. Prior to the start of each game participants read written instructions, had the option to receive further instruction via a YouTube video[13], and were required to get all answers correct on a quiz that tested comprehension of the game rules.[14] The Sender/Receiver exchange occurred via email within the Facebook API. Players were first told the role to which they were randomly assigned, and then the Sender was sent an email containing a link to the decision screen (Figure 3). After the Sender's investment decision was made the Receiver was sent an email notification reporting that choice, and which also contained a link to the response screen. After the Receiver submitted his or her return amount the game ended and payoffs were reported to each player in a follow up email. Each individual only played one round of the game and subjects never switched roles at any time. After one round of the game both players were removed from the pool of future eligible subjects.

Our initial pilot tests revealed (via a post-game survey) strong tendencies towards collusion among participants who knew each other well, which prompted several iterations of the design in attempts to mitigate this potential confound. Thus, for the final data collection event each Sender was matched with three different and randomly[15] chosen Receivers, each of whom was a Facebook friend of that Sender. To be clear, an individual was first randomly selected to play the game and a coin toss was used to determine whether that person would assume the role of Sender or Receiver. Next, if the selected individual was deemed a Sender we randomly selected three of his or her friends to assume the role of Receiver. Once allocation decisions were input by the Sender our system randomly chose and *implemented only one* of the three potential Receivers to actually complete the game; however, none of the players nor the game administrators knew who would be chosen as the actual Receiver. The point of using three potential Receivers, only one of whom was subsequently implemented, was to increase

[12] Anonymous players in the validity treatments were never told the identity of the person they were paired with and were for the most part not friends on Facebook.
[13] http://www.youtube.com/watch?v=na1Pe39XYO8
[14] Display panels of the game protocol are available from the authors upon request.
[15] Pairings were computer generated.

the costs of collusion such that subjects would be deterred from doing so. With this design modification in place, we again asked participants in a post-game questionnaire if they attempted to collude with their matched partners and their overwhelming response was that they did not.

We believe this element of our design, which we adopted from the experimental economics literature (e.g., Leider et al. 2010), has multiple strengths. First, it forces the Sender to assess the underlying level of trust as a function of varying social tie strength between the three Receivers, which is exactly the effect we want to capture. Second, although only one Receiver was randomly selected to complete the game, Senders had no information as to which Receiver this might be, as this choice was made randomly by the computerized delivery system. Because of the stochastic nature of the outcome, Sender's choices were theoretically equivalent to a setting where all three Receivers are chosen to complete the game. That is, because Senders could not predict which of the three Receivers would actually play the second stage, the rational response was to treat *all* Receivers as though they were the paired outcome. When the Sender has incomplete information as to which Receiver will be chosen, the equilibrium is to behave as though they all would be selected (Varian 1992). This is one of the nuances of the design that permits us to conserve economic resources while also gaining insight into the tradeoffs made as a function of the variables of interest. The design is also economical because our protocol pairs a randomly selected Sender with three randomly selected and known Facebook "friends", giving us three dyadic data points using four subjects, whereas a classic between subjects design would require six subjects to gather the same amount of information. To empirically address the issue of multiple observations per individual Sender, we use panel data techniques (i.e., clustering by Sender due to the three separate Receiver choices) to account for the possibility of systematic and correlated errors across each Sender.

As mentioned earlier, the Sender was given a $10 endowment for *each* Receiver choice, and Senders were asked to indicate how much of the $10 endowment they would send to *each* of the three Receivers shown on their screen. In other words, Sender's received a total of $30 at the start of the round, and the most that could be sent to each Receiver was $10. Senders and Receivers were recruited in the same manner and of these groupings we ended up with a total of 77 completed games to analyze. There were several cases where either the Sender or the Receiver did not make a move and we removed these incomplete games from our dataset.[16] We found no bias among those games that were

[16] There were a total of seven games that did not complete in the twenty four hour window allotted and these were removed from the study. There were an additional five games where the Sender never responded to the email initiating the game and these were also removed from the study. Failure to initiate the game was not treated the same way as Senders who specified $0 as their first move.

not started or completed. Figure 3 depicts a screenshot of what the Sender saw at the start of the game.

