Repeated Interactions vs. Social Ties: Quantifying the Economic Value of Trust, Forgiveness, and Reputation Using a Field Experiment\textsuperscript{1}

Ravi Bapna\textsuperscript{2}, Liangfei Qiu\textsuperscript{3}, Sarah Rice\textsuperscript{4}

Abstract

The growing importance of online social networks provides fertile ground for researchers seeking to gain a deeper understanding of fundamental constructs of human behavior, such as trust, forgiveness, and their linkage to social ties. To address the challenge of endogenous social ties, we design a field experiment that uses data from the Facebook API to measure social ties that connect our subjects, and show that the level of trust and forgiveness, and the effect of forgiveness on deterring future defections, crucially depend on the presence of social ties. We find that the level of trust under social repeated play is greater than the level of trust under anonymous repeated play, which in turn is greater than the level of trust under anonymous one shot games. We uncover forgiveness as a key mechanism that facilitates the cooperative equilibrium being more stable in the presence of social ties: If the trading partners are socially connected, the equilibrium is more likely to return to the original cooperative one after small disturbances.

Keywords: Trust, Forgiveness, Social Ties, Repeated Games

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\textsuperscript{2} Carlson School of Management, University of Minnesota, rbapna@umn.edu
\textsuperscript{3} Warrington College of Business Administration, University of Florida, liangfei.qiu@warrington.ufl.edu
\textsuperscript{4} Mays School of Business, Texas A&M University, srice@mays.tamu.edu
“The best way to find out if you can trust somebody is to trust them.”

~ Ernest Hemingway

1. Introduction

What determines trust levels between individuals? Granovetter (1985) offers two explanations: 1) “Individuals with whom one has a continuing relation have an economic motivation to be trustworthy, so as not to discourage future transactions” and 2) “Departing from pure economic motives, continuing economic relations often become overlaid with social content that carries strong expectations of trust and abstention from opportunism.” Following these two explanations, prior experimental literature confirms that trust can be sustained by repeated interactions between the same trading partners (Cochard et al. 2004; Ba and Pavlou 2002) or by the strength of social ties (Bapna et al. 2013; Bapna and Umyarov 2014; Rand et al. 2011; Sundararajan et al. 2013).

The growing importance of the online social graph, comprised of the two billion plus global citizens that are connected to each other by online social networks such as Facebook, Twitter, and “Weibo” in China, provides fertile ground for researchers seeking to gain a deeper understanding of fundamental constructs of human behavior, such as trust, forgiveness, and their linkage to social ties. If social capital, inherent in social ties, can indeed enhance trust built through repeated non-social interactions, then this has broader welfare implications in reducing frictions of market entry and in improving the allocative efficiency in a variety of emerging online platforms. For instance, consider trust mediated sharing platforms (Sundararajan 2013), such as the peer-to-peer room rental exchange, Airbnb. In such markets it could be argued that existing social ties could prompt potential renters to enter the market more readily. Further, we are also interested in
settings involve repeated interactions that can benefit from forgiving behavior, wherein cooperation is given a second chance (Fudenberg et al. 2012; Dal Bo and Fréchette 2011), we are interested in knowing to what extent forgiveness is influenced by the presence of social ties.

In both contexts, a challenge in the literature on repeated interactions and social ties is the econometric task of accounting for endogenous social ties (Manski 1993; Aral and Walker 2011; Godinho de Matos, Ferreira, and Krackhardt 2012). The reality, and possible confound, is that repeated interactions may create a context in which social ties can emerge as the outcome of a repeated relationships that take on a social element. As such, measuring the extent to which these repeated interactions can impact social distance and economic decision-making remains an important challenge, particularly when testing these associations empirically. For example, in many real-world markets, contracts specify traders’ obligations imprecisely and trading relations are riddled with informal agreements and unwritten codes of conduct. Subsequently, this type of relational contract is based upon a relationship of trust between parties, and has been widely studied analytically in the economics literature (Levin 2003). However, empirical evidence has been limited in part because it is almost impossible to generate ideal field data that permits researchers to separate whether successful long-term relations between trading parties are driven either by reputation built through repeated play or by social ties that emerge endogenously from long-term interactions. In other words, in the absence of third-party enforceability of contracts and institution-based trust (Pavlou and Gefen 2004), people care about the “identity” of their trading partners (Brown, Falk, and Fehr 2004; Forman, Ghose, and Wiesenfeld 2008; Taylor, Muchnik, and Aral 2014; Burtch, Ghose, and Wattal 2014). However, the identity could be based on what
they know about their partners’ reputation and/or based on the social accountability (social ties).

