Who gets the job referral?

Evidence from a social networks experiment *

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Abstract

We use recruitment into a laboratory experiment in Kolkata, India to analyze how job networks select individuals for employment opportunities. We present evidence that individuals face a tradeoff between choosing the most qualified individual for the job and the individual who is ideal from the perspective of their social network. The experiment allows randomly selected subjects to refer members of their social networks to subsequent rounds of the experiment and varies the incentive schemes offered to these participants. We find that when faced with performance pay, individuals are more likely to refer co-workers and less likely to refer family members. High ability participants who are offered performance pay recruit referrals who perform significantly better on a cognitive ability task and also prove to be more reliable as evidenced by their choices in the trust game and performance on an effort task.

1 Introduction

Social networks influence labor markets worldwide. An extensive empirical literature has documented the role networks play in job search in many contexts[1], and found that social connections assist in search for a tremendous fraction of all jobs (including 30-60% of U.S. jobs (Bewley,

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[1] See for example Bayer et al. (2005); Beaman (2009); Kramarz and Skans (2007); Granovetter (1973); Laschever (2005); Magruder (2010); Munshi (2003); Munshi and Rosenzweig (2008); Topa (2001).

1999; Ioannides and Loury, 2004)). There is less evidence on how urban labor markets in developing countries operate, despite the knowledge that poverty is increasingly becoming an urban phenomenon (Ravallion et al., 2007). Recent cross country comparisons also show that many of the world's poor work as laborers in urban areas (Banerjee and Duflo, 2007). Our sample from Kolkata suggests that social networks play a similarly important role in job access as in the U.S.: over 40% of employed respondents helped a friend or relative find a job with their current employer.[2] Understanding who gains access to jobs through these networks is therefore an important part of understanding urban labor markets in developing countries.

Theoretical arguments have emphasized that the use of social networks in recruiting may smooth several information asymmetries (Montgomery, 1991; Munshi, 2003). Through frequent social interactions, employees may be able to identify new hires who are productive in hard to observe ways, or productive employees may simply have productive friends through assortative matching. However, disseminating job information is rarely the primary reason that social relationships are formed and maintained. There is an extensive literature in development economics stressing the important role that social connections play in coping with risk, rather than emphasizing their utility in job search. Altruism, heredity, and a variety of cultural institutions are surely also central in determining social interactions. Thus, it is far from theoretically clear that the type of information that network members need to have about each other for risk sharing is the same type of information required to screen for a particular job with a specific set of required skills. In addition, the incentives an employee faces from his employer to refer his most productive friend may not be sufficient to overcome those provided by the network, who may pressure employees with referral opportunities to refer needy, but poorly qualified, friends. Depending on how these incentives balance out, there could be strong implications

[2]Recruitment through current employee referrals is common in the U.S.: over 35% of employers reported in the National Organizations Study that they frequently use this mechanism of recruitment (Fernandez et al., 2000).

for employee productivity and access to jobs for the unemployed. The empirical evidence that networks can screen or follow assortative matching, above and beyond the evidence that network size and quality affects labor market outcomes, is extremely limited.[3] Very basic questions such as whether references have sufficient information about their friends and neighbors to select good matches for a specific job and whether they in practice use this information to refer good matches remain open. Indeed, while a large literature has examined productivity implications of heterogeneous on-the-job relationships, (Mas and Moretti, 2009; Bandiera, Barankay, and Rasul, 2005, 2007, 2010, 2009a,b), much less research has been devoted to a direct examination of the social relationships which referral systems bring onto the job. If social connections matter through the referral process, there will surely be interactions between recruitment and on-the-job productivity.

This study examines the job referral process in Kolkata, India, using a laboratory experiment which exploits out-of-laboratory behavior. We set up a temporary laboratory in a peri-urban area, and create jobs in an experimental setting by paying individuals to take a survey and complete tasks which alternatively emphasize cognitive skills or effort. Our employees are offered a financial incentive to refer a friend or relative to the job. While everyone is asked to refer a friend who will be highly skilled at the job, the type of referral contract and amount is randomized: some are offered a fixed payment while others are offered a guaranteed sum plus the possibility of a bonus based on the referrals' performance (performance pay). The referrals are not themselves given any direct financial incentive to perform well. This allows us to see which incentives lead to high quality workers, which incentives lead to the systematic referral of relatives or coworkers, and which individuals respond best to these incentives. In order to isolate the effect of the performance pay contract on the selection of referrals, we give individuals

[3] Castilla (2005) uses personnel data from a call center in the U.S. to argue that workers hired through employee referrals have high productivity and lower turnover.

in the performance pay treatments, once they have returned to the lab, the maximum payment from the range stipulated in their contract.[4] Finally, all participants are invited to play a series of dictator and trust games at the end of the second round of the experiment.

The controlled setting we create allows us to examine the complete set of on-the-job incentives faced by each of our employees, which would be difficult in a non-experimental setting. We find that there is a tension between the incentives constructed by the employer and the social incentives within a network. When individuals in our study receive performance pay, they respond by being 8% more likely to refer coworkers and 8% less likely to refer relatives. This is a large change since less than 15% of individuals refer relatives. Second, analysis of referrals' actual performance in the cognitive task treatments shows that high performing original participants (OPs) are capable of selecting individuals who are themselves highly skilled, but that these individuals only select highly skilled network members when properly incentivized. Low ability original participants, however, show little capacity to recruit high performing referrals. This result is consistent with the idea that only individuals who performed well on the test can effectively screen network members, and we provide evidence that low ability participants can not predict the performance of their referrals.[5] We also document that high ability OPs facing performance pay are aware that they are bringing in higher quality referrals, and that performance pay leads to a more accurate assessment of referral capabilities.

Finally, we explore which characteristics are sought by the successful high ability, incentivized OPs. A feature of the experimental design is that referrals have no direct financial incentive to perform well, as the experiment will pay them a fixed sum regardless of how well

[4] If there are side payments in which the original participant indexes the payment to the referral as a function of his performance, we would conflate the selection effect with the impact of the indirect incentives created by such a side contract. The experimental design is similar in spirit to Karlan and Zinman (2009) and Cohen and Dupas (2009).

[5] Low ability participants may also have a lower network quality, an alternative hypothesis we can not rule out as we discuss in section 2.3.

they do. This contract structure means that the original participants - especially those in performance pay treatments - need to select a referral who will perform well in a setting with a moral hazard problem. We provide evidence that OPs in performance pay treatments help solve this problem by recruiting inherently reliable referrals. First, their referrals transfer more money, in the role of player 2, to their partners in the trust game. Such transfers have traditionally been interpreted as a measure of trustworthiness (Karlan, 2005; Schechter, 2007a). We argue that it also reflects reliability and dependability. Second, high ability original participants in the performance pay cognitive treatments refer individuals who perform better on the effort task, even though there is no incentive for a strong performance for either the OP or the referral. High ability, incentivized OPs also systematically bring in the type of young, high cognitive ability recruits who on average are successful at the task. However, neither these nor other observable characteristics can explain the productivity premium their referrals enjoy. This suggests that the information being harnessed by these high ability types is difficult for the econometrician to observe, and may be difficult for prospective employers as well.

The paper is organized as follows. The next section summarizes the incentives networks face in allocating jobs and provides a theoretical framework for interpreting the experiment. The experimental design is described in detail in section 3, and the implementation of the experiment and data is presented in section 4. The results are presented in two sections. Section 5 shows how OPs respond to incentives in terms of their relationship with the referral, referral performance on the cognitive task, and how OPs anticipated their referrals to perform. The characteristics of the referrals, including measures of their reliability, are analyzed in section 6. We discuss policy implications and conclude in section 7.

2 Network Incentives in Job Allocation

2.1 Background

The potential of networks to better solve the firm's screening problem has been a key argument used by economists to explain why social networks play a large role in the labor market. The argument is that employees have information about their network members which would be expensive for employers to collect, and so employers encourage the use of social connections in recruitment. While the empirical works by Munshi (2003) and others have provided empirical evidence consistent with this model - that individuals with larger or higher quality networks are more likely to be employed - there is scant direct empirical evidence showing that social networks have and exploit informational advantages. By contrast, some models focus on a simple information dissemination mechanism, where social networks reduce search costs but do not necessarily exploit a heightened ability to screen fellow network members (Calvo-Armengol and Jackson, 2004; Beaman, 2009; Mortensen and Vishwanath, 1994).[6]

Social networks also serve as important sources of insurance, particularly in developing countries (Udry, 1994; Townsend, 1994; Rosenzweig and Stark, 1996). In the absence of formal contracts, these networks likely depend on more than just the repeated game nature of their interactions, but also other-regarding preferences, such as notions of trust, altruism and reciprocity (Foster and Rosenzweig, 2001).

In order for networks to resolve asymmetric information problems associated with the firm's screening problem, job networks must identify and refer systematically qualified members.[7] However, the altruistic and insurance nature of social ties discussed above also suggests

[6] There are also numerous indirect mechanisms through which networks can affect labor market outcomes, including networks' effect on welfare usage and crime (Bertrand, Luttmer, and Mullainathan, 2000; Glaeser, Sacerdote, and Scheinkman, 1996).

[7] Since network-based recruitment may be lower cost than other methods, it may only be necessary that social networks identify referrals who are not sufficiently worse than workers recruited through formal methods as to offset the savings into recruitment cost.

that individuals may face a multitude of incentives, including those constructed from their social network. Accordingly, an employee may prefer to refer network members with whom they share a particular social bond, a relative for example, at the expense of referring the most productive member. This paper seeks to identify these tradeoffs. A large body of research has mapped network connections co-authorship networks, and other researchers have examined the structure of insurance and learning networks (Conley and Udry, 2009; Ligon and Schechter, 2008). However, there is little empirical evidence on the composition of job networks, where individuals use networks to share scarce opportunities at low individual cost. In fact, several studies (Loury, 2006; Magruder, 2010; Munshi and Rosenzweig, 2008) have suggested that particular family relationships may be quite important in job network contexts, while an older tradition (Granovetter, 1973) has emphasized the frequency by which jobs are spread through "weak ties." This contrast recalls the two uses of networks described above: ideally job information filters efficiently and meritocratically to the best match within a network. In contrast, if the insurance and altruistic motivations dominate job allocation decisions, then one might imagine job information would remain within a tight network of individuals. This suggests that the use of networks may restrict the mobility of the qualified but poorly connected, exacerbating inequality. This potential of social networks to exacerbate inequality has been long described by a literature in Sociology (Peterson et al., 2000) as well as some more recent theory in economics (Calvo-Armengol and Jackson, 2004).

