# Social Information as a Strategic Tool:

# Evidence from a Randomized Field Experiment

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**Abstract**: Management research has documented how firm behavior is shaped by social influence, yet has generally overlooked how a firm might attempt to strategically trigger social influence processes for its own benefit. We address this possibility with two randomized experiments—a field experiment with 96,065 users of an online investment platform and a follow-on vignette experiment—where participants were provided different types of information about others' behavior in the context of a referral program. We find evidence for the efficacy of the traditional "descriptive norm" treatment, but that the effects are moderated in important ways by simultaneously disclosing information about the collective consequences of the focal behavior. The field experiment indicates that disclosing social information can lead to increased resource acquisition for the firm via a change in the frequency and characteristics of incoming referrals. The vignette experiment provides more granular evidence for what underlies the effect as well as the boundary conditions that explain when the strategy should be most effective. In sum, the study highlights that, 1) social information can alter both the frequency and nature of enacted behavior, and 2) the ability of an organization to strategically trigger social influence depends not only on the level of stakeholders' understanding about the collective prevalence of a behavior but also its collective consequences.

## INTRODUCTION

Social influence has been explored in a range of organizational contexts, including entry into entrepreneurship (e.g., Azoulay et al. 2017, Eesley and Wang 2017, Kacperczyk 2013), the adoption and abandonment of organizational practices (e.g., Gaba and Dokko 2016), and the general valuation of objects (Salganik et al. 2006, Zuckerman 2012). Further, adherence to (or deviance from) social norms has been shown to have important performance implications for organizations (e.g., Fauchart and von Hippel 2008, Ody-Brasier and Vermeulen 2014, Philippe and Durand 2011, Stefano et al. 2014), and even scientific inquiry itself is structured by norms (Merton 1973). Despite these findings, management research has often treated firms as passive and ignored the possibility that a firm can proactively trigger social influence processes among its own stakeholders. In this paper we experimentally explore whether, how, and to what end a firm can strategically broker information it holds about the collective behavior of its stakeholders in order to improve its own performance.

This seems plausible given the literature in social psychology that has found that people's behavior can be shaped by the simple knowledge of how others have behaved—also called "descriptive norms" (Cialdini and Trost 1998). That literature has studied a range of outcomes, including those related to environmental friendliness (Ferraro and Price 2013, Goldstein et al. 2008, Nolan et al. 2008), healthy eating (Robinson et al. 2014), and ethical decisions (Cialdini et al. 2006). One commonality of such contexts is the strong prosocial or moral component (e.g., environmentalism, health) where people feel pressure from others to conform their own behavior. However, many, if not most, organizational contexts lack these strong normative pressures, meaning it is not immediately clear that firms can apply the results of such research to strategically influence the behavior of customers, employees, or other transaction partners.

Even though many organizational contexts lack the predominant pro-social or normative pressures of past research settings, there is reason to believe social information about how others have behaved may still influence decisions. That is because information about others' behavior may serve as a quality signal, and experimental work finds that people's own quality judgements are influenced by the behavior of others (Muchnik et al. 2013, Salganik et al. 2006). However, this also implies that the provision of basic prevalence information studied in past research (i.e., the number of people that have done something) should be moderated by information about the collective consequences of that behavior. This is because in settings without explicit normative pressures, prevalence information may primarily function as a proxy for beliefs about the consequences of the behavior, and providing direct information about collective consequences will alter its impact.

We conducted two experiments in the context of a referral program, one field experiment on an online investment platform—and one vignette experiment on Amazon Mechanical Turk (MTurk)—to understand to what extent people acted on information about the collective behavior of others. Referral programs are a type of network brokering and an important channel to access resources outside of a firm's immediate network, including new customers (e.g., Ryu and Feick 2007) and employees (e.g., Granovetter 1995). In our context referrals result in the conversion of a firm's social capital (i.e., relationships with existing users) into literal financial capital (i.e., investment on the platform by new users). In the field experiment, we used two treatments: 1) a traditional descriptive social norm treatment containing information about the *prevalence* of the referral behavior among other stakeholders, and 2) a version of the first treatment that was moderated with information about the collective *consequence* of the behavior among those same stakeholders. We then measured the likelihood that the behavior was enacted (i.e., a referral was made) and the impact on actual firm performance via the number of new users that joined the platform and the amount of money invested by those new users.

In the field experiment we were restricted to disclosing the actual social information already held by the firm (i.e., how many people had made referrals and how much money they had made from doing so). Theoretically, however, the magnitude of these values should alter their impact. Therefore, we next conducted a vignette experiment in which we were able to vary both the visibility of the social information and its magnitude. This allowed us to measure participants' perceptions of the specific costs and benefits of the behavior, which provided more detailed evidence for the processes underlying the effects identified in the field experiment.

We found that disclosing prevalence information increased referral likelihood but did not increase the number of new users or their investment on the platform. We also found that when arguably high-magnitude prevalence information was moderated by low-magnitude consequence information, referral likelihood and the number of new users did not significantly increase but it brought in more investment from new users. These findings show that disclosing social information can lead to tangible gains for the firm by helping to access resources held in existing stakeholders' extended networks: the treatment groups generated roughly $200,000 of additional investment from new users compared to the control group. We suggest that it did so by shifting both the likelihood of referral and also the characteristics of the people being referred.

This paper makes three main contributions. First, although prior organizational studies have documented the importance of social influence in affecting organizational or individual conformity, it largely ignores whether and how it can be strategically leveraged by firms to benefit themselves. Our results suggest it can serve as a particularly cost-effective strategic tool for firms even in settings without very clear normative pressures. Second, we document the moderating role of collective consequence information on the effect of prevalence information. This is important because firms have access to both pieces of information and can choose how much to disclose. We suggest that the interaction of prevalence and consequence information changes the pool of referrals and leads to better outcomes for firm performance, despite that it does not necessarily increase the frequency of the underlying behavior. This finding is particularly important when the ultimate goal is organizational performance (e.g., acquiring resources), meaning quality and quantity of behavior should be evaluated separately. Finally, we employ a field experiment to establish causality between social influence and its effects. In this way we contribute to a growing body of research that develops and tests management theory using experiments, including experiments using real firms and important performance outcomes (Chatterji et al. 2016).

## CONTEXT AND THEORY

### Referrals

The context for our study is a referral program, a form of network brokerage. Referral programs are closely associated with firm social capital, because they allow firms to access resources through their extended networks (Fernandez et al. 2000). The literature on employee referrals is a prominent example of this (e.g., Granovetter 1995, Topa 2011). Overall, more than 50 percent of U.S. jobs are found through informal networks and about 70 percent of firms have programs encouraging referral-based hiring (e.g., Topa 2011). Another example is the customer referral literature (e.g., Ryu and Feick 2007). Not surprisingly, recommendations from friends and family are trusted more than other forms of advertising and promotion (Stokes et al. 2013). Compared with the non-referred, referred workers yield substantially higher profits and have higher commitment (Burks et al. 2015), and referred customers exhibit higher margins and lower churn (Van den Bulte et al. 2018). Referrals, therefore, are perhaps the most direct and frequently adopted tool for firms to access resources held outside of their immediate networks.

The referral phenomenon consists of three distinct sets of actors: 1) a firm, 2) its existing stakeholders, and 3) the external ties of those stakeholders. These relationships are summarized in Figure 1. The goal of the firm is to access the resources held by the external actors by leveraging its ties to current stakeholders. In our context of an online investment platform, referrals represent quite literally the conversion of social capital into financial capital, given that referrals lead to new monetary investments on the platform.

[Insert Figure 1 about here]

However, a stakeholder will only make a referral when their personal benefits of doing so outweigh the costs. These costs and benefits are often uncertain. Costs might include the time and effort required to make a referral, the social irritation caused by asking friends to use the company, as well as broader reputational risks involved in referring a company to others. The benefits are equally uncertain. They could include potential reputation gain from referring a good company, but quality is often imperfectly known. For this reason, firms often attempt to directly resolve uncertainty about the overall benefit of making referrals by creating formal referral programs and offering financial incentives to existing stakeholders (Ryu and Feick 2007). Simple examples include the type of affiliate programs used by companies such as Amazon and eBay, or the cash bonuses offered for employee referrals at many large companies (PayScale 2018), where it is common to reward successful employee referrals with bonuses of a few thousand dollars (WorldatWork 2016).

The firm in our field experiment provided existing users a contingent financial incentive equal to a small percentage (0.2%) of any referred new users' initial investments. However, the contingent nature of this incentive meant it was not clear to an individual stakeholder whether they would make any money at all, or precisely how much money they would make from making a referral until after it was completed. We next theorize how social information may impact the decision to refer.

**Social influence and the brokerage of social information by firms**

Social influence theory suggests that people are influenced by the behavior of others (Cialdini and Goldstein 2004). This basic insight has been explored from different theoretical perspectives in different fields, including social contagion (e.g., Aral and Walker 2011), herding and information cascades (e.g., Lee et al. 2015), word-of-mouth marketing (e.g., Ryu and Feick 2007), and social learning (Bandura 1977). Researchers that have experimentally assigned peer ratings to an offering found that it impacted how subsequent people evaluated the same offering (Muchnik et al. 2013, Salganik et al. 2006). This was even true in decisions driven largely by personal tastes such as the evaluation of music (Salganik et al. 2006). In short, actors will look to the behavior of others when there is plausible uncertainty about their own choices. The pervasiveness of social influence phenomena in the literature is likely driven by the fact that precise ex-ante costs and benefits of decisions are often uncertain because of imperfect information (Gilbert 1995, Stiff 1994).

Perhaps the most extensive experimental research on social influence is the social psychology work focused largely on socially desirable or undesirable behaviors (Cialdini and Trost 1998). There, information about the behavior of others is considered a "descriptive norm" because it allows people to understand how similar their own behavior is to the collective's. This work has studied decisions related to healthy eating (Robinson et al. 2014) and ethical behavior (Cialdini et al. 2006), as well as the natural environment, such as water usage (Ferraro and Price 2013), energy consumption (Nolan et al. 2008), and product reusage (Goldstein et al. 2008). Social information in these contexts can resolve uncertainty about how someone normatively “should” behave in such scenarios even when the individual costs and benefits of the decisions may be largely intangible. In such contexts, social information may impact behavior via individual psychological benefits such as a stronger sense of approval, group identity, or reputation gain (Cialdini and Trost 1998). These outcomes are determined by how one is treated or perceived by others. Importantly, this work has historically focused on contexts where social pressure is potentially important, such as decisions related to ethics or the natural environment.