To address the challenge of endogenous social ties, we design a field experiment that uses data from the Facebook API to measure social ties between subjects, and subsequently deploy an interactive voice response system based randomized experiment (to avoid collusion between socially connected subjects in a repeated game setting) that implements our various treatments. Specifically, we manipulate the level of connectivity between individuals such that some pairings are between socially connected players, while others play anonymously and are only connected through repeated economic transactions. We then test how the manipulation of connectivity impacts observed trust and forgiveness outcomes. The prior studies on social capital assumed that social connections can facilitate cooperative social interaction (Knack and Keefer, 1997). We begin by asking the following research questions: 1) how trust or cooperation can be enhanced by the strength of social ties? Answering this question requires composing quantifiable metrics of trust and social tie strength, and this drives our research design. Accordingly, our study is one where we conduct a field experiment on Facebook using the investment game, a well-validated two person game that provides an economic measure of trust (Berg, Dickhaut, McCabe 1995). By conducting this experiment within the Facebook social network we gain access to quantifiable social measures, which allows us to categorize different levels of social ties between players, and we use these as covariates in our analyses.

In prior experimental literature subjects showed a considerable level of forgiveness, that is, they are willing to give cooperation a second chance when they know repeated play will continue (Fudenberg et al. 2012). Accordingly, our research agenda also involves comparing the two
repeated play treatments to test the notion of forgiveness. Benefits of forgiveness in psychology have been well documented (Wallace, Exline, and Baumeister 2008), but past research has not directly addressed our next two research questions: 2) *Are people more willing to forgive “bad” behaviors when they are network friends?* 3) *Does expressing forgiveness discourage future malfeasance (offenses) in the presence of social ties?* With respect to research question 2, strong social ties may serve to repair and enhance relationships, and people may thus be more willing to forgive their friends’ malfeasance. However, one could also argue that perhaps people are less likely to forgive in this setting because they have positive expectations based on prior experiences with that individual. When those expectations are not met and/or non-cooperative outcomes are realized, it is possible lower levels of forgiveness would ensue. Both cases are theoretically plausible, which presents a viable opportunity for our empirical tests. With respect to research question 3, expressions of forgiveness often convey a willingness to maintain or build positive relationships with offenders. In contrast, offenders who have not received forgiveness may view their relationship as irreparably damaged and may therefore have little incentive to treat the victim better in the future. However, in repeated games, forgiveness may also encourage future offenses, and expressing forgiveness could cause problems for victims if offenders get the false impression they will bear no consequences for their transgressions. Our experimental results provide a complete picture of the role of forgiveness by reconciling these two different views in a unified framework: When individuals are anonymous forgiveness tends to encourage future malfeasance, however, forgiveness can deter future offenses in the presence of social ties.

2. **Experimental Design**
Corresponding to each of our research questions, we implement four experimental treatments (see Table 1) which involve manipulating the social “connectedness” of players (i.e., players are anonymous or identities are known), as well as manipulating the extent of player interaction over time (i.e., single shot vs. repeated game play): one period games between anonymous pairings (hereafter referred to as the AnonONE treatment), one period investment games between socially connected individuals known as “Facebook friends” (hereafter referred to as the SocialONE treatment), multi-period games between individuals who are otherwise anonymous (hereafter referred to as the AnonRP treatment), and multi-period games between Facebook friends (hereafter referred to as the SocialRP treatment). It is worth noting that in our treatments SocialONE and SocialRP, the participants know the identity of the other participant in their pair.

The literature on experimental economics demonstrated that decreases in anonymity frequently increase cooperative behavior due to social incentives, but they don’t have good measures for the absence of anonymity (Gächter and Fehr 1999; Masclet et al. 2003).

[Insert Table 1 Here]

Our experiment utilizes the Facebook social network to recruit subjects to play the investment game (Berg et al. 1995). To mitigate the risk of collusion between subjects, which is of particular concern in the repeated play treatments, we conduct the experiment via a conference call and only inform subjects about the identity of their partner (in the non-anonymous treatments) at the start of the call. The game begins when subject pairs call in to our system at a certain time, after which they receive verbal prompts directing them through the game. All decisions made by subjects are input over their keypad and communication occurs via an automated voice system to avoid any
social cues that could occur if subjects were to converse directly.