Figure 3: Screenshot of Sender's Move in the Facebook Investment Game

While obtaining subjects from which general inferences can be drawn is a challenge in most experimental settings, it becomes particularly so when implementing our study in a real-world social network. While Facebook is a large global network, the effects that we are interested in, namely the heterogeneity in the strength of ties, are local and materialize at the dyadic level. Thus, it is not enough to get a subject pool of a certain size to meet the power requirements of statistical inference. In addition, the subject pool must exhibit sufficient network connectedness, and often these can be conflicting in their impact on the overall research. For instance, while it seems appealing to have participants from a large geographical swath of users, such a sample might be relatively less clustered than subjects who were members of an interest group, a company, or a university. Given that our unit of analysis is a connected friend dyad, a large random sample of unconnected global users would be useless. Thus, there is a classic *generality-clustering trade off* in the sampling procedure for social network based economic games of the sort we are interested in. We expect this to be an interesting area for future developments in the design of network field studies and empirical research.

3.2 Measuring the Strength of Social Ties

Quantifying the strength of social ties between individuals in an online social network is a critical aspect of our study. We achieve this by incorporating two measures validated by Gilbert and Kavahalois (2009), and a third measure from the social networks literature, to estimate tie strength based on readily available information found on individual Facebook pages. The Gilbert and Kavahalois study identifies two primary factors that help explain much of their predictive tie strength model. The first measure is the number of common wall posts shared between Sender and Receiver (*WallPostShared*). The second strength of ties measure is the number of tagged photos (*PhotosTagged*) [17], meaning the number of instances where the Sender was tagged in the Receiver's photo, or vice versa. Because our data was collected within a three month window and we could only observe activity during that time, we did not have access to more historical data. As a result of this restriction the most common number of photos tagged during the three months of observation is one. There are only five cases where two common tags occurred in this period and only two instances where the number of photos tagged was greater than two. Due to the skewed nature of the data we collapse tagged photos into a binary measure and code it as one if there is *any* photo tagged between the dyad within our three month window of data collection, and zero otherwise.[18]

We incorporate the sociology and social networking literature to define a measure that is a function of the number of mutual friends shared between two people (e.g., Granovetter 1973, 1974). We refer to this measure as embeddedness (*Embed*), which is defined as:

$Embed_{s,r} = (\textit{number of common friends})_{s,r} / \textit{total number of friends}_{s,r}$

In our empirical analysis, we also control for Sender and Receiver type by including his or her network degree centrality (*ReceiverDegree, SenderDegree*), as well as the overall activity level of the users, captured as the total number of wall posts each has received in the last three months (*ReceiverWall*, *SenderWall*). We also control for the gender of both Sender and Receiver.

4. Analysis and Results

4.1 Trust in Socially Mediated Exchanges

The first step in our research program establishes the methodological validity of our Facebook based protocol for playing the Investment Game. We achieved this by comparing an anonymous version of the Investment Game to the non-anonymous version of the game, and found that the levels of trust and reciprocity were not significantly different from the range of values observed by Berg et al. (1995).[19] As expected, the average amounts sent and returned in the non-anonymous treatment were higher than in the anonymous treatment. These comparisons are statistically significant and are consistent

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[17] We include the square term of WallPostsShared, *WallPostShared SQR,* to account for the possibility of a non-linear relationship.

[18] We also ran our models with the raw number of photos tagged and results are the same.