Complementing this work is research that is less concerned with social pressures or perceptions and more concerned with informational signals. There, decision makers simply do not have (or believe they do not have) enough information to make rationally optimal decisions on their own, so they use the behavior of others as a signal of decision quality (Banerjee 1992). People may mimic the behavior of others because they believe others know something they themselves do not. Therefore, access to social information can help actors resolve uncertainty and potentially improve the objective quality of their own decisions.

These two broad mechanisms—the normative pressure mechanism and the rational expectations mechanism—each provides only a partial explanation for why social information may be effective in influencing behavior. This is because many organizational phenomenon such as referrals are socially situated (e.g., involve expectations about other social actors) but not explicitly normative (e.g., unlike recycling, stealing, etc.), and simultaneously involve tangible financial outcomes for which “optimal” outcomes may exist. This can make it difficult to understand how effectively social information can be used as a strategic tool by organizations, because basic descriptive norms should trigger both of these, yet the rational expectations effect should be heavily moderated by other information.

This is important to firms because social influence is only possible if the behavior of others is known. However, in many cases, information about others’ behavior is not widely available. For example, in Figure 1, stakeholder A and stakeholder B do not have a direct tie to each other, but both of them have a tie to the firm. This configuration provides the firm control over whether A and B are aware of the other’s behavior (Burt 2009). However, from the above logic stakeholders may respond to social information for different reasons meaning firms must be cognizant of exactly how they disclose social information. In this paper we therefore explore to what extent disclosing information about the *prevalence* of a behavior among stakeholders alters referral behavior, and the extent to which adding information about the *consequence* of a behavior among stakeholders might moderate the effect of prevalence information.

**Prevalence information**

The most basic form of social information describes the *prevalence* of a behavior: "X number of people have made a particular decision." In the social psychology literature is this called a "descriptive norm" (Cialdini and Trost 1998). As reviewed above, this type of information is useful because it can help to resolve multiple types of uncertainty about a decision. This includes uncertainty about the normative elements of the decision (e.g., "is it socially ok to do this?") as well as quality uncertainty (e.g., "is this objectively a good choice?").

Social acceptability concerns are largely about the legitimacy of a behavior. People desire their behavior to be perceived as legitimate because legitimacy may help to bring benefits and/or avoid punishment (Suchman 1995, Suddaby and Greenwood 2005). For example, people engage in environmentally friendly behavior and want to be seen as helping the environment, because it is widely considered a good thing (Ariely et al. 2009). A significant literature has documented that deviating from established behaviors can lead to punishment from others (Fauchart and von Hippel 2008, Ody-Brasier and Vermeulen 2014, Philippe and Durand 2011, Stefano et al. 2014). Legitimacy concerns are present in the mechanisms of institutional isomorphism described by DiMaggio and Powell (1983). When there is uncertainty whether an action is socially acceptable, knowledge of its adoption increases its legitimacy and enhances the likelihood of subsequent adoption by others. Such effects have been documented in prior literature including studies on the adoption of contentious practices (Briscoe and Safford 2008), multidivisional form (Palmer et al. 1993), disclosure of climate change strategy (Reid and Toffel 2009), and corporate philanthropy (Marquis and Tilcsik 2016).

Likewise, prevalence information may also serve as a quality indicator of an action when there is uncertainty about its actual, but unobserved, quality. Actors may infer that the choice is good if many others have made the choice and thus are more likely to choose it themselves (Banerjee 1992). Studies on innovation diffusion (Greve 2011) and investment decisions (Scharfstein and Stein 1990) support this insight.

In our context there is significant uncertainty about referral behavior. Referrals might be perceived as selfish (e.g., motivated primarily by personal benefit rather than others' welfare) or even harmful (e.g., annoying) and hence prevent users from making referrals. These concerns would be more severe if the quality of the firm is low. At the same time, even if people believe they can help a friend if they refer a useful product or service to her, they are unsure of the firm's true quality (Kornish and Li 2010). The lack of perfect information about firm quality means the behavior of others becomes informative (Banerjee 1992). Firms should be able to actively influence this uncertainty by disclosing information about the prevalence of a behavior when it is not already known among stakeholders. Providing this information should lower the perceived costs and/or enhance the perceived benefits of making a referral and thus increase the chance stakeholders will enact the behavior.

**The moderating role of consequence information**

One of the reasons that people respond to prevalence information is that it may help resolve uncertainty about outcomes, however, this logic requires that people do not have better methods to resolve such uncertainty. Therefore, in many settings prevalence information should be moderated by the availability information about the *consequences* that others have experienced from their behavior: "X number of people have made a particular decision and made $Y from doing so." Information about the collective consequences of a behavior more directly resolves uncertainty about the often financial benefits of that behavior. This helps decision makers to better understand what their own financial outcome might be if they make the same decision and should lessen the impact of prevalence information.

Supporting this logic is evidence that actors are broadly attentive to not only what their peers do but also the consequences of their peers' choices. For example, Lerner and Malmendier (2013) find that MBA students who are exposed to peers with unsuccessful pre-business-school entrepreneurship are less likely to start ventures. In a study of performance-enhancing drug use in the 2010 Tour de France, Palmer and Yenkey (2015) found that professional cyclists are more likely to engage in wrongdoing when their peer offenders are not punished and vice versa. Conell and Cohn (1995) find that early strike success in French coal mining increased the chances of strike imitation by others. On the firm level, prior studies also suggest the same pattern (Mansfield 1961, March et al. 1991). For example, Argote and colleagues (1990) find that shipyard factories that started production later were more productive than those with earlier start dates and suggest the late firms imitate practices proven efficient from the early ones. Haunschild and Miner (1997) find that firms chose the investment banker as advisor on an acquisition based on the other firms' acquisition outcome (e.g., premium) with the same investment banker. Therefore, it is useful for people to know not only how other people behave but also what happens to them as a result of that behavior.

A frequent benefit of making referrals is a financial reward provided by the firm (Neckerman and Fernandez 2003). Such rewards are often contingent on the value that the referral generates for the firm. For example, a contingent financial benefit might take the form of $Y for *each* new stakeholder (e.g., customer, employee) that is successfully referred. Importantly, the reward is not for the behavior itself, but for the outcome of the behavior. This introduces uncertainty about the exact financial benefit to actors. Individuals may enact a behavior but receive no reward for it because the reward depends on elements beyond their control, such as whether the person they made the referral to accepts the referral and how that person behaves once they accept the referral.

In the baseline referral program in our field context, individuals knew how the financial benefit would be calculated but not the exact ex-ante financial benefit they would gain from the behavior. That is, they were promised 0.2 percent of the first investment of any successful referrals they made, but they would have to actually make referrals before they could determine whether they would personally receive money from the behavior: even if they made a referral it might not be accepted, and even if it was accepted, the new user might not invest, and even if the new user invested they might invest a small or large amount. These are outside of existing users' direct control, so introduce considerable uncertainty about the decision to make a referral in the first place.

These considerations indicate the providing information about the collective consequences of a behavior will moderate the impact of information about the collective prevalence, particularly in settings such as this where normative pressures are not overriding. For example, very high-magnitude prevalence information may lead people to believe the behavior is particularly beneficial, but if low-magnitude consequence information is simultaneously provided this may negate the prevalence information. The experimental designs we introduce next test these possibilities.

**FIELD EXPERIMENT METHODOLOGY AND DATA**

The context for the field experiment was one of the twenty largest online peer-to-peer (P2P) lending platforms in China (hereafter referred to as "the platform" for confidentiality). The platform was already using a referral program before we began our collaboration. This program was focused on attracting new lenders to the platform by encouraging referrals from existing lenders. The existing program offered current lenders an individual economic reward if they successfully invited new users who subsequently invested on the platform. To register, new lenders needed to provide their national identification card and cellphone numbers and link their bank accounts to the platform. Each account on the platform had to be registered using a single national identification card number. Because this information is highly sensitive, and the registration process was fairly complex, only serious lenders were likely to complete the registration procedures.

In collaboration with the platform, we designed a randomized field experiment to study the impact of providing social information on existing users' referral behaviors and firm resource acquisition outcomes. We worked closely with the Chief Operating Officer (COO) of the platform and a supporting team of six members throughout the experiment. We spent more than half a year discussing the experiment details, including how to send text messages to users, how users could log into their accounts, what webpages they would see, how they could forward referral links to friends, and how friends could register after receiving a registration link. We worked with the platform to optimize every detail, and we tested every step before the formal implementation. We also ensured procedures were implemented as planned without error. On the day of implementation, we were onsite at the firm to ensure smooth operations and to verify that nothing unexpected occurred during the experiment. To reduce interference, the platform agreed not to conduct any other promotion activities during the experiment month and over the following three months.[1]

**Field experiment design**

We worked with the platform to send one of three different mobile phone messages to sets of existing users (see Table 1 for details). A baseline control group message already in use by the firm included information about the calculation of the potential individual economic benefit of making a referral (i.e., that the user would receive 0.2 percent of their invited new user's first investment). We created two other messages that included the two social information treatments. The first treatment group (T1) received the same base information as the control group, plus prevalence information about the number of existing users who had already made referrals (i.e., the number of existing users who made successful referrals, calculated from the founding of the platform until the time the experiment began). The second treatment group (T2) received the same information as T1, coupled with consequence information regarding the collective economic consequence of that behavior (i.e., the total amount of money those users made from referrals).

The experiment lasted for one month in which existing users could forward referral link(s) to their friends. One month allowed existing users adequate time to make referrals if they wanted to. After one month, the referral links became invalid. The total sample consisted of 96,065 existing users who had created a lender account before the experiment.[2] There were a number of known heterogeneities in these existing users, including age, gender, investment amount, investment times, location, the experience with the platform (months since registration), and the number of users referred before the experiment (see variable definitions in Table 2). We therefore employed a basic form of stratified randomization (Kernan et al. 1999) to ensure that the three treatment groups we created did not differ on baseline characteristics before proceeding; if differences were detected then the entire sample was re-randomized. Table 3 describes the

[1] Two other experiments testing completely unrelated theories and employing entirely separate samples of treatment participants were also conducted at the firm. The results from these other two experiments are reported in separate working papers.