The investment game begins with two players randomly chosen to be either a sender or receiver. For ease of exposition, we refer to the sender as “he” and the receiver as “she”. If the player is a sender, he will receive 10 tokens (10 tokens = $1)\textsuperscript{5} from the experimenter and will then be asked to decide how many tokens he wants to send to the other player (the receiver). If she is a receiver she will get a message telling her how much the sender has sent her. The sender may send any amount between 0 and 10. The amount sent to the receiver is then tripled by the experimenter; so for example if the sender sends 5 tokens, the receiver gets 15. After the receiver gets the tripled amount, she may send a portion back to the sender. We play this game with real US Dollars and a one to one correspondence with what is earned in the experiment. The individual payoffs per round are as follows:

Sender’s payoff (tokens): 10 - (amount sent) + (amount returned), \hspace{1cm} (1)

Receiver’s payoff (tokens): 3*(amount sent) - (amount returned). \hspace{1cm} (2)

As previously stated, subjects do not know for certain when the final round of play will occur. They play six rounds with certainty and then we impose an uncertain endpoint, such that the probability the game ends at the end of each stage is \( q = 0.25 \). By obfuscating the endpoint of the game we approximate an infinite play setting, and also mitigate end game effects which could lead to potential unraveling via backward induction. When subjects sign up for our experiment and agree to participate they grant us access to their Facebook wall. This means that in the treatments

\textsuperscript{5} Following Rice (2012), a sender is assigned $1 in each round of the game in our experiment. Note that although $1 is not a large amount of money, in a stage game the maximum payoff of a receiver/sender will be tripled as $3. Considering that the expected number of the round of repeated games is 10, the total amount of monetary reward in a repeated game is considerable: $3 \times 10 = $30.
where subjects are socially connected on Facebook we are able to use individuals’ data to characterize the social ties between sender and receiver using well validated proxies (Gilbert et al. 2006, Bapna et al. 2013). These measures are:

- **Embeddedness**<sub>s,r</sub> = \frac{\text{(number of common friends)}_{s,r}}{\min(k_s - 1, k_r - 1)}, where \(k_s\) and \(k_r\) are the network degree of the Sender and Receiver respectively.\(^6\)

- **PhotosTagged** = total number of photos in which Sender/Receiver are tagged together,

- **SharedWallposts** = total number of times Sender/Receiver post on the others wall.

We also control for the following variables:

- **Sender/ReceiverWall** = total number of wall posts for Senders/Receivers,

- **Sender/ReceiverDegree** = total number of Facebook Friends for Senders/Receivers.

[Insert Figures 1, 2 and Table 2 Here]

Participants were recruited via an initial email asking that any interested parties sign up for our Facebook application. This initial list of email addresses was obtained from undergraduate and graduate students, as well as from staff and co-workers, in a large university. Our subject pool consists of 200 people who have Facebook accounts. From this pool of potential players, subjects were randomly paired. The requirement was that non-anonymous pairings be known “friends” on Facebook under SocialONE and SocialRP, otherwise there would be no existing social tie to analyze. It is worth noting that we have a within subject design: each sender and each receiver are assigned to all four treatments, and they are paired with different opponents randomly in different treatments. The order of presenting the treatments is also randomized for each pair. The roles of

\(^6\) We also use another definition: **Embeddedness**<sub>s,s</sub> = \frac{\text{(number of common friends)}_{s,s}}{k_s + k_r}, and the empirical results are similar.
senders and receivers do not rotate. The summary statistics of the tie strength measures are shown in Table 2. Prior to the start of our game, participants read written instructions, had the option to receive further instruction via a YouTube video (Figure 1), and had to get all answers correct on a quiz that tested comprehension of the game rules (Figure 2). Display panels of the game protocol are available upon request from the authors. Each participant played several rounds of our games in our pilot tests, so they are familiar with the experiment procedures and the learning effect during the game should be minimized.