[19] Berg et al. (1995) find in the anonymous treatments approximately 90% of subjects sent amounts greater than $0, even though the theoretical expectation is for all to send $0. Scaled to our $10 endowment, Berg et al. find average return in the anonymous treatments was approximately -$5 and in the non-anonymous treatments the average return was approximately $10.10. The number of subjects per treatment in Berg et al. (1995) ranges from 33 to 52.

with expectations based on extensive prior literature, namely that strangers are more trusting when identities are known. While the findings are relatively intuitive, and are not directly related to our research question, it was important to conduct this manipulation within our setting to further validate the design, thereby permitting us to move forward with our analysis of the non-anonymous treatment data.

4.2 Empirical Analysis of Trust Predictors

We turn to the non-anonymous data to explore the relationships between the strength of ties measures and Senders' level of trust. We begin by estimating an OLS regression model with clustered errors to account for Sender specific correlated errors across decisions.[20] Recall that users are first randomly selected to either the anonymous or non-anonymous treatment, and then, in the non-anonymous game users are paired randomly, under the condition they are already Facebook friends. This matching protocol avoids obvious selection problems that might have arisen from a non-randomized procedure, where users may have selected to play the game with those they trusted. Further, our design relies on collecting our dependent variable and independent variables from two separate processes, the former via our trust game application and the latter from naturally occurring field data from Facebook. This avoids common source bias (King et al 2007) and rules out sources of endogeneity such as reverse causality (e.g., people socially interacting with someone more because they acted in a trust worthy manner). Consistent with the economics literature, we use the natural log of the amount sent by the Sender to the Receiver as our dependent variable. Descriptive statistics for all variables included in our analyses are shown in the Appendix.

Because our variables of interest are correlated we first include each one individually in Models 1 through 3, then combine them into a comprehensive model (Model 4). It is important to note that while these measures are correlated, theoretically and econometrically they are not perfect substitutes, so the inferences one can make from Model 4 are with respect to marginal differences. We test for muticolliniarity in each model, and while the highest variance inflation factor is reported in Model 4, the score is still well below the threshold of 10, indicating the multicollinearity is not obviously problematic. Results of the OLS regression are reported in Table 3.[21]

	Model 1		Model 2		Model 3		Model 4	
	Coeff	P>t	Coeff	P>t	Coeff	P>t	Coeff	P>t

[20] As a reminder, Senders designate amounts for three different possible Receivers, only one of whom is randomly selected to complete the exchange. So when analyzing the amount sent in order to account for the possibility of correlated errors across these three choices we must cluster the choice by Sender.
[21] Recall each Sender was paired with three Receivers so we must cluster by Sender to account for correlated errors across each of the three choices.

Constant	1.21300	0.01***	1.31618	0.003***	1.31232	0.008***	1.3528	0.01***
Embed					-0.01820	0.984	-0.14027	0.885
SenderWall	0.00019	0.607	0.00028	0.415	0.00014	0.719	0.00028	0.770
SenderDegree	-0.00048	0.442	-0.00079	0.195	-0.00044	0.510	-0.00081	0.209
ReceiverDegree	0.00042	0.152	0.00023	0.403	0.00033	0.172	0.00024	0.280
WallPostShared			0.14668	0.023**			0.15408	0.036**
WallPostSharedSQR			-0.00538	0.032**			-0.00561	0.048**
PhotosAny	0.25531	0.164					-0.04128	0.839
ReceiverWall	0.00046	0.507	0.00052	0.466	0.00038	0.578	0.00052	0.482
Sender Male	0.65630	0.055*	0.62618	0.063*	0.607102	0.066*	0.62310	0.063**
Receiver Male	0.0904	0.630	0.06164	0.72	0.11327	0.559	0.054054	0.729
R^2		.22		.28		.20		.28
VIF		1.50		4.73		1.54		4.51

Table 3: How trust is related to direct and "shared friends" measures of the strength of ties

DV =natural log of the amount "trusted" by the Sender to their Receiver; errors are clustered by Sender

Embed = *number of common friends$_{s,r}$/total number of friends$_s$*

PhotosTagged = coded as 1 if there are any photos of the dyad tagged, and zero otherwise