[2] It is worth noting that many of these accounts had very limited interaction with the platform, for example, they had registered on the platform but never made an investment. Our results are largely consistent if these potential "dead accounts" are excluded from the analyses.

final three experimental groups and indicates that there are no observable differences based on baseline characteristics. The sizes of the three final groups were also very similar: the control group consisted of 31,811 existing lenders, T1 group consisted of 32,196 existing lenders, and T2 group consisted of 32,058 existing lenders.

[Insert Tables 1, 2, and 3 about here]

In the experiment, existing users in each group could log into their account on the platform and forward their referral link(s) to friends after they received the text message. To facilitate the referral, the platform created a copy-and-paste button in lenders' accounts. By clicking on the button, lenders could send a referral link to their friends via email or instant message, and the friend was then able to register on the platform. Alternatively, the platform also created a scanning Quick Response ("QR") code in lenders' accounts, so that lenders could use their smartphones or other mobile devices to scan the code and forward a referral link to their friends via text message or other instant message applications. Existing users' identification was embedded in the referral link but not visible, so that the platform could track which existing user invited each new user. The platform also tracked whether or not and the number of times an existing user clicked the copy-and-paste button and/or scanned the QR code to capture their referral behaviors. A single referral link could be used by multiple new users. When potential new users received referral links, the links directed them to a webpage where they could register on the platform by providing national identification cards, cellphone numbers, and bank account information, as previously described.

## RESULTS OF FIELD EXPERIMENT

Compared to the control group, users in T1 were more likely to make referrals (forward at least one referral link). Specifically, 0.292 percent (93/31,811) of existing users from the control group sent out at least one referral link, compared to 0.376 percent (121/32,196) of existing users from T1 and 0.318 percent (102/32,058) of existing users from T2 (see Figure 2, T1 versus control, *t*-test p=0.067; T2 versus control, *t*-test p=0.554). Although these response rates are generally low, they are very similar to those found in prior studies that are also based on large Internet platforms and text messages (e.g., Singh et al. 2019), and are also consistent with the experience of the platform's managers.[3] With these referrals, on average, each existing user in the control group brought in 0.004 (136/31,811) new users who registered on the platform, compared to 0.005 (166/32,196) for existing users from T1 and 0.006 (200/32,058) for existing users from T2 (see Figure 3a, T1 versus control, *t*-test p=0.592; T2 versus control, *t*-test p=0.298). Lastly, in the control group, each existing user's invited new users made an average investment of 8.6 RMB (272,200 RMB/31,811) on the platform in the 10 weeks following their registration, compared to 9.8 RMB (315,500 RMB/32,196) for existing users in T1 and 51.1 RMB (1,639,400 RMB/32,058) for existing users in T2 (see Figure 3b, T1 versus control, *t*-test p=0.869; T2 versus control, *t*-test p=0.062)[4]. From the firm's standpoint, these two treatments therefore generated an additional 1.4 million RMB (approximately $200,000) above the control baseline.

[Insert Figures 2 and 3 about here]

To further identify the effect of social information on existing users' referral behaviors and outcomes, we ran econometric estimations at the existing user level. This strategy has been used frequently in field experiment studies in economics and psychology (e.g., Karlan and List 2007, Nolan et al. 2008).

$$Y_i = \sum \beta_g * T_g + \text{LenderChar}_i + \text{error}_i$$

$Y_i$ indicates an existing user i's referral behavior and subsequent outcomes: (1) whether the existing user made any referrals (i.e., sent out at least one referral link), (2) the number of new users who registered on the platform as a result of the existing user's invitation(s), and (3) the amount of investments made by these new users invited by each existing user. The dummy variable $T_g$ indicates the experiment group to which the existing user was assigned. $\text{LenderChar}_i$ indicates existing user-level characteristics, including age, gender,

[3] The top managers of the platform confirmed that these response rates were consistent with their expectations and common for other large-scale Internet platforms with which they were familiar. If we excluded the potential "dead accounts," these response rates would be much higher.
[4] The top five new users with the highest investment in each group account for a high share of investment in the group, specifically, they account for 95% for the control group, 92% for T1 group, and 79% for T2 group. We further checked the existing user (i.e., referrers) for these top 15 new users and find none of the 15 new users were referred by the same existing user.

cumulative investment amount, investment times, number of users referred before, and local residence. Table 4 reports the full sample descriptive statistics and correlations.

[Insert Table 4 about here]

Table 5 presents the regression tests of our general theory that social information can be used as a strategic tool. T1 and T2 are binary variables coded as 1 if the existing user was in the relevant treatment group and 0 otherwise. We first test whether including *prevalence* information increases existing users' referral likelihood. We used Logit estimators in Models 1 and 2, where the dependent variable was a binary outcome of whether the existing user made any referrals. Model 1 is the baseline model. In Model 2, the estimated coefficient of T1 is positive ($\beta$=0.268; p=0.058). The result suggests that relative to the control group, the prevalence information increased each existing user's likelihood of making referrals. Specifically, T1 enhances the likelihood by 30.7 percent relative to the control group. These results provide support for the efficacy of disclosing basic prevalence information to encourage behavior even in settings without clear normative processes.

[Insert Table 5 about here]

A natural extension of the above finding would be that prevalence information would increase the number of new users who join the platform and the amount of money invested by these new users, two dependent variables that are more directly linked to overall firm performance. In Models 3 and 4, we used the number of new users referred by each exiting user as the dependent variable. Because of the over-dispersion of the dependent variable, we adopt a negative binomial estimator. In Model 4, the estimated coefficient of T1 is positive ($\beta$=0.444; p=0.235). In Models 5 and 6, we used the total amount of investments made by the new users referred by each existing user as the dependent variable along with an OLS estimator. To reduce the skewness, we log transformed the dependent variable. In Model 6, the coefficient of T1 is positive ($\beta$=0.002; p=0.218). These results provide some indication that disclosing the prevalence information enhanced the likelihood of behavior, but did not bring in more new users or their investment.

We next test the moderating effect of *consequence* information included in the T2 treatment for each of the three DVs: the likelihood of behavior, the number of new users, and the money actually invested. In

Model 2, the estimated coefficient of T2 is positive (β=0.09; p=0.54), however, there is little evidence that T2 meaningfully increased the likelihood of an existing user making a referral compared to the control group. In Model 4, the estimated coefficient of T2 is positive (β=0.557; p=0.17). We do not find strong evidence that T2 increases the number of new users. In Model 6, the coefficient of T2 is positive (β=0.005; p=0.014), suggesting that compared to the control group, T2 increased investment by the new users referred by each existing user. Specifically, relative to the control group, each users in T2 group brought in extra 42.27 RMB investment. These results provide evidence for the general efficacy of social information as a strategic tool with two caveats. First, in settings such as this, consequence information importantly moderates prevalence information, indicating the former is at least partly being used as a proxy for the later. And second, the likelihood of behavior and the ultimate outcome of that behavior are not always coupled; we find this for both T1 and T2.

Although we did not find evidence that T2 increased existing users' referral likelihood, it increased the amount of investment from new users. This may be because the financial consequence information communicated in T2 is rather small (i.e., 10 RMB per person, or $1.45), potentially unattractive to existing users, and an even smaller value than users would have inferred from the T1 treatment alone. If existing users in T2 wanted to make referrals despite knowing the small referral bonus, they may have been more driven by non-financial motives. If this was the case, existing users may have referred the platform to closer friends who had a true interest in investing, and as a result, were more likely to register on the platform and actually make investments. In contrast, participants that received T1 did not understand how much financial consequences they could really obtain from referrals, so they may have been more motived by the potential to make money. Because of this, they may have sent referrals to more distant and larger numbers of friends in the hope more of them would register and invest on the platform. These weaker ties may not have been very interested in the platform, so the number of them who actually registered was low, as was their investment. However, the field experiment is unable to provide direct evidence of this. We therefore designed a second controlled experiment to explore these possibilities.

## VIGNETTE EXPERIMENT METHODOLOGY AND DATA

The field experiment provides evidence that social information matters for existing users' referral behavior and firm resource acquisition, as well evidence of the moderating effects of consequence information on the traditional prevalence information treatment. However, it featured two limitations common to many field experiments: 1) we were restricted to using actual context information from the setting (i.e., the specific values of 70,000 people and 700,000 RMB), and 2) we were unable to survey the full participant sample to collect direct evidence about what drove the results. We therefore subsequently designed and executed a between-subject vignette experiment using participants from Amazon Mechanical Turk (Mason and Suri 2012).

In a vignette experiment, participants read a brief hypothetical scenario, imagine themselves in that situation, and then answer questions about how they would behave and why they would behave that way. We designed our vignette experiment to mirror the earlier field setting in order to provide additional insight into the underlying processes and the boundary conditions of the effects that were identified in the original field experiment. We provided all participants a stylized description of our field setting where they were asked to imagine themselves as a user of an online lending platform. Like the field experiment, we randomly assigned each participant to one of three different conditions. All participants then answered questions about their likelihood of making a referral, characteristics of their referral behavior, their perceptions of the costs and benefits of making referrals, and some basic demographic questions.

The main departure from the field experiment treatments was that we were able to manipulate the magnitude of information within each treatment group. We created a "low" value and a "high" value for both the prevalence information and consequence information. For the prevalence information (i.e., how many people have already made referrals), we displayed either a low value of 100 people or a high value of 140,000 people. We chose these two values because their mean is roughly equal to the value from the field experiment (i.e., 70,000 people). For the consequence information (i.e., how much money people made from the behavior), we slightly changed the wording of the treatment so that it communicated the average money made thus far rather than the total pool of money made thus far.[5] Participants were shown either a low value of $1 or a high value of $100 to communicate the average bonus people have made thus far from making referrals.[6] We chose these extreme values in order to test how sensitive the field results might be to the particular values that existed at the time at the company.