The theoretical work of Montgomery sidesteps the problem that employees may not have the proper incentives to refer good people by assuming that the ability of network members are correlated with one another. Munshi makes a weaker assumption: that a high ability worker has a higher fraction of high ability types within his network and assumes, without supporting empirical evidence, that incumbent workers have the appropriate incentives to refer the able type.

In this paper, we provide direct evidence on whether an employee referral system can generate highly productive workers, and how incentives provided by the employer - in this case the research team - affect the characteristics and productivity of individuals referred by existing employees.[8] In the next section we provide an overview of the experimental design and the context of the study, and section 2.3 presents a stylized model to facilitate interpretation of the experiment.

2.2 Context

The experiment is designed to test if networks recruit individuals with match-specific skills and if so, under what conditions. Building on other studies which have examined the capacity of laboratory experiments to predict outcomes outside of the laboratory (Karlan, 2005; Ashraf, Karlan, and Yin, 2006), our study utilizes the actual recruitment process into a laboratory experiment in the field to observe behavior which occurs outside of the laboratory.

The general setup of the experiment is that an initial pool of randomly selected subjects are asked to refer members of their social networks to participate in the experiment in subsequent rounds. The idea is that paid laboratory participants are fundamentally day labor. If we draw from a random sample of laborers, and allow these laborers to refer others into the study, we can learn about how networks work to identify individuals for casual labor jobs by monitoring the characteristics of the referrals, the relationships between the original participants and their referrals, and the performance of the referrals at the "job." By varying the types of financial incentives provided to employees, we observe aspects of the decision-making

[8]This paper looks at how social connections and workplace incentives affect the productivity of the firm, as in Bandiera et al. (2009a) and Bandiera et al. (2009b). In contrast to their studies, we evaluate how incentives affect the selection of potential workers rather than on-the-job effort of existing workers. Moreover, we observe choices over the entire set of social network members not just those who are already employed by the firm.

that occurs within networks and the tradeoffs network members face when making referrals.

Our study takes place in peri-urban Kolkata. Many of our subjects work in informal and casual labor markets, where employment is often temporary and uncertain; these conditions are closely approximated by the day-labor nature of the task in our laboratory. Moreover, social networks are an important part of job search in this context as already discussed. In the experiment, we directly observe a job network allocating jobs, in this case the position of being a laboratory subject. Participants receive payment in the first round of the study, Rs. 135 ($3.00), which is higher than the median daily income for the population in this study (Rs. 110). Participants in the second round can earn even more. While the experiment can not mimic employee referrals for permanent, salaried positions, it does generate real world stakes and offers what could be viewed as one additional temporary or uncertain employment opportunity among many available in a fluid labor market. Moreover, and important for our interpretations, we have full control over the various static and dynamic incentives provided by the employer.

2.3 Theoretical Framework

We present a simple stylized model to illustrate the potential tradeoffs an individual faces when asked to make a referral by his employer. By incorporating financial incentives provided by the firm and heterogeneity in ability and imperfect information on the part of the network member, it also highlights how incentives can affect the choice of the referral.

Individual i is choosing between two friends for a job referral. Each friend has an ability level θ, and a transfer t that he will give to person i if he is selected. This transfer can be thought of as the altruistic benefit i receives from referring that friend, the expected value of the favor the friend will return to i in reciprocation, or a direct monetary transfer.[9]

[9]Symmetrically we could think of this as a reduction in future transfers i would otherwise have to make to

For each of these friends, i observes $\hat{\theta} \in \{\theta_H, \theta_L\}$. Similarly, the true ability of each friend is $\theta \in \{\theta_H, \theta_L\}$. We assume that $P\left(\theta = \theta_H | \hat{\theta} = \theta_H\right) = P\left(\theta = \theta_L | \hat{\theta} = \theta_L\right) = \beta$, and that $\beta \in [0.5, 1]$.[10] Thus, if $\beta > .5$, the individual has useful information on his friends' capabilities. Suppose friend 1 has $\hat{\theta} = \theta_H$ and friend 2 has $\hat{\theta} = \theta_L$.

If i selects friend 1, then he will receive

$$\beta\pi\left(\theta_H\right) + \left(1 - \beta\right)\pi\left(\theta_L\right) \tag{1}$$

The friend with $\hat{\theta} = \theta_L$ will also give i a transfer, t, if he is selected. Thus, if i selects friend 2, he will receive

$$t + \beta\pi\left(\theta_L\right) + \left(1 - \beta\right)\pi\left(\theta_H\right) \tag{2}$$

In this set up, there is by construction a tradeoff between choosing the friend who an individual believes to be high ability and the friend who will provide a transfer with certainty but is believed to be low ability. This type of tradeoff is crucial to the experiment inducing changes in referral behavior based on performance pay incentives. The stylized model presented here demonstrates this through one particular functional form but this type of tradeoff will be present in any network where the highest ability member is not the member who provides the largest transfer.

Consider first a firm which pays a fixed fee for any employee who makes a referral. In this case, $\pi\left(\theta_H\right) = \pi\left(\theta_L\right) = \pi$. Accordingly, friend 2 will always be chosen as long as $t > 0$, even if π is increased or decreased. This implies that experimental manipulation of a fixed finder's fee should result in no changes in referral behavior.

Second, consider the role of information in the selection of a network member. If

this friend due to other risk sharing or network-based agreements.

[10] The assumption that β is not less than 0.5 is an innocuous assumption. If $\beta < .5$, an analogous yet less intuitive problem can be set up where friend 1 provides the transfer and the results described here hold.

individual i has no information about friends' ability, then $\beta = 0.5$. Again, friend 2 will always be chosen as long as $t > 0$.

When will performance pay affect the selection of a referral? We have already seen that friend 2 will be chosen under fixed payment. For a fixed $\beta > .5$, i chooses friend 1, the friend who is believed to be high ability, if the performance payment is large enough relative to the transfer friend 2 will provide. That is, if

$$\beta\pi\left(\theta_H\right) + (1-\beta)\,\pi\left(\theta_L\right) > t + \beta\pi\left(\theta_L\right) + (1-\beta)\,\pi\left(\theta_H\right)$$

or

$$\pi\left(\theta_H\right) - \pi\left(\theta_L\right) > \frac{t}{2\beta - 1} \tag{3}$$

Therefore, under the conditions that $t > 0$, $\beta > .5$ and condition 3, individual i will choose a different friend in a fixed payment scheme compared to a performance pay scheme. This means that performance pay will only affect the performance of referrals if networks have information to screen participants, there is a tradeoff between ability and out of laboratory transfers, and the performance pay stakes given the distribution of abilities in the network are sufficiently high relative to the network-based payoffs.

Equation 3 also shows that as information, β, increases, individual i will be increasingly willing to give up larger and larger transfers in order to refer friend 1 under a performance pay system. That is, increases in β above .5 means that friend 1 is more likely to be chosen since condition 3 will hold for higher and higher values of t. In terms of the experiment, this implies that a group with better information about their network members will be more likely to respond to performance pay incentives.

This theoretical example helps illustrate what can and can not be identified in the experiment. There are four necessary conditions for performance pay to sponsor a change in the choice of referrals: (i) the variation in ability in the network must be substantial enough: i.e. θ_H and θ_L are different enough such that $\pi(\theta_H) - \pi(\theta_L)$ is not too small; (ii) the performance pay regime must be sufficiently high stakes compared to the network-based transfers t; (iii) individuals must be able to screen network members, i.e. $\beta > .5$; and (iv) there must be a tradeoff between ability and transfers, i.e. $t > 0$. If we observe no differences in referral performance or referral characteristics between fixed and performance pay treatments, we will not be able to determine which of these four conditions have not been met. However, if we observe that referrals recruited under performance pay do perform better, this is evidence that networks have valuable information about their members' abilities and face a tradeoff between referring the best person for the job and the best person "for the network".

An additional prediction of the model regards heterogeneity in the observed effects. If we observe that a sub-group (notationally, group A) of our OPs respond to our incentives by bringing in highly skilled referrals and that another group (say, group B) does not, then we will have identified that information and tradeoffs do exist at least for group A, i.e. that $\beta_A > 0.5$ and $t_A > 0$. However, the response of referral performance to OP incentives will not help us identify whether group A has greater information than group B, access to a network with a greater dispersion in member ability, or lower tradeoffs in terms of network transfers provided by low ability members. Any investigation into these channels will have to rely on supplementary information (for example, differences between groups in the ability to predict referral performance, which would be indicative of differences in information).

3 Experimental Design

As already described, the experiment consists of multiple rounds. In the first round, a random sample of men between the ages of 18 and 65 is invited to take a survey and perform either an effort-intensive or cognitive-intensive task for a fixed wage. They are offered incentives to refer another individual to the study. In subsequent rounds, the initial participants return with their referrals, who complete a survey and both tasks. Finally, all participants play a series of trust and dictator games and respond to a short concluding survey.

This section describes the three main parts to the experiment: the initial recruitment; the return of the original participants with the referrals, and the economic games.

3.1 Initial Recruitment

We draw a random sample of households in a peri-urban residential area of Kolkata, India. Sampled households are offered a fixed wage if they send an adult male household member to the study site, which is located nearby. Participants are assigned an appointment time, requested to be available for two hours of work, and are provided with a single coupon to ensure that only one male per household attends. Upon arrival at the study site, individuals are asked to complete a survey on demographics, labor force participation and social network members. In addition, the survey includes two measures of cognitive ability: the Digit Span Test and Raven's Matrices.[11] The initial group (OPs) faces an experimental treatment randomized along several dimensions. OPs are asked to complete one of two (randomly chosen) tasks: a task emphasizing cognitive ability or a second task emphasizing pure effort. The effort task asks participants to create small bags of peanuts for 30 minutes and is similar in spirit to the effort task in Jakiela (2009). This task was chosen to mimic the relatively simple and repetitive

[11]These two measures have been validated by psychologists and are increasingly used in household surveys in developing countries.

tasks which are often required in market work.[12] In the cognitive task, participants are asked to design "quilts" from a group of colored swatches according to a series of four different rules.[13] We have data on whether the participant gets the puzzle correct, the time it takes to complete the puzzle correctly, and the number of times he indicates to the experimenter that he thinks he has gotten the puzzle correct.