WallPostShared = total number of times Sender/Receiver post on the others wall

ReceiverWall/SenderWall = total number of wallposts for each player

ReceiverDegree/SenderDegree = network degree centrality for each player, total number of Facebook Friends[22]

ReceiverMale/SenderMale = Control variables for Reciever/Sender Gender

We find that each additional wall-post made on a friend's wall is associated with an increase in trust. Surprisingly, we find that instances of photo tagging (a signal of social affinity and physical world ties) has no significant association with an increase in trust. However, the result we find most striking is that the coefficient of *Embeddedness* is also insignificant. This runs counter to social networks literature, which suggests that triadic closure signals a stronger tie (which in turn should be associated with higher trust). It also counters literature suggesting that trust is directly enhanced by the presence of shared friends, either through an increase in the "bandwidth" of the channel or an increase in the "echo", the threat of being ostracized by shared friends for untrustworthy behavior (Burt 1992). This unexpected result motivates us to deepen our understanding as to the true nature of friendship ties in online social networks such as Facebook.

4.3 A Closer Look at the Nature of Friendship Link Formation on Facebook

It is important to acknowledge that social connections within the Facebook network are likely quite heterogeneous across the population, such that some users are more likely to form mostly close social ties, while others may also have a large number of weaker links. Weak connections may be established based on fleeting shared activities, business affiliations or simply casual interest (e.g., "I like

[22] At the suggestion of an anonymous reviewer we also ran the analysis with log transformed degree centrality measures. Inferences remained unchanged, although goodness of fit was negatively impacted (R^2 dropped to .19). We report the raw degree centrality measures in Table 3.

your picture, let's be friends") and it is reasonable to assume that users with a large number of friends might also have a large number of both strong ties *and* weak ties. Alternatively, it could be the case that users with fewer friends might be more selective in who they choose to connect with or are relatively new to Facebook, which suggests the possibility that for this group of users the majority of their Facebook ties are strong.

Towards uncovering some of this latent heterogeneity in user type we first partition Senders by splitting their total number of Facebook friends at the median and classifying users with more friends as MF Users and users with fewer friends as FF Users. We do the same with Receivers and then compare means as a function of both the Sender and Receiver number of friends. We first find that on average, Senders with fewer friends (FF Users) send more than Senders with more friends (MF Users). Specifically, FF Users send an average amount of $7.04 while MF Users send an average amount of $5.80. Next, to explore whether Receiver type plays a role in Sender's investment choice we identify pairings where both Sender and Receiver have many friends (MF Pair) and fewer friends (FF Pair). For completeness we also include the marginal pairs, where Sender's have fewer friends (FF Send) and Receivers have more friends (MF Rec), and conversely when Senders have more friends (MF Send) and Receivers have fewer friends (FF Rec). We are most interested in seeing if conditioning our analysis on user type can provide additional insights into our findings and further our model of trust. These means are shown in Table 4.

	MF Pair	MF Send FF Rec	FF Send MF Rec	FF Pair
Amount Sent	$3.84	$7.30	$7.70	$7.35
Mutual Friends	93	34	64	33
Sender Total Friends	637	668	292	319
Receiver Total Friends	677	115	676	293

Table 4: Descriptive Mean Comparisons of Sender and Receiver Pairings

Table 4 shows that on average, observed trust in the MF Pair is by far the lowest of the four dyads. We find no statistical difference between the average amounts of trust observed in the other three groups. However, the extreme difference in the average amount sent in the MF User pairing is stark and suggests further scrutiny of user type is warranted. Thus, we estimate a switching regression model (Maddala 1975, Lokshin and Sajaia 2004) with two regimes. The observations are endogenously partitioned into two sets based on the Senders' total number of Facebook friends, which reflects an underlying latent model that links trust to social tie characteristics. By design, the switching regression assumes non-linearity among the covariates. The partition between the two regimes is such that it maximizes the likelihood of observing the realized data and assigns a probability to each Sender as to whether he or she is a FF or MF User. In particular, the model we estimate using maximum likelihood describes the differential behavior of FF and MF Facebook Users under two latent regimes identified by a criteria function I_i, such that:

$$Regime\ FF: I_i = 1\ if\ \rho Z_i + u_i > 0$$

$$Regime\ MF: I_i = 0\ if\ \rho Z_i + u_i \leq 0$$

$$\begin{aligned} Regime\ FF: (AMTSENT &= \alpha + \beta_1 WallPostShared + \beta_2 PhotosTagged + \beta_3 Embed + \beta_4 MutulFriends \\ &+ ReceiverLO + \varepsilon_{1i}\ if \quad I_i = 1 \end{aligned} \qquad (1)$$

$$\begin{aligned} Regime\ MF: (AMTSENT &= \alpha + \delta_1 WallPostShared + \delta_2 PhotosTagged + \delta_3 Embed \\ &+ MutualFriends + \delta_5 ReceiverLO + \varepsilon_{2i}\ if \quad I_i = 0 \end{aligned} \qquad (2)$$

Note I_i^*, which in general is the utility of participating in a certain manner (in our case its being FF or MF), as determined by Z_i (a vector of characteristics that influence the participation) is not observed, but when it exceeds a certain (a priori unknown) threshold, the individual decides to participate. This is endogenously estimated. The corresponding observable variable I_i is dichotomous, and takes the value 1 if the individual 'participates' (in our case if the person has greater than median number of friends) and is 0 if he/she does not 'participate.' The errors u_i, e_{1i}, e_{2i}, have a trivariate normal distribution with mean zero. Note that the covariates corresponding to $\mathbf{Z}$ in the selection equation to assign the Sender's regime (whether the Sender is endogenously selected into the MF or FF regime) include a binary variable for his or her degree centrality (high or low), as well as the Sender's wall count, and a control for gender. The model includes our social distance measures of *Embed*, *WallPostShared* and *PhotosTagged,* along with *ReceiverLO,* which is a dummy variable coded as 1 if the Receiver's total number of Facebook friends is lower than the median. We include this variable in the model to further examine whether the Receiver's type has some impact on the amount sent and that FF User pairings differ from MF User pairings.

Results of the maximum likelihood estimation of the switching regression for FF and MF Users are shown below in Table 5.

	FF User		MF User	
	Coefficient	P>t	Coefficient	P>t
Constant	-0.788	0.00***	6.49	0.000***
Embed	0.019	0.00***	2.44	0.151
PhotosTagged	0.068	0.00***	0.26	0.017**
WallPostShared	0.396	0.00***	0.244	0.151
Receiver LO	9.80	0.00***	-1.020	0.253

Table 5: Switching Regression Results for FF and MF Facebook Users (errors clustered by Sender)

Our results show those individuals with fewer total Facebook friends (FF User) exhibit markedly different outcomes than individuals with more Facebook friends (MF User). Specifically, for those users with fewer Facebook friends, our social distance measures (both behavioral and structural) all have a significant association with the amount sent. One explanation is that FF Users may have stronger connections with Facebook friends and this may extend beyond an online medium. As such, the larger number of strong ties increases the likelihood of observing higher levels of trust within that population. The number of wall posts shared by the dyad represents communication, while tagged photos suggest an offline connection, and both seem more apt to encompass trust in the FF User. At the same time, the coefficient on *ReceiverLO* is also significant and positive suggesting Receiver's with fewer friends appear to be more trusted by Senders of the same type.

Turning to our results for non-selective users, we find the only significant factor in explaining trust levels is whether the dyad appeared in photos together during our three month data collection window. One explanation for this interesting finding is that a positive and significant coefficient on *PhotosTagged* (p-value = 0.017) serves as an indicator of trust by identifying strong offline connections. An offline friendship implies less social distance, which could help explain why the number of mutually tagged photos is positively associated with trust levels in both regimes, and holds the most explanatory power over the variation of trust within the MF User group.