The structure of the treatments mirrored the field experiment. Participants assigned to the new Control group were provided no social information, participants assigned to the new T1 group were provided one of the two different versions of prevalence information (i.e., low or high prevalence information), and participants assigned to the new T2 treatment group received one of the four combinations of prevalence and consequence information (i.e., low-low, low-high, high-low, or high-high prevalence-consequence information). We aimed for roughly 100 participants for the new control group (henceforth "Control"), 200 for the new T1 treatment group (henceforth "T1-L" and "T1-H"), and 400 for the new T2 treatment group (henceforth "T2-LL", "T2-LH", "T2-HL", and "T2-HH"). The increasing sample size ratios for the new Control, T1, and T2 groups were chosen due to the variance that we created within the new T1 and T2 groups by randomizing low and high values within these treatments. We used Qualtrics to randomize each participant into one of the treatment groups as they began the experiment (either Control, T1-L, T1-H, T2-LL, T2-LH, T2-HL, or T2-HH). This design is summarized in Table 6.

[Insert Table 6 about here]

The main dependent variable was a seven-point Likert-scale measuring each participant's stated likelihood of making a referral, ranging from "Extremely unlikely" to "Extremely likely". We then asked

[5] This eases the interpretation of the consequence variable because it does not depend on the value of the prevalence information, and it helps with the interpretation of the interaction between different levels of the prevalence and consequence variables.

[6] In addition to these three main treatments we simultaneously included three additional groups beyond the scope of the original field experiment. First, we included a "blank" scenario where only the base vignette was presented and there was no financial incentive (i.e., no 0.2% reward) nor social prevalence nor consequence information. Second, we included a treatment with only the consequence information including a scenario of low value and another of high value; that is, how much money people made but not how many referred. Third, we removed the baseline financial incentive (i.e., 0.2% reward) and only provided prevalence information including a scenario of low value and another of high value. These results are available from the authors.

about three characteristics of their referral behavior: 1) how many people they would refer, 2) how well they knew those people (contingent on referring at least one person), and 3) their perception of the average income of those people (the measurement of these variables is summarized in Appendix Table A1).

Our theory posits that providing social information reduces specific uncertainty about the costs and benefits of making referrals. We therefore asked participants their level of agreement with eight specific reasons they might (benefits) or might not (costs) make a referral. We constructed these statements based on our review of the literature as well as interviews and surveys with individuals from the context of the original field experiment. Based on this background research, the scope of these questions covered what we considered to be the most important considerations of the referral decision. Participants were asked the extent to which they agreed or disagreed with each statement using a five-point Likert scale. Finally, we asked a range of basic demographic questions including age, gender, salary, and how much experience the participant had with financial investing. Full details of these materials can be found in Appendix Tables A2 and A3.

For consistency and quality control, we required all participants to be in the U.S., to have completed at least 500 other Amazon Mechanical Turk tasks, and to have an overall past approval rate of at least 98 percent on those tasks. We also included two basic attention-checking questions at different points in the survey (i.e., “For this question please choose the option somewhat disagree” and a multiple-choice question: “Please confirm the focus of this study. What did you read about in the scenario?”). In the final data we excluded the 88 participants that failed these checks. This led to a total sample of 616 valid responses. 47 percent were women. The modal response for the age category was 35-44 years old, annual income category was $40,000 to $49,999, and most participants indicated they were slightly or moderately knowledgeable about financial investing. Table 7 summarizes the self-reported demographic variables for each treatment group; we found no significant differences across groups.

[Insert Table 7 about here]

**RESULTS OF VIGNETTE EXPERIMENT**

The main result of the experiment—the likelihood of referral—is plotted in Figure 4. The control group, T1-L, and T1-H resulted in mean referral likelihoods of 3.94, 4.24, and 4.85, respectively. Specifically, T1-H (high value of prevalence) had a significantly higher mean referral likelihood than the control group (T1-L versus Control: *t*-test p=0.297; Mann-Whitney test p=0.267; T1-H versus Control: *t*-test p=0.001; Mann-Whitney test p=0.0003). The results suggest that providing prevalence information with a sufficiently high value can increase participants' referral likelihood. This is consistent with what we found in the field experiment, which indicates that the value used in the field (i.e., 70,000 people) may have already crossed some latent threshold in the number of people required to trigger the social influence process.

The four versions of the second treatment, T2-LL, T2-LH, T2-HL, and T2-HH, resulted in mean referral likelihoods of 4.06, 4.28, 3.68, and 4.59, respectively, compared to the control of 3.94. Specifically, T2-HH (high values of both prevalence and consequence) had a significantly higher mean referral likelihood than the control group (T2-LL versus Control: *t*-test p=0.688; Mann-Whitney test p=0.654; T2-LH versus Control: *t*-test p=0.242; Mann-Whitney test p=0.207; T2-HL versus Control: *t*-test p=0.353; Mann-Whitney test p=0.328; T2-HH versus Control: *t*-test p=0.022; Mann-Whitney test p=0.013). The results suggest that providing consequence information will moderate the value of prevalence information. The combination of both high prevalence and high consequence information appears useful for generating referrals. These results indicate our version of T2 in the original field experiment, however, is likely most similar to the T2-HL scenario (high value of prevalence and low value of consequences) as neither leads to more referrals.

[Insert Figure 4 about here]

The three measures related to the characteristics of participants' referral behaviors are plotted in Figure 5: how many people they would refer, how well they know the people they would refer (if they indicated they would refer at least one person), and the estimated yearly income of the people they would refer. To simplify the analyses we treated these variables as continuous.[7] Participants that received either version of the prevalence information (T1-L and T1-H) indicated they would refer more people than the control group (Control: 2.70, T1-L: 3.42, T1-H: 3.54; T1-L versus Control: *t*-test p=0.011; Mann-Whitney test p=0.020; T1-H versus Control: *t*-test p=0.002; Mann-Whitney test p=0.002). When asked how well they knew the people they would refer, both versions of prevalence information responded with lower scores than the control (Control: 3.91, T1-L: 3.45, T1-H: 3.51; T1-L versus Control: *t*-test p=0.014; Mann-Whitney test p=0.017; T1-H versus Control: *t*-test p=0.02; Mann-Whitney test p=0.027). However, people referred by both versions of prevalence information were similarly wealthy to the people referred by the control group (Control: 6.291, T1-L: 6.758, T1-H: 6.827; T1-L versus Control: *t*-test p=0.297; Mann-Whitney test p=0.518; T1-H versus Control: *t*-test p=0.235; Mann-Whitney test p=0.464). These results suggest that participants in the prevalence groups tend to make referrals to more but less familiar friends than the control group.

[Insert Figure 5 about here]

These results help explain the findings from the field experiment. In the field experiment, the prevalence information group (T1) led to a higher likelihood of referral, but not a higher number of new users, or a higher amount of investment than the control group. This may be because that people tend to make referrals to more people, however, the vignette experiment indicates that the referrals were likely made to less-familiar people, so it is possible that those people did not actually register or invest much on the platform.

For the four versions of the new T2, T2-HH made referrals to significantly more people than the control group (Control: 2.70, T2-LL: 3.1, T2-LH: 2.92, T2-HL: 2.8, T2-HH: 4.49; T2-LL versus Control: *t*-test p=0.148; Mann-Whitney test p=0.234; T2-LH versus Control: *t*-test p=0.392; Mann-Whitney test p=0.400; T2-HL versus Control: *t*-test p=0.707; Mann-Whitney test p=0.804; T2-HH versus Control: *t*-test p=0.006; Mann-Whitney test p=0.015). In terms of how well participants knew those people, T2-HL had the

[7] The number of people referred was right truncated at “5 or more” and yearly income at “More than $150,000”.

highest score although it was not statistically significantly different from the control group. (Control: 3.91, T2-LL: 3.9, T2-LH: 3.95, T2-HL: 4.11, T2-HH: 3.69; T2-LL versus Control: *t*-test p=0.958; Mann-Whitney test p=0.962; T2-LH versus Control: *t*-test p=0.792; Mann-Whitney test p=0.933; T2-HL versus Control: *t*-test p=0.226; Mann-Whitney test p=0.200; T2-HH versus Control: *t*-test p=0.24; Mann-Whitney test p=0.316). In terms of the estimated yearly income of the people participants would refer, T2-HL again had the highest score but was not statistically significantly different from the control group (Control: 6.291, T2-LL: 6.12, T2-LH: 6.85, T2-HL: 7.00, T2-HH: 6.56; T2-LL versus Control: *t*-test p=0.693; Mann-Whitney test p=0.513; T2-LH versus Control: *t*-test p=0.193; Mann-Whitney test p=0.41; T2-HL versus Control: *t*-test p=0.134; Mann-Whitney test p=0.283; T2-HH versus Control: *t*-test p=0.526; Mann-Whitney test p=0.646). Among the four versions of the new T2, T2-HL had the lowest number of people participants would like to refer, however, it had the highest score in terms of how well participants know the people and the estimated yearly income of those people. Its lack of statistical significance may be resulted from the small sample size.

Again, this sheds light on the particular pattern observed from the field experiment. There, T2 did not have a very high referral likelihood but nevertheless led to a higher amount of investment from those new users. The vignette experiment provides one possible explanation: the T2 group in the field may have referred people they knew better and that were wealthier. Those close friends registered on the platform and actually invested. Overall, the results from the vignette experiment are consistent with and help explain the findings from the field experiment.

**Evidence of underlying motivations**

We next analyze how the treatments may have altered participants' uncertainty about the benefits and costs of making referrals. After measuring the likelihood of referral and characteristics of the referral behavior, we next asked participants about four specific reasons they might want to make a referral (perceived benefits of making a referral) and four reasons they might not want to make a referral (perceived costs of making a referral). These are summarized in Appendix Table A3. The results are plotted in Figure 6 (with average responses of each group in Appendix Table A4).

[Insert Figure 6 about here]

For brevity, we only discuss the high-level results here, and later interpret how they help explain the earlier findings from the field experiment. It is clear from the plots that the treatments impacted all eight perceptions to varying degrees (with the potential exception of Cost 2, guilt related to making money from the referral). Further, results varied within both T1 and T2. T1 generally led to increased benefits and decreased costs, with T1-H amplifying the effects compared to T1-L. This provides evidence that larger magnitudes of prevalence information are useful for both increasing perceived benefits and decreasing perceived costs.

The effects of T2 are more nuanced. With the exception of T2-HH, providing consequence information actually increased the perception that it was not worth the time and effort to make a referral (Cost 3). Further, providing even very high levels of consequence information (T2-LH and T2-HH) did not significantly increase the motive related to acquiring the monetary bonus (Benefit 3). It appears that providing low values of consequence information (T2-LL and T2-HL) actually decreased that motive. This increase in perceived cost coupled with a lack of change in benefits may be the reason that T2 in the vignette experiment—with the exception of T2-HH—did not generate higher overall likelihoods of referral. Overall, the vignette experiment provides clearer evidence that social information alters specific uncertainty about both the costs and benefits of the referral behavior.