At the end of the experiment, individuals are paid Rs. 135 for their participation. They are also invited to return with a male friend or family member (a referral) between 18 and 60 and offered to be paid for the reference. A second randomization occurs to determine the amount of payment the OP will receive when he returns with a referral. Payment varies along two dimensions: the amount of pay and whether pay may depend on the referral's performance. Participants are ensured that their payment will be at least a minimal threshold. OPs are informed of the offer payment immediately prior to their exit from the laboratory[14].

There are seven treatment groups as demonstrated in the table below:

	Cognitive Task	Effort Task
Performance Pay	Low: Rs. 60-80	Low: Rs. 60-80
	High: Rs. 60-110	-
Fixed Payment	Very Low: Rs. 60	-
	Low: Rs. 80	Low: Rs. 80
	High: Rs. 110	-

[12]At the same time, we did not want to use a task which is commonly done among this population, as it would be too easy to simply refer an individual who has precisely that job. We are instead interested in networks' ability to identify individuals with skills which are difficult for firms to observe.

[13]In one puzzle, for example, the participant must fill in a four by four pattern with 16 different color swatches - 4 swatches of 4 colors - and ensure that each row and column has only one of each color. Participants (both OPs and referrals) are given one of two sets of analogous puzzles at random, allowing us to confirm empirically that in fact referrals do not perform better if they are given the same puzzles as their OPs. Puzzle type is used as a control in all regressions. These puzzles are presented in greater detail in the appendix. The left side represents unmovable squares in each puzzle and the right panel shows one possible solution.

[14]Both the group of OPs who responded to our solicitation to come into the study and the group of OPs who return with referrals are selected samples. The selection of OPs into the study mimics the selection that an employer would face after providing notice of a new casual job; as such this selected sample mimics a "selected sample" of employees and it does not confound inference. The selection of OPs to return with referrals will be explored carefully in what follows.

For OPs doing the effort task, they are offered either Rs. 60-80 depending on performance pay or Rs. 80 as a fixed finder's fee. In all cases, the exact level of performance for the given task is specified in the offer. In the cognitive treatments, there are multiple levels. The highest performance pay offers between Rs. 60 and 110 while the low performance pay is Rs. 60-80 as in the effort task. As fixed finder's fees, OPs are randomly offered either Rs. 60, 80 or 100. All participants are asked to make an appointment to return with a referral in a designated three day window.[15]

3.2 Return of OPs with referrals

When the original participants return with their referrals, the referrals fill out the survey and perform both the effort and the cognitive ability tasks. In order to minimize the ability for OPs to cheat by telling their referrals the solutions to the puzzles, we developed two sets of puzzles which are very similar and randomized which set was used in each laboratory session.[16] A key feature of this study is that both OPs and referrals have no private incentive to perform well on either task. However, there may be unobserved side payments which OPs make to bring in referrals. To be sure that any unobserved side payments are not indexed to referral performance (creating a private incentive for referrals to try harder), all OPs are paid the maximum amount within the pay range they were told, eliminating any motivation for such a side payment. Participants in the cognitive task performance pay-high category, for example, are all paid 110 Rs.[17] While referrals perform the tasks and complete the survey, OPs fill out a short interim

[15] Paying a financial reward to employees to make referrals may not seem representative of how most firms operate. However, we have anecdotal evidence that some Indian firms do pay finder's fees and evidence from the U.S. (Castilla, 2005) that firms pay financial rewards to employees and the rewards can be tied to performance. Finally, the financial reward in this case proxies for other, more diffuse, returns to making a good referral such as the opportunity to refer additional people to the firm in the future or a positive reputation in the eyes of one's supervisor.

[16] The type of puzzle used is included as a control in tables focused on the cognitive task.

[17] The experimental protocol states that both the OP and referral are informed of the good news before the referral performs either task. This eliminates the incentive for OPs to indirectly incentivize their referrals' performance.

survey about the process they went through in recruiting referrals. Both the OP and the referral are informed when they arrive at the lab that there is an additional opportunity to earn more money by participating in a round of economic games after the referral has completed his tasks.

3.3 Economic Games

Once the referrals have completed the tasks, each OP and referral play two versions of the dictator game and two versions of the trust game. Every OP plays four economic games: two dictator and two trust games, one with his own referral and one randomly selected referral.[18] In this paper, we focus primarily on the version of the games where the OP and referral play together.

Economic games, particularly dictator and trust games, have been widely used in development economics (Schechter, 2007a; Barr and Genicot, 2008). In the dictator game, player 1 is given Rs. 160 ($3.50) and asked how many Rupees he would like to give to player 2, who is specified by name. The literature has typically found that proposers give a non-zero amount to their partners in both anonymous and non-anonymous versions of the dictator game (Ligon and Schechter, 2008).

The protocol for the trust game is as follows: player 1 is given Rs. 80, with the option of dividing it between himself and his partner. His partner receives triple the amount donated, and, in turn, faces the choice of how much to return to the first actor. While trust games have been played extensively in many contexts, a demonstrated limitation is that the first player's trust decision is confounded by risk preferences (Karlan, 2005; Schechter, 2007b). However, since surplus is not created when the second player returns some of the asset, the second player's decisions can be viewed as an estimate of "trustworthiness" as confirmed empirically in Karlan

[18] The order of games, in terms of play with the random or referral partner, is randomized.

(2005). Trustworthiness may be closely related to reliability or dependability, evaluated in this context by the effort a friend exerts in the absence of monitoring by the OP or direct private incentives for the referral. The sociology literature suggests that reliability and trustworthiness are important traits an employee seeks in a referral, especially in an environment with limited trust overall (Smith, 2008).

At the end, each participant gets an independent die roll to determine which game determines his pay. Participants are not told which game is used to determine their payment, and therefore the play of their partners (referral or otherwise) is almost unverifiable.

Finally, participants were administered a post survey which asks whether the participant anticipates sharing any of his earnings. There is no evidence that OPs provide indirect incentives to their referrals, as discussed in section 3.2. Zero OPs report that they will share their finder's fees with their referral. Moreover, there is little evidence of side payments in general: only 14 referrals reported they would share their payment with their OP.

4 Data and Descriptives

There are multiple aspects of performance on each of the two tasks. The measure of performance we use for the cognitive ability task takes into account three aspects of performance: the time a participant spent on each puzzle, the number of incorrect attempts and whether the participant ultimately got the puzzle correct. We use a single metric in order to incorporate these three important components using the following functional form. A perfect score for a given puzzle, which would involve getting the correct answer in under one minute with no incorrect attempts, has a value of 20. Incorrect attempts and more time spent to get the correct answer lowers the score. The participate receives a zero if the puzzle is not completed within the allotted time. The score of the four puzzles is then averaged and standardized using the mean and standard deviation of the entire original participant sample. Performance on the effort task is relatively straight-forward. We observe the number of bags of peanuts counted during three consecutive 10 minute intervals, and the number of bags with the correct number of peanuts in bags which were chosen at random. We use the normalized total number of bags created as our measure of peanut performance.

Table 1 shows a number of characteristics of original participants from the baseline survey of OPs and round 1 performance as a function of treatment type. Overall, the randomization created balance on observed characteristics. One exception is that OPs in the high powered incentives treatment group performed worse on the cognitive task compared to OPs in other treatments.[19] Due to attrition, the sample of OPs who participate in round 2 is highly balanced. We note that this complicates the interpretation of the attrition results, especially with respect to heterogeneous responses by OP initial performance.

The average OP in the sample is approximately 30 years old, and 34% of the initial subjects are young, between 18 and 25. Households tended to send an adult son within the age range to participate in the study: only 33% of OPs are heads of households. Almost all of the participants in the study are literate.

Which original participants chose to participate in the second round of the study? Approximately 70% of OPs returned to the laboratory with a referral. Table 2 shows how the decision to return with a referral is a function of treatment type. The first column suggests that participation does not vary significantly with treatment type in the full sample. None of the treatment indicators are individually significant and, while not shown in the table, they are not jointly significant. Performance pay may induce differential attrition by ability. Low

[19] As randomization was done on a rolling basis through the roll of a die, it was not possible to use stratification or pair-wise matching, as described by Bruhn and McKenzie (2008). Note, however, that the correlation between OP performance and referral performance is only .15. Therefore even a relatively large imbalance such as .19 of a standard deviation is unlikely to significantly alter the results.

ability individuals who are given high stakes incentives may be less likely to participate in the study. Indeed, column (2) demonstrates that individuals with a high initial test score randomly assigned a high stakes performance pay offer are more likely to recruit a referral. Columns (3) and (4) split the sample into high ability participants, those with normalized test scores greater than 0, and low ability participants, those with normalized scores less than 0. These columns reveal divergent responses to performance pay based on an individual's initial performance: high ability OPs are more likely to participate while low ability OPs are less likely. These results indicate that the type of incentive provided by an employer will affect the type of employee who chooses to engage in the recruitment process and make a referral. If only high ability employees bring in good referrals, as we investigate in the next section, performance pay may serve as a way for firms to screen employees to solicit referrals from and induce self-selection.

5 Tradeoffs

5.1 Relationship between Referrals and OPs

The model described in section 2.3 highlighted the potential tradeoffs an individual faces when making a referral. As a proxy variable for the social transfer j that a referral is making to an OP, we use their relationship. We anticipate that relatives in particular differ from friends and coworkers in the types of transfers - financial, insurance-oriented or altruistic - exchanged between two individuals. In this section, we analyze whether the relationship between the OP and referral changes when the offered contract from the employer is altered.

Random assignment of the recruitment contract provides a straightforward strategy to analyze how performance pay affects the type of referral an OP recruits:

$$y_{ik} = \beta_0 + \phi_k + X_k\gamma + \epsilon_{ik} \tag{4}$$

where y_{ik} is an indicator for the type of relationship between referral i and OP k and ϕ_k represents the 7 treatment categories. We focus on three salient relationships: co-workers, relatives and friends. X includes demographic characteristics of OPs from round 1 of the study and are described in the footnotes of Table 3.