3. Empirical Framework

3.1 Reputation: AnonRP vs. SocialONE

As per our first research question, one of the primary goals of this paper is to test whether reputation formed via social interaction can enhance trust. Under AnonRP, we denote $a_{it}$ as the amount sent by sender $i$ in period $t$ in a repeated game. In the repeated investment game, the level of trust, $a_{it}$, will be influenced by past experiences of trusting behavior:

$$a_{it} = \beta_0 + \beta_1 b_{jt-1} + \mu_i + \epsilon_{it},$$

(3)

where $b_{jt-1}$ is the amount returned by the receiver $j$ in the prior round, $\mu_i$ represents the unobserved individual heterogeneity, and $\epsilon_{it}$ is the error term. Under SocialONE, socially connected individuals play a one-round game, and $\tilde{a}_i$ is the amount sent by sender $i$. The level of trust is given by

$$\tilde{a}_i = \gamma_0 + \gamma_1 \text{Embeddedness}_{ij} + \gamma_2 \text{PhotosTagged}_{ij}$$

$$+ \gamma_3 \text{SharedWallposts}_{ij} + \gamma_4 X_i + \mu_i + \theta_i,$$

(4)

where $X_i$ is a vector of control variables listed in Section 2. Note that each sender was assigned to
our four treatments, and they match randomly with different receivers in different treatments.\footnote{Our pilot experiments show that the order of presenting the treatments (order effects) does not affect the experimental results.} The advantage of this experimental design is that the unobserved individual heterogeneity, $\mu_i$, can be differenced out by subtracting equation (3) from equation (4):

$$\tilde{a}_i - a_{it} = (\gamma_0 - \beta_0) - \beta_1 b_{jt-1} + \gamma_1 \text{Embeddedness}_{ij}$$

$$+ \gamma_2 \text{PhotosTagged}_{ij} + \gamma_3 \text{SharedWallposts}_{ij} + \gamma_4 X_i + (\theta_i - \epsilon_{it})$$

$$= \pi_0 - \beta_1 b_{it-1} + \gamma_1 \text{Embeddedness}_{ij} + \gamma_2 \text{PhotosTagged}_{ij}$$

$$+ \gamma_3 \text{SharedWallposts}_{ij} + \gamma_4 X_i + \delta_{it},$$

(5)

where $\pi_0 = (\gamma_0 - \beta_0)$, $\delta_{it} = (\theta_i - \epsilon_{it})$, and $\tilde{a}_i - a_{it}$ is the relative trust level.

If social capital can enhance trust, we would expect the coefficients on the tie strength measures, $\gamma_1$, $\gamma_2$, and $\gamma_3$, are positive. When we match players, we require non-anonymous pairings to be known “friends” on Facebook under SocialONE and SocialRP. In other words, the matching process is not completely random. One may wonder whether the homophily effect could bias our estimation results: there are inherent similarities in unobserved personal characteristics between a sender and a receiver if they are friends (Aral and Walker 2011; Bapna and Umyarov 2014). In our econometric specification, equation (4), it implies that the unobserved individual heterogeneity of sender $i$, $\mu_i$, is likely to correlated with the unobserved individual heterogeneity of receiver $j$ because they are Facebook friends. Therefore, our tie strength measures could be endogenous in the sense that they are correlated with the unobserved individual heterogeneity, $\mu_i$, in equation (4). However, in a within subject design, we can address this endogeneity concern by differencing out $\mu_i$ in equation (5).
3.2 Forgiveness: AnonRP vs. SocialRP

Addressing our second set of research questions requires comparing the different strategies employed by players in the AnonRP treatment and SocialRP treatments in order to study forgiveness in the presence of repeated interactions with and without social ties. The repeated game strategies in prior literature provide us with a validated measure of forgiveness (Fudenberg et al. 2012) and we expect to observe heterogeneity, such that people with different strength of social ties are more/less likely to forgive offenses. We also expect that for people with different strength of social ties, forgiveness may deter/encourage repeat offenses. Our comparison of AnonRP and SocialRP tests whether senders are more/less likely to forgive as a function of their social ties. From a theoretical point of view, we are actually asking how the strategies used by players vary with the strength of social ties. Because repeated-game strategies map game histories into actions, we explore the relationship between game histories and the level of trust to measure forgiveness. We can also examine whether expressing forgiveness deters repeat offenses when receivers defect in repeated interactions. If the amount returned is positively correlated with the amount sent following a non-cooperative prior round, we can infer the expression of forgiveness leads to fewer future offenses in the presence of social ties. That is, expressing forgiveness can act as a deterrent to future non-cooperative outcomes and can serve as a mechanism by which social ties ameliorate market frictions. Alternatively, if the correlation is negative then it shows forgiveness could encourage future offenses by failing to punish prior poor behavior.