## DISCUSSION

In this study we examined whether and how a firm can trigger social influence processes as a resource acquisition strategy. We did so by studying the phenomenon of referrals, where firms attempt to acquire resources from second-degree connections by leveraging ties to existing stakeholders. We experimentally tested whether disclosing two configurations of social information was effective: 1) basic prevalence information about how many people had already made referrals—what has traditionally been referred to as a "descriptive norm" in the literature—and, 2) the same prevalence information moderated by consequence information about how much money people had already made from making referrals. Using a field experiment involving 96,065 existing users of an online lending platform, we found evidence that providing social information generally impacted existing users' referral behaviors and real firm resource acquisition. We found that the two forms of social information shift the behavior itself and the characteristics of the behavior in different ways. We designed and ran a vignette experiment to provide insights into why that might have occurred.

Results from this second experiment indicate that the level of the consequence in the field experiment was simply too low for users to make a referral. Thus, it appears that prevalence information was incorrectly being used as an informational proxy by at least some users, and when it was supplemented with the actual consequence information, they reduced their likelihood of referral. In the field experiment we were obligated to use the actual historical data from the platform, which at the time of the experiment was 70,000 existing users and 700,000 RMB. Therefore, existing users would have expected to gain only 10 RMB (equivalent to $1.45) on average. This means the T2 field experiment treatment was possibly more similar to T2-HL (high prevalence and low consequence) than T2-HH (high prevalence and high consequence) in the vignette experiment. This would have triggered an increase in perceived costs without a corresponding increase in benefits. The vignette experiment indicates that if the value of the consequences in the field had been higher, T2 in the field may have led to more referrals.

However, the more interesting findings may be related to the characteristics of the referral behavior itself. In the field experiment, T2 led to much higher investment by new users that joined through the referrals. The vignette experiment indicates that the T2 treatments led to changes in the referral pool (i.e., the people that accepted the referrals). This provides evidence for the mechanism by which T2 in the field led to more actual investments despite not increasing referral likelihood in the first stage. Based on the vignette experiment, it now seems the most plausible interpretation of T2 in the field is that it caused people to refer friends they knew better, and that were ultimately more likely to follow-through and actually use the platform. This highlights the importance of triggering not only the first-order behavior (i.e., the referral) but triggering it in a way that is favorable to the firm (i.e., referring someone who will actually invest).

**Theoretical contribution**

Although past research has documented how firms' behavior and performance are significantly shaped by social influence, prior management research has usually assumed a passive role for firms when it comes to causing that influence. Our study suggests that firms can strategically trigger social influence processes for their own benefit. Compared with other strategies, it is nearly costless to disclose information to stakeholders. In addition, firms are in a unique position to access information about collective stakeholder behavior that stakeholders do not individually possess. Therefore, the type of strategy explored in this study may be a particularly cost-effective tool for firms.

Our study also shows that disclosing different types of social information has different outcomes. Specifically, information about the prevalence of a behavior (T1) led to a higher likelihood of referral, but not a higher number of new users, or a higher investment by those new users. The vignette experiment confirmed that one reason for this is that providing such information appears to alter the pool of people that are referred, leading to weaker connections being referred.

When the collective economic consequence information was added in T2 in the field experiment, it did not have a significant effect on referral likelihood or the number of new users but it brought in more investment from those new users. We suggest that this result is because the economic consequence information resolves uncertainty about extrinsic motivation. The presence of economic consequences changes how existing users interpret the referral decision (Deci et al. 1999, Heyman and Ariely 2004). When it is small in magnitude it may suppress the overall motive. This is supported by the T2 treatments in the vignette experiment where the economic consequence information could lead to a perception that making a referral is not worth the time and effort, unless the consequence is high enough. Therefore, T2 in the field experiment may have caused participants to make referrals to closer friends.

This provides clearer boundary conditions regarding when a specific firm should or should not employ the strategy. Like the firm in the field experiment, any given firm's strategic choice is simply whether to make visible the social information it already holds; it is unable to manipulate the level of that information as we did in the vignette experiment. Firms with high prevalence and high consequence information should unambiguously make this information visible to users. However, counterintuitively, firms with low consequence values can still benefit from disclosing that information, because while it might not increase the likelihood of referral, it may shift who is referred in a way that benefits the firm.

Finally, it is often difficult to identify the impact of social information or other social effects based on observational data alone, because user characteristics and behavior tend to cluster (Azoulay et al. 2017). We responded to this challenge in two ways. First, by employing a field experiment in which we could better identify the effect of information on multiple important real-world outcomes—we therefore address recent calls for more field experimental tests of management theories (Chatterji et al. 2016). And second, we designed a vignette experiment to address the limitations of the field experiment. This process allowed for clearer boundary conditions to the strategy as well as more direct measurement of the potential explanations of the field results.

**Future research opportunities**

The fact that such a small manipulation increased resource acquisition for a large firm indicates that knowledge of such "social" strategic tools may still be lacking for practitioners. Given that the strategy field itself has often been subdivided into economic and behavioral approaches (Levinthal 2011), it seems fitting that a similar dichotomy may be useful for classifying the different tools that firms themselves can employ to increase performance. The price mechanism, economic contracts, and many other tools have already been extensively explored from an "economic" perspective. This study demonstrates that firms also have the ability to develop and deploy tools of a more "behavioral" nature. The communication of social information that we tested in this study is one such strategic tool, but there are likely others. Given that such tools may be cheaper to employ than economic ones, it seems worthwhile for strategy scholars to direct more attention toward their theoretical development and use.

In this study we chose to only vary the provision of information but hold the direct financial incentive offered by the firm constant (i.e., the 0.2% contingent reward). This is useful for two reasons. First, this study is theoretically about the provision of information itself, and how information alone may be able to resolve decision uncertainty in ways that improve firm performance, rather than how real economic incentives change behavior. Second, firms (such as the one in our field experiment) incur direct costs when manipulating financial incentives, which makes them potentially more limited in their use. That said, other studies have found interaction effects between social information and direct financial incentives (e.g., Burtch et al. 2017). While the current study was not focused on providing incentives per se (i.e., unconditional payment for a behavior), future work might further consider this possibility.

The effects that we identified are strategically useful for firms given that they highlight the type of information that should be communicated in this particular context. However, this study represents just a single stakeholder within a single firm. For example, other studies may attempt to test these findings in settings such as employee referrals. It is encouraging, however, that we find largely consistent results across both a field and "lab" setting, each with very different participant samples.

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Table 1: Experimental groups and messages for the field experiment.

| | Group | Message (original in Chinese) |
|---|---|---|
| 1 | Control group (C) | Invite your friend to invest on the platform. You can gain an additional benefit equivalent to 0.2% of your friend's first investment. |
| 2 | Prevalence (T1) | Invite your friend to invest on the platform. You can gain an additional benefit equivalent to 0.2% of your friend's first investment. 70,000 people already gained this benefit from referrals. |
| 3 | Prevalence + consequence (T2) | Invite your friend to invest on the platform. You can gain an additional benefit equivalent to 0.2% of your friend's first investment. 70,000 people already gained this benefit from referrals, with a total of more than 700,000 RMB received. |

Table 2: Variable definitions for the field experiment sample.

| | Variable | Definition |
|---|---|---|
| 1 | Cumulative investment | Each lender's cumulative investment amount on the platform. |
| 2 | Average amount per investment | The average amount for each investment. Calculated based on all transaction data for each lender. |
| 3 | No. users referred before | Number of referrals before the experiment. |
| 4 | VIP level | Platform's rating system ranging from 0 to 9. It depends on lenders' cumulative investment amount. The more investment, the higher the VIP level. |
| 5 | Investment times | Total number of investments made by each lender before the experiment. |
| 6 | Gender | Male is coded as 1 and female is coded as 0. |
| 7 | Age | Lenders' age at the time of experiment. |
| 8 | Local residence | Coded as 1 if a lender lives in the same province as the platform, 0 otherwise. |

Table 3: Descriptive statistics of existing users in each group for the field experiment. See Appendix Table A5 for pairwise comparisons of each mean.

| | | Control group | | Prevalence (T1) | | Prevalence + consequence (T2) | |
|---|---|---|---|---|---|---|---|
| | Variables | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| 1 | Cumulative investment amount (1,000 RMB) | 6.499 | 39.511 | 6.866 | 40.939 | 7.065 | 46.340 |
| 2 | Average amount per investment (1,000 RMB) | 0.872 | 4.348 | 0.910 | 4.872 | 0.908 | 4.722 |
| 3 | No. users referred before | 0.263 | 1.806 | 0.251 | 1.663 | 0.246 | 1.646 |
| 4 | VIP level | 0.034 | 0.182 | 0.035 | 0.184 | 0.034 | 0.181 |
| 5 | Investment times | 1.265 | 4.487 | 1.289 | 4.475 | 1.279 | 4.450 |
| 6 | Gender | 0.709 | 0.454 | 0.706 | 0.456 | 0.707 | 0.455 |
| 7 | Age | 32.578 | 10.692 | 32.672 | 10.872 | 32.655 | 10.774 |
| 8 | Local residence | 0.141 | 0.348 | 0.142 | 0.349 | 0.142 | 0.349 |
| | Observations | 31,811 | | 32,196 | | 32,058 | |

Table 4: Descriptive statistics and correlations for the field experiment sample.

| | Variables | Mean | S.D. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Referral likelihood | 0.003 | 0.057 | | | | | | | | | |
| 2 | No. new users | 0.005 | 0.234 | 0.389 | | | | | | | | |
| 3 | Investment by new users (1,000 RMB) | 0.023 | 2.414 | 0.167 | 0.058 | | | | | | | |
| 4 | Cumulative investment (1,000 RMB) | 6.811 | 42.371 | 0.064 | 0.001 | 0.030 | | | | | | |
| 5 | No. users referred before | 0.254 | 1.706 | 0.071 | 0.074 | 0.003 | 0.017 | | | | | |
| 6 | VIP level | 0.034 | 0.182 | 0.078 | 0.001 | 0.032 | 0.667 | 0.014 | | | | |
| 7 | Investment times | 1.278 | 4.471 | 0.088 | 0.004 | 0.023 | 0.659 | 0.051 | 0.610 | | | |
| 8 | Gender | 0.707 | 0.455 | -0.005 | 0.003 | -0.003 | -0.010 | -0.005 | -0.004 | -0.023 | | |
| 9 | Age | 32.635 | 10.780 | 0.011 | -0.002 | 0.004 | 0.097 | 0.016 | 0.111 | 0.154 | -0.144 | |
| 10 | Local residence | 0.142 | 0.349 | 0.002 | 0.004 | -0.003 | 0.012 | 0.004 | 0.020 | 0.017 | 0.032 | -0.050 |