Interestingly we find the coefficient on *Embed* is not significant for MF User's. One possible explanation for this finding is that as previously discussed, Senders with a lot of friends may have a large proportion of both strong ties and weak ties in their network. To the extent this is true, the insignificant coefficient on *Embed* may reflect the fact this usually robust measure of triadic closure does not effectively distinguish between strong versus weak ties. Specifically, the lack of significance on our social distance coefficients among MF Users could be due to the fact our measures capture *average* tie strength, and are not able to separate out strong versus weak ties. Therefore, based on our results we cannot say MF Users are less trusting of their Facebook friends, we can only say this measure may not capture the variation in tie strength within their social network.

5. Discussion and Conclusion

As large-scale online social networks consume an ever-increasing portion of our time and attention, and as trust serves as a primitive for the spread of social and economic influence in such networks, this study informs us on the relative importance of key strength of ties measures that can be computed from observing users' activities. We differentiate between two types of users based on their total number of Facebook friends by estimating a maximum likelihood endogenous switching regression model with two regimes based on the total number of Facebook friends. Our results show that individuals with fewer total number of Facebook friends exhibit different outcomes than those with a greater number of Facebook friends. Specifically, our social distance measures are all positive and significantly associated with trust for FF Users, perhaps due to their propensity for greater discretion in acquiring Facebook friends, or their relatively new Facebook membership. For those users with more Facebook friends, we find only our measure reflecting an offline relationship (*PhotosTagged*) has a significant association with trust. This suggests our other measures of social distance may be ineffective for users with a larger number of friends, and perhaps photo tagging is the best predictor of strong ties for this population.

There are several limitations of this study that should be considered, and which could prove important in developing extensions of this work. One potential limitation is the choice to use student subjects which could restrict the generalizability of our findings. However, these concerns are only specific to our not having access to the entire Facebook social graph thus, we do not believe that they are a critique of our method. For instance, a data scientist at Facebook running the same analysis would have no such limitations. Further, given the sophistication of the average user in our age demographic, we believe this is an ideal group to employ for our study. We did not rely on general advertising on Facebook to recruit subjects because we were likely to get a network structure that was not clustered or connected enough. However, a case could be made that our sophisticated users are not as heterogeneous as might be preferred.

Another limitation of this study is our smaller sample size. While the original Berg et al (1995) study had 32 pairs as their sample size, a meta-analysis of future replications reported that the median subject pool size of prior studies is 140 (Johnson and Mislin 2011). Note that all of these are offline studies, and ours is one of the first instances of an online replication. As we experienced, subject recruitment in online networks for economic games is different and not yet a common practice. Nevertheless, while statistical significance does not seem to be an issue for our study, more data would increase statistical power and strengthen the veracity of our inferences. Also, there are limitations to the type of data we can collect from Facebook. We would like to have had more demographic information about users, such as the amount of time they had been on Facebook, ethnicities, and common affiliations. In experimental work there is always a possibility that results could be attributed to subjects' latent characteristics, and more finely partitioned data may help control for these unobservables. Unfortunately we did not have the option to collect this data at the time of the experiment, therefore further refining our model could be a topic for future work if more specific data becomes available. Additionally, time stamps on photos, text analysis of wall posts, and information about individual's overall usage of social media could offer additional measures that might help explain exhibited trust in our setting.

A final limitation of this work is the possibility that observed behavior, as per our trust measure, could be influenced by varying preferences for kindness or different types of risk aversion. Looking more closely at how different levels of risk tolerance could impact behavior might be an interesting extension to our work. For example, it is plausible a risk averse individual would invest less even when social ties are strong, or perhaps not invest at all when ties are weak. Risk seeking individuals might invest more, relative to risk averse individuals, even when social ties are weak or even non-existent. However, Etang et al. (2011) show that Trust Game transfers are uncorrelated with risk attitudes, hence the effect of risk profiles on our results is unclear. Further exploring these possibilities seems like a rich opportunity for future research. Specifically, researchers could employ well-validated surveys such as the one presented in Weber et al. (2002) to quantify individual risk profiles, and then use these measures as covariates to test whether they explain variation in observed trust in this setting.