As seen in section 4, approximately 70% of original participants returned with a referral in the second round. While attrition is an interesting outcome in its own right, selective attrition between rounds 1 and 2 in the study could generate biased results. Table 2 shows evidence of selective attrition since low ability OPs are less likely to participate in the study if they are randomly assigned the performance pay treatment. While the lowest possible payment in the performance pay treatment is equal to the lowest fixed payment, Rs. 60, in the cognitive treatment, we can not rule out ex ante a negative behavioral response to performance pay.

Therefore, we employ the Heckman two step selection model with a first stage probit and second stage estimation including the inverse mills ratio from the first stage (Heckman, 1976). Rainfall serves as an exclusion restriction, as it affects attendance but should not be correlated with performance in our (indoor) laboratory.[20] Estimates are robust to allowing temperature, which is correlated with rainfall, to have a direct effect on performance; that specification is presented in Appendix Table 2. The weather data we have available includes an indicator for whether there was non-zero rainfall on each day of the study as well as the mean and maximum temperature on each day.[21] While the exact day that an OP and his referral would have participated is unknown among the attrited population, we do know each OP's window of 3 days in which he had to return with his referral. We therefore use the number of days, from 0 to 3, in each OP's window that it rained. All of the results presented in the paper

[20]As there may be selectivity into the first round of the study, we also include rainfall on the day the OP participants. Indeed, we find that OPs who join the study on rainy days are less likely to attrit in the subsequent round.

[21]The daily rainfall and temperature data were downloaded from Weather Underground, `http://www.wunderground.com`.

are robust to an alternative specification which relaxes the normality assumption by including a polynomial of the predicted values from a first stage probit in the second stage instead of the inverse Mills ratio (Deaton, 1997).

Table 3 shows the relationship between OPs and their referrals as a function of treatment type. Columns (1) and (2) demonstrate that rainfall during the OP's window for recruitment significantly lowers the probability that the OP completes the study. While not shown in the table, the marginal effect at the mean of the covariates of the number of days of rain during the OP's referral cycle in specification (1) implies that one extra day of rainfall makes it 21% less likely an OP will return with his referral to the laboratory. Moreover, the instruments jointly have power: the chi squared statistic is over 12 in both specifications. In subsequent tables, only the chi squared statistic from the joint test of significance of the two rainfall variables is shown.

Columns (4) through (8) examine the three most salient relationships identified in the survey using the Heckman selection model: coworkers, relatives and friends. Column (3) shows that only 15% of OPs returned with a coworker as their referral. Individuals assigned to the high stakes performance pay treatment were significantly more likely to refer a coworker. Columns (5) and (6) show that the high stakes group was also less likely to refer a relative. Both results represent an economically significant change given that a small fraction of OPs refer relatives. This result is consistent with the model's prediction that performance pay may lead to a shift from a preferred reference, in this case a relative, to one with better skills, a coworker. Columns (7) and (8) show that there is no change in the probability of referring a friend.[22] Whether the performance pay resulted in higher performing referrals is investigated in the next section.

[22]This may be due to the fact that the category friend is too broad to pick up changes and may mask changes in degree of friendship.

5.2 Referral Performance and Response to Incentives

Random variation in treatment type provides exogenous variation to analyze whether the treatment type of the OP affects his referrals' performance:

$$y_{ik} = \beta_0 + \beta_1 \theta_k + \phi_k + X_k \gamma \ + \varepsilon_{ik} \tag{5}$$

where y_{ik} is the performance of referral i who was recruited by OP k; θ_k is the OP k's ability, as measured by the OP's performance of the task in phase 1 of the experiment; and ϕ_k is defined as before. If there is positive assortative matching in networks, we would expect that $\beta_1 > 0$. We test whether financial incentives alter a network members' referral choice - i.e. selecting a referral based more on ability than on other criteria - if OPs in the performance pay treatments recruit referrals who perform better than referrals in fixed pay treatments.

Bandiera et al. (2010) find significant heterogeneity in social effects according to worker ability, which accords with the theoretical assumptions in Montgomery (1991).[23] If high ability workers receive a more accurate signal of their network members' ability, β is larger, then they will recruit higher ability referrals when given a performance pay incentive. Moreover, the work by Munshi (2003) suggests that high ability workers will have higher ability social network members to choose from, if properly incentivized. In this spirit, we also evaluate:

$$y_{ik} = \beta_0 + \beta_1 \theta_k + \beta_2 perf_k * \theta_k + \phi_k + X_k \gamma + \epsilon_{ik} \tag{6}$$

where $perf_k * \theta_k$ is the interaction of an indicator for whether the OP was in a performance pay treatment and the OP's ability. If high ability OPs respond more to high powered incentives, then we anticipate $\beta_2 > 0$. If the across-the-board assortative matching assumption in

[23]In context of Bandiera et al. (2010), evaluating spillovers from an individual working in close proximity to his or her friend, they found that the average social effect was zero since high ability workers had the opposite response to peers than low ability workers.

Montgomery (1991) is correct, then $\beta_1 > 0$ in this specification as well.

Table 4 shows how OPs responded to the incentives on the cognitive ability task.[24] The first estimates are from OLS in columns (1) through (4) then the Heckman selection model in columns (5) through (8). Correcting for attrition is important: other than the result that an OP's initial score is positively correlated with a referral's test score, there is no significant relationship between treatment type and performance. Using exogenous variation in rainfall reveals much more. Column (5) shows that there is no significant relationship between treatment type and performance in the full sample. However, as seen in column (6), more able OPs recruited higher performing referrals. As discussed in the theoretical example, this is consistent with a positive correlation between an OP's ability and the overall ability of the OP's network, or it may represent differential ability to screen.

By interacting initial OP ability with performance pay in columns (7) and (8), we see that the differential performance of referrals recruited by high ability OPs is actually driven by OPs who face performance pay incentives. Therefore, high ability individuals refer high ability people only when properly incentivized.[25] Column (7) versus (8) shows that this effect is stronger among OPs in the high stakes performance pay treatment. We discuss columns (9) and (10) in section 6.

[24]Appendix table 1 shows that there is no effect of the treatments on referral performance at the peanut task. This may be the result of the smaller sample size as the effort treatments constitute only 32% of the entire sample. The experimental design may have also made it difficult to observe a differential performance on the effort task. Suppose there are two components of performance: an inherent ability or work ethic and a portion based on effort. Referrals were chosen when OPs knew there was the possibility of performance pay. Accordingly, OPs may have selected people that would be likely to put in effort under a performance pay contract, if they indirectly incentivized their referrals. By removing the performance pay incentive, referrals had less of an incentive to perform well. If there is no inherent effort quality in these referrals, we would not observe any difference in performance. We do, however, observe a differential performance in the effort task among referrals recruited by incentivized cognitive OPs, suggesting that there are inherent qualities which affect performance on the effort task.

[25]While rainfall may affect the probability an OP-referral pair participate in the second round of the study, rainfall is also correlated with temperature. Rainfall means lower temperature, which may increase performance in a hot climate such as Kolkata. Appendix Table 2 shows the results of the same specification as in Table 4 with an average maximum temperature on referral days an additional covariate. The results are robust to this specification.

A key component of the experimental design is paying the OPs the maximum amount of the performance pay range to disentangle selection of the referral from any indirect performance pay incentive the OP could have given the referral in an out-of-laboratory contract. Essential is that both the OP and the referral were informed of the change so that any informal contract can be renegotiated and the referral not be indirectly incentivized. In order to investigate first whether this part of the protocol was implemented rigorously, especially when the laboratory was busy, and second whether side payment contracts (to the extent they exist) were in fact renegotiated, we ran an additional set of experiments. There are three treatments: the first informed the OP of the good news about his payment but the referral was told nothing; the second was the full information treatment as described in the experimental protocol; and the third paid the OP according to the performance pay contract. Appendix Table 3 shows the results. If there were side payments indirectly incentivizing referrals, we would anticipate that referrals in treatments 1 and 3 would have better performance than those in treatment 2. This is not the case: there are no significant differences across any of the treatments. The standard errors are large, which may be the result of a relatively small sample size even though the number of observations per treatment is approximately 60% of the size of the treatments in the main study. Moreover, the coefficients on the interaction terms in column (2) are negative, the opposite of what would occur if there were side performance pay contracts, and so is the coefficient on the level effect of the no information to referral treatment. This is consistent with the data already discussed on anticipated transfers between OPs and referrals, showing no informal contracts where the OP pays the referral.

5.2.1 Anticipated Performance

We observed in Table 3 that all OPs in the performance pay treatments respond to incentives by recruiting coworkers more often and recruiting relatives less often. Only high ability OPs, however, recruited referrals who actually performed better on the cognitive task. In this section we use data from the interim survey where OPs were asked how they expected their referrals to perform. The question was simply "How many puzzles do you think he [your referral] will solve correctly without making any mistakes?" The answer is between 0 and 4 puzzles. Column (1) shows that on average OPs thought their referrals would get 3.5 puzzles correct.

Table 5 shows the results of estimating both OLS in columns (1) and (3), and a Heckman selection model of referrals' test score performance on anticipated performance. Columns (1) and (2) show that high ability OPs, those with a normalized test score above zero, are able to predict their referrals' ability. The coefficient on anticipated performance implies that if an OP anticipated a perfect score, the referral did on average .8 of a standard deviation better than if the OP expected 0 correct puzzles. Low ability OPs, on the other hand, are not systematically able to predict their referrals' performance. A caveat applies however since the rainfall instruments are not powerful in the Heckman selection model in the low ability OP sample, as shown in column (4).

The evidence suggests that high ability OPs are able to predict performance, thereby enabling them to effectively screen network members, and that they choose high ability referrals when properly incentivized. We would therefore expect that this sub-group would report significantly higher anticipated performance. We estimate equation 6 where y_{ik} is anticipated performance instead of actual performance. If the above prediction holds, β_2 would be positive and the level effect of the performance pay treatments would not be significantly different from zero.

Table 6 shows the results of estimating equation 6 with anticipated performance. While high ability OPs do anticipate greater referral performance than low ability OPs differentially in performance pay treatments ($\beta_2 > 0$), the level effect is somewhat surprisingly: low ability OPs in high stakes performance pay treatments report a lower anticipated performance relative to low ability OPs in fixed pay treatments, as shown in columns (1) through (3). This means that the total effect for high performing OPs is not significantly different from zero.