N=96,065

Table 5: Predicting existing users' referral likelihood and outcomes in the field experiment. Models 1 and 2 are logit models; Models 3 and 4 are negative binomial models; Models 5 and 6 are OLS models.

| | Logit regressions | | Negative binomial regressions | | OLS regressions | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Variables | Made a referral (1/0) | | No. new users | | Investment by new users (RMB) | |
| T1 | | 0.268* | | 0.444 | | 0.002 |
| | | (0.058) | | (0.235) | | (0.218) |
| T2 | | 0.090 | | 0.557 | | 0.005** |
| | | (0.540) | | (0.170) | | (0.014) |
| Age | -0.007 | -0.007 | -0.018 | -0.016 | -4.01e-05 | -4.05e-05 |
| | (0.211) | (0.215) | (0.149) | (0.177) | (0.594) | (0.590) |
| Cumulative investment amount | 0.582*** | 0.581*** | 0.056 | 0.062 | 0.007*** | 0.007*** |
| | (0.000) | (0.000) | (0.614) | (0.561) | (0.007) | (0.007) |
| Investment times | 0.003 | 0.003 | 0.048* | 0.042* | -0.0002 | -0.0002 |
| | (0.689) | (0.676) | (0.075) | (0.079) | (0.686) | (0.686) |
| No. users referred before | 0.119*** | 0.120*** | 0.757*** | 0.787*** | 0.011*** | 0.011*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Gender | -0.168 | -0.169 | 0.560* | 0.559* | -0.001 | -0.001 |
| | (0.174) | (0.172) | (0.092) | (0.071) | (0.613) | (0.615) |
| Local residence | -0.008 | -0.009 | 0.865 | 0.758 | -0.001 | -0.001 |
| | (0.962) | (0.954) | (0.123) | (0.134) | (0.716) | (0.714) |
| Constant | -6.076*** | -6.203*** | -6.045*** | -6.467*** | 0.005* | 0.003 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.080) | (0.348) |
| | | | | | | |
| Observations | 96,065 | 96,065 | 96,065 | 96,065 | 96,065 | 96,065 |
| Log likelihood/R-squared | -1861 | -1859 | -1357 | -1355 | 0.006 | 0.006 |

*p*-value in parentheses; Robust standard errors; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Hypothetical scenario and treatments for the vignette experiment. Each participant was randomly shown one version of the treatment text as indicated in the table.

<table>
<tr><td>Scenario text seen by all participants</td><td colspan="3">Imagine you have been making loans using an online company. This company serves as an intermediary between lenders like you and borrowers who are seeking loans. You have already made some money by making loans using this company.<br><br>However, if a borrower does not repay their loan, you will lose your money. Further, the company is quite new and is not yet well established. You will also lose your money if the company goes bankrupt.<br><br>The company wants to increase its number of new lenders, so it asks you to refer your friends to the company.<br>[Treatment text inserted here; see below]</td></tr>
<tr><td>Randomized experimental text displayed above</td><td>Vignette Control:<br>For each referral you make, the company will provide you a bonus of 0.2% of the value of the first loan your friend makes.</td><td>Vignette T1:<br>For each referral you make, the company will provide you a bonus of 0.2% of the value of the first loan your friend makes. [100 or 140,000] people have already referred their friends.</td><td>Vignette T2:<br>For each referral you make, the company will provide you a bonus of 0.2% of the value of the first loan your friend makes. [100 or 140,000] people have already referred their friends and gained an average bonus of $[1 or 100] each.</td></tr>
<tr><td>Group labels</td><td>Control</td><td>T1-L: 100<br>T1-H: 140,000</td><td>T2-LL: 100 and $1<br>T2-LH: 100 and $100<br>T2-HL: 140,000 and $1<br>T2-HH: 140,000 and $100</td></tr>
</table>

Table 7: Descriptive statistics of Amazon Mechanical Turk participant sample for the vignette experiment. See Appendix Table A2 for description of how demographic variables were measured. Slight variance in sample sizes is because we excluded participants that failed the attention-check questions. See Appendix Table A6 for pairwise comparisons of each mean.

| | Control | | T1-L | | T1-H | | T2-LL | | T2-LH | | T2-HL | | T2-HH | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| Financial experience | 2.529 | 0.938 | 2.348 | 0.918 | 2.527 | 1.089 | 2.522 | 0.877 | 2.540 | 0.998 | 2.247 | 0.937 | 2.494 | 0.951 |
| Annual salary | 4.885 | 2.379 | 5.124 | 2.575 | 5.308 | 2.792 | 5.056 | 2.465 | 5.345 | 2.956 | 5.212 | 2.722 | 5.241 | 2.828 |
| Gender | 1.483 | 0.503 | 1.506 | 0.503 | 1.560 | 0.499 | 1.422 | 0.497 | 1.437 | 0.499 | 1.412 | 0.495 | 1.471 | 0.502 |
| Age | 3.713 | 1.170 | 3.876 | 1.136 | 4.055 | 1.369 | 3.644 | 0.998 | 3.839 | 1.219 | 3.882 | 1.286 | 3.609 | 1.175 |
| No. participants | 87 | | 89 | | 91 | | 90 | | 87 | | 85 | | 87 | |

Figure 1: The relationship between the firm, its current stakeholders (denoted with letters), and second-degree resource holders (denoted with numbers). The goal of the firm is to acquire as many resources as possible from the numbered actors, which requires the active cooperation of existing stakeholders who must make referrals. One strategy to do this is to disclose to the current stakeholders how many other stakeholders have already made referrals and the consequences of that behavior.

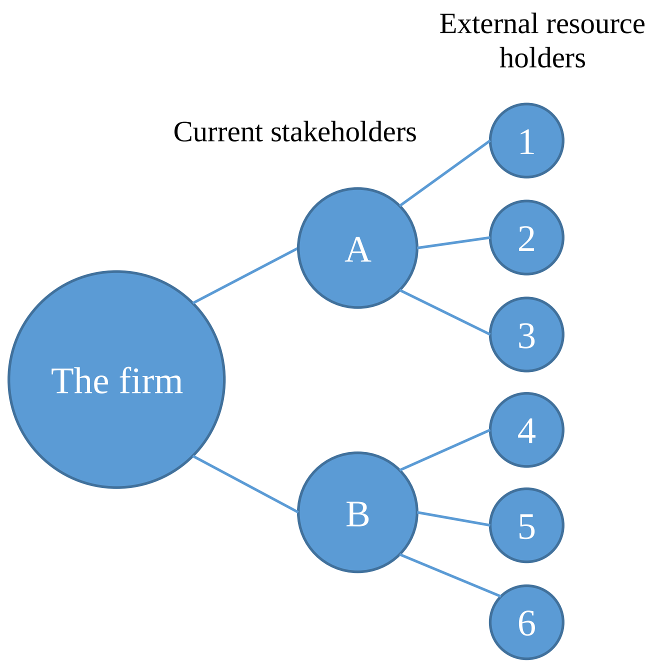



Figure 2: Field experiment average referral likelihood of each group, with standard error bars.

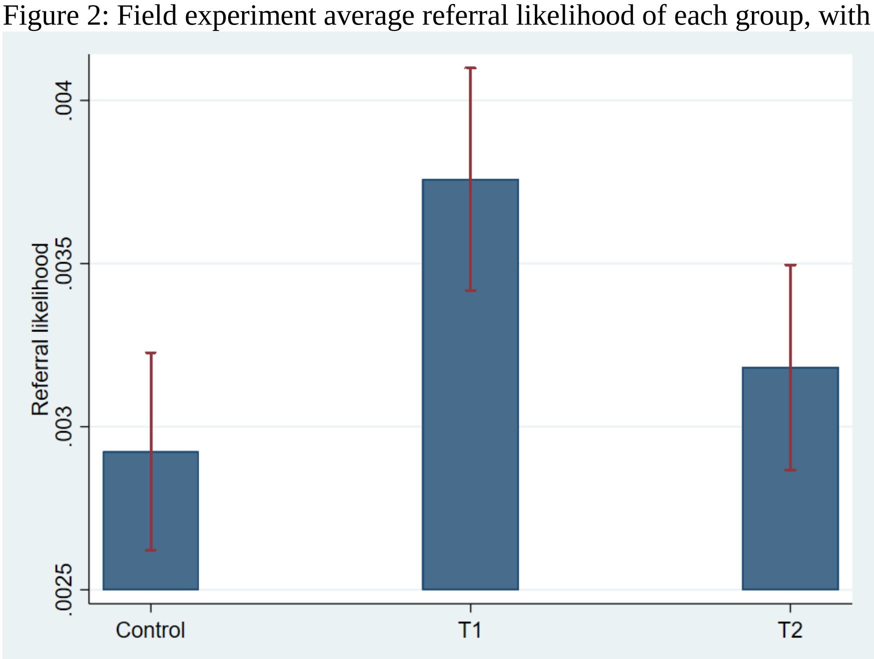


Figure 3: Field experiment average number of new users per existing users (a; left panel) and average investment (b; right panel), with standard error bars.