In our experiment, a larger amount returned means that a receiver is willing to forgive a sender’s “bad” behavior or defection. Our definition of a “bad” behavior or defection is that the
amount sent in a stage game (period $t$) under AnonRP or SocialRP is less than the average amount sent under AnonONE. We collect a subsample that includes all defections (the amount sent), $a'_{it}$, and the corresponding amount returned, $b'_{jt}$, from the observations under AnonRP and SocialRP. First, we can compare the amount returned from receivers under AnonRP and under SocialRP in this sample. If the amount returned under SocialRP is higher/lower than that under AnonRP in the subsample, we would say people are more/less willing to forgive their friends’ defections. To further investigate the effect of the tie strength, we formalize the regression equation as follows:

$$b'_{jt} = c_0 + c_1 \text{SocialRP} + c_2 \text{Embeddedness}_{ij}$$

$$+ c_3 \text{PhotosTagged}_{ij} + c_4 \text{SharedWallposts}_{ij} + c_5' X_i + c_6 a'_{it} + \mu_j + \epsilon_{jt}, \quad (6)$$

where the binary variable SocialRP takes the value 1 if the treatment is SocialRP, and 0 if the treatment is AnonRP, and $X_i$ are control variables. Note that if a game is played by anonymous strangers, the value of the tie strength measures, Embeddedness$_{ij}$, PhotosTagged$_{ij}$, and SharedWallposts$_{ij}$, are zero. If people are more willing to forgive their closer friends’ defections, we would expect $c_1, c_2, c_3$, and $c_4$ to be significantly positive. A similar challenge is how to deal with the individual heterogeneity, $\mu_j$. Each receiver in equation (6) was also assigned to the treatment AnonONE:

$$\bar{b}'_j = d_0 + d_1 \bar{a}'_i + \mu_j + \rho_j, \quad (7)$$

where $\bar{b}'_j$ and $\bar{a}'_i$ are the amount returned and the amount sent under AnonONE, respectively. Parameters $c_1, c_2, c_3$, and $c_4$ can be identified by subtracting equation (7) from equation (6):

$$b'_{jt} - \bar{b}'_j = (c_0 - d_0) - d_1 \bar{a}'_i + c_1 \text{SocialRP} + c_2 \text{Embeddedness}_{ij}$$

$$+ c_3 \text{PhotosTagged}_{ij} + c_4 \text{SharedWallposts}_{ij} + c_5' X_i + c_6 a'_{it} + (\epsilon_{jt} - \rho_j). \quad (8)$$
4. Experimental Results

We start our analysis by conducting univariate comparisons of the four treatments. The results of mean comparisons are shown in Table 3. We find that the mean amount sent under SocialONE, SocialRP, or AnonRP is significantly larger than the mean under AnonONE. It shows that social ties and repeated play matter in building trust.

[Insert Tables 3 and 4 Here]

We examine our research question 1 more carefully in estimating the regression equation (5), and the results are shown in Table 4. Results of the Ordinary least squares (OLS) regression are reported in column 1 of Table 4. We find significant positive effects of wall-post made on a friend’s wall and tagged photos on the level of trust. The size of coefficient is also considerable. For instance, one-standard-deviation increase in the number of tagged photos together raises amount sent by 0.81 token. Small sample size is a common problem for the experimental method. When the sample size is insufficient for straightforward statistical inference, bootstrapping is useful for estimating the distribution of a statistic without using asymptotic theory. In column 2 of Table 3, we use bootstrapping to compute the standard errors and find that the result is robust. Potential problems arise with statistical inference when data are grouped into clusters (Cameron, Gelbach, and Miller 2008). In our case, within-cluster error correlation means that a participant’s error term in period $t$, $\varepsilon_{it}$, could correlate with the error term in period $t - 1$, $\varepsilon_{it-1}$. In column 3 of Table 4, we compute the statistics that are robust to arbitrary cluster correlation and unknown heteroskedasticity. Although the statistics become smaller, the basic results still hold.

Our second set of research questions focuses on forgiveness. In Figure 3, we compare the
amount returned from a receiver if a sender defects under AnonRP and under SocialRP. We find that the amount returned under SocialRP is higher than that under AnonRP. The implication is that in contrast with anonymous participants, people are more willing to forgive their friends’ defections. In other words, the level of forgiveness is higher in the presence of social ties.