Why does this result diverge from the expected coefficients? Columns (5) and (6) of Table 6 and Table 7 provide evidence that the cognitive treatment also induces OPs to reflect more seriously on the anticipated performance of their referrals. In particular, most OPs are overly optimistic of their referrals' ability to successfully complete all four puzzles. Figure (1) shows a histogram of the anticipated number of correct puzzles and the actual number of correct puzzles completed by referrals. Few OPs report that they expect their referral to get zero or one puzzle correct. A majority are sufficiently confident to say their referral will get all four puzzles correct. Actual performance, however, falls far short of reported expectations.

We argue that original participants who are randomly given a finder's fee contingent on performance are systematically less likely to be overly optimistic of their referrals' performance. This may happen as the performance incentive induces greater consideration of friends' abilities, and could explain an overall lower anticipated performance by low ability OPs and an insignificant difference between high ability OPs in high stakes treatments versus fixed pay treatments, as seen in Table 6. To provide evidence of this hypothesis, we provide a number of pieces of evidence. First, column (5) of Table 6 shows that referrals recruited by OPs in the cognitive high performance pay treatment group are less likely to be overly optimistic. Overly optimistic is defined as the OP expecting the referral to perform better than he actually did. This suggests that OPs in performance pay treatments may have more carefully reflected upon how well their referral will perform on the cognitive task.

Several OPs responded to the question about anticipated performance with "I don't know."[26] Column (6) of Table 6 shows that OPs in performance pay treatments are less likely to report that they do not know how well their referral will perform. We argue that the inability to report an expectation on a referral's performance is additional evidence of how much an OP can predict performance. However, it also introduces a potential attrition bias in the results in tables 7, and 9 and must be viewed as suggestive evidence.

We saw in Table 3 that incentivized OPs were more likely to recruit coworkers. If the expected performance of coworkers varies systematically compared to relatives or friends, this may also explain the result in Table 6. In particular, we may expect that OPs would be overly optimistic of their relatives. An alternative hypothesis is that coworkers are better able to observe each other's work-related skills than relatives. While we are unable to disentangle those two explanations, we do observe in Table 7 that coworkers are systematically expected to perform worse and relatives better than the omitted category of friends and neighbors. However, high ability OPs are less likely to demonstrate this systematic bias towards expecting relatives to perform well. Column (2) attempts to demonstrate that relatives do not in fact out perform other referrals, as this would be inconsistent with the results in Tables 3 and 4. Relatives recruited by low ability OPs are significantly more likely to under perform relative to expectations. However, while the signs of the coefficients are all consistent with the idea that the anticipated performance is out of alignment with actual performance, the dependent variable is quite noisy and the other estimates are not significant at conventional levels.

Consistent with the evidence that high ability OPs recruit productive referrals when properly incentivized, low ability OPs do not appear able to predict their referrals' perfor-

[26] These observations are treated as censored in the Heckman model in columns (1) through (4).

mance. However, when incentivized they are less likely to be overly optimistic about their referrals' performance. The evidence presented above highlights two channels: first, all performance pay OPs are more likely to have carefully reflected upon their referrals' expected performance, resulting in fewer responses of "I don't know" to the anticipated performance question, and a more accurate match between anticipated performance and true performance; second, OPs systematically expect coworkers to perform worse than relatives or friends. Given that performance pay induces all OPs to refer coworkers, this contributes to the finding in Table 6 that incentivized, low ability OPs expect their referrals to perform badly. However, conditional on the overall pessimism (or realism) shared by incentivized OPs, high ability incentivized OPs have a more positive expectation of referral performance than their low ability colleagues, suggesting that they are choosing referrals who they expect to perform well.

6 Reliability and Referral Characteristics

Reliability

An important characteristic of a good employee, and therefore a good referral as argued by some sociologists, is reliability and trustworthiness. That is, an OP must be confident that the referral will perform well on the job and realize his potential as a good match. The structure of the contract in the experiment emphasizes this aspect of referral choice. The OP could earn a bonus based on the referral's performance, but the referral himself has no performance incentive. Therefore the OP must select a referral who will exert effort without any monitoring by the OP. As already discussed, the OP can minimize this principle-agent problem by either choosing inherently reliable referrals or by introducing a side contract where the referral is paid by the OP based on his performance.[27] We start this section by investigating whether OPs selected

[27] In the theoretical framework presented in this paper, the optimal choice between the two will depend on how reliability is distributed with ability and private transfers.

more reliable referrals as a response to incentives.

Reliability is measured two ways in this study: first, by the referral's play as player 2 in the trust game, where referrals similarly take a hidden, unincentivized, and unmonitored action which can directly contribute to the OPs payoff. Second, we also observe cognitive ability treatment referrals perform the effort task. Table 8 shows how referrals play the trust game with their OPs. Recall that referrals play the role of player 2 in the trust game, deciding how much to return to player 1 for eight different possible allocations. The dependent variable used in this specification is the average transfer across all eight decisions, normalized separately at each Rs 10 interval.

Columns (3) and (4) show that high ability OPs in performance pay treatments refer individuals who transfer significantly more to their OPs. The literature usually interprets player 2's decisions as a measure of trustworthiness. However, the measure may conflate trustworthiness with other preferences such as altruism. Therefore, column (5) presents the results of a specification which also includes both the amount the OP and the referral decided to transfer to one another in the dictator game. These measures should capture the altruistic relationship between the OP and referral. The effect of performance pay among high ability OPs continues to be positive and statistically significant. We interpret this as evidence consistent with the trust game measuring the referral's trustworthiness.[28] Recall that each referral played the trust game with his OP and then another randomly selected OP. Column 9 shows that referrals of incentivized, high ability OPs are more trustworthy vis-a-vis random partners, providing further evidence of the interpretation of referral trustworthiness as reliability and not reciprocity towards OPs who just did them a favor.

Consistent with this result, we return to Table 4 where in columns (9) and (10) we show

[28]The result is more precisely estimated and similar in magnitude looking at the interaction of OP Cognitive Test Score * Cog Perf Pay.

how referrals recruited by OPs in the cognitive ability treatments perform on the peanut task. If incentivized OPs recruited individuals who would perform well and consistently, as we have argued, they would likely also perform well on the peanut task. This is in spite of the fact that the OPs did not know their referral would be asked to perform the effort task, and there was accordingly no incentive attached to the task. Column (9) shows that the interaction between OP ability and high stakes performance pay is positive and significant.

Characteristics of Referrals

Do referrals recruited by performance pay OPs differ in other dimensions? Appendix Table 4 looks at other characteristics, including other cognitive tests, age, education and income. Panel A shows how the referral's performance on the puzzle test correlates with these characteristics. Columns (1) and (3) show that the two cognitive ability tests we included in the background survey, the Raven Test and the Digit Span Test, are positively and significantly correlated with puzzle performance. Panel B shows the same specification as used in Tables 4 and 9 with alternative dependent variables. Column (1) shows that high ability OPs in the high stakes treatment referred individuals who also performed better on the Raven test. Since the Raven test asks participants to identify patterns, it is the closest conceptually to the puzzle test. Education is also positively correlated with referral puzzle performance, as shown in column 5. Similar to the digit span test, however, we do not observe any significant differences in these characteristics by treatment type.

Columns 7 and 9 highlight an interesting aspect of the cognitive ability task used in this study. Referrals' age and income are both negatively correlated with puzzle performance[29]. OPs therefore had to find referrals who would do well on the task specifically, not just the most successful individual in the network - as income would proxy for. We also see that high

[29]The negative correlation between income and puzzle performance is largely driven by the age effect.

ability OPs in the low stakes cognitive ability treatment in particular respond to incentives by recruiting younger referrals - consistent with the finding in Table 4. Finally, columns (11) and (12) look at how referrals play the trust game with their OP. We find no correlation between puzzle performance and transfers in the dictator game, nor any systematic differences across treatment type. This highlights that the effect in Table 8 is unlikely to reflect altruism between the referral and his OP but instead a measure of reliability or trustworthiness.

Identifying Good Referrals

As discussed in the introduction, theoretical models suggest that social networks may smooth information asymmetries as employees can identify referrals who are productive in a way which is hard to observe for a prospective employer. Here, we have provided evidence that high ability OPs do identify high ability referrals when properly incentivized. However, we have said little about whether the information they use is something which should be easy or difficult for an employer to observe. In fact, we have also provided evidence that some easy to observe characteristics like age and education are strong predictors of performance.

While we cannot mimic the full range of information that any prospective employer could observe through resumes, interviews, and other recruitment methods, we can at least discuss whether the productivity characteristics which our high ability OPs are identifying can be explained by the other characteristics in our data. To test this, we regress

$$y_{ik} = \beta_0 + \beta_1\theta_k + \beta_2 perf_k * \theta_k + \phi_k + X_k\gamma + W_i\delta + \epsilon_{ik}$$

where θ_k, ϕ_k, and X_k is $\mathrm{OP}_k's$ ability, treatment group, and characteristics as before, but now we control also for a vector of the referral's characteristics, W_i, observable in our data. Thus, we will test whether high ability, incentivized OPs bring in referrals who are highly productive in a way which is hard to observe in the data. Table 9 presents the results of this estimation. In column (1), we reproduce the analysis from Table 4. Column (2) adds in characteristics which should be easily observable in a resume and allow for a flexible relationship between these characteristics and productivity: specifically, we add in indicators for the referral's 5-year age group, each education level, and occupational category. As the reader can evaluate, these resume controls do not impact the size or precision of the coefficient estimate, suggesting that what OPs are identifying is something that would be hard to observe in a resume. The rest of table 9 includes other covariates which may be less frequent on a resume but which we can observe and may be correlated with other characteristics observable to prospective employers. Column (3) adds the referral's performance on the Ravens and Digit Span tests, while column (4) includes the referral's transfer during the trust game. Column (5) includes the referral's income as well. As before, referral performance on the cognitive tests is associated with referral performance on the puzzle task. However, in all specifications, β_2 remains statistically significant and the point estimate does not change dramatically. That is, highly skilled, incentivized OPs are bringing in referrals who are highly skilled in ways which are hard to predict by the covariates in our data, even though some of those covariates are highly correlated with puzzle task performance. These results suggest that networks are identifying skillsets which may indeed be hard for prospective employers to observe.