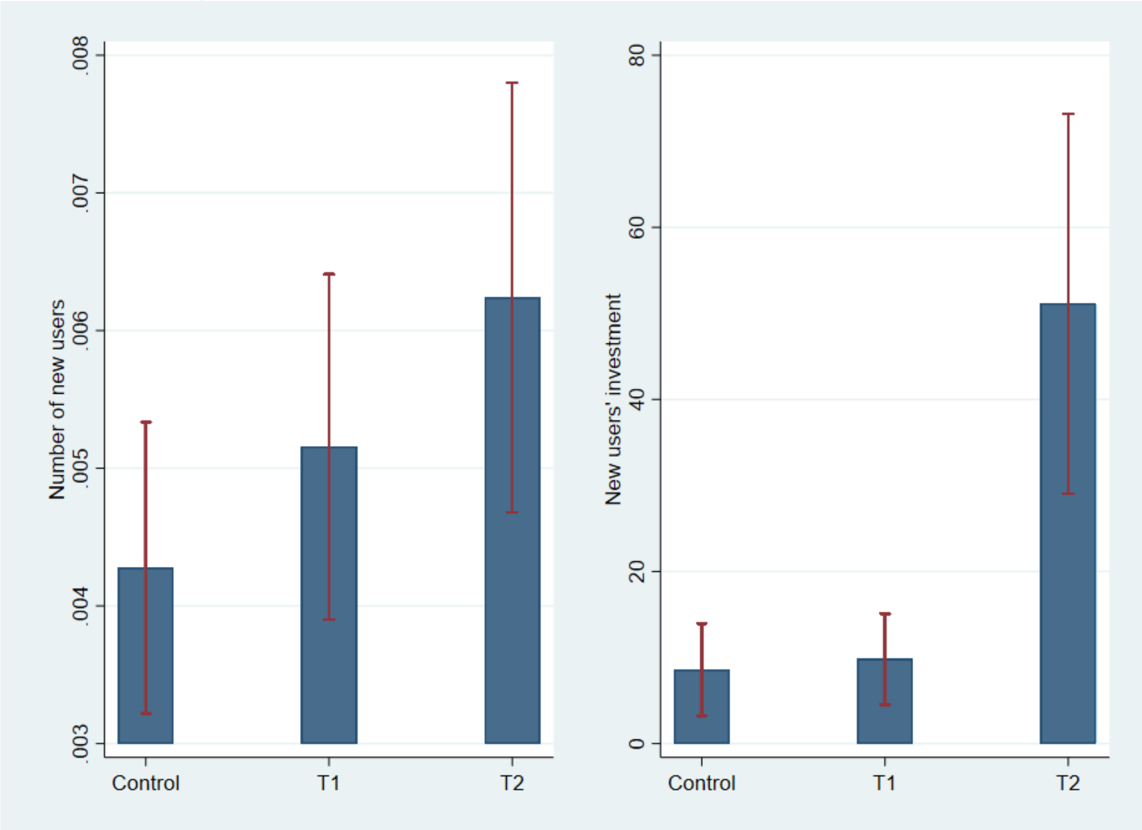



Figure 4: Vignette experiment average referral likelihood of each group, with standard error bars. Scale is 7-point Likert scale ranging from "Extremely unlikely" (1) to "Extremely likely" (7) for the question: "Considering the above information, how likely are you to make a referral?"

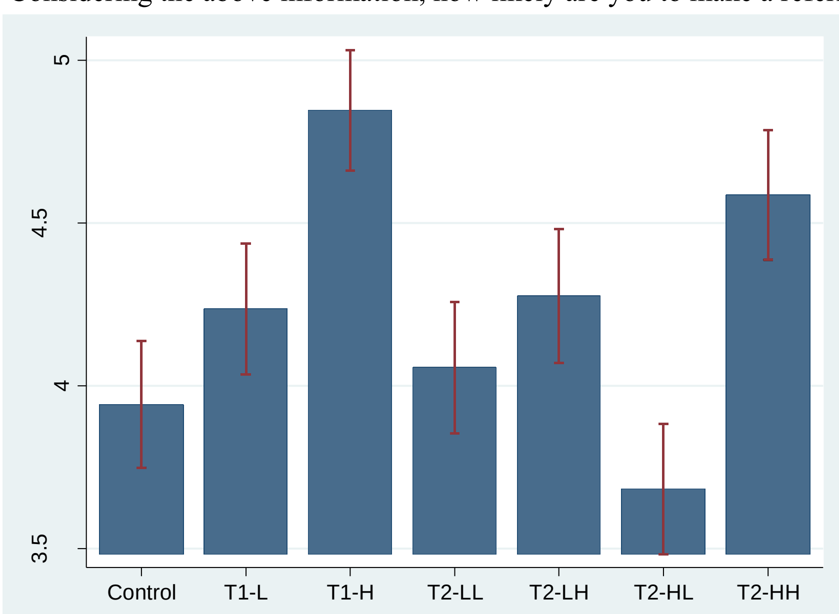


Figure 5: Vignette experiment average responses for questions about characteristics of the referral behavior, with standard error bars. Note, the scale for each variable is different (see Appendix Table A1 for complete descriptions):

1) how many people they would refer, where 1 = no one and 6 = five or more people.
2) how well they knew those people (contingent on referring at least one person), where 1 = " Not well at all" and 5 = "Extremely well".
3) their perception of the average income of those people (also contingent on referring at least one person), where 1 = “less than $10,000”, values of 2 to 10 are increased in $10,000 increment windows, 11 = “$100,000 to $149,000”, and 12 = "More than $150,000".

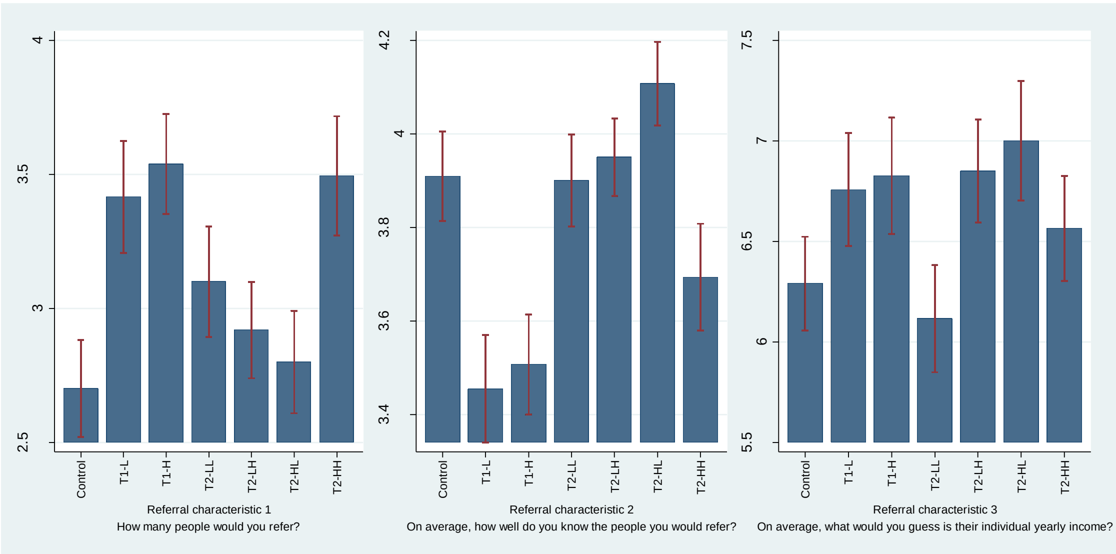
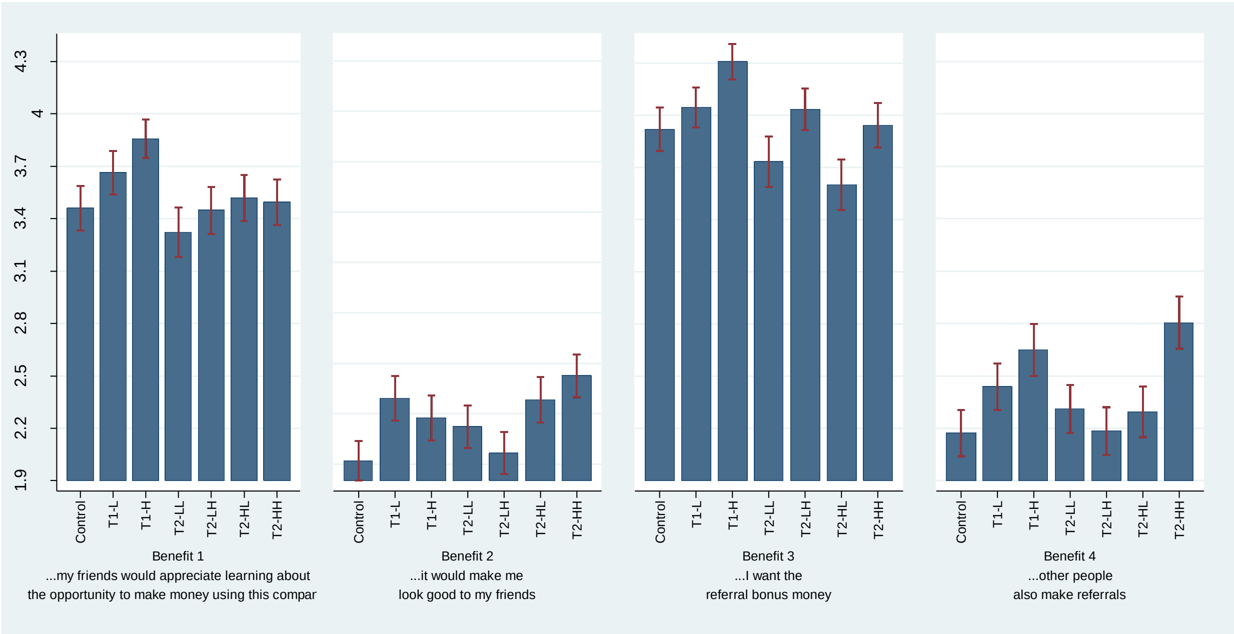
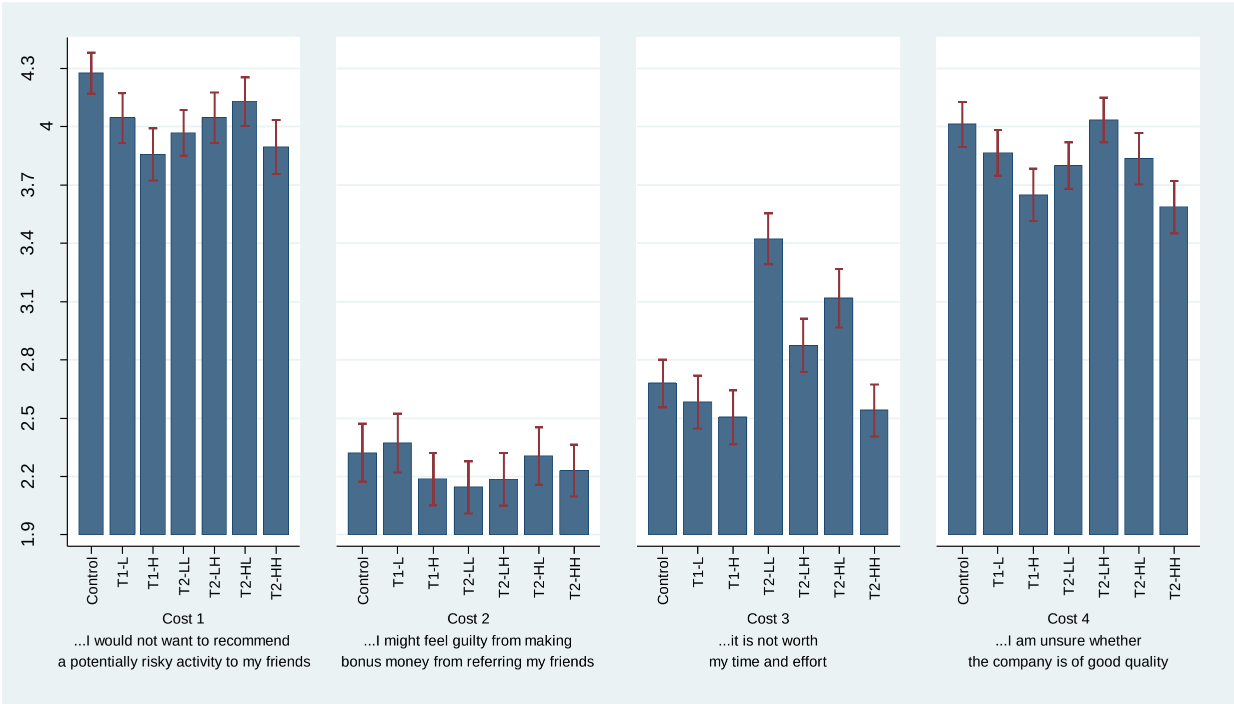