[Insert Figure 3 and Table 5 Here]

We further investigate how the level of forgiveness varies with the strength of social ties by estimating the regression model (8). Table 5 shows the estimation results. In column 1 of Table 5, we find that the level of forgiveness is positively associated with the tie strength measures. The results show that people are more likely to forgive their closer friends. Similarly, our results are robust when we compute the statistics using bootstrapping and clustered standard errors in columns 2 and 3 of Table 5. It is worth noting that the sample size in Table 5 has been significantly decreased because we focus only on the subsample that contains senders’ defections.

Then, we examine whether expressing forgiveness deters future malfeasance in repeated interactions. Li and Chen (2012) summarized the measurement of forgiveness in the sociology and psychology literature. Most of these studies measure forgiveness as a disposition using self-reported questionnaires and might suffer from common method biases (Berry et al. 2001, Podsakoff et al. 2003). In this study, we propose a behavioral measure of forgiveness based on the repeated economic games, and empirically investigate the effect of forgiving perpetrators on deterring future malfeasance. Recall that the definition of a defection is that the amount sent in a stage game (period t) under AnonRP or SocialRP is less than the average amount sent under AnonONE. We define forgiving behavior as follows: the amount returned by the receiver after
observing a defection is larger than the average amount returned under AnonONE. This means that the receiver forgives the sender’s bad behavior. According to this definition of forgiving behavior, we divide the subsample including all defections into two groups: one group contains forgiving behavior, and the other does not contain forgiving behavior. Therefore, we can examine the effect of forgiveness in the prior round on the amount sent in the current round. If we observe that the average amount sent in the group that includes forgiving behavior is larger than that in the group that does not include forgiving behavior, we would know expressing forgiveness can deter future malfeasance, otherwise, expressing forgiveness could encourage future malfeasance.

[Insert Figure 4 Here]

In Figure 4, we find that the answer to our research question 3 crucially depends on the presence of social ties. First, Figure 4 shows that the amount sent under AnonRP & No Forgiveness is larger than that under AnonRP & Forgiveness. In anonymous repeated games, expressing forgiveness could encourage future malfeasance because the receiver’s punishment strategy is not sufficiently harsh to deter the sender’s deviation from the cooperative equilibrium. However, surprisingly, we also find that the amount sent under SocialRP & No Forgiveness is smaller than that under SocialRP & Forgiveness. This implies that forgiving friends’ defection can deter future malfeasance. Our experimental results show that the effect of forgiveness in the presence of social ties is different from the theoretical conclusions in the economics literature on repeated games (Fudenberg and Tirole 1991). The reason is that in the standard game-theoretical

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8 Axelrod (1984) noted that the “TIT-FOR-TWO-TATS” strategy may produce a better outcome than the “TIT-FOR-TAT” strategy because forgiving once could avoid falling into a war of defection.
setup, the role of social ties has been abstracted away. However, the effect of forgiveness on deterring future defections crucially depends on the presence of social ties. Forgiving friends’ defection often conveys a strong willingness to maintain friendship with them.

5. Implications and Conclusions

We contribute to related literature by parsing out two types of networks, a social network with varying the level of subject interaction over time versus a more market based network, to determine how these two types of networks relate to each other with respect to trust and forgiveness in an economic context. We also uncover that the expression of forgiveness is a key mechanism that links social interactions to a higher level of trust. Our experimental design allows us to test the presence of forgiveness as a self-correcting mechanism in the presence of social ties. Specifically, when person A accidentally deviates from the cooperative behavior, we find that her closer friend is more likely to forgive her relative to an anonymous trader, and this forgiving behavior deters future offenses from person A. In other words, the cooperative equilibrium is more stable in the presence of social ties: If the trading partners are socially connected, the equilibrium is more likely to return to the original cooperative one after small disturbances. An applicable setting might relate to how social ties add value to online reputation mechanisms (like Ebay’s). Besides online feedback (Ba and Pavlou 2002), technology has made it so that companies can seamlessly engage their customers through social media outlets such as Facebook and twitter. Furthermore, computer-mediated communication technologies can mimic traditional face-to-face social relations and help build trust by enhancing buyers’ perceptions of interactivity and social presence (Ou, Pavlou, and Davison 2014). For example, a seller on Ebay may have a Facebook
account that has social ties with customers (customer service). The obvious question, and one we aspire to shed light on, is how do these social ties affect the online reputation mechanism (trust and forgiveness in an online transaction)? While ours is some of the first work that could apply to these settings, we also provide impetus for other researchers to follow suit. We have merely scratched the surface of what can be learned by leveraging the powerful tools of experimental economics to exploit the rich data that can be gathered from online social media platforms.