7 Conclusion

Job networks are a ubiquitous phenomenon in labor markets, in both developed and developing countries. Individuals serve as explicit references for other individuals and also as conduits of information about new job postings. While a large literature in economics and sociology have described the presence of these networks, we know little about how these networks select referrals. Simply understanding that social connections facilitate job allocation says little about the welfare consequences of this system, both from the perspective of potential workers and firms. This paper begins to look inside the black box of social networks and concretely identifies the efficiency gains from using job networks to spread jobs under a variety of incentive schemes. First, financial incentives do lead to a change in the type of referral who is chosen: coworkers are more likely to be referred at the expense of relatives. This points to a tradeoff individuals may face between a potentially more productive referral and a referral who has other network-oriented benefits.

The analysis also indicates that performance pay induces employees to refer more productive workers, but only employees with an initially high ability respond to incentives. This suggests directly that high ability workers have information on the capabilities of network members and that they face a trade-off between the friend who will reward them most for the referral (either in terms of monetary or social payments) and the friend who they think will perform well on the task. Low ability coworkers, in contrast, do not respond to performance incentives by referring a high quality referral, which could in principle result either because they do not have the capacity to screen their network members effectively or because they do not have enough high ability coworkers in their network to take advantage of the incentive. We further present evidence that low ability workers are unable to predict the performance of their referrals (in contrast to high ability workers, who can do so successfully). This suggests that a lack of information may hamper the effectiveness of low ability individuals. This interpretation is supported by evidence that OPs of all ability levels appear to spend more time considering their referral's capabilities when incentivized, as incentivized OPs are more likely to have an opinion on how their referrals will perform and are better able to predict their performance.

Taken together, the evidence suggests that incentives induce employees to exploit informational advantages on behalf of the firm. More broadly, the responsiveness of network members to incentives also suggests that it is reasonably easy to affect how social networks function and job opportunities which are spread through informal channels do not necessarily get "stuck" in family networks. The results in this paper are important for firms but they also imply that incentives can precipitate a social network to behave more efficiently. This could also be of use for policymakers looking to use social networks to disseminate other types of goods or information, such as agricultural extension services in developing countries.

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Table 1: Randomization Check

	OP Treat 1	OP Treat 2	OP Treat 3	OP Treat 4	OP Treat 5	OP Treat 6	Constant	N	P value of joint test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age of Resp	-0.344	-0.599	1.164	0.215	0.742	-0.074	29.84	829	0.87
	(1.171)	(1.181)	(1.373)	(1.135)	(1.186)	(1.152)	(0.81)		
Resp is literate	-0.016	-0.002	-0.046	-0.014	-0.011	0.005	0.934	831	0.91
	(0.033)	(0.033)	(0.039)	(0.032)	(0.034)	(0.033)	(0.023)		
Resp had 5 or less years of schooling	0.056	0.037	0.023	0.049	0.057	0.014	0.132	831	0.85
	(0.047)	(0.047)	(0.055)	(0.045)	(0.047)	(0.046)	(0.032)		
Resp had 5-10 yrs schooling	-0.029	0.006	-0.030	-0.087	-0.097	0.002	0.537	831	0.49
	(0.062)	(0.063)	(0.073)	(0.060)	(0.063)	(0.061)	(0.043)		
Resp was married	-0.115	-0.124	-0.038	-0.037	-0.125	-0.066	0.574	831	0.29
	(0.062)	(0.063)	(0.073)	(0.060)	(0.063)	(0.061)	(0.043)		
Resp was employed	-0.012	0.010	0.061	-0.006	-0.009	0.072	0.897	831	0.12
	(0.035)	(0.036)	(0.042)	(0.034)	(0.036)	(0.035)	(0.024)		
Resp is sole earner in HH	-0.064	-0.050	-0.052	-0.029	0.026	-0.056	0.508	757	0.83
	(0.066)	(0.066)	(0.076)	(0.064)	(0.067)	(0.064)	(0.045)		
Ln of Income earned by respondent	-0.186	-0.041	0.458	0.089	-0.033	0.649	6.907	831	0.09
	(0.301)	(0.303)	(0.353)	(0.291)	(0.305)	(0.296)	(0.207)		
Resp is HH Head	-0.036	-0.017	0.007	-0.048	-0.064	0.015	0.331	831	0.82
	(0.058)	(0.058)	(0.068)	(0.056)	(0.059)	(0.057)	(0.040)		
Resp is 18-25 Years Old	0.075	-0.004	0.009	-0.010	0.036	0.026	0.343	829	0.83
	(0.060)	(0.061)	(0.071)	(0.058)	(0.061)	(0.059)	(0.042)		
Number of Ravens Correct	-0.016	-0.136	0.028	-0.116	-0.198	-0.108	2.000	831	0.56
	(0.119)	(0.120)	(0.139)	(0.115)	(0.120)	(0.117)	(0.082)		
Number of Digits Correct	0.258	-0.256	-0.493	-0.577	-0.324	-0.579	12.324	830	0.42
	(0.433)	(0.437)	(0.509)	(0.420)	(0.439)	(0.427)	(0.298)		
Normalized Test Score on All Puzzles	0.141	0.119	0.000	-0.194	0.014	0.000	-0.011	563	0.06
	(0.149)	(0.150)	(0.000)	(0.146)	(0.150)	(0.000)	(0.118)		
Different puzzle types	-0.022	-0.039	0.000	0.008	-0.018	0.000	0.268	565	0.93
	(0.065)	(0.066)	(0.000)	(0.064)	(0.066)	(0.000)	(0.052)		
Normalized Score for Peanuts	0.000	0.000	0.000	0.000	0.000	-0.022	0.011	261	0.86
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.124)	(0.087)		
Puzzle Test Scores of Non-Attriting OPs	0.135	0.130	-0.033	-0.032	0.000	0.000	-0.008	408	0.65
	(0.150)	(0.154)	(0.173)	(0.148)	(0.000)	(0.000)	(0.110)		
Ln Income Among Non-Attriting OPs	0.074	0.002	0.575	0.075	0.136	0.843	6.660	597	0.20
	(0.375)	(0.385)	(0.436)	(0.369)	(0.387)	(0.372)	(0.263)		

Notes

1 Columns 1-6 are the coefficients from a regression and column 7 is the constant. The omitted group is treament group 7. Column 9 shows the p value for the joint test of significance of all the treatment dummies.

2 The following describes the treatment groups. The first five, OP treatments 1 - 5, are cognitive ability: OP treatment 1 is high fixed payment; OP treatment 2 low fixed payment; OP treatment 3 very low fixed payment; OP treatment 4 high performance pay; OP treatment 5 low performance pay. The final two, OP treatments 6 and 7, are effort task: OP treatment 6 is low fixed payment and OP treatment 7 is low performance pay.

Table 2: Participation in Second Round of survey

	(1)		(2)		(3)		(4)	
OP Test Score * OP Treat 4 (Cog High Perf)			0.121	***				
			(0.043)					
OP Test Score			-0.009					
			(0.021)					
OP Treatment 1: Cog High Fixed	0.043		0.040					
	(0.051)		(0.051)					
OP Treatment 4: Cog High Perf Pay	-0.003		0.022		0.123	**	-0.113	*
	(0.049)		(0.050)		(0.060)		(0.064)	
OP Treatment 5: Cog Low Perf Pay	-0.005		-0.013					
	(0.052)		(0.051)					
OP Treatment 6: Effort Low Fixed	-0.028							
	(0.050)							
OP Treatment 7: Effort Low Perf Pay	-0.014							
	(0.049)							
Constant	0.842	***	0.799	***	0.852	***	0.717	***
	(0.077)		(0.091)		(0.105)		(0.154)	
N	831		563		307		256	
Sample	ALL		COG		COG HIGH		COG LOW	

Notes

1 The dependent variable is 1 if the respondant returned to the laboratory with a referral. The coefficients are from a linear probability model where week indicators are also included.

2 The excluded treatment category is cognitive ability, fixed performance low (pooled low and very low).

3 Columns (2)-(4) restrict the sample to OPs in the cognitive ability treatments. Column (3) restricts the sample to high ability OPs (with a normalized test score above 0) while column (4) includes only OPs with a normalized test score less than 0.

Table 3: Relationship between OP and Referral

	First Stage		Co-worker		Relative		Friend	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Days with Rainfall during OP's Referral Cycle	-0.653 ***	-0.571 ***						
	(0.205)	(0.161)						
Rainfall on OP Arrival Day	0.436 *	0.432 **						
	(0.241)	(0.205)						
OP Treatment 1: Cog High Fixed		0.096		-0.013		-0.049		-0.019
		(0.174)		(0.044)		(0.047)		(0.065)
OP Treatment 4: Cog High Perf Pay	-0.045	-0.027	0.078 **	0.078 *	-0.086 **	-0.082 *	0.022	-0.005
	(0.143)	(0.162)	(0.037)	(0.042)	(0.039)	(0.045)	(0.055)	(0.062)
OP Treatment 5: Cog Low Perf Pay		-0.082		0.002		0.056		-0.078
		(0.171)		(0.045)		(0.048)		(0.066)
OP Treatment 6: Effort Low Fixed		-0.039		0.029		-0.030		-0.055
		(0.175)		(0.044)		(0.047)		(0.066)
OP Treatment 7: Effort Low Perf Pay		-0.088		0.005		0.004		-0.095
		(0.174)		(0.044)		(0.047)		(0.066)
N	547	825	564	825	564	825	564	825
Mean			0.145		0.132		0.618	
SD			0.352		0.339		0.487	
Chi^2 statistic: joint test of rainfall variables	12.75	15.74						
Mills: Coefficient			-0.078	-0.147	-0.068	-0.037	0.099	0.026
Mills: SE			0.144	0.126	0.150	0.135	0.213	0.187
N Censored Obs			157	231	157	231	157	231

Notes

1 The excluded treatment category is cognitive ability, fixed performance low (pooled low and very low).

2 An OP's "Referral Cycle" is the three days the OP had to choose from to bring in his referral. The exclusion restriction uses the number of days, from 0 to 3, where there was non-zero rainfall among the potential referral days for each OP.

3 Additional covariates of each Original Participant include: indicators for age group (18-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54 and 55 and above); highest grade level attained, ln of income +1 of respondent in previous month; the performance on the Raven's Test and Digit Span Test; indicator dummies for week of participation in the study and an indicator for partication during a weekend.

4 Relative, co-worker, and friend are dummy variables indicating the relationship between the Original Participant and the referral. Estimates are the result of a heckman two step procedure using rainfall instruments as shown in Table 3.