Figure 6: Vignette experiment responses to questions on benefits and costs, measured on a 5-point Likert scale from "Strongly disagree" (=1) to "Strongly agree" (=5). The question was: "Using the information from the scenario, consider the following reasons you MIGHT make a referral?" and "…reasons you MIGHT NOT make a referral?". Includes standard error bars. See Appendix Table A3 for the structure of these questions.

"I might make a referral because..."




"I might NOT make a referral because..."



**APPENDIX**

Table A1: Outcome variables in the vignette experiment: likelihood of referral and characteristics of the referral behavior.

| | |
|---|---|
| *Main DV* | Considering the above information, how likely are you to make a referral? |
| | 7-point Likert scale from "Extremely unlikely" to " Extremely likely" |
| *Number of people* | How many people would you refer? |
| | 6-choice question:<br>1 = "No one"; 2 = “One person”; 3 = “Two people”; 4 = “Three people”; 5 = “Four people”; 6 = "Five or more people" |
| | Please think about the people that you indicated you would refer on the previous page. |
| *Strength of relationship* | On average, how well do you know the people you would refer? |
| | 5-point Likert scale from " Not well at all" to "Extremely well" |
| *Income of the referred* | On average, what would you guess is their individual yearly income? |
| | 12- choice question:<br>1 = "Less than $10,000"; 2 = “$10,000 to $19,999”; 3 = “$20,000 to $29,999”; 4 = “$30,000 to $39,999”; 5 = “$40,000 to $49,999”; 6 = “$50,000 to $59,999”; 7 = “$60,000 to $69,999”; 8 = “$70,000 to $79,999”; 9 = “$80,000 to $89,999”; 10 = “$90,000 to $99,999”; 11 = “$100,000 to $149,000”; 12 = "More than $150,000" |

Table A2: Survey questions for vignette experiment participants’ demographic information.

| | |
|---|---|
| 1 | How would you describe your own experience with financial investing? |
| | 5-point Likert scale from "Not knowledgeable at all" to "Extremely knowledgeable" |
| 2 | What is your annual salary? |
| | 12- choice questions:<br>1 = "Less than $10,000"; 2 = “$10,000 to $19,999”; 3 = “$20,000 to $29,999”; 4 = “$30,000 to $39,999”; 5 = “$40,000 to $49,999”; 6 = “$50,000 to $59,999”; 7 = “$60,000 to $69,999”; 8 = “$70,000 to $79,999”; 9 = “$80,000 to $89,999”; 10 = “$90,000 to $99,999”; 11 = “$100,000 to $149,000”; 12 = "More than $150,000" |
| 3 | What is your gender? |
| | Male 1; Female 2 |
| 4 | How old are you? |
| | 9-choice questions:<br>1 = "Under 18"; 2 = “18-24”; 3 = “25-34”; 4 = “35-44”; 5 = “45-54”; 6 = “55-64”; 7 = “65-74”; 8 = “75-84”; 9 = "85 or older" |

Table A3: Vignette experiment questions about the perceived benefits and costs of making a referral measured on a 5-point Likert scale from "Strongly disagree" to "Strongly agree". Each block of questions was presented in a random order and the order of each question was randomized within the block.

| Using the information from the scenario, consider the following reasons you **MIGHT** make a referral? | |
|---|---|
| *Benefit_1* | I might make a referral because my friends would appreciate learning about the opportunity to make money using this company |
| *Benefit_2* | I might make a referral because it would make me look good to my friends |
| *Benefit_3* | I might make a referral because I want the referral bonus money |
| *Benefit_4* | I might make a referral simply because other people also make referrals |
| Using the information from the scenario, consider the following reasons you **MIGHT NOT** make a referral? | |
| *Cost_1* | I might not make a referral because I would not want to recommend a potentially risky activity to my friends |
| *Cost_2* | I might not make a referral because I might feel guilty from making bonus money from referring my friends |
| *Cost_3* | I might not make a referral because it is not worth my time and effort |
| *Cost_4* | I might not make a referral because I am unsure whether the company is of good quality |

Table A4: Average responses of each treatment group for each benefit and cost question in the vignette experiment. See Table A3 for full description of benefit/cost questions.

| Benefits & costs: | B1 | B2 | B3 | B4 | C1 | C2 | C3 | C4 | N |
|---|---|---|---|---|---|---|---|---|---|
| Control | 3.46 | 1.92 | 3.92 | 2.172 | 4.276 | 2.322 | 2.678 | 4.011 | 87 |
| T1-L | 3.663 | 2.292 | 4.045 | 2.438 | 4.045 | 2.371 | 2.584 | 3.865 | 89 |
| T1-H | 3.857 | 2.176 | 4.308 | 2.648 | 3.857 | 2.187 | 2.505 | 3.648 | 91 |
| T2-LL | 3.322 | 2.122 | 3.733 | 2.311 | 3.967 | 2.144 | 3.422 | 3.8 | 90 |
| T2-LH | 3.448 | 1.966 | 4.034 | 2.184 | 4.046 | 2.184 | 2.874 | 4.034 | 87 |
| T2-HL | 3.518 | 2.282 | 3.6 | 2.294 | 4.129 | 2.306 | 3.118 | 3.835 | 85 |
| T2-HH | 3.494 | 2.425 | 3.943 | 2.805 | 3.897 | 2.23 | 2.54 | 3.586 | 87 |
| All | 3.539 | 2.169 | 3.943 | 2.409 | 4.029 | 2.248 | 2.817 | 3.825 | 616 |

Table A5: Pairwise randomization check of the means of each group from the field experiment. T-test p-values are reported.

| | Cumulative investment amount | Average amount per investment | No. users referred before | VIP level | Investment times | Gender | Age | Local residence |
|---|---|---|---|---|---|---|---|---|
| T1 vs Control | 0.517 | 0.554 | 0.634 | 0.844 | 0.775 | 0.652 | 0.511 | 0.974 |
| T2 vs Control | 0.21 | 0.594 | 0.414 | 0.907 | 0.913 | 0.839 | 0.634 | 0.966 |
| T2 vs T1 | 0.823 | 0.998 | 0.932 | 0.59 | 0.959 | 0.946 | 0.98 | 1 |

Table A6: Pairwise randomization check of the means of each group from the vignette experiment. P-values are reported.

| Pairwise Test | Financial experience | Annual salary | Gender | Age |
|---|---|---|---|---|
| T1-L vs Control | 0.88 | 1.00 | 1.00 | 0.97 |
| T1-H vs Control | 1.00 | 0.94 | 0.95 | 0.48 |
| T2-LL vs Control | 1.00 | 1.00 | 0.98 | 1.00 |
| T2-LH vs Control | 1.00 | 0.92 | 1.00 | 0.99 |
| T2-HL vs Control | 0.47 | 0.99 | 0.97 | 0.97 |
| T2-HH vs Control | 1.00 | 0.98 | 1.00 | 1.00 |
| T1-H vs T1-L | 0.87 | 1.00 | 0.99 | 0.95 |
| T2-LL vs T1-L | 0.89 | 1.00 | 0.92 | 0.85 |
| T2-LH vs T1-L | 0.84 | 1.00 | 0.97 | 1.00 |
| T2-HL vs T1-L | 0.99 | 1.00 | 0.88 | 1.00 |
| T2-HH vs T1-L | 0.95 | 1.00 | 1.00 | 0.76 |
| T2-LL vs T1-H | 1.00 | 1.00 | 0.51 | 0.24 |
| T2-LH vs T1-H | 1.00 | 1.00 | 0.65 | 0.89 |
| T2-HL vs T1-H | 0.46 | 1.00 | 0.43 | 0.96 |
| T2-HH vs T1-H | 1.00 | 1.00 | 0.90 | 0.17 |
| T2-LH vs T2-LL | 1.00 | 0.99 | 1.00 | 0.93 |
| T2-HL vs T2-LL | 0.49 | 1.00 | 1.00 | 0.85 |
| T2-HH vs T2-LL | 1.00 | 1.00 | 1.00 | 1.00 |
| T2-HL vs T2-LH | 0.42 | 1.00 | 1.00 | 1.00 |
| T2-HH vs T2-LH | 1.00 | 1.00 | 1.00 | 0.87 |
| T2-HH vs T2-HL | 0.63 | 1.00 | 0.99 | 0.75 |