Our work is just one of many ways a game theoretic design can be implemented to refine big data. In a business context, we expect such methods to improve our understanding of consumer preferences, as well as pinpoint causal mechanisms underlying peer-to-peer influence and targeted marketing (Aral 2011; Aral, Muchnik and Sundararajan 2009; Bapna and Umyarov 2015). Our results also speak to practical applications in the areas of on-line product marketing and development, suggesting care be taken when identifying influential users in online social networks. Overall, we showcase how large-scale online social networks can serve as platform to bring social science and behavioral economics research to a highly generalizable real-world context. We believe our protocol can be extended to play anonymous repeated investment games, using say an infinite (implemented as uncertain number of rounds) horizon, and this can be compared with a one shot non-anonymous social game. Thus, we would randomize the shadow of the future to isolate the effect of the shadow of the past from social ties versus repeated exchanges.

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Appendix A

Figure 1: Variable Definitions

AmtSent	The amount sent to the Receiver
LNAmtSent	The natural log of the amount sent to the Receiver
AmtReturned	The amount returned by the Receiver
PhotosTagged	Coded as 1 if at any point in the 3 month data collection window the dyad was tagged in a photo together.
WallPostShared	The number of wallposts exchanged by Sender and Receiver
ReceiverDegree	The Network Degree of the Receiver
ReceiverWall	The number of total posts on the Receiver's wall
ReceiverLO	Coded as 1 if the total number of Receiver friends is below the median
SenderDegree	The network degree of the Sender
SenderWall	The total number of posts on the Sender's wall
Embed	A normalized measure of common friends: (number of common friends)$_{s,r}$/total number of friends$_{s,r}$

Figure 2: Descriptive Statistics

Variable	Mean	Std Dev	Median
AmtSent	6.38	3.59	6
LNAmtSent	2.07	0.584	1.83
AmtReturned	10.23	8.69	8
PhotosTagged	2.22	15.88	0.000
WallPostShared	1.73	3.48	1.00
ReceiverDegree	502.29	254.37	502
ReceiverWall	141.45	163.15	101
ReceiverLO	0.456	0.502	0
SenderDegree	435.40	214.32	415
SenderWall	215.22	286.74	123
Embed	0.176	0.115	0.1617

Figure 3: Correlation of Facebook Strength of Ties Measures

	WallpostsShared	PhotosTagged	Embeddedness
WallPosts Shared	1.000		
PhotosTagged	0.052	1.000	
Embeddedness	0.207***	0.430***	1.00

NOTE: There is some level of correlation between our social network measures, however our VIF tests indicate we have no issues with multicollinearity in our regression analysis.

Figure 4: Reciprocity Analysis

Variable	Coefficient (std errors)	p-value (t-statistic)
Constant	-3.33 (4.28)	0.455 (-0.79)
Embeddedness	-0.003 (0.038)	0.944 (-0.07)
PhotosTagged	-0.023 (0.020)	0.27 (-1.14)
WallPostShared	0.592 (0.135)	0.002*** (4.37)
ReceiverWall	0.0003 (0.003)	0.921 (0.10)
SenderWall	0.0002 (0.004)	0.965 (0.05)
ReceiverDegree	0.005 (0.004)	0.164 (1.53)
SenderDegree	-0.006 (0.007)	0.363 (-0.96)
AmountSent	1.824 (0.227)	0.000*** (8.03)
VIF	1.56	
R square	.90	
Number of Dyads*	18	

DV= the total amount returned to the Sender by the Receiver

* By design we randomly select one Receiver out of each Sender's three investment choices, therefore we have fewer Receiver decision points.

OLS Regression Results of Reciprocity