5 Columns (1) and (2) show the probit coefficients, not marginal effects.

6 Columnns (3) through (8) used the heckman two step methodology with the rainfall variables from columns (1) and (2) as exclusion restrictions.

Table 4: Cognitive Ability Task Performance and Treatment Type

	OLS				Selection Model				Peanut Performance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OP Cognitive Test Score * Cog Perf Pay				0.140				0.244 *		-0.019
				(0.100)				(0.131)		(0.109)
OP Cognitive Test Score * Cog High Perf Pay			0.127				0.343 **		0.310 *	
			(0.120)				(0.157)		(0.161)	
OP Cognitive Test Score		0.095 *	0.061	0.030		0.154 **	0.058	0.039	-0.018	0.049
		(0.053)	(0.061)	(0.071)		(0.071)	(0.067)	(0.089)	(0.069)	(0.075)
OP Treatment 1: Cog High Fixed	-0.136	-0.139			-0.026	-0.039				
	(0.130)	(0.130)			(0.177)	(0.170)				
OP Treatment 4: Cog High Perf Pay	-0.144	-0.134	-0.116		-0.154	-0.123	-0.098		-0.188	
	(0.129)	(0.129)	(0.113)		(0.167)	(0.162)	(0.126)		(0.129)	
OP Treatment 5: Cog Low Perf Pay	0.083	0.084			0.036	0.038				
	(0.139)	(0.138)			(0.180)	(0.174)				
Treatments 4 and 5: Cog Perf Pay				0.015				-0.040		-0.109
				(0.098)				(0.125)		(0.103)
N	406	406	406	406	564	562	562	562	562	562
Mean	0.056									
SD	1.000									
Chi^2 statistic: joint test of rainfall variables					12.275	13.032	13.065	13.063	13.057	13.057
Mills: Coefficient					1.336	1.290	1.112	1.283	0.948	0.477
Mills: SE					0.563	0.520	0.432	0.507	0.449	0.377
N Censored Obs					158	156	156	156	155	155

Notes

1 Also included are individual characteristics of the Original Participant, as defined in Table 3, plus the type of puzzle task administered to the OP.

2 Columns (9) and (10) use the normalize performance on the peanut task as the dependent variable in a specification otherwise identidical to those in columns (7) and (8).

Table 5: OP Ability to Predict Performance

	High Ability OPs			Low Ability OPs	
	(1)		(2)		(3)	(4)
OP's Anticipated Performance: Puzzle	0.203	**	0.186	**	0.040	0.035
	(0.102)		(0.093)		(0.091)	(0.081)
N	197		278		153	230
Mean	3.520				3.208	
SD	0.703				0.883	
Chi^2 statistic: joint test of rainfall variables			13.608			4.139
Mills: Coefficient			1.006			0.221
Mills: SE			0.426			0.531
N Censored Obs			81			77

Notes

1 The independent variable is the number of puzzles, from 0 to 4, that the OP expects the referral to solve correctly in the allotted time. The dependent variable is the measure of actual performance used in Table 4.

2 Columns (1) and (3) are OLS and columns (2) and (4) are estimates from a heckman two step selection model.

3 Columns (1) and (3) restrict the sample to high ability OPs: those with a normalized test score greater than 0. Columns (2) and (4) are restricted to OPs with a normalized test score less than 0.

Table 6: OP's Anticipated Performance on Cognitive Ability Task and Treatment Type

	Selection Model: Anticipated Performance				Overly optimstic	Don't Know Performance
	(1)	(2)	(3)	(4)	(5)	(6)
OP Cognitive Test Score * Cog Perf Pay				0.141		
				(0.097)		
OP Cognitive Test Score * Cog High Perf Pay			0.296 **		0.015	-0.024
			(0.132)		(0.077)	(0.047)
OP Cognitive Test Score		0.220 ***	0.137 **	0.152 **	-0.029	0.000
		(0.053)	(0.056)	(0.069)	(0.033)	(0.020)
OP Treatment 1: Cog High Fixed	-0.003	-0.027				
	(0.133)	(0.123)				
OP Treatment 4: Cog High Perf Pay	-0.257 **	-0.241 **	-0.229 **		-0.109 *	-0.060 *
	(0.128)	(0.120)	(0.105)		(0.062)	(0.037)
OP Treatment 5: Cog Low Perf Pay	-0.013	-0.001				
	(0.140)	(0.130)				
Treatments 4 and 5: Cog Perf Pay				-0.133		
				(0.093)		
N	564	562	562	562	562	562
Mean	3.384				0.402	
SD	0.801				0.491	
Chi^2 statistic: joint test of rainfall variables	9.020	9.621	8.963	9.352	9.461	12.047
Mills: Coefficient	0.881	0.680	0.606	0.739	-0.212	0.008
Mills: SE	0.471	0.423	0.404	0.435	0.237	0.134
N Censored Obs	213	211	211	211	212	155

Notes

1 Also included are individual characteristics of the Original Participant, as defined in Table 4.

2 Column (5) shows the same specification as in columns (1) through (4) where the dependent variable is an indicator for the OP being overly optimistic. Overly optimistic is defined as expecting the referral to perform better than he actually did.

3 Column (6) again uses the same specification where the dependent variable is an indicator for whether the OP responded that he did not know how well his referral will perform on the cognitive task.

Table 7: OP Anticipated Performance by Relationship

	Anticipated Performance		Anticipated Peformance - Actual Performance	
	(1)		(2)	
OP and Referral are Coworkers	-0.333	***	-0.144	
	(0.127)		(0.217)	
OP and Referral are Coworkers * OP Test Score	-0.261	**	-0.285	
	(0.117)		(0.201)	
OP and Referral are Relatives	0.227	*	0.371	*
	(0.118)		(0.204)	
OP and Referral are Relatives * OP Test Score	-0.295	***	-0.271	
	(0.114)		(0.198)	
OP Test Score	0.306	***	0.140	
	(0.058)		(0.096)	
N	505		506	
Mean			0.365	
SD			1.345	
Chi^2 statistic: joint test of rainfall variables	11.393		11.549	
Mills: Coefficient	0.653		-0.646	
Mills: SE	0.377		0.619	
N Censored Obs	155		156	

Notes

1 The dependent variable in column (1) is the number of puzzles, from 0 to 4, that the OP expects the referral to solve correctly in the allotted time. The dependent variable in column (2) is anticipated performance as in column (1) minus the number of puzzles, from 0 to 4, that the referral actually got correct.

2 All columns present estimates from a heckman two step selection model using rainfall as exclusion restrictions as in Table 2.

3 All specifications exclude observations where the OP responded that he did not know how well the referral would perform.

4 Also included are control variables as listed in Table 4.

Table 8: Trust Game Play and Treatment Type

	(1)	(2)	(3)	(4)	(5)	(6)
OP Cognitive Test Score * Cog Perf Pay				0.240 **		
				(0.103)		
OP Cognitive Test Score * Cog High Perf Pay			0.257 *		0.216 *	0.273 **
			(0.142)		(0.114)	(0.138)
OP Cognitive Test Score		-0.016	-0.071	-0.131 *	-0.093	-0.017
		(0.058)	(0.060)	(0.071)	(0.059)	(0.059)
OP Treatment 1: Cog High Fixed	0.035	0.047				
	(0.134)	(0.133)				
OP Treatment 4: Cog High Perf Pay	0.038	0.037	0.041		0.008	0.012
	(0.127)	(0.127)	(0.112)		(0.105)	(0.109)
OP Treatment 5: Cog Low Perf Pay	-0.083	-0.086				
	(0.138)	(0.137)				
Treatments 4 and 5: Cog Perf Pay				-0.044		
				(0.097)		
Referral's Transfer during Dictator Game					0.0102 ***	
					(0.0013)	
OP's Transfer During Dictator Game					0.0008	
					(0.0013)	
N	552	550	550	550	549	550
Mean of Pre-Normalization Transfer Amount at Rs. 40	56.313					
SD	31.663					
Chi^2 statistic: joint test of rainfall variables	11.185	12.002	12.072	12.155	12.160	12.072
Mills: Coefficient	-0.142	-0.005	0.139	0.020	-0.403	0.502
Mills: SE	0.459	0.432	0.401	0.417	0.388	0.386
N Censored Obs	157	155	155	155	155	155

Notes

1 All specifications use the heckman selection model. Also included are individual characteristics of the Original Participant, as defined in Table 4.

2 Excludes pairs who did not choose to participate in economic games.

3 Dependent variable in columns (1)-(5) is an index constructed from each referral's decisions in the trust game for all possible OP transfers. At each 10 Rs interval, the transfer amount was normalized and the index takes the average of the 8 decisions.

4 The dependent variable in Column 6 is an analagous index as in columns (1)-(5) but uses each referral's decisions in the trust game with his randomly paired partner, someone else's OP.

Table 9: Puzzle Performance with Referral Characteristics

	(1)		(2)		(3)		(4)		(5)	
OP Cognitive Test Score * Cog High Perf Pay	0.352	**	0.380	***	0.312	**	0.343	**	0.347	**
	(0.158)		(0.143)		(0.140)		(0.142)		(0.143)	
OP Cognitive Test Score	0.053		0.014		0.013		-0.002		-0.008	
	(0.067)		(0.062)		(0.060)		(0.061)		(0.061)	
OP Treatment 4: Cog High Perf Pay	-0.100		-0.178		-0.161		-0.153		-0.161	
	(0.143)		(0.129)		(0.125)		(0.126)		(0.127)	
Referral's Ravens Test Score					0.146	***	0.173	***	0.173	***
					(0.052)		(0.054)		(0.054)	
Referral's Digit Span Score					0.058	***	0.060	***	0.060	***
					(0.013)		(0.013)		(0.013)	
Referral's Transfer during Dictator Game							-0.051		-0.049	
							(0.046)		(0.046)	
Ln Referral Income									-0.047	
									(0.039)	
N	563		556		556		544		544	
Resume Controls	NO		YES		YES		YES		YES	
Chi^2 statistic: joint test of rainfall variables	12.600		12.563		12.563		11.545		11.545	
Mills: Coefficient	1.114		0.869		0.863		0.859		0.880	
Mills: SE	0.440		0.396		0.384		0.389		0.392	
N Censored Obs	156		156		156		156		156	