Appendix: Tables and Figures

![Welcome to Online Token Sharing Game!](image)

**General Guidelines:**
This is an economic experiment as it is conducted with Real Money! The experiment has multiple rounds. The show-up fee you can get is $10. In the experiment, you are tokens, and 10 tokens = $1.

**Experiment Description:**
The experiment is run as a repeated-play setting. Your role is as follows: If you are a sender, you will get tokens from the experiment in each round and will then be asked to decide how much of the tokens you want to send to your partner (the receiver). If you are a receiver, you will know how much the sender has sent you. The sender may send any amount between 0 and 10 tokens in each round. The amount sent to you is then multiplied by the experiment, so for example if the sender sends 5 tokens, you get 15 tokens. Allow you to show any portion back to the sender.

- **In each round:**
  - Sender’s payoff = (amount sent) - (amount returned)
  - Receiver’s payoff = (amount sent) - (amount returned)

The experiment is conducted over multiple rounds. The probability that the experiment ends at the end of each round is = 0.12. The total payoff is the sum of the payoff in each round.

**Note:** You need to complete your tokens and earn the rewards from tokens. Please also note that you have to decide and click on “End.”

![Figure 1. A YouTube Video on Experimental Instruction](image)

**Quiz**
To make sure you understand how the game is played, we would like you to take this short quiz. If you answer all the questions correctly, on the following page you can start playing the game.

**Q1. Divide 10 tokens: Initially the sender is given 10 tokens.**

- **a.** If you are the sender, you choose to Pass 4 tokens, and the receiver returns back 4 tokens, how many tokens do you earn as a result of the choice?
  
  0.04 0.13 0.05

- **b.** How many tokens does the receiver earn as a result of the choice?
  
  0.24 0.23 0.16

**Q2. Divide 10 tokens: Initially the sender is given 10 tokens.**

- **a.** If you are the receiver, the sender chooses to Pass 4 tokens, and you return back 4 tokens, how many tokens does the sender earn as a result of the choice?
  
  0.02 0.13 0.11

- **b.** How many tokens do you earn as a result of the choice?
  
  0.03 0.07 0.12

![Figure 2. Screenshot of Quiz Testing Comprehension of Game Rules](image)
Figure 3. AnonRP Forgiveness vs. SocialRP Forgiveness

Note: The figure displays boxes bordered at the 25th and 75th percentiles of the amount returned after a “bad” outcome with a median line at the 50th percentile. Whiskers extend from the box to the upper and lower adjacent values and are capped with an adjacent line.
Figure 4. Whether Expressing Forgiveness can Deter Future Malfeasance

Note: The figure displays boxes bordered at the 25th and 75th percentiles of the amount returned after a “bad” outcome with a median line at the 50th percentile. Whiskers extend from the box to the upper and lower adjacent values and are capped with an adjacent line.

AnonRP & No Forgiveness: the amount sent by the sender if the receiver does not forgive the sender’s defection in the prior round under AnonRP

AnonRP & Forgiveness: the amount sent by the sender if the receiver forgives the sender’s defection in the prior round under AnonRP

SocialRP & No Forgiveness: the amount sent by the sender if the receiver does not forgive the sender’s defection in the prior round under SocialRP

SocialRP & Forgiveness: the amount sent by the sender if the receiver forgives the sender’s defection in the prior round under SocialRP
<table>
<thead>
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<th>VARIABLES</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
</tr>
</thead>
<tbody>
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<td>19.26</td>
<td>1</td>
</tr>
<tr>
<td>SharedWallposts</td>
<td>2.98</td>
<td>5.26</td>
<td>2</td>
</tr>
<tr>
<td>ReceiverDegree</td>
<td>423.52</td>
<td>320.15</td>
<td>487</td>
</tr>
<tr>
<td>ReceiverWall</td>
<td>182.22</td>
<td>188.42</td>
<td>157</td>
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<tr>
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<td>455.56</td>
<td>284.57</td>
<td>432</td>
</tr>
<tr>
<td>SenderWall</td>
<td>228.21</td>
<td>208.51</td>
<td>179</td>
</tr>
<tr>
<td>Embeddedness</td>
<td>0.16</td>
<td>0.45</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Table 3. Comparisons of Amount Sent and Amount Returned in Four Treatments