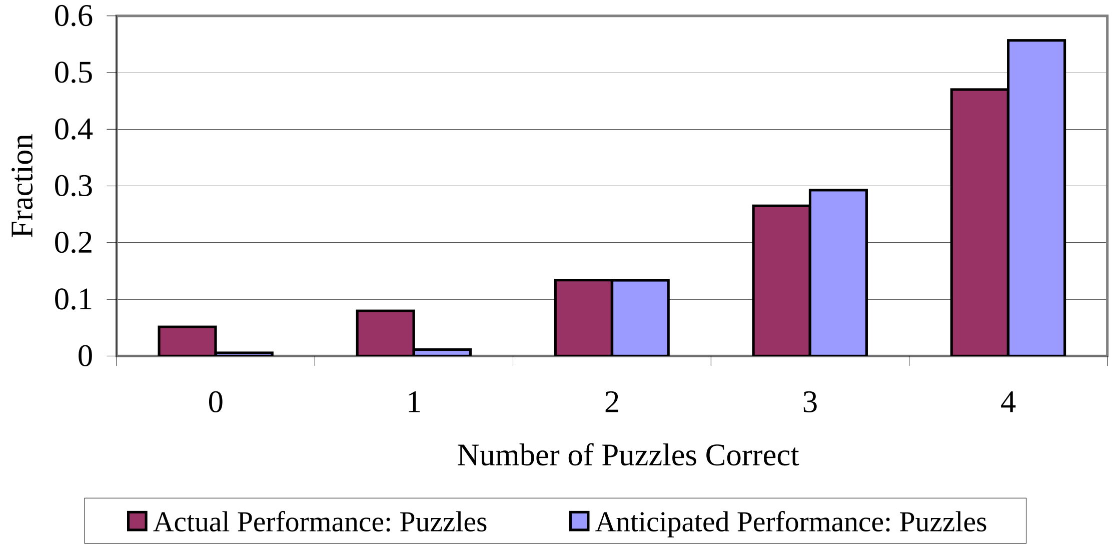
Notes

1 All specifications use the heckman selection model. Also included are individual characteristics of the Original Participant, as defined in Table

2 Resume controls include the following characteristics of the referral: (i) indicators for 5 year age groups; (ii) indicators for each educational level and (iii) occupation code.

3 Ln Referral Income is the ln of referral income plus 1.

Figure 1: Anticipated and Actual Performance



Appendix Table 1: Peanut Task Performance and Treatment Type

	Selection Model		
	(1)	(2)	(3)
OP Peanut Test Score * Peanut Perf Pay			-0.140
			(0.164)
OP Peanut Test Score		0.064	0.141
		(0.112)	(0.107)
OP Treatment 7: Peanut Perf Pay	-0.156	-0.224	-0.231
	(0.142)	(0.145)	(0.143)
N	261	257	257
Mean	-0.246		
SD	(0.959)		
Chi^2 statistic: joint test of rainfall variables	3.079	2.567	3.052
Mills: Coefficient	0.529	0.697	0.623
Mills: SE	0.768	0.790	0.754
N Censored Obs	74	73	73

Notes

1 Also included are individual characteristics of the Original Participant, as defined in Table 3.

Appendix Table 2: Cognitive Ability Task Performance Robustness

	(1)		(2)		(3)		(4)	
OP Cognitive Test Score * Cog Perf Pay							0.226	**
							(0.103)	
OP Cognitive Test Score * Cog High Perf Pay					0.350	**		
					(0.164)			
OP Cognitive Test Score			0.161	**	0.061		0.033	
			(0.078)		(0.071)		(0.073)	
OP Treatment 1: Cog High Fixed	-0.013		-0.026					
	(0.193)		(0.188)					
OP Treatment 4: Cog High Perf Pay	-0.158		-0.126		-0.099			
	(0.182)		(0.179)		(0.132)			
OP Treatment 5: Cog Low Perf Pay	0.030		0.032					
	(0.196)		(0.192)					
Treatments 4 and 5: Cog Perf Pay							0.015	
							(0.098)	
N	564		562		562		562	
Chi^2 statistic: joint test of rainfall variables	12.275		13.032		13.065		13.065	
Mills: Coefficient	1.451		1.420		1.190		0.915	
Mills: SE	0.634		0.595		0.465		0.381	
N Censored Obs	158		156		156		156	

Notes

1 Temperature on day the referral performed the cognitive ability task is also included in specifications (1)-(4).

2 Also included are individual characteristics of the Original Participant, as defined in Table 4.

Appendix Table 3: Experiment with Full Info, No Info and Perf Pay

	Selection Model	
	(1)	(2)
OP Cognitive Test Score * No Info		-0.106
		(0.251)
OP Cognitive Test Score * Perf Pay		-0.145
		(0.280)
OP Cognitive Test Score		0.236
		(0.188)
Treatment: No Information to Referral	-0.103	-0.102
	(0.370)	(0.296)
Treatment: Performance Pay to OP	0.128	0.145
	(0.380)	(0.309)
N	193	193
Chi^2 statistic: joint test of rainfall variables	8.549	9.024
N Censored Obs	68	68

Notes

1 All specifications includes same controls as in Table 4.

Appendix Table 4: Other Referral Characteristics

	Raven Test		Digit Span Test		Education		Age		Ln Income		Dictator Play	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A												
Referral Puzzle Performance	0.257 ***		1.260 ***		0.754 ***		-1.268 ***		-0.375 **		2.423	
	(0.047)		(0.184)		(0.164)		(0.395)		(0.148)		(1.968)	
N	406		406		404		403		406		394	
Panel B												
OP Cognitive Test Score * Cog High Perf Pay	0.227 *		0.225		-0.096		-0.053		-0.269		3.326	
	(0.129)		(0.524)		(0.448)		(1.053)		(0.399)		(5.722)	
OP Cognitive Test Score * Cog Perf Pay		0.083		-0.112		-0.280		-1.558 **		-0.404		3.486
		(0.096)		(0.394)		(0.330)		(0.779)		(0.294)		(4.260)
OP Cognitive Test Score	0.025	0.044	0.084	0.219	0.126	0.240	0.243	0.985 *	0.050	0.206	0.734	-0.127
	(0.055)	(0.064)	(0.224)	(0.264)	(0.191)	(0.223)	(0.455)	(0.527)	(0.170)	(0.197)	(2.452)	(2.962)
OP Treatment 4: Cog High Perf Pay	-0.079		0.133		0.153		-1.028		-0.487		3.884	
	(0.103)		(0.417)		(0.356)		(0.842)		(0.317)		(4.540)	
Treatments 4 and 5: Cog Perf Pay		-0.022		0.076		-0.005		0.173		0.206		-3.868
		(0.090)		(0.371)		(0.313)		(0.738)		(0.276)		(4.055)
N	562	562	562	562	562	562	562	562	562	562	550	550
Mean	2.071		12.545		8.526		28.0		6.664		63.8	
SD	(0.927)		(3.714)		(3.301)		(8.6)		(2.858)		(37.8)	
Chi^2 statistic: joint test of rainfall variables	13.057	13.076	13.057	13.076	12.854	12.933	14.710	14.726	13.057	13.076	12.072	12.155
Mills: Coefficient	0.076	0.047	1.122	1.669	0.525	0.748	-0.463	-0.755	-0.815	-0.472	31.734	34.767
Mills: SE	0.367	0.382	1.484	1.555	1.285	1.335	2.858	2.952	1.128	1.164	15.937	16.899
N Censored Obs	155	155	155	155	157	157	158	158	155	155	155	155

Notes

1 Also included are individual characteristics of the Original Participant, as defined in Table 3.

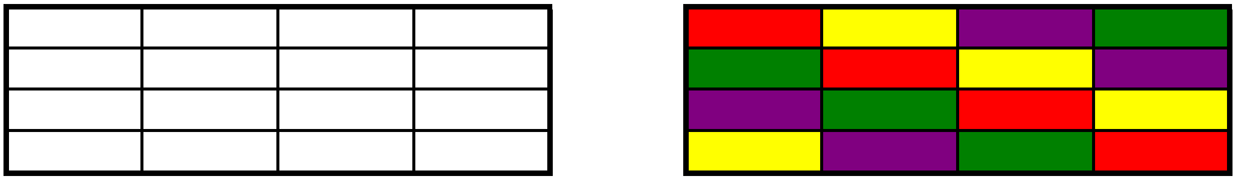
2 Panel A show OLS estimates while Panel B show estimates from the Heckman two step.

3 The Raven Test measure is on a scale of 1 to 3, capturing the number of patterns identified correctly. The Digit Span Test measure is the number of series repeated correctly. Each respondent did two trials for the Digits Forward Game and two trials of the Digits Backward Game. The maximum correct score is 32.

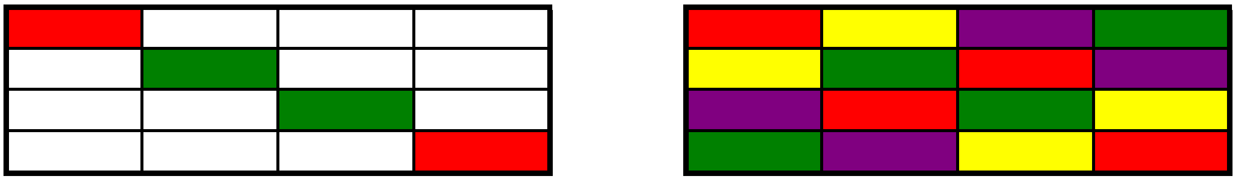
Appendix Figure 1: Puzzles

Initial Setup	Proposed Solution

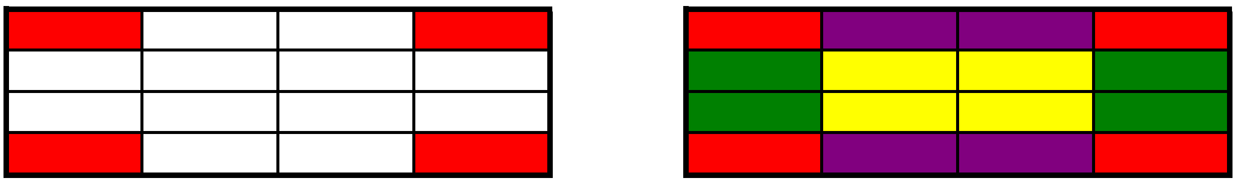
Puzzle A



Puzzle B



Puzzle C



Puzzle D