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) SocialONE</th>
<th>(2) AnonONE</th>
<th>(3) SocialRP</th>
<th>(4) AnonRP</th>
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</thead>
<tbody>
<tr>
<td>Mean of Amount Sent</td>
<td>6.02</td>
<td>4.03</td>
<td>6.93</td>
<td>6.08</td>
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<tr>
<td>Std Dev of Amount Sent</td>
<td>3.01</td>
<td>2.45</td>
<td>3.21</td>
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<td>Mean of Amount Returned</td>
<td>9.55</td>
<td>6.22</td>
<td>10.34</td>
<td>9.02</td>
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<tr>
<td>Std Dev of Amount Returned</td>
<td>7.49</td>
<td>6.05</td>
<td>8.12</td>
<td>7.84</td>
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</table>

Note: the unit is a token.
Table 4. How Social Capital Substitutes for Trust Built through Repeated Interactions: Estimating Regression Model (5)

<table>
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<th>VARIABLES</th>
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<th>(3)</th>
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<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>Bootstrapping</td>
<td>Cluster-Robust Inference</td>
</tr>
<tr>
<td>Embeddedness</td>
<td>0.00312*</td>
<td>0.00312*</td>
<td>0.00312</td>
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<tr>
<td></td>
<td>[1.832]</td>
<td>[1.765]</td>
<td>[1.264]</td>
</tr>
<tr>
<td>PhotosTagged</td>
<td>0.0422**</td>
<td>0.0422**</td>
<td>0.0422**</td>
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<tr>
<td></td>
<td>[2.205]</td>
<td>[1.992]</td>
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</tr>
<tr>
<td>SharedWallposts</td>
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<td>0.0591**</td>
<td>0.0591**</td>
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<tr>
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<td>[3.142]</td>
<td>[2.233]</td>
<td>[2.301]</td>
</tr>
<tr>
<td>$b_{jt-1}$</td>
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<td>0.0914**</td>
<td>0.0914**</td>
</tr>
<tr>
<td></td>
<td>[2.154]</td>
<td>[2.021]</td>
<td>[1.997]</td>
</tr>
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<td>0.00315</td>
<td>0.00315</td>
<td>0.00315</td>
</tr>
<tr>
<td></td>
<td>[0.542]</td>
<td>[0.332]</td>
<td>[0.281]</td>
</tr>
<tr>
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<td>0.00126</td>
<td>0.00126</td>
<td>0.00126</td>
</tr>
<tr>
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<td>[0.661]</td>
<td>[0.533]</td>
<td>[0.473]</td>
</tr>
<tr>
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<td>[-0.303]</td>
<td>[-0.115]</td>
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<tr>
<td>SenderDegree</td>
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<td>0.00236</td>
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<tr>
<td></td>
<td>[0.685]</td>
<td>[0.411]</td>
<td>[0.529]</td>
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<td>0.422***</td>
<td>0.422**</td>
<td>0.422**</td>
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<tr>
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<td>[2.654]</td>
<td>[2.016]</td>
<td>[2.157]</td>
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</table>

R-squared  0.263  0.263  0.263
Observations 469  469  469

z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1
Table 5. Forgiveness as a Function of Social Ties: Regression Model (8)

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(3)</th>
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<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>Bootstrapping</td>
<td>Cluster-Robust Inference</td>
</tr>
<tr>
<td>Embeddedness*SocialRP</td>
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<td>0.00724**</td>
<td>0.00724**</td>
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<tr>
<td></td>
<td>[2.332]</td>
<td>[2.012]</td>
<td>[2.072]</td>
</tr>
<tr>
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<td>0.0871**</td>
<td>0.0871**</td>
</tr>
<tr>
<td></td>
<td>[2.282]</td>
<td>[2.031]</td>
<td>[1.994]</td>
</tr>
<tr>
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<td>0.0722***</td>
<td>0.0722***</td>
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<tr>
<td></td>
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<td>[3.014]</td>
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<tr>
<td></td>
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<td>1.613**</td>
<td>1.613**</td>
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<tr>
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<tr>
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<tr>
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<td>[0.668]</td>
<td>[0.684]</td>
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<td>0.00326</td>
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<tr>
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<td>[0.821]</td>
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<td>[0.773]</td>
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<tr>
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<td>0.00425</td>
<td>0.00425</td>
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<td>0.00318</td>
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<tr>
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<td>2.654***</td>
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<td>[3.557]</td>
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</table>

R-squared 0.192 0.192 0.192
Observations 264 264 264

z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1